MedChain: Bridging the Gap Between LLM Agents and Clinical Practice with Interactive Sequence

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 Project: https://github.com/ljwztc/MedChain

Abstract

Clinical decision making (CDM) is a complex, dynamic process crucial to health-care delivery, yet it remains a significant challenge for artificial intelligence systems. While Large Language Model (LLM)-based agents have been tested on general medical knowledge using licensing exams and knowledge question-answering tasks, their performance in the CDM in real-world scenarios is limited due to the lack of comprehensive benchmark that mirror actual medical practice. To address this gap, we present MedChain, a dataset of 12,163 clinical cases that covers five key stages of clinical workflow. MedChain distinguishes itself from existing benchmarks with three key features of real-world clinical practice: personalization, interactivity, and sequentiality. Further, to tackle real-world CDM challenges, we also propose MedChain-Agent, an AI system that integrates a feedback mechanism and a MedCase-RAG module to learn from previous cases and adapt its responses. MedChain-Agent demonstrates remarkable adaptability in gathering information dynamically and handling sequential clinical tasks, significantly outperforming existing approaches.

1 Introduction

At the intersection of artificial intelligence and healthcare lies one of medicine's most complex challenges: Clinical Decision Making (CDM). In healthcare delivery, CDM demands not only the integration of diverse data sources and continuous assessment of evolving clinical scenarios, but also evidence-based judgments for diagnosis and treatment [46]. While crucial for optimal patient care, this intricate process imposes significant cognitive demands on healthcare professionals, making it an ideal candidate for AI assistance [42].

Recent advances in Large Language Model (LLM)-based agents [34, 49, 15, 44, 16, 71] have emerged as an effective solution for complex decision-making tasks, from software development [38] to office automation [57]. In the medical domain, these LLMs have demonstrated impressive performance on medical licensing exams [45, 36] and knowledge-based assessments [13, 10, 30]. While LLMs have consistently scored well above passing thresholds in these benchmark [45], it is crucial to recognize that these assessments fall short of capturing the complexity of real-world CDM, where errors can cascade through multiple decision stages, as illustrated in Figure 1. Based on our analysis, CDM exhibits three key characteristics.

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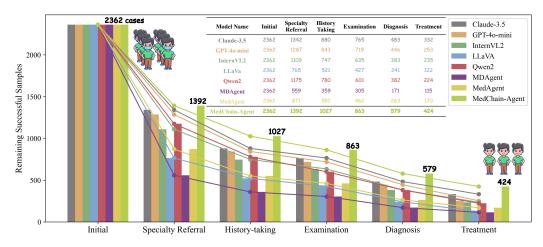


Figure 1: **Demonstration of error propagation of CDM in MedChain.** Starting with 2,362 initial cases, the diagram illustrates how diagnostic errors cascade through five clinical stages. Cases with incorrect diagnoses carry forward problematic information to subsequent stages, leading to a cumulative decrease in accuracy. After completing the treatment phase, we count cases that maintain correctness through each consecutive phase up to the each stage. Our MedChain-Agent achieves best performance in CDM comparing with other SOTA methods.

Firstly, these benchmarks rarely account for patient-specific information such as past medical history and present illness [36], which significantly influence clinical decisions in real clinical scenarios. This omission fails to capture the nuanced context that often shapes *personalized* diagnosis. **Secondly**, unlike real clinical scenarios where decisions build upon previous steps, existing benchmarks present clinical tasks as independent problems [40], missing the critical interdependencies in the diagnostic process. In reality, clinical decision-making is a *sequential* process where each step is contingent upon the preceding ones, and an error in one stage can profoundly impact subsequent decisions. **Thirdly**, most benchmarks present all relevant information upfront, providing a static, and comprehensive dataset [51]. However, real clinical workflow demand multiple rounds of dynamic information gathering through ongoing patient *interaction*.

MedChain: To address these critical gaps, we introduce MedChain, a novel benchmark designed to evaluate LLM-based agents in real-world clinical scenarios. Specifically, MedChain comprises 12,163 diverse cases spanning 19 medical specialties and 156 sub-categories, including 7,338 medical images with corresponding reports. Each case progresses through five crucial stages: specialty referral, history-taking, examination, diagnosis, and treatment. Unlike existing benchmarks, MedChain uniquely emphasizes three key features. 1) *Personalization:* Each case incorporates detailed patient-specific information. At first, agents are provided with only the patient's chief complaint and basic information. 2) *Interactivity:* Information must be actively gathered through dynamic consultation from patient. 3) *Sequentiality:* Decisions at each stage influence subsequent steps. Only after agent sequentially completes all five stages, the overall diagnostic process is evaluated.

MedChain-Agent: Given the novel features and challenges presented by this benchmark, existing agent frameworks struggle to address these issues adequately. To overcome these limitations, we propose MedChain-Agent, a multi-agent collaborative framework that enables LLMs with feedback mechanism and MedCase-RAG to dynamically gather information and handle sequential clinical tasks. Specifically, MedChain-Agent facilitates a synergistic interplay among three specialized agent types: General Agents for task-specific expertise, a Summarizing Agent for insight synthesis, and a Feedback Agent for iterative refinement. This multi-layered, iterative approach ensures decisions are products of thorough analysis and diverse perspectives. Additionally, to address the multifaceted nature of CDM, which demands the integration of evidence-based research, and patient-specific factors, we incorporate a novel MedCase-RAG module into our MedChain-Agent framework. Unlike conventional medical RAG methods, MedCase-RAG dynamically expand its database and employs a structured approach to data representation, mapping each medical case into a 12-dimensional feature vector. This system enables efficient retrieval of relevant cases and helps the model make informed decisions.

Our contributions are summarized as follows:

- We represent the first effort to propose a CDM benchmark, MedChain, providing a holistic assessment of diagnostic capabilities of LLLM-based agents, closely reflecting real-world patient care.
- We propose a multi-agent framework based on the characteristics of CDM, called MedChain-Agent. This system enables efficient retrieval of relevant cases and helps the model make informed decisions.
- Through extensive experiments, we compare the performance of existing works on Med-Chain and the superiority of MedChain-Agent in CDM and realibility.

2 Related Works

2.1 Evaluation of LLM in Medcine

Benchmarking plays a vital role as a key performance indicator, directing model improvements, pinpointing weaknesses, and shaping the course of model evolution. The evaluation of LLMs in medicine
has primarily focused on testing general medical knowledge through structured assessments [33].
Leading benchmarks such as MultiMedQA [45] integrate various medical QA datasets (e.g., MedQA
[19], MedMCQA [36]), emphasizing performance on medical licensing examination materials. Other
benchmarks like PubMedQA [20] focus on research-oriented queries, while several Chinese medical
benchmarks [55, 2] evaluate models through multiple-choice questions from medical licensing exams.
While these benchmarks effectively assess general medical knowledge, they fail to capture three
critical aspects of real-world clinical decision-making (see Appendix Table 6), i.e., personalization in
patient care, the interactive nature of clinical consultations, and the sequential dependency of medical
decisions, where each step builds upon previous findings.

Recently, several benchmarks [59, 35, 28, 26, 24, 8] have been proposed to evaluate LLMs across diverse clinical scenarios and tasks, including information extraction, text summarization, and clinical outcome prediction. However, these benchmarks primarily consist of independent question-answer pairs, where each task is evaluated in isolation. Sequential decision-making is critical in medical practice, as each patient experiences a continuous journey from initial triage through treatment to recovery. Therefore, it is essential to evaluate how LLMs perform throughout this entire clinical pipeline. Our work distinguishes itself from existing benchmarks by focusing on sequential decision-making within interactive environments, specifically evaluating LLM performance in realistic clinical scenarios that require executing the complete patient care workflow.

2.2 LLM-based Agent in Medicine

LLM-based agents have demonstrated significant potential across various medical applications [53, 32], encompassing tasks such as medical examination questions, clinical diagnoses, and treatment plans. Recent research has explored different approaches: Agent Hospital [25] provides medical scenario simulation, while several frameworks [66, 47, 22] focus on specific medical stages with multi-agent architectures. Some works target specialized aspects, such as CoD [4] for interpretable diagnostics and Ehragent [43] for electronic health records (EHRs) analysis. Others, like Almanac Copilot [67], assist clinicians with EMR-specific tasks. AI Hospital [11] explores interactive clinical scenarios, but it falls short in handling multi-modal medical imaging and lacks a comprehensive benchmark for evaluating multi-agent performance. To enhance these agents' capabilities, researchers have integrated Retrieval-Augmented Generation (RAG), as demonstrated by MIRAGE [64]'s searchenhanced framework and Medical Graph RAG [61]'s knowledge-based approach.

However, current approaches face two major limitations. First, existing frameworks focus on isolated medical tasks rather than providing seamless integration across different clinical stages, making them insufficient for complex scenarios requiring effective inter-stage communication [14]. Second, current medical RAG systems' reliance on chunk-based indexing leads to context inconsistency and computational inefficiencies [18, 12], highlighting the need for more sophisticated approaches to medical knowledge integration.

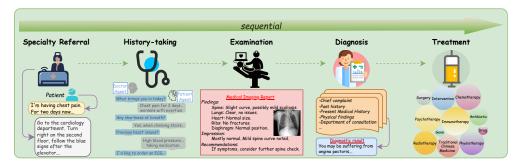


Figure 2: **MedChain Pipeline.** The MedChain is composed of a sequential medical process, including specialty referral, history-taking, examination, diagnosis, and treatment.

3 MedChain Benchmark

Overview. We introduce MedChain, a comprehensive clinical decision-making benchmark designed to simulate real-world scenarios. Built upon 12,163 Electronic Health Records (EHRs) spanning 19 medical specialties and 156 sub-categories, including 7,338 medical images with reports, MedChain uniquely emphasizes three key characteristics:

- Personalization: Each case includes detailed patient profiles that influence decision-making
- Sequentiality: Cases involve multiple interconnected decision-making stages
- Interactivity: Information must be actively gathered through dynamic consultation

3.1 Data Collection

Data Source and Processing. Our dataset is sourced from the Chinese medical website "iiYi" ², which provides over 20,000 validated clinical cases spanning 28 disease categories. These cases are verified by professional doctors and have undergone de-identification to ensure patient privacy. We obtained formal permission from the website administrators to use the data for scientific research purposes. Each case typically contains the patient's chief complaint, medical history, examination results, treatment process, and other relevant information, which insure the **personalization** of MedChain. Following the government standards ³ and Medical Subject Headings ⁴, we extracted and organized key information including patient basics, chief complaints, specialty referrals, examinations, imaging reports, diagnoses, and treatments. Cases with incomplete information were removed, resulting in 12,163 high-quality cases.

Quality Control. To ensure the highest standards of data integrity and clinical relevance in our benchmark, we implemented a rigorous quality control process involving a panel of five senior physicians, each with over 10 years of clinical experience. Our evaluation process examined a random sample of 6,000 cases (49.3% of the dataset). We developed a standardized scoring system that presents physicians with comprehensive case information alongside six binary quality dimensions: disease prevalence, clinical relevance, accuracy of patient history, appropriateness of diagnostic procedures, correctness of diagnosis, and suitability of treatment recommendations. Physicians evaluate each dimension through yes/no responses, with cases satisfying all dimensions considered valid.

The quality assessment yielded strong results, with 94.7% of evaluated cases meeting or exceeding our quality thresholds. Dimension-specific quality rates ranged from 92.9% to 97.2%, demonstrating consistently high standards across all evaluation criteria. Inter-rater reliability analysis produced a Cohen's kappa coefficient of 0.82, indicating substantial agreement among our expert reviewers. Cases that failed to meet the thresholds (5.3%) were either revised or excluded from the final dataset to maintain benchmark integrity.

²https://www.iiyi.com

³National Standards for Medical Items

⁴https://www.ncbi.nlm.nih.gov/mesh/1000048

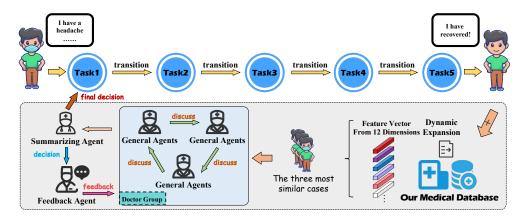


Figure 3: **MedChain-Agent framework.** Depicts a cyclical feedback medical multi-task system, where decisions are supported by retrieving similar past cases from a medical database.

3.2 Clinical Workflow Simulation

Sequential Stages. MedChain simulates the complete clinical workflow, comprising five sequential tasks, each representing a different stage of the clinical decision-making process, as shown in Figure 2. The results from each stage serve as inputs for the subsequent stage, creating a dependency where later decisions are influenced by the quality of earlier ones. This design guarantees the **sequentiality** of MedChain, mimicking the interconnected nature of real-world clinical decision-making processes. The pipeline consists of: *1) Specialty Referral:* Assessment of case urgency and appropriate department selection; *2) History-taking:* Dynamic information gathering through doctor-patient dialogue; *3) Examination:* Medical image analysis and report generation; *4) Diagnosis:* Comprehensive diagnosis based on accumulated information; *5) Treatment:* Treatment plan formulation considering patient-specific factors.

The construction pipeline of MedChain is sketched out here. The standardization process and the format of each pipeline can be refer to Appendix A. We demonstrate an example in Appendix Figure 4 and Figure 5.

3.3 Interaction Environment

To simulate authentic doctor-patient consultations, we developed an **interactive** environment where LLM-based agents must actively gather information through dynamic interactions. We employ Gemma2 (9b) [50] as the patient agent, initializing it with pre-defined case information while withholding the actual diagnosis. Each tested LLM serves as a doctor simulator. This setup enables the agent to provide symptom information and respond to inquiries in a manner that mirrors real patient experiences, drawing inspiration from standardized patients in medical education [1]. We conduct systematic evaluation with senior physician to validate the effectiveness of patient agent. The details can be found in Appendix A.2.2.

3.4 Benchmark Evaluation

Given the complexity of medical decision-making, we developed a comprehensive evaluation framework that goes beyond simple binary assessments. The standard answer for each stage comprises multiple key points. The evaluated agent's score increases with the number of standard points addressed, while irrelevant content leads to score reduction. For each task, we employ specific evaluation metrics: Task 1 (Specialty Referral) uses accuracy and Intersection over Union (IoU) to compare predictions with ground truth. Task 2 (History-taking) calculates IoU between predicted and ground truth examination items. Task 3 leverages DocLens [63] for assessing image interpretation quality. Task 4 employs a carefully designed prompt based on National Health Commission of China guidelines to evaluate diagnostic accuracy. Task 5 measures IoU between predicted and ground truth examination items. We elaborate the evaluation metrics in Appendix A.

4 MedChain-Agent Framework

4.1 Multi-agent System with Feedback

The MedChain-Agent framework introduces a multi-agent system that simulates the complex, interconnected nature of medical decision-making. This system integrates specialized agents that contribute distinct expertise to the diagnostic and treatment process. We sketch the main content here and more details please refer to Appendix B.

4.1.1 Agent Roles

Our framework comprises three agent types:

General Agents: Task-specific agents recruited based on domain requirements. For specialty referral tasks, these agents possess expertise in medical specialties and triage protocols, enabling effective patient routing. They engage in collaborative discussions that mirror real-world medical consultations.

Summarizing Agent: Acts as a central coordinator, consolidating insights from general agents into coherent decisions. This agent synthesizes collective expertise and delivers final recommendations, similar to a senior physician's role in clinical settings.

Feedback Agent: Maintains decision quality through continuous evaluation and refinement. This agent assesses outputs, provides targeted feedback, and initiates improvements when necessary, creating a self-correcting decision process.

4.1.2 Decision Making with Feedback

The decision-making process begins with general agents analyzing patient data and engaging in structured discussions. The summarizing agent then consolidates these assessments into preliminary decisions, which undergo review by the feedback agent. When issues are identified, the feedback agent initiates an iterative refinement cycle, with general agents reconsidering their assessments and the summarizing agent adjusting decisions accordingly. This process continues until reaching consensus or completing a preset number of iterations.

4.2 MedCase-RAG

To enhance decision-making capabilities, we developed MedCase-RAG, a specialized Retrieval-Augmented Generation system for medical applications. Unlike traditional medical RAG systems, our approach employs structured case representation using feature vectors that encode 12 key clinical dimensions: Age, Sex, Chief Complaint, Symptoms, Medical History, Physical Examination, Laboratory Tests, Imaging Reports, Diagnosis, Treatment Plan, Primary Department, and Secondary Department. This feature vectors is extracted by text-embedding-ada-002 from openai. When processing new cases, MedCase-RAG performs similarity searches, identifying the three most similar cases using cosine similarity metrics. This approach provides agents with comprehensive reference points for decision-making. The MedCase-RAG also features dynamic knowledge base expansion, incorporating resolved cases as pseudo-data. This mechanism enables continuous learning from new clinical experiences, adapting to evolving medical knowledge and practices.

5 Experiments

5.1 Experimental Setup

We split the dataset into training, validation, and testing sets with a ratio of 7:1:2. Our study evaluates both single-agent and multi-agent systems. For base LLM, we test two closed-source models (gpt-4o-mini [34], and claude-3.5-sonnet [49]) and four open-source models (InternVL2-8b [6], llava-llama-3-8b-v1_1 [27], HuaTuoGPT [68], and Qwen2-7B-Instruct [52]), with model weights obtained from official Hugging Face repositories. In the single-agent evaluation, we compare with zero-shot manner, few-shot manner, CoT [58], Self-consistency [56] and RAG [23]. In the multi-agent evaluation, we compare MedChain-Agent against DyLAN [31], AutoGen [62], MedAgent [48] and MDAgent [21]. All agent framework are based on InternVL2-8b [6]. The deployment was conducted using the LMDeploy framework [7]. All tests executed on NVIDIA A100 GPUs featuring

Table 1: **Evaluation of various LLM-based agent in MedChain.** The best performance for each task is highlighted in **bold**.

