# Agentic large language models improve retrieval-based radiology question answering

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#### **Abstract**

Clinical decision-making in radiology increasingly benefits from artificial intelligence (AI), particularly through large language models (LLMs). However, traditional retrieval-augmented generation (RAG) systems for radiology question answering (QA) typically rely on single-step retrieval, limiting their ability to handle complex clinical reasoning tasks. Here we propose an agentic RAG framework enabling LLMs to autonomously decompose radiology questions, iteratively retrieve targeted clinical evidence from Radiopaedia.org, and dynamically synthesize evidence-based responses. We evaluated 24 LLMs spanning diverse architectures, parameter scales (0.5B to >670B), and training paradigms (general-purpose, reasoning-optimized, clinically fine-tuned), using 104 expert-curated radiology questions from previously established RSNA-RadioQA and ExtendedQA datasets. Agentic retrieval significantly improved mean diagnostic accuracy over zero-shot prompting (73% vs. 64%; P =  $2.3 \times 10^{-7}$ ) and conventional online RAG  $(73\% \text{ vs. } 68\%; 5.0 \times 10^{-6})$ . The greatest gains occurred in mid-sized models (e.g., Mistral Large improved from 72% to 81%) and small-scale models (e.g., Qwen 2.5-7B improved from 55% to 71%), while very large models (>200B parameters) demonstrated minimal changes (<2% improvement). Additionally, agentic retrieval reduced hallucinations (mean 9.4%) and retrieved clinically relevant context in 46% of cases, substantially aiding factual grounding. Even clinically fine-tuned models exhibited meaningful improvements (e.g., MedGemma-27B improved from 71% to 81%), indicating complementary roles of retrieval and fine-tuning. These results highlight the potential of agentic frameworks to enhance factuality and diagnostic accuracy in radiology QA, particularly among mid-sized LLMs, warranting future studies to validate their clinical utility.

# 1. Introduction

Artificial intelligence (AI) is rapidly transforming diagnostic radiology by enhancing imaging interpretation, improving diagnostic precision, and streamlining clinical workflows<sup>1,2</sup>. Recent advances in large language models (LLMs)<sup>3–7</sup>, such as GPT-4<sup>8</sup>, have shown remarkable capability in tasks ranging from extracting structured information from radiology reports and assisting in clinical reasoning, to facilitating seamless natural language interfaces<sup>3,9–12</sup>. Despite these capabilities, a significant limitation persists: the static nature of LLMs' training data, which can lead to incomplete, outdated, or biased knowledge, thus compromising clinical accuracy and reliability.

Retrieval-augmented generation (RAG)<sup>13</sup>, which combines LLMs with domain-specific external knowledge sources, has emerged as a promising strategy to address these limitations. By grounding model-generated outputs in up-to-date and verified information, RAG could enhance the factual accuracy of LLM responses and reduces the risk of hallucinations, generated outputs without factual basis<sup>6,14–17</sup>. Tayebi Arasteh et al. recently introduced Radiology RAG (RadioRAG)<sup>18</sup>, an online RAG framework utilizing real-time information from Radiopaedia<sup>19</sup>, demonstrating substantial accuracy improvements in certain LLMs, such as GPT-3.5-turbo

compared to conventional zero-shot inference. Nevertheless, these improvements were inconsistent across all evaluated models, with models like Llama3-8B showing negligible gains, highlighting inherent limitations in traditional single-step retrieval architectures. Current online RAG frameworks<sup>16</sup>, including RadioRAG<sup>18</sup>, primarily employ a single-step retrieval and generation process, limiting their ability to manage complex, multi-part clinical questions effectively<sup>20</sup>. This design lacks the capability to iteratively refine queries, dynamically seek additional information, or systematically evaluate intermediate uncertainty<sup>21</sup>. Consequently, there is a clear need to evolve RAG approaches towards more sophisticated reasoning and retrieval strategies<sup>18</sup>.

Recently, agentic frameworks have emerged as an advanced paradigm within Al research, particularly for LLMs<sup>3,22-24</sup>. These frameworks enable models to autonomously orchestrate retrieval<sup>25</sup>, reasoning, and synthesis in iterative multi-step chains<sup>26,27</sup>, allowing for dynamic adaptation and enhanced problem-solving capabilities<sup>28-30</sup>. Agentic approaches have demonstrated notable success across various domains, including clinical decision-making, oncology, and scientific research, by enabling models to dynamically select retrieval strategies, systematically evaluate intermediate results, and adapt their reasoning strategies based on evolving contexts<sup>23,31</sup>. For example, agent-based systems have improved the accuracy and interpretability of Al-driven decisions in oncology<sup>23</sup>, general clinical tasks, and biomedical research<sup>22</sup>, demonstrating clear advantages over static prompting and traditional RAG methodologies. However, despite these promising outcomes in other clinical domains, the utility and effectiveness of agentic LLMs for specialized radiological applications remain largely unexplored. Radiology presents unique challenges, characterized by diverse and complex clinical questions often requiring nuanced, multi-step reasoning and domain-specific knowledge retrieval<sup>32</sup>.

In this study, we address this crucial gap by systematically evaluating the effectiveness of agentic LLMs in radiology question answering (QA), specifically by integrating them into an online RAG framework leveraging the comprehensive radiological knowledge base of Radiopaedia.org. Our approach leverages a multi-agent pipeline that autonomously decomposes each clinical question into structured diagnostic options, retrieves targeted evidence from Radiopaedia.org, and synthesizes evidence-based responses through iterative reasoning steps. We utilize a benchmark dataset comprising 104 expert-curated radiology questions from previously established RSNA-RadioQA and ExtendedQA datasets, both from the RadioRAG study18, comparing the diagnostic performance of zero-shot inference, non-agentic online RAG, and our agentic approach. Supplementary Table 1 reports the characteristics of the datasets. Our evaluation spans 24 different LLMs encompassing a broad spectrum of architectures, parameter scales, and training paradigms. These include proprietary models (e.g., GPT-4-turbo<sup>8</sup>, GPT-3.5turbo), open-weight models (e.g., Mistral Large, Qwen 2.5<sup>33</sup>), and domain-specialized variants fine-tuned for clinical applications (e.g., MedGemma<sup>34</sup>, Llama3-Med42<sup>35</sup>). The models range from small-scale architectures (as low as 0.5 billion parameters) to mid-sized (17-110B) and very large models exceeding 200 billion parameters, including substantially sized systems such as DeepSeek-R1<sup>36</sup> and o3. For details on different models used in this study, refer to **Table 1**. This breadth allows us to systematically assess the impact of agentic retrieval across general-purpose, medically fine-tuned, and reasoning-optimized LLMs within a heterogeneous model landscape for radiology QA.

Our results show that agentic retrieval consistently enhances diagnostic accuracy and factual reliability across most model classes. The improvements are most prominent in small and mid-sized models, where conventional retrieval methods are often insufficient. In contrast, very large models (>200B parameters) with strong internal reasoning capabilities tend to benefit less from external evidence, reflecting their extensive pretraining and broad generalization ability. Nonetheless, even clinically fine-tuned models exhibit meaningful gains from agentic reasoning, suggesting that retrieval and fine-tuning offer complementary strengths. Additionally, we show that agentic retrieval reduces hallucinations and retrieves clinically relevant content that can assist not only LLMs but also expert radiologists. These findings highlight the potential of agentic frameworks to improve factuality and diagnostic accuracy in radiology QA, warranting further investigation into their clinical utility and practical integration. We provide an overview of our entire pipeline in Figure 1 and illustrate a full worked representative example for a clinical question in Figure 2, with additional methodological details outlined in Materials and Methods.

#### MULTI-AGENT LLM RESEARCH PIPELINE ARCHITECTURE

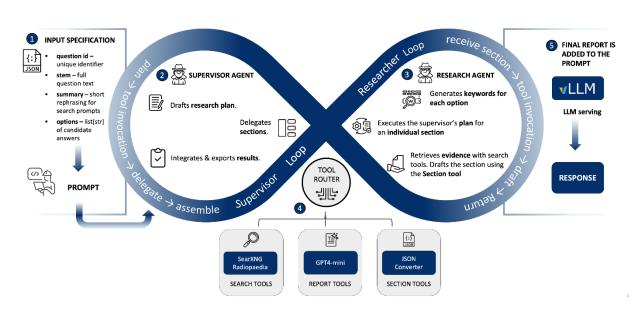


Figure 1: Multi-agent architecture of the agentic retrieval framework for radiology question answering. The pipeline combines structured retrieval with multi-step reasoning to generate evidence-grounded diagnostic reports. (1) Each question is preprocessed to extract key diagnostic concepts (using Mistral Large) and paired with multiple-choice options. (2) A supervisor agent creates a structured research plan, delegating each diagnostic option to a dedicated research agent. (3) Research agents iteratively retrieve targeted evidence from www.radiopaedia.org via a SearXNG-powered search tool, refining queries when needed. (4) Retrieved content is synthesized into structured report sections (using GPT-4o-mini and formatting tools), including supporting and contradicting evidence with citations. (5) The supervisor compiles all sections into a final diagnostic report (introduction, analysis, and conclusion), which is appended to the prompt for final answer selection. The entire workflow is coordinated through a stateful directed graph that preserves shared memory, retrieved context, and intermediate drafts.

**Table 1: Specifications of the language models evaluated in this study.** Summary of the 24 large language models assessed across zero-shot prompting, traditional online RAG, and agentic retrieval. Listed for each model are parameter count (in billions), training category (e.g., instruction-tuned (IT), reasoning-optimized, clinically aligned), accessibility, knowledge cutoff date, developer, and context length (in thousand tokens). All evaluations were conducted using outputs generated between July 1–27, 2025.

