Are LLMs Ready to Assist Physicians? PhysAssistBench for Interactive Doctor-Patient-EHR Assistance

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Abstract

The most plausible near-term role of medical LLMs is to assist rather than replace physicians, yet current evaluations often test isolated capabilities: clinical knowledge, EHR system interaction, or patient communication. Physician assistance instead requires coordinating these capabilities within the same interaction, where physicians issue underspecified requests, patients describe symptoms ambiguously, and EHR systems demand precise tool use. We introduce **PhysAssistBench**, a benchmark for interactive doctor-patient-EHR assistance. Built from real MIMIC-IV cases, PhysAssistBench uses a scalable pipeline to construct *agentic patients*: interactive, record-grounded agents that turn static EHR records into multi-turn clinical scenarios while preserving clinical factuality. PhysAssistBench provides a curated bilingual evaluation set of 1,296 manually reviewed and physician-validated turns. Experiments with leading LLMs show that current models remain unreliable in this setting, which exposes a key bottleneck for clinical LLMs: reliable assistance requires coordination across knowledge, communication, and systems, not isolated gains in any of them.

1 Introduction

LLMs have generated substantial optimism for clinical AI (Thirunavukarasu et al., 2023; Moor et al., 2023; Rajpurkar et al., 2022). Much of this optimism comes from their strong performance on medical examinations and question-answering benchmarks (Kung et al., 2023; Singhal et al., 2023), motivating visions of LLMs as a new "front door to healthcare" (NHS England-South East, 2024; Kyle, 2025). However, recent studies suggest that such performance may not transfer to interactive clinical use. Laban et al. (2025) found that shifting from fully specified single-turn prompts to multi-turn, under-specified interactions caused an average 39% performance drop. Similarly, Bean et al. (2026) found that LLMs performed strongly when tested alone, but failed to improve user performance in a randomized medical self-assessment study, identifying user interaction as a key barrier.

These findings reveal a gap in current evaluation practice: practical failures may arise not only from insufficient medical knowledge, but from failures of interaction. As summarized in Table 1, prior medical LLM benchmarks mostly evaluate three isolated roles: *knowledge*, where models act as medical experts; *system*, where models retrieve or manipulate clinical records; and *communication*, where models interact with patients or generate clinical text. These roles are useful, but they miss the most plausible near-term deployment setting: assisting physicians under human oversight, as emphasized by ethical and regulatory expectations (World Health Organization, 2021; U.S. Food and Drug Administration, 2025). Technically, this setting is also where recent studies expose a key bottleneck: interaction (Laban et al., 2025; Bean et al., 2026). Physician assistance is not static question answering, but interactive coordination across incomplete physician intent, ambiguous patient information, and precise EHR actions.

Figure 1 illustrates the setting studied in this paper. Even for medical professionals, physician requests are often context-dependent, elliptical, and spread across turns. The assistant must map these implicit requests to two distinct interfaces: EHR systems requiring precise tool calls, and patients providing colloquial, incomplete, and clinically imprecise information. It must decide when to query the EHR, when to ask the patient, and how to integrate evidence into a physician-facing response. As will be discussed in Section 2, this combination is not captured by existing benchmarks.

We introduce PhysAssistBench, a benchmark for interactive doctor-patient-EHR assistance. Evaluating such interactions requires more than

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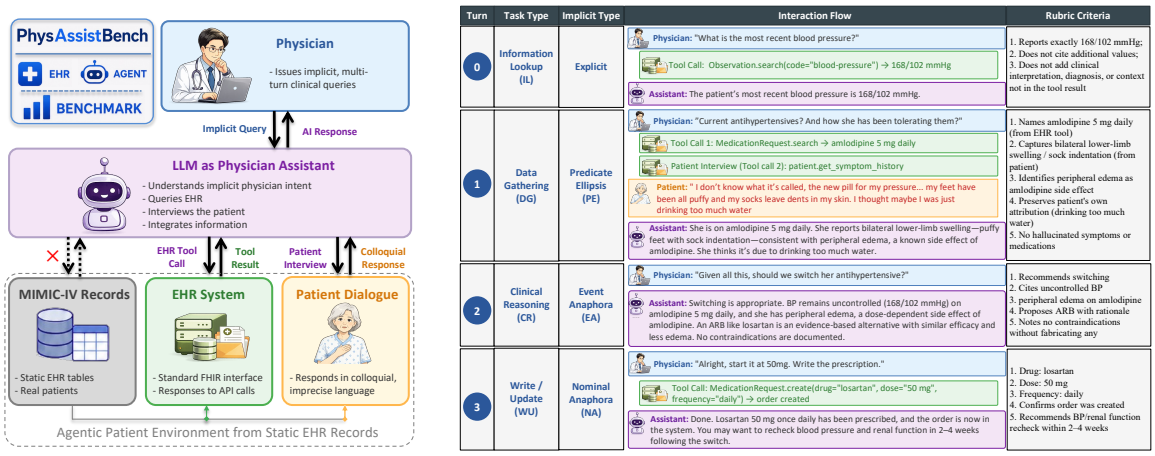

Figure 1: **Left:** PHYSASSISTBENCH evaluates LLMs as physician assistants, not physicians: the assistant follows physician requests while interacting with a record-grounded FHIR-based EHR system and a dialogue patient. A multi-agent pipeline transforms static MIMIC-IV records into this *agentic patient* environment, exposing them through standardized FHIR interfaces rather than direct record access. **Right:** A representative hypertension case in PHYSASSISTBENCH. The 4-turn session progresses from explicit lookup to implicit assistance involving patient dialogue, clinical reasoning, and EHR actions, with each turn paired with its interaction flow and rubric criteria.

static clinical records (Li et al., 2025): it must provide patients who can respond across turns, EHR systems that can be queried through structured tools, and physician requests that evolve with context. To make this scalable while preserving clinical grounding, PHYSASSISTBENCH repurposes real MIMIC-IV (Johnson et al., 2023) cases through a multi-agent synthetic data pipeline. The pipeline plans clinically plausible scenarios from eligible records and constructs *agentic patients*: interactive, record-grounded agents that turn static EHR cases into multi-turn clinical scenarios. Unlike unconstrained patient simulation, these agents are grounded in existing EHR evidence; unsupported cases are filtered rather than counterfactually rewritten.

The formulated benchmark contains 324 multi-turn sessions and 1,296 turns. Eight trained annotators collectively verified and corrected the annotated fields of every turn. Separately, a board-certified physician and the trained annotators assessed query realism and trajectory coherence for all 324 sessions. It spans 4 clinical scenarios (Diagnostic Workup, Med Safety, Treatment Response and Discharge Planning), 4 tasks (Information Lookup, Data Gathering, Clinical Reasoning, and Write/Update), and 3 physician-query implicitness subtypes: Nominal Anaphora (NA), Predicate Ellipsis (PE), and Abstract Event Anaphora (AE). Each session uses a standardized FHIR R4 tool set and is evaluated in English and Chinese. Turn-level rubrics are provided for stable and interpretable assessment. Figure 1 shows a representative 4-turn session, illustrating how implicit physician requests, patient ambiguity, and EHR precision co-occur within the same workflow.

Our contributions are threefold. First, we formulate interactive physician assistance as a coordination problem across clinical knowledge, patient communication, and EHR systems, a setting overlooked by existing evaluations of isolated roles. Second, we develop a scalable multi-agent synthetic data pipeline that repurposes static MIMIC-IV records into *agentic patients*, enabling clinically grounded multi-turn doctor-patient-EHR scenarios. Third, we release PHYSASSISTBENCH, a manually reviewed and physician-validated benchmark of 324 sessions and 1,296 turns, and show that leading LLMs are not yet reliable physician assistants, especially when resolving physician intent, handling patient ambiguity, issuing grounded EHR queries, and integrating evidence across sources. Dataset and code are made publicly available[1].

2 Related Work

2.1 EHR and Medical Agent Benchmarks

Table 1 compares existing benchmarks by evaluation focus and interaction dimensions. Most prior benchmarks evaluate isolated capabilities rather than integrated physician-assistant workflows.

A large body of work focuses on *knowledge*, testing medical reasoning over questions, notes, records, or agent-style clinical tasks (Jin et al.,

[1] https://github.com/HINTLab/PhysAssistBench

Benchmark	Evaluation Focus	Implicit Queries	Patient Interaction	Tool Use	Turns
PubMedQA (Jin et al., 2019)	Knowledge	✗	✗	✗	Single
EHRSQL (Lee et al., 2022)	System	✗	✗	✗	Single
EHRXQA (Bae et al., 2023)	System, Knowledge	✗	✗	✗	Single
EHRAgent (Shi et al., 2024)	Knowledge	✗	✗	✓	Single
EHRNoteQA (Kweon et al., 2024)	Knowledge	✗	✗	✗	Single
ClinicalBench (Chen et al., 2024)	Knowledge	✗	✗	✗	Multi
ER-REASON (Mehandru et al., 2025)	Knowledge	✗	✗	✗	Single
CSEDB (Wang et al., 2025)	Knowledge	✗	✗	✗	Single
MedThink-Bench (Zhou et al., 2025)	Knowledge	✗	✗	✗	Single
MedAgentsBench (Tang et al., 2025)	Knowledge	✗	✗	✓	Single
MedAgentBench (Jiang et al., 2025)	System	✗	✗	✓(FHIR)	Single
FHIR-AgentBench (Lee et al., 2025)	System	✗	✗	✓(FHIR)	Single
AgentClinic (Schmidgall et al., 2026)	Knowledge, Communication	✗	✓	✓	Multi
MedAgentGym (Xu et al., 2026a)	System, Knowledge	✗	✗	✓	Multi
PHYSASSISTBENCH (Ours)	**Assistance**	✓	✓	✓(FHIR)	Multi

Table 1: Comparison of existing EHR and medical agent benchmarks. *Evaluation Focus* denotes the primary capability tested: *knowledge* for medical expertise, *system* for EHR or tool use, and *communication* for patient dialogue. PHYSASSISTBENCH is the only benchmark with integrated *assistance* focus across all three interaction dimensions. *Implicit Queries*, *Patient Interaction*, *Tool Use*, and *Turns* denote underspecified physician requests, simulated-patient interaction, executable tools with FHIR noted when applicable, and single- or multi-turn evaluation.

2019; Shi et al., 2024; Kweon et al., 2024; Chen et al., 2024; Mehandru et al., 2025; Wang et al., 2025; Zhou et al., 2025; Tang et al., 2025). These benchmarks assess clinical expertise, but mostly assume fully specified, static inputs without patient or EHR interaction across turns. Another line focuses on *system* interaction, evaluating EHR retrieval or clinical tool use (Lee et al., 2022; Bae et al., 2023; Jiang et al., 2025; Lee et al., 2025; Xu et al., 2026a). However, they typically treat EHR access as standalone tool use and do not test implicit references, argument elision, or cross-turn carry-over. A third line focuses on *communication*, where models interact with patients or generate clinical text. AgentClinic (Schmidgall et al., 2026) supports multi-turn doctor-patient interaction and is closest to the dialogue side of our setting, but does not jointly evaluate structured EHR tool use, patient dialogue, and implicit physician requests.

Overall, existing benchmarks cover important pieces of clinical LLM evaluation, but not the integrated *assistance* setting, where an LLM must coordinate *knowledge*, *communication*, and *system* interaction under evolving physician instructions. Luo et al. (2026) also articulate a research vision for evaluating clinical LLMs through realistic EHR interfaces in dynamic, interactive clinical settings, sharing our critique of current evaluation paradigms. As shown in Table 1, PHYSASSISTBENCH is the only benchmark covering implicit queries, patient interaction, FHIR-based EHR tool use, and multi-turn evaluation together. This coverage is made possible by a scalable multi-agent synthetic data pipeline that turns MIMIC-IV records into interactive doctor-patient-EHR scenarios.

2.2 Medical Synthetic Data

Medical synthetic data has become an important strategy for addressing data scarcity, privacy, and bias in healthcare. Most prior work follows a *generative* synthesis paradigm, creating realistic medical images, clinical text, tabular EHR data, or multimodal patient records for training and evaluation via generative models (Fansi Tchango et al., 2022; Li et al., 2023b; Seo and Lee, 2024; Zhang et al., 2025, 2026). Beyond sample generation, recent work also studies *agentic* data synthesis, where LLMs or multi-agent systems construct clinical dialogues through prompt-encoded constraints (Das et al., 2024) or clinician-patient role simulation grounded in EHR-derived evidence (Wang et al., 2024; ALMutairi et al., 2024; Xu et al., 2026b).

PHYSASSISTBENCH differs by using synthetic data to construct an interactive evaluation environment. Its scalable multi-agent synthetic data pipeline plans clinically plausible scenarios from real records and constructs *agentic patients*, which are grounded in existing EHR evidence rather than unconstrained simulation; unsupported cases are filtered instead of counterfactually rewritten. The resulting evaluation set is further manually reviewed and physician-validated for reliability.

2.3 Tool Use and Function Calling

General-domain tool-use benchmarks evaluate API selection, function calling, and tool-mediated task completion (Li et al., 2023a; Qin et al., 2023; Kr-

ishna et al., 2025; Yu et al., 2026). While useful for studying agent tool use, they mostly assume general-purpose domains and do not model clinical tool schemas, FHIR-based EHR actions, or implicit physician queries. PHYSASSISTBENCH instead embeds tool use in an interactive doctor-patient-EHR workflow requiring coordination between FHIR-based EHR tools, ambiguous patient dialogue, and evolving physician instructions.

2.4 Ellipsis and Anaphora in Dialogue

Ellipsis and anaphora are pervasive in natural dialogue and have long been studied in linguistics and NLP (Gerber and Chai, 2010; Lee et al., 2017, 2018; Marasović et al., 2017; Kolhatkar and Hirst, 2014). They cover phenomena such as omitted predicates or arguments, entity references, and abstract event references, all of which require context-dependent interpretation. In clinical communication, especially physician instructions, such implicitness is common: clinicians often rely on shared context, abbreviate repeated actions, and refer back to prior findings across turns. Despite this, existing EHR and medical agent benchmarks typically formulate queries as explicit, standalone instructions, leaving implicit physician requests overlooked.

3 PHYSASSISTBENCH

3.1 Overview

PHYSASSISTBENCH is a multi-turn benchmark built on real MIMIC-IV patient data that evaluates LLMs on realistic doctor-patient-EHR interaction. It comprises 324 sessions and 1,296 turns, evaluated in both English and Chinese using a standardized FHIR R4 tool set (Mandel et al., 2016).

3.2 Benchmark Structure

Sessions and Turns. The primary unit of evaluation is a *session*: four consecutive turns (Turn 0–Turn 3) simulating a single clinical encounter. Turns are not independent: each builds on prior retrieved data and established context, requiring the assistant to track what has already been answered and reason across the full conversation.

Task Types. Each turn is labeled among four task types reflecting the clinical intent of the physician's query. *Information Lookup (*IL*)* retrieves a single clinical fact via one EHR read tool. *Data Gathering (*DG*)* collects information from two or more sources (EHR tools, patient-interview tools) with calls that may be parallel or adaptive. *Clinical Reasoning (*CR*)* combines retrieved findings with medical knowledge to produce a clinical recommendation optionally involving tool calls. *Write/Update (*WU*)* executes a FHIR write operation whose parameters are inferred from session context. Turn 0 is always IL, anchoring the session in a concrete data request; Turn 3 always ends in DG, CR, or WU.