Framework	Methods	Specialty Referral		History-taking	Examination	Diagnosis	Treatment	Average	
		Level 1	Level 2			8		C	
	GPT-4o-mini [34]	0.5449	0.2871	0.3399	0.5112	0.4177	0.3930	0.4156	
	GPT-o3	0.5495	0.2866	0.3493	-	0.4891	0.3343	0.4017	
	Claude-3.5-sonnet [49]	0.5681	0.3050	0.3562	0.5018	0.4207	0.4053	0.4262	
	MedGemma [41]	0.5063	0.1975	0.3315	0.6324	0.4668	0.3558	0.4105	
	LLaVA [27]	0.3240	0.0730	0.3182	0.5165	0.3667	0.1060	0.2841	
Base LLM	Qwen2 [52]	0.4975	0.2215	0.4226	0.4829	0.4530	0.2193	0.3828	
	InternVL2 [52]	0.4811	0.1935	0.4645	0.4490	0.4367	0.2903	0.3859	
	Baichuan [9]	0.2959	0.0532	0.3264	-	0.4297	0.2591	0.2728	
	HuaTuoGPT [68]	0.0707	0.0207	0.3465	-	0.4163	0.1780	0.2064	
	MedReason [60]	0.4602	0.1258	0.3315	-	0.4741	0.2993	0.3381	
	FineMedLM-o1 [65]	0.1502	0.0124	0.3969	-	0.2772	0.1345	0.1942	
	Zero-shot	0.4811	0.1935	0.3450	0.4994	0.4572	0.2817	0.3763	
	Few-shot	0.5584	0.2481	0.4870	0.3758	0.4382	0.3553	0.4105	
Single-agent	CoT [58]	0.5698	0.1484	0.3750	0.6396	0.4382	0.3421	0.4189	
	RAG [23]	0.5927	0.2467	0.4732	0.6408	0.4167	0.4524	0.4704	
	Self-consistency [56]	0.5143	0.2319	0.4213	0.4144	0.4198	0.3441	0.3910	
	DyLAN [31]	0.4415	0.1731	0.4434	0.4980	0.3863	0.2983	0.3734	
	AutoGen [62]	0.5228	0.2347	0.4528	0.4559	0.4250	0.3590	0.4084	
Multi-agent	MedAgent [48]	0.3830	0.2039	0.4454	0.4456	0.4102	0.3673	0.3759	
-	MDAgent [21]	0.2398	0.1343	0.4240	0.4983	0.3973	0.3620	0.3426	
	MDAgent + RAG [21]	0.4754	0.2063	0.4412	0.5346	0.4198	0.4371	0.4190	
	MedChain-Agent	0.5873	0.3505	0.5836	0.6566	0.4807	0.4613	0.5200	

Table 2: **Performance Comparison of LLM-based Agents across Other Diagnosis Benchmarks.** Implementation of agent frameworks based on InternVL2, evaluated on multiple medical benchmarks including MedQA [19], PubMedQA [20], PathVQA [17], and MedBullets [3].

Framework	Method	MedQA	PubMedQA	PathVQA	MedBullets	Average
	Zero-shot	0.426	0.668	0.449	0.490	0.508
Cinala agant	Few-shot	0.477	0.648	0.448	0.503	0.519
Single-agent	CoT	0.470	0.714	0.465	0.500	0.537
	Self-consistency	0.460	0.688	0.482	0.500	0.533
	MedAgents	0.501	0.622	0.569	0.435	0.532
	MDAgents	0.435	0.744	0.582	0.422	0.546
Multi-agent	AutoGen	0.395	0.656	0.568	0.448	0.517
	DyLAN	0.414	0.610	0.540	0.448	0.503
	MedChain-Agent	0.462	0.746	0.621	0.474	0.576

80GB of memory. To enhance output stability and reliability across all experiments, we consistently set the temperature parameter to 0. The experiments were conducted in Chinese.

5.2 Benchmark Performance Results

The results of our evaluation in the MedChain are presented in Table 1. Our analysis yields two significant insights:

- (1) Sequential decision-making tasks continue to pose significant challenges, even for advanced models. For instance, within the single-agent frameworks, GPT-40-mini and InternVL2 achieve average scores of 0.4156 and 0.3859, respectively. These results indicate that despite their sophistication, these models struggle to maintain consistent performance across the sequential stages of clinical decision-making, highlighting the inherent difficulty of these tasks.
- (2) The integration of the MedChain-Agent framework with open-source LLMs demonstrates significant superiority over proprietary models like GPT-40-mini. The substantial performance gain observed with MedChain-Agent (average score of 0.5200) implies that our framework can leverage the strengths of open-source LLMs to achieve superior outcomes. This suggests that open-source

Table 3: **Ablation Study for Key Components for MedChain-Agent.** This table presents the performance impact of sequentially removing the Feedback mechanism and MedCase-RAG from the full MedChain-Agent framework.

Feedback	MedCase-RAG	Specialty referral		History-taking	Examination	Diagnosis	Treatment	Average
1 ccdback		Level 1	Level 2	Thistory-taking	Lxammation	Diagnosis	Treatment	Average
		0.5523	0.2228	0.3285	0.6369	0.4724	0.3915	0.4341
\checkmark		0.5739	0.2906	0.4222	0.6377	0.4299	0.4209	0.4692
	✓	0.5928	0.3353	0.5801	0.6488	0.4699	0.4568	0.5140
✓	\checkmark	0.5873	0.3505	0.5836	0.6566	0.4804	0.4613	0.5200

Table 4: **Generalizability of MedChain-Agent with Various Base LLM.** We apply the MedChain-Agent framework to different base LLMs to validate its generalizability. Performance changes are highlighted with light green for improvements and light red for decreases. Results demonstrate that the MedChain-Agent framework consistently brings performance gains across different base LLMs.

Base LLM	Specialty Referral		History-taking	Examination	Diagnosis	Treatment	Average	
	Level 1	Level 2	g					
GPT-4o-mini	0.6065 (+0.0616)	0.2302 (-0.0569)	0.6205 (+0.2806)	0.6279 (+0.1167)	0.4975 (+0.0798)	0.4329 (+0.0399)	0.5026 (+0.0870)	
HuaTuoGPT	0.2554 (+0.1847)	0.0097 (-0.0110)	0.3722 (+0.0257)	-	0.4159 (-0.0004)	0.1450 (-0.0330)	0.2396 (+0.033)	
Qwen2	0.5818 (+0.0843)	0.2781 (+0.0566)	0.5962 (+0.1736)	0.6534 (+0.1705)	0.4628 (+0.0098)	0.4315 (+0.2122)	0.5006 (+0.1178)	
InternVL2	0.5873 (+0.1062)	0.3505 (+0.1570)	0.5836 (+0.1191)	0.6566 (+0.2076)	0.4806 (+0.0439)	0.4613 (+0.1710)	0.5200 (+0.1341)	

models, when enhanced with our framework, are not only competitive but can also excel in handling intricate medical decision-making tasks.

5.3 Evaluation in Existing Diagnosis Datasets

Moreover, we evaluate MedChain-Agent on several well-established medical QA datasets, including MedQA [19], PubMedQA [20], PathVQA [17], and MedBullets [3]. As shown in Table 2, our framework demonstrates strong performance compared to both single-agent baselines and multi-agent alternatives. MedChain-Agent achieves the highest average score (0.576). This consistent superiority across various medical QA benchmarks further validates the effectiveness of our framework, even on simpler, more structured tasks that differ from our real-world clinical scenarios.

5.4 Ablation Studies and Discussion

(1) Ablation Study for Key components in MedChain-Agent: To assess our framework's components, we conduct ablation studies as shown in Table 3. Both the Feedback mechanism and MedCase-RAG module demonstrate significant individual contributions to overall performance. The Feedback mechanism alone improves the average score from 0.4341 to 0.4692, with notable gains in History-taking and Level 2 Specialty referral. MedCase-RAG shows stronger individual impact, boosting the average score to 0.5140, with substantial improvements in History-taking and Specialty referral tasks. While MedCase-RAG excels in diagnostic phases, the Feedback mechanism appears more beneficial for Treatment tasks. When combined, these components show synergistic effects, achieving the highest average performance (0.5200) and optimal scores across five of six evaluated tasks, validating their complementary roles in enhancing clinical reasoning capabilities.

(2) Ablation Study for Three Key Characteristics in MedChain: To validate the effectiveness of personalization, interactivity, and sequentiality within our benchmark, we conduct an ablation study as shown in Table 5. We systematically remove each characteristic and observe its impact on model performance across Diagnosis and Treatment tasks. 'w/o Person' means all detailed patient profiles are omitted from the input, resulting in a lack of personalized information that makes correct diagnosis more challenging for the model. 'w/o Seq' means we use the ground truth from the previous stage as input to the next stage, rather than using the model's previous output, which simplifies the benchmark. 'w/o Inter' means we directly provide all patient examination results as input without requiring the agent to autonomously inquire about the patient's condition, also simplifying the benchmark. Removing patient-specific information (w/o Person.) consistently degrades performance across all models in diagnosis tasks (with drops ranging from 2.51% to 10.31%), demonstrating that personalized information is crucial for accurate clinical decision-making.

Table 5: **The ablation study for three key characteristics in MedChain.** This table presents the impact of personalization, interactivity, and sequentiality on Diagnosis and Treatment tasks. The arrows ↑↓ next to settings indicate expected performance change direction. The arrows next to results show actual changes (highlighted in gray when matching expectations).

Setting	Model	Diagnosis	Treatment	
	MedAgent	0.4106	0.3673	
	MDAgent	0.3959	0.3620	
Full	gpt-4o-mini	0.4157	0.3930	
	InternVL2	0.4378	0.4472	
	MedChain-Agent	0.4802	0.4613	
	MedAgent	0.3075 ↓	0.3754 ↑	
a) w/o Person. ↓	MDAgent	0.3283 ↓	0.3109 ↓	
a) w/o i cisoli. ↓	gpt-4o-mini	0.3906 ↓	0.3406 ↓	
	InternVL2	0.3702 ↓	0.2527 ↓	
	MedChain-Agent	0.4159 ↓	0.4310 ↓	

Setting	Model	Diagnosis	Treatment
	MedAgent	0.4030 ↓	0.4456 ↑
b) w/o Seq. ↑	MDAgent	0.4497 ↑	0.4418 ↑
b) w/o seq.	gpt-4o-mini	0.4522 ↑	0.4423 ↑
	InternVL2	0.4481 ↑	0.2903↓
	MedChain-Agent	0.4807 ↑	0.4743 ↑
	MedAgent	0.3129 ↓	0.4109 ↑
c) w/o Inter. ↑	MDAgent	0.3998 ↑	0.3627 ↑
c) w/o inter.	gpt-4o-mini	0.4663 ↑	0.4003 ↑
	InternVL2	0.4550 ↑	0.3173 ↓
	MedChain-Agent	0.4634 ↓	0.5207 ↑

Interestingly, when removing the sequential dependency between stages (w/o Seq.), most models show improved performance, indicating that sequential decision-making poses greater challenges that better reflect real-world clinical scenarios. Similarly, the improved performance observed after removing interactive information gathering (w/o Inter.) confirms the effectiveness of interactivity in our benchmark design. These results collectively suggest that while both sequentiality and interactivity make the benchmark more challenging, they are essential components that better simulate the complexity of real-world clinical decision-making processes.

(3) Generalizability for MedChain-Agent: To evaluate the generalizability of our framework, we apply MedChain-Agent to various base LLMs as shown in Table 4. The results demonstrate substantial performance improvements across most models and tasks. InternVL2 shows the most significant enhancement with a 13.41% average improvement, followed by Qwen2 (11.78%) and GPT-40-mini (8.70%). Even with HuaTuoGPT, which has relatively lower baseline performance, our framework still achieves a 3.33% improvement. Notably, the improvements are particularly pronounced in complex tasks such as History-taking and Examination, where gains of up to 28.06% are observed. These consistent enhancements across diverse models and tasks strongly validate the framework's robust generalizability and effectiveness in medical decision-making scenarios.

6 Conclusion

In this paper, we introduced MedChain, a novel benchmark for evaluating LLM-based agents in clinical decision-making that authentically reflects real-world medical practice through three essential characteristics: personalization, interactivity, and sequentiality. Our comprehensive dataset encompasses 12,163 diverse clinical cases across 19 medical specialties, including 7,338 medical images with corresponding reports, providing a robust foundation for evaluating AI systems in complex healthcare scenarios. To address the challenges presented by this benchmark, we also introduced MedChain-Agent, a multi-agent framework enhanced by feedback mechanisms and MedCase-RAG, which demonstrates superior performance across various clinical tasks. This work establishes new benchmarks for evaluating medical AI systems and provides practical solutions for enhancing their clinical decision-making capabilities. As AI continues to evolve in healthcare applications, frameworks that can navigate the complexities of real-world clinical scenarios will be increasingly valuable for improving patient care and supporting healthcare professionals.

7 Limitations

This paper has two primary limitations that offer avenues for future research:

1) Data Source Diversity: The MedChain benchmark is constructed from 12,163 electronic health records obtained from the Chinese medical website "iiYi." Although this dataset is extensive and covers 19 medical specialties and 156 sub-categories, it is derived from a single source. Additionally,

there exists a notable imbalance in data distribution across different medical specialties, with some departments having significantly more cases than others. This imbalance may introduce bias in model evaluation and limit performance in underrepresented specialties. In our future work, we will incorporate additional data sources from different regions or healthcare systems to further enrich the dataset and address the specialty imbalance.

2) Patient Interaction Simulation: In our interactive environment, the patient responses during the history-taking stage are generated by the Gemma 2 language model. While this approach ensures consistency and control in evaluating the LLM-based agent, the real patient interactions can be more varied and complex. Future work could explore more advanced patient simulators or incorporate real dialogue data to capture a wider range of communication styles and behaviors.

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Appendix for MedChain

Abstract.

Appendix A describes the process of standardizing and organizing the dataset for the Med-Chainbenchmark.

Appendix B provides a detailed explanation of the MedChain-Agent framework, including its implementation, feedback mechanism, and the novel Retrieval-Augmented Generation (RAG) approach used to enhance decision-making.

Appendix C lists the additional details for experiment.

Appendix D discuss the difference between MedChain and several similar related works.

A Benchmark Construction and Evaluation

A.1 Dataset Standardization

We employed a combination of large language models and human verification to label data across different tasks. Our methodology involves task-specific prompt construction and output matching to ensure data quality and diversity while maintaining alignment with real clinical case scenarios.

To ensure consistency and comparability across the benchmark, we standardized the classification of examination items into two main categories: Physical Examinations and Auxiliary Examinations. Physical Examinations include evaluations of various body systems and general health indicators, while Auxiliary Examinations encompass different imaging techniques and laboratory tests. We utilized GPT-40 to extract and classify examination items from each case, followed by manual verification to ensure accuracy. For medical imaging, we classified images into seven types, and manual review ensured the correctness of the classifications. Additionally, treatment items were extracted and categorized from each case. This standardization process ensures that the dataset is consistent, facilitating accurate and comparable evaluations of LLM performance. Figure 4 and Figure 5 demonstrate a case after standardization in English and Chinese. Figure 6 shows the statistics of different departments.

A.2 Tasks Details

This section provides a comprehensive description of the five specific tasks that make up the Med-Chainbenchmark. Each subsection elaborates on a particular task, detailing its input, output, and evaluation methods. Figure 9 visualizes the differences between MedChainand other methods.

A.2.1 Task 1: Specialty referral

The specialty referral task evaluates the LLM's ability to assess the urgency of a patient's condition and determine the appropriate department based on the patient's chief complaint. The input consists of the patient's chief complaint, and the output space includes 19 first-level departments and 156 second-level departments. The LLM must first assign the patient to one of the 19 first-level departments, then to one or more of the 156 second-level departments based on the primary symptoms.

Evaluation metrics include accuracy for first-level department assignment and Intersection over Union (IoU) for second-level department assignment. IoU is used for second-level departments to account for the possibility of multiple correct assignments and to reflect partial correctness, which can occur in complex cases. This metric better captures the nuanced nature of departmental referrals in clinical practice.

A.2.2 Task 2: History-taking

The history-taking task is designed to simulate doctor-patient communication, where the goal is to obtain relevant information and infer necessary examination items. We employ a multi-agent system to evaluate this process:

```
"tags": {
            "department": ["Pediatrics", "Pediatric Immunology"],
           "disease": ["Uterine fibroids", "Constipation"]
      "[Case Introduction]": {
            "Physical Examination": {
                 "General Examination": "Heart and lungs normal",
                 "Urogenital System Examination": "Cervical erosion grade II, uterus enlarged to the size of a duck egg, left
adnexa palpable mass size of a goose egg"
            "Auxiliary Examinations": {
                   "CT": "CT plain scan: A mixed-density lesion in the middle of the pelvis, about 10.0cm×7.0cm×6.5cm, with
uneven internal density, CT value -146~45HU, and a round high-density focus, CT value 623HU (Fig 1, 2), with smooth
edges. Uterus enlarged, rounded, protruding slightly anteriorly, with uneven internal density, CT value 32~48HU.
Intrauterine device visible in the uterine cavity, bladder compressed and displaced. Imaging diagnosis: Uterine fibroids,
ovarian teratoma.",
                       \hbox{"Ultrasound": "Color Doppler: A $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus, with $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus, with $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus, with $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus, with $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus, with $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus, with $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus, with $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus, $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus, $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus, $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus, $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus, $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus, $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus, $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus, $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus, $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus, $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus, $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus of $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus of $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus of $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus of $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus of $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus of $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus of $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus of $10.0cm \times 6.0cm$ cystic-solid mass visible anterior to the uterus of $10.0cm \times 6.0cm$ cystic-solid mass visible and $10.0cm \times 6.0cm$ cystic-solid mass visible mass visible mass visible mass visible mass visible mass v
heterogeneous internal echo. A medium-echo mass visible on the right side, with a strong echo focus inside, rich color
blood flow can be drawn out inside and around. The left side is cystic, with chaotic internal echo, cord-like strong
echo visible. Right ovary normal",
                 "Blood Test": "Alkaline phosphatase: 89u/L (normal range 100~290u/L)",
                   "Pathological Examination": "Tumor diameter 8.0cm, intact capsule, smooth surface: partly cystic diameter
about 3.0cm, containing fat and hair, solid area gray-yellow on section, soft and brittle. Another uterine upper segment
5.0cm×5.0cm×4.0cm, intramural tumor tissue about 2.0cm in diameter, yellowish-white on section, hard and tough. Microscopy: Rich fibrous stroma separating long, wavy, parallel cell bands composed of columnar cells; elongated nuclei
perpendicular to the long axis of the cell bands (Fig 4). Intracystic lipid seen, cyst wall with squamous epithelium and
sebaceous glands (Fig 3). Another tumor cells spindle-shaped, rod-shaped nuclei, interlaced arrangement, cells without
atypia (Fig 5). Immunohistochemistry: inhibin (-), ck (+), cy (+). Pathological diagnosis: Ovarian carcinoid (trabecular
type) with mature cystic teratoma, uterine leiomyoma."
             .
"Chief Complaint": ["Patient is 8 years old", "Constipation for nearly 1 year, weight loss of 20 pounds in the
past half year. Regular menstruation, no frequent urination"],
                 {"filename": "133.png", "category": ["Pathological Examination"]},
                 {"filename": "131.png", "category": ["CT"]},
                 {"filename": "132.png", "category": ["Pathological Examination"]}
                   "CT": "CT plain scan: A mixed-density lesion in the middle of the pelvis, about 10.0cm×7.0cm×6.5cm, with
uneven internal density, CT value -146\sim45HU, and a round high-density focus, CT value 623HU (Fig 1, 2), with smooth
edges. \ \ Uterus \ \ enlarged, \ \ rounded, \ \ protruding \ \ slightly \ \ anteriorly, \ \ with \ \ uneven \ \ internal \ \ density, \ \ CT \ \ value \ \ 32 \sim 48 \, HU.
Intrauterine device visible in the uterine cavity, bladder compressed and displaced. Imaging diagnosis: Uterine fibroids,
ovarian teratoma.",
                   "Pathological Examination": "Tumor diameter 8.0cm, intact capsule, smooth surface; partly cystic diameter
about 3.0cm, containing fat and hair, solid area gray-yellow on section, soft and brittle. Another uterine upper segment
5.0cm×5.0cm×4.0cm, intramural tumor tissue about 2.0cm in diameter, yellowish-white on section, hard and tough.
Microscopy: Rich fibrous stroma separating long, wavy, parallel cell bands composed of columnar cells; elongated nuclei
perpendicular to the long axis of the cell bands (Fig 4). Intracvstic lipid seen, cvst wall with squamous epithelium and
sebaceous glands (Fig 3). Another tumor cells spindle-shaped, rod-shaped nuclei, interlaced arrangement, cells without
atypia (Fig 5). Immunohistochemistry: inhibin (-), ck (+), cy (+). Pathological diagnosis: Ovarian carcinoid (trabecular
type) with mature cystic teratoma, uterine leiomyoma."
     },
       '[Diagnosis and Treatment Process]": {
            "Initial Diagnosis": ["Uterine fibroids, ovarian teratoma."],
            "Treatment Course": ["Intramural fibroid nodules visible in the uterus; left ovary enlarged, multilocular, with
intact and smooth capsule. Left fallopian tube normal, right adnexa normal. Subtotal hysterectomy and left adnexectomy
performed. Pathological examination: Tumor diameter 8.0cm, intact capsule, smooth surface; partly cystic diameter about
3.0cm, containing fat and hair, solid area gray-yellow on section, soft and brittle. Another uterine upper segment
5.0cm×5.0cm×4.0cm, intramural tumor tissue about 2.0cm in diameter, yellowish-white on section, hard and tough.
Microscopy: Rich fibrous stroma separating long, wavy, parallel cell bands composed of columnar cells; elongated nuclei
perpendicular to the long axis of the cell bands (Fig 4). Intracystic lipid seen, cyst wall with squamous epithelium and
sebaceous glands (Fig 3). Another tumor cells spindle-shaped, rod-shaped nuclei, interlaced arrangement, cells without
atypia (Fig 5). Immunohistochemistry: inhibin (-), ck (+), cy (+). Pathological diagnosis: Ovarian carcinoid (trabecular
type) with mature cystic teratoma, uterine leiomyoma."]
      "[Treatment Items]": ["Surgery"]
```

Figure 4: Case Report "77_Ovarian Carcinoid with Mature Cystic Teratoma: A Case Report."