Model name	Parameters (billion)	Category	Accessibility	Knowledge cutoff date	Developer	Context length (thousand tokens)
Ministral-8B	8	IT	Open-source	October 2023	Mistral Al	128
Mistral Large	123	IT	Open-source	November 2024	Mistral Al	128
Llama3.3-8B	8	IT	Open-weights	March 2023	Meta Al	8
Llama3.3-70B	70	IT	Open-weights	December 2023	Meta Al	128
Llama3-Med42-8B	8	IT, clinically-aligned	Open-weights	August 2024	M42 Health Al Team	8
Llama3-Med42-70B	70	IT, clinically-aligned	Open-weights	August 2024	M42 Health Al Team	8
Llama4 Scout 16E	17	IT, 17B active parameters	Open-weights	August 2023	Meta Al	10,000 (10M)
DeepSeek R1-70B	70	Reasoning	Open-source	January 2025	DeepSeek	128
DeepSeek-R1	671	Reasoning	Open-source	January 2025	DeepSeek	128
DeepSeek-V3	671	Mixture of experts	Open-source	July 2024	DeepSeek	128
Qwen 2.5-0.5B	0.5	IT	Open-source	September 2024	Alibaba Cloud	32
Qwen 2.5-3B	3	IT	Open-source	September 2024	Alibaba Cloud	32
Qwen 2.5-7B	7	IT	Open-source	September 2024	Alibaba Cloud	131
Qwen 2.5-14B	14	IT	Open-source	September 2024	Alibaba Cloud	131
Qwen 2.5-70B	70	IT	Open-source	September 2024	Alibaba Cloud	131
Qwen 3-8B	8	Reasoning, mixture of experts	Open-source	December 2024	Alibaba Cloud	32
Qwen 3-235B	235	Reasoning, mixture of experts	Open-source	July 2025	Alibaba Cloud	32
GPT-3.5-turbo	Undisclosed	IT	Proprietary	September 2021	OpenAl	16
GPT-4-turbo	Undisclosed	IT	Proprietary	December 2023	OpenAl	128
о3	Undisclosed	Reasoning	Proprietary	June 2024	OpenAl	200
MedGemma-4B-it	4	Gemma 3-based, multimodal, IT, clinical reasoning	Open-weights	July 2025	Google DeepMind	128
MedGemma-27B- text-it	27	Gemma 3-based, text only, IT, clinical reasoning	Open-weights	July 2025	Google DeepMind	≥ 128
Gemma-3-4B-it	4	IT	Open-weights	August 2024	Google DeepMind	128
Gemma-3-27B-it	27	IT	Open-weights	August 2024	Google DeepMind	128

# 2. Results

# 2.1. Agentic retrieval improves radiology QA performance on average

We assessed the diagnostic performance of 24 LLMs across three distinct inference strategies: zero-shot prompting, conventional online RAG, and our proposed agentic RAG framework. The LLMs included: Ministral-8B, Mistral Large, Llama3.3-8B<sup>37,38</sup>, Llama3.3-70B<sup>37,38</sup>, Llama3-Med42-8B35, Llama3-Med42-70B35, Llama4 Scout 16E33, DeepSeek R1-70B36, DeepSeek-R1<sup>36</sup>, DeepSeek-V3<sup>39</sup>, Qwen 2.5-0.5B<sup>33</sup>, Qwen 2.5-3B<sup>33</sup>, Qwen 2.5-7B<sup>33</sup>, Qwen 2.5-14B<sup>33</sup>, Qwen 2.5-70B<sup>33</sup>, Qwen 3-8B<sup>40</sup>, Qwen 3-235B<sup>40</sup>, GPT-3.5-turbo, GPT-4-turbo<sup>8</sup>, o3, MedGemma-4B-it<sup>34</sup>, MedGemma-27B-text-it<sup>34</sup>, Gemma-3-4B-it<sup>41,42</sup>, and Gemma-3-27B-it<sup>41,42</sup>. Accuracy was measured using the 104-question RadioRAG benchmark dataset, with detailed results presented in Table 2. When aggregating results across all LLMs, the agentic RAG framework demonstrated a statistically significant improvement in accuracy compared to zeroshot prompting (P =  $2.3 \times 10^{-7}$ ). As previously established, the traditional RAG approach also outperformed zero-shot prompting, showing a smaller but statistically significant gain (P = 0.013). Importantly, the proposed agentic framework further outperformed traditional online RAG (P =  $5.0 \times 10^{-6}$ ), underscoring the benefit of iterative retrieval and autonomous reasoning over singlepass retrieval pipelines. These findings indicate that, at the group level, agentic reasoning introduces measurable and additive improvements in radiology question answering, even when compared against established, high-performing RAG systems.

# 2.2. Agentic retrieval improves factual grounding and reduces hallucination

To assess factual reliability under the agentic framework, we conducted a hallucination analysis across all 24 LLMs using the 104-question RadioRAG benchmark. Each response was reviewed by a board-certified radiologist (TTN) to evaluate (i) whether the retrieved context was clinically relevant, (ii) whether the model's answer was grounded in that context, and (iii) whether the final output was factually correct. Context was classified as relevant only if it contained no incorrect or off-topic content relative to the diagnostic question, a deliberately strict criterion. Under this definition, clinically relevant evidence was retrieved in 46% of cases (48/104). Detailed results are provided in **Table 3**.

When relevant context was available, most models demonstrated strong factual alignment. Hallucinations, defined as incorrect answers despite the presence of relevant context, occurred in only 9.4% ± 5.9 of questions. The lowest hallucination rates were observed in large-scale and reasoning-optimized models such as o3 (2%), DeepSeek R1 (3%), and Qwen 3-235B (5%), reflecting their superior ability to integrate and interpret retrieved content (see **Figure 3**). In contrast, smaller models such as Qwen 2.5-0.5B (26%) and Gemma-3-4B-it (20%) struggled to do so reliably, exhibiting significantly higher rates of unsupported reasoning.

#### DETAILS OF THE AGENT'S PIPELINE REPORT AND PROMPT ASSEMBLY

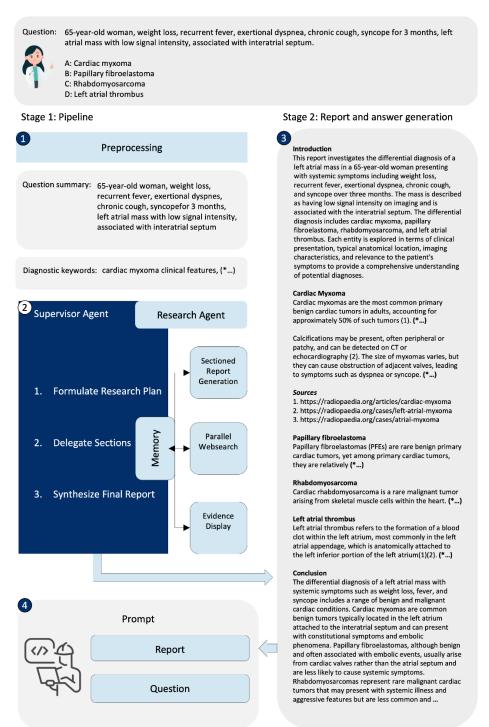


Figure 2: Representative example of the agentic retrieval process for a radiology question answering item. This figure shows the full agentic workflow for a representative question (RSNA-RadioQA-Q53) involving a patient with systemic symptoms and a low signal intensity left atrial mass associated with the interatrial septum. The pipeline begins with keyword-based summarization to guide retrieval, followed by parallel evidence searches for each diagnostic option using Radiopaedia.org. Retrieved content is synthesized into a structured report, including an introduction, citation-backed analyses of all options (cardiac myxoma, papillary fibroelastoma, rhabdomyosarcoma, and left atrial thrombus), and a neutral conclusion. The approach supports interpretable, evidence-grounded radiology question answering.

Table 2: Accuracy of language models across zero-shot prompting, traditional online RAG, and agentic retrieval on the RadioRAG dataset. Accuracy is reported in percentage as mean ± standard deviation, with 95% confidence intervals shown in brackets. Results are based on 104 questions, using bootstrapping with 1,000 repetitions and replacement while preserving pairing. P-values were calculated for each model using McNemar's test on paired outcomes relative to the agentic method and adjusted for multiple comparisons using the false discovery rate. A p-value < 0.05 was considered statistically significant. Accuracy is presented alongside total correct answers per method.

	Zero-shot			Online RAG			Agentic	
Model name	Accuracy (%)	Total correct (n)	P- value	Accuracy (%)	Total correct (n)	P- value	Accuracy (%)	Total correct (n)
Ministral-8B	47 ± 5 [38, 57]	49	0.019	51 ± 5 [41, 61]	53	0.049	66 ± 5 [57, 76]	69
Mistral Large	72 ± 4 [63, 81]	75	0.158	74 ± 4 [65, 83]	77	0.292	81 ± 4 [72, 88]	84
Llama3.3-8B	62 ± 5 [53, 71]	65	0.813	63 ± 5 [55, 72]	66	0.999	65 ± 5 [57, 74]	68
Llama3.3-70B	76 ± 4 [67, 84]	79	0.219	73 ± 4 [63, 81]	76	0.103	83 ± 4 [75, 89]	86
Llama3-Med42-8B	67 ± 5 [58, 77]	70	0.270	67 ± 5 [59, 77]	70	0.405	75 ± 4 [66, 84]	78
Llama3-Med42-70B	72 ± 4 [63, 80]	75	0.270	75 ± 4 [67, 83]	78	0.717	79 ± 4 [71, 87]	82
Llama4 Scout 16E	76 ± 4 [67, 85]	79	0.400	80 ± 4 [72, 88]	83	0.999	81 ± 4 [73, 88]	84
DeepSeek R1-70B	78 ± 4 [70, 86]	81	0.862	76 ± 4 [67, 84]	79	0.678	80 ± 4 [72, 88]	83
DeepSeek R1	82 ± 4 [74, 89]	85	0.862	79 ± 4 [71, 87]	82	0.999	80 ± 4 [72, 88]	83
DeepSeek-V3	76 ± 4 [67, 84]	79	0.128	80 ± 4 [72, 88]	83	0.292	86 ± 4 [78, 92]	89
Qwen 2.5-0.5B	37 ± 5 [27, 46]	38	0.738	46 ± 5 [37, 56]	48	0.747	42 ± 5 [32, 52]	43
Qwen 2.5-3B	54 ± 5 [44, 63]	56	0.158	53 ± 5 [43, 62]	55	0.197	65 ± 5 [56, 74]	68
Qwen 2.5-7B	55 ± 5 [45, 64]	57	0.040	59 ± 5 [49, 68]	61	0.197	71 ± 4 [62, 80]	74
Qwen 2.5-14B	68 ± 4 [59, 77]	71	0.762	67 ± 5 [57, 76]	69	0.568	72 ± 4 [63, 81]	75
Qwen 2.5-70B	70 ± 5 [62, 79]	73	0.193	73 ± 4 [64, 82]	76	0.616	78 ± 4 [70, 86]	81
Qwen 3-8B	66 ± 5 [57, 75]	69	0.165	73 ± 4 [65, 81]	76	0.872	76 ± 4 [68, 84]	79
Qwen 3-235B	84 ± 4 [75, 90]	87	0.999	82 ± 4 [74, 89]	85	0.999	83 ± 4 [75, 89]	86
GPT-3.5-turbo	57 ± 5 [47, 66]	59	0.158	62 ± 5 [53, 71]	64	0.562	68 ± 5 [60, 77]	71
GPT-4-turbo	76 ± 4 [67, 84]	79	0.999	76 ± 4 [67, 84]	79	0.999	77 ± 4 [69, 85]	80
03	86 ± 4 [78, 92]	89	0.789	85 ± 4 [77, 91]	88	0.717	88 ± 3 [81, 93]	91
MedGemma-4B-it	56 ± 5 [46, 65]	58	0.165	52 ± 5 [42, 62]	54	0.049	66 ± 5 [57, 75]	69
MedGemma-27B-text-it	71 ± 4 [62, 79]	74	0.158	75 ± 4 [66, 84]	78	0.458	81 ± 4 [73, 88]	84
Gemma-3-4B-it	46 ± 5 [37, 56]	48	0.090	53 ± 5 [43, 62]	55	0.292	62 ± 5 [52, 71]	64
Gemma-3-27B-it	65 ± 5 [57, 75]	68	0.165	66 ± 5 [58, 75]	69	0.292	76 ± 4 [67, 85]	79

Interestingly, a substantial proportion of agentic responses were correct despite the retrieved context being clinically irrelevant. On average, 37.4% ± 4.2 of responses fell into this category. This behavior was particularly pronounced among models with strong internal reasoning capabilities, DeepSeek-V3, o3, and Qwen 3-235B each exceeded 40%, suggesting that in the absence of relevant evidence, these models often defaulted to internal knowledge. Similar trends were observed in mid-sized and clinically aligned models, such as Llama3.3-70B, Mistral Large, and MedGemma-27B-text-it, which also maintained high accuracy without external grounding. Conversely, smaller models like Qwen 2.5-0.5B (21%) and Ministral-8B (35%) were less effective under these conditions, indicating greater dependence on successful retrieval.