Physician-Query Implicitness Types. Task type captures *what* is being requested; the implicitness type captures *how* the physician expresses it. As shared context accumulates, physicians naturally abbreviate: referring back to prior entities by pronoun, dropping predicates, or compressing the clinical picture into a brief phrase. PHYSASSISTBENCH encodes three implicitness types assigned to Turns 1–3. *Nominal Anaphora (*NA*):* a pronoun or noun phrase refers to a specific entity from a prior turn. *Predicate Ellipsis (*PE*):* the verb and arguments are omitted; only the new focus item is stated. *Abstract Event Anaphora (*AE*):* a phrase such as "given all this" refers to the accumulated clinical picture. Examples are in Table E1.

Tool Set. The assistant draws on two tool families. *EHR tools* are FHIR R4 read and write operations over MIMIC-IV resources. *Patient-interview tools* elicit subjective information absent from structured records (chief complaint, symptom history, medication adherence, and functional status) with responses pre-generated from the same admission records as the EHR snapshot and held fixed at evaluation time. Treating patient interaction as a tool call unifies EHR queries and patient questions under a single decision interface and enables deterministic evaluation via response replay. The full tool inventory is provided in Appendix D.

Clinical Scenarios. The task and implicitness types instantiate across four clinical scenarios spanning the physician's core decision cycle: Diagnostic workup, Medication safety review (Med Safety), treatment response monitoring (Treatment Response), and discharge planning. Each scenario constrains which FHIR resources and tool combinations are exercised, ensuring structural distinctiveness. The scenario design is inspired by Jiang et al. (2025); Lee et al. (2025); Liu et al. (2026).

Data-Richness Tiers. Each session is assigned among three *data-richness tiers* reflecting the depth of structured evidence in the MIMIC-IV

record: a coverage dimension rather than a difficulty ranking. *Data-sparse* sessions require a single lab value or prescription. *Data-moderate* sessions require a trend-bearing time series or a co-occurring drug-lab pair. *Data-rich* sessions require multi-dimensional evidence such as multiple drug-monitoring pairs or multi-system differential findings. Tier eligibility is verified offline against raw MIMIC-IV CSV files without LLM involvement (Appendix H). Complete scenario-by-tier, task-by-turn, and implicitness-by-turn distributions are reported in Appendix G, Tables G1–G3.

3.3 Quality Assurance

All 324 sessions underwent physician validation for clinical plausibility, query realism, and trajectory coherence. The session-level realism assessment yielded an overall mean of 4.37/5 and a minimum mean of 3.5, with no session falling below the quality threshold. Separately, eight trained annotators verified and corrected all turn-level annotated fields, including the implicitness labels, rubric items, and gold tool calls, across all 1,296 turns. Appendix C documents the reviewer qualifications, review and correction protocol, and complete annotation results. Appendix C.3 and Tables C1–C3 report the full-benchmark realism analysis.

3.4 Evaluation

Task Formalization. We formulate each PHYSASSISTBENCH session as a finite-horizon partially observable Markov decision process (POMDP) $(\mathcal{S}, \mathcal{A}, \mathcal{O}, T, R, \mathcal{U})$, with state space $\mathcal{S}$, action space $\mathcal{A}$, observation space $\mathcal{O}$, transition function $T : \mathcal{S} \times \mathcal{A} \to \mathcal{S} \times \mathcal{O}$, reward $R : \mathcal{S} \to [0, 1]$, and physician-instruction space $\mathcal{U}$. The state decomposes as $\mathcal{S} = \mathcal{S}_{\text{ehr}} \cup \mathcal{S}_{\text{pat}} \cup \mathcal{S}_{\text{ctx}}$: $\mathcal{S}_{\text{ehr}}$ is the MIMIC-IV patient snapshot frozen at t_{anchor} and hidden from the agent; $\mathcal{S}_{\text{pat}}$ is the patient-interview state, constructed from the same admission-period records as $\mathcal{S}_{\text{ehr}}$ and fixed at pipeline initialization time. $\mathcal{S}_{\text{ctx}}$ is the accumulated dialogue history $H_t = ((q_0, y_0), \ldots, (q_{t-1}, y_{t-1}))$. The action space partitions as $\mathcal{A} = \mathcal{A}_{\text{ehr}} \cup \mathcal{A}_{\text{pat}} \cup \mathcal{A}_{\text{nl}}$: FHIR R4 tool calls (read and write), patient-interview tool calls, and the natural-language answer y_t returned to the physician. The instruction space $\mathcal{U}$ contains the physician's queries q_t. A session is the tuple $\sigma = (t_{\text{anchor}}, q_0, q_1, q_2, q_3)$ paired with gold tool calls and gold answers; at each turn the agent produces (τ_t, y_t), where τ_t is the executed tool-call trace and y_t is the response.

Rubric-Based Scoring. Each turn is scored by an LLM judge on several independent rubric items designed for the turn's task type. Items cover factual accuracy of reported values, correctness of clinical interpretation, appropriate integration of prior session context, and absence of hallucinated facts. The score for turn t is the fraction of items passed, $r_t \in [0, 1]$; the session-level Rubric Score is $\bar{r}(\sigma) = \frac{1}{4}\sum_{t=0}^{3} r_t$ and the corpus-level *mean rubric score (mRS)* reported in Table 2 is $\mathbb{E}_\sigma[\bar{r}(\sigma)]$.

Pass@Turn and Pass@Session. The continuous rubric score is binarised at threshold τ to yield 2 reliability metrics. *Pass@Turn* (@T_τ) is the fraction of turns whose rubric score meets the threshold:

$$@\mathrm{T}_\tau = \frac{\sum_\sigma \sum_{t=0}^{3} \mathbf{1}[r_t \geq \tau]}{4|\mathcal{D}|}.$$

Pass@Session (@S_τ) is the fraction of sessions in which all four turns meet the threshold:

$$@\mathrm{S}_\tau = \frac{\sum_{\sigma \in \mathcal{D}} \mathbf{1}\left[\min_{t \in \{0,1,2,3\}} r_t \geq \tau\right]}{|\mathcal{D}|}.$$

We report $\tau \in \{0.60, 0.75\}$. $|\mathcal{D}|$ is the number of sessions. @S is the demanding metric: single weak turn fails entire session, reflecting the multi-turn, context-dependent character of clinical practice.

Tool Use Evaluation Tool invocation is evaluated implicitly through rubric-based scoring: a response grounded in correct EHR values necessarily required correct tool calls to retrieve them. This also accommodates cases where a model deviates from the gold tool trajectory but still produces a clinically correct answer, as the rubric rewards correctness rather than procedural conformity.

4 Agentic Patient Environment from Static EHR Records

We design the pipeline around a generative principle: each patient's EHR record, rather than serving as a static lookup table, acts as the *driving participant* of an *agentic patient* environment. Given one admission's data, a coordinated set of agents decides what clinical questions the record can support, plans the required EHR and patient-tool interactions, executes real FHIR queries against the actual data, and produces verifiable gold responses without human authorship of the scenario itself. The same record can therefore generate different

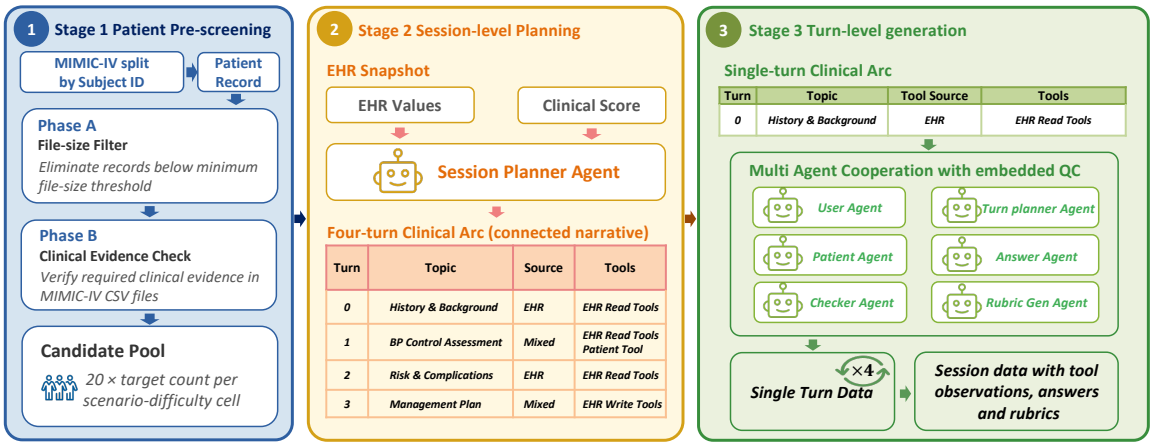

Figure 2: Multi-agent data synthesis pipeline. A static MIMIC-IV record is transformed into a grounded, multi-turn benchmark entry in the *agentic patient* environment, through patient pre-filtering, session-level planning, and turn-level generation with embedded quality control.

conversations across scenarios, difficulty tiers, and languages, making the pipeline scalable while remaining grounded in which specific admission contains. In this sense, the pipeline turns static EHR records into interactive *agentic patients* capable of driving complex doctor-patient-EHR interactions.

As illustrated in Figure 2, the pipeline comprises 3 stages. *(1) Patient pre-filtering* applies a two-stage offline filter: first file-size thresholds, then scenario- and tier-specific content checks ensuring every retained patient has sufficient EHR evidence before any LLM is invoked. *(2) Session planning* reads the patient's EHR snapshot and produces a coherent four-turn clinical arc specifying the per-turn topic, FHIR tools or patient tools, transforming isolated tabular data into a connected clinical narrative. *(3) Turn-level generation* instantiates each planned turn through multi-agent cooperation with tool-call planning, FHIR execution against real data, and gold answer generation, with three embedded quality gates rejecting hallucinated, structurally invalid, or clinically unsafe outputs.

The pipeline scales by instantiating multiple sessions from a single patient record across scenarios, difficulty tiers, and languages; quality is enforced by a three-stage checker that filters hallucinations, structural errors, and unsafe content. Full pipeline details (Figure H1), prompt templates, and per-gate failure statistics are provided in Appendix H.

5 Experiments

5.1 Models

We benchmark 5 closed-source models: GPT-5.4, GPT-5.4 mini (OpenAI, 2026), Claude-Opus-4.7 (Anthropic, 2026), Gemini-3.1-Pro (Google, 2026), Seed-1.8(ByteDance Seed Team, 2026) and 9 open-weight models: DeepSeek-V4-Pro and DeepSeek-V4-Flash (DeepSeek-AI, 2026), Qwen3.5 series models (Qwen Team, 2026), GLM-5 (GLM-5 Team, 2026), Kimi-K2.6 (Kimi Team, 2026), MiniMax (Chen et al., 2026). For each model we run the full English and Chinese benchmark (324 sessions $\times$ 4 turns $\times$ 2 languages = 2,592 turns), under identical evaluation conditions.

Eval Configuration & Judge Model. All models run with reasoning ("thinking") mode enabled (`reasoning_effort=high` for the GPT-5 series), temperature $= 0.2$, and a maximum of 16 tool calls per turn, with all 18 EHR, patient-interview and control tools available at every turn. Rubric scoring is performed by a fixed GPT-5.4-mini judge which is identical across all models. It receives the model's answer, EHR ground-truth, and rubric items, returning binary scores with reasoning for each item.

Judge Reliability. Judge reliability was measured on GLM-5 outputs from 108 sessions per language, covering 3,864 rubric items. The fixed GPT-5.4-mini judge achieved 95.37% agreement with trained-annotator labels (95% CI: $\pm$0.66 percentage points), with agreement exceeding 91% across every reported task-, language-, and rubric-category subset. Appendix C.4 and Tables C4–C5 provide the protocol and breakdowns.

5.2 Main Results

Table 2 reports performance of 14 LLMs on PhysAssistBench. Closed-source and open-weight models perform comparably at the top end.

Model	English					Chinese				
	mRS	Pass@Turn		Pass@Session		mRS	Pass@Turn		Pass@Session	
		τ=.60	τ=.75	τ=.60	τ=.75		τ=.60	τ=.75	τ=.60	τ=.75
Closed-Source Model (Anthropic, 2026; OpenAI, 2026; Google, 2026; ByteDance Seed Team, 2026)										
Claude-Opus-4.7	68.3	67.7	52.5	23.5	8.0	69.9	70.1	55.1	26.9	9.0
GPT-5.4-high	64.1	63.4	42.3	17.3	2.2	65.9	63.0	43.8	18.8	4.9
Gemini-3.1-Pro	62.1	59.9	40.3	11.1	1.5	68.0	68.8	48.5	22.5	4.6
Seed-1.8	67.4	66.4	46.5	18.5	3.1	68.7	67.4	48.0	20.4	6.8
GPT-5.4-mini	57.8	53.8	37.6	8.0	1.2	61.5	58.7	41.7	11.7	2.2
Open-Weight Model (GLM-5 Team, 2026; Kimi Team, 2026; DeepSeek-AI, 2026; Chen et al., 2026; Qwen Team, 2026)										
GLM-5	69.4	67.6	53.1	21.3	6.5	71.5	71.3	55.3	26.5	8.3
Kimi-K2.6	68.0	66.6	51.7	15.7	4.6	69.9	69.7	53.4	24.7	8.3
DS-V4-Pro	68.1	66.7	52.9	20.7	6.5	64.8	63.4	48.8	19.4	5.6
DS-V4-Flash	64.3	62.7	49.1	17.0	4.6	60.6	59.7	46.2	19.4	7.1
MiniMax-M2.7	63.2	60.4	43.4	10.8	2.2	66.8	63.9	47.3	13.3	4.3
Qwen3.5-35B-A3B	66.3	65.0	49.4	18.8	3.7	65.8	63.3	50.0	17.3	5.9
Qwen3.5-27B	58.3	55.6	40.2	11.1	1.2	61.4	57.6	42.4	10.8	3.1
Qwen3.5-9B	55.2	49.5	34.2	11.7	1.9	58.0	52.9	35.7	12.3	3.7
Qwen3.5-4B	48.7	40.1	29.6	1.9	0.0	47.4	40.4	27.4	1.9	0.6

Table 2: Performance on PHYSASSISTBENCH across 1,296 turns over 324 clinical sessions (4 scenarios $\times$ 3 data richness tiers $\times$ 27 sessions each). *mRS*: mean rubric score (%) over all 1,296 turns. *Pass@Turn (@T)*: the fraction of turns with rubric score $\geq \tau$ (%). *Pass@Session (@S)*: the fraction of complete 4-turn sessions where every turn passes threshold τ (%). Numbers highlighted in red and blue denote the best and second-best results, respectively.