Figure 5: Case Report Chinese Version with Corresponding Medical Imaging. "77_Ovarian Carcinoid with Mature Cystic Teratoma: A Case Report." (a), (b) and (c) Medical Imaging. (d) Chinese version.

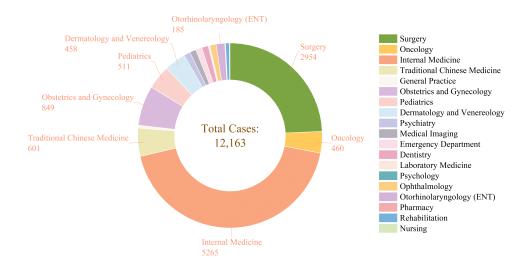


Figure 6: Multi-departmental Distribution

- Doctor Agent: The LLM being evaluated plays this role, asking questions and suggesting examinations based on the patient's responses.
- Patient Agent: A local large model (such as Google's gemma2/9b) simulates the patient, responding based on pre-defined case information. This includes the patient's chief complaint, medical history, and examination results.

Prompt for Patient: You are to role-play as a Standardized Patient. Here is your case information: {patient information}. You need to answer the doctor's questions directly based on the case information (do not fabricate doctor-patient dialogues). Note that unless the doctor explicitly asks about physical examination and auxiliary examination findings, please do not proactively mention or inquire about physical examination and auxiliary examination related content. If the doctor asks about content that does not exist in the case, please indicate that you don't know and avoid fabricating information. At all times, remember that you are only playing the role of a standardized patient.

Prompt for Doctor: You are a doctor. The patient's chief complaint is as follows: {chief complaints}. You need to gather more information through conversation with the patient. Physical examination includes: general examination (including height, weight, temperature, blood pressure, pulse, etc.), head, eyes, ears, nose, and throat examination, neck examination (including thyroid, cervical lymph nodes), chest examination (including lungs, heart), abdominal examination, spine and limb examination, skin examination, neurological examination, and genitourinary system examination. Auxiliary examinations include: X-ray, MRI, CT, ultrasound, nuclear medicine imaging, hematological tests, urine tests, stool tests, endoscopic examination, and pathological examination. After obtaining certain information (such as past history and present illness history), please select the physical examinations and auxiliary examinations to inquire about based on the patient's condition. Ask about only one or two items per conversation round. Please inquire about as many examination items as possible (ask at least one item each for physical examination and auxiliary examination) until you can determine the condition. At the end of the conversation, please say "Wishing you a speedy recovery."

Evaluation metrics is the IoU between the predicted examination items and the ground truth set. This patient-agent design simulates a realistic clinical history-taking process, allowing the doctor-LLM to demonstrate its ability to ask relevant follow-up questions, interpret patient responses, and determine appropriate examinations. The use of a local large model as the Patient Agent ensures consistency in evaluations and improves the reproducibility of the benchmark.

Systematic Evaluation: Furthermore, we conducted a systematic evaluation with a senior physician (10+ years clinical experience) across 10 simulated cases to validate the patient agent's effectiveness. The evaluation focused on three key dimensions: medical history accuracy (match rate between simulated and original EHR data), symptom consistency (temporal coherence of symptom pro-

Evaluation Prompt

Extract Reference Claims

Next, I will give you an imaging report. Please divide it into several statements, ensuring there are no omissions or repetitions between the statements. Output the resulting statements in the form of a list. The output format should be: ["Statement 1", "Statement 2", "Statement 3", ...]

Imaging report:

Entailment Evaluation

Please evaluate whether the following AI assistant-provided imaging report can fully include each of the following statements. Also, explain your answer. For each statement, output "1" or "0", where "1" means the statement can be fully included in the imaging report, and "0" means the statement contains information not included in the imaging report. Output the answers as a list composed of dictionaries in text form, not JSON. The output format should be: ["Statement": "Original Statement 1", "Explanation": "Reason for the prediction", "Inclusion Prediction": 1 or 0 (whether the statement is included in the imaging report)}, {"Statement": "Original Statement 2", "Explanation": "Reason for the prediction", "Inclusion Prediction": 1 or 0 (whether the statement is included in the imaging report)}, ...]

Statements:

Imaging report:

Figure 7: The prompt for Evaluation in Task3 Examination.

gression), and treatment response fidelity (accuracy of responses to medications and interventions). Each dimension was rated on a 5-point Likert scale (1=poor, 5=excellent). Results demonstrated strong performance across all metrics, with mean scores of 4.0 (variance=1.0) for match rate, 3.9 (variance=1.49) for temporal coherence, and 3.7 (variance=0.81) for treatment response accuracy.

A.2.3 Task 3: Examination

The examination task assesses the LLM's ability to analyze medical images and generate corresponding image reports. The input consists of the medical images from each case, and the output is a free-text image report. This task tests the LLM's capability to interpret visual medical data and articulate findings in a clear, professional manner.

Evaluation metrics: Given the complexity of medical reports, conventional NLP metrics such as BLEU [37] and BERTScore [69] are inadequate for evaluating this task, as they do not capture whether the generated report aligns with the ground truth in terms of medical claims. Instead, we adopt the Claim Recall metric proposed in DocLens [63] to evaluate the completeness of the generated report. First, GPT-40-mini is used to extract a list of claims from the original ground truth report. Then, GPT-40-mini assesses whether the generated report entails these reference claims, and the recall score measures the proportion of claims that are correctly reflected in the generated report. The prompts used for this evaluation can be found in Figure 7.

A.2.4 Task 4: Diagnosis

The diagnosis task evaluates the LLM's ability to identify the patient's illness based on the provided symptoms and examination results. The input includes the patient's chief complaint, medical history, examination results, and the department visited. The output is a diagnosis in free-text format.

Evaluation metrics: We use a five-level grading system to evaluate the accuracy of the diagnosis, ranging from 1 to 5. The prompt we used in LLM-based evaluation is followed the instruction of People's Medical Publishing House ⁵. The system accounts for the complex nature of medical diagnoses, where multiple factors may contribute to the patient's condition. The prompt is shown in Figure 8.

A.2.5 Task 5: Treatment

The treatment task involves formulating a treatment plan based on the patient's diagnosis and examination results. The input includes the patient's chief complaint, medical history, examination results, and diagnosis. The output is a set of proposed treatment items. This task tests the LLM's ability to synthesize the gathered information and apply medical knowledge to develop an appropriate treatment plan, considering factors such as drug interactions, treatment protocols, and patient-specific considerations.

⁵Diagnostics. 9th Ed. Beijing: People's Medical Publishing House; 2018

Diagnosis Evaluation Prompt You are a physician specializing in diagnostic evaluation. Below, a diagnosis result will be provided alongside the actual diagnosis (ground truth). Your task is to assess the accuracy of the diagnosis result by comparing it to the ground truth. Use the following criteria to assign an accuracy score from 1 to 5. You should only output the score as single number without any explanation. Scoring Criteria: Score 1: The diagnosis is completely inaccurate, with no elements matching the ground truth diagnosis. e.g., appendicitis is diagnosed as a migraine. Score 2: The diagnosis is mostly inaccurate, with only a few elements matching the ground truth diagnosis, and the overall deviation is significant. e.g., asthma is diagnosed as pneumonia. Score 3: The diagnosis is partially accurate, with some correct elements that are relevant to the ground truth diagnosis but the overall result shows large discrepancies. e.g., Crohn's disease is diagnosed as irritable bowel syndrome (IBS). Score 4: The diagnosis is mostly accurate, with most elements matching the ground truth diagnosis, but there are minor errors or omissions. e.g., type 1 diabetes is diagnosed as type 2 diabetes. Score 5: The diagnosis is completely accurate and matches the ground truth diagnosis entirely. Actual Diagnosis (Ground Truth): Diagnosis Result: {test}

Figure 8: The prompt for Evaluation in Task4 Diagnosis.

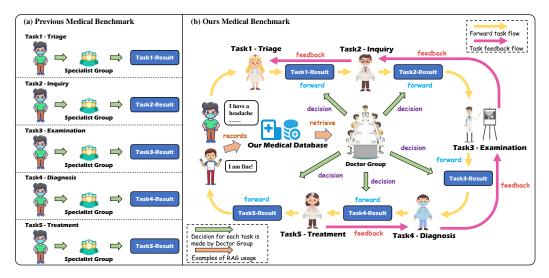


Figure 9: Comparison between our benchmark method and previous benchmarks. In Figure (a), the benchmark methods used in previous work are shown, which are based on specific domain problems and cannot achieve a complete end-to-end medical task workflow. In Figure (b), our proposed benchmark is presented, where we effectively accomplish the full workflow of medical tasks through our proposed MedCase-RAG method and the ACFM mechanism.

Evaluation metrics is the IoU between the proposed treatments and the ground truth treatment set. Since multiple treatment options may be appropriate, IoU allows for partial credit when the LLM suggests a subset of the recommended treatments or proposes additional reasonable treatments that are not part of the ground truth.

A.3 Examination Items in Task 2

Physical Examination: General examination (including height, weight, temperature, blood pressure, pulse, etc.), head, eyes, ears, nose and throat examination, neck examination (including thyroid, cervical lymph nodes), chest examination (including lungs, heart), abdominal examination, spine and limb examination, skin examination, neurological examination, urogenital system examination.

Auxiliary Examinations: X-ray, MRI, CT, ultrasound, nuclear medicine imaging, blood tests, urine tests, stool tests, endoscopy, pathological examination.

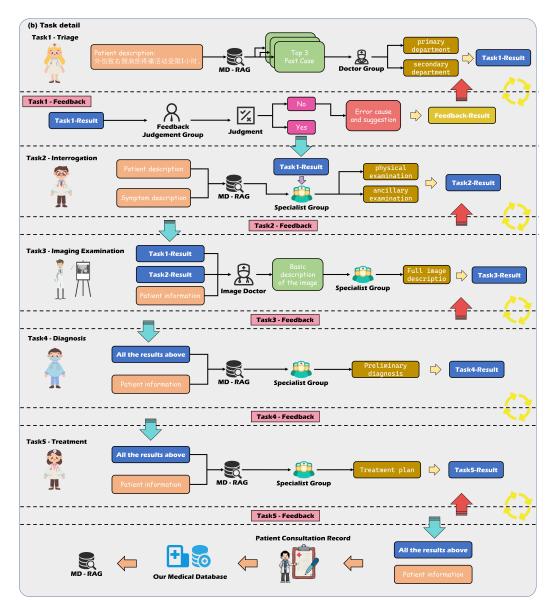


Figure 10: The specific agent design for each task in our MedChain-Agent and the ACFM of the entire process are presented.

A.4 Treatment Items in Task 5

Surgery, interventional therapy, medication, chemotherapy, antibiotic therapy, radiation therapy, physical therapy, immunotherapy, psychological therapy, traditional Chinese medicine, gene therapy.

B MedChain-Agent

B.1 Implementation Details

The overall process and output flow of our framework are illustrated in Figure 10. The patient first describes their condition, after which Task 1 performs specialty referral, assigning the patient to the appropriate primary and secondary departments. Once Task 1 is completed, the doctor group consists of specialists from the corresponding primary department, enabling better analytical decision-making. Task 2 involves these specialists prescribing suitable medical examinations based on the patient's

current situation. Task 3 focuses on analyzing the patient's imaging data to generate a detailed and comprehensive imaging report. Task 4 consists of the specialists conducting a comprehensive analysis based on the results from Task 2 and the imaging report from Task 3 to provide an initial diagnosis for the patient. Finally, Task 5 involves the specialists formulating an appropriate treatment plan based on all the previous tasks' results and analyses.

Additionally, in the aforementioned description, the decision-making and analytical processes for all tasks are conducted through discussions within the Doctor Group. Specifically, three specialists from the same department first engage in discussions and analysis, after which they summarize their findings and results to the final medical generalist (primary care physician) for the final decision. At each step, relevant similar cases are retrieved from our medical database to assist in decision-making. For Task 1, we will divide the tasks of identifying primary and secondary departments into two subtasks based on the Chain of Thought (CoT) approach: first identifying the primary department, followed by identifying the secondary department. Similarly, for Task 2, we first prescribe specific tests before additional examinations, optimizing the decision-making process.

Once the patient completes the entire medical process, a comprehensive treatment follow-up record will be compiled, including treatment outcomes and reports from each stage, along with the patient's information. This data will then be reintroduced into our medical database. Since these data have not been fully validated (we do not know how reasonable the decisions made for the current cases are), we will treat this data as pseudo-data based on the principles of semi-supervised learning and assign it a lower priority. This means that we will first retrieve data from completely validated sources, and if retrieval fails or data is insufficient, we will resort to retrieving from the pseudo-data.

B.2 Feedback Mechanism Details

To date, no work has proposed a multi-agent framework for simulating the entire medical process. Although existing frameworks demonstrate efficiency in specific medical tasks, their performance is suboptimal when linking various medical stages together. In sequential task scenarios, simply concatenating individual tasks is not feasible. Therefore, our full-process task can be regarded as a multi-sequence task, which necessitates a deeper exploration of the issue of error propagation. When a problem arises in the first task, subsequent tasks will analyze and make decisions based on erroneous results, potentially leading to severe impacts on the entire process.

To address this issue, we have introduced a feedback mechanism within the full-process framework, tightly connecting the current task with all subsequent tasks. After the current task is completed, the output results are evaluated by the physicians of the subsequent tasks (Feedback Judgement Group). Only when the results are confirmed to be accurate will the process advance to the next task; if issues are identified, the reasons for the errors and improvement suggestions will be output and fed back to the current task for re-discussion and decision-making. This process will continue iteratively until consensus is reached on the results or the maximum number of discussion rounds is achieved.

By implementing a feedback mechanism between each task, we can effectively manage the propagation of errors while significantly enhancing collaboration and communication among agent groups. This mechanism encourages agents to share information in real-time, improving mutual understanding and allowing for rapid strategic adjustments when issues are identified, thereby enhancing the overall flexibility and adaptability of the system. Each agent can better respond to changes in a dynamic environment, facilitating more efficient medical services. This feedback-driven collaborative model lays the foundation for the efficient operation of multi-agent systems, aiding in the provision of precise and reliable medical decision support in complex clinical environments.

B.3 RAG Details

We performed data restructuring on the original dataset, where each case is mapped into feature vectors from 12 dimensions. Among these, "Symptom Description" is identified as the most representative feature of the current patient and is processed through a Text Embedding model for quantification, which is stored in the database for subsequent dense retrieval tasks.

Previous Medical-RAG methods relied on medical question-answering (QA) databases and predominantly used chunked indexing for retrieval. Our approach differs in several ways. Firstly, the content of our foundational medical database is distinct; while most methods have built their databases

using medical OA data, ours utilizes a tree structure. We initially categorize patient information according to primary medical departments (in the experimental section, we categorized into 19 primary departments) and then extract and map patient information into a two-dimensional feature representation. This storage design allows for better retention of the patient's crucial clinical information to assist in decision-making. Secondly, our retrieval method also diverges from theirs. In our retrieval process, we simulate the everyday practice of physicians. When faced with challenging cases that require decision-making, doctors often refer to past cases as references to enhance current decisions and judgments. We treat these two-dimensional features as the minimal unit of a case, using "Symptom description" as the basis for retrieval. When a new patient arrives, we extract and refine their "Symptom description" feature (approximately 70 characters). We employ direct quantitative matching without tokenizing this feature, using a Text Embedding model for quantification. The resulting feature vector is then compared to each case in our database corresponding to the relevant department through cosine similarity calculations, selecting the top three cases with the highest symptom similarity as the current retrieval results. These results, combined with the current case features, are forwarded to subsequent agents for comprehensive decision-making and judgment, enhancing the agents' output. Since our retrieval method does not utilize document chunking but rather employs direct matching, it retains more matching information, leading to improved matching accuracy.

B.4 Task Prompts

Figure $11 \sim$ page 30 showcase prompts for each task and stage within our MedChain-Agent framework.

Table 6: **Comparison of Benchmarks for LLM-based Agent.** The MedChaincomposed of 12, 163 case with five sequential stages of the clinical workflow. It provide interaction environment for LLM-based agent evaluation.

Benchmark	#Num	Modality	Personal Information	Sequential Evaluation	Interaction
MedQA [70]	1,273	Text	✓	X	X
PubMedQA [20]	500	Text	X	X	X
MedMCQA [36]	193,155	Text	✓	X	X
MMedBench [39]	53,566	Text	X	X	X
MedBench [29]	300,901	Text	✓	X	X
Asclepius [54]	3,232	Text, Imaging	X	X	X
GMAI-MMBench [5]	26,000	Text, Imaging	×	X	X
MedChain	12,163	Text, Imaging	√	✓	√

C Supplementary for Experiment

Tasks 1 and 2 are subdivided based on the Chain of Thought (CoT) reasoning approach for decision-making. Consequently, Task 1 is split into "specialty referral (Level 1)" and "specialty referral (Level 2)" to evaluate performance at both primary and secondary department levels. Task 2 is divided into "Physical" and "Ancillary," representing performance in physical examinations and ancillary tests. or both ablation and comparative experiments, we split our dataset into training and test sets in a 7:3 ratio. We extracted 12-dimensional features from each training set case and stored them in our Medical Dataset for subsequent retrieval tasks.

