

CXReasonAgent: Evidence-Grounded Diagnostic Reasoning Agent for Chest X-rays



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Abstract. Chest X-ray plays a central role in thoracic diagnosis, and its interpretation inherently requires multi-step, evidence-grounded reasoning. However, large vision-language models (LVLMs) often generate plausible responses that are not faithfully grounded in diagnostic evidence and provide limited visual evidence for verification, while also requiring costly retraining to support new diagnostic tasks, limiting their reliability and adaptability in clinical settings. To address these limitations, we present CXReasonAgent, a diagnostic agent that integrates a large language model (LLM) with clinically grounded diagnostic tools to perform evidence-grounded diagnostic reasoning using image-derived diagnostic and visual evidence. To evaluate these capabilities, we introduce CXReasonDial, a multi-turn dialogue benchmark with 1,946 dialogues across 12 diagnostic tasks, and show that CXReasonAgent produces faithfully grounded responses, enabling more reliable and verifiable diagnostic reasoning than LVLMs. These findings highlight the importance of integrating clinically grounded diagnostic tools, particularly in safety-critical clinical settings.

Keywords: Chest X-ray · Evidence-Grounded Reasoning · Agent

1 Introduction

Chest X-ray (CXR) is a primary imaging modality for thoracic diagnosis and is widely used in clinical practice [3]. Inherently, CXR interpretation is a multi-step, evidence-grounded reasoning process that involves identifying relevant anatomical regions, deriving quantitative measurements or spatial observations, and applying diagnostic criteria [7]. Consequently, for diagnostic assistants to be trustworthy and clinically useful, their intermediate diagnostic steps should be grounded in clinically valid and verifiable image-derived diagnostic evidence, and their reasoning must remain coherent and consistent throughout the process.

However, recent studies [10,14,15] demonstrate that LVLMs often generate plausible responses but are not faithfully grounded in the diagnostic evidence present in the image, thereby undermining the reliability of their conclusions in clinical practice. Moreover, LVLMs typically present their reasoning through

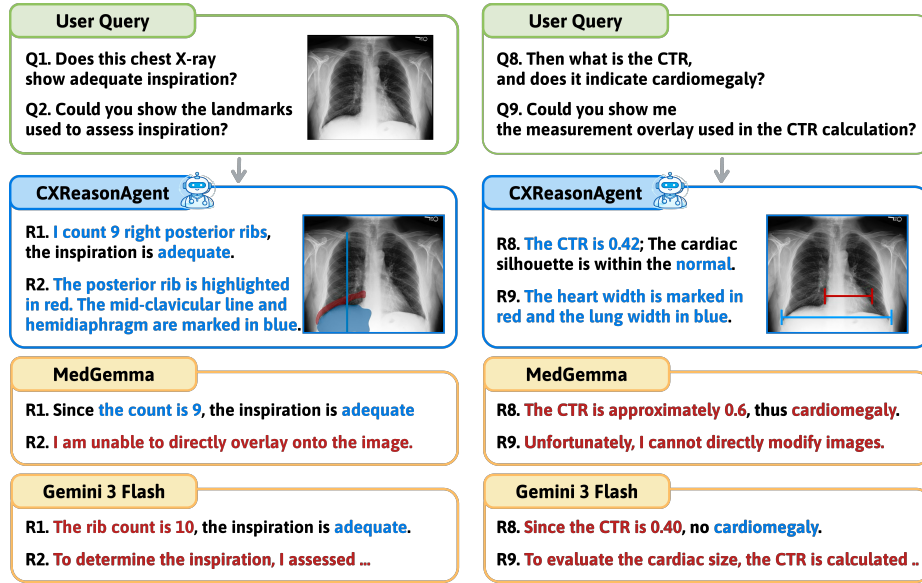


Fig. 1. Qualitative examples on CXReasonDial. CXReasonAgent produces responses faithfully grounded in image-derived diagnostic and visual evidence, whereas LVLMs often generate ungrounded responses and fail to provide visual evidence.