GLM-5 achieves the highest mRS among all models (69.4 EN, 71.5 ZH), narrowly outperforming Claude-Opus-4.7 (68.3 EN, 69.9 ZH) on this metric. However, Pass@Session tells a different story: Claude-Opus-4.7 leads all models on session-level consistency, reaching 23.5% (EN) and 26.9% (ZH) at τ=.60, and 8.0% (EN) and 9.0% (ZH) at τ=.75. This gap between turn-level and session-level rankings highlights that sustaining quality across all four turns within a session is a distinct capability, not captured by mean rubric score alone. Within the Qwen3.5 family, mRS increases with model size (48.7→55.2→58.3→66.3 from 4B to 35B), with the 4B model recording 0.0% Pass@Session at τ=.75. Scenario and data-richness-level breakdowns are reported in Appendix I

Implicitness Type and Task Type: Heatmap Analysis Figure 3 decomposes the rubric score by implicitness (rows) and task (columns) across all 14 models. The heatmap reveals three patterns. First, task type defines a stable difficulty hierarchy: IL 82.6 $>$ WU 76.1 $>$ CR 54.9 $>$ DG 47.5, with DG as the universal bottleneck whose narrow cross-model standard deviation (5.6–7.6) indicates that multi-tool composition resists model scale. Second, implicitness interacts non-uniformly with task type: PE is the weakest row (59.6) but collapses specifically on WU (55.6), where dropping the verb creates syntactic ambiguity between a write instruction and a verification query; NA and AE preserve the write-verb in the antecedent, recovering to 87.2 and 90.7: the two highest cells on average. Third, cross-model variance is lowest on AE $\times$ WU (σ=4.0) and highest on NA $\times$ IL (σ=13.6), concentrating the capability gap in implicit DG and CR cells; Claude-Opus-4.7 and GLM-5 are the most balanced systems, while Qwen3.5-4B shows the widest within-model spread (98 on NA $\times$ WU vs. 27 on AE $\times$ DG), suggesting surface-pattern acquisition without underlying composition skill.

Language-Conditioned Tool-Invocation Bias. All models trained by non-Chinese organizations achieve higher scores on Chinese than English sessions (up to +11.4 pp Pass@Session for Gemini 3.1 Pro). A turn-level breakdown for Gemini 3.1 Pro shows that 23% of turns where Chinese passed but English failed involve insufficient tool use (the English session skips EHR calls correctly invoked in Chinese), and 3% are outright refusals absent in Chinese entirely. We attribute this to a language-conditioned safety prior: English training data reinforces disclaimers about AI systems not accessing clinical records, suppressing EHR tool calls in English sessions. This motivates reporting multilingual results separately.

A Narrow Flagship Band. Among the flagship models, performance compresses into a narrow band: the top contenders (GPT-5.4-high, GLM-5, Claude-Opus-4.7, Kimi-K2.6, Seed-1.8) fall

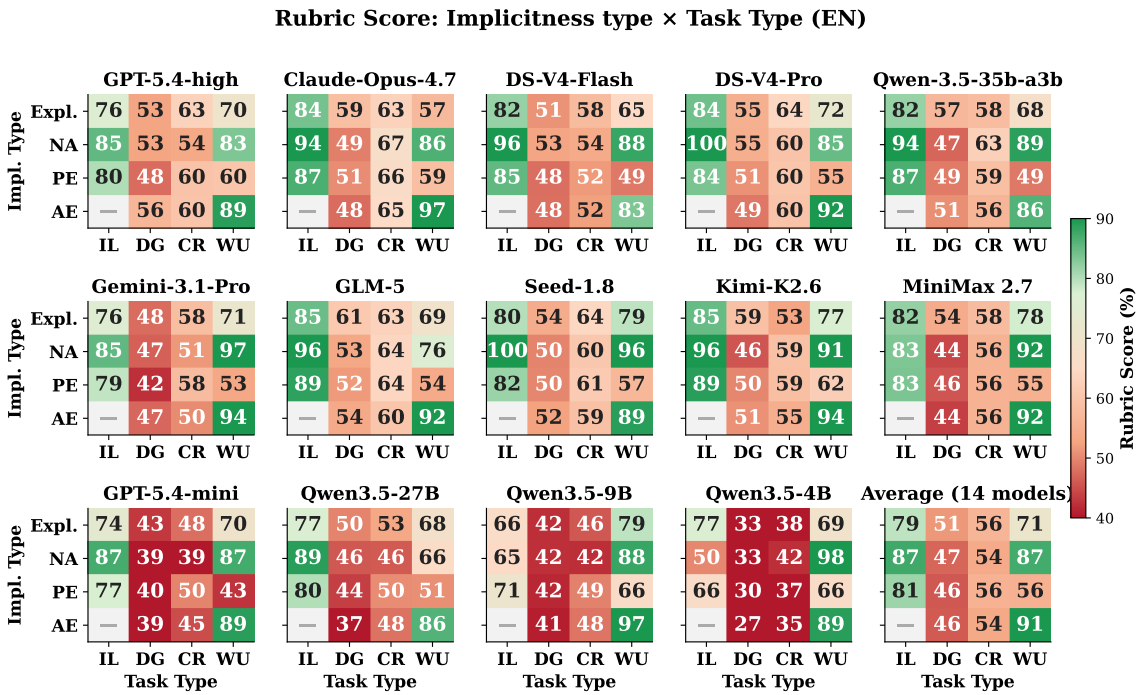

Figure 3: Rubric score (%) by implicitness type × task type (EN), for 14 models and their average. Information Lookup stays robust across all implicitness types, while Data Gathering (multi-tool composition) and Clinical Reasoning (knowledge-grounded inference) are the consistent weak points across models. Both demand reasoning beyond single-point retrieval. Results for Chinese (ZH) are presented in Appendix I2

within ~5 points on EN despite differences in scale and architecture. We attribute this to the information filtering inherent in the data construction pipeline: since EHR evidence is fetched on demand, parametric knowledge differences are removed at the data-construction stage, so models differ in how they *compose* tool calls, not in what they *know*. Lightweight models stay clearly behind, with Qwen3.5-4B trailing GLM-5 (EN 69.4) by ~20 points. As retrieval already removed the knowledge axis, this gap isolates a reasoning deficit: smaller models obtain the same evidence but fail to reliably chain tool calls and integrate the results.

Invariance Across Data Richness Tiers. Performance is broadly invariant to the L1–L3 stratification. Across evaluated models (Appendix I2), mRS varies by less than ~4 points between L1 and L3, and the ranking is not monotonic for any model (L3 exceeds L1, e.g., Seed-1.8 EN, Qwen3.5-35B EN). This is a positive finding: under the FHIR tool abstraction, EHR scale is not the dominant bottleneck. Models navigate information-dense encounters via targeted tool calls just as effectively as sparse ones; the dominant axes of variance are instead task type and implicit-query type (Figure 3).

5.3 Effect of Implicit Queries

Model	NA			PE			AE		
	Expl.	Impl.	Δ	Expl.	Impl.	Δ	Expl.	Impl.	Δ
Claude-Opus-4.7	63.2	60.8	−2.4	67.0	65.7	−1.3	63.8	58.1	−5.7
GPT-5.4-high	60.3	59.5	−0.8	64.7	60.7	−4.0	61.5	58.7	−2.8
Gemini-3.1-Pro	56.2	54.9	−1.3	57.7	57.7	+0.0	55.2	48.8	−6.4
DeepSeek-V4-Pro	62.8	61.7	−1.1	62.8	63.0	+0.2	58.2	55.5	−2.7
DeepSeek-V4-Flash	65.8	59.9	−5.9	64.1	59.4	**−4.7**	60.1	50.2	**−9.9**
Seed-1.8	64.0	63.2	−0.8	67.7	65.7	−2.0	60.0	55.7	−4.3
Qwen3.5-35B-A3B	59.1	59.2	+0.1	64.9	62.5	−2.4	57.1	54.0	−3.1
Qwen3.5-27B	57.8	48.0	**−9.8**	59.2	55.9	−3.3	51.3	44.1	−7.2
Average	61.2	58.4	**−2.8**	63.5	61.3	**−2.2**	58.4	53.1	**−5.3**

Table 3: Explicit vs. implicit ablation (per subtype). Each model is evaluated twice over the entire benchmark: once with every query restored to a *fully explicit* paraphrase (*Expl.*), and once with the original *implicit* physician queries (*Impl.*); all other inputs (patient data, tools, gold answers) are held fixed. $\Delta = Impl. - Expl.$ is the performance lost to implicit phrasing (negative = implicitness hurts). Columns report the comparison restricted to turns of each implicit subtype (NA, PE, AE). The magnitude of Δ consistently grows with subtype difficulty (PE < NA < AE). All are rubric scores (%).

PhysAssistBench preserves both implicit and explicit versions of each query, allowing us to isolate the effect of implicit phrasing while keeping patient data, tools, and gold answers fixed. As shown in Table 3. The implicit penalty Δ is negative in 21 of 24 model×subtype cells, showing

that implicitness introduces a real difficulty rather than annotation noise: making queries explicit almost always improves accuracy. The penalty increases with anaphoric complexity, averaging -2.2 for Predicate Ellipsis, -2.8 for Nominal Anaphora, and -5.3 for Abstract Event Anaphora (AE), the only subtype where every model degrades. This ordering is intuitive: predicate ellipsis omits a locally recoverable verb, nominal anaphora refers to a specific entity, while AE requires reconstructing an accumulated clinical state across multiple turns. Implicit penalties also separate models more clearly than raw accuracy. Stronger systems (e.g., DeepSeek-V4-Pro, GPT-5.4-high) remain within -4.0 across all subtypes, whereas smaller open models are much more fragile (e.g., Qwen3.5-27B: -9.8 on NA; DeepSeek-V4-Flash: -9.9 on AE). Since real physicians do not usually restate full context, this explicit-implicit gap highlights a fundamental weakness of current EHR assistants in everyday clinical dialogue.

5.4 Effect of Patient Communication

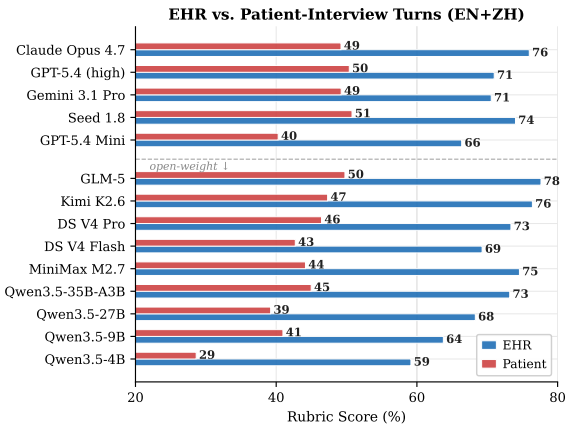

Figure 4: The comparison of rubric scores between EHR-only and Patient-interview turns.

Figure 4 compares model performance on structured EHR-access turns versus patient-interview turns. Across the benchmark (EN+ZH), each model is evaluated on approximately 1,944 EHR-only turns and 648 patient-interview turns. All fourteen models show a substantial drop on patient-interview turns, with an average decrease of 26.4 points. EHR-turn scores range from 59% to 78%, while patient-interview scores drop to 29%–51%.

The gap reflects a key difference in task structure. EHR turns mainly require retrieving or filtering well-defined records, where the correct tool usage is largely determined by the query. In contrast, patient-interview turns require models to elicit subjective information through natural dialogue and determine medically relevant follow-up questions, combining conversational ability with clinical reasoning. The gap is slightly smaller for stronger proprietary models (20.6–26.8 points) than for smaller open-weight models (22.8–30.5 points), but remains substantial across all models. While AgentClinic (Schmidgall et al., 2026) evaluates doctor-patient dialogue only, our results show that EHR access does not reduce this difficulty; integrating both sources only compounds the challenge. This gap persists uniformly across all models, suggesting that patient communication is a capability bottleneck independent of general model capacity.

6 Conclusion

We introduced PHYSASSISTBENCH, the first benchmark that jointly evaluates LLMs on three co-occurring challenges of physician-EHR interaction: implicit physician queries, structured FHIR-based EHR tool use, and ambiguous patient communication. Built from real MIMIC-IV cases, PHYSASSISTBENCH uses a scalable multi-agent synthetic data pipeline to construct *agentic patients* for interactive doctor-patient-EHR scenarios. Our results show that even the strongest LLMs remain far from reliable as physician assistants, highlighting interaction and coordination as key bottlenecks for clinical LLMs. We release the benchmark and code to support research on LLM clinical deployments.

Limitations

Scenario Coverage. PHYSASSISTBENCH spans four clinical scenarios chosen to cover a representative range of EHR reasoning and tool-use demands. Real-world clinical workflows include many additional contexts, such as critical-care management, specialist referral, and post-discharge follow-up, that fall outside the current scope. We plan to extend the scenario set in future releases, especially to higher-stakes and time-sensitive settings.

Model Coverage and Task Depth. PHYSASSISTBENCH is designed to stress-test multi-turn reasoning, structured tool use, and implicit query understanding rather than biomedical knowledge recall alone. We therefore focus on frontier general-purpose LLMs with strong tool-use capabilities. Domain-specific medical LLMs, such as Med-PaLM 2 and HuatuoGPT, are important baselines, but many are primarily optimized for biomedical

QA or clinical knowledge tasks, are not publicly accessible, or are not readily adapted to FHIR-style tool interfaces. Evaluating medical specialist models with comparable tool-use scaffolds is an important direction for future work.

Agent Design Generality. Although *agentic patients* are grounded in real records, they remain tailored to predefined scenarios and task types. In principle, static patient records could be transformed into richer interactive environments beyond dialogue, including more complex simulations such as in-silico clinical trials. Our current pipeline, however, uses a manually designed agent workflow for doctor-patient-EHR assistance and does not yet include a meta-pipeline for automatically designing new agent structures for substantially different scenarios. Developing such adaptive agent-pipeline design is an interesting direction for future work.

Data Source. All patients are drawn from MIMIC-IV, a US academic medical dataset with a heavy ICU focus, which may not generalize to documentation styles or disease prevalence in other healthcare systems.

Language. PHYSASSISTBENCH is currently available in English and Chinese; supporting additional languages would require re-grounding clinical terminology and patient persona behaviour in language-specific medical corpora.

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A Data, Licensing, and Ethical Considerations

A.1 Data Licence and Distribution

PHYSASSISTBENCH is built on MIMIC-IV (Johnson et al., 2023), released on PhysioNet under the **PhysioNet Credentialed Health Data Licence 1.5.0**. Access requires completing a recognised human-subjects research training programme (e.g. CITI "Data or Specimens Only Research" course) and signing a data-use agreement on PhysioNet. Because every PHYSASSISTBENCH session is a derivative of MIMIC-IV patient records, the benchmark session files inherit the same licence conditions and **may not be redistributed publicly**.

We release all artefacts independently under separate terms:

- **Code and evaluation harness** (tool API, judge prompts, scoring scripts): released under the Apache License 2.0.
- **Benchmark session files** (JSONL containing patient-derived data): distributed through a PhysioNet-linked repository; requesters must hold an active MIMIC-IV data-use agreement before access is granted.
- **Pre-computed evaluation results** (model outputs, rubric scores): released openly as they contain no patient-level data.

A.2 Consistency with Intended Use

MIMIC-IV was created to support clinical and translational research, quality improvement, and the development of clinical decision-support tools (Johnson et al., 2023). Constructing a benchmark to evaluate LLMs on physician–EHR interaction is fully consistent with that intent.

We impose the following restrictions on downstream use of PHYSASSISTBENCH:

- The benchmark is intended for *research and evaluation only* and must not be deployed in real clinical workflows.
- Benchmark sessions must not be used as training data for evaluated models, to prevent leaderboard contamination.
- Derivative works must respect the original PhysioNet access conditions and must not be used outside research contexts.

A.3 Privacy and De-identification

MIMIC-IV is de-identified by the MIT Laboratory for Computational Physiology following HIPAA Safe Harbor standards (Johnson et al., 2023):

- **Direct identifiers removed:** patient names, geographic subdivisions finer than state, telephone numbers, and device identifiers are absent from the released data.
- **Date shifting:** all dates are offset by a random, per-patient amount anchored to the patient's `anchor_year`, making true calendar dates unrecoverable.
- **Age capping:** patients older than 89 are grouped into a single 90+ anchor-year bin to prevent age-based re-identification.

