# MMedAgentBench: A Multi-Stage Benchmark for Evaluating LLM-based Medical Agents

Anonymous ACL submission

## Abstract

Large language models (LLMs) have demonstrated remarkable potential in medical AI through their natural language understanding and reasoning capabilities. However, real clinical practice involves multi-stage, dynamically evolving decision-making where physicians continuously adjust pathways based on updated examination results—far more complex than single-turn question answering. Existing medical benchmarks focus on static scenarios, failing to evaluate LLMs in realistic clinical environments. We present **MMedAgentBench**, a comprehensive benchmark for evaluating LLM-based medical agents in multi-stage clinical decision-making. Unlike previous benchmarks, MMedAgentBench captures the temporal complexity of clinical workflows by simulating authentic patient journeys across multiple diagnostic and treatment stages. The benchmark comprises a high-quality dataset of over 150 de-identified clinical cases from tertiary hospitals, encompassing 500+ clinical stages, with each case meticulously structured into sequential stages and annotated by board-certified physicians. Our evaluation framework simultaneously assesses diagnostic accuracy and resource efficiency, requiring agents to plan examinations and control costs while navigating progressive information disclosure. This enables systematic evaluation of medical agents across dynamic decision-making, cost control, and multi-stage reasoning dimensions, providing a realistic testbed for advancing medical AI toward clinical deployment.

## 1 Introduction

With the rapid advancement of large language model (LLM) technology, application of AI in the medical field has gradually become a focal point. LLMs can process and understand vast amounts medical data. Particularly when faced with diverse and extensive medical information, they have potential in medical decision support through their natural language processing and reasoning capabilities (Thirunavukarasu et al., 2023; Singhal et al., 2023; Zhang et al., 2025). In medicine, doctors must analyze extensive data—including patient histories, symptom presentations, and test results—while making accurate diagnostic and treatment decisions within limited timeframes. This poses a significant challenge for manual processing. LLMs, however, leverage their robust information retrieval and reasoning capabilities to extract relevant insights from vast medical literature and case data, thereby accelerating the diagnostic process and enhancing accuracy (Tian et al., 2025b,a).

Particularly during disease diagnosis, LLM-based agent models can provide effective assistance throughout the multi-stage, dynamic decision-making process. By simulating a doctor's thought process, these agent models adapt subsequent decision paths based on current examination results, enabling more precise decisions in complex, evolving diagnostic scenarios (Li et al., 2024). Doctors must repeatedly adjust diagnostic hypotheses based on varying symptoms and test outcomes to narrow down the most probable conditions. Therefore, LLM-based agents which are capable of flexibly adapting to changes and progressively refining pathways based on each round of test results are particularly crucial in medical clinical decision-making. They can not only process medical texts but also dynamically adjust diagnostic strategies, helping doctor make the most appropriate treatment decisions at every stage.

However, most current LLM models and evaluation methods focus on single-task processing, overlooking the complexity of multi-stage decision-making in medical practice. Existing benchmark evaluation methods predominantly employ static assessments, failing to authentically reflect how doctors dynamically adjust subsequent examinations and treatment plans based on patient conditions, test results, and diagnostic progress during actual

diagnosis. Consequently, the absence of an evaluation framework that accurately mirrors doctors' reasoning and decision-making processes limits the applicability of current evaluation standards when assessing medical diagnostic assistance systems.

To address this issue, our work proposes an innovative evaluation framework designed to overcome the shortcomings of existing methods. Built upon a high-quality dataset comprising over 150 clinical cases and 500+ diagnostic stages, our framework incorporates the characteristics of multi-stage dynamic decision-making, accurately simulating the evolving reasoning and decision paths of doctors during diagnosis. This novel evaluation approach dynamically adjusts diagnostic strategies based on test results at each stage, enabling a more comprehensive assessment of LLM-based agents' capabilities in medical clinical decision-making. Through this methodology, we deliver more precise and thorough evaluations for LLM-based medical models, advancing LLM applications in clinical decision support and better assisting doctors in complex disease diagnosis. Our contributions are threefold:

- We propose **MMedAgentBench**, a benchmark comprising over 150 clinical cases and more than 500 diagnostic stages, designed to systematically evaluate LLM-based medical agents in multi-stage clinical decision-making.
- This benchmark is an LLM-based agent evaluation framework that simulates a doctor's reasoning and judgment during multi-stage decision-making. The LLM plays a central role here, handling dynamic decision-making and outcome updates at each stage.
- We established multiple evaluation dimensions within the benchmark framework, including diagnostic accuracy, cost-effectiveness, and multi-stage decision-making, to provide a more comprehensive assessment of LLM applications in medical diagnosis.