D Related Work Discussion

We compare MedChain with most of related work in Table 6 and Figure 9. Especially, we analyze MedChain with AI Hospital and CoD as following:

AI Hospital [11]: While both AI Hospital and our work aim to evaluate LLMs in clinical scenarios through multi-agent interactions, there are several key distinctions. Firstly, MedChain significantly

Task1 Triage Prompt

Mission1: Classification of Primary Medical Departments

sys_prompt: You are a professional triage doctor with extensive experience in triage. Based on the patient's condition, you need to accurately assign them to the appropriate medical department.

user_input: You need to assign the patient to the appropriate department for consultation based on the "patient condition" described below. You must select only one department from the 19 "available departments" listed below.Refer to the "past cases" below to assist in making your decision.Patient condition:"[condition]"Past cases:"\$[case1],[case2],[case3]\$"Available departments: ['Nursing Department', 'Pharmacy Department', 'Dentistry', 'Pediatrics', 'Medical Imaging', 'Ophthalmology', 'Laboratory Medicine', 'Surgery', 'Dermatology and Venereology', 'Psychiatry', 'General Medicine', 'Otolaryngology', 'Internal Medicine', 'Emergency Medicine', 'Oncology', 'Traditional Chinese Medicine', 'Rehabilitation', 'Obstetrics and Gynecology', 'Psychology']Output example (output only your selection, no extra text):"Surgery"

Mission2: Mission1-Feedback

sys_prompt: You are a triage result evaluator with extensive experience in triage. Please review the triage doctor's "triage result" to determine whether the primary department assignment is correct.

user_input: Please review the triage doctor's "triage result" to determine whether the primary department is correct. Refer to the "past cases" department assignment to assist in decision-making.Output requirements: (You must follow these instructions carefully)1. If you think it is correct, output "Correct," if it is incorrect, output "Incorrect," and explain the reason!!!2. You must answer first, then give a reason!Triage result:"[result]"Past cases:"\$[case1][case2][case3]\$"Output example:For correct result (no need to explain):"Correct"For incorrect result (with reason):"IncorrectReason: {your opinion on the primary department assignment}"

Feedback_result_example: Here is the triage result for the "primary department" based on the patient's condition:"[result]". Here is the feedback from other doctors regarding the current "primary department" triage:"[feedback]"

Mission3: Feedback-Answer

sys_prompt: You are a professional triage doctor with extensive experience in triage. You need to assign the patient to the appropriate department based on their condition with precision.

user_input: Please reasonably consider the opinions of the clinic doctors and assign the patient to the appropriate department for treatment. You need to select only one department from the following 19 "available departments."The original triage result and other doctors' suggestions:"[feedback]"Past cases:"\$[past_case]\$"Available departments: ['Nursing Department', 'Pharmacy Department', 'Dental Department', 'Pediatrics', 'Medical Imaging Department', 'Ophthalmology', 'Laboratory Department', 'Surgery', 'Dermatology', 'Psychiatry', 'General Medicine', 'Otorhinolaryngology', 'Internal Medicine', 'Emergency Department', 'Oncology', 'Traditional Chinese Medicine', 'Rehabilitation Department', 'Obstetrics and Gynecology', 'Psychology']Output example: (Directly output your choice, without extra content) "Surgery"

Mission4: Secondary Department Classification

sys_prompt: You are a professional triage doctor with extensive experience in triage, and you need to accurately allocate patients to the appropriate department based on their conditions.

user_input: You need to allocate the patient to the appropriate department for treatment based on the described "patient condition." You can choose from the following "available departments," and you may select multiple suitable departments. Refer to the "previous cases" for guidance in your decision-making.Patient condition: "[condition]"Previous cases: "\$ [case1],[case2],[case3] \$"Available departments: [list]Output example: (Directly output your options without any extra content)For a single department: "Surgery"For multiple departments: (separated by commas)"Joint Orthopedics,

Mission5: Mission4-Feedback

sys_prompt: You are a triage result evaluator with extensive triage experience. Please check whether the "secondary department" in the triage result provided by the triage doctor is correct.

user_input: Please check whether the "secondary department" in the triage result provided by the triage doctor is correct. Refer to the "past case" department allocation to assist in your decision-making.Output requirements: (You must think according to the following requirements) If you believe there are no errors, output "Correct." If there is an error output "Incorrect" and explain the reason!Always respond first, then provide the reason!Triage result:"[result]"Past cases:"\$[case1],[case2],[case3]\$"Output example:If you believe it is correct (no need to provide a reason):"Correct"If you believe it is incorrect (explain the reason):"IncorrectReason: {Your opinion on the secondary department triage result}"

Feedback_result_example: This is the triage result for the "secondary department" based on the patient's condition:"[result]"This is the triage opinion from other doctors regarding the current "secondary department":"[feedback]"

Mission6: Feedback-Answer

sys_prompt: You are a professional triage doctor with extensive experience in triage, and you need to accurately allocate patients to the appropriate department based on their conditions.

user_input: Please reasonably consider the opinions of the clinic doctors and assign the patient to the appropriate department for treatment. You need to choose the suitable departments from the list below and can select multiple appropriate departments.Directly output your selection without additional content!!!Original triage result and other doctors' suggestions:"[feedback]"Available departments: [list]Output example:Single department output:"Surgery"Multiple departments output: (separated by commas)"Joint Orthopedics, Orthopedics"

Figure 11: The prompt for Task 1 in the MedChain-Agent.

```
Task1 Triage Prompt
 Mission1: Classification of Primary Medical Departments
    sys_prompt: 你是一个专业的分诊医生,有着丰富分诊经验,你需要根据病人的情况,进行精确的科室分诊。
    user_input: 你需要根据下面描述的"病人情况",将病人分到合适的科室进行就诊,你需要从以下19个"可选择的科室"中仅选择1个科室进行
分配。参考下面的"过往病例"的科室分配情况,辅助做出决策。病人情况:"[condition]"过往病例: "$[case1]、[case2]、[case3]"$.可选择的
科室: ['护理科', '药剂科', '口腔科', '儿科', '医学影像科', '眼科', '检验科', '外科', '皮肤性病科', '精神科', '全科', '耳鼻咽喉
科','内科','急诊科','肿瘤科','中医科','康复科','妇产科','心理科'].输出示例:(直接输出你的选项,不要输出多余的内容)"外科".
 Mission2: Mission1-Feedback
    sys_prompt: 你是一名分诊结果判别者,拥有着丰富的分诊经验,请你检查分诊医生的"分诊结果"中一级科室是否正确。
    user_input:请你检查分诊医生的'分诊结果'中一级科室是否正确。参考下面的'过往病例'的科室分配情况,辅助做出决策。输出要求:(你
-定要按下面的要求进行思考)1、认为没有错误则输出"正确",有错误则输出"错误",并且说明原因!!! 2、一定要先回答,然后再回答原因!
分诊结果: "[result]" 过往病例: "$ [case1] [case2] [case3] "$。输出示例: 认为正确的输出示例: (认为正确则无需输出原因)"正确"。认
为错误的输出示例: (认为错误要说明原因)"错误原因: {对一级科室分诊结果的意见}"
    Feedback_result_example: 这是基于病人情况做出的"一级科室"的分诊结果: "[result]"。这是其他医生对当前"一级科室"的分诊意见:
"[feedback]"
 Mission3: Feedback-Answer
    sys_prompt: 你是一个专业的分诊医生,有着丰富分诊经验,你需要根据病人的情况,进行精确的科室分诊。
   user_input:请你合理参考诊室医生的意见,将病人分到合适的科室进行就诊,你需要从以下19个"可选择的科室"中仅选择1个科室进行分配。
诊室医生的意见不一定正确,请你合理对待。参考下面的"过往病例"的科室分配情况,辅助做出决策。原来的分诊结果和其他医生的建议:
"[feedback]"。过往病例:"$[past_case]"$。可选择的科室:['护理科','药剂科','口腔科','儿科','医学影像科','眼科','检验科'
'外科','皮肤性病科','精神科','全科','耳鼻咽喉科','内科','急诊科','肿瘤科','中医科','康复科','妇产科','心理科']。输出
示例: (直接输出你的选项,不要输出多余的内容) "外科"
  Mission4: Secondary Department Classification
   sys prompt: 你是一个专业的分诊医生,有着丰富分诊经验,你需要根据病人的情况,进行精确的科室分诊。
  user_input: 你需要根据下面描述的"病人情况",将病人分到合适的科室进行就诊,你需要从下面"可选择的科室"中选择合适的科室进行分配,
可以选择多个合适的科室。参考下面的"过往病例"的科室分配情况,辅助做出决策。病人情况:"[condition]"。过往病例:"$[case1]、[case2]、
[case3]"$。可选择的科室: [1ist]。输出示例: (直接输出你的选项,不要输出多余的内容),输出为单个科室: "外科"。输出为多个科室: (用逗号
分隔开) "关节骨科,骨科"
  Mission5: Mission4-Feedback
    sys_prompt: 你是一名分诊结果判别者,拥有着丰富的分诊经验,请你检查分诊医生的"分诊结果"中二级科室是否正确。
    user input: 请你检查分诊医生的"分诊结果"中二级科室是否正确。参考下面的"过往病例"的科室分配情况,辅助做出决策。输出要求: (你
一定要按下面的要求进行思考): 1、认为没有错误则输出"正确",有错误则输出"错误",并且说明原因!!!  2、一定要先回答,然后再回答原因!
分诊结果:"[result]"。过往病例:"$[case1]、[case2]、[case3]"$。输出示例:认为正确的输出示例:(认为正确则无需输出原因)"正确"。认
为错误的输出示例:(认为错误要说明原因):"错误,原因:{对二级科室分诊结果的意见}"
    Feedback_result_example: 这是基于病人情况做出的"二级科室"的分诊结果: "[result]"。这是其他医生对当前"二级科室"的分诊意
见:"[feedback]"
  Mission6: Feedback-Answer
    sys_prompt: 你是一名专业的分诊医生,在分诊方面有丰富的经验,你需要根据患者的情况,准确地将患者分配到合适的科室。
    user_input:请你合理参考诊室医生的意见,将病人分到合适的科室进行就诊,你需要从下面"可选择的科室"中选择合适的科室进行分配,可
以选择多个合适的科室。直接输出你的选项,不要输出多余的内容!!!原来的分诊结果和其他医生的建议: "[feedback]"。可选择的科室: [list],
输出示例:输出为单个科室: "外科"。输出为多个科室: (用逗号分隔开): "关节骨科,骨科"。
```

Figure 12: The prompt for Task 1 in the MedChain-Agent in Chinese.

expands the scale and diversity of medical cases, comprising 12,163 cases across 19 specialties and 156 subspecialties, including 7,338 medical images. This represents a substantial advancement over AI Hospital's dataset of 506 cases with limited specialty coverage, enabling more comprehensive evaluation of LLMs' medical capabilities across diverse clinical scenarios. Secondly, MedChain introduces a more sophisticated multi-agent collaboration mechanism. While AI Hospital employs a basic agent interaction model, our framework incorporates a feedback-driven multi-agent system enhanced by the MedCase-RAG module. This module enables dynamic knowledge base expansion and supports case-based reasoning through structured feature representation.

CoD [4] introduces an interactive approach to enhance the interpretability of medical diagnosis. While both CoD and our work incorporate interactive components, they differ substantially in both design objectives and implementation mechanisms. CoD primarily focuses on improving the interpretability of the diagnostic phase through confidence-driven interactions that demonstrate the reasoning process. In contrast, MedChain takes a more comprehensive approach by simulating the complete clinical workflow through a multi-agent collaborative framework. Our framework encompasses five sequential stages from triage to treatment, with each stage's decisions being evaluated and guided by subsequent stages through a novel cross-stage feedback mechanism. This design enables MedChain to capture the interdependent nature of clinical decision-making, where decisions at each stage influence and are influenced by other stages in the workflow.

```
Task2 Inquiry Prompt
  Mission1: Physical examination
      sys_prompt: You are a professional [first_room] physician with extensive clinical experience, and you need to
prescribe appropriate medical examinations for the patient.
      user_input: Task Description:Based on the current case situation and with appropriate reference to past cases,
prescribe suitable "[task_obj]" for the current patient. If no physical examination is needed, you can output
"[task_obj]: None." Please adhere strictly to the output format.Only output the examinations that need to be performed;
no need to provide examination results!!!Past Cases:"$[case1][case2][case3]$"Current Case:"Patient's complaint: [case
now]"Output Format:"[task_obj]: {.....}"
    Mission2: Mission1-Feedback
     sys_prompt: You are a medical physical examination result evaluator with extensive experience in medical
examinations. Please review the physical examination items in the physician's "physical examination" to determine
whether they are correct.
      user_input: Please review the physical examination items in the physician's "physical examination" to determine
whether they are correct. Refer to the "past cases" below to assist in your decision-making.Output requirements: (You
must follow the requirements below)Output "Correct" if there are no errors, or "Incorrect" if there are errors, and
provide reasons!!!Always answer first, then explain the reasons!Physical Examination: " [result] "Past Cases: "$
[past case] $"Output Example: If correct, the output example is: (No reason needed if correct) " Correct " If incorrect.
the output example is: (Must explain the reasons for being incorrect!!!) " Incorrect Reason: {Opinion on the items in
the "physical examination" result} "
      Feedback_result_example: Here are the "physical examination" items ordered by the medical examination
physician:"[result]"Here are the opinions of other doctors regarding the ordered "physical examination
items:"[feedback]"
  Mission3: Feedback-Answer
      sys_prompt: You are a specialized [first_room] physician with extensive clinical experience in patient
consultations, and you need to prescribe appropriate medical examinations for the patient.
      user_input: Please reasonably consider the opinions and suggestions of other doctors regarding the "physical
examination" items. Based on the patient's condition and the opinions of the consulting physician, reissue the
appropriate examination items for the patient's "physical examination" according to the original format. The opinions of
other doctors may not be correct, so please evaluate them critically. Only output the modified "physical examination"
items without providing reasons or additional explanations. Reference the "past cases" for assistance in decision-
making.Original physical examination items and other doctors' suggestions: " [feedback] "Past cases: "$ [past_case]
$"Output format: " Physical Examination: {.....} "
   Mission4: Auxiliary Examination
      sys prompt: You are a professional [first room] doctor with extensive clinical interview experience, and you need
to prescribe appropriate medical examinations for the patient.
      user_input: Task Description:You need to prescribe appropriate "[task_obj]" for the current patient based on the
current case situation, with suitable reference to past cases. If no physical examination is required, you can output
"[task_obj]: None." Please adhere strictly to the output format.Only output the required examinations, without providing
the examination results.Past Cases: "$[case1][case2][case3] $"Current Case: " Patient's Chief Complaint: [case now]
"Output Format: " [task obj]: {.....} '
   Mission5: Mission4-Feedback
     sys_prompt: You are a medical auxiliary examination result evaluator with extensive experience in medical testing.
Please review the auxiliary examination items listed by the medical examination doctor to determine their accuracy.
     user_input: Please review the auxiliary examination items provided by the medical examination doctor to determine
their accuracy. Use the following "past cases" distribution of departments to assist in your decision-making.Output
requirements: (You must follow the requirements below for your reasoning) If you believe there are no errors, output
"Correct." If there are errors, output "Incorrect" and explain the reason!!!Always respond first, then provide the
reason!Auxiliary examination: " [result] "Past cases: "$ [past_case] $"Output examples: If you believe it's correct (no
reason needed): " Correct " If you believe it's incorrect (you must explain the reason!!!): " Incorrect Reason: {Your
opinion on the "auxiliary examination" items} "
     Feedback_result_example: Here are the "auxiliary examination" items prescribed by the medical examination
doctor:"[result]"Here are the opinions of other doctors regarding the prescribed "auxiliary examination"
items:"[feedback]"
   Mission6: Feedback-Answer
      sys prompt: You are a specialized [first room] physician with extensive clinical examination experience, and you
need to prescribe appropriate medical tests for the patient.
      user input: Please reasonably consider the opinions and suggestions of other doctors regarding the "auxiliary
examination" items. Based on the patient's condition and the opinions of the consulting physician, please rewrite the
appropriate examination items for the patient's "auxiliary examination" according to the original format. The opinions
of other doctors may not be correct, so please evaluate them judiciously. Only output the modified "auxiliary
examination" items without providing reasons or additional explanations. Refer to the following "past cases" to assist
in decision-making.Original auxiliary examination items and other doctors' suggestions: " [feedback] "Past cases: "$
```

Figure 13: The prompt for Task 2 in the MedChain-Agent.