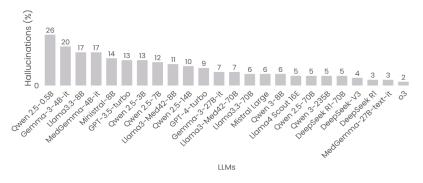
Across models, an average of  $14.6\% \pm 6.4$  of questions were answered incorrectly under zero-shot prompting but correctly after agentic retrieval, highlighting the additive diagnostic value of structured evidence acquisition. **Supplementary Tables 2** and **3** provide example responses from GPT-3.5-turbo with and without agentic retrieval, alongside the corresponding retrieved content. These findings indicate that agentic retrieval improves factual grounding and reduces hallucination by enabling structured, clinically aware evidence refinement. However, model behavior in the absence of relevant context varies substantially, with larger and reasoning-tuned models demonstrating greater resilience through fallback internal reasoning.

## 2.3. Agentic retrieval improves performance in small-scale LLMs

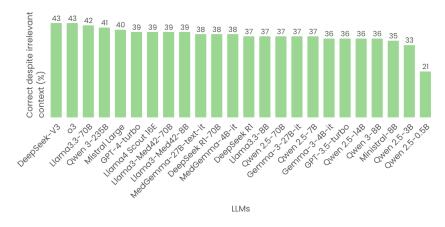
We next assessed whether model size influences the effectiveness of agentic retrieval in radiology question answering (see **Figure 4**). Across the seven smallest models in our study (including Ministral-8B, Gemma-3-4B-it, Qwen 2.5-7B, Qwen 2.5-3B, Qwen 2.5-0.5B, Qwen 3-8B, and Llama-3-8B), we observed a consistent trend: conventional online RAG outperformed zero-shot prompting (P = 0.002), and the agentic framework further improved over both baselines (P = 0.016 vs. zero-shot; P = 0.035 vs. traditional online RAG). When examining individual models, only two of the seven demonstrated statistically significant improvements with agentic retrieval compared to zero-shot prompting: Qwen 2.5-7B (71%  $\pm$  4 [95% CI: 62, 80] vs. 55%  $\pm$  5 [95% CI: 45, 64]; P = 0.040) and Ministral-8B (66%  $\pm$  5 [95% CI: 57, 76] vs. 47%  $\pm$  5 [95% CI: 38, 57]; P = 0.019). The remaining models exhibited absolute accuracy improvements ranging from 3% to 16%, though these did not reach statistical significance after correction for multiple comparisons.

These findings suggest that agentic RAG can enhance performance in small-scale LLMs. However, the degree of benefit varied across models, likely reflecting differences in pretraining data, instruction tuning, and architectural design, even within a similar parameter range.

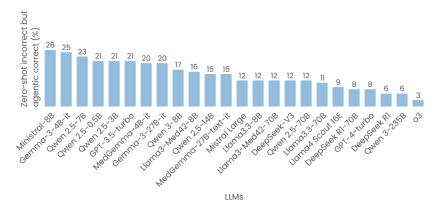
#### a Hallucination rates using the agentic framework



#### b Correctness rates despite irrelevant context



#### c Agentic gain over zero-shot responses



**Figure 3. Factuality assessment of LLM responses on the RadioRAG dataset (n = 104).** Each bar plot shows the proportion of cases per model falling into a specific factuality category, with models ordered by descending percentage. **(a)** Hallucinations: Cases in which the provided context was relevant, but the model still generated an incorrect response (context = 1, response = 0). **(b)** Context irrelevance tolerance: Cases where the model produced a correct response despite the retrieved context being unhelpful or irrelevant (context = 0, response = 1). **(c)** Agentic correction: Instances where the zero-shot response was incorrect but the Agentic strategy successfully produced a correct response (zero-shot = 0, agentic = 1).

## 2.4. Very large LLMs show no benefit from retrieval augmentation

We next evaluated the effect of agentic retrieval on the largest LLMs in our study, comprising DeepSeek-R1, DeepSeek-V3, o3, Qwen 3-235B, and GPT-4-turbo, all likely to be exceeding 200 billion parameters. These models demonstrated strong performance under zero-shot prompting alone, achieving diagnostic accuracies ranging from 76% to 86% on the RadioRAG benchmark (**Table 2**). Neither conventional online RAG (P = 0.757) nor agentic retrieval (P = 0.299) led to meaningful improvements.

Across all five models, accuracy differences between the three inference strategies were minimal (see **Figure 4**). For example, DeepSeek-R1 performed at  $82\% \pm 4$  [95% CI: 74, 89] with zero-shot,  $80\% \pm 4$  [95% CI: 72, 88] with agentic retrieval, and  $79\% \pm 4$  [95% CI: 71, 87] with conventional online RAG; o3 improved marginally from  $86\% \pm 4$  [95% CI: 78, 92] to  $88\% \pm 3$  [95% CI: 81, 93] with agentic RAG; and Qwen3-235B and GPT-4-turbo showed ≤1% changes across conditions. DeepSeek-V3 showed slightly higher improvement (from  $76\% \pm 4$  [95% CI: 67, 84] to  $86\% \pm 4$  [95% CI: 78, 92]) but still not significant. Traditional RAG showed similarly negligible differences.

These findings indicate that very large LLMs can already handle complex radiology QA tasks with high accuracy without requiring external retrieval. This likely reflects their extensive pretraining on large-scale corpora, improved reasoning abilities, and domain-general coverage, diminishing the marginal value of either conventional or agentic retrieval augmentation in high-performing settings.

## 2.5. Agentic RAG yields consistent gains in mid-sized models

Mid-sized models, typically ranging between 17B and 110B parameters, represent a particularly relevant category for clinical deployment, offering a favorable trade-off between performance and computational efficiency. This group in our study included GPT-3.5-turbo, Llama 3.3-70B, Mistral Large, Qwen 2.5-70B, Llama 4 Scout 16E, Gemma-3-27B-it, and DeepSeek-R1-70B, Across this cohort, the conventional online RAG framework did not yield a statistically significant improvement in accuracy over zero-shot prompting (P = 0.253). In contrast, the agentic RAG framework significantly outperformed both zero-shot (P = 0.001) and traditional RAG (P = 0.002), suggesting that the benefits of agentic reasoning become more apparent in this model size range, where LLMs are strong enough to follow reasoning chains but may still benefit from structured multi-step guidance. While every model in this group showed an absolute improvement in diagnostic accuracy with the agentic system, for example, GPT-3.5-turbo improved from 57% to 68%, Llama 3.3-70B from 76% ± 4 [95% CI: 67, 84] to 83% ± 4 [95% CI: 75, 89], and Mistral Large from 72%  $\pm$  4 [95% CI: 63, 81] to 81%  $\pm$  4 [95% CI: 73, 88], none of these increases reached statistical significance when evaluated individually (see Figure 4). Nonetheless, the consistency of the improvements across models suggests a robust and reproducible trend that favors agentic retrieval strategies in this deployment-friendly tier.

Table 3: Hallucination and relevance metrics for agentic responses on the RadioRAG dataset (n = 104). "Context relevant" was evaluated at the dataset level: each question was labeled as having relevant or irrelevant retrieved context, and the same label was applied across all models (48/104 questions were judged to have clinically appropriate context). "Hallucination" refers to incorrect model answers despite relevant context. "Correct despite irrelevant context" captures correct answers when the retrieved context was not clinically useful. The final column reports the percentage of questions that were incorrect in zero-shot prompting but answered correctly using the agentic framework. Percentages and raw counts are shown per model.

Model name	Context relevant	Hallucination (relevant context, incorrect response)	Correct despite irrelevant context	Zero-shot incorrect → agentic correct
Ministral-8B	46% (48/104)	14% (15/104)	35% (36/104)	26% (27/104)
Mistral Large	46% (48/104)	6% (6/104)	40% (42/104)	12% (13/104)
Llama3.3-8B	46% (48/104)	17% (18/104)	37% (38/104)	12% (13/104)
Llama3.3-70B	46% (48/104)	6% (6/104)	42% (44/104)	11% (11/104)
Llama3-Med42-8B	46% (48/104)	11% (11/104)	39% (41/104)	16% (17/104)
Llama3-Med42-70B	46% (48/104)	7% (7/104)	39% (41/104)	12% (13/104)
Llama4 Scout 16E	46% (48/104)	5% (5/104)	39% (41/104)	9% (9/104)
DeepSeek R1-70B	46% (48/104)	5% (5/104)	38% (40/104)	8% (8/104)
DeepSeek R1	46% (48/104)	3% (3/104)	37% (38/104)	6% (6/104)
DeepSeek-V3	46% (48/104)	4% (4/104)	43% (45/104)	12% (13/104)
Qwen 2.5-0.5B	46% (48/104)	26% (27/104)	21% (22/104)	21% (22/104)
Qwen 2.5-3B	46% (48/104)	13% (14/104)	33% (34/104)	21% (22/104)
Qwen 2.5-7B	46% (48/104)	12% (12/104)	37% (38/104)	23% (24/104)
Qwen 2.5-14B	46% (48/104)	10% (10/104)	36% (37/104)	15% (16/104)
Qwen 2.5-70B	46% (48/104)	5% (5/104)	37% (38/104)	12% (13/104)
Qwen 3-8B	46% (48/104)	6% (6/104)	36% (37/104)	17% (18/104)
Qwen 3-235B	46% (48/104)	5% (5/104)	41% (43/104)	6% (6/104)
GPT-3.5-turbo	46% (48/104)	13% (14/104)	36% (37/104)	21% (22/104)
GPT-4-turbo	46% (48/104)	9% (9/104)	39% (41/104)	8% (8/104)
о3	46% (48/104)	2% (2/104)	43% (45/104)	3% (3/104)
MedGemma-4B-it	46% (48/104)	17% (18/104)	38% (39/104)	20% (21/104)
MedGemma-27B-text-it	46% (48/104)	3% (3/104)	38% (39/104)	15% (16/104)
Gemma-3-4B-it	46% (48/104)	20% (21/104)	36% (37/104)	25% (26/104)
Gemma-3-27B-it	46% (48/104)	7% (7/104)	37% (38/104)	20% (21/104)
Average	46% ± 0	9.4% ± 5.9	37.4% ± 4.2	14.6% ± 6.4

To further probe the relationship between model scale and accuracy, we conducted a targeted scaling experiment using the Qwen 2.5 model family, which spans a wide range of sizes (Qwen 2.5-70B, 14B, 7B, 3B, and 0.5B) while maintaining consistent architecture and training procedures. This allowed us to isolate the influence of model size from confounding variables such as instruction tuning or pretraining corpus. We computed Pearson correlation coefficients between model size and diagnostic accuracy for each inference strategy. All three methods including zero-shot (r = 0.68), traditional RAG (r = 0.81), and agentic RAG (r = 0.61) showed strong positive correlations with parameter count, reflecting the general performance advantage of larger models. However, as detailed in earlier findings, the relative benefit of retrieval strategies was not uniformly distributed: conventional RAG was most beneficial for small models, while agentic reasoning consistently enhanced performance in mid-sized models (see **Figure 4**). These findings highlight the importance of aligning retrieval strategies with model capacity and deployment constraints.