## 2 Related Work

A large body of work has focused on evaluating medical AI systems through benchmark datasets. Early efforts such as MedQA (Jin et al., 2021) and MedMCQA (Pal et al., 2022) introduced large-scale multiple-choice examinations to assess factual medical knowledge, while benchmarks like PubMedQA (Jin et al., 2019) and emrQA (Pampari et al., 2018) targeted question answering from biomedical literature or clinical notes. More recently, comprehensive resources such as MultifacetEval (Zhou et al., 2024) expanded the scope to cover broader clinical reasoning tasks. However, these benchmarks are primarily designed around single-turn question answering or isolated decision-making tasks, which fail to capture the temporal dependencies and sequential nature of real-world clinical workflows.

With the rapid development of large language models (LLMs), increasing research efforts have extended medical agents from static question answering to interactive and workflow-oriented scenarios. Several representative works are particularly noteworthy in this direction.

First, MedAgentBench (Jiang et al., 2025) introduced a virtual electronic health record (EHR) environment for comprehensive evaluation of medical LLM agents. The benchmark covers 300 clinical tasks across 10 types of medical scenarios and supports interactive simulations through FHIR-compliant interfaces. Unlike traditional static QA, MedAgentBench emphasizes tool usage, information retrieval, and task planning capabilities. Second, $\tau$ bench (Yao et al., 2024) highlights the interaction ability of language agents with users and tools in real-world domains. It simulates dynamic dialogues and tool invocation processes, while also proposing new reliability metrics to assess an agent's consistency and robustness across multiple interactions. Finally, AgentClinic (Schmidgall et al., 2024) is specifically designed for medical settings, supporting doctor–patient dialogues, multimodal information acquisition and tool usage. However, it still lacks explicit control over multi-stage patient journeys, making it less aligned with the sequential nature of real-world clinical workflows.

## 3 MMedAgentBench: A Multi-Stage Medical Agent Benchmark

We present MMedAgentBench, a comprehensive benchmark designed to evaluate medical AI agents in realistic multi-stage clinical workflows, shown as Figure 1. Unlike existing medical benchmarks that focus on single-turn question-answering or isolated diagnostic tasks, MMedAgentBench captures the temporal complexity and resource constraints inherent in real-world clinical decision-making. Our benchmark simulates complete patient journeys through multiple clinical stages, where agents must balance diagnostic accuracy with examination costs

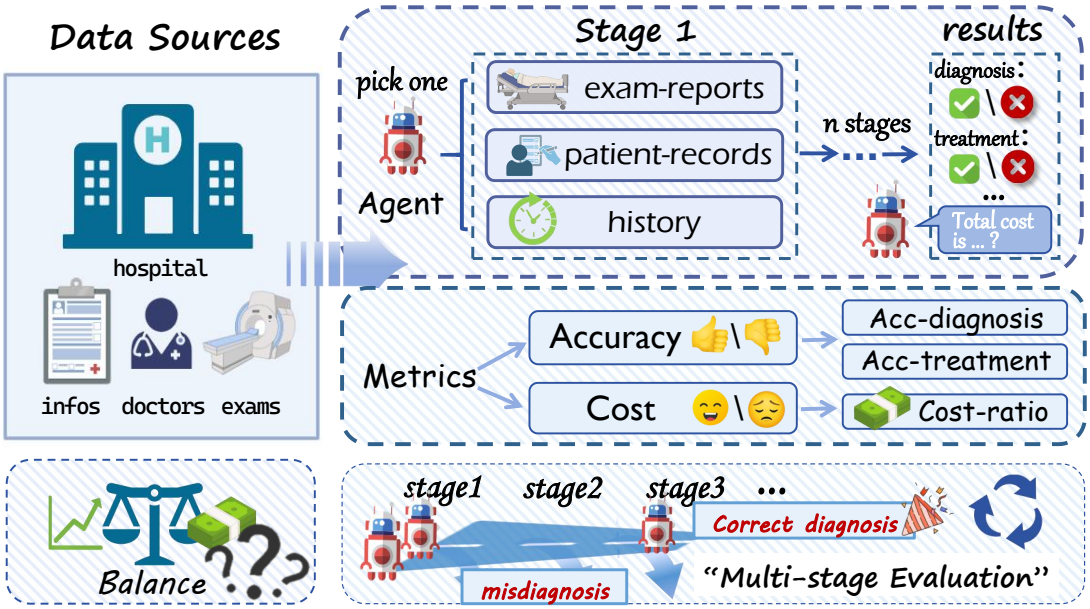


Figure 1: Overview of the MMedAgentBench. The benchmark models real-world clinical decision-making as a sequential, cost-aware reasoning process. Each case unfolds through multiple diagnostic stages, where the agent iteratively selects examinations, interprets results, and updates its diagnostic hypotheses. The evaluation metrics consider both diagnostic accuracy and resource costs, aiming to promote more balanced clinical decision-making.

while maintaining coherent reasoning across stages.