[past_case] \$"Output format: " Auxiliary examination: {.....} '

```
Task2 Inquiry Prompt
  Mission1: Physical examination
    sys_prompt: 你是一名专业的[first_room]医生,拥有着丰富的临床问诊经验,您需要为患者开具合适的医学检查。
    user_input: 任务说明: 1、你需要根据当前病例的情况,适当参考过往病例,为当前患者开具合适的"[task_obj]",若无需开局体格检查
则可以输出"[task_obj]: None",请你严格按照输出格式进行输出。2、只输出需要做的检查即可,无需输出检查结果!!! 过往病例:
Mission2: Mission1-Feedback
    sys_prompt: 你是一名医学体格检查结果判别者,拥有着丰富的医学检查经验,请你检查医学检查医生的"体格检查"中的这些体格检查项目是
   user_input:请你检查医学检查医生的"体格检查"中的这些体格检查项目是否正确。参考下面的"过往病例"的科室分配情况,辅助做出决策。
输出要求: (你一定要按下面的要求进行思考)1、认为没有错误则输出"正确",有错误则输出"错误",并且说明原因!!! 2、一定要先回答,然后
再回答原因!体格检查: "[result]"过往病例: "$[past_case]"$输出示例: 认为正确的输出示例: (认为正确则无需输出原因)"正确"认为错误的输
出示例: (认为错误要说明原因,一定要说明原因!!!)"错误原因: {对"体格检查"项目结果的意见}"
    Feedback_result_example: 这是医学检查医生开具的"体格检查"项目: "[result]"这是其他医生对开具的"体格检查"项目的意
见:"[feedback]"
 Mission3: Feedback-Answer
    sys_prompt: 你是一名专业的[first_room]医生,拥有着丰富的临床问诊经验,您需要为患者开具合适的医学检查。
    user_input:请你合理参考其他医生的关于"体格检查"项目的看法和建议,基于病人情况和诊室医生的意见按照原来的格式重新对病人的"体
格检查"开具合适的检查项目。其他医生的意见不一定正确,请你合理对待。只输出修改后的"体格检查"项目即可,无需输出原因和其他说明。参考下
面的"过往病例"的科室分配情况,辅助做出决策。原来的体格检查项目和其他医生的建议:"[feedback]"过往病例:"$[past_case]"$输出格式:
体格检查: {.....}"
  Mission4: Auxiliary Examination
    sys_prompt: 你是一名专业的[first_room]医生,拥有着丰富的临床问诊经验,您需要为患者开具合适的医学检查。
    user_input: 任务说明: 1、你需要根据当前病例的情况,适当参考过往病例,为当前患者开具合适的"[task_obj]",若无需开局体格检查
则可以输出"[task_obj]: None",请你严格按照输出格式进行输出。2、只输出需要做的检查即可,无需输出检查结果!!! 过往病例:
"$[case1][case2][case3]"$当前病例: "病人主诉: [case now]"输出格式: "[task_obj]: {......}"
  Mission5: Mission4-Feedback
    sys prompt: 你是一名医学辅助检查结果判别者。拥有着丰富的医学检查经验。请你检查医学检查医生的"辅助检查"中的这些辅助检查项目是
    user_input: 请你检查医学检查医生的辅助检查"中的这些辅助检查项目是否正确。参考下面的"过往病例"的科室分配情况,辅助做出决策。
输出要求:(你一定要按下面的要求进行思考)1、认为没有错误则输出"正确",有错误则输出"错误",并且说明原因! !! 2、一定要先回答,然后
再回答原因!体格检查: "[result]"过往病例: "$[past_case]"$输出示例: 认为正确的输出示例: (认为正确则无需输出原因)"正确"认为错误的输
出示例: (认为错误要说明原因,一定要说明原因!!!)"错误原因: {对"辅助检查"项目结果的意见}"
    Feedback_result_example: 这是医学检查医生开具的"辅助检查"项目: "[result]". 这是其他医生对开具的"辅助检查"项目的意
见:"[feedback]"
 Mission6: Feedback-Answer
   sys_prompt: 你是一名专业的[first_room]医生,拥有着丰富的临床问诊经验,您需要为患者开具合适的医学检查。
    user input: 请你合理参考其他医生的关于"辅助检查"项目的看法和建议,基于病人情况和诊室医生的意见按照原来的格式重新对病人的"辅
助检查"开具合适的检查项目。其他医生的意见不一定正确,请你合理对待。只输出修改后的"辅助检查"项目即可,无需输出原因和其他说明。参考下
面的"过往病例"的科室分配情况,辅助做出决策。原来的辅助检查项目和其他医生的建议:"[feedback]"过往病例:"$[past_case]"$输出格式:'
辅助检查: {.....}"
```

Figure 14: The prompt for Task 2 in the MedChain-Agent in Chinese.

```
Task3 Examination Prompt
  Mission1: Description of imaging by a professional radiologist
      sys_prompt: You are a professional medical imaging physician, and you need to provide a feature description based
on the input medical images.
      user_input: The following are the "basic patient information" and the patient's [img_class] imaging. Please
provide a concise and comprehensive description of the imaging.
Basic Patient Information:
[symptom]
Output Example: (The descriptions in both the imaging and conclusion sections should be as detailed and comprehensive as
Chest CT: (Description should be as detailed and comprehensive as possible)
1. Multiple abnormal density shadows in both lungs, mostly located subpleurally, with a large lesion in the right upper
lobe accompanied by multiple cavitary formations, raising the possibility of infection;
2. Small amount of pericardial effusion and a small amount of pleural effusion on the right side;
3. Slight thickening of both pleurae.
**Imaging Report Conclusion:** (Description should be as detailed and comprehensive as possible)
1. No clear abnormal density shadows were seen in both lungs, bronchial structures appear normal, and no significant
2. No obvious enlarged lymph nodes were seen in the mediastinum or at both lung hilum.
3. An approximately 8.3 cm soft tissue density mass was observed in the anterior mediastinum.
4. Other structures within the mediastinum showed no significant displacement, and the heart size and shape were normal.
Recommendations:
1. ......
2. .....
   Mission2: Image report generation
     sys prompt: You are a professional {first room} radiologist with extensive clinical experience, capable of
generating medical imaging reports effectively.
     user_input: Below is the imaging report generated by the previous radiologist based on the 'patient condition'
and the patient's imaging. Please re-evaluate the 'imaging report' below to check for any omissions, incompleteness, or
errors, and if any are found, provide the output as per the example.Patient condition: '[now_case] 'Imaging report:
[img_report] 'Output instructions:If there are no suggestions and you consider it correct, output: ' None 'If there are
supplementary suggestions, output: ' It is recommended to supplement, improve, or modify the following parts of the
"imaging report"...'
  Mission3: Mission2-Feedback
      sys_prompt: You are a specialized {first_room} radiologist with extensive clinical experience in imaging. You
need to evaluate whether the previously analyzed report by the expert physician is reasonable based on the patient's
imaging findings.
     user input: Task Instructions:Below is the imaging report provided by the radiologist.Based on the report and the
patient's imaging, do you think there are issues with this imaging report?If you think the result is correct, output
"Correct"; if you think it is incorrect, output "Incorrect" and explain the reason!You must answer first and then
provide your reasoning. You only need to output your reason or opinion; do not output the original report result or
information.Imaging Doctor's Report Result:"[result]"Output Example:[Correct/Incorrect]Reason:.....
  Mission4: Feedback-Answer
     sys prompt: You are a specialized {first room} radiologist with extensive clinical experience in imaging. You
need to evaluate whether the previously analyzed report by the expert physician is reasonable based on the patient's
imaging findings.
      user_input: Task Instructions:Please reasonably consider the clinic doctor's opinions and suggestions regarding
the imaging results for the above patient. Based on the patient's imaging and the opinions of other expert doctors,
modify the "current imaging report" according to the original format.Patient Situation:"[now_case]"Current Imaging
Report:"[img report]"Expert Doctor's Opinion:"[feedback]"Output Example:"Imaging Report: {.....}"
```

Figure 15: The prompt for Task 3 in the MedChain-Agent.

```
Task3 Examination Prompt
  Mission1: Description of imaging by a professional radiologist
   sys_prompt: 你是一名专业的医学影像医生,你需要根据输入的医学影像对其进行特征描述。
    user_input: 下面传进来的是"病人的基本情况"和病人的[img_class]影像,请你进行精简、全面的影像描述。病人的基本情况:
"[symptom]"输出示例: (影像描述和结论部分的描述尽量详细! )"胸部CT: (描述尽可能详细、全面)1、两肺内多发异常密度影,大部位于胸膜下,
右肺上叶病变范围较大伴多发空洞形成,考虑感染可能大;2、心包少量积液,右侧胸腔少量积液;3、两侧胸膜稍肥厚影像报告结论:(描述尽可能详细、
全面)1. 两肺内未见明确异常密度影,支气管正常,未见明显扩张。2. 纵隔内及两肺门未见明显肿大淋巴结影。3. 前纵隔内见一直径约8.3cm的软
组织密度肿块。4. 余纵隔内诸结构未见明显移位,心影大小形态正常。建议: 1. ......2. ......"
  Mission2: Image report generation
    sys_prompt: 你是一名专业的{first_room}影像学医生,拥有丰富的临床经验,能够很好地生成医学影像报告。
    user_input: 下面是之前的影像学医生基于"病人情况"和病人的影像生成的影像报告。请你基于"病人情况"和病人的影像再次检查一下下面
的"影像报告"是否有遗漏、不完善或者错误的部分,若有则按照输出示例进行输出。仅做补充说明即可,无需完整回答! ! 病人情况:"[now_case]"
影像报告:"[img_report]"输出说明: 1. 若无建议,认为正确则输出: "无"2. 若有补充建议则输出: "认为"影像报告"中需要补充、完善、修改的
部分.....*
  Mission3: Mission2-Feedback
    sys_prompt: 你是一名专业的{first_room}影像医生,拥有丰富的影像学临床经验,您需要基于患者的影像情况,判断之前专家医生分析的
报告是否合理。
    user_input: 任务说明: 1、下面是影像医生开具影响报告结果。2、基于下面的报告和病人的影像, 你认为这个影像报告结果有问题吗? 3、
你认为这个结果正确则输出-"正确",认为不正确则输出-"错误",并且说明原因!!! 4、你一定要先回答,然后再回答原因。5、你只需要输出你的
原因或观点即可,不要输出原来的报告结果或者信息。影像医生的报告结果: "[result]"输出示例: [正确/错误]原因: .....
  Mission4: Feedback-Answer
   sys_prompt: 你是一名专业的放射科医生,在影像方面有丰富的临床经验。您需要根据患者的影像学检查结果评估专家医师之前分析的报告
是否合理。
   user input: 任务说明: 请你合理参考诊室医生关于上述病人影像结果的看法和建议,基于病人影像图片和其他专家医生的意见按照原来的
格式修改"当前影像报告"。病人情况: "[now_case]"当前影像报告: "[img_report]"专家医生的意见: "[feedback]"输出示例: "影像报告:
{.....}"
```

Figure 16: The prompt for Task 3 in the MedChain-Agent in Chinese.

```
Task4 Diagnosis Prompt
    Mission1: Medical Diagnosis
        sys_prompt: You are a professional {first_room} physician with extensive clinical diagnostic experience. You need
to output the diagnosis based on the patient's condition.
user_input: You need to provide an appropriate "diagnosis" for the current patient based on the described 
"patient condition" and consider past cases for reference. Only reply with one or more diagnosis names, without any
                                   and strictly follow the output format.Patient
additional explanations.
                                                                                                               condition:"[case
cases:"$[case1][case2][case3]$"Output example: (directly output your options without additional content)For a single
diagnosis: "Ankylosing Spondylitis' "For multiple diagnoses: (separated by commas)" Rheumatoid Arthritis', 'Fracture'
     Mission2: Mission1-Feedback
        sys_prompt: You are a professional {first_room} physician with extensive clinical diagnostic experience, and you
need to analyze whether the diagnosis made by the clinic doctor is reasonable based on the patient's condition.
       user input: Please check whether the diagnosis in the "current patient condition and diagnosis results" is
correct. Refer to the "past cases" below to assist in making your decision. Output requirements: (You must follow the
requirements below in your reasoning)If you believe there are no errors, output "Correct." If there are errors, output
 "Incorrect," and explain the reason!!!You must answer first, and then provide your reasoning!Current patient condition
and diagnosis results: "[result]"Past cases: " [case1][case2][case3] "Output example: If you believe it is correct, output example: (No reason is needed if you think it is correct) " Correct " If you believe it is incorrect, output example: (If you think it is incorrect, provide the reason; you must explain the reason!!!) " Incorrect Reason: {Your
opinion on the "diagnosis result"} "
        Feedback_result_example: Here is the diagnosis result made by the doctor based on the current patient
condition:"[result]"Here are the opinions of other doctors regarding the diagnosis result:"[feedback]"
    Mission3: Feedback-Answer
        sys_prompt: You are a specialized {first_room} physician with extensive clinical diagnostic experience, and you
need to provide a diagnosis based on the patient's condition.
        user input: Please reasonably consider other doctors' opinions and suggestions regarding the current case's
diagnosis." Based on the patient's condition and the opinions of the clinic doctor, revise the patient's "diagnosis"
according to the original format. Other doctors' opinions may not be correct, so please assess them critically. Only
output the modified "diagnosis" without any reasons or additional explanations. You can refer to the "past cases'
diagnosis situation to assist in decision-making.Original diagnosis results and other doctors' suggestions:
"Past cases: "$ [past_case] $"Output example: (directly output your options without additional content) For a single diagnosis: "'Spondyloarthritis' " For multiple diagnoses: (separated by commas) " 'Rheumatoid arthritis', 'Fracture' "
Task5 Treatment Prompt
    Mission1: Medical treatment
        sys_prompt: You are a specialized {first_room} doctor with extensive clinical treatment experience, and you need
to provide a treatment plan based on the patient's condition.
        user_input: You need to prescribe appropriate treatment options for the current patient based on the described
 "patient condition." You should choose suitable options from the "available treatment options" list below, and you can
select multiple options.Refer to the "past cases" treatment options for assistance in making your decision.Patient condition: "[case now] "Past cases: "$ [case1][case3] "$Available treatment options: ["Surgery", "Interventional Therapy", "Medication Therapy", "Chemotherapy", "Antibiotic Therapy", "Radiation Therapy", "Physical Therapy", "Immunotherapy", "Psychotherapy", "Traditional Chinese Medicine", "Gene Therapy"]Output example: (directly output your options without additional content)For a single treatment option: "Surgery "For multiple treatment options: (separate
with commas) " Medication Therapy, Antibiotic Therapy, Physical Therapy
    Mission2: Mission1-Feedback
        sys_prompt: You are a professional {first_room} doctor with extensive clinical treatment experience. You need to
analyze whether the treatment results provided by the clinic doctor are reasonable based on the patient's condition.

user_input: Please check whether the "treatment items" prescribed by the doctor are correct. Refer to the
department allocation situation of the "past cases" below to assist in making your decision.Output requirements: (You
must think according to the requirements below) If you believe there are no errors, output "Correct." If there are errors
output "Incorrect," and provide a reason! You must answer first, then provide the reason! Treatment items prescribed by
the doctor based on the patient's condition: " [result] "Past medical records: " [case1][case2][case3] "Output example:
If you believe it is correct, the output example is as follows: (If you believe it is correct, no reason is needed)
Correct " If you believe it is incorrect, the output example is as follows: (If you believe it is incorrect, you must explain the reason!!!) " Incorrect Reason: {Opinion on the treatment item results} "
Feedback_result_example: The following are the "diagnosis results" you provided: "[Result]." Below are the opinions from other doctors regarding your "diagnosis results": "[Feedback]."
        sys_prompt: You are a specialized {first_room} doctor with extensive clinical treatment experience, and you need
to provide a treatment plan based on the patient's condition.
```

user_input: Please reasonably consider the opinions and suggestions of other doctors regarding the "treatment options" for the current case, and based on the patient's condition and the doctor's opinions, re-prescribe appropriate treatment options" for the patient according to the original format. You need to choose appropriate options from the following "available treatment options," and you can select multiple suitable options. Only output the modified "treatment options," without providing reasons or additional explanations. You may refer to the "past cases" treatment options to assist in your decision-making Original treatment options and other doctors' suggestions: " [feedback] "Past cases: "\$ [past_case] \$"Available treatment options: ["Surgery", "Interventional Therapy", "Medication", "Chemotherapy", "Antibiotic Therapy", "Radiation Therapy", "Physical Therapy", "Immunotherapy", "Psychotherapy", "Traditional Chinese Medicine", "Gene Therapy"]Output example: (directly output your options, do not output extra content) For a single treatment option: "Surgery " For multiple options: (separated by commas) " Medication, Antibiotic Therapy, Physical

Figure 17: The prompt for Task 4 and Task5 in the MedChain-Agent.

```
sys_prompt: 你是一名专业的{first_room}医生,有着丰富的临床诊断经验,你需要根据病人的情况,输出诊断结果。
user_input: 你需要根据下面描述的"病人情况",适当参考过往病例,为当前患者进行合适的"诊断"。仅回复一个或多个诊断结果的名称,不要包含其他任何解释,请严格按照输出格式进行输出。参考下面的"过往病例"的诊断情况,辅助做出决策。病人情况:"[case_now]"过往病例:
"$[case1][case2][case3]"$输出示例:(直接输出你的选项,不要输出多余的内容)输出为单个诊断: "'强直性脊柱炎'"输出为多个诊断:(用逗号
分隔开)"'风湿性关节炎','骨折'"
    Mission2: Mission1-Feedback
      sys_prompt: 你是一名专业的{first_room}医生,拥有着丰富的临床诊断经验,您需要从患者的情况分析诊室医生的诊断结果是否合理。
user_input: 请你检查下面"当前病人情况和诊断结果"中的诊断结果是否正确。参考下面的"过往病例"的科室分配情况,辅助做出决策。输
出要求: (你一定要按下面的要求进行思考) 1、认为没有错误则输出"正确",有错误则输出"错误",并且说明原因!!! 2、一定要先回答,然后再
回答原因! 当前病人情况和诊断结果: "[result]"过往病历: "[case1][case2][case3]"输出示例: 认为正确的输出示例: (认为正确则无需输出原
因为"正确",当时别为[周边和沙阳》(认为错误要说明原因,一定要说明原因[Lasez][Lasez][和山水内。以为证明为湖口水内。(以为江明为汉元
因)"正确"认为错误的输出示例:(认为错误要说明原因,一定要说明原因!!)"错误则因"(对"体格检查"项目结果的意见)"
Feedback_result_example: 这是医生基于当前病人情况的诊断结果: "[result]".这是其他医生对诊断结果的意见:"[feedback]"
   Mission3: Feedback-Answer
      sys_prompt: 你是一名专业的{first_room}医生,有着丰富的临床诊断经验,你需要根据病人的情况、输出诊断结果。
user_input: 请你合理参考其他医生的关于当前病例"诊断"的看法和建议,基于病人情况和诊室医生的意见按照原来的格式重新对病人进行
合适的"诊断"。其他医生的意见不一定正确,请你合理对待。只输出修改后的"诊断"即可,无需输出原因和其他说明。可以参考下面的"过往病例"的
诊断情况,辅助做出决策。原来的诊断结果和其他医生的建议:"[feedback]"过往病例:"$[past_case]"$输出示例:(直接输出你的选项,不要输
出多余的内容)输出为单个诊断: "'强直性脊柱炎'"输出为多个诊断: (用逗号分隔开)"'风湿性关节炎','骨折'"
Task5 Treatment Prompt
       sys_prompt: 你是一名专业的{first_room}医生,有着丰富的临床治疗经验,你需要根据病人的情况,输出治疗方案。
       user_input: 你需要根据下面描述的"病人情况",为当前患者开具合适的治疗项目。你需要从下面"可选择的治疗项目"中选择合适的项目
可以选择多个合适的项目。参考下面的"过往病例"的治疗项目情况、辅助做出决策。病人情况: "[case now]"过往病例: "$[case1][case2][case3]"$可选择的治疗项目: ["手术", "介入治疗", "药物治疗", "化学治疗", "抗生素治疗", "放射治疗", "物理疗法", "免疫疗法", "心理治疗", "中医治疗", "基因治疗"]输出示例: (直接输出你的选项, 不要输出多余的内容)输出为单个治疗项目: "手术"输出为多
个科室: (用逗号分隔开)"药物治疗,抗生素治疗,物理疗法"
   Mission2: Mission1-Feedback
       sys_prompt: 你是一名专业的{first_room}医生,拥有着丰富的临床治疗经验,您需要从患者的情况分析诊室医生的治疗结果是否合理。
       user_input:请你检查医生开具的"治疗项目"是否正确。参考下面的"过往病例"的科室分配情况,辅助做出决策。输出要求:(你一定要按
To an Base_Input. 请你这是位于对关的"启力或力"是自正明。参与"固的"及证对的"自对证别的"同时",拥切成出次。调出安本。(你"定安校下面的要求进行思考)1、认为没有错误则输出"正确",有错误则输出"错误",并且说明原因!! 2、一定要先回答,然后再回答原因!医生基于病人情况开具的治疗项目:"[result]"过往病历:"[case1][case3][case3]"输出示例:认为正确的输出示例:(认为正确则无需输出原因)"正确"认为错误的输出示例:(认为错误要说明原因,一定要说明原因!!)"错误原因:{对治疗项目结果的意见}"Feedback_result_example:以下是您提供的"诊断结果":"[结果]。"以下是其他医生对您的"诊断结果"的意见:"[反馈]。"
   Mission3: Feedback-Answer
       sys_prompt: 您是一名专业的第一诊室医生,有丰富的临床治疗经验,需要根据患者的情况提供治疗方案。
       user_input: 您是一名专业的第一诊室医生,有丰富的临床治疗经验,需要根据患者的情况提供治疗方案。请合理考虑其他医生对当前病例
"治疗方案"的意见和建议,并根据患者的病情和医生的意见,按照原格式重新为患者开出合适的"治疗方案"。您需要从以下"可用的治疗选项"中选择合适
/ 为17 元 的思见中国建筑,开始构造有的别情和位益中的思想,这种标准设置到为这有广田古通的 787 万架。 这些要从这下"可用的语力"是吸了中途中古通的选项,只有出版的"治疗方案来有助您做出决策原治疗方案及其他医生建议。"[反馈]"既往病例。"$ [past_case] $"可用治疗方案:""手术"。"介入治疗"、"药物"。"化疗"、"抗生素治疗"、"放射治疗"、"物理治疗"、"免疫治疗"、"心理治疗"、"中药"、"基因治疗"]输出示例: (直接输出您的选项,不输出额外内容)对于单一治疗方案:"手术"对于多个选项: (以逗号分隔)"药物治疗,抗生素治疗,物理治疗
```

Task4 Diagnosis Prompt

Mission1: Medical Diagnosis

Figure 18: The prompt for Task 4 and Task5 in the MedChain-Agent in Chinese.