# 2.6. Agentic retrieval enhances performance in fine-tuned clinical models

To examine whether domain-specific fine-tuning diminishes the utility of retrieval-based strategies, we evaluated four clinically optimized language models: MedGemma-27B-text-it, MedGemma-4B-it, Llama3-Med42-70B, and Llama3-Med42-8B. These models are specifically fine-tuned for biomedical or radiological applications, making them suitable test cases for understanding the complementary role of agentic retrieval and reasoning. Despite already possessing clinical specialization, all four models exhibited improved diagnostic QA performance under the agentic framework. On average, accuracy increased from 67% ± 6 under zero-shot prompting to 75% ± 6 with agentic RAG (P = 0.001). Traditional online RAG, in contrast, did not show a significant improvement over zero-shot prompting (67%  $\pm$  9 vs. 67%  $\pm$  6, P = 0.704). Notably, agentic RAG also significantly outperformed traditional online RAG (P = 0.034), suggesting that structured multi-step reasoning contributes meaningfully even when baseline knowledge is embedded through fine-tuning. Each model in this group followed a similar pattern. For instance, MedGemma-27B-text-it improved from 71% ± 4 [95% CI: 62, 79] to 81% ± 4 [95% CI: 73, 88] with agentic inference, MedGemma-4B-it from 56% ± 5 [95% CI: 46, 65] to 66% ± 5 [95% CI: 57, 75], Llama3-Med42-70B from 72% ± 4 [95% CI: 63, 80] to 79% ± 4 [95% CI: 71, 87], and Llama3-Med42-8B from 67% ± 5 [95% CI: 58, 77] to 75% ± 4 [95% CI: 66, 84] (see Figure 4). While these individual gains were not statistically significant on their own, the collective improvement supports the hypothesis that retrieval-augmented reasoning provides additive benefits beyond those conferred by fine-tuning alone.

These results suggest that domain-specific fine-tuning and agentic reasoning serve complementary roles: fine-tuning equips the model with foundational knowledge, while the agentic framework enhances factual grounding, synthesis, and contextual accuracy through structured information-seeking behavior.

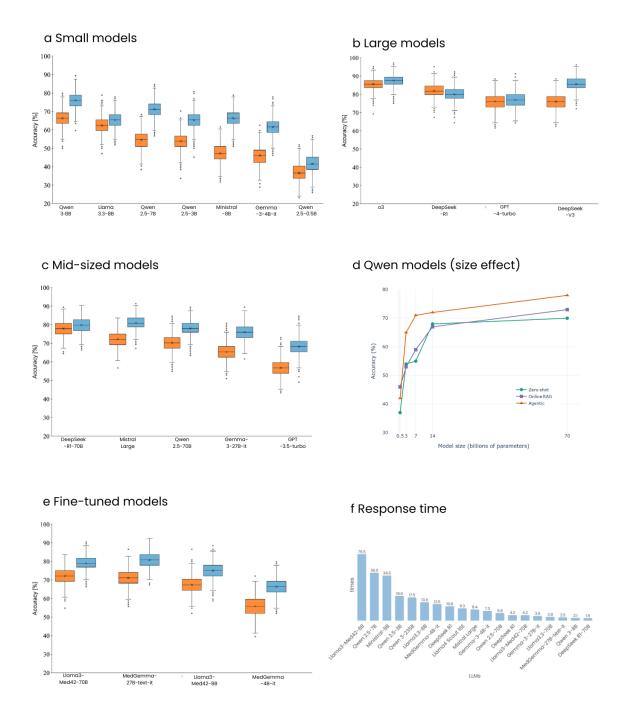


Figure 4. Comparative accuracy distributions and inference-time multipliers for zero-shot versus agentic strategies across model groups. Accuracy results are shown for (a) small-scale models (Ministral-8B, Gemma-3-4B-it, Qwen 2.5-7B, Qwen 2.5-3B, Qwen 2.5-0.5B, Qwen 3-8B, Llama 3-8B), (b) large models (DeepSeek-R1, DeepSeek-V3, o3, Qwen 3-235B, GPT-4-turbo), (c) mid-sized models (Mid-Sized Models: GPT-3.5-turbo, Llama 3.3-70B, Mistral Large, Qwen 2.5-70B, Llama 4 Scout 16E, Gemma-3-27B-it, DeepSeek-R1-70B), (d) across Qwen 2.5 family for different parameter sizes: Qwen 2.5-70B, 14B, 7B, 3B and 0.5B, and (e) medically fine-tuned models (MedGemma 27B-text-it, MedGemma 4B-it, Llama3-Med42-70B, Llama3-Med42-8B). (f) Distribution of agentic-to-zero-shot runtime multipliers (× slower/faster) across all models. Boxplots display accuracy (%) distributions (n = 1 000) for zero-shot (orange) and agentic (blue): boxes span Q1–Q3, central line is the median (Q2), whiskers extend to 1.5×IQR and dots mark outliers. Line chart shows mean accuracy versus model size for zero-shot (green), online RAG (orange) and agentic (purple) across Qwen 2.5 family.

# 2.7. Agentic retrieval increases response time but remains computationally tractable

To evaluate the computational impact of agentic reasoning, we measured and compared perquestion response times between zero-shot prompting and agentic RAG across all models using the RadioRAG benchmark. As shown in **Table 4**, agentic retrieval introduced a substantial latency overhead across all model groups, with the average response time increasing from  $54 \pm 28$  seconds under zero-shot prompting to  $324 \pm 270$  seconds under agentic inference, equivalent to a  $6.71\times$  increase.

As shown in Figure 4, this increase varied considerably by model group. Small-scale models (7-8B parameters), including Qwen 2.5-7B, Qwen3-8B, Llama3-Med42-8B, Llama3-Med42-8B, and Ministral-8B, showed a 6.04× average increase, with individual models ranging from modest (2.06× for Qwen3-8B) to substantial (35.98× for Qwen 2.5-7B). Mini models (3–4B parameters), such as Gemma-3-4B-it, MedGemma-4B-it, and Qwen 2.5-3B, exhibited the highest relative increase, averaging 11.10×, with Qwen2.5-3B peaking at 18.59×. In contrast, mid-sized models (~70B parameters), including DeepSeek-R1-70B, Llama-3.3-70B, Qwen 2.5-70B, and Llama3-Med42-70B, had a more moderate increase of 2.93x. This reflects a balance between computational capacity and the overhead introduced by iterative reasoning. For example, DeepSeek-R1-70B showed only a 1.87× increase. The large-model group (120–250B), including Qwen 3-235B, Mistral Large, and Llama4 Scout 16E, had the largest absolute latency, with a group average increase of 13.27×. Qwen3-235B showed the most pronounced jump, from 97 seconds to 1703 seconds per question. Despite high computational costs, these models showed only minimal diagnostic improvement with agentic reasoning, emphasizing a potential efficiencyperformance trade-off. Notably, the DeepSeek mixture of experts<sup>43</sup> (MoE) group (DeepSeek-R1 and DeepSeek-V3) exhibited relatively efficient scaling under agentic reasoning, with an average increase of 4.19×, suggesting that sparsely activated architectures may offer runtime advantages in multi-step retrieval tasks. Similarly, the Gemma-27B group (Gemma-3-27B-it and MedGemma-27B-text-it) demonstrated a low variance and consistent response time increase of 2.82x, indicating reliable timing behavior under agentic workflows.

Despite these increases, the absolute response times remained within feasible limits for many clinical applications. Furthermore, because evaluations were conducted under identical system conditions, the relative timing metrics provide a robust measure of computational scaling. These findings suggest that while the agentic RAG introduces additional latency, its time cost may be acceptable, especially in mid-sized and sparse-activation models depending on deployment requirements and accuracy demands.

Table 4: Response time comparison between zero-shot and the agentic method across model groups. Average per-question response times (n = 104) are reported in seconds as mean ± standard deviation for both individual models and aggregated model groups. A fixed overhead of 10,554.64 seconds per model, corresponding to context generation, was evenly distributed across all questions, contributing approximately 101.5 seconds per question. For time analysis, models were grouped based on parameter scale and architectural characteristics into six categories: the DeepSeek mixture of experts (MoE) group, the large model group (120–250B), the medium-scale group (~70B), the Gemma-27B group, the small model group (7–8B), and the mini model group (3–4B). "Absolute difference" denotes the increase in average response time per question introduced by the agentic method, and "Relative increase" refers to the ratio of mean agentic time to mean zero-shot time per group. Final statistics are computed at the group level.