### 3.1 Multi-Stage Clinical Workflow Design

Real clinical practice rarely involves single-point decisions. Patients typically progress through multiple stages of care, each with distinct objectives and available resources. We model this reality by organizing evaluation scenarios into sequential stages $S = \{s_1, s_2, ..., s_n\}$ that mirror actual hospital workflows. Each stage $s_i$ represents a distinct clinical phase such as initial assessment, follow-up examination, or pre-discharge evaluation. The agent must navigate through these stages sequentially, making decisions based on available information at each stage while considering the accumulated evidence from previous stages.

For each stage $s_i$, we define two catalogs: $C_i^{exam}$ containing available diagnostic examinations and $C_i^{patient}$ containing accessible patient records. The agent can select items from these catalogs, with each selection revealing detailed clinical information. Formally, at stage $s_i$, the agent's action space is defined as:

$$A_i = \{\text{pick}(c) : c \in C_i^{exam} \cup C_i^{patient}\} \quad (1)$$
$$\cup \{\text{retrieve}(h) : h \in H_{i-1}\} \quad (2)$$

where $H_{i-1} = \bigcup_{j=1}^{i-1} X_j$ represents the set of historical items selected in all previous stages.

The design of MMedAgentBench addresses several critical challenges in medical AI evaluation. First, temporal coherence is enforced through our stage-wise information access control, where agents cannot access future-stage information, preventing unrealistic perfect foresight scenarios. This mirrors how clinicians must make decisions based on currently available information without knowing future developments.

Second, our historical information retrieval mechanism allows agents to access previously obtained information without additional cost, simulating how clinicians reference prior test results and observations. This design tests an agent's ability to synthesize longitudinal patient data while avoiding redundant examinations.

Finally, the transition between stages is governed by a judgment function $J : (D_i, T_i) \rightarrow \{0, 1\}$, where $D_i$ and $T_i$ represent the diagnosis and treatment outputs at stage $s_i$. The agent proceeds to stage $s_{i+1}$ only if $J(D_i, T_i) = 1$, ensuring that stage-specific clinical objectives are met before progression. This mirrors real clinical workflows where certain milestones must be achieved before proceeding to the next phase of care. The judgment function is implemented using a large language model to assess whether the agent's conclusions adequately address the clinical requirements of the current stage.

### 3.2 Dataset Construction

Our dataset is constructed from authentic clinical cases collected from real hospital settings, ensuring the benchmark reflects genuine medical complexity and decision-making scenarios. We collaborate with multiple tertiary hospitals to obtain de-identified patient records spanning various medical specialties, including internal medicine, surgery, pediatrics, and emergency care. Each case represents a complete patient journey from initial presentation through discharge or transfer, capturing the full spectrum of clinical decision-making.

The raw clinical data undergoes a rigorous structuring process to transform unstructured medical records into our standardized format. We employ a structured representation that separates examination reports from patient records, each organized by clinical stages. For each item $x$ in the dataset, we define a tuple $(title_x, details_x, price_x, stage_x)$ where $title_x$ serves as the unique identifier, $details_x$ contains the complete clinical information, $price_x \in \mathbb{R}^+$ represents the associated cost based on actual hospital pricing, and $stage_x \in S$ indicates the stage affiliation.

To ensure clinical accuracy and relevance, our annotation process involves multiple rounds of expert review. Board-certified physicians from relevant specialties annotate each case with clinical key points rather than exact text matches. Specifically, for stage $s_i$, we define the ground truth as $G_i = (P_i^{diag}, P_i^{treat})$, where $P_i^{diag} = \{p_{i,1}^{diag}, p_{i,2}^{diag}, ..., p_{i,m}^{diag}\}$ represents diagnostic key points and $P_i^{treat} = \{p_{i,1}^{treat}, p_{i,2}^{treat}, ..., p_{i,k}^{treat}\}$ represents treatment key points. This point-based representation allows for semantic flexibility while maintaining evaluation rigor.

The annotation guidelines ensure consistency across different annotators. Cases with low agreement undergo additional review and discussion until consensus is reached. Furthermore, we implement quality control measures including random audits and cross-validation to maintain high annotation standards throughout the dataset construction process.

### 3.3 Evaluation Framework

Our evaluation framework integrates both clinical accuracy and resource efficiency, reflecting the dual objectives of real-world medical practice. We assess agent performance through comprehensive metrics that balance diagnostic precision with cost-conscious decision-making.