textual explanations alone, which makes it difficult to verify how conclusions are derived from the image. Effective diagnostic support instead requires presenting diagnostic evidence directly on the image, enabling direct verification. However, such visual evidence is rarely provided in practice, thereby limiting verifiability of diagnostic reasoning [2,20]. Furthermore, building LVLMs that handle diverse diagnostic tasks often introduces significant complexity and inefficiency, motivating tool-augmented diagnostic agents [4,8,11] that integrate task-specific models as tools [6,12,21,23], enabling extension to new tasks without costly retraining. However, these approaches typically rely on tools that provide final diagnostic conclusions or region-level visualizations, without exposing the intermediate diagnostic steps used to derive these conclusions from image-derived evidence. Consequently, they still fall short of supporting reliable and verifiable evidence-grounded diagnostic reasoning. Notably, recent work in ECG analysis [5] demonstrates that integrating measurement-based tools [13] can provide quantitative diagnostic evidence, pointing toward more reliable diagnostic reasoning.

Based on these observations, we propose CXReasonAgent, a diagnostic agent that integrates an LLM with clinically grounded diagnostic tools to perform evidence-grounded diagnostic reasoning. Unlike prior approaches, the tools return diagnostic evidence, including image-derived quantitative measurements and spatial observations, and diagnostic conclusions, along with visual evidence that presents this evidence on the image. The agent then produces responses grounded in this evidence. To evaluate these abilities, we introduce CXReason-

Dial, a multi-turn dialogue benchmark comprising 1,946 dialogues spanning 12 diagnostic tasks, designed to measure whether responses are correctly grounded in image-derived evidence, reflecting the iterative nature of diagnostic reasoning in user-assistant interactions. Experimental results show that CXReasonAgent produces correctly grounded responses, whereas LVLMs often generate ungrounded responses (Fig. 1). These findings highlight the importance of integrating clinically grounded diagnostic tools for reliable and verifiable evidence-grounded diagnostic reasoning, particularly in safety-critical clinical settings.

2 CXReasonAgent

As shown in Fig. 2, CXReasonAgent is a diagnostic agent that integrates an LLM with clinically grounded diagnostic tools to perform evidence-grounded diagnostic reasoning through multi-turn interactions. To ensure clinical verifiability, the agent operates within 12 predefined diagnostic tasks whose image-derived evidence can be reliably extracted by the integrated tools, covering cardiac size (cardiomegaly), mediastinal and aortic abnormalities (mediastinal widening, aortic knob, ascending, and descending aorta enlargement, descending aorta tortuosity), airway alignment (trachea deviation, carina angle), and image quality assessment (inspiration, rotation, projection, inclusion) [10].