PHYSASSISTBENCH preserves all of these protections and introduces no additional identifiers. Session files contain MIMIC-IV `subject_id` values, which are surrogate keys with no mapping to real-world identities outside the MIMIC-IV access-controlled environment. Clinical note content reproduced in sessions (discharge summaries, radiology reports) retains no names or explicit dates.

Despite these protections, re-identification risk is non-zero: discharge summaries may describe unusual disease combinations that, combined with external auxiliary information, could narrow a patient's identity. We therefore require credentialed access for all session files, consistent with PhysioNet terms.

We additionally note that MIMIC-IV clinical text reflects real physician language, which may contain implicit demographic biases or culturally specific clinical framing. Systematic content auditing beyond the PhysioNet de-identification pipeline was not performed; this is acknowledged as a limitation in §6.

A.4 Artefact Documentation and Coverage

Domain and source. All patient data originate from Beth Israel Deaconess Medical Center (BIDMC), Boston, MA, USA, collected approximately 2008–2019. BIDMC is a large academic tertiary-care centre with a heavy ICU and internal-medicine case mix. Benchmark performance may

not generalise to community hospitals, non-US healthcare systems, or populations with substantially different disease prevalence.

Languages. All sessions are provided in English and Mandarin Chinese. English queries are generated directly from MIMIC-IV data; Chinese queries are produced via a round-trip translation pipeline with semantic verification. Underlying clinical notes (discharge summaries, radiology reports) remain in English throughout, as MIMIC-IV contains no Chinese-language source records. Patient-simulation responses are available in both languages.

A.5 Dataset Statistics

Dataset statistics. The complete benchmark composition, including scenario, data-richness, task-type, and implicitness distributions, is reported in Appendix G.

A.6 Use of AI Assistance

During manuscript preparation, we used LLMs only for grammar correction, language refinement, and limited assistance in literature search. All cited references were manually checked and verified by the authors. The authors reviewed and edited all AI-assisted text and take full responsibility for the content of the manuscript.

Other uses of LLMs are part of the scientific design of this work and are explicitly described in the relevant sections. First, LLMs are the evaluated models in all experiments (Section 5). Second, LLMs are used as components of the multi-agent benchmark construction pipeline, including the Session Planner, Doctor Agent, Patient Agent, and quality checker (Section 3). Third, GPT-5.4-mini is used as the automated rubric judge for turn-level scoring (Section 3.4), with human agreement validation reported in Appendix C.4.

A.7 Ethical Considerations

PHYSASSISTBENCH is built from MIMIC-IV, a publicly available de-identified clinical dataset, and we followed its standard data-use and access requirements. The benchmark is intended only for research evaluation, not for clinical deployment or autonomous decision-making. As a secondary-use benchmark with synthetic interactions, PHYSASSISTBENCH may inherit biases from the source records and introduce additional biases through scenario planning, patient personas, LLM-generated dialogue, and record filtering. In particular, because the pipeline selects records that can support predefined scenarios, it may introduce implicit cohort-selection effects, which should be considered for clinically sensitive evaluations. We mitigate these risks through record grounding, filtering, and manual review, but the benchmark should still be interpreted as an evaluation resource rather than a representation of real patient experience.

B Data and Code Availability

Our dataset is derived from MIMIC-IV (Johnson et al., 2023) under the PhysioNet Credentialed Health Data License. Following the re-distribution requirements of the original license, the dataset will be released formally via PhysioNet. Access requires a valid PhysioNet credentialed account and acceptance of the corresponding data use agreement. The released dataset includes: (1) de-identified EHR snapshots extracted from MIMIC-IV admissions used as session inputs; (2) per-subject patient records partitioned by `subject_id`, containing structured clinical data (diagnoses, medications, observations, procedures); (3) 324 annotated clinical sessions 1296 turns in both English and Chinese; (4) gold-standard tool-call trajectories and reference answers for each turn; and (5) evaluation rubrics per turn with per-item pass/fail annotations. All protected health information (PHI) has been removed.

The codebase is publicly available on GitHub under the Apache License 2.0. It includes scripts to extract and partition raw MIMIC-IV records by `subject_id`, converting them into EHR snapshots, running the scalable multi-agent synthetic data pipeline for constructing *agentic patients* (Section 4) and reproducing reported evaluations. It also provides sample data for setup without requiring full MIMIC-IV access.

C Human Evaluation Details

C.1 Expert Reviewer Backgrounds

Clinical Expert. We recruited one volunteer senior physician (female), board-certified in her country of practice and with 15 years of clinical experience. Participation was voluntary and uncompensated (no monetary reward). The participant used English and Chinese as the language of instruction.

Trained Annotators. We recruited 8 volunteer trained annotators (two female, six male), each

with several years of clinical AI and NLP research experience. Those with more than 8 years of NLP research experience are regarded as NLP experts. Participation was voluntary and uncompensated (no monetary reward). The participants used English and Chinese as the languages of instruction.

C.2 Human Review and Field Verification

The physician review and trained-annotator review served distinct purposes. The former assessed session-level clinical plausibility, whereas the latter performed field-level verification and correction across the released data.

Stage 1: Clinical Plausibility Review. After the pipeline produced the initial dataset, we sampled 25% of the sessions for clinical review. The clinical expert assessed each sampled dialogue for clinical plausibility, i.e., whether the interaction could realistically occur in practice and whether the content contained any internal medical contradictions. On the sampled subset, 95% of sessions were judged clinically plausible. Two NLP experts then collected the sessions flagged as implausible, distilled the clinical expert's comments into additional pipeline prompt constraints, and regenerated those sessions.

Stage 2: Field-Level Verification. In the second stage, all 8 trained annotators verified the correctness of each annotated field of every session, covering both the previously approved sessions and the regenerated ones. Three fields were checked: (i) the implicitness type, i.e., whether the assigned type matches the actual implicit query; (ii) the rubric, i.e., whether each item corresponds one-to-one with its gold answer; and (iii) the gold tool calls, i.e., whether their parameters are correct. The implicitness-type assignment matched the query in 87% of cases, and only 8% of rubric items required revision. The trained annotators reviewed and corrected all flagged fields, yielding 100% turn-level coverage.

C.3 Full-Benchmark Realism Assessment

The board-certified physician and the trained annotators rated each session along two dimensions: *query realism*, whether the physician's query resembles a request that could occur in practice, and *trajectory coherence*, whether the four turns form a clear clinical workflow. Each dimension was scored from 1 (lowest) to 5 (highest); scores below 3 were designated as low quality. The session-level realism score is the mean of the two dimension scores.

Scenario	n	Mean	Min.	≥ 4.5
Diagnostic Workup	81	4.42	4.00	73%
Medication Safety	81	4.47	4.00	79%
Treatment Response	81	4.39	4.00	78%
Discharge Planning	81	4.20	3.50	47%
Overall	**324**	**4.37**	**3.50**	**69%**

Table C1: Session-level realism ratings by clinical scenario. The final column reports the percentage of sessions with a mean score of at least 4.5.

Scenario	Query realism	Trajectory
Diagnostic Workup	4.33	4.51
Medication Safety	4.28	4.65
Treatment Response	3.80	4.98
Discharge Planning	3.70	4.69
Overall	**4.03**	**4.71**

Table C2: Mean scores for the two realism dimensions.

The overall mean is 4.37/5, and no session falls below the quality threshold. Table C3 shows the lowest-scoring session. Its mean score of 3.5 reflects the textbook-like wording of Turn 1, rather than a clinical contradiction; the four turns still form a coherent workflow.

Turn	Task type	Subtype	Physician query
T0	Information Lookup	Explicit	What was the reason for this admission?
T1	Data Gathering	AE	In summary, what is the management plan for catheter-related infection in patients receiving immunosuppressive drugs?
T2	Data Gathering	PE	Is the patient taking Tacrolimus as prescribed, and how are they managing daily activities at home?
T3	Write/ Update	NA	Add the medication I just mentioned, 2 mg orally twice daily, to the medication list, as the patient reported not taking it and is currently using other immunosuppressants.

Table C3: The lowest-scoring session (`discharge_planning_15`): query realism 3, trajectory coherence 4, and mean realism 3.5.

C.4 Judge Model Reliability

We evaluated the judge-agreement study on 108 sessions per language, one third of the 324-session

benchmark in each language. Using GLM-5 responses as the scoring target, the eight trained annotators scored the same rubric items as the fixed GPT-5.4-mini judge. The resulting comparison contains 3,864 rubric items. The judge and trained-annotator labels agree on 3,685 items, yielding 95.37% agreement. A two-sided normal-approximation binomial confidence interval, $\hat{p} \pm 1.96\sqrt{\hat{p}(1-\hat{p})/n}$, has a half-width of 0.66 percentage points.

	IL	DG	CR	WU
EN agreement	0.9621	0.9518	0.9605	0.9782
ZH agreement	0.9431	0.9419	0.9542	0.9455
EN disagreements	16	29	25	6
ZH disagreements	24	35	29	15
Total items	844	1,204	1,266	550

Table C4: Judge agreement by task type and language. Total-item counts combine English and Chinese; each language contributes half of the items in every task column.

	Factual	Clinical	Context	Safety
EN agreement	0.9654	0.9596	0.9355	0.9641
ZH agreement	0.9578	0.9358	0.9113	0.9521
EN disagreements	32	29	8	6
ZH disagreements	39	46	11	8
Total items	1,848	1,434	248	334

Table C5: Judge agreement by rubric category and language: factual accuracy, clinical interpretation, context integration, and hallucination/safety. Total-item counts combine English and Chinese.

Agreement exceeds 91% in every reported task-, language-, and rubric-category subset. This study evaluates agreement on one target model (GLM-5) and should therefore be interpreted as evidence for judge reliability on the sampled outputs, rather than exhaustive validation across all model output distributions.

D EHR Tool Inventory

PHYSASSISTBENCH exposes **18 tools** to the evaluated agent, organized into four groups: EHR read tools, EHR write tools, patient-interview tools, and one control tool. All EHR tools follow the FHIR R4 naming convention (`ResourceType.operation`); patient-interview tools use the `patient.*` namespace. Each tool call requires a `subject_id` (MIMIC-IV patient identifier); most read tools also accept an optional `hadm_id` to scope results to a single admission.

D.1 EHR Read Tools (9)

As shown in Table D1, these 9 read-only tools expose MIMIC-IV structured records via a FHIR R4–compatible interface, covering patient demographics, encounters, diagnoses, observations (lab, vitals, microbiology), medications, diagnostic reports, clinical notes, and care plans. `Observation.search` is the most heavily used tool, unifying laboratory, vital-sign, and microbiology data under one parameterised call.

D.2 EHR Write Tools (3)

As shown in Table D2, these 3 tools simulate EHR write operations and are used primarily in *Write/Update* turns (T3) of the Discharge Planning scenario, and also appear in Diagnostic Workup, Medication Safety, and Treatment Response turns that require ordering or flagging actions.

D.3 Patient Interview Tools (5)

As shown in Table D3, patient-interview tools expose a simulated patient agent to the evaluated model. The patient responses are pre-generated during benchmark construction, grounded in the same admission records as the corresponding EHR snapshots, and stored with each session. During evaluation, each tool call returns the corresponding fixed response through deterministic replay; the patient LLM is not invoked online. All patient tools require `subject_id` and `session_id`.

D.4 Control Tool (1)

`prepare_to_answer` (Table D4) is a mandatory bookkeeping call that every turn must end with. It separates the *information-gathering* phase from the *answer-generation* phase: the benchmark records whether the agent issues this call, and omitting it is penalised as an incomplete plan regardless of the quality of the final answer.

D.5 Tool Usage by Scenario

Table D5 shows which tools appear as gold-standard actions in at least one session of each benchmark scenario. During *data generation*, the reference trajectories were constructed under scenario-specific constraints: only clinically relevant tools were included in the gold plans to ensure grounded and parsimonious annotations. During *evaluation*, however, all 18 tools are exposed to the model without restriction, so that the benchmark can assess whether the model selects the appropri-

Tool name	Description	Key opt. params
Patient.read	Returns demographic information (gender, anchor age, deceased date).	—
Encounter.search	Retrieves all hospital admissions with admission/discharge times, admission type, ward, and discharge disposition.	hadm_id
Condition.search	Returns ICD diagnosis conditions ordered by seq_num (principal diagnosis first). Supports filtering by ICD code prefix (e.g. K74) or clinical status (*active / resolved / inactive*).	hadm_id, code, clinical_status
Observation.search	The primary data-retrieval tool. Covers laboratory results (category=laboratory), ICU vital signs (category=vital-signs), and microbiology culture results (category=microbiology). The code parameter accepts a free-text lab/vital name (e.g. *Creatinine*, *Heart Rate*); results are sorted newest-first.	hadm_id, category, code, date_from, date_to, _count
MedicationRequest.search	Returns prescription (medication order) records sorted by start time newest-first. Accepts drug-name substring filter and order-status filter (*active / completed / stopped*).	hadm_id, medication, status
MedicationAdministration.search	Returns eMAR records showing which medications were *actually administered*, when, and at what dose—distinct from what was prescribed.	hadm_id, medication
DiagnosticReport.search	Returns radiology and other diagnostic reports with full report text. Accepts modality filter (*CT, MRI, X-ray, Echo*).	hadm_id, report_type
DocumentReference.search	Searches clinical notes (discharge summaries and radiology reports). Supports document-type selection (*discharge-summary / radiology*) and full-text keyword search.	hadm_id, type_code, keyword
CarePlan.search	Returns post-discharge care plan sections extracted from MIMIC-IV discharge notes: discharge instructions, follow-up schedules, and inpatient treatment plans. Filter by category (*discharge-planning / followup / treatment*).	hadm_id, category

Table D1: EHR read tools (FHIR R4 naming). All tools require subject_id; most accept an optional hadm_id to scope results to a single hospital admission.

Tool name	Description	Required params
MedicationRequest.create	Creates a new medication order (prescription). Used for discharge medication additions or inpatient dose changes.	medication, dose, route, frequency
ServiceRequest.create	Creates a referral or service request for discharge planning (e.g. home health, physical therapy, social work, specialist follow-up).	service_type, priority
Flag.create	Creates a safety-critical alert flag on the patient record (e.g. high fall risk, allergy update, mandatory follow-up).	category, code, detail

Table D2: EHR write tools. All tools additionally require subject_id.

Tool name	Description
patient.get_symptom_history	Asks the patient to describe their symptom history in OPQRST style (onset, provocation, quality, radiation, severity, timing). An optional query parameter focuses the response on a specific symptom (e.g. *abdominal pain*).
patient.get_medication_adherence	Asks whether the patient is taking a specific medication as prescribed. The required drug parameter names the medication of interest. For patients with *critical_withheld* profiles, naming the drug explicitly may surface intentionally withheld non-adherence.
patient.get_social_history	Asks about the patient's social situation: living arrangements, occupation, smoking, alcohol use, and support system.
patient.get_functional_status	Asks about functional capacity and ability to perform activities of daily living (ADLs); returns any reported limitations.
patient.get_pain_assessment	Asks the patient to characterise any pain: location, severity (0–10 NRS), character, onset, and radiation.

Table D3: Patient-interview tools (patient.* namespace). All tools require subject_id and session_id.

Tool name	Description
prepare_to_answer	Signals that sufficient information has been gathered and the agent is ready to produce the final answer to the user. The optional answer_type parameter distinguishes tool-grounded answers (tool) from knowledge-only responses (chat). This tool must appear as the final action of every turn; omitting it is counted as an incomplete plan.