#### 3.3.1 Cost Tracking and Resource Utilization

Healthcare resources are inherently limited and expensive. To evaluate cost efficiency, we establish a baseline cost for each stage through expert annotation. For each stage $s_i$, experienced physicians annotate a reasonable reference cost $\text{Cost}_i^{ref}$ that represents the expected expense for appropriate clinical decision-making at that stage. This reference cost serves as a normalization factor for evaluating the agent's resource utilization.

For stage $s_i$, let $X_i$ be the set of unique items selected by the agent. The actual stage cost is calculated as:

$$\text{Cost}_i = \sum_{x \in X_i \cap C_i^{exam}} price_x \tag{3}$$

Note that patient record items typically have zero cost, reflecting their nature as readily available clinical information. To prevent artificial inflation of costs, we implement a deduplication mechanism where multiple selections of the same item within a stage incur cost only once.

The cost efficiency for each stage is then evaluated through a cost ratio:

$$\text{CostRatio}_i = \frac{\text{Cost}_i}{\text{Cost}_i^{ref}} \tag{4}$$

For the overall evaluation, we compute the average cost ratio across all stages that the agent has experienced. Let $m$ denote the number of stages the agent successfully completes, the average cost ratio is:

$$\text{CostRatio}_{avg} = \frac{1}{m} \sum_{i=1}^{m} \text{CostRatio}_i \tag{5}$$

#### 3.3.2 Clinical Accuracy Metrics

We evaluate clinical accuracy using LLM-based semantic matching to assess coverage of key points. Let $\hat{D}_i$ and $\hat{T}_i$ denote the agent's diagnosis and treatment outputs at stage $s_i$. We define a semantic matching function $M : (\text{prediction}, \text{key point}) \rightarrow \{0, 1\}$ that determines whether a key point is covered by the prediction.

For stages that the agent successfully completes, the stage-wise diagnostic and treatment accuracies are calculated as:

$$\text{Acc}_i^{diag} = \frac{1}{|P_i^{diag}|} \sum_{p \in P_i^{diag}} M(\hat{D}_i, p) \tag{6}$$

$$\text{Acc}_i^{treat} = \frac{1}{|P_i^{treat}|} \sum_{p \in P_i^{treat}} M(\hat{T}_i, p) \quad (7)$$

For stages that the agent fails to reach or complete, we assign an accuracy of 0, reflecting the failure to address those clinical scenarios. Let $n$ be the total number of stages in the complete patient journey. The aggregate accuracies are computed as:

$$\text{Acc}_{avg}^{diag} = \frac{1}{n} \sum_{i=1}^{n} \text{Acc}_i^{diag}, \quad (8)$$

$$\text{Acc}_{avg}^{treat} = \frac{1}{n} \sum_{i=1}^{n} \text{Acc}_i^{treat} \quad (9)$$

where $\text{Acc}_i = 0$ for all $i > m$ (stages not reached by the agent). This formulation ensures that agents are penalized for incomplete patient journeys, encouraging comprehensive clinical coverage while maintaining accuracy at each completed stage.

# 4 Experiments

## 4.1 Experimental Setup

### 4.1.1 Benchmark Details

MMedAgentBench represents a high-quality, comprehensive medical agent benchmark dataset specifically designed for evaluating AI agents in clinical decision-making scenarios. The dataset comprises 167 carefully curated patient cases, as shown in Table 1.

Table 1: Summary of MMedAgentBench:

| Description | Value |
|---|---|
| Number of Patients | 167 |
| Number of Clinical Stages | 527 |
| Number of Examination Records | 4,019 |
| Number of Patient Records | 701 |
| Average Stages per Patient | 3.16 |
| Average Exam Records per Patient | 24.07 |
| Average Exam Records per Patient | 4.19 |

### 4.1.2 Models

We conduct an extensive evaluation covering a diverse spectrum of large language models that vary in scal to ensure a comprehensive capability assessment. Among open-source models, our benchmark includes the Qwen2.5 family (14B/72B) (Team, 2024), the Llama series (Touvron et al., 2023; Meta AI, 2024; Dubey et al., 2024) encompassing Llama-3.1-70B and Llama-3.1-405B, as well as GLM-4-32B (GLM et al., 2024), DeepSeek-v3.1 (DeepSeek-AI, 2024), and Kimi-K2 (Team et al., 2025). For closed-source models, we evaluate the GPT family—including GPT-3.5, GPT-4o, and GPT-5 (OpenAI, 2023a,b)—alongside Claude-4-sonnet (Anthropic, 2025) and Gemini-2.5-Flash (Comanici et al., 2025). All models are tested under unified prompting strategies and standardized evaluation protocols to guarantee fairness and comparability across results.