Model / group name	Time					
Model / group name	Zero-shot (s)	Zero-shot (s) Agentic (s) Absolute difference (s		Relative increase (times)		
DeepSeek-V3 group	98.55 ± 53.58	412.7 ± 156.7	314.2 ± 141.6	4.2 x		
Large (120 – 250B) group	63.7 ± 29.4	845.1 ± 744.7	781.4 ± 715.2	13.3 x		
Llama4 Scout 16E	49.6 ± 24.6	462.3 ± 190.2	412.6 ± 169.7	9.3 x		
Mistral Large	43.9 ± 23.9	369.7 ± 142.0	325.8 ± 126.0	8.4 x		
Qwen 3-235B	97.5 ± 54.6	1703.3 ± 787.6	1605.8 ± 744.0	17.5 x		
Medium (≈ 70B) group	78.7 ± 51.4	230.58 ± 44.8	151.8 ± 34.3	2.9 x		
DeepSeek R1-70B	151.3 ± 83.4	282.8 ± 95.0	131.3 ± 68.3	1.9 x		
Llama3-Med42-70B	42.2 ± 22.4	177.0 ± 39.5	134.8 ± 27.9	4.2 x		
Llama3.3-70B	78.5 ± 43.6	216.7 ± 60.7	138.2 ± 34.7	2.8 x		
Qwen 2.5-70B	42.6 ± 22.2	245.7 ± 76.8	203.1 ± 58.5	5.8 x		
Gemma 27B group	75.8 ± 38.2	214.1 ± 54.9	138.3 ± 16.7	2.8 x		
Gemma-3-27B-it	48.8 ± 28.6	175.3 ± 37.4	126.5 ± 26.2	3.6 x		
MedGemma-27B-text-it	102.8 ± 56.1	253.0 ± 75.2	150.1 ± 38.4	2.5 x		
Small (7 – 8B) group	22.0 ± 39.9	132.9 ± 33.9	110.9 ± 9.3	6.0 x		
Llama3-Med42-8B	1.4 ± 0.7	108.0 ± 3.7	106.6 ± 3.3	76.5 x		
Llama3.3-8B	8.4 ± 4.0	116.3 ± 7.6	107.9 ± 4.6	13.9 x		
Ministral-8B	3.7 ± 2.2	124.9 ± 11.8	121.2 ± 10.4	34.0 x		
Qwen 2.5-70B	3.4 ± 1.6	122.8 ± 11.4	119.4 ± 10.4	36.0 x		
Qwen 3-8B	93.2 ± 53.4	192.3 ± 49.8	99.1 ± 33.9	2.1 x		
Mini (3 – 4B) group	11.4 ± 5.4	126.3 ± 6.3	114.9 ± 8.4	11.1 x		
Gemma-3-4B-it	17.5 ± 7.9	127.7 ± 13.1	110.2 ± 7.0	7.3 x		
MedGemma-4B-it	9.6 ± 5.4	119.4 ± 9.9	109.8 ± 9.1	12.5 x		
Qwen 2.5-3B	7.1 ± 3.7	131.7 ± 13.7	124.6 ± 11.0	18.6 x		
Average	53.7 ± 28.4	324.4 ± 270.2	271.2 ± 257.3	6.7 ± 4.1 x		

# 2.8. Agentic retrieval provides human-interpretable context and enables performance gains for expert radiologists

To better understand the source of diagnostic improvements conferred by the agentic framework, we conducted an additional experiment involving a board-certified radiologist (TTN) with seven years of experience in diagnostic and interventional radiology. As in previous evaluations, the expert first answered all 104 RadioRAG questions unaided, i.e., without access to external references or retrieval assistance, achieving an accuracy of  $51\% \pm 5$  [95% CI: 41, 62] (53/104). This baseline performance was significantly lower than that of 16 out of 24 evaluated LLMs in their zero-shot mode (P  $\leq$  0.017 for all), and not significantly different from 7 models, including GPT-3.5-turbo, Llama3.3-8B, Qwen 2.5-7B, Ministral-8B, MedGemma-4B-it, Gemma-3-4B-it, and Qwen 2.5-3B. Only Qwen 2.5-0.5B, the smallest model tested, performed significantly inferior to the radiologist (37%  $\pm$  5 [95% CI: 27, 46]; P = 0.044).

To isolate the contribution of retrieval independent of generative reasoning, we repeated the experiment with the same radiologist using the contextual reports retrieved by the agentic system, that is, the same Radiopaedia content supplied to the LLMs. With access to this structured evidence, the radiologist's accuracy increased to  $68\% \pm 5$  [95% CI: 60, 77] (71/104), a significant improvement over the unaided baseline (P = 0.010). This finding demonstrates that the agentic system successfully retrieves clinically meaningful and decision-relevant information, which can support human diagnostic accuracy even in the absence of language model synthesis.

When comparing the radiologist's context-assisted performance to that of the LLMs, only 1 out of 24 models significantly outperformed the radiologist under zero-shot conditions (o3; P = 0.018). In contrast, when compared to LLM performance under the full agentic framework, only 2 models, i.e., DeepSeek-V3 (P = 0.016) and o3 (P = 0.012) achieved statistically significant improvements over the context-assisted radiologist.

# 3. Discussion

In this study, we introduced an agentic RAG framework designed to enhance the performance, factual grounding, and clinical reliability of LLMs in radiology QA tasks. To the best of our knowledge, this is the first application of an agentic retrieval method in radiology, and our large-scale evaluation across 24 diverse LLMs, including different architectures, parameter scales, training paradigms, and clinical fine-tuning, represents one of the most comprehensive comparative analysis of its kind to date<sup>44</sup>. Our findings indicate that agentic retrieval can improve diagnostic accuracy relative to conventional zero-shot prompting and traditional RAG approaches, especially in small- to mid-sized models, while also reducing hallucinated outputs. However, the benefits of agentic retrieval were not uniformly observed across all models or scenarios, underscoring the need for careful consideration of model scale and characteristics when deploying retrieval-based systems.

A central finding of this study is that the effectiveness of retrieval strategies strongly depends on model scale. While traditional single-step online RAG16,18,21, and generally nonagentic RAG<sup>16,17,45,46</sup>, approaches have previously been shown to primarily benefit smaller models (<8 billion parameters) with diminishing returns at larger scales 16,18,21, our agentic framework expanded performance improvements into the mid-sized model range (approximately 17–150 billion parameters). Mid-sized models such as GPT-3.5-turbo, Mistral Large, and Llama3.3-70B have sufficient reasoning capabilities to follow structured logic but frequently struggle to independently identify and incorporate relevant external clinical evidence. By decomposing complex clinical questions into structured subtasks and iteratively retrieving targeted evidence, the agentic approach consistently improved accuracy across these mid-sized models, gains that conventional RAG did not achieve in this important segment. Similarly, smaller models also benefited from structured retrieval, overcoming some limitations associated with fewer parameters and less comprehensive pretraining. However, the magnitude of improvements varied between individual small-scale models, likely reflecting differences in architectural design, instruction tuning, and pretraining data. These results suggest that while agentic retrieval can broadly enhance performance across smaller and mid-sized models, model-specific optimizations may be required to fully capitalize on its potential.

In contrast, the largest evaluated models (more than 200 billion parameters), such as GPT-4-turbo, o3, DeepSeek-R1, and Qwen 3-235B exhibited minimal to no gains from either conventional or agentic retrieval methods. These models achieved high performance with zero-shot inference alone, suggesting that their extensive pretraining on large-scale and potentially clinically relevant data already equipped them with substantial internal reasoning capabilities and domain-specific knowledge. While retrieval augmentation offered limited incremental accuracy benefits at this scale, it may still provide value in clinical practice by enhancing transparency, auditability, and alignment with established documentation standards. Future studies should explore whether agentic retrieval can improve interpretability and traceability of decisions made by these high-capacity models, even when accuracy alone does not increase significantly.

To further examine the relationship between model scale and retrieval benefit, we conducted a controlled scaling analysis using the Qwen 2.5 model family. This approach, which held architecture and training constant, revealed a strong positive relationship between model size and diagnostic accuracy across all tested inference strategies<sup>47,48</sup>. Nevertheless, the optimal retrieval approach varied: traditional single-step RAG offered the greatest advantage for smaller models, whereas agentic retrieval consistently enhanced mid-sized model performance. These results highlight the importance of aligning retrieval strategies with the intrinsic reasoning capacity of individual models, emphasizing tailored rather than universal implementation of retrieval augmentation.

A key consideration in clinical applications is whether domain-specific fine-tuning reduces the necessity or utility of external retrieval. Clinically specialized LLMs, such as variants of MedGemma and Llama3-Med42, are increasingly available and presumed to contain embedded medical knowledge sufficient for diagnostic tasks<sup>6</sup>. However, our results show that even these fine-tuned models consistently benefited from agentic retrieval, whereas traditional single-step RAG provided little additional improvement. The additive benefit of agentic retrieval in fine-tuned models suggests that structured, case-specific external evidence complements internal

knowledge by providing context-sensitive, up-to-date information. Thus, agentic retrieval and clinical fine-tuning should be viewed as complementary strategies, jointly optimizing model performance and reliability rather than being seen as mutually exclusive.

Beyond accuracy, our analysis demonstrated that agentic retrieval improved factual grounding<sup>6,14</sup> and reduced hallucinations in model outputs. By systematically associating diagnostic responses with specific retrieved content from Radiopaedia.org<sup>19</sup>, the framework promoted evidence-based reasoning, which is critical in safety-sensitive applications like radiology. Although clinically relevant evidence was retrieved in less than half of the evaluated cases, most models successfully leveraged this content to produce factually correct responses when it was available. Larger and clinically tuned models demonstrated robustness by correctly responding even when retrieved evidence was irrelevant or insufficient, likely relying on internal knowledge<sup>15</sup>. However, such internally derived answers, while accurate, lack explicit grounding in external sources, raising potential concerns for interpretability and clinical accountability<sup>49</sup>. Smaller models were less resilient when retrieval failed, highlighting their greater reliance on structured external support. Consequently, ensuring high-quality retrieval remains paramount, especially for deployment scenarios where transparency and traceability of decisions are required.

The increased diagnostic reliability introduced by agentic retrieval came at a computational cost. Response times significantly increased compared to zero-shot inference due to iterative query refinement, structured evidence gathering, and multi-agent coordination. This latency varied substantially by model size and architecture, with smaller models experiencing the largest relative increases, and mid-sized or sparsely activated architectures demonstrating comparatively moderate overhead. Very large models, although capable of achieving high accuracy without retrieval, experienced substantial absolute latency increases without commensurate accuracy gains. Future work should therefore explore optimization strategies to manage computational overhead, such as selective retrieval triggering, parallel evidence pipelines, or methods to distill agentic reasoning into more efficient inference paths.

Furthermore, agentic retrieval demonstrated value as a decision-support tool for human experts. Providing a board-certified radiologist with the same retrieved context as the agentic system substantially improved their diagnostic accuracy compared to unaided performance. This finding illustrates that the agentic retrieval process successfully identified and presented clinically meaningful, decision-relevant evidence that directly supported expert reasoning. The limited number of LLMs significantly outperforming the context-assisted radiologist further underscores the complementary strengths of human expertise and agentically retrieved information. Thus, agentic retrieval may serve dual purposes in clinical environments, simultaneously enhancing LLM performance and providing interpretable, actionable evidence to clinicians.

Our study has several important limitations. First, our evaluation relied exclusively on Radiopaedia.org, a trusted but singular radiology knowledge source. Dependence on a single data provider can restrict retrieval coverage and may not represent the full breadth of available radiological information. Incorporating multiple authoritative sources, structured knowledge bases, or clinical ontologies could improve the generalizability and relevance of retrieved content. Second, although rigorous, our benchmark dataset comprised a relatively limited number of

expert-curated radiology questions (n=104). While these questions spanned diverse subspecialties and were carefully constructed, larger and more varied datasets encompassing broader clinical scenarios, different imaging modalities, and increased diagnostic complexity are required to fully assess the robustness and effectiveness of agentic retrieval frameworks. Third, the agentic retrieval process incurs significant computational overhead, substantially increasing response times compared to conventional zero-shot prompting and traditional single-step RAG. Although response durations remained within feasible limits for non-emergent clinical use cases, the practicality of the proposed method in time-sensitive settings (e.g., acute diagnostic workflows) remains uncertain. Future research should explore optimization techniques, such as parallelization or selective agent activation, to mitigate latency without sacrificing diagnostic accuracy or reasoning quality. Fourth, our evaluation relied on retrospective, static radiology QA items drawn from the recently published RSNA-RadioQA and ExtendedQA datasets. These datasets were curated and released shortly before our study, lowering the likelihood that included items appeared in model pretraining. However, despite their clinical rigor, such benchmark-style questions do not fully capture the complexity of real-world radiology workflows, which often involve evolving diagnostic contexts, iterative communication, and integration of multimodal imaging data. Our results therefore reflect performance in a controlled QA setting rather than in live clinical environments. Future work should evaluate agentic retrieval under prospective, clinically embedded conditions, such as within reporting workflows or decision support systems to better understand its utility in practice. Fifth, despite evaluating a broad range of LLM architectures, parameter scales, and training paradigms, we observed substantial variability in the diagnostic gains attributable to agentic retrieval across individual models. This likely reflects a combination of factors, including architectural differences, instruction tuning approaches, and pretraining data composition, as well as implementation-specific elements such as prompt design and agent orchestration. Because the agentic pipeline relies on structured prompting and task decomposition, its performance may be sensitive to changes in phrasing, retrieval heuristics, or agent coordination. Future work should systematically investigate both model-level and implementation-level sources of variability to develop more robust, generalizable retrieval strategies tailored to different model configurations.