Table D4: Control tool. No mandatory parameters.

Tool	Diag. Workup	Discharge Plan	Med. Safety	Treat. Response
EHR Read				
Patient.read	✓	✗	✓	✗
Encounter.search	✗	✓	✗	✗
Condition.search	✓	✓	✓	✓
Observation.search	✓	✓	✓	✓
MedicationRequest.search	✓	✓	✓	✓
MedicationAdministration.search	✓	✓	✓	✓
DiagnosticReport.search	✓	✓	✗	✗
DocumentReference.search	✗	✓	✗	✗
CarePlan.search	✗	✓	✗	✗
EHR Write				
MedicationRequest.create	✓	✓	✓	✓
ServiceRequest.create	✓	✓	✗	✓
Flag.create	✓	✓	✓	✓
Patient Interview				
patient.get_symptom_history	✓	✓	✓	✓
patient.get_medication_adherence	✓	✓	✓	✓
patient.get_social_history	✓	✓	✓	✗
patient.get_functional_status	✗	✓	✗	✗
patient.get_pain_assessment	✗	✗	✗	✓
Control				
prepare_to_answer	✓	✓	✓	✓

Table D5: Tool usage across the four benchmark scenarios. ✓ = appears in the gold-standard trajectory of at least one session; ✗ = not required by any gold trajectory in that scenario.

ate tools, avoids unnecessary calls, and handles the full tool vocabulary rather than a curated subset.

E Physician Query Implicitness Example

Table E1 shows representative examples about different physician query implicitness.

F Full Session Example

Figure F1 and F2 present two representative full-session examples illustrating the tool calls, explicit and implicit query reformulations, and the corresponding evaluation rubrics.

G Benchmark Statistics

Table G1 reports session counts by clinical scenario and data-richness tier. Table G2 reports turn counts by task type and turn position. Table G3 reports implicitness-type counts over Turns 1–3.

PHYSASSISTBENCH contains 324 sessions and 1,296 turns. The sessions are evenly distributed across four clinical scenarios, with 81 sessions per scenario, and three data richness tiers, with 108 sessions per tier. This balance applies to the scenario and data richness dimensions at the session level. The distributions of task types and implicitness types are not uniform because of the benchmark's four turn structure. Information Lookup accounts for 463 turns (35.7%), including all 324 fixed anchor turns at Turn 0 and 139 occurrences at later positions. Data Gathering contributes 357 turns (27.5%), Clinical Reasoning contributes 341 turns (26.3%), and Write/Update accounts for 135 turns (10.4%). Write/Update occurs only at Turn 3. All Turn 0 queries are explicit. Among the 972 queries from Turn 1 to Turn 3, 182 remain explicit and 790 carry an implicitness type. Across the full benchmark, there are 506 Explicit queries, 472 Predicate Ellipsis queries, 196 Abstract Event Anaphora queries, and 122 Nominal Anaphora queries.

H Data Generation Pipeline

H.1 Patient Pre-Filtering

Patients are pre-filtered in two stages. Stage 1 applies file-size thresholds to exclude patients with sparse records. Stage 2 enforces scenario-specific content criteria: each scenario requires that the relevant FHIR resource types contain sufficient records within the target admission (e.g., at least two time-stamped infection markers for *treatment_response*; at least three active prescriptions and a discharge summary for *discharge_planning*). Data-richness tier further refines eligibility: the *data-moderate* tier requires at least two time-stamped values for the same lab to support trend queries; the *data-rich* tier additionally requires multiple drug-lab monitoring pairs to be present.

H.2 EHR Snapshot

For each entry, all available data for the target patient-admission is extracted from MIMIC-IV and consolidated into a structured text snapshot injected into every downstream agent prompt. The snapshot contains two key annotated blocks. The **Queryable Items** block lists every queryable FHIR resource with data-availability annotations: items with only a single record are restricted to *Information Lookup* turns, while items with two or more records are additionally eligible for trend-based *Data Gathering* and *Clinical Reasoning* turns. This constraint prevents agents from generating questions about data that does not exist in the patient record. The **Clinical Scoring Opportunities** block identifies clinical scores computable from the available data (e.g., SOFA, SIRS, CHA_2DS_2-VASc); the session planner is required to incorporate a scoring-based turn when this block is present.

H.3 Session Planner

Before turn-level generation begins, the Session Planner produces a coherent four-turn clinical narrative plan specifying, for each turn, the topic to investigate, the recommended tool call(s), and the tool source (`ehr` / `mixed` / `patient`). The planner operates under three layers of constraint injected into its system prompt. **Scenario constraints** specify which FHIR resource types are permitted or forbidden per scenario, and which Workup patterns are required. **Data-richness tier constraints** are summarised in Table H1. **Tool diversity constraints** require each session to span at least two distinct FHIR resource types, with any single resource type appearing in at most two turns. At most one turn per session may be assigned a patient interview (`tool_source=mixed` or `patient`).

H.4 Two-Stage Question Generation

Stage 1: Explicit question. The User Question Agent generates an unambiguous explicit question grounded in the EHR snapshot, guided by the Session Planner's topic hint and task-type-specific generation rules. *Data Gathering* questions must not pre-state any lab value or drug name, ensuring the

Session A: Discharge Planning | HIV^{+}, type-2 diabetes, CKD (eGFR $\approx$ 35)

Type / Impl.	Implicit query	Explicit query	Tool calls & patient response	Model answer	Rubric criteria
T0 IL ehr / —	What's the latest HIV viral load?	What's the latest HIV viral load?	`Observation.search(code=HIV Viral Load)` → *0.0 log10 copies/mL*	HIV viral load: 0.0 log10 copies/mL (undetectable).	• States VL = 0.0 log10 copies/mL • Interprets as undetectable • No fabricated data
T1 IL ehr / PE	Creatinine?	What's the latest creatinine?	`Observation.search(code=Creatinine` → *Cr = 1.2 mg/dL*	Creatinine: 1.2 mg/dL (within normal range).	• Cites Cr = 1.2 mg/dL • Interprets as within normal range • Gives a clear conclusion

T2 DG mixed / AE	Given all this, is metformin still appropriate?	Based on the creatinine value, is metformin still appropriate?	`Observation.search(Creatinine)`
			→ *Cr = 1.2 mg/dL*
			`MedReq.search(Metformin)`
			→ *Metformin 500 mg order (active)*
			`patient.get_med_adherence(Metformi`
			"No, I'm actually not taking the Metformin. It makes me so nauseous I stopped a few weeks ago. I never brought it up."
				• Cr 1.2 does not contraindicate metformin on renal grounds
				• Patient stopped metformin due to GI nausea, not renal safety
				• Barrier is tolerability; suggest dose reduction or extended-release
				• Consider SGLT2/GLP-1 if GI effects persist
					• Cites Cr 1.2; renal function does not contraindicate
					• Quotes patient stopping metformin for nausea
					• Identifies tolerability (not renal) as the barrier
					• Recommends dose reduction / XR; alt. agent if persists

T3 WU write / NA	OK, please create a medication order to reduce it to 250 mg orally once daily, given an estimated eGFR of 35 mL/min/1.73m^2.	OK, please create a medication order to reduce metformin to 250 mg orally once daily, given an estimated eGFR of 35 mL/min/1.73m^2.	`MedicationRequest.create(`
			`medication=Metformin,`
			`dose=250 mg, route=oral,`
			`frequency=once daily)`
			→ *order created (active)*
				• Metformin 250 mg PO once daily ordered
				• Reduced dose appropriate for eGFR $\approx$ 35
				→ renally-adjusted, safe for discharge
					• Calls `MedicationRequest.create` (no other write)
					• `medication=Metformin`
					• `dose=250 mg` (not $\geq$500 mg)
					• `route=oral; frequency=once daily`

会话 **A**：出院规划 | HIV^{+}，2型糖尿病，慢性肾病（eGFR $\approx$ 35）

类型 / 隐式性	隐式查询	显式查询	工具调用与病人回答	模型回答	评分标准
T0 IL ehr / —	最新的HIV病毒载量是多少?	最新的HIV病毒载量是多少?	`Observation.search(code=HIV Viral Load)` → *0.0 log10 拷贝/mL*	HIV病毒载量：0.0 log10 拷贝/mL（检测不到）。	• 指出病毒载量为0.0 log10拷贝/mL • 解读为检测不到 • 不编造额外数据
T1 IL ehr / PE	肌酐?	最新的肌酐是多少?	`Observation.search(code=Creatinine` → 肌酐 = *1.2 mg/dL*	肌酐：1.2 mg/dL（在正常范围内）。	• 引用肌酐为1.2 mg/dL • 解读为正常范围内 • 给出明确结论

T2 DG mixed / AE	那这样的话，二甲双胍是否仍然适用?	根据肌酐值，二甲双胍是否仍然适用?	`Observation.search(Creatinine)`
			→ 肌酐 = *1.2 mg/dL*
			`MedReq.search(Metformin)`
			→ 二甲双胍 *500 mg* 医嘱（活跃）
			`patient.get_med_adherence(Metformi`
			"其实.....我没在吃二甲双胍。它让我特别恶心，几周前我就停了，一直也没好意思提。"
				• 肌酐1.2不构成二甲双胍的肾功能禁忌
				• 患者因胃肠道恶心停药，并非肾脏安全问题
				• 主要障碍是耐受性；建议减量或换用缓释剂型
				• 若胃肠道反应持续，可考虑SGLT2/GLP-1
					• 引用肌酐1.2；肾功能不构成禁忌
					• 引用患者因恶心停用二甲双胍
					• 指出障碍是耐受性而非肾功能
					• 建议减量/缓释；持续则换药

T3 WU write / NA	好的，请开具医嘱，减量至250 mg口服每日一次，因估算eGFR为35 mL/min/1.73m^2。	好的，请开具医嘱，将二甲双胍减量至250 mg口服每日一次，因估算eGFR为35 mL/min/1.73m^2。	`MedicationRequest.create(`
			`medication=Metformin,`
			`dose=250 mg, route=oral,`
			`frequency=once daily)`
			→ 医嘱已创建（活跃）
				• 已开具二甲双胍250 mg口服每日一次
				• 减量符合eGFR $\approx$ 35的肾功能调整
				→ 经肾功能调整，可安全出院
					• 调用 `MedicationRequest.create`（无其他写工具）
					• `medication=Metformin`
					• `dose=250 mg`（非$\geq$500 mg）
					• `route=oral; frequency=once daily`

IL Information Lookup | DG Data Gathering | CR Clinical Reasoning | WU Write/Update | **Impl.:** PE Predicate Ellipsis | NA Nominal Anaphora | AE Abstract Event Anaphora | — Explicit

Figure F1: **Session A** (discharge planning), shown in both languages: (a) English and (b) Chinese. Each turn lists both the *implicit* query actually posed to the model and its *explicit* paraphrase (used in the explicit-query ablation), so the contrast is visible per turn: e.g. T1 "Creatinine?" vs. "What's the latest creatinine?" (PE), and T3 "reduce *it* to 250 mg" vs. "reduce *metformin* to 250 mg" (NA). The patient has HIV (undetectable viral load), type-2 diabetes and CKD. The `mixed` DGturn (T2) is pivotal: the patient interview reveals the patient has *silently stopped* metformin due to nausea, reframing the question from renal safety to tolerability, information absent from the structured EHR. Patient responses (*italic quotes*) come from the patient-simulation agent grounded in MIMIC-IV discharge notes; the Chinese panel uses Chinese patient replies. Tool calls (`monospace`) remain in English as issued against the FHIR API.

Session B: Medication Safety | 51 M, hyperkalemia management

Type / Impl.	Implicit query	Explicit query	Tool calls & patient response	Model answer	Rubric criteria
T0 IL ehr / —	What's the latest potassium level?	What's the latest potassium level?	`Observation.search(code=Potassium)` → *K = 5.2 mEq/L (↑)*	Potassium: 5.2 mEq/L (↑ above normal range 3.3–5.1; hyperkalemia).	• States K = 5.2 mEq/L • Interprets as elevated (hyperkalemia) • Provides conclusion on K level
T1 CR mixed / AE	Given all this, is the current dose of spironolactone still safe?	Based on this potassium level, is the current dose of spironolactone still safe?	`Observation.search(Potassium)` → *K = 5.2 mEq/L (↑)* `patient.get_med_adherence(lisinopr` *"Yes, I'm taking lisinopril exactly as prescribed, 10 mg once daily. Haven't missed any doses."*	• K = 5.2 (hyperkalemia): spironolactone should be paused or reduced • Recheck K and renal function before resuming • Patient adherent to lisinopril 10 mg daily	• States K = 5.2 mEq/L • K above 3.3–5.1 (hyperkalemia) • Suggests pausing/reducing spironolactone • Recommends rechecking K + renal fn.
T2 CR ehr / AE	Given these circumstances, can ACE-i still be used?	In the context of K = 5.2 mEq/L and concurrent spironolactone, is it safe to continue ACE-i?	`Observation.search(Potassium)` → *K = 5.2 mEq/L (↑)* `Observation.search(Creatinine)` → *Cr = 1.2 mg/dL (upper normal)*	• K = 5.2 (↑), Cr = 1.2 mg/dL (stable renal fn.) • Hyperkalemia + spironolactone co-use: ACE-i should be paused or dose-reduced • Recheck K before continuing ACE-i	• States K = 5.2 and Cr = 1.2 mg/dL • Indicates hyperkalemia + spironolactone • Suggests pausing ACE-i or reducing dose • Recommends rechecking K
T3 CR ehr / PE	What about furosemide?	In the context of K = 5.2 mEq/L with concurrent spironolactone and ACE-i, how should furosemide be managed?	`MedReq.search()` → *furosemide up to 160 mg IV used* `Observation.search(Potassium)` → *K = 5.2 mEq/L (↑)*	• K = 5.2 (↑); high-dose IV furosemide (up to 160 mg) administered • Furosemide may continue (promotes K excretion despite hyperkalemia) • Monitor K closely; prioritise reducing spironolactone	• States K = 5.2 above 5.1 • States high-dose IV furosemide used • Furosemide may continue (promotes K excretion) • Recommends monitoring K closely

会话 **B**：用药安全 | 51岁男性，高钾血症管理

类型 / 隐式性	隐式查询	显式查询	工具调用与病人回答	模型回答	评分标准
T0 IL ehr / —	最新的血钾水平是多少?	最新的血钾水平是多少?	`Observation.search(code=Potassium)` → *K = 5.2 mEq/L (↑)*	血钾：5.2 mEq/L（↑高于正常范围3.3–5.1，高钾血症）。	• 指出血钾为5.2 mEq/L • 正确解读为升高（高钾血症） • 给出血钾水平结论
T1 CR mixed / AE	那这样的话，螺内酯当前剂量还安全吗?	这个血钾水平，螺内酯当前剂量还安全吗?	`Observation.search(Potassium)` → *K = 5.2 mEq/L (↑)* `patient.get_med_adherence(lisinopr` "是的，我一直按医嘱服用赖诺普利，每天*10 mg*一次，一次都没漏过。"	• K=5.2（高钾血症）：应暂停或减少螺内酯 • 恢复前复查肾功能和血钾 • 患者按医嘱服用赖诺普利10 mg，依从性好	• 引用K=5.2 mEq/L • 指出高于正常范围（高钾血症） • 建议暂停/减少螺内酯 • 建议恢复前复查K和肾功能
T2 CR ehr / AE	鉴于这些情况，ACE-i还能继续使用吗?	在血钾5.2 mEq/L且同时使用螺内酯的情况下，继续使用ACE-i是否安全?	`Observation.search(Potassium)` → *K = 5.2 mEq/L (↑)* `Observation.search(Creatinine)` → 肌酐 = *1.2 mg/dL*（正常上限）	• K=5.2（↑），肌酐=1.2 mg/dL（肾功能稳定） • 高钾血症+螺内酯联用：应暂停ACE-i或减量 • 继续用药前复查血钾	• 引用K=5.2和肌酐=1.2 mg/dL • 指出高钾血症及螺内酯联用 • 建议暂停ACE-i或减量 • 建议继续前复查血钾
T3 CR ehr / PE	那呋塞米呢?	在血钾5.2 mEq/L且同时使用螺内酯和ACE-i的情况下，呋塞米应如何处理?	`MedReq.search()` → 呋塞米最高*160 mg*静注已用 `Observation.search(Potassium)` → *K = 5.2 mEq/L (↑)*	• K=5.2（↑），已使用高剂量静脉呋塞米（最高160 mg） • 呋塞米可继续使用（促进钾排泄，适用于高钾血症） • 密切监测血钾；优先减少保钾利尿剂剂量	• 指出K=5.2高于5.1 • 指出已使用高剂量静脉呋塞米 • 指出已使用高剂量静脉呋塞米 • 呋塞米可继续（促进钾排泄） • 建议密切监测血钾