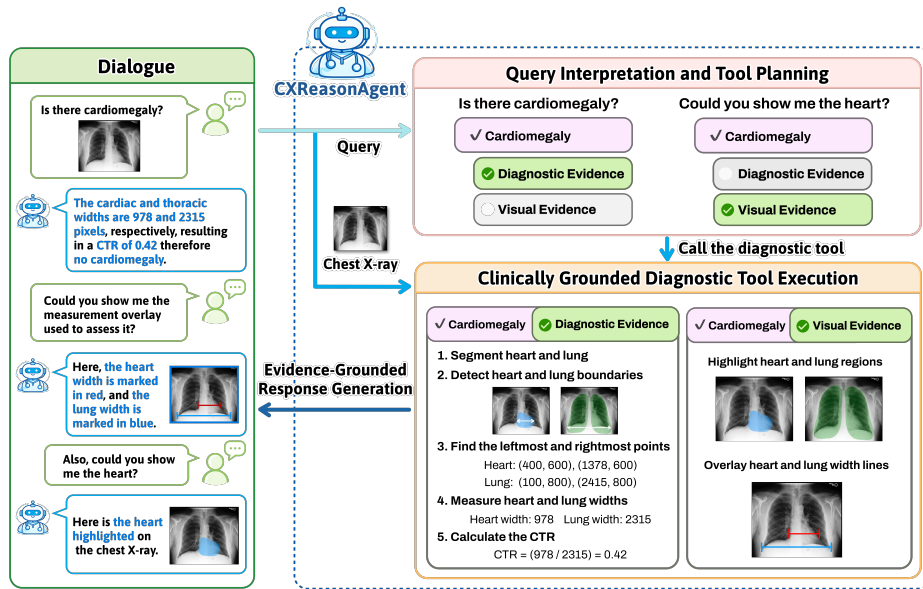


Fig. 2. Overview of CXReasonAgent. The pipeline comprises three stages: (1) interpreting the user query and planning the appropriate diagnostic tool call, (2) constructing diagnostic and visual evidence from the chest X-ray using clinically grounded diagnostic tools, and (3) generating responses solely grounded in this evidence.

Query Interpretation and Tool Planning. Given a user query paired with a chest X-ray, the agent interprets the query to identify the requested diagnostic task and the type of evidence required to answer it. Queries are categorized into two types: *1) Diagnostic Evidence Request*, which asks for image-derived diagnostic evidence, such as quantitative measurements and spatial observations, and their corresponding diagnostic conclusions and criteria (*e.g.*, *What is the cardiothoracic ratio?*), and *2) Visual Evidence Request*, which asks to present the image-derived diagnostic evidence directly on the image (*e.g.*, highlighting anatomical regions or showing measurement overlays). Based on the identified diagnostic task and evidence type, the agent requests the appropriate diagnostic tool call to obtain the required evidence.

Clinically Grounded Diagnostic Tool Execution. The selected diagnostic tool analyzes the chest X-ray and returns clinically grounded evidence derived from the image. For a diagnostic evidence request, the tool outputs diagnostic evidence, including quantitative measurements, spatial observations, and their corresponding diagnostic criteria and conclusions. For a visual evidence request, it returns annotated images that visualize the image-derived diagnostic evidence directly on the image. The tools are implemented using CheXStruct [10], a pipeline designed based on clinically grounded criteria defined with board-certified radiologists to ensure accurate evidence extraction. Because the pipeline relies on rule-based geometric computations derived from these criteria, the extraction process is deterministic, ensuring reproducible evidence for a given image and supporting reliable evidence-grounded diagnostic reasoning.

Evidence-Grounded Response Generation. Given the image-derived evidence, the agent produces a response solely grounded on this evidence, without directly accessing the chest X-ray. This enables users to verify the evidence used to generate the response, supporting reliable and coherent evidence-grounded diagnostic reasoning across multi-turn interactions.

3 CXReasonDial

CXReasonDial is a multi-turn dialogue benchmark designed to evaluate whether responses are correctly grounded in image-derived evidence across dialogue turns. The benchmark is constructed as follows.

Dialogue Scenario Definition. To cover diverse dialogue conditions, we define dialogue scenarios along two aspects: *1) Task Coverage.* The benchmark is restricted to the same 12 predefined diagnostic tasks as CXReasonAgent. We vary the number of diagnostic tasks addressed within a single dialogue: single-task dialogues focus on one diagnostic task, multi-task dialogues cover two diagnostic tasks, and global-to-task dialogues begin with a global question (*e.g.*, overall presence of abnormalities) and then explore one to four specific diagnostic tasks in detail. *2) Question Flow Patterns.* We define three question flow patterns to reflect different styles of diagnostic questioning. In the *top-down* pattern, the dialogue starts with a diagnostic conclusion question and progressively requests supporting evidence (*e.g.*, quantitative measurements or annotated images). The

bottom-up pattern follows the reverse order, beginning with specific evidence and gradually leading to the diagnostic conclusion. In the *random* pattern, questions appear in a flexible order, reflecting less structured user interactions.