For the stage judgment function $J : (D_i, T_i) \rightarrow 0, 1$ and the semantic matching function $M$ : (prediction, key point) $\rightarrow 0, 1$, we implemented them using Gemini-2.5-Flash and GPT-4o, respectively. The former requires high-level integration and reasoning over long clinical texts, while the latter focuses solely on evaluating semantic similarity and matching accuracy.

## 4.2 Results

The benchmark consists of a vast array of complex medical data, ranging from simple outpatient records to intricate multi-disease co-occurrence patterns. Based on MMedAgentBench, we evaluated multiple large models' diagnostic capability ($\text{Acc}^{diag}$), treatment capability ($\text{Acc}^{treat}$), and cost ratio (CostRatio), results are shown as Table 2. We run the benchmark for 5 times to get the average value. Even the best-performing model, GPT-5, achieves only 35.62% diagnostic accuracy and 38.33% treatment accuracy, highlighting the substantial challenges posed by our multi-stage clinical diagnosis dataset. This relatively modest performance ceiling underscores the complexity of real-world clinical decision-making, where agents must navigate through sequential stages, synthesize evolving patient information, and make interconnected diagnostic and treatment decisions. Furthermore, the wide variation in CostRatio across models (ranging from 0.44 to 1.41) provides valuable insights into different models' examination ordering strategies, enabling researchers to better understand the trade-offs between diagnostic thoroughness and resource efficiency, and identify models that can achieve clinical objectives while maintaining cost-conscious medical practice.

## 4.3 Model Scale Effects

Evaluation results reveal a clear correlation between model scale and clinical performance within the

Table 2: Evaluation results on MMedAgentBench. $\text{Acc}^{diag}$ and $\text{Acc}^{treat}$ denote diagnostic and treatment accuracy respectively (in %). CostRatio measures resource utilization efficiency, where smaller values indicate better cost control relative to expert baseline. We use **bold** with gray shading to highlight the best-performing model in each metric, and *italics* for the second-best.

| Model | $\text{Acc}^{diag}$ (%) | $\text{Acc}^{treat}$ (%) | CostRatio |
|---|---|---|---|
| Open-Weight Models | | | |
| Llama-3.1-70B | 7.75 | 4.47 | *0.46* |
| Llama-3.1-405B | 16.07 | 8.60 | 0.75 |
| Qwen2.5-14B | 17.47 | 14.04 | 0.66 |
| Qwen2.5-72B | 21.76 | 17.77 | 0.85 |
| Qwen3-14B | 17.66 | 16.28 | 0.63 |
| GLM-Z1-32B | 22.59 | 20.69 | 1.28 |
| DeepSeek-V3.1 | 25.12 | 23.99 | 0.69 |
| Kimi-K2 | 28.30 | *31.10* | 1.14 |
| Closed-Weight Models | | | |
| Claude-Sonnet-4 | 31.89 | 30.13 | 1.30 |
| Gemini-2.5-Flash | *32.88* | 28.67 | 1.41 |
| GPT-3.5 | 15.30 | 10.50 | **0.44** |
| GPT-4o | 22.13 | 18.68 | 0.74 |
| GPT-5 | **35.62** | **38.33** | 0.93 |

same model families. Examining the Llama-3.1 series, we observe substantial improvements as parameters increase from 70B to 405B: $\text{Acc}^{diag}$ improves from 7.75% to 16.07% , while $\text{Acc}^{treat}$ rises from 4.47% to 8.60%. Similarly, the Qwen2.5 series demonstrates consistent scaling benefits, with $\text{Acc}^{diag}$ increasing from 17.47% (14B) to 21.76% (72B) and $\text{Acc}^{treat}$ from 14.04% to 17.77%. These within-family improvements underscore that parameter scaling directly enhances models' ability to process complex medical information and generate accurate clinical decisions.

However, the results also highlight that base model capabilities and training methodologies are equally crucial for medical tasks. Notably, Qwen2.5-14B achieves superior performance ($\text{Acc}^{diag}$: 17.47%, $\text{Acc}^{treat}$: 14.04%) compared to Llama-3.1-70B despite having significantly fewer parameters, suggesting that architectural design and pre-training quality on medical-relevant data can compensate for raw parameter count. This pattern is further evidenced by comparing Qwen3-14B (17.66%, 16.28%) with larger models from other families, demonstrating that effective medical knowledge encoding in the base model is fundamental.

The scaling effects observed across different model families suggest that while increasing parameters generally improves medical reasoning capabilities, the efficiency of this scaling varies significantly based on the underlying model architecture and training approach. This indicates that future development of medical AI systems should balance parameter scaling with targeted improvements in base model design and domain-specific pre-training strategies.