IL Information Lookup | DG Data Gathering | CR Clinical Reasoning | WU Write/Update | **Impl.:** PE Predicate Ellipsis | NA Nominal Anaphora | AE Abstract Event Anaphora | — Explicit

Figure F2: **Session B** (medication safety), shown in both languages: (a) English and (b) Chinese. Each turn lists both the *implicit* query and its *explicit* paraphrase. A 51-year-old man with hyperkalemia (K = 5.2 mEq/L). The four IL/CRturns form a single safety thread in which each successive implicit question ("*Given all this…*", "*What about furosemide?*") refers back to the accumulating clinical picture, while the explicit column restates that context in full, exercising abstract-event (AE) and predicate-ellipsis (PE) implicitness. The `mixed` turn (T1) confirms lisinopril adherence via the patient interview. Patient responses (*italic quotes*) come from the patient-simulation agent grounded in MIMIC-IV discharge notes; the Chinese panel uses Chinese patient replies. Tool calls (`monospace`) remain in English as issued against the FHIR API.

Implicitness Type	Linguistic Mechanism	Prior Context	Explicit Query	Implicit Query
NA *Nominal Anaphora*	A pronoun or noun phrase refers back to a specific entity or value introduced earlier.	Turn 0: "What is this patient's most recent creatinine?" → Cr = 1.8 mg/dL	"Is that creatinine value consistent with Stage 3 CKD?"	"Is *it* consistent with Stage 3 CKD?"
PE *Predicate Ellipsis*	The main verb and its arguments are omitted; only the new focus element is stated.	Turn 0: "What is this patient's most recent creatinine?" → Cr = 1.8 mg/dL	"What is this patient's most recent eGFR?"	"*eGFR?*"
AE *Abstract Event Anaphora*	A phrase such as "given all this" refers to the accumulated clinical context across prior turns.	Turn 0: Cr = 1.8 mg/dL. Turn 1: eGFR = 35 mL/min. Turn 2: metformin 500 mg BID.	"Given the patient's creatinine and eGFR, is it safe to continue the metformin?"	"*Given all of this,* is it safe to continue the metformin?"

Table E1: The three physician-query implicitness types in PHYSASSISTBENCH, illustrated with a CKD–metformin scenario. In the Prior Context column, "→" denotes the tool output returned by the agent after executing the query. For AE row, prior turns are summarized directly and the earlier queries are omitted for brevity. Explicit queries are semantically complete physician requests, whereas implicit queries omit recoverable information and more closely resemble real clinical conversation. AE is generally more challenging than NA and PE.

Scenario	Data-sparse	Data-moderate	Data-rich	Total
Diagnostic Workup	27	27	27	81
Medication Safety	27	27	27	81
Treatment Response	27	27	27	81
Discharge Planning	27	27	27	81
Total	108	108	108	**324**

Table G1: Session distribution by clinical scenario and data-richness tier.

Task Type	T0	T1	T2	T3	Total
Information Lookup (IL)	324	78	61	0	463
Data Gathering (DG)	0	121	141	95	357
Clinical Reasoning (CR)	0	125	122	94	341
Write/Update (WU)	0	0	0	135	135
Total	324	324	324	324	**1,296**

Table G2: Turn distribution by task type and turn position. Turn 0 is fixed as IL; WU is restricted to Turn 3.

Type	T1	T2	T3	Total
Nominal Anaphora (NA)	35	40	47	122
Predicate Ellipsis (PE)	204	190	78	472
Abstract Event Anaphora (AE)	59	63	74	196
Explicit	26	31	125	182
Total	324	324	324	**972**

Table G3: Implicitness-type distribution over Turns 1–3 (972 turns). Turn 0 carries no implicitness type.

Table H1: Data-richness tier constraints injected into the session planner.

Tier	Required complexity
Data-sparse	Single data point per turn; no formula or multi-drug reasoning.
Data-moderate	At least one turn requires lab trend analysis, clinical formula application, or a drug-lab threshold safety check.
Data-rich	Must include conflicting evidence, multi-drug competing safety concerns, or sequential turn dependency where one turn's result drives the next clinical action. Must span ≥3 FHIR resource types. Patient interview is mandatory.

Planner Agent is required to retrieve data via tool calls rather than reading it from the question.

Stage 2: Implicit transformation. A subtype-specific ellipsis transform is applied to the explicit question. **NA** (Nominal Anaphora) replaces named entities with pronouns or deictic expressions referring to prior-turn mentions. **PE** (Predicate Ellipsis) deletes the main predicate, leaving a noun-phrase fragment that implies the same query action. **AE** (Abstract Event Anaphora) compresses the preceding clinical situation into an abstract event expression. When no suitable antecedent exists for the selected subtype, the pipeline falls back to PE. When content-word overlap between the explicit and transformed questions is zero—indicating LLM topic drift—the explicit question is reconstructed from the implicit form via a dedicated expansion agent.

H.5 Quality Gates

Each turn passes through three sequential quality gates; failure at any gate triggers a retry up to three times before the patient is skipped.

Gate 1 – Plan validation. Rule-based structural checks verify tool cardinality (Table H2) and parameter completeness.

Table H2: Rule-based plan validation criteria.

Condition	Rule
Information Lookup	Exactly 1 non-`prepare_to_answer` tool
Data Gathering	$\geq$2 non-`prepare_to_answer` tools
`tool_source=mixed`	$\geq$1 `patient.*` call required
`tool_source=patient`	All tools must be `patient.*`
Any EHR tool	`subject_id` must be present in arguments
Write/Update turn	$=$1 write tool call required

Gate 2 – Observation validation. A deterministic checker verifies that key EHR tool calls returned non-empty results (FHIR bundle `total` > 0). Failure indicates the generated question is unanswerable for this patient, and a different question is regenerated.

Gate 3 – Answer validation. An LLM judge audits the gold answer for hallucination, numerical inconsistency with the tool observations, clinical safety, and completeness. Safety violations or clear hallucination trigger rejection.

H.6 Pipeline Statistics

Table H3: Pipeline-generation statistics. Gate failure rates are estimated from pilot generation logs.

Metric	Value
Patient pool (`qualified_patients.json`)	
Diagnostic Workup	1,540
Medication Safety	1,894
Treatment Response	1,500
Discharge Planning	1,313
Total across four scenarios	6,247
Unique patients in final benchmark	293
Average patient attempts per session	≈ 2.5
Quality-gate terminal failure rates (turn level)	
Gate 1: plan validation	$\approx 12\%$
Gate 2: observation validation	$\approx 5\%$
Gate 3: answer validation	$\approx 10\%$

Data Generation Pipeline is shown as H1.

I Full Experiment Results

I.1 Performance by Clinical Scenario

Table I1 reports rubric scores broken down by the four clinical scenarios. Discharge Planning is consistently the hardest scenario across all models (column average 57.3%), likely because it requires integrating longitudinal EHR context, patient preferences, and multi-step care coordination rather than a single lookup. Treatment Response and Medication Safety are comparatively easier (68.1% and 67.1%), and show the largest spread between strong and weak models. Notably, Qwen3.5-35B-A3B achieves 74.9% on Medication Safety, on par with GLM-5 and well above its overall average (66.0%), suggesting that some open-weight models have uneven scenario-level strengths.

I.2 Performance by Data Richness

Table I2 reports rubric scores across three data richness tiers (High / Medium / Low). Tier gaps are small (typically 2–3 pp), and, counter-intuitively, High-richness sessions score slightly above Low-richness ones (64.5% vs. 63.5%), suggesting denser records offer disambiguation cues that offset added complexity. Weaker models (Qwen3.5-9B, Qwen3.5-4B) trend downward with declining richness while stronger models do not, implying richness matters more when capacity is limited. However, these differences are descriptive rather than causal, since tier assignment changes evidence availability, case composition, and required retrieval patterns.

I.3 Pass Rate Curves across Thresholds

Figure I1 plots Pass@Turn and Pass@Session against threshold $\tau \in [0, 1]$ for all fourteen models, separately for English and Chinese. Three patterns hold across both languages. First, Pass@Session decays far faster than Pass@Turn: at τ=0.60, Claude-Opus-4.7 reaches 67.7% Pass@Turn (EN) but only 23.5% Pass@Session, and by τ=0.75 most models drop below 10% Pass@Session even with Pass@Turn above 40%. Second, the spread between strong and weak models widens at the session level: Qwen3.5-4B records 1.5% Pass@Session at τ=0.60 (EN), approximately 20 pp below Claude and GLM-5. Third, Chinese scores stay slightly higher than English at every threshold (e.g., Claude 23.5%→26.9%, GLM-5 21.3%→26.5% at τ=0.60).

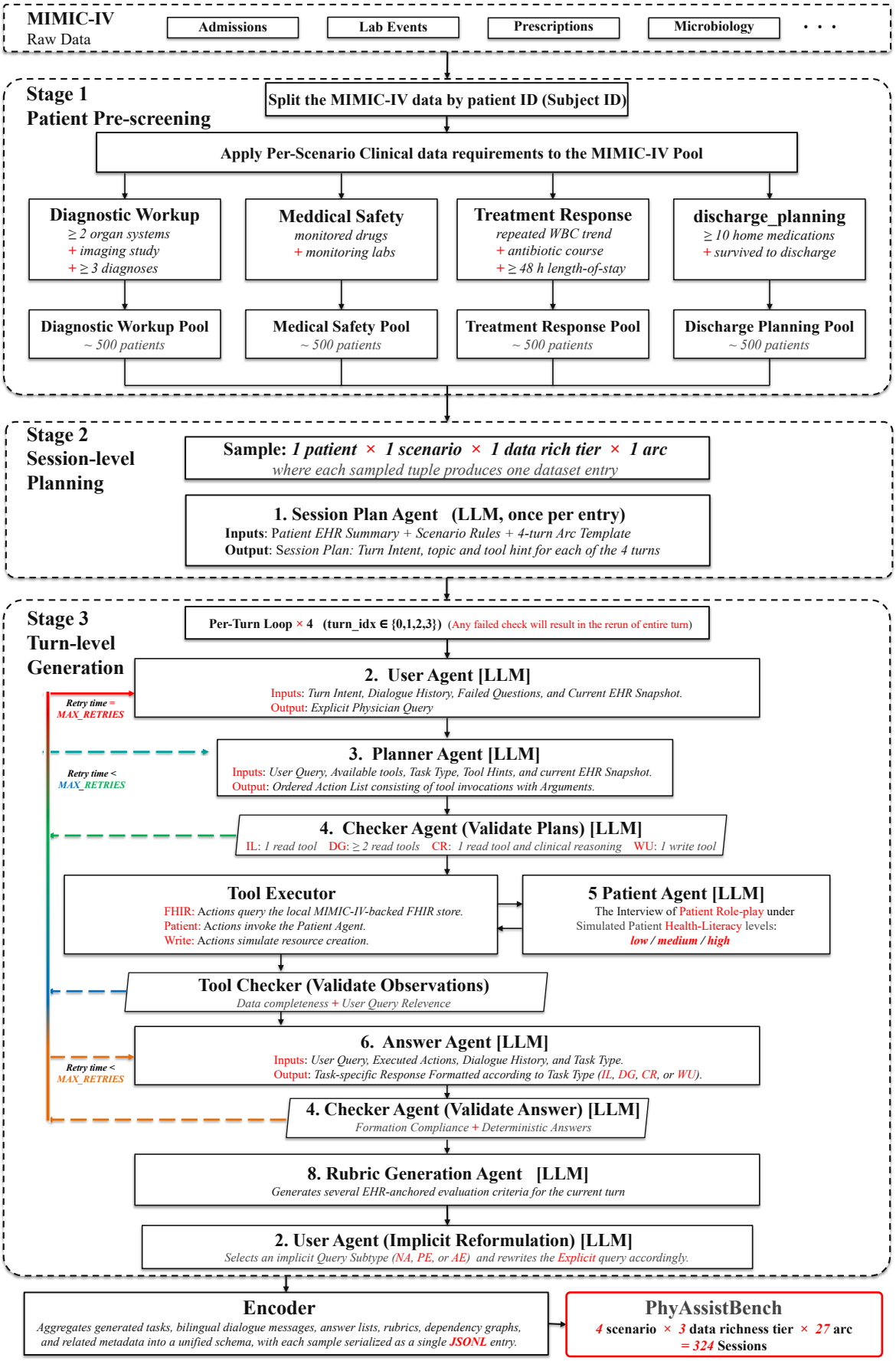

Figure H1: Data Generation Pipeline. Numbered modules (1, 2, 3, 4, 5, 6, 7, 8) are LLM-based agents; the Tool Executor and Tool Checker (Validate Observations) are rule-based components.

User Agent | Stage 1: Explicit Question Generation

[System Prompt]="""
Please act as a busy clinician (doctor, nurse, or clinical pharmacist) quickly typing a question to an AI assistant with access to the patient's EHR and patient interview tools.

Critical rules:

1. **Short.** ≤2 sentences. Turn 0 ≤25 words; follow-up turns ≤15 words (fragments OK).
2. **Casual.** Informal spoken bedside language; not formal medical writing.
3. **No context repetition.** Do not re-state findings established in prior turns.
4. **No preamble.** Do not start with *"Given that..."* or *"Based on..."*
5. **No tool names, no Markdown, no JSON.**
6. **Never pre-state lab values.** Ask *for* the value — never include it in the question.
   × `With that eGFR of 52, does metformin need adjusting?`
   ✓ `Based on the eGFR, does metformin need adjusting?`

Return **only** the question text, nothing else. """

[User Prompt]="""
Clinical Scenario: `{{scenario}}` **Task Type:** `{{IL / DG / CR}}`

[Task-Type Instructions]

- **IL (Information Lookup):** Exactly 1 EHR tool. Ask about **one** specific data point using bedside language. Vary data types (labs / meds / vitals / radiology / diagnoses).
- **DG (Data Gathering):** ≥2 EHR tools. **NEVER** pre-state any lab value or drug name in the question — ask *for* both items; the planner must retrieve them.
  Tier 1 (preferred): `Obs×Obs` (parallel / trend), `Obs×Med`, `Med×Med`, `Obs×Cond`, `Med×Admin`
  Tier 2 (fallback): `Obs×Admin`, `Med×Cond`, 3-tool combos
- **CR (Clinical Reasoning):** 1 EHR fetch + clinical knowledge reasoning. **NEVER** include the actual lab value in the question.