Action Sequence Construction. Given a dialogue scenario, we construct an action sequence to specify the turn-by-turn interaction structure of the dialogue, as in ToolDial [17]. Specifically, it defines, for each turn, the type of user request, which in turn determines the expected response behavior of the model. We consider two user request types: diagnostic evidence requests (*e.g.*, measurements, spatial observations, or diagnostic conclusions) and visual evidence requests (*e.g.*, highlighting anatomical regions). For example, a sequence may follow: *Diagnostic evidence request* $\rightarrow$ *Model response* $\rightarrow$ *Visual evidence request* $\rightarrow$ *Model response* $\rightarrow \dots \rightarrow$ *User bye* $\rightarrow$ *Model bye*. These action sequences serve as dialogue skeletons that guide the subsequent dialogue generation process.

Dialogue Generation. Using the defined dialogue scenarios and action sequences, we generate multi-turn dialogues turn by turn using Gemini-3-Flash. For each turn, we prompt the model with the dialogue scenario, the user request type assigned to that turn, and the request-specific evidence extracted from the chest X-ray by the CheXStruct pipeline [10], along with the previously generated dialogue turns. The user question is generated to be consistent with the dialogue scenario and request type and to be answerable using the provided evidence, while the response is grounded in the same evidence. CXReasonDial is constructed from 1,200 chest X-rays adopted from CXReasonBench [10], which were manually reviewed by a board-certified radiation oncologist to support reliable extraction of diagnostic evidence using CheXStruct. In total, CXReasonDial comprises 1,946 dialogues with an average of 10.87 turns per dialogue (Table 1).

Dialogue Validation. We validate 100 randomly sampled dialogues using both an LLM-as-a-Judge [24] (*i.e.*, Gemini-3-Flash) and human evaluation conducted by 10 graduate students under the supervision of a radiation oncologist. Dialogue quality is assessed using three criteria: *Question Compliance* (0/1): whether each question follows the assigned diagnostic task and request type. *Answer Correctness* (0/1): whether the response correctly addresses the question and is grounded in the provided evidence. *Naturalness* (1–5): coherence across turns and adherence to the predefined question flow patterns. As shown in Table 2, the dialogues adhere to the intended dialogue design, provide evidence-grounded responses, and exhibit natural multi-turn interactions.

Table 1. Dialogue statistics.

Statistic	Value
Total dialogues	1,946
Single-task	1,200
Multi-task	660
Global-to-task	86
Avg. turns / dialogue	10.87

Table 2. Dialogue validation results.

Criterion	Gemini Human	
Question Compliance	0.981	0.970
Answer Correctness	0.997	0.982
Naturalness	4.20	4.26

4 Experiments and Results

Evaluation Models. We evaluate CXReasonAgent with multiple LLM backbones, including the closed-source models, Gemini-3-Flash [19] and GPT-5 mini [18], and the open-source models, Llama 3.3-70B [9] and Qwen3 (4B, 8B, 32B) [22]. We compare against three LVLm baselines: Gemini-3-Flash [19], Pixtral-Large [1], and MedGemma 27B [16]. Open-source models are run with vLLM on NVIDIA A100 GPUs (4 GPUs for Pixtral-Large and Llama-3.3-70B) and RTX A6000 GPUs (2 GPUs for Qwen3 variants and MedGemma 27B).

Evaluation Metrics. We evaluate models using the following metrics. **1) Turn-level Metrics.** Each metric is evaluated as a binary score at the turn level using an LLM-as-a-Judge [24] (*i.e.*, Gemini-3-Flash). *(i) Diagnostic Task Identification* and *(ii) Evidence Type Identification* assess whether the agent correctly identifies, from the user query, the requested diagnostic task and evidence type, respectively. These two metrics are evaluated only for CXReasonAgents, as they assess the tool planning stage. *(iii) Coverage* assesses whether the response fully addresses the user query, regardless of factual correctness. *(iv) Faithfulness* evaluates whether the response is consistent with the request-specific ground-truth evidence used during CXReasonDial construction. *(v) Hallucination* is defined as the case where *Coverage*=1 and *Faithfulness*=0. When evaluating LVLms, turns requesting visual evidence are excluded, as these models do not produce visual evidence. **2) Dialogue-level Metrics.** A turn is considered successful only if all applicable turn-level metrics are correct. *(i) Average Dialogue Success* is the average ratio of successful turns per dialogue. *(ii) Strict Dialogue Success* is the proportion of dialogues in which all turns are successful.