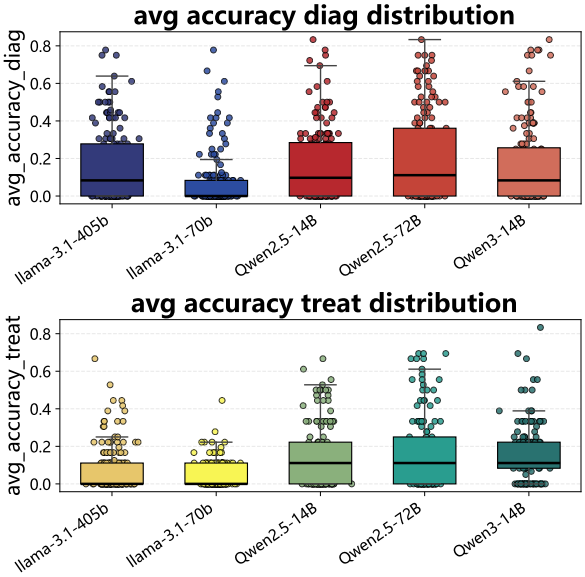


Figure 2: $\text{Acc}^{diag}$ and $\text{Acc}^{treat}$ distribution of Qwen and Llama family.

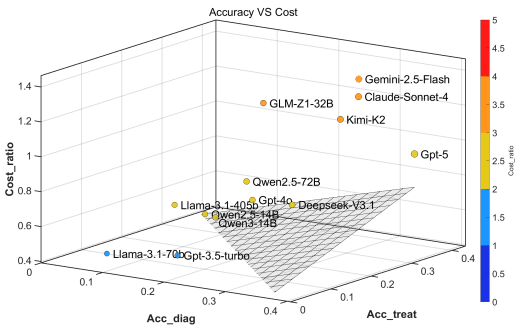


Figure 3: 3D chart visualizing accuracy and cost metrics, where points closer to the bottom right corner indicate higher clinical accuracy at lower cost.

## 4.4 Comparison of Open-Weight and Closed-Weight Models

Our evaluation reveals that closed-weight models generally achieve superior performance in medical diagnosis tasks, with GPT-5 leading at $\text{Acc}^{diag}$ of 35.62% and $\text{Acc}^{treat}$ of 38.33%, followed by Gemini-2.5-Flash (32.88%, 28.67%) and Claude-Sonnet-4 (31.89%, 30.13%). This performance advantage likely stems from their extensive training resources, proprietary medical datasets, and sophisticated alignment techniques that are not publicly disclosed.

However, the gap between open-weight and closed-weight models is narrowing, particularly with recent advances in open-weight model development. Notably, Kimi-K2 achieves impressive results with $\text{Acc}^{diag}$ of 28.30% and $\text{Acc}^{treat}$ of 31.10%, where its treatment accuracy even surpasses some closed-weight models like Gemini-2.5-Flash (28.67%). Similarly, DeepSeek-V3.1 demonstrates competitive performance (25.12%, 23.99%), outperforming GPT-4o (22.13%, 18.68%) in both metrics. These results suggest that well-designed open-weight models can approach or even exceed the capabilities of certain closed-weight counterparts in specific medical tasks.

The strong showing of models like Kimi-K2 and DeepSeek-V3.1 indicates that the open-weight community is successfully developing models with robust clinical reasoning capabilities. While the top-tier closed-weight models maintain their lead, the diminishing performance gap suggests that architectural innovations and improved training strategies in open-weight models are effectively capturing medical knowledge, potentially democratizing access to high-quality medical AI systems.

### 4.4.1 Cost Sensitivity and Diagnostic-Therapeutic Balance

In this study, CostRatio represents the relative cost of models during medical diagnosis and treatment recommendation generation. Results reveal distinct trade-offs between performance and cost across different models. We visualize acc vs cost in Figure 3.

Overall, closed-source models like Claude-Sonnet-4 (1.30), Gemini-2.5-Flash (1.41), and GPT-5 (0.93) exhibit cost ratios close to or slightly exceeding real-world medical scenarios. In contrast, certain open-source models (e.g., DeepSeek-V3.1 at 0.69, Qwen2.5-14B at 0.66) demonstrate lower costs. However, high cost does not directly equate to high efficiency: at similar cost levels, significant gaps exist in diagnostic accuracy among different models. For instance, GPT-5 achieves a significantly higher diagnostic accuracy (35.62%) than Claude-Sonnet-4 (31.89%) at a lower cost, demonstrating superior "performance-cost ratio."