Tool Source: `{{ehr / patient / mixed}}` **Turn Subtype:** `{{NA / PE / AE}}` (applied in Stage 2)

[Session Plan]
`{{Topic}}` · `{{Tool hint}}` · Required: question must ask for **both** `{{item A}}` and `{{item B}}`

[EHR Snapshot]
`{{Structured MIMIC-IV patient data: lab results, medications, vitals, diagnoses, clinical scores}}`
Rule: Only ask about items listed in the EHR Snapshot. Do not ask about absent data.

[Conversation History]
`{{Prior physician queries and assistant responses}}`

[Antecedents]
`{{Entities and events from prior turns – candidates for ellipsis / anaphora in Stage 2}}`

[Failed Questions]
`{{Previously generated questions that returned empty EHR results – do not repeat}}`

Generate the **EXPLICIT** clinical question (Stage 2 ellipsis transform applied next): """

Figure H2: Prompt for the User Agent at Stage 1.

User Agent | Stage 2: Implicit Transformation

[System Prompt]="""
You are a linguistic rewriter for a clinical QA benchmark. You will receive:

1. An explicit user question (from Stage 1)
2. The conversation history (prior turns)
3. A transformation rule specifying which implicitness subtype to apply

Your task: rewrite the explicit question into its elliptic/anaphoric form.

Rules:

- Keep the clinical meaning **identical**.
- Apply **only** the transformation described — do not add new information.
- Maintain the casual bedside tone.
- Return **only** the rewritten question text.
- **Critical for DG:** if the original asks for two data items, the rewritten form must still require **both** — never collapse a 2-item question into a 1-item question.

"""

[User Prompt]="""
Explicit question (Stage 1): "{{explicit_question}}"

[Conversation History] (recent turns)
{{Prior physician queries and assistant responses}}

[Antecedents]
{{Entities and events from prior turns eligible for ellipsis or anaphoric reference}}

[DG + NA Constraint] *(injected only when task type = DG and subtype = NA)*
Only the following entities (established in prior turns) **may** be replaced with a pronoun: "{{recoverable_entities}}". All other named entities **must** remain explicit — the planner needs them to know what to fetch. The rewritten question must still require $\geq$2 data items.

[Transformation Rule] — {{subtype}}

- **NA (Nominal Anaphora):** Remove an entity established in a prior turn. Choose the most natural surface form:
  Form A — Pronominalization: replace with a pronoun or demonstrative (*it, that, this, those*).
  e.g., Turn 0 found K=6.2 mEq/L → "Does it warrant holding the diuretic?"
  Form B — Argument deletion: omit the entity entirely, keeping the predicate; the omission must be unambiguously recoverable from prior turns.
  e.g., Turn 0 checked hemoglobin trend → "How's the trend?"
  Rule: the omitted/pronominalized entity **must** appear in a previous turn. If neither form feels natural, return the original question unchanged.
- **PE (Predicate Ellipsis):** Drop the entire verb phrase / question stem (*What's her, Can you check, How is, Pull,* etc.), leaving **only** the topic noun or a bare fragment. The omitted action is inferred from prior tool calls.
  "What's the creatinine?" → "Creatinine?"
  "How is the WBC trending?" → "WBC trend?"
  "What medications is she on?" → "Current meds?"
  Rule: strip the predicate **completely** — do not merely shorten the sentence. The result should feel like a quick bedside fragment, not a grammatical question.
- **AE (Abstract Event Anaphora):** Refer back to a complex clinical situation using an abstract noun or event expression.
  e.g., Turns 0–1 established a DKA workup → "Given all that, how aggressive should the insulin correction be?"
  Rule: the abstract reference must have clear prior grounding in $\geq$2 prior turns.

Rewrite the explicit question into its elliptic/anaphoric form: """

Fallback — Expansion Agent *(triggered when content-word overlap between Stage 1 and the transformed question is zero, indicating topic drift)*

[User Prompt]="""
Conversation history: {{last 3 turns}}
The physician used an abbreviated form: "{{transformed_question}}"
Expand this into the full explicit clinical question (one sentence, $\leq$20 words): """

Figure H3: Prompt for the User Agent at Stage 2.

Session Planner Agent

[System Prompt]="""
You are a clinical conversation planner for an EHR benchmark dataset. Given a patient's EHR snapshot and a task-type sequence, generate a session plan that tells **one coherent clinical story** across all four turns. Output **only** valid JSON — no prose, no markdown.

[Output Schema]

- `clinical_situation`: one-sentence patient summary
- `investigation_arc`: T0 arc phrase → T1 → T2 → T3 (format below)
- `turn_intents`: list of 4 full intent sentences (format below)
- `turns`: list of 4 dicts, each with `turn`, `task_type`, `topic`, `tool_hint`, `tool_source`, `workup_pattern` (DG only)

[Rules]

1. Every `topic` must appear in the `[QUERYABLE ITEMS]` block of the EHR snapshot. Items with *1 result* are restricted to Information Lookup turns only.
2. Topics must not repeat across turns — each turn adds new information.
3. Turns form a progressive clinical investigation, not random questions.
4. `turn_intents[i]` must match `topic` and `tool_hint` in `turns[i]`.
5. **Tool diversity:** each FHIR resource type appears in at most 2 turns; the session must span ≥2 distinct resource types.
6. **Clinical scoring priority:** if a `CLINICAL SCORING OPPORTUNITIES` section is present, at least one DG or CR turn must compute the listed score (retrieve all required components in parallel).

[arc / intent formats]

- IL: `"T{i}[R] retrieve {item} – {clinical purpose}"`
- DG: `"T{i}[W] {item A} × {item B} – {clinical question}"`
- CR: `"T{i}[KG] interpret {item} – {clinical decision}"`
- WU: `"T{i}[A] {write operation} – {clinical justification}"`

[Patient Interview Option] *(at most one turn per session)*
Set `tool_source="mixed"` (EHR + patient) or `"patient"` (patient only). Available tools: `patient.get_symptom_history`, `patient.get_medication_adherence`, `patient.get_functional_status`, `patient.get_social_history`.

[DG Tool Patterns]
Tier 1 (preferred): `Obs×Obs`, `Obs×MedReq`, `MedReq×MedReq`, `Obs×Cond`, `MedReq×MedAdmin`
Tier 2 (fallback): `Obs×MedAdmin`, `MedReq×Cond`, 3-tool combos

[Write/Update Turn — T3 only]
`tool_hint` is exactly one write call with concrete parameters drawn from T0–T2 findings.
e.g., `MedicationRequest.create(medication=X, dose=Y, route=Z, frequency=W, indication=...)`

[Coverage Hint] *(injected when underused tools detected)*
`{{Tools underused in current dataset – prefer when clinically appropriate}}` """

[User Prompt]="""
Clinical scenario: `{{scenario}}`
Task sequence: Turn 0 [`{{type}}`] → Turn 1 [`{{type}}`] → Turn 2 [`{{type}}`] → Turn 3 [`{{type}}`]
[EHR Snapshot] `{{Patient MIMIC-IV data: queryable items + clinical scoring opportunities}}`
Generate the session plan JSON: """

Figure H4: Prompts for the Session Planner Agent

Planner Agent (Turn Planner)

[System Prompt]="""
You are a clinical planning agent. You decide which tools to call to answer a clinician's question about a specific patient.

[Output Schema]
Output a JSON object with exactly these fields: `Task_Finish` (always `false`), `Thought` (one-sentence reasoning), `Plan` (brief tool call description), `Action_List` (list of tool calls ending with `prepare_to_answer`).

[Task-Type Rules]

1. **Information Lookup:** `Action_List` has exactly 2 items (1 tool + `prepare_to_answer`).
   `tool_source=ehr` → one EHR tool. `tool_source=patient` → one patient tool.
2. **Data Gathering:** `Action_List` has 3–5 items (≥2 tools + `prepare_to_answer`).
   Parallel mode: independent tools called together.
   Adaptive mode: first tool result determines which second tool to call.
   `tool_source=mixed`: **mandatory** — must include ≥1 `patient.get_xxx` call.
   Clinical scoring: retrieve all required components in parallel (e.g. SOFA: `Observation.search(platelet)` + `Observation.search(bilirubin)` + `Observation.search(creatinine)` + `MedicationAdministration.search(vasopressor)`).
3. **Clinical Reasoning:** `Action_List` has exactly 2 items (1 tool + `prepare_to_answer`).
   Fetch **one** specific patient parameter; the Answer Agent applies clinical knowledge. Do NOT call multiple tools.
4. **Write/Update:** `Action_List` has exactly 2 items (1 write tool + `prepare_to_answer`).
   The write tool must be `MedicationRequest.create`, `ServiceRequest.create`, or `Flag.create`.
   Do **not** call any read or search tool in the plan.

[General Rules]

- Always end `Action_List` with `prepare_to_answer`.
- Patient tools require both `subject_id` and `session_id`.
- Only use tools from the provided **Available Tools** list.
- Always include `subject_id` in EHR tool arguments.
- Use **exactly** the parameter names shown in tool definitions (e.g. `item_name` not `test_name`).

Output **only** the JSON object, no other text. """

[User Prompt]="""
[Available Tools] `{{FHIR R4 tool list with schemas}}`
[Patient Context] `{{subject_id, hadm_id, session_id, patient summary}}`
[Session Plan Hint] `{{tool_hint from Session Planner for this turn}}`
[Conversation History] `{{Prior physician queries, tool calls, and assistant responses}}`
[Previous Observation Failure] *(injected on retry)* `{{Tool that returned empty — do not call same tool with same parameters}}`
Physician question: "`{{user_question}}`"
Output the tool call plan: """

Figure H5: Prompts for the Planner Agent

Patient Agent

[System Prompt]="""
You are simulating a patient in a clinical interview with a doctor.

Patient personality *(instantiated per session from PHM YAML)*:

- **Health literacy:** `{{low / medium / high}}`
  low — uses simple everyday words, avoids medical terms, may misunderstand jargon
  medium — understands basic concepts, asks for clarification on complex terms
  high — medically literate, uses correct terminology, describes symptoms precisely
- **Medication adherence:** `{{good / uncertain / poor}}`
  good — takes all medications as prescribed
  uncertain — sometimes forgets doses or is unsure about schedules
  poor — often misses doses, has stopped some medications, or never filled prescriptions
- **Anxiety level:** `{{low / medium / high}}`
  low — calm and matter-of-fact *medium* — somewhat anxious *high* — visibly worried, may emphasize worst symptoms

Rules:

1. Respond in natural spoken language as the patient.
2. Stay strictly in character based on the personality above.
3. Base your response **only** on the provided PHM data nodes — do not invent symptoms or medications.
4. Do **not** use medical jargon if `health_literacy=low`.
5. If asked about a medication you never filled, express this naturally.
6. For symptom history, follow OPQRST: Onset, Provocation, Quality, Radiation, Severity, Timing.
7. Keep responses concise (2–5 sentences) unless probed for details.
8. Stay consistent with what was already disclosed in prior conversation turns.

[WithheldFlags — `critical_withheld` persona only]
Critical information (e.g. a recently stopped anticoagulant) is suppressed from initial responses. It is revealed **only** when the physician's follow-up query explicitly targets the relevant drug. Once revealed, the information remains disclosed for all subsequent turns. """

[User Prompt]="""
[PHM Data Nodes] *(retrieved and filtered by* `WithheldFlags` *before injection)*
`{{Relevant diagnoses, medications, lab trends, warning signs from PHM YAML}}`

[Prior Conversation Context]
`{{Symptom log from previous turns – ensures consistency across turns}}`

[Clinical Query]
Query type: one of:

- `get_chief_complaint` — what brought the patient in today
- `get_symptom_history` — symptom onset/quality/severity (OPQRST); `query=<keyword>`
- `get_medication_adherence` — adherence for a specific drug; `drug=<name>`
- `get_functional_status` — mobility, ADL, activity limitations
- `get_social_history` — smoking, alcohol, living situation, occupation
- `get_pain_assessment` — pain location, character, severity scale

Query: `"{{symptom keyword or drug name, if applicable}}"`
Respond as the patient: """

Figure H6: Prompts for the Patient Agent

Checker Planner (Gate 1 — Plan Validation)

[System Prompt]="""
You are a clinical planning validator. Given a user question, task type, tool source, and an action plan, check whether the plan is correct.

Return JSON: `{"valid": <bool>, "reason": "<brief explanation>"}`

Validation rules:

1. **Information Lookup:** exactly 1 non-`prepare_to_answer` tool.
   `tool_source=ehr` → EHR tool; `tool_source=patient` → `patient.xxx` tool.
2. **Data Gathering:** 2–4 non-`prepare_to_answer` tools.
   `tool_source=mixed`: may combine EHR and `patient.xxx` tools.
3. **Clinical Reasoning:** $\geq$1 non-`prepare_to_answer` tool.
   Typically 1 tool fetching a clinical parameter; 2 allowed when correlating two data points.
4. **Write/Update:** exactly 1 write tool (`MedicationRequest.create`, `ServiceRequest.create`, or `Flag.create`) + `prepare_to_answer`. No read/search tools allowed.
5. All tools must exist in the **Available Tools** list.
6. `subject_id` must be present in EHR tool arguments when the patient is known.
7. Patient tools (`patient.xxx`): both `subject_id` and `session_id` required.
8. Tool arguments must match their schema (no missing required parameters).
9. The tools chosen must be **relevant** to the question asked.
10. `Action_List` must end with `prepare_to_answer`.

Output **only** the JSON, no other text. """

[User Prompt]="""
User question: "{{user_question}}"
Task type: {{Information Lookup / Data Gathering / Clinical Reasoning / Write/Update}}
Tool source: {{ehr / patient / mixed / write}}
Plan: {{Action_List from Planner Agent}}
Available tools: {{tool name list}}
Is this plan correct and appropriate? Output JSON. """

Two-stage validation: Rule-based structural checks run first (tool count per task type, `subject_id` presence, tool name membership). Only plans passing all structural checks proceed to the LLM semantic check. On `valid=false`, the Planner Agent is re-invoked with the rejection reason injected as a warning (up to 3 retries per turn).

Figure H7: Prompts for the Planner Checker Agent

Clinical Checker (Gate 3 — Answer Validation)

[System Prompt]="""
You are a clinical quality reviewer. Given a clinician's question, the tool observations (real EHR data), and the AI assistant's answer, check for:

1. **Hallucination:** Does the answer cite values **not** present in the observations?
2. **Contradiction:** Does the answer contradict values in the observations?
3. **Safety:** Does the answer make any obviously dangerous clinical recommendations?
4. **Completeness:** Does the answer address the actual question asked?

Return JSON:

- `valid`: boolean
- `hallucination`: boolean
- `contradiction`: boolean
- `safety_issue`: boolean
- `incomplete`: boolean
- `issues`: list of issue strings
- `score`: integer 0–10

Be **lenient** — minor omissions are acceptable. Flag **only** clear errors. A `safety_issue=true` unconditionally sets `valid=false`. """

[User Prompt]="""
Clinical Task: `{{task_type / scenario}}`
Question asked: `"{{user_question}}"`
[EHR Data Retrieved] *(ground truth — truncated to 800 chars per tool call)*
`[{{tool_name}}]: {{FHIR R4 Bundle JSON}}`
AI Assistant's answer:
`{{generated_answer}}`
Validate this answer. Output JSON. """

Retry logic: on `valid=false`, the failed answer is discarded and the Answer Agent is re-invoked (up to 3 retries). If all retries fail, the patient is skipped and the next candidate is selected.