Evaluation Settings. We evaluate models under three complementary settings. While CXReasonDial uses pre-generated user queries to ensure controlled comparison on identical questions, these fixed queries do not adapt to erroneous responses. In this default setting, **1) Without GT**, the dialogue history is constructed from the model’s own outputs, allowing errors to accumulate across turns and potentially reducing interaction naturalness. **2) With GT** provides the ground-truth dialogue history at each turn, preventing error propagation and serving as an upper-bound setting under fixed user queries [17]. However, because the history is corrected at every turn, this setting can mask how models behave when their own errors accumulate in interactive use. **3) Dynamic User Simulator** addresses these limitations by evaluating performance under adaptive multi-turn interactions. Following the same dialogue design (*i.e.*, dialogue scenario and action sequence) as CXReasonDial, Gemini-3-Flash generates user queries conditioned on the model-generated dialogue history at each turn, allowing the queries to adapt to model responses while maintaining a similar structural pattern to the original dialogues.

Results: Importance of Clinically Grounded Diagnostic Tools. Tables 3 and 4 indicate that LVLms often generate plausible responses that appear reasonable but are not correctly grounded in the image-derived diagnostic evidence. In contrast, CXReasonAgent grounds each response in diagnostic and visual evidence extracted from the chest X-ray by clinically grounded diagnostic tools, en-

ensuring that the reasoning remains faithfully grounded in verifiable image-derived evidence. This advantage is further reflected in the dialogue-level metrics, where CXReasonAgent achieves higher success rates, indicating more stable and coherent multi-turn diagnostic reasoning. Overall, these results highlight the importance of integrating clinically grounded diagnostic tools for enabling reliable and verifiable evidence-grounded diagnostic reasoning, particularly in safety-critical clinical settings.

Table 3. Results on CXReasonDial under the Without GT (w/o) and With GT (w/) settings. DTI: Diagnostic Task Identification; ETI: Evidence Type Identification; Cov: Coverage; Faith: Faithfulness; Hall: Hallucination; Avg: Average Dialogue Success; Strict: Strict Dialogue Success; Best results are underlined.

Model	Turn-level										Dialogue-level			
	DTI ↑		ETI ↑		Cov ↑		Faith ↑		Hall ↓		Avg ↑		Strict ↑	
	w/o	w/	w/o	w/	w/o	w/	w/o	w/	w/o	w/	w/o	w/	w/o	w/
CXReasonAgent														
Gemini-3-Flash	99.8	99.8	97.6	97.6	99.5	99.4	<u>99.7</u>	<u>99.7</u>	<u>0.3</u>	<u>0.3</u>	96.8	96.6	73.4	72.2
GPT-5 mini	<u>99.9</u>	<u>99.9</u>	<u>98.2</u>	98.2	99.5	99.5	99.2	99.2	0.8	0.8	<u>96.9</u>	<u>96.9</u>	<u>74.8</u>	<u>74.2</u>
Llama 3.3-70B	99.3	99.4	96.7	96.9	99.4	99.4	99.3	99.2	0.7	0.8	95.3	95.5	65.8	65.2
Qwen3-32B	98.6	97.0	97.0	97.3	<u>99.6</u>	99.5	97.6	98.6	2.3	1.4	94.2	91.6	61.1	59.0
Qwen3-8B	86.3	89.5	86.6	90.0	<u>99.6</u>	<u>99.7</u>	93.7	95.3	6.3	4.6	76.6	80.6	21.1	23.1
Qwen3-4B	91.6	92.6	92.1	93.7	<u>99.6</u>	99.4	94.7	96.3	5.3	3.7	80.4	82.2	31.6	32.9
LVLm Baselines														
Gemini-3-Flash	-	-	-	-	98.3	98.3	43.1	81.1	55.6	18.0	36.9	69.1	8.6	9.8
Pixtral-Large	-	-	-	-	98.8	98.8	57.9	79.8	41.5	20.1	48.6	65.4	5.9	6.0
MedGemma 27B	-	-	-	-	98.9	98.5	53.9	76.2	45.4	23.2	46.1	64.1	6.1	6.5