Task 1 - Input:

atient Information

"Chief Complaint: Right shoulder pain and limited mobility due to trauma, lasting 1 hour.

Detailed Situation: Patient fell to the ground while working 1 hour ago, landing on their back. They experienced severe pain in the right shoulder immediately, with limited mobility in the right shoulder and right upper limb. At the time, there was no headache, chest pain, or abdominal pain, and no loss of consciousness. Patient came to our hospital for examination. X-ray shows: right scapular fracture. Proposed admission for right scapular fracture treatment. Since admission, patient appears weak, has not had bowel or bladder movements.'

Output Example: (If there are multiple options for Secondary Department, separate them with commas)

Primary Department: Obstetrics and Gynecology

econdary Department: Gynecologic Endocrinológy, Gynecologic Oncology

Reasoning: Because.

AutoGen

Role1: Experienced Triage Nurse

"Primary Department: Surgery

econdary Department: Trauma Orthopedics

Reasoning: Based on the patient's chief complaint of 'right shoulder pain and limited mobility due to trauma for 1 hour,' and the detailed description of 'right scapular fracture," we can determine that the patient needs further treatment in the Surgery Department. This is because Surgery is the main department for eating trauma and fractures.

Role1: Experienced Triage Nurse

'Primary Department: Surgery

econdary Department: Trauma Orthopedics

Reasoning: Based on the patient's chief complaint of 'right shoulder pain and limited mobility due to trauma for 1 hour,' and the detailed description of 'right scapular fracture, we can determine that the patient needs further treatment in the Surgery Department. This is because Surgery is the main department for reating trauma and fractures, and Trauma Orthopedics specifically specializes in treating shoulder fractures."

Role1: Experienced Triage Nurse

"Primary Department: Surgery

Secondary Department: Trauma Orthonedics

easoning: Based on the patient's chief complaint of 'right shoulder pain and limited mobility due to trauma for 1 hour,' and the detailed description of 'right scapular fracture," we can determine that the patient needs further treatment in the Surgery Department. This is because Surgery is the main department for reating trauma and fractures, and Trauma Orthopedics specifically specializes in treating shoulder fractures.

DyLAN

Agent1: Question: Patient's Chief Complaint: Right shoulder pain and limited mobility due to trauma, lasting 1 hour.

Detailed Situation: Patient fell to the ground while working I hour ago, landing on their back. They experienced severe pain in the right shoulder immediately with limited mobility in the right shoulder and right upper limb. At the time, there was no headache, chest pain, or abdominal pain, and no loss of consciousness. Patient came to our hospital for examination. X-ray shows: right scapular fracture. Since admission, patient appears weak, has not had bowel or bladder movements.

Primary Department: Surgery

Secondary Department: Trauma Orthopedics
 Agent2: Question: Patient's Chief Complaint: Right shoulder pain and limited mobility due to trauma, lasting 1 hour.

Detailed Situation: Patient fell to the ground while working 1 hour ago, landing on their back. They experienced severe pain in the right shoulder immediately with limited mobility in the right shoulder and right upper limb. At the time, there was no headache, chest pain, or abdominal pain, and no loss of consciousness. Patient came to our hospital for examination. X-ray shows: right scapular fracture. Since admission, patient appears weak, has not had bowel or

bladder movements. Primary Department: Surgery

Secondary Department: Trauma Orthopedics, Vascular Surgery

Agent Importance Scores: [2.0, 1.0]

Final Answer: "Primary Department": "Surgery", "Secondary Department": ["Orthopedics", "Vascular Surgery"]

MedAgent

Expert Gathering: Trauma Medicine, Pain Management, Orthopedics, Rehabilitation Medicine, Emergency Medicine

Analysis Proposition: Trauma Medicine: 'Right shoulder pain and limited mobility due to trauma for 1 hour. This description indicates the patient experienced right shoulder trauma within the past hour, resulting in pain and limited mobility. This condition may be caused by various factors, including but not limited to shoulder dislocation, rotator cuff tear... Therefore, it is recommended that the patient seek medical attention promptly for detailed physical examination and maging studies to determine specific diagnosis and treatment plan.

Pain Management: 'Right shoulder pain and limited mobility due to trauma for 1 hour. This description indicates the patient experienced right shoulder trauma within the past hour, resulting in pain and limited mobility. This condition may be caused by various factors, including but not limited to muscle strain, ligament tear, bone... If the patient experiences other symptoms such as numbness, tingling, or sensory abnormalities, immediate medical attention should be sought as these symptoms may indicate nerve damage."

Orthopedics: 'Right shoulder pain and limited mobility due to trauma for 1 hour.

Rehabilitation Medicine: 'Right shoulder pain and limited mobility due to trauma for 1 hour. This description indicates the patient experienced right shoulder trauma within the past hour, resulting in pain and limited mobility. This condition may be caused by various factors, including but not limited to muscle strain ligament tear, bone... If the patient experiences other symptoms such as numbness, tingling, or sensory abnormalities, immediate medical attention should be sought as these symptoms may indicate nerve damage.

Emergency Medicine: 'Right shoulder pain and limited mobility due to trauma for 1 hour. This description suggests possible shoulder injury, specifically shoulder dislocation, rotator cuff tear, subacromial impingement syndrome, etc. Among these, shoulder dislocation is the most severe injury requiring mmediate medical attention. Rotator cuff... Additionally, if the patient has other underlying conditions such as heart disease, hypertension, etc., prompt nedical attention is needed to avoid complications.'

Report Summarization: 'Key Points: Right shoulder pain and limited mobility due to trauma for 1 hour. The most concerning aspect is shoulder dislocation, as delayed treatment may lead to permanent joint dysfunction. Additionally, if the patient has other underlying conditions such as heart disease, hypertension, etc., prompt medical attention is needed to avoid complications. Overall Analysis: Right shoulder pain and limited mobility due to trauma for 1 hour. The most concerning aspect is shoulder dislocation, as delayed treatment may lead to permanent joint dysfunction. Additionally, if the patient has other underlying conditions such as heart disease, hypertension, etc., prompt medical attention is needed to avoid complications.

Collaborative Consultation: Trauma Medicine: yes Pain Management: yes Orthopedics: yes Rehabilitation Medicine: yes Emergency Medicine: yes Decision Making: Prompt: Based on the discussion results from each expert above, choose the most appropriate department for patient triage from the given primary and secondary departments.

Final Answer: '-Primary Department: Emergency Department\n-Secondary Department: Trauma Orthopedics

MDAgent

Complexity Check: basic

Final Answer: 'Recommended Department Classification:\n-Primary Department: Orthopedics\n-Secondary Department: Trauma Orthopedics'

MedChain-Agent

rimary Department Classification by doctor (Agent): Surgery

eedback: Correct

Secondary Department Classification by doctor (Agent): (Subdivision under Surgery as the primary department) Orthopedics

eedback: Correct Final Answer

Primary Department: Surgery Secondary Department: Orthopedics

Ground Truth:

Primary Department: "Surgery

Secondary Department: "Orthop

Figure 19: The case study among different multi-agent for task1.

```
Task 1 - Input:
 病人主诉
 "病人主诉
外伤致右侧肩部疼痛活动受限1小时。
详细情况
|| 記載 || 記述 || 記
   二级科室: 妇科内分泌,妇科肿瘤
 判断理由: 因为...
AutoGen
 role1:经验丰富的分诊护士
TOBE 1. 经验干商的3776年上
"一级科室: 外科
二级科室: 创伤骨科
判断理由: 根据病人的主诉,"外伤致右侧肩部疼痛活动受限1小时",以及详细情况中描述的"右侧肩胛骨骨折",可以判断病人需要到外科进行进一步治疗
因为外科是处理创伤和骨折等外伤的主要科室。"
 role1: 经验丰富的分诊护士
  一级科室: 外科
一級科学・パペー
二級科室・创伤骨科
判断理由:根据病人的主诉,"外伤致右侧肩部疼痛活动受限1小时",以及详细情况中描述的"右侧肩胛骨骨折",可以判断病人需要到外科进行进一步治疗
判断理由:根据病人的主诉,"外伤致右侧肩部疼痛活动受限1小时",以及详细情况中描述的"右侧肩胛骨骨折",可以判断病人需要到外科进行进一步治疗
 role1: 经验丰富的分诊护士
  一级科室: 外科
二级科室:创伤骨科
判断理由:根据病人的主诉,"外伤致右侧肩部疼痛活动受限1小时",以及详细情况中描述的"右侧肩胛骨骨折",可以判断病人需要到外科进行进一步治疗
 因为外科是处理创伤和骨折等外伤的主要科室,而创伤骨科是处理肩部骨折的专业科室。
DyLAN
 Agent1:问题:病人主诉:外伤致右侧肩部疼痛活动受限1小时。
•详细情况:患者于1小时前干活时不慎摔倒在地,背部着地,当时感右侧肩部疼痛难忍,右侧肩部及右上肢活动受限,当时无头痛、胸痛、腹痛,无昏迷.
 入我院就诊,行X片检查示:右侧肩胛骨骨折。入院来,患者精神软,大小便未解。
•一级科室:外科
 二级科室: 创伤骨科、血管外科
 Agent Importance Scores: 智能体重要性评分: [2.0, 1.0]
 Final Answer:
  MedAgent
expert gethering:创伤医学、疼痛管理、骨科、康复医学、急诊医学
analysis proposistion:创伤医学:'外伤致右侧肩部疼痛活动受限1小时。该描述表明患者在过去1小时内经历了右侧肩部的外伤,导致疼痛和活动受限。这种情况可能由多种原因引起,包括但不限于肩关节脱位、肩袖撕裂、...因此,建议患者尽快就医,进行详细的体格检查和影像学检查,以确定具体的诊断和
 治疗方案。
             :'外伤致右侧肩部疼痛活动受限1小时。该描述表明患者在过去1小时内经历了右侧肩部的外伤,导致疼痛和活动受限。这种情况可能由多种原因
序编音程: 715数名 阅读用的资格相似文化。这话是农的总者正是公司的自己知识。
引起。包括但不限于肌肉拉伤、韧带撕裂、骨...患者出现其他症状,如麻木、刺痛或感觉异常,应立即就医,因为这些症状可能表明神经损伤。'
骨科: 外伤致右侧肩部疼痛活动受限1小时。'
康复医学: 外伤致右侧肩部疼痛活动受限1小时。该描述表明患者在过去1小时内经历了右侧肩部的外伤,导致疼痛和活动受限。这种情况可能由多种原因
引起,包括但不限于肌肉拉伤、韧带撕裂、骨...患者出现其他症状、如麻木、刺痛或感觉异常,应立即就医,因为这些症状可能表明神经损伤。'
急诊医学:'外伤致右侧肩部疼痛活动受限1小时。该描述提示患者可能发生了肩部损伤,具体可能是肩关节脱位、肩袖撕裂、肩峰下撞击症等。其中,肩关
 节脱位是最严重的损伤,需要立即就医。肩袖...外,如果患者有其他基础疾病,如心脏病、高血压等,也需要及时就医,以避免并发症的发生。
 report summarization:
"关键点",外伤致右侧肩部疼痛活动受限1小时。最令人担忧的方面是肩关节脱位,因为如果不及时治疗,可能会导致永久性的关节功能丧失。此外,如果患者有其他基础疾病,如心脏病、高血压等,也需要及时就医,以避免并发症的发生。总分析:外伤致右侧肩部疼痛活动受限1小时。最令人担忧的方面是肩关节脱位,因为如果不及时治疗,可能会导致永久性的关节功能丧失。此外,如果患者有其他基础疾病,如心脏病、高血压等,也需要及时就医,以避免
 并发症的发生。
Collaborative consultation:创伤医学:yes 疼痛管理:yes 骨科:yes 康复医学:yes 急诊医学:yes
Decision Making:prompt:基于上面各个专家给出的讨论结果,在下述给定的一级科室和二级科室中选择最合适的科室进行病患分诊。
                      -级科室: 急诊科\n-二级科室: 创伤骨科'
final answer: '-
MDAgent
Complexity Check: basic
 Final Answer: '建议科室分级: \n-一级科室: 骨科\n-二级科室: 创伤骨科'
MedChain-Agent
  -级科室分类doctor (Agent): 外科
 eedback: 正确
 二级科室分类doctor(Agent): (外科为一级科室的前提下在讲行细分) 骨科
  eedback: 正确
 Final Answer:
  -级科室: 外科
   级科室:
               骨科
Ground Truth:
  -级科室: "外科"
-级科室: "骨科"
```

Figure 20: The case study among different multi-agent for task 1in Chinese.

```
Task 2 - Input:
                ## Detailed Updated Answer:

**Physical Examination:

**Physical Examin
    MDAgent
                        yeard exemination. Occor group:

The semination occor group:

The seminati
Ground Truth:

Physical examination: General examination, Spine and extremity examination
```

Figure 21: The case study among different multi-agent for task2.

```
Task 2 - Input:
      馬八円の・
"病人主诉:
は作数右側肩部疼痛活动受限1小时。
   "明好办公人公为。

"明了办公人公为。

"有了根本资本"必要,用于了餐桌有的整体状况。

"有限的基本"必要,但是是有的基本。

"可能的基本的原始"的一个重要现象的。这是一个重要环节。

"必是可能"的重要的是有多种。

"在自然的",就是他们是是一个重要。

"是在一个人工",并是他们是一个人工作。

"是在一个人工",并是他们是一个人工作。

"是在一个人工",并是他们是一个人工作。

"是在一个人工",并是他们是一个人工作。

"是在一个人工",并是他们是一个人工作。
             - "母遊送遊遊遊樓盒(RO加)"。 傳集稳定性、并检查是否存在任何回的伤导致的活动限制成损伤。
- 把意身化等。
- 地名森大地:用于初步评估骨徵完整性。
- 地名森大地:用于初步评估骨徵完整性。
- 地名森八地:用于经验含管像、光彩和验组织。
- 地名森川地:提供这组织的全面密像,包括南坡、海囊和韧带,对于火光或CT未能显示的撕裂韧带成严重较组织损伤之为重要。
- 地名森川地 - 地名森山地 - 地名加纳 - 地名森山地 - 地名加纳 
        ### Agent Importance Scores:
**智能体重要性评分**: 智能体重要性评分: [2.0, 1.0]
     ### Final Answer:
辅助检查: "MRI","CT"
体格检查: "一般检查","颈部检查"
   eport summiscizion:
某些此外伤弦名倒的原味痛活动受阻1小时,着令人担忧的方面是角关节配位。建议尽快进行详细的体格检查和影像学检查,如然或MRI、以得定是在存
在角关节既促成其格组长规仿、1xm品分析"该将侧推送"一个参考在1xh的内进宏右侧部的疾机形态必规指价系。这种病之可能由各种服因引起、包括
你用于身大节股位、角排股伤,扁体下面最近,向组长节发光,最少人世达或最简单注意的方面是多大配位。角关节是位是一种严重的指向,而能导致
病态疾痛,无动无限和前部部形。如果不及时诊断和应疗,可能会导致水人性残疾。因此,对于该患者,应尽快进行详细的体格检查和影像学检查,如戏戏《MRI、因像是是存在角关节股位,并是对某事组织的经济措施。
          社会 ステット

大学の American Maleria

中の American Maleria

中の
                                                          "\n体格检查: 口腔检查\n辅助检查: CT, 血常规\n"
            MedChain-Agent
格检查doctor groun
             ·格格盖含0.000 (2010):

- 《格格·维尔· (一般检查、"共用取耳鼻喉检查",预部检查、预部检查、得性和回肢检查、使肢检查)
2002 ( ·格格·维尔· (一般检查、"共用取耳鼻喉检查",则即检查、调即检查、"有性和回肢检查、皮肤检查)
2002 ( ·格格·维尔· (一般检查、"共用取耳鼻栓体"。 "明显检查",则是检查、"相比和现故会"。 及此检查)
2003 ( · 保格·维尔· (一般检查、"头相取耳鼻栓体"。 "那么检查","有性和现故会"。 "我也被定

2003 ( · 保格·维尔· (一般检查、"头相取耳鼻栓体"。 "那么检查","都比检查",看往和回战检查,这就检查",并且不能够有

2003 ( · 保格·维尔· (一般检查、"头相对果操栓法","那么检查",那能检查、"器比检查",有性和回肢检查",这就检查,并且
      Refine: 「体格检查' 「一般检查',实规联耳鼻喉检查,领部检查,胸部检查,避路检查,脊柱和
键检查或dotor (3 插附检查' (X-ray', CTT) "线统")
dotor(3 插附检查' (X-ray', CTT)
Stort(3 插附检查' (X-ray', CTT)
Stort(3 插形检查' (X-ray', CTT)
Feedback: 植物检查形象,但随即检查可且应根据患者的具体情况进行选择,不应一板而论。}
Refine: 植物检查 (X-ray', CTT)
      Final Answer:
体格检查:「一般检查:"头明眼耳鼻喉检查,颈部检查,胸部检查,强部检查,脊柱和四肢检查,皮肤检查,神经系统检查!
插助检查:「X-ray,、CT」
```