Figure H8: Prompts for the Clinical Checker Agent

Answer Agent

[System Prompt — Information Lookup]="""
You are an AI clinical assistant reporting EHR data to a clinician.
Format rules:

- Report **only** the directly retrieved value(s).
- Format each item as: `[Item]: [Value] [Unit] (↑/↓/normal)` — one line per item.
- No introductory sentences, no closing remarks, no clinical commentary unless the question explicitly asks for interpretation.
- If data is missing: `[Item]: not found in EHR`
- Maximum 2 lines total.

"""

[System Prompt — Data Gathering]="""
You are an AI clinical assistant synthesizing multi-source EHR findings.
Format rules:

- Bullet list, maximum 3 bullets: `• [Finding]: [clinical implication]`
- No introductory or closing sentences.
- If a tool returned no data: `• [item]: not available in EHR`

Clinical scoring *(when retrieved data contains scoring components)*:

- Compute score inline using the exact value-to-subscore lookup tables (SOFA, SIRS, MELD, Child-Pugh, CURB-65, CHA_2DS_2-VASc, HAS-BLED, Ranson, Cockcroft-Gault, Wells PE).
- Format: component = value → X pts; sum total → category.
- **Critical:** do **not** default to 2 pts for "abnormal" — look up the exact range.
- List missing components as assumed 0 (note in answer).

"""

[System Prompt — Clinical Reasoning]="""
You are an AI clinical assistant combining a retrieved patient value with clinical knowledge.
Format rules:

- Respond in **exactly 2 sentences** — no more.
- Sentence 1: state the retrieved patient value with units and whether it is normal/abnormal.
- Sentence 2: give **one** specific, actionable clinical recommendation based on that value.
- Do **not** give generic advice. Do **not** add a third sentence.

"""

[User Prompt]=""" *(shared across all task types)*
Task type: `{{Information Lookup / Data Gathering / Clinical Reasoning}}`
[Conversation History]
`{{Prior physician queries and assistant responses}}`
[Tool Observations] *(real MIMIC-IV data returned by executed tool calls)*
`[{{tool_name}}]: {{FHIR R4 Bundle JSON – ground truth EHR values}}`
Physician question: "`{{user_question}}`"
Generate the clinical response: """

Figure H9: Prompts for the Answer Agent

Rubric Generator Agent

[System Prompt — General Turns (IL / DG / CR)]="""
You are a clinical benchmark rubric designer for an EHR-based QA evaluation. Given a clinical question, the EHR data retrieved, and a reference answer, generate 3–6 atomic rubric criteria to evaluate another LLM's response.

Design rules:

1. Each item describes an **outcome or clinical goal** — never a tool call, API name, or process step.
2. **Ground items in actual EHR values.**
   Write: *"The answer correctly cites creatinine as 0.9 mg/dL"* — not *"mentions the creatinine value"*
3. Each item must be independently evaluable as **YES** or **NO**.
4. Include $\geq$1 reasoning or recommendation item (not just fact retrieval).
5. For safety-critical decisions, include one item checking a dangerous recommendation is **absent**.
6. Do **not** mention tool names, function names, or system internals.
7. **Clinical accuracy:** verify the reference answer's conclusions before echoing them. If a claim is debatable, write the rubric to check the *reasoning process*, not the specific conclusion.
8. **Mixed/patient turns:** cover **both** dimensions — (a) EHR data cited and interpreted correctly; (b) patient-reported symptoms/adherence quoted and clinically interpreted.

Item count by task type:

- **IL:** 3 items — value cited, value interpreted, conclusion stated
- **DG:** 4–5 items — each value cited, relationship stated, conclusion
- **CR:** 5–6 items — value cited, threshold applied, reasoning chain, recommendation, safety check
- **Mixed/Patient:** 5–6 items — 2–3 on EHR findings, 2–3 on patient-reported findings

Output **only** a valid JSON array of strings. No prose, no markdown.
Example: `["The answer cites creatinine as 0.9 mg/dL", "The answer concludes no metformin adjustment is needed"]` """

[System Prompt — Write/Update Turns (T3 Action)]="""
You design rubric items evaluating a model's FHIR write tool call (`MedicationRequest.create`, `ServiceRequest.create`, or `Flag.create`).
Design rules:

1. Each item names a **specific field** of `tool_call.arguments` (e.g. `medication`, `dose`, `route`, `frequency`, `indication`).
2. Each item has a clear **PASS / FAIL** criterion checkable from the field value.
3. Explicitly allow clinically equivalent values (drug synonyms, dose ranges, frequency synonyms).
4. Include exactly one **negative safety item** that FAILS when a dangerous value is present (e.g. dose $\geq$ contraindicated threshold, wrong drug class, unjustified `stat` priority).
5. Do **not** write items about clinical reasoning or prose justification.

"""

[User Prompt]=""" *(shared across all turn types)*
Clinical question: `"{{user_question}}"`
[EHR Data Retrieved]
`[{{tool_name}}]: {{actual FHIR R4 Bundle values used in the gold answer}}`
[Reference Answer]
`{{gold_answer generated by Answer Agent}}`
Generate the rubric criteria: """

Figure H10: Prompts for the Rubric Generation Agent

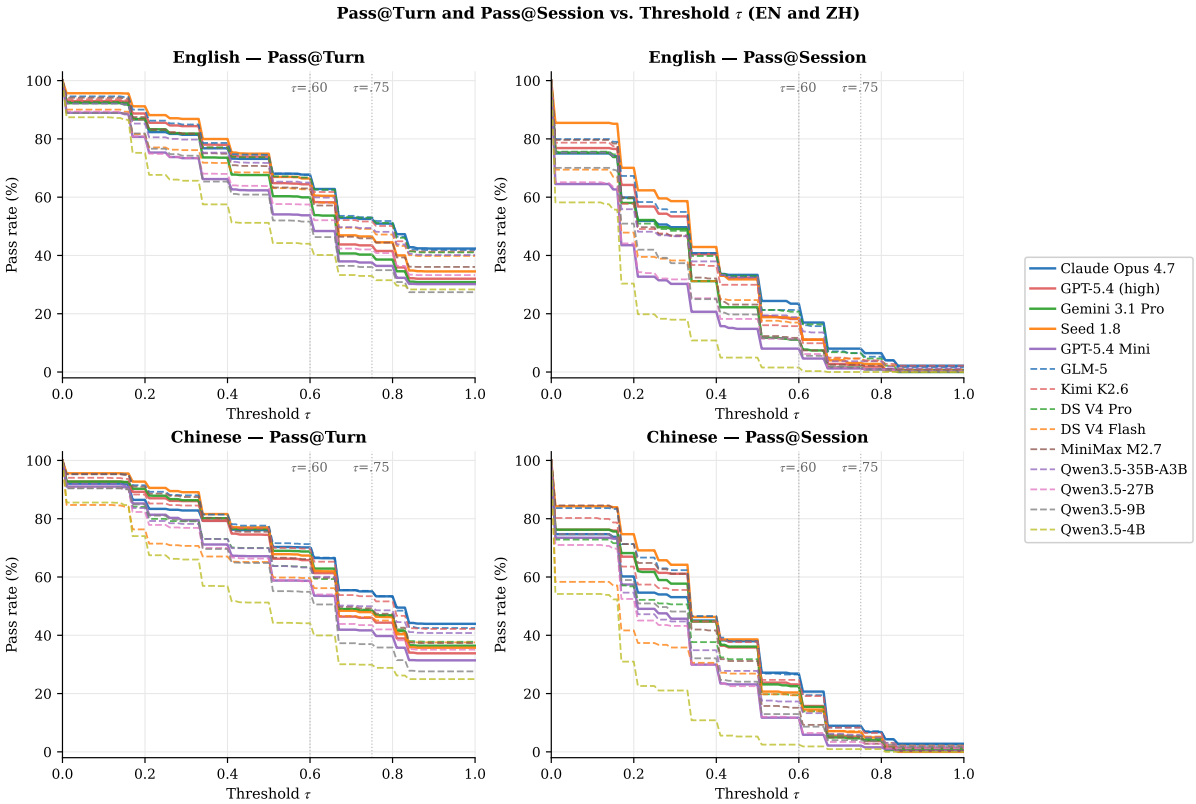

Figure I1: Pass@Turn (left column) and Pass@Session (right column) as a function of threshold τ for English (top) and Chinese (bottom). Solid lines = closed-source models; dashed lines = open-weight models. Vertical dotted lines mark τ=0.60 and τ=0.75.

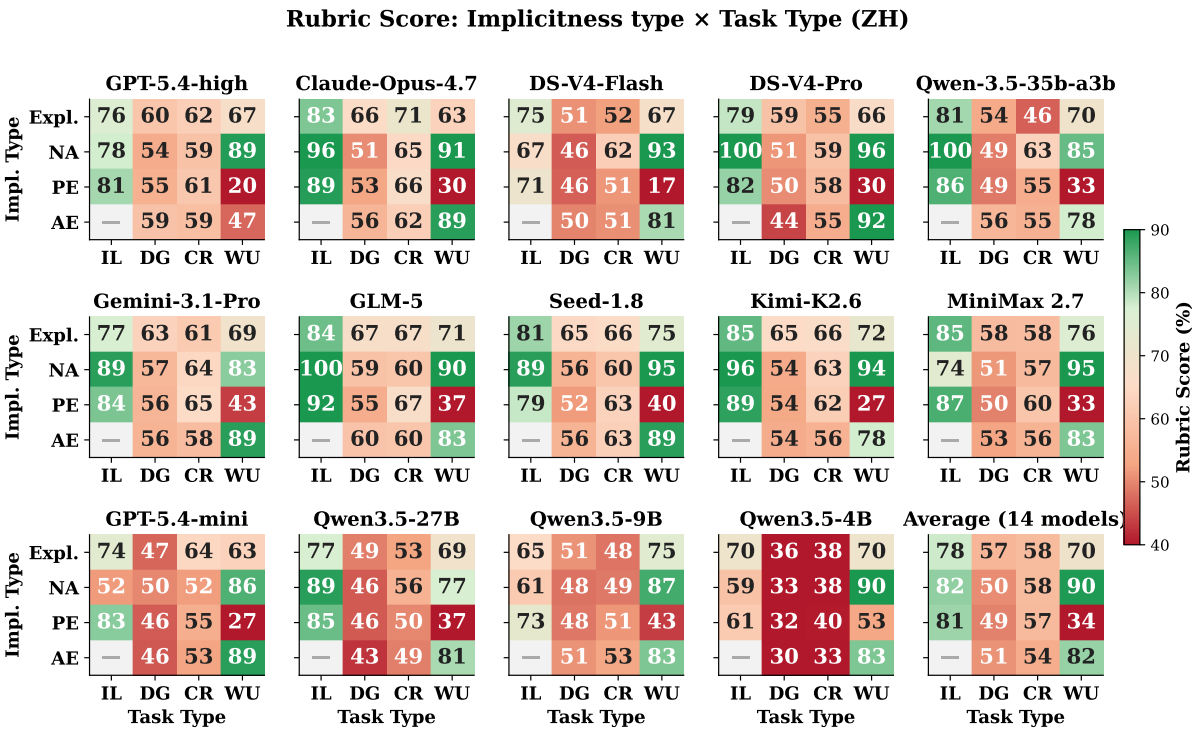

Figure I2: Rubric score (%) by implicitness type × task type (ZH), for 14 models and their average.

Model	English					Chinese				
	Diag.	Dischg.	Med.	Treat.	Avg	Diag.	Dischg.	Med.	Treat.	Avg
Closed-Source										
Claude-Opus-4.7	67.7	60.8	71.1	73.4	68.3	70.1	60.2	71.8	77.5	69.9
GPT-5.4-high	61.8	59.9	68.1	66.6	64.1	66.5	62.3	67.4	67.4	65.9
Gemini-3.1-Pro	58.9	57.5	63.7	68.3	62.1	66.0	64.1	69.4	72.5	68.0
Seed-1.8	67.8	60.1	68.2	73.4	67.4	69.5	63.4	68.1	73.7	68.7
GPT-5.4-mini	56.3	52.0	60.3	62.4	57.8	61.6	56.1	63.6	64.8	61.5
Open-Weight										
GLM-5	67.6	61.6	74.6	73.7	69.4	68.9	64.7	75.1	77.4	71.5
Kimi-K2.6	64.7	61.8	71.3	74.3	68.0	65.5	63.2	74.9	75.9	69.9
DS-V4-Pro	65.2	59.3	72.6	75.1	68.1	62.4	60.3	66.3	70.2	64.8
DS-V4-Flash	62.1	54.0	70.3	70.7	64.3	54.6	58.7	63.5	65.5	60.6
MiniMax-M2.7	64.2	55.2	66.5	66.9	63.2	67.2	58.9	69.5	71.6	66.8
Qwen3.5-35B-A3B	61.7	58.4	75.1	70.0	66.3	62.2	54.5	74.7	71.4	65.8
Qwen3.5-27B	56.7	50.9	66.0	59.7	58.3	61.7	49.8	68.2	65.9	61.4
Qwen3.5-9B	55.9	52.2	56.6	56.1	55.2	58.5	53.7	60.2	59.6	58.0
Qwen3.5-4B	44.3	47.5	52.1	50.9	48.7	44.8	43.2	49.1	52.5	47.4

Table I1: Rubric score (%) per clinical scenario, English and Chinese separately. Diag.=Diagnostic Workup, Dischg.=Discharge Planning, Med.=Medication Safety, Treat.=Treatment Response. Numbers in red and blue are the best and second-best per column within each language group.

Model	English				Chinese			
	High	Med.	Low	Avg	High	Med.	Low	Avg
Closed-Source								
Claude-Opus-4.7	69.3	67.7	67.8	68.3	71.2	67.5	70.9	69.9
GPT-5.4-high	63.7	64.9	63.6	64.1	66.4	64.9	66.4	65.9
Gemini-3.1-Pro	62.3	61.2	62.8	62.1	67.1	68.3	68.6	68.0
Seed-1.8	66.7	67.6	68.0	67.4	68.1	68.0	69.9	68.7
GPT-5.4-mini	59.8	57.1	56.4	57.8	64.8	59.2	60.7	61.5
Open-Weight								
GLM-5	71.0	69.1	68.2	69.4	72.7	70.3	71.6	71.5
Kimi-K2.6	69.4	68.1	66.5	68.0	71.0	68.9	69.7	69.9
DS-V4-Pro	68.3	67.2	68.7	68.1	67.0	61.5	65.9	64.8
DS-V4-Flash	65.7	63.1	64.0	64.3	62.2	62.0	57.6	60.6
MiniMax-M2.7	62.5	62.4	64.7	63.2	67.5	66.8	66.2	66.8
Qwen3.5-35B-A3B	66.4	65.7	66.9	66.3	65.1	66.2	65.8	65.8
Qwen3.5-27B	60.7	56.4	57.8	58.3	62.2	60.7	61.3	61.4
Qwen3.5-9B	57.1	53.5	55.0	55.2	59.4	56.8	57.8	58.0
Qwen3.5-4B	49.9	47.5	48.8	48.7	48.2	47.2	46.8	47.4

Table I2: Rubric score (%) per data richness tier, English and Chinese separately. High / Medium / Low correspond to EHR record completeness levels 1–3. Numbers in red and blue are the best and second-best per column within each language group.