Results: Effect of Backbone Scale and Design Flexibility. Tables 3 and 4 further analyze the effect of backbone scale within CXReasonAgent. While larger backbones consistently improve performance across most turn-level metrics, the gains are generally moderate, whereas more noticeable improvements are observed in dialogue-level success. This suggests that increased model capacity primarily enhances query interpretation accuracy and multi-turn reasoning stability. Importantly, even small backbones (*e.g.*, Qwen3-4B and 8B) already surpass all LVLms across all metrics, indicating that the primary performance gains arise from the agent design, namely clinically grounded diagnostic tool-based evidence grounding, rather than from model scale alone. These results highlight the cost-efficiency and flexibility of the proposed agent design: the core diagnostic reasoning capability is largely preserved across backbone sizes, allowing practitioners to flexibly trade off performance and computational cost by swapping the underlying language model without redesigning the system.

Results: Robust Evidence Grounding Across Evaluation Settings. In Table 3, CXReasonAgent maintains strong performance in both Without GT and

Table 4. Results with the Dynamic User Simulator based on the CXReasonDial dialogue design. Best results are underlined.

Model	Turn-level					Dialogue-level	
	DTI $\uparrow$	ETI $\uparrow$	Cov $\uparrow$	Faith $\uparrow$	Hall $\downarrow$	Avg $\uparrow$	Strict $\uparrow$
CXReasonAgent							
Gemini-3-Flash	98.0	98.5	<u>99.9</u>	<u>99.9</u>	<u>0.1</u>	93.3	75.7
GPT-5 mini	<u>99.9</u>	<u>98.8</u>	<u>99.9</u>	99.8	0.2	<u>98.4</u>	<u>85.8</u>
Llama 3.3-70B	98.8	98.3	<u>99.9</u>	99.7	0.3	96.1	79.9
Qwen3-32B	96.5	97.4	<u>99.9</u>	98.7	1.3	92.4	67.8
Qwen3-8B	83.0	84.7	<u>99.9</u>	96.8	3.2	76.4	29.4
Qwen3-4B	88.7	89.6	99.8	97.3	2.7	81.7	38.5
LVLm Baselines							
Gemini-3-Flash	-	-	98.5	46.3	52.3	33.8	9.10
Pixtral-Large	-	-	98.5	48.2	50.3	35.5	7.70
MedGemma 27B	-	-	98.7	44.9	53.8	34.8	5.10

With GT settings, indicating robust evidence-grounded reasoning even when relying on its own generated dialogue history, where errors can accumulate across turns. In contrast, LVLms show substantial gains in faithfulness and reduced hallucination when ground-truth history is provided, suggesting that they may leverage diagnostic evidence already present in the ground-truth history rather than consistently grounding their responses in image-derived evidence. Under the dynamic user simulator (Table 4), CXReasonAgent continues to outperform LVLms by a similar margin, demonstrating that its evidence grounding remains stable under realistic interactive conditions. Overall, these results show that CXReasonAgent maintains reliable evidence-grounded reasoning across both controlled fixed-query evaluations and response-adaptive multi-turn interactions.

5 Conclusion

We presented CXReasonAgent, a diagnostic agent that integrates an LLM with clinically grounded diagnostic tools to perform evidence-grounded diagnostic reasoning through multi-turn dialogue. We also introduce CXReasonDial to systematically evaluate whether responses are correctly grounded in image-derived evidence across dialogue turns. Experiments demonstrate that CXReasonAgent consistently produces faithfully grounded responses and enables more coherent multi-turn diagnostic reasoning than LVLms. These findings highlight the importance of integrating clinically grounded diagnostic tools for reliable and verifiable diagnostic reasoning, particularly in safety-critical clinical settings. The current scope is limited to 12 diagnostic tasks on chest X-rays; future work will extend the agent to broader diagnostic tasks and modalities.

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