Figure 22: The case study among different multi-agent for task2 in Chinese.

```
Task 3 - Input:
I need you to analyze these medical images through discussion, and ultimately provide a concise Chinese comprehensive imaging report.
Image path; [//datasets/Medlmg/20807.png]
            AutoGen

old : Experienced radiologist 1

ased on the provided medical images, the patient may have a certain type of tumor. The images show clear abnormal tissue, with irregular borders that contrast significantly with the

urrounding tissue. The imaging report recommends further examinations, such as MRI or CT scans, as well as possible pathological examination, to determine the type and stage of the tumor,

old further formulate a treatment plan.

ole 2: Experienced radiologist 2

he patient may have a certain type of tumor. The images show clear abnormal tissue, with irregular borders that contrast significantly with the surrounding tissue. It is recommended to

notice further than the provided in the provided in the patient to the provided in the patient plan and the provided in the patient may have a certain type of tumor, and further formulate a treatment plan.

old : Experienced radiologist 1

as a further than the patient may have a certain type of tumor. The images show clear abnormal tissue, with irregular borders that contrast significantly with the

urrounding tissue. The imaging report recommends further examinations, such as MRI or CT scans, as well as possible pathological examination, to determine the type and stage of the tumor,

old 2: Experienced radiologist 2.
   DyLAN
            ## Agent1:
### Agent1:
### Agent2:
### Agent3:
### Agent4:
### Age
                        *** TRANSMENT TRANSMENT.

Metallic internal fixation devices, including screws and plates, are visible in the proximal right femur.

Metallic internal fixation devices are also visible in the proximal left femur, including screws and plates.

### Diagnosis and Analysis
                  ### Diagnoss and Analysis

Proximal Right Femul Internal Fixation**:

The position of the internal fixation in the proximal right femur is good, with no obvious displacement or loosening.

The screws and plates are in normal position, with no signs of foreign body reaction.

*Proximal Left Femur Internal Fixation**:

The position of the internal fixation in the proximal left femur is good, with no obvious displacement or loosening.

The screws and plates are in normal position, with no signs of foreign body reaction.
                     This imaging examination shows that the patient's bilateral proximal femur internal fixation devices are in good position, with no obvious displacement or loosening the skeletal structure and soft tissues show no significant abnormalities.
                     f the patient experiences any discor
### Reporting Physician
*Signature**: [Physician Signature]
*Date**: [Report Date]
      **Date:* [Report Date]

**MediAgent*

**Order** [Report Date]

**MediAgent*

**Order** [Perior or chropedics, radiology, imaging, thoracis medicine, spine medicine properties of the patient's left shoulder and left upper arm. The following points can be observed from the image's what. Facture: The humans (i.e. upper arm bone) of the left upper arm bas no obsous fracture near the shoulder joint. The fracture line is clearly visible, indicating has the bone is broken here. **NNZ.* [Internal** [Sacion devices. Including sorcew and places can be seen at facture set. This indicates that the patient may have undergone surgery to stabilize the fracture and promote healing. **NnX.* Soft issue condition. Around the fracture area, the soft fracture is the size density is high, and there may be swelling or hematoma. **NnX.* Soft issue condition. Around the fracture area, the soft fracture is the size density is high, and there may be swelling or hematoma. **Order* [Internal Internal Intern
                  esson Making: ompt: Based on the discussion results given by the experts above, start with an appropriate imaging report.

all answer? Overall analysis: This X-ray shows the patient's left shoulder and left upper arm. The humerus of the left upper arm has an obvious fracture near the shoulder joint and has dedergone internal faxion. The soft tissue condition needs further observation to rule out possible infection or other complications. It is recommended that the patient seek medical attention soon as possible for detailed examination and follow-up treatment to ensure the stability of the fracture and the progress of rehabilitation."
                  implexity Check: basic all Anomers of the Check of the Ch
                     ch is in a normer position and the source and the s
                           ation of the fracture and the soft tissue injury. \n3. Depending on the specific situation of the fracture, surgical fixation or erve the fracture healing and functional recovery. \n\n"
                     neon should:
ctor1: The report content is sufficient, no additional content
ctor2: The report content is sufficient, no additional content
ctor3: The report content is sufficient, no additional content
sloback Correct
                     etbask Correct
al Answer*Unimage description:\nl. The X-ray shows a clear fracture line in the right scapula area, which is oblique and extends from the top to the bottom of the scapula.\n2. The bone snsty around the fracture line is uneven, and there may be slight callus formation.\n3. The joint space of the shoulder joint is well maintained, and no obvious joint efficiency in the soft issue structure of the scapula.\n\n2. The joint space of the shoulder joint is well maintained, and no obvious joint efficiency in the soft issue structure of the scapula.\n\n2. The colors of the imaging report.\n3. The joint scapula is fractured, and the fracture is is oblique, extending from the top to the bottom of the scapula.\n2. The bone density around the fracture line is uneven, and there may be slight callus formation.\n3. The joint space of shoulder joint is well maintained, and there is no obvious joint effisision or joint destruction.\n4. There is no obvious abnormality in off issue structure of the scapula.\n8. The joint space of shoulder joint is well maintained, and there is no obvious joint effision or joint destruction.\n4. There is no obvious abnormality in off issue structure of the scapula.\n8. The joint space of shoulder joint is well maintained, and there is no obvious pint efficiency in \n8. The joint space of shoulder joint is uneventained to evaluate the specific situation of the cture and soft issue injury.\n8. Depending on the specific situation of the fracture is uneventained to evaluate the specific situation of the cture and soft issue injury.\n8. Depending on the specific situation of the fracture is uneventained to evaluate the specific situation of the fracture is uneventained.\n8. The pint is sufficient to the same and the second in the sufficient is uneventained.\n8. The pint is uneventained to evaluate the specific situation of the cture and soft issue injury.\n8. Depending on the specific situation of the fracture is uneventained to evaluate the specific situation of the fracture in the same 
                  round Truth:

mminuted fracture of the right calcaneus, please combine with clinical findings; no obvious fractures were found in the bones of the right ankle joint.
```

Figure 23: The case study among different multi-agent for task3.

```
Task 3 - Input:
我需要你们通过讨论,对这些医学影像进行分析,最终提供一个中文简短的综合性影像报告。
 影像路径: ['./datasets/MedImg/20807.png']
 AutoGen
  role1: 经验丰富的影像科医生1
 NOBEL 医扭手角引擎液体医生1
根据提供的医学影像,患者可能患有某种类型的肿瘤,影像显示有明显的异常组织,边界不规则,与周围组织对比明显。影像报告建议进行进一步的检查,例如MRI或CT扫描,以及可能的病理学检查,以确定肿瘤的类型和分期,并进一步制定治疗计划。
role2:经验丰富的影像科医生2
 public 宝池+角町影琢件医生4
患者可能患有某种类型的肿瘤。影像显示有明显的异常组织,边界不规则,与周围组织对比明显。建议进行进一步的检查,例如MRI或CT扫描,以及可能的病理学检查,以确定肿瘤的类型和分期,并进一步制定治疗计划。
 限75別, 升进一岁制定治771別。
foole1:经验丰富的影像科医生1
根据提供的医学影像,患者可能患有某种类型的肿瘤。影像显示有明显的异常组织,边界不规则,与周围组织对比明显。影像报告建议进行进一步的检查,例如MRI或CT扫描,以及可能的
病理学检查。以确定肿瘤的类型和分期,并进一步制定治疗计划。
foole2:经验丰富的影像科医生2
根据提供的医学影像,患者可能患有某种类型的肿瘤。影像显示有明显的异常组织,边界不规则,与周围组织对比明显。建议进行进一步的检查,例如MRI或CT扫描,以及可能的病理学检
MRIABERTS AND MESS AND 
 查,以确定肿瘤的类型和分期,并进一步制定治疗计划
 DyLAN
  #### 患者信息
   #### 患者信息

**姓名**: 患者姓名患者姓名

**性别**: 患者性别患者性别

**年龄**: 患者年齡患者年龄

**检查日期**: 检查日期检查日期

#### 影像描述
  本次影像检查包括前后位(AP)和侧位(Lateral)X线片。影像显示如下:
    **骨骼结构**
     **软组织**:
· 双侧肩关节和髋关节周围软组织未见明显异常。
      双侧股骨头和髋臼显示下常。
      *内固定物**
      · 右侧股骨近端可见金属内固定物,包括螺钉和钢板。
· 左侧股骨近端亦可见金属内固定物,包括螺钉和钢板。
    ### 诊断与分析
    **右侧股骨近端内固定物**
     ### 结论
   77777 - 343.
本次影像检查显示,患者双侧股骨近端内固定物位置良好,未见明显移位或松动。
骨骼结构及软组织未见明显异常。
    胃酚结构及软组织木见明亚开幕。
### 建议
建议患者继续按医嘱进行复查,观察内固定物情况。
如有任何不适或症状变化,请及时就医。
據复进展。

report summarization: 关键点:骨折,内固定装置、软组织情况。肩关节,骨折稳定性、感染风险、康复进展、详细检查、后续治疗、Wn总分析:这张X光片显示了患者的左肩和左上臂的影像、其中左上臂的肱骨在靠近肩关节处有明显的骨折,并已进行了内固定装置的手术。软组织情况需要进一步观察,以排除可能的感染或其他并发症。建议患者尽快就医,进行详细检查和后续治疗。以确保骨折的稳定性和康复进展。

Collaborative consultation: 骨料: yes 放射学: yes 影像学: yes 胸腔医学: no. 建议: "修订:在报告中,建议患者尽快就医,进行详细检查和后续治疗,以确保骨折的稳定性和康复进展。
建议可以进一步明确患者需要就医的具体医院或诊断,并建议患者在就医前先进行初步的自我护理,如冰敷、抬高患肢等,以减轻疼痛和肿胀。此外,建议报告中增加对患者进行康复指导的建议、如适当的物理治疗和康复训练,以促进骨折的愈合和恢复功能。
特柱医学: no. 建议: "修订:在报告中,建议患者尽快就医,进议可以进一步明确患者需要接受的具体检查和治疗方案,例如
是否需要进行物理治疗或康复训练,以及是否需要定期复查X光片以监测骨折愈合情况。此外,建议关注患者的疼痛管理,以确保患者在康复过程中能够舒适地进行必要的活动。

Pacision Making:
 person making...
prompt:基于上面各个专家给出的讨论结果,开局合适的影像报告。
final answer:'总分析: 这张X光片显示了患者的左肩和左上臂的影像,其中左上臂的肱骨在靠近肩关节处有明显的骨折,并已进行了内固定装置的手术。软组织情况需要进一步观察,以排除
可能的感染或其他并发症。建议患者尽快就医,进行详细检查和后续治疗,以确保骨折的稳定性和康复进展。'
IMUAgent
Complexity Check: basic
Final Answer: "X-ray." 影像报告\n\n患者编号: XX\n检查日期: XX年XX月XX日\n\n影像描述: \n1. 胸片影像显示胸腔内含有大量气体,肺组织被压缩,肺组织透明度增加,提示可能存在气胸,\n\n2. 骨盆及双侧股骨处线影像显示右侧股骨近端存在金属异物,异物位置与髋臼关节接触,提示可能的手术内固定装置。\n\n3. 双侧股骨上端有金属内植入物,位置正确,未见异物移位或断裂。\n\n4. 有性影像显示脊柱排列整齐,未见明显畸形或脱位。\n\n5. 肺野中未见明显异常病变,如结节或肿块。\n\n综上所述,影像提示患者存在气胸,可能需要进一步的临床评估及治疗。骨盆及股骨线影像提示存在手术内固定装置,位置正常,未见异常。"
    ledChain-Agent
亚影像学医生描述:"\n影像描述:\n1. 该X光片显示右侧肩胛骨区域有明显的骨折线,骨折线星斜行,从肩胛骨的上方延伸至下方。\n2. 骨折线周围的骨质密度不均,可能存在轻微的骨
亚影像学医生描述:"\n影像描述:\n1. 该X光片显示右侧肩胛骨区域有明显的骨折线,骨折线星斜行,从肩胛骨的上方延伸至下方。\n2. 骨折线周围的骨质密度不均,可能存在轻微的骨
 专业影像学医生描述:
 ミェ家原子&生油&・VIIIを原用途・VIII、III、ACACA、企业人の周用所は必有可能的有效。 行りは受けて、外国原可可以一及原用上了。VIIC、育的绘画由的月间在发行处。 9能代任在探询月间
施形成。NO.3 角头节的关节间除保持良好,无以明显关节积液或关节破坏。Nd、肩胛骨的软组织结构未取明显异常。Nna影像报告结论・VIII、T 在侧肩胛骨骨折,骨折线星斜行、从肩胛骨的
上方延伸至下方。N2. 骨折线周围的骨质密度不均,可能存在轻微的骨痂形成。N3. 肩关节的关节间隙保持良好,未见明显关节积液或关节破坏。N4. 肩胛骨的软组织结构未见明显异常。
Nnn違议:NL 患者应避免剧烈活动,避免进一步损伤,N2. 建议进一步行CT或MRI检查,以评估骨折的具体情况及软组织损伤情况。N3. 根据骨折的具体情况,可能需要手术固定或保守;
f5。Nn4. 定期复查,观察骨折愈合情况及功能恢复情况。NnNn"
  Doctor Group
  doctor1:报告内容充分,无补充内容
  UOLOUI. 报告[内各九分,无朴元内各
doctor2: 报告内容充分,无朴充内容
Feetback: 正确
Final Answer: "'Nn影像描述:'\n1. 该X光片显示右侧肩胛骨区域有明显的骨折线,骨折线星斜行,从肩胛骨的上方延伸至下方。\n2. 骨折线周围的骨质密度不均,可能存在轻微的骨痂形成。
 Final Answer: "小影像描述。'N.1. 该火货片显示右侧肩胛骨区域有明显的骨折线。骨折线星斜行,从肩胛骨的上方堆押单 P.7。'N.2. 有约45河油以为8,440本(**)。"8.77—4.50。"
N.3. 肩关节的关节间隙保持良好,未见明显关节积凝或关节破坏。 v.4. 肩胛骨的软组织结构未见明显异常。 hnn影像报告结论:'N.1. 右侧肩胛骨骨折,骨折线星斜行,从肩胛骨的软组,并不见
至下方。 v.C. 骨折线周围的骨质密度不均,可能存在轻微的骨痂形成。 v.3. 肩关节的关节间隙保持良好,未见明显关节积液或关节破坏。 v.4. 肩胛骨的软组织结构未见明显异常。 hnn建议:
hn1. 患者应避免剧烈活动,避免进一步损伤。 v.2. 建议进一步行CT或MRI检查,以评估骨折的具体情况及软组织损伤情况。 vn3. 根据骨折的具体情况,可能需要手术固定或保守治疗。 vn4.
   定期复查,观察骨折愈合情况及功能恢复情况。\n\n
 Ground Truth:
    。
。跟骨粉碎性骨折,请结合临床;右侧踝关节诸骨未见明显骨折。
```

Figure 24: The case study among different multi-agent for task3 in Chinese.

```
Task 4 - Input:
  The patient's comprehensive report is as follows:

Patient's main complaint right shoulder pain and limited movement for 1 hour due to trauma.

Details: The patient accidentally fell to the ground while working 1 hour ago, and landed on his back. At that time, he felt unbearable pain in the right shoulder, and limited movement of the right shoulder and right upper limb. He had no headache, chest pain, abdominal pain, or coma at the time. He was admitted to our hospital for treatment. X-ray examination showed: right
         apula fracture. He was hospitalized for right scapula fracture. Since admission, the patient was weak and had difficulty urinating and defecating.
  Only reply with the name of one or more diagnosis results, and do not include any other explanations.
  Only reply with the findine of one of findi
Output example:
"Diagnosis result: fracture, knife wound
Judgment reason: because..."
  AutoGen
     ole1: Experienced general practitioner 1
Diagnosis: right scapula fracture
ludgment reason: X-ray examination shows: right scapula fracture.'
ole2: Experienced general practitioner 2
  rouez: experiences general practitioner 2
Diagnosis: right scapula fracture
Judgment reason: X-ray examination shows: right scapula fracture."
role2: Experienced general practitioner 2
Diagnosis: right scapula fracture
Judgment reason: X-ray examination shows: right scapula fracture."
    role1: Experienced general practitioner 1
  "Diagnosis: right scapula fracture
     ludgment reason: X-ray examination shows: right scapula fracture."
  DyLAN
 DYLAN
Agent 1: Shoulder joint
Agent 2: Shoulder dislocation
Agent Importance Scores: [2.0, 1.0]
Final Answer: Diagnosis: Shoulder dislocation
      expert gethering: Traumatology, Orthopedics, Pain Management, Imaging, Rehabilitation
 expert gethering: Traumatology, Orthopedics, Pain Management, Imaging, Rehabilitation 
analysis proposition: Traumatology. The patient was diagnosed with right shoulder pain and limited mobility due to trauma, and was treated at Traumatology and Orthopedics. X-rays showed 
degenerative lesions of bilateral shoulder joints and a history of surgery on the right shoulder joint. The most worrying aspect is the history of surgery on the right shoulder joint. The most worrying aspect is the history of surgery on the right shoulder joint, which may 
indicate that the patient has...disease, which may further affect the function of the shoulder joint. Therefore, timely treatment is required to avoid further loss of joint function. 
Orthopedics: The patient was diagnosed with right shoulder pain and limited mobility due to trauma, and was treated at Traumatology and Orthopedics. Arrays showed degenerative lesions of 
bilateral shoulder joints and a history of surgery on the right shoulder joint. The most worrying aspect is the history of surgery on the right shoulder joint, which may indicate that the patient 
have diseased that the patient of the patie
blateral shoulder joints and a history of surgery on the right shoulder joint. The most worrying aspect is the history of surgery on the right shoulder joint, which may further affect the function of the shoulder joint. Therefore, timely treatment is required to avoid further loss of joint function.

Pain management: According to the information provided, the patient has right shoulder pain and limited mobility due to trauma, and X-rays show bilateral degenerative lesions of the shoulder joints and a history of surgery on the right shoulder point. These findings suggest that the patient may have chronic problems with the shoulder joint, such as rotator cuff injury, shoulder degeneration.. Treatment options. This may include physical therapy, medication, or surgical intervention, depending on the patient's specific situation and medical history, Imaging: According to the information provided, the patient has right shoulder pain and limited mobility due to trauma, and X-rays show bilateral degenerative lesions of the shoulder joints and a history of surgery on the right shoulder joint. These findings suggest that the patient may have chronic problems with the shoulder joint, such as rotator cuff injury, shoulder degeneration.. Further imaging examinations, such as MRI or CT scans, are required to determine the specific pathological changes and develop an appropriate treatment plan. Rehabilitation: The patient was treated by trauma orthopedics and orthopedics due to right shoulder pain and limited mobility caused by trauma. X-rays show bilateral degenerative lesions of the shoulder joints and a history of surgery on the right shoulder joint. The most worrying aspect is the surgical history of the right shoulder joint, the may indicate that the patient has a loss of joint function in the next step. It is recommended that the patient seek medical attention as soon as possible for detailed examination and treatment to relieve symptoms and prevent worsening of the condition.
        report summarization: Key points: Traumatic right shoulder pain and limited activity for 1 hour. X-rays show degenerative lesions of bilateral shoulder joints and a history of surgery on the right houlder joint. The most worrying aspect is the surgical history of the right shoulder joint, which may indicate that the patient has previous shoulder surgery, such as shoulder replacement or
        evision surgery. Although these surgeries can relieve pain and improve function, they may also increase the risk of postoperative complications such as infection, dislocation, or prosthesis bosening. In addition, the degenerative lesions shown in the X-rays may indicate that the patient has osteoarthritis or other joint diseases, which may further affect the function of the shoulder
  joint. Timely treatment is required to avoid further loss of joint function. NinSummary analysis: The patient was treated in the trauma orthopedics and orthopedics department due to right shoulder pain and limited activity caused by trauma. X-rays show degenerative lesions of bilateral shoulder joints and a history of surgery on the right shoulder joint. The most worrying aspect is the surgical history of the right shoulder joint, which may indicate that the patient has previous shoulder surgery, such as shoulder replacement or revision surgery. Although these surgeries
        an relieve pain and improve function, they may also increase the risk of postoperative complications, such as infection, dislocation, or loosening of the prosthesis. In addition, the degenerative
  changes shown in the X-ray may indicate that the patient has osteoarthritis or other joint diseases, which may further affect the function of the shoulder joint. Therefore, timely treatment is
         equired to avoid further loss of joint function
    Collaborative consultation: Traumatology: yes Orthopedics: yes Pain management: yes Imaging: yes Rehabilitation: yes
    conadorative consultation: Traumatology; yes Ortriopedics; yes Pain management; yes imaging; yes Kenadiilation; yes
Decision Making:
prompt: Based on the discussion results given by the experts above, make a reasonable diagnosis. If no decision can be made, output None.
final answer: None
  MDAgent
 | MDAgent
Complexity Check: intermediate
| Expert Requitment:
| Agent 1 ($\frac{\pi}{2}$.) Orthopedic Surgeon): Specializes in the surgical and non-surgical;
| Agent 2 ($\frac{\pi}{2}$.) 2. Radiologist): Focuses on the interpretation and diagnosis of medical images such as X;
| Agent 3 ($\frac{\pi}{2}$.) 3. Traumatologist): Specializes in the diagnosis, treatment, and rehabilitation of trauma
    Collaborative Decision Making:
Hierarchy Selection
Participatory Debate
     orthopedic surgeon): Trauma (radiologist): Multiple comminuted fractures of the left tibia and fibula with soft tissue swelling of the right calf and left ankle (traumatologist): Fracture of the left
     ibia and fibula, fracture of the left patella
    Analysis and Synthesis:
  Ear Round 1 == [Turn 1]

Agent 1 ( Round 1 == [Turn 1]

Agent 
 ulsorders, Toelieve that the patient requires a unorough evaluation of ner inactures and potential complications. The opinions from the radiologist and unaffactoring are valuable, out an orthopedic surgeon's expertise is crucial in determining the most appropriate management plan, which may include surgical intervention if needed. It's essential to address any potential issues that may arise from the fractures, such as joint instability, infection, or non-union.; Agent 2 (  radiologist): No; Agent 3 (  radiologist): No [Turn 2 Agent 1 (  rothopedic surgeon): No; Agent 2 (  radiologist): No; Agent 3 (  radiologist): No [Turn 2 Agent 1 (  rothopedic surgeon): No; Agent 3 (  radiologist): No [Turn 2 Agent 1 (  rothopedic surgeon): No; Agent 3 (  radiologist): No [Turn 2 Agent 1 (  rothopedic surgeon): No; Agent 3 (  radiologist): No [Turn 2 Agent 1 (  rothopedic surgeon): No; Agent 3 (  rothopedic surgeon): No; Agent 3
  MedChain-Agent
        octor group:
  doctor1: fracture
  doctor2: scapula fracture
doctor3: fracture
    Summary: fracture
Summary: fracture
Feedback: correct
Final Answer: fracture
  Ground Truth:
```