This study presents a proof-of-concept for an agentic retrieval framework capable of enhancing diagnostic accuracy, factual reliability, and clinical interpretability of LLMs in radiology QA tasks. Our extensive, large-scale analysis of 24 diverse models highlights the complex relationships between retrieval strategy, model scale, and clinical fine-tuning. While agentic retrieval shows clear promise, particularly for mid-sized and clinically optimized models, future research is essential to refine retrieval mechanisms, mitigate computational overhead, and validate these systems across broader clinical contexts. As generative AI continues to integrate into medical practice, frameworks emphasizing transparency, evidence-based reasoning, and human-aligned interpretability, such as the agentic approach introduced here, will become increasingly critical for trustworthy and effective clinical decision support.

# 4. Materials and Methods

## 4.1. Ethics statement

The methods were performed in accordance with relevant guidelines and regulations. The data utilized in this research was sourced from previously published studies. As the study did not involve human subjects or patients, it was exempt from institutional review board approval and did not require informed consent.

## 4.2. Dataset

This study utilized a combination of two carefully curated datasets specifically designed to evaluate the performance of agentic LLMs in retrieval-augmented radiology QA.

We utilized two previously published datasets from the RadioRAG study<sup>18</sup>: the RSNA-RadioQA<sup>18</sup> and ExtendedQA<sup>18</sup> datasets. The RSNA-RadioQA dataset consists of 80 radiology questions derived from peer-reviewed cases available in the Radiological Society of North America (RSNA) Case Collection. This dataset covers 18 radiologic subspecialties, including breast imaging, chest radiology, gastrointestinal imaging, musculoskeletal imaging, neuroradiology, and pediatric radiology, among others. Each subspecialty contains at least five questions, carefully crafted from clinical histories and imaging descriptions provided in the original RSNA case documentation. Differential diagnoses explicitly listed by original case authors were excluded to avoid biasing model responses. Images were intentionally excluded. Detailed characteristics, including patient demographics and subspecialty distributions, have been previously published and are publicly accessible. The ExtendedQA dataset consists of 24 unique, radiology-specific questions initially developed and validated by board-certified radiologists with substantial diagnostic radiology experience (5–14 years). These questions reflect realistic clinical diagnostic scenarios not previously available online or included in known LLM training datasets. The final RadioRAG dataset used in this study subsequently contains 104 questions combining both RSNA-RadioQA and ExtendedQA.

## 4.2.1. Dataset postprocessing

To ensure consistent evaluation across all models and inference strategies, we applied structured preprocessing to the original RadioRAG dataset, particularly the ExtendedQA portion (n=24), which was initially formatted as open-ended questions.

All questions from the RSNA-RadioQA dataset (n=80) were left unchanged. However, for the ExtendedQA subset, each question was first converted into a multiple-choice format while preserving the original stem and correct answer. To standardize the evaluation across both RSNA-RadioQA and ExtendedQA, we then generated three high-quality distractor options for

every question in the dataset (n = 104), resulting in a total of four answer choices per item. Distractors were generated using OpenAl's GPT-40 and o3 models, selected for their ability to produce clinically plausible and contextually challenging alternatives. Prompts were designed to elicit difficult distractors, including common misconceptions, closely related entities, or synonyms of the correct answer. This ensured that diagnostic complexity was maintained across all questions. A representative prompt used for distractor generation was:

"I have a dataset of radiology questions that are currently open-ended, each with a correct answer provided. I want to transform these into multiple-choice questions (MCQs) by generating four answer options per question (one correct answer + three distractors). The distractors should be plausible and the level of difficulty must be high. If possible, include distractors that are synonyms, closely related concepts, or common misconceptions related to the correct answer."

**Supplementary Table 1** summarizes the characteristics of the datasets used in this study. The original RSNA-RadioQA questions are publicly available through their original publication <sup>18</sup>.

## 4.3. Experimental Design

### 4.3.1. System architecture

The experimental design centers on an agentic retrieval and reasoning framework adapted from LangChain's Open Deep Research pipeline, specifically tailored for radiology QA tasks. As illustrated in **Figure 1**, the pipeline employs a structured, multi-agent workflow designed to produce comprehensive, evidence-based diagnostic reports for each multiple-choice question. The reasoning and content-generation process is powered by OpenAl's GPT-4o-mini model, selected for its proficiency in complex reasoning tasks, robust instruction-following, and effective tool utilization. The architecture consists of two specialized agents: (i) a supervisor agent and (ii) a research agent, coordinated through a stateful directed graph framework. State management within this directed graph framework ensures that all steps in the workflow remain consistent and coordinated. The system maintains a shared memory state, recording the research plan, retrieved evidence, completed drafts, and all agent interactions, enabling structured progression from planning through final synthesis.

## 4.3.2. Agentic preprocessing

To enable structured, multi-step reasoning in the agentic retrieval framework, we implemented a preprocessing step focused on diagnostic abstraction. For each question in the RadioRAG dataset, we used the Mistral Large model to generate a concise, comma-separated summary of key clinical concepts. This step was designed to extract the essential diagnostic elements of each question while filtering out rhetorical structure, instructional phrasing (e.g., "What is the most likely

diagnosis?"), and other non-clinical language. These keyword summaries served exclusively as internal inputs to guide the agentic system's retrieval process and were not shown to the LLMs as part of the actual question content. The intent was to ensure retrieval was driven by the clinical essence of the question rather than superficial linguistic cues. The prompt used for keyword extraction was:

"Extract and summarize the key clinical details from the following radiology question. Provide a concise, comma-separated summary of keywords and key phrases in one sentence only.

Question: {question\_text}. Summary:"

### 4.3.3. Agent roles and responsibilities

The workflow is coordinated primarily by two agents, each with distinct responsibilities: (i) supervisor agent and (ii) research agent. The supervisor acts as the central orchestrator of the pipeline. Upon receiving a question, the supervisor reviews the diagnostic keywords and multiple-choice options, then formulates a structured research plan dividing the task into clearly defined sections, one for each diagnostic option. This agent assigns tasks to individual research agents, each responsible for exploring a single diagnostic choice. Throughout the process, the supervisor ensures strict neutrality, focusing solely on evidence gathering rather than advocating for any particular option. After research agents complete their tasks, the supervisor synthesizes their outputs into a final report, utilizing specialized tools to generate an objective introduction and conclusion.

Each research agent independently conducts an in-depth analysis focused on one diagnostic option. Beginning with a clear directive from the supervisor, the research agent employs a structured retrieval strategy to obtain relevant evidence. This involves an initial focused query using only essential terms from the diagnostic option, followed by contextual queries combining these terms with clinical features from the question stem (e.g., imaging findings or patient demographics). If retrieval results are inadequate, the agent adaptively refines queries by simplifying terms or substituting synonyms. In cases where sufficient evidence is not available after four attempts, the agent explicitly documents this limitation. All retrieval tasks utilize Radiopaedia.org exclusively, ensuring clinical accuracy and reliability. After completing retrieval, the research agent synthesizes findings into a structured report segment, explicitly highlighting both supporting and contradicting evidence. Each segment includes clearly formatted citations linking directly to source materials, ensuring transparency and verifiability.

### 4.3.4. Retrieval and writing tools

To facilitate structured retrieval and writing processes, the pipeline utilizes a suite of specialized computational tools dynamically selected based on specific task requirements: (i) search tool, (ii) report structuring tools, and (iii) content generation tool. In the following, details of each tool is explained.

The retrieval mechanism is powered by a custom-built search tool leveraging a locally hosted instance of SearXNG, a privacy-oriented meta-search engine deployed within a containerized Docker environment. This setup ensures consistent and reproducible search results. To maintain quality and clinical reliability, the search tool restricts results exclusively to content from Radiopaedia.org through a two-layer filtering process: first by appending a "site:radiopaedia.org" clause to all queries, and subsequently by performing an explicit domain check on all retrieved results. Raw results are deduplicated and formatted into markdown bundles suitable for seamless integration into subsequent reasoning steps.

The supervisor agent employs specific tools to structure the diagnostic report systematically. An initial Sections tool is used to outline the report into distinct diagnostic sections, aligning precisely with the multiple-choice options. Additional specialized tools generate standardized Introduction and Conclusion sections: the Introduction tool summarizes essential clinical details from the question, and the Conclusion tool objectively synthesizes findings from all diagnostic sections, emphasizing comparative diagnostic considerations without bias.

The research agent utilizes a dedicated Section writing tool to construct standardized report segments. Each segment begins with a concise synthesis of retrieved evidence, followed by interpretive summaries clearly identifying points supporting and contradicting each diagnostic choice. Citations are integrated inline, referencing specific Radiopaedia<sup>19</sup> URLs for traceability.

### 4.3.5. Report assembly and persistence

Upon completion of individual research segments, the supervisor agent compiles the final diagnostic report, verifying the completeness and quality of all sections. The resulting structured report, including introduction, detailed analysis of diagnostic options, and conclusion, is then immediately persisted in a robust manner. Reports are streamed incrementally into newline-delimited JSON (NDJSON) format, preventing data loss in case of interruptions. This storage method supports efficient resumption by checking previously completed entries, thus avoiding redundant processing. After processing all questions within a given batch, individual NDJSON entries are consolidated into a single comprehensive JSON file, facilitating downstream analysis and evaluation.

## 4.4. Baseline comparison systems

Each model was evaluated under three configurations: (i) zero-shot prompting (conventional QA), (ii) traditional online RAG<sup>18</sup>, and (iii) our proposed agentic retrieval framework.

### 4.4.1. Baseline 1: Zero-shot prompting pipeline

In the zero-shot prompting baseline, models received no external retrieval assistance or context. Instead, each model was presented solely with the multiple-choice questions from the RadioRAG

dataset (question stem and four diagnostic options) and prompted to select the correct answer based entirely on their pre-trained knowledge. Models generated their responses autonomously without iterative feedback, reasoning prompts, or additional information.