It is noteworthy that Qwen2.5-72B (CostRatio = 0.85) and GPT-5 (CostRatio = 0.93) present a typical contrast: both models incur similar medical examination costs, yet GPT-5 significantly outperforms Qwen2.5-72B in diagnostic accuracy (35.62% vs. 21.76%) and treatment recommendation accuracy (38.33% vs. 17.77%). This demonstrates that effective utilization of medical examinations is more critical than merely minimizing costs. This highlights that the key challenge in medical AI is not just reducing examination costs, but effectively synthesizing the resulting information to reach accurate clinical conclusions—achieving the optimal balance between diagnostic accuracy and resource efficiency.

### 4.4.2 Case Study: Misleading Information Distorting Diagnostic Direction

When confronted with complex medical records, models are susceptible to misleading clues that can cause significant deviations in diagnostic direction.

In this case shown as Figure 4, the data input to the model included comprehensive clinical information: the patient's complete blood count results, MRI imaging descriptions, and biopsy reports. The blood test results indicated mild anemia and mild liver function abnormalities, while the MRI and biopsy information revealed abnormal prostate signals and related histological features, with the actual diagnosis being prostate cancer. However, when generating its diagnosis, the model primarily focused on hematological indica-

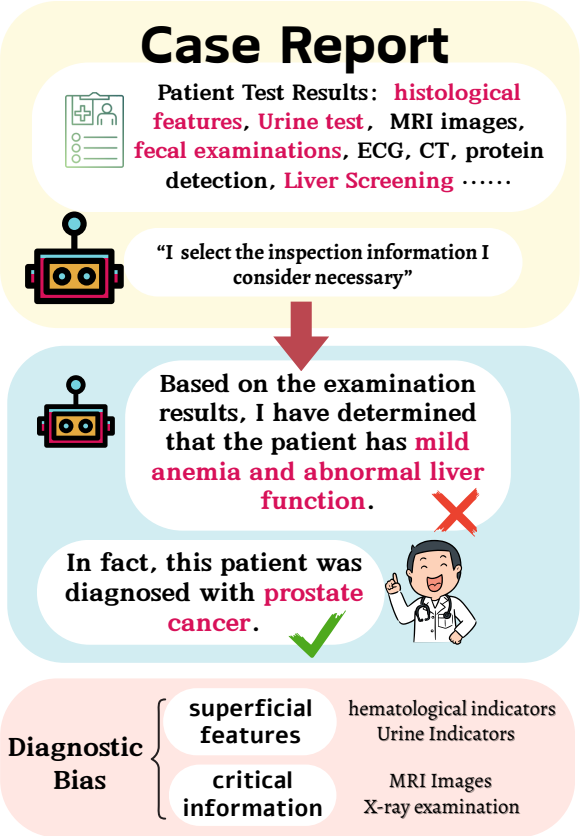


Figure 4: The case illustrates diagnostic bias in medical reports. Routine tests like blood and urine analyses often dominate reports, causing models to overemphasize them while neglecting critical indicators such as MRI or biopsy results. Here, the model misdiagnosed mild anemia with abnormal liver function, whereas the true condition was prostate cancer, revealing the risk of focusing on superficial features instead of key diagnostic evidence.

tors, outputting a diagnosis and treatment recommendation of "mild anemia and liver function abnormalities," completely ignoring the malignant tumor risk suggested by the imaging and pathology information.

This outcome demonstrates that even with comprehensive clinical information, the model may exhibit systemic bias due to overemphasis on superficial features. Its reasoning process showed excessive sensitivity to prominent data (e.g., blood indicators) while undervaluing critical information (e.g., imaging and pathology reports). The diagnostic logic lacked hierarchical judgment capabilities, failing to perform causal reasoning and diagnostic hypothesis verification based on the overall clinical picture as clinical physicians do.

## 5 Conclusion

We presented MMedAgentBench, a comprehensive benchmark designed to evaluate LLM-based medical agents in realistic multi-stage clinical workflows. Unlike existing medical benchmarks that focus on static, single-turn question answering, our framework captures the temporal complexity and resource constraints inherent in real clinical practice. Through a high-quality dataset comprising over 150 clinical cases and 500+ diagnostic stages, we enable systematic evaluation of medical agents across dynamic decision-making, cost control, and multi-stage reasoning dimensions.

MMedAgentBench establishes a crucial testbed for advancing medical AI toward clinical deployment. By requiring agents to navigate sequential clinical stages while balancing accuracy and resource efficiency, our benchmark pushes the development of more sophisticated medical reasoning capabilities. Future work can leverage this framework to develop specialized medical agents that better handle temporal dependencies, cost constraints, and the inherent uncertainty in clinical workflows, ultimately contributing to more practical and deployable medical AI systems.