Figure 25: The case study among different multi-agent for task4.

```
Task 4 - Input:
 患者综合报告如
还有45-0740-294-1-"疾人主","疾人主","疾人主","疾人主","外院致右侧肩部疼痛难忍,右侧肩部及右上肢活动受限,当时无头痛、胸痛、腹痛,无昏迷,入我院就诊,行x片检查示:右侧肩胛骨骨折,拟右侧肩胛骨骨折收入住院,入院来,患者精神软,大小便未解。"
role1: 经验丰富的全科医生1
role! 经验丰富的全科医生1

"诊断结果: 右侧肩胛骨骨折。"

疗的是? 经验丰富的全科医生2

"诊断结果" 云侧肩胛骨骨折。"

role? 经验丰富的全科医生2

"诊断结果" 云侧肩胛骨骨折。"

role? 经验丰富的全科医生2

"诊断结果" 云侧肩胛骨骨折。"

role! 经验丰富的全科医生1

"诊断结果" 右侧肩胛骨骨折,"

role! 经验丰富的全科医生1

"诊断结果" 右侧肩胛骨骨折,"
DyLAN
Agent1
肩关节
 Agent2:
肩关节脱位
 Agent Importance Scores:
[2.0, 1.0]
 Final Answer:
诊断结果: 肩关节脱位
 MedAgent
expert gethering:创伤骨科、骨科、疼痛管理、影像学、康复
  ecision Making
  rompt:基于上面各个专家给出的讨论结果,进行合理的诊断。若无法做出决策,则输出None.
 MDAgent
MDAgent
Complexity Check: intermediate
Expert Recruitment:
Agent 1 (♥ 1. Orthopedic Surgeon): Specializes in the surgical and non;
Agent 2 (♥ 2. Radiologist): Focuses on the interpretation and diagnosis of medical images such as X;
Agent 3 (№ 3. Traumatologist): Specializes in the diagnosis, treatment, and rehabilitation of trauma
 Collaborative Decision Making:
Hierarchy Selection
Participatory Debate
 (orthopedic surgeon): 创伤 (radiologist): 左胫腓骨多处粉碎性骨折伴右小腿及左踝部软组织肿胀 (traumatologist): 左胫腓骨骨折,左髌骨骨折
 Analysis and Synthesis:
  = Round 1 ==
Final Decision: 右侧肩胛骨骨折
 MedChain-Agent
Doctor group:
doctor1: 骨折
doctor2: 肩胛骨骨折
doctor3: 骨折
Summary: 骨折
Feedback: 正爾
 Final Answer
             骨折
 Ground Truth:
```

Figure 26: The case study among different multi-agent for task4 in Chinese.

```
Task 5 - Input:
         he patient's comprehensive report is as follows:
   ine patients comprenensive report is as toilows:

Patient's main complaint: right shoulder pain and limited movement for 1 hour due to trauma.

Details: The patient accidentally fell to the ground while working 1 hour ago, and landed on his back. At that time, he felt unbearable pain in the right shoulder, and limited movement of the right shoulder and right upper limb. He had no headache, chest pain, abdominal pain, or coma at the time. He was admitted to our hospital for treatment. X-ray examination showed: right scapula fracture. He was planned to be hospitalized for right scapula fracture. Since admission, the patient was weak and had difficulty urinating and defecating."

Only reply with the name of one or more treatment items, do not include any other explanations, and make sure the answer is among the above eleven items!!!
   If there are multiple options, separate them with commas
     Output example
      Treatment items: Traditional Chinese medicine treatment, gene therapy, surgery
   Judgment reason: because
  AutoGen
      ole1: Experienced general practitioner 1
     'Treatment: Surgery
ludgment reason: The patient has a scapula fracture and needs surgical treatment."
     ole2: Experienced general practitioner 2
   Treatment: Surgery
Judgment reason: The patient has a scapula fracture and needs surgical treatment."
Tole2: Experienced general practitioner 2
   "Treatment: Surgery
Judgment reason: The patient has a scapula fracture and needs surgical treatment."
  DvLAN
     Agent1:
       reatment: Surgery
   Aaent2:
      reatment: Surgery
  Agent Importance Scores:
[0.5, 0.5]
Final Answer:
Treatment: Surgery
  MedAgent
     Expert gethering: Traumatology, Orthopedics, Pain Management, Imaging, Rehabilitation Medicine
Expert gethering: Traumatology, Orthopedics, Pain Management, Imaging, Rehabilitation Medicine analysis proposition: Traumatology: The patient had alimited right shoulder pain for 1 hour due to trauma, and X-ray examination showed a right scapula fracture. The patient had no history of hypertension, diabetes, coronary heart disease, infectious diseases such as hepatitis and tuberculosis, no history of drug and food allergies, and no history of trauma surgery. After admission, he suffered from... changes and a history of surgery on the right shoulder pain for 1 hour due to trauma, and X-ray examination showed a right scapula fracture. The patient had no history of hypertension, diabetes, coronary heart disease, infectious diseases such as hepatitis and tuberculosis, no history of drug and food allergies, and no history of trauma surgery. After admission, he suffered from... changes and a history of surgery on the right shoulder point. These lesions and surgical history may lead to further loss of joint function and need to be treated in time. Pain management: The patient had limited right shoulder pain and activity for 1 hour due to trauma, and X-ray examination showed a right scapula fracture. The patient had no history of hypertension, diabetes, coronary heart disease, infectious diseases such as hepatitis and tuberculosis, no history of drug and food allergies, and no history of trauma surgery. Admission... Changes and right shoulder joint surgery history. These lesions and surgical history may lead to further loss of joint function and need to be treated in time. Imaging: The patient had limited right shoulder pain and activity for 1 hour due to trauma, and X-ray examination showed a right scapula fracture. The patient had no history of hypertension, diabetes, coronary heart disease, infectious diseases such as hepatitis and tuberculosis, no history of drug and food allergies, and no history of frauma surgery. Admission... Changes and right shoulder pain and activity for 1 hour due to trauma, and X-ray exami
  International medicine. The gate in that diminised right ishoulder pain and activity for a floor of the diagraph, and a floor of against and a floor of the state of the state
  surgery on the right shoulder joint. These lesions and surgical history may lead to further loss of joint function and need to be treated in time. Invividual analysis. The patient had right shoulder joain and limited activity for 1 hour due to trauma, and X-ray examination showed a right scapulal fracture. The patient has no history of breathers, on the patient disease, infectious diseases such as hepatitis and tuberculosis, no history of drug and food allergies, and no history of trauma surgery. After admission, the patient was weak and had difficulty urinating and defectating. The most worrying aspect is the degenerative lesions of the bilateral shoulder joints and the surgical history of the right shoulder joint. These lesions and surgical history may lead to further loss of joint function and need to be treated in time. Collaborative on sultation: Traumatology: yes Orthopedics: yes Pain management: yes Imaging: yes Rehabilitation medicine: yes Decision Making:
         rompt: Please propose the treatment items that need to be taken for this patient based on the patient's chief complaint, past history, current medical history, physical examination results, siting department and diagnosis results provided below.
       nal answer: Surgery
  MDAgent
   Complexity Check-intermediate Expert Recruitment: Agent 1 ( 2 . Pulmonologist): Specializes in the diagnosis and treatment of respiratory system disorders. Agent 2 ( 2 . 2. Trauma Surgeon): Focuses on the diagnosis and treatment of injuries caused by trauma. Agent 3 ( 3 . 3. Orthopedic Surgeon): Specializes in the surgical treatment of injuries caused by trauma. Agent 3 ( 3 . 3. Orthopedic Surgeon): Specializes in the surgical treatment of musculoskeletal disorders and injuries. Collaborative Decision Making: Hierarchy Selection Participatory Debate (pulmonologist): antibiotic treatment (trauma surgeon): interventional treatment (orthopedic surgeon): surgery, antibiotic treatment, physical therapy
  Analysis and Synthesis:
== Round 1 == LTurn 1 Agent 1 ($\frac{\mathbb{R}}{2}$ pulmonologist): No Agent 2 ($\frac{\mathbb{R}}{2}$ trauma surgeon): No Agent 3 ($\frac{\mathbb{R}}{2}$ orthopedic surgeon): No
     Final Decision: Medication
  MedChain-Agent
       octor group:
     doctor1: surgery, physical therapy
 doctor1: surgery, pny
doctor2: surgery
doctor3: surgery
Summary: surgery
Feedback: correct
Final Answer: surgery
   Data summary: extract 12-dimensional information from the current case and add it to RAG—DataSet
   Ground Truth:
         urgery
```

Figure 27: The case study among different multi-agent for task5.

```
Task 5 - Input:
 四·4 绿石放百刈 F:
"病,上主诉",外伤致右侧肩部疼痛活动受限1小时。
详细情况:患者于小时前干活时不慎摔倒在地,背部着地,当时感右侧肩部疼痛难忍,右侧肩部及右上肢活动受限,当时无头痛、胸痛、腹痛,无昏迷,入我院就诊,行x片检查示:右侧
肩胛骨骨折,拟右侧肩胛骨骨折收入住院,入院来,患者精神软,大小便未解。"
仅回复一个或多个治疗项目的各称,不要包含其他任何解释,并确保回答在上述十一项之中!!!
拾者多个选项,则用逗号隔开。
  输出示例:
   "治疗项目:中医治疗,基因治疗,手术
  判断理由: 因为..
  AutoGen
  7010日: 经验丰富的全科医生1
"治疗项目: 手术
判断理由: 患者有肩胛骨骨折,需要手术治疗。"
role2: 经验丰富的全科医生2
  "治疗项目:手术
判断理由:患者有肩胛骨骨折,需要手术治疗。"
   刊创建日: 悉有得用所背骨切,需要于不治疗。
role2: 经验丰富的全科医生2
"治疗项目: 手术
判断理由: 患者有肩胛骨骨折,需要手术治疗。"
  DyLAN
  Agent1:
治疗项目: 手术
  Agent2:
治疗项目: 手术
  Agent Importance Scores:
[0.5, 0.5]
  Final Answer:
治疗项目: 手术
expert gethering: 创伤骨科、骨科、疼痛管理、影像学、康复医学
analysis proposistion:创伤骨科、患者因外伤效右侧肩部疼痛活动受限1小时、X片检查示右侧肩胛骨骨折。患者无高血压、糖尿病、冠心病等病史、无肝炎、肺结核等传染病史,无药物及食
物过敏史、无外伤手术史。入院后患。变和右侧肩衫疼痛活动受限1小时、X片检查示右侧肩胛骨骨折。患者无高血压、糖尿病、冠心病等病史、无肝炎、肺结核等传染病史,无药物及食物过敏史、无外伤手术史。这些病变和手术史可能导致进一步的关节功能丧失,需要及时处理。
释痛管理、患者因外伤效右侧肩部疼痛活动受限1小时、X片检查示右侧肩胛骨骨折、患者无高血压、糖尿病、冠心病等病史、无肝炎、肺结核等传染病史、无药物及食物过敏史、无外伤手术史。
及痛管理、患者因外伤效右侧肩部疼痛活动受限1小时、X片检查示右侧肩胛骨骨折、患者系高血压、糖尿病、冠心病等病史、无肝炎、肺结核等传染病史、无药物及食物过敏史、无外伤手术史。
及解言理、患者因外伤效右侧肩部疼痛活动受限1小时、X片检查不右侧肩胛骨骨折、患者无高血压、糖尿病、冠心病等病史、无肝炎、肺结核等传染病史、无药物及食物过敏史、无外伤手术史。
入院后患、变和右侧肩条节的手术史。这些病变和手术史可能导致进一步的关节功能疾失,需要及时处理。
影像学:患者因外伤致右侧肩部疼痛活动受限1小时、X片检查示右侧肩胛骨骨折。患者无高血压、糖尿病、冠心病等病史、无肝炎、肺结核等传染病史、无药物及食物过敏史、无外伤手术
束。入院后患。变和右侧肩关节的手术史、这些病变和手术史可能导致进一步的关节功能较失,需要及时处理。
康复医学:患者因外伤致右侧肩部疼痛活动受限1小时、X片检查示右侧肩胛骨骨折。患者无高血压、糖尿病、冠心病等病史、无肝炎、肺结核等传染病史、无药物及食物过敏史、无外伤手术史,入院后患者精神软、大小便未痛。最令人担忧的方面是双侧肩关节的影化大力,患者无高血压、糖尿病、冠心病等病史、无肝炎、肺结核等传染病史、无药物及食物过敏史、无外伤手术史。入院后患者精神软,大小便未解。最令人担忧的方面是双侧肩关节的退行性病变和右侧肩关节的手术史。这些病变和手术史可能导致进一步的关节功能丧失,需要及时处理。
  MedAgent
   Collaborative consultation:创伤骨科:yes 骨科:yes 疼痛管理:yes 影像学:yes 康复医学:yes
   Decision Making:
prompt:请根据以下提供的病人的主诉、既往史、现病史、查体结果、就诊科室以及诊断结果,提出需要对该病人采取的治疗项目。
   final answer: 手术
  MDAgent
  Collaborative Decision Making
  Collaborative Decision Making:
Hierarchy Selection
Participatory Debate
(pulmonologist): 抗生素治疗 (trauma surgeon): 介入治疗 (orthopedic surgeon): 手术... 抗生素治疗、物理疗法
Analysis and Synthesis:
== Round 1 ==
    Turn 1
  LTurn 1
Agent 1 (東
Agent 2 (東 trauma surgeon): No
Agent 3 (東 orthopedic surgeon): No
Final Decision: 药物治疗
  MedChain-Agent
   Doctor group
  Doctor group:
doctor1: 手术、物理疗法
doctor2: 手术
doctor3: 手术
Summary: 手术
Feedback: 正确
Final Answer: 手术
Data summary: 把当前病例的情况提取出12维信息,加入RAG—DataSet
  Ground Truth:
```

Figure 28: The case study among different multi-agent for task5 in Chinese.

```
作为一名专业的分诊医生,你需要根据病人的主诉,将其分诊至适当的科室。分诊流程分为两步
1. 首先将病人分诊至唯一的第一级科室。
2. 然后将病人分诊至一个或多个对应的第二级科室。
- 我们中的人力步生 1439 / 为证的第一表标点。
请仪回复海角人分诊的第一级解在前车。强料在的名称,不要包含其他任何解释。科室必须从以下列表中选择:
护理科:基础护理、内科护理、外科护理
药剂料: 西药房、药理实验室、中药房、调剂料
厄路科: 口腔拍肠科、牙周科、儿童口腔科、口腔修复科、牙体牙髓科、种植科、正畸科、口腔急诊科、口腔预防科、颌面外科
ル料: 小儿感染料、儿童保健科、小儿耳鼻喉、小儿免疫科、小儿面液科、小儿肾内科、小儿内科、小儿心外科、小儿呼吸科、小儿骨科、小儿内分泌
科、小儿整形科、小儿消化科、小儿泌尿科、小儿精神科、儿童康复科、小儿神经外科、小儿外科、小儿心内科、小儿皮肤科、新生儿科、小儿神经内
科,小儿急诊科
医学影像科:MRI室、CT室、B超科、X线室、彩超科、放射科、心超科、超声科、核医学科
眼科: 眼外伤、青光眼、眼眶及肿瘤、眼视光学、角膜科、白内障、小儿眼科、眼底
检验科: 体液检验、临床检验室、血液检验、生化室、病理科
外科:胰腺外科、创伤骨科、脊柱外科、外伤科、麻醉疼痛科、骨肿瘤科、泌尿外科、胃肠外科、神经外科、心脏外科、器官移植、普外科、乳腺外科
关节骨科、骨科、血管外科、肝胆外科、手外科、甲状腺外科、心胸外科、整形科、烧伤科、胸外科、肛肠外科、微创外科
皮肤性病科: 激光室、性病科、皮肤美容、皮肤科精神科: 精神科
全科: 全科
耳鼻咽喉科: 耳鼻咽喉科
耳鼻咽喉科: 手鼻咽喉科
内科: 肾脏内乳、结核胸科、肝胸科、营养科、消化内科、内分泌科、神经内科、传染科、过敏反应科、干部诊疗科、呼吸科、免疫科、心血管内科、
血溶科、老年崇料、普通内科、艾滋病科、风湿科、感染科
念诊科: 念诊科
肿瘤科: 肿瘤外科、放疗科、肿瘤内科
康复科: 理疗科、康复科
妇产科: 妇科内分泌、生殖中心、产前检查科、妇科肿瘤、计划生育科、妇泌尿科、高危产科、产科、妇科
心理科: 心理科
病人主诉: {pation_contribution}
你是一个医生。已知病人的主诉如下:
{chief_complaints}
(CILET_COMPLAINES)
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Figure 29: The prompt of task 1 to 5 for other baseline.

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