The exact standardized prompt used for this configuration is provided below:

"You are a highly knowledgeable medical expert. Below is a multiple-choice radiology question. Read the question carefully. Provide the correct answer by selecting the most appropriate option from A, B, C, or D.

Question: {question}

Options: {options}"

#### 4.4.2. Baseline 2: Traditional online RAG pipeline

The traditional online RAG baseline was implemented following a state-of-the-art non-agentic retrieval framework previously developed for radiology question answering by Arasteh et al<sup>18</sup>. The system employs GPT-3.5-turbo to automatically extract up to five representative radiology keywords from each question, optimized experimentally to balance retrieval quality and efficiency. These keywords were used to retrieve relevant articles from Radiopaedia.org, with each article segmented into overlapping chunks of 1,000 tokens. Chunks were then converted into vector embeddings (OpenAl's text-embedding-ada-002) and stored in a temporary vector database. Subsequently, the embedded original question was compared against this database to retrieve the top three matching text chunks based on cosine similarity. These retrieved chunks served as external context provided to each LLM alongside the original multiple-choice question. Models were then instructed to answer concisely based solely on this context, explicitly stating if the answer was unknown.

The exact standardized prompt used for this configuration is provided below:

"You are a highly knowledgeable medical expert. Below is a multiple-choice radiology question accompanied by relevant context (report). First, read the report, and then the question carefully. Use the retrieved context to answer the question by selecting the most appropriate option from A, B, C, or D. Otherwise, if you don't know the answer, just say that you don't know.

Report: {report} Question: {question} Options: {options}"

## 4.5. Evaluation

SW, JS, TTN, and STA performed model evaluations. We assessed both small and large-scale LLMs using responses generated between July 1–27, 2025. For each of the 104 questions in the RadioRAG benchmark dataset, models were integrated into a unified evaluation pipeline to ensure consistent testing conditions across all settings. The evaluation included 24 LLMs: Llama3.3-8B<sup>37,38</sup>, Llama3.3-70B<sup>37,38</sup>, Ministral-8B, Mistral Large, Llama3-Med42-8B<sup>35</sup>, Llama4 Scout 16E<sup>33</sup>, DeepSeek R1-70B<sup>36</sup>, DeepSeek-R1<sup>36</sup>, Llama3-Med42-70B<sup>35</sup>, DeepSeek-V3<sup>39</sup>, Qwen 2.5-0.5B<sup>33</sup>, Qwen 2.5-3B<sup>33</sup>, Qwen 2.5-7B<sup>33</sup>, Qwen 2.5-14B<sup>33</sup>, Qwen 2.5-70B<sup>33</sup>, Qwen 3-8B<sup>40</sup>, Qwen 3-235B<sup>40</sup>, GPT-3.5-turbo, GPT-4-turbo<sup>8</sup>, o3, MedGemma-4B-it<sup>34</sup>, MedGemma-27B-text-it<sup>34</sup>, Gemma-3-4B-it<sup>41,42</sup>, and Gemma-3-27B-it<sup>41,42</sup>. These models span a broad range of parameter scales (from 0.5B to over 670B), training paradigms (instruction-tuned, reasoning-optimized, clinically aligned, and general-purpose), and access models (open-source, open-weights, or proprietary). They also reflect architectural diversity, including dense transformers and MoE<sup>43</sup> systems. Full model specifications, including size, category, accessibility, knowledge cutoff date, context length, and developer are provided in Table 1.

### 4.5.1. Accuracy assessment

Accuracy was determined by comparing each LLM's response to the correct option. We used Mistral Large as an automated adjudicator for this process. For each multiple-choice question, both the LLM's response and the correct answer (including its corresponding letter and option) were provided to Mistral Large via a standardized prompt. Mistral Large was instructed to respond "Yes" if the correct answer was present in the model's response, either explicitly or as a clear component of the explanation, even if the phrasing differed. Otherwise, it was instructed to respond "No." A "Yes" was scored as 1 (correct), and a "No" was scored as 0 (incorrect), ensuring a consistent and unbiased measure of diagnostic accuracy.

The exact standardized prompt used for this configuration is provided below:

"You are a highly knowledgeable medical expert. Determine whether the Correct Answer appears within the LLMs response, fully or as a clear part of the explanation, even if the wording differs. Respond with 'Yes' if the Correct Answer can be found in the LLMs response; otherwise respond with 'No'.

LLMs response: {|llms\_response} Correct Answer: {correct\_answer}"

### 4.5.2. Factuality assessment

To evaluate the factual reliability of model outputs under the agentic retrieval framework, we conducted a targeted hallucination analysis across all 104 questions in the RadioRAG benchmark<sup>18</sup>. This analysis aimed to differentiate model errors due to flawed reasoning from those caused by insufficient or irrelevant evidence, and to assess the extent to which final answers were grounded in the retrieved context.

Each agentic response was reviewed by a board-certified radiologist (TTN) with seven years of experience in diagnostic and interventional radiology. For every question, the following three criteria were assessed: (i) whether the retrieved Radiopaedia context was clinically relevant to the question, (ii) whether the model's final answer was consistent with that context, and (iii) whether the final answer was factually correct.

Context was classified as clinically relevant only if it contained no incorrect or off-topic content with respect to the diagnostic question. This strict definition ensured that relevance was not based on superficial keyword overlap but on the actual clinical utility of the content. Retrievals were deemed relevant only when the retrieved material included appropriate imaging findings, clinical clues, or differential diagnoses applicable to the question stem.

Hallucinations were defined as cases in which the model produced an incorrect answer despite being provided with clinically relevant context. These represent failures of reasoning or synthesis rather than of retrieval. Given the high-stakes nature of radiologic diagnosis, identifying such errors is essential for understanding model reliability and safety.

We also documented instances where models answered questions correctly despite being supplied with irrelevant or unhelpful context. These "correct despite irrelevant context" cases reflect scenarios in which the model relied on internal knowledge rather than external grounding. While not classified as hallucinations, these responses raise questions about the transparency, traceability, and consistency of model behavior in the absence of meaningful retrieval.

#### 4.5.3. Time analysis

To evaluate the computational cost associated with agentic reasoning, we measured per-question response times for both zero-shot prompting and the agentic retrieval framework using the 104-question RadioRAG benchmark. Timing logs were collected from structured output directories for each model. A fixed initialization overhead of 10,554.6 seconds per model, arising from the context construction phase unique to agentic inference, was distributed uniformly across all questions, resulting in an adjusted time increase of approximately 101.5 seconds per question.

To ensure robust comparison and mitigate the influence of extreme values, outlier durations were handled using the Tukey method<sup>50</sup>. Specifically, any response time that exceeded the typical upper range, defined as values greater than the third quartile by more than 1.5 times the interquartile range, was considered an outlier and replaced with the mean of the remaining non-outlier values for that model and inference strategy. For each model, we computed the mean

and standard deviation of response times under both conditions. Additionally, we calculated the absolute difference in average response time per question and the relative increase, defined as the ratio of mean agentic response time to mean zero-shot response time.

To contextualize timing behavior across a heterogeneous model set, we grouped models according to both parameter scale and architectural characteristics. This grouping approach reflected the practical computational load of each model more accurately than parameter count alone. Six distinct groups were defined: (i) the DeepSeek MoE group, including DeepSeek-R1 and DeepSeek-V3; (ii) the large model group (120–250 billion parameters), including Qwen 3-235B, Mistral Large, and Llama4 Scout 16E; (iii) the medium-scale group (~70B), comprising DeepSeek R1-70B, Llama3.3-70B, Qwen2.5-70B, and Llama3-Med42-70B; (iv) the Gemma-27B group, containing Gemma-3-27B-it and MedGemma-27B-text-it; (v) the small model group (7–8B), including Qwen 2.5-70B, Qwen3-8B, Llama3-Med42-8B, Llama3.3-8B, and Ministral-8B; and (vi) the mini model group (3–4B), consisting of Gemma-3-4B-it, MedGemma-4B-it, and Qwen 2.5-3B. Group-level averages and standard deviations were calculated across constituent models and are reported in **Table 4**.

All timing evaluations were performed under identical system conditions to ensure fair comparisons. While absolute response times may vary with hardware and load, the relative increases provide a stable and interpretable metric for assessing the computational implications of agentic retrieval.

#### 4.5.4. Human evaluation

To benchmark LLM performance against domain expertise, we conducted a human evaluation involving a board-certified radiologist (TTN) with seven years of experience in diagnostic and interventional radiology. The evaluation followed a two-phase design to mirror the LLM configurations.

In the first phase, the radiologist answered all 104 questions from the RadioRAG benchmark without any external assistance, analogous to zero-shot prompting. The expert was blinded to the LLM responses, dataset construction process, and reference standard answers. Responses were recorded as final, and no additional time or information resources were permitted during this phase.

In the second phase, we aimed to isolate the contribution of the agentic retrieval component, independent of generative reasoning. For this, the same radiologist was provided with the contextual evidence retrieved by the agentic system for each question, the same Radiopaedia excerpts that were used as inputs for LLM agentic inference. The radiologist answered the same 104 questions again, this time using the retrieved context as decision support, without access to the original question-answer pairs or their previous responses. The format and presentation of the contextual evidence were identical to what the LLMs received during agentic inference, ensuring comparability.

This design enabled us to disentangle the effects of information retrieval from language model reasoning, by comparing unaided radiologist performance, radiologist performance with context, and agentic LLM outputs under standardized conditions. Accuracy was computed using the same evaluation criteria applied to LLMs. Statistical comparisons between human and model responses were performed using McNemar's test on paired question-level outcomes. Confidence intervals and p-values were adjusted for multiple comparisons using the false discovery rate.

## 4.6. Statistical analysis

Statistical analysis was performed using Python v3.11 with SciPy v1.10, NumPy v1.25.2, and statsmodels v0.14.5 packages. For each dataset, bootstrapping with 1,000 redraws was used to estimate means, standard deviations, and 95% confidence intervals (CI)<sup>51</sup>. A strictly paired design ensured identical redraws across conditions<sup>52</sup>. To assess statistical significance of pairwise method comparisons across all LLMs, exact McNemar's test<sup>53</sup> (based on the binomial distribution) was applied to each model individually. Resulting p-values were corrected for multiple comparisons using the false discovery rate, with a significance threshold of 0.05. For group-level comparisons between inference strategies (e.g., zero-shot vs. agentic RAG), paired two tailed t-tests were used to compare average accuracy across models. To explore the relationship between model size and performance, Pearson correlation coefficients were computed between parameter counts and accuracy values within the Qwen 2.5 model family, separately for each inference strategy.

## 4.7. Data availability

All data are available via either the original RadioRAG publication<sup>18</sup>.