## 6 Limitations

**Dataset Scope and Representativeness.** Our dataset of 167 patient cases, though carefully curated from tertiary hospitals, may not fully represent the diversity of global clinical practice. The cases primarily reflect medical practices in specific geographic regions and healthcare systems, potentially limiting generalizability to different medical contexts or rare diseases.

**Simplification of Clinical Complexity.** Real clinical practice involves nuances that benchmark cannot fully capture, including non-verbal patient cues, urgency considerations, and real-time collaborative decision-making among healthcare teams. We assumes perfect information retrieval once an examination is ordered, whereas real-world scenarios often involve incomplete, ambiguous, or delayed results.

**Static Ground Truth Assumption.** Our benchmark assumes fixed ground truth diagnoses and treatments annotated by experts. However, medical knowledge evolves, and legitimate clinical disagreements exist even among specialists. The benchmark may not adequately capture this inherent uncertainty and variability in medical practice.

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# A Appendix

## A.1 Annotation Guidelines and Protocol

The creation of MMedAgentBench relied on a rigorous annotation protocol executed by board-certified physicians. These guidelines were provided to each annotator to ensure consistency, clinical accuracy, and relevance across all cases in the dataset. The objective was to establish a gold-standard ground truth for evaluating an AI agent's multi-stage clinical reasoning.

### A.1.1 General Principles

Annotators were instructed to approach each case as a real-world clinical scenario. The primary goal was to define what a competent, cost-conscious physician would conclude and do at each stage of the patient's journey, based only on the information available at that point.

### A.1.2 Per-Stage Annotation Form

For each clinical stage ($s_i$) of a patient case, annotators were required to complete a structured form with three main components:

**Part 1: Clinical Key Points.**

This section captures the essential diagnostic and therapeutic conclusions for the stage. Annotators were asked to provide a list of short, distinct points.

**Diagnostic Key Points ($P_i^{diag}$):**

- **Objective:** List the most critical diagnoses, differential diagnoses, or significant findings that should be identified at this stage.
- **Instructions:**
  1. Focus on the most probable diagnoses and critical "can't-miss" diagnoses (e.g., myocardial infarction, pulmonary embolism).
  2. Points should be justifiable based on the evidence presented up to stage $s_i$.
  3. Avoid vague statements. Instead of "abnormal lab results," specify "leukocytosis with a left shift suggesting infection."

**Treatment Key Points ($P_i^{treat}$):**

- **Objective:** List the essential treatment actions, management plans, or further consultations that should be initiated.
- **Instructions:**
  1. List specific actions (e.g., "Administer intravenous antibiotics," "Consult cardiology").
  2. Include key monitoring plans (e.g., "Monitor vital signs every 4 hours").
  3. The treatment plan should directly address the diagnostic findings.

**Part 2: Reference Cost (Cost$_i^{ref}$).**

This section establishes a cost baseline for efficient and effective clinical investigation.

- **Objective:** Identify a set of examinations that represents a reasonable and cost-effective diagnostic strategy for the stage.
- **Instructions:**
  1. From the list of all available examinations at stage $s_i$, select only those that are **essential** to confirm or rule out the primary differential diagnoses.
  2. Balance diagnostic yield against cost. Avoid ordering overly broad or low-yield tests unless clinically crucial.
  3. The final Cost$_i^{ref}$ is the sum of the prices of the selected essential examinations. Patient record items have a cost of zero.

**Part 3: Stage Progression Criteri.**

This defines the minimum requirements for an agent's performance to be considered successful for the current stage, allowing it to proceed to the next.

- **Objective:** Define the primary clinical goal of the current stage.
- **Instructions:**
  1. Answer the question: "What is the minimum level of understanding or action required at this stage to ensure patient safety and effective progression of care?"
  2. This is a holistic judgment. For example, the criterion might be "The agent must recognize the signs of sepsis and initiate fluid resuscitation and antibiotics" or "The agent must correctly interpret the

MRI as highly suspicious for malignancy and recommend a biopsy."

3. An agent failing to meet this criterion would not proceed, simulating a critical clinical error.

### A.2 Recruitment and Payment

All data annotation for MMedAgentBench was conducted manually by a team of trained medical annotators with relevant clinical backgrounds. Each annotation underwent a multi-stage verification pipeline, including internal cross-checking and random sampling review, to minimize potential bias and human error. A subset of the annotated data was further proofread and refined by the authors to ensure accuracy and adherence to medical logic. Reasonable compensation was provided to all annotators according to their workload and contribution, ensuring fairness and quality throughout the entire annotation process.

## B LLM Usage

LLM was used for drafting and language polishing. Except these uses, no AI tools were involved in study design, core experiments, result analysis, or interpretation. The authors are fully responsible for the accuracy of the work.