## 4.8. Code availability

All source code, configurations, and parameters used in this work are publicly available. The agentic RAG pipeline, developed in **Python** 3.11, is available at: https://github.com/sopajeta/agentic-rag. Our implementation relies on several key frameworks and tools. We used LangChain Open Deep Research (https://github.com/langchain-ai/deepresearch) for experimental agent modules, LangChain v0.3.25 (https://github.com/langchainai/langchain) for orchestration and agent management, and LangGraph v0.4.1 (https://github.com/langchain-ai/langgraph) to support multi-step control flow and task decomposition. Model access and embedding generation were handled via the OpenAl Python SDK v1.77.0 (https://platform.openai.com). The SearxNG metasearch engine (https://github.com/searxng/searxng) was also deployed via Docker v25.0.2 (https://www.docker.com) and used for online web retrieval.

The traditional online RAG pipeline is hosted at <a href="https://github.com/tayebiarasteh/RadioRAG">https://github.com/tayebiarasteh/RadioRAG</a>, which relies on the LangChain v0.1.0, Chroma (<a href="https://www.trychroma.com">https://www.trychroma.com</a>) for vector storage, and the OpenAl API v1.12 for embeddings. All locally deployed language models sourced from Hugging Face, were assessed and used between July 1–27, 2025, and are explicitly listed below, with corresponding URLs:

- Qwen 2.5-0.5B: https://huggingface.co/Qwen/Qwen2.5-0.5B
- Qwen 2.5-3B: https://huggingface.co/Qwen/Qwen2.5-3B
- Qwen 2.5-7B: https://huggingface.co/Qwen/Qwen2.5-7B
- Qwen 2.5-14B: https://huggingface.co/Qwen/Qwen2.5-14B
- Qwen 2.5-70B: https://huggingface.co/Qwen/Qwen2.5-72B
- Qwen 3-8B: https://huggingface.co/Qwen/Qwen3-8B
- Qwen 3-235B: https://huggingface.co/Qwen/Qwen3-235B-A22B
- Llama 3.3-8B: <a href="https://huggingface.co/meta-llama/Meta-Llama-3-8B">https://huggingface.co/meta-llama/Meta-Llama-3-8B</a>
- Llama 3.3-70B: https://huggingface.co/meta-llama/Llama-3.3-70B-Instruct
- Llama 3-Med42-70B: https://huggingface.co/m42-health/Llama3-Med42-70B
- Llama 3-Med42-8B: https://huggingface.co/m42-health/Llama3-Med42-8B
- Llama4 Scout 16E: https://huggingface.co/meta-llama/Llama-4-Scout-17B-16E
- Mistral Large: <a href="https://huggingface.co/mistralai/Mistral-Large-Instruct-2407">https://huggingface.co/mistralai/Mistral-Large-Instruct-2407</a>
- Ministral 8B: https://huggingface.co/mistralai/Ministral-8B-Instruct-2410
- Gemma-3-4B-it: <a href="https://huggingface.co/google/gemma-3-4b-it">https://huggingface.co/google/gemma-3-4b-it</a>
- Gemma-3-27B-it: https://huggingface.co/google/gemma-3-27b-it
- Medgemma-4B-it: https://huggingface.co/google/medgemma-4b-it
- Medgemma-27B-text-it: <a href="https://huggingface.co/google/medgemma-27b-text-it">https://huggingface.co/google/medgemma-27b-text-it</a>
- DeepSeek-V3: https://huggingface.co/deepseek-ai/DeepSeek-V3
- DeepSeek-R1: https://huggingface.co/deepseek-ai/DeepSeek-R1
- DeepSeek-R1-70B: https://huggingface.co/deepseek-ai/DeepSeek-R1-Distill-Llama-70B

All LLMs were served using vLLM v0.9.0 (<a href="https://github.com/vllm-project/vllm">https://github.com/vllm-project/vllm</a>) with tensor parallelism set to the number of GPUs inside the node, except for models under 3 billion parameters, which were served without tensor parallelism.

## 4.9. Hardware

For the majority of experiments, particularly those involving standard LLMs, the computations were performed on GPU nodes equipped with Nvidia H100 and H200 accelerators. The H100 configuration consisted of four Nvidia H100 GPUs, each providing 94 GB of HBM2e memory and operating at a 500 W powerlimit. These GPUs were paired with two AMD EPYC 9554 "Genoa" processors based on the Zen 4 architecture, each offering 64 high-performance cores running at 3.1 GHz. The H200 configuration featured four Nvidia H200 GPUs, each offering 141 GB of high-bandwidth memory also at 500 W, coupled to the same dual AMD EPYC 9554 processor configuration. This combination of high-end Nvidia accelerators from NHR@FAU's Helma Cluster

(<u>https://doc.nhr.fau.de/clusters/helma/</u>) provided the necessary computational capabilities for inferencing the majority of the LLMs used during our experiments.

Experiments involving extremely large-scale architectures, such as the DeepSeek R1 or V3 model and other similarly demanding workloads, were executed on nodes equipped with AMD's MI300-series accelerators. In these cases, the MI300X configuration was utilized, which combined a dual-socket AMD EPYC 9474F platform with a total of 96 CPU cores and 2304 GiB of DDR5-5600 system memory, together with eight AMD Instinct MI300X accelerators. Each MI300X GPU offered 192 GiB of memory, enabling inference runs that required massive parameter counts and exceptional memory capacity (Deepseek R1 with 671 billion parameters). Additional experimentation also leveraged AMD Instinct MI300A nodes that integrate 24-core CPUs with unified on-package memory, with a total of 512 GiB shared across four accelerators. The hardware used in our experiments included a local machine with an Intel Pentium CPU with 2 cores and 8 GB Memory for consuming API endpoints.

# 5. Additional information

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## 5.2. Author contributions

The formal analysis was conducted by SW, JS, and STA. The original draft was written by STA, JS, and SW and edited by STA. JS developed the codes for analysis and pipeline; SW configured and maintained the LLM-serving infrastructure. The experiments were performed by SW and JS. The statistical analyses were performed by SW, JS, and STA. DT, TTN, KB, LA, MR, and STA provided clinical expertise. SW, JS, DT, ML, TTN, KB, MR, HK, GW, AM, and STA provided technical expertise. The study was defined by STA. All authors read the manuscript and agreed to the submission of this paper.

## 5.3. Competing interests

SW is partially employed by DATEV eG, Germany. DT received honoraria for lectures by Bayer, GE, Roche, AstraZeneca, and Philips and holds shares in StratifAl GmbH, Germany, and in Synagen GmbH, Germany. ML is employed by Generali Deutschland Services GmbH, Germany and is an editorial board at European Radiology Experimental. KB and LA are trainee editorial boards at Radiology: Artificial Intelligence. AM is an associate editor at IEEE Transactions on Medical Imaging. STA is an editorial board at Communications Medicine and European Radiology Experimental, and a trainee editorial board at Radiology: Artificial Intelligence. The other authors do not have any competing interests to disclose.

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Supplementary Table 1: Characteristics of the RadioRAG dataset used in this study. The RadioRAG dataset combines RSNA-RadioQA and ExtendedQA, as introduced in the original RadioRAG study. Patient demographic information (age and sex) is based solely on the RSNA-RadioQA subset due to missing metadata in ExtendedQA. Each question may be assigned to multiple radiology subspecialties. \*Age and sex statistics reflect only the RSNA-RadioQA subset. \*Youngest patient was 2 days old. SD: Standard deviation; N/A: Not available.

Value	RadioRAG dataset	
Patient age [years]*  Median  Mean ± SD  Range	44 44 ± 21 (0**, 80)	
Patient sex [n (%)]* Total Female Male	80 (100%) 37 (46%) 43 (54%)	
Number of questions per subspecialty [n (%)]		
Total	104 (100%)	
Breast Imaging	10 (10%)	
Cardiac	10 (10%)	
Chest	20 (19%)	
СТ	35 (34%)	
Emergency Radiology	9 (9%)	
Gastrointestinal	18 (17%)	
Genitourinary	9 (9%)	
Head and Neck	10 (10%)	
MRI	27 (26%)	
Molecular Imaging	11 (11%)	
Musculoskeletal	20 (19%)	
Neuroradiology	11 (11%)	
Nuclear Medicine	13 (12%)	
Oncologic Imaging	16 (15%)	
Pediatric	8 (8%)	
Radiation Oncology	9 (9%)	
Ultrasound	10 (10%)	
Vascular Imaging	16 (15%)	

Supplementary Table 2: Agentic responses and retrieved sources for GPT-3.5-turbo on two RSNA-RadioQA questions. Full answers generated by GPT-3.5-turbo using the agentic framework for the first two questions of the RSNA-RadioQA dataset, along with the most relevant sources retrieved from Radiopaedia. Responses illustrate the model's reasoning and evidence grounding within the agentic pipeline.

Question identifier	LLM's (GPT-3.5-turbo) answer	Most relevant sources
RSNA-RadioQA-Q1	A: BI-RADS 4 - Suspicious abnormality requiring biopsy: BI-RADS 4 lesions are characterized by suspicious findings with an intermediate risk of malignancy. The presence of rim calcifications within a fat-containing mass raises concern for malignancy. Biopsy is generally recommended for BI-RADS 4 lesions, especially if calcifications are suspicious. B: BI-RADS 2 - Rim Calcifications: Rim calcifications in fat-containing masses are typically benign and classified as BI-RADS 2. These calcifications are often associated with benign processes like fat necrosis or oil cysts. The imaging features of a round, circumscribed fat-containing mass with rim calcifications align with a benign diagnosis. C: BI-RADS 3 - Probably benign finding: BI-RADS 3 category is designated for probably benign lesions with a low likelihood of malignancy. Fat-containing lesions with rim calcifications may fall into this category if they demonstrate typical benign features. Short-interval follow-up is recommended for BI-RADS 3 lesions to monitor for any interval changes. D: Oil cyst secondary to fat necrosis: Oil cysts are benign lesions resulting from fat necrosis, often following trauma or surgery. These cysts typically present as fat-containing masses with rim calcifications, consistent with the imaging findings described. The absence of a clear history of trauma or surgery does not exclude the possibility of an oil cyst. Conclude with a Final Answer: Based on the detailed analysis of the imaging findings and the differential diagnosis provided in the report, the most likely diagnosis for the 66-year-old female with a palpable right breast lump at 10 o'clock, characterized by a round, circumscribed fat-containing mass with rim calcifications on mammography, is: D: Oil cyst secondary to fat necrosis. Reasoning: The presence of a round, circumscribed fat-containing mass with rim calcifications in the absence of a clear history of trauma or surgery aligns with the typical imaging features of an oil cyst secondary to fat necrosis. Oil cysts are	https://radiopaedia.org/articles/breast-imaging-reporting-and-data-system-bi-rads-assessment-category-4, https://radiopaedia.org/cases/suspicious-breast-calcifications-bi-rads-4, https://radiopaedia.org/articles/fat-containing-breast-lesions, https://radiopaedia.org/articles/breast-calcifications, https://radiopaedia.org/cases/screening-mammography-rim-calcifications, https://radiopaedia.org/articles/breast-imaging-reporting-and-data-system-bi-rads-assessment-category-2, https://radiopaedia.org/articles/breast-imaging-reporting-and-data-system-bi-rads-assessment-category-3, https://radiopaedia.org/articles/breast-imaging-reporting-and-data-system-bi-rads-assessment-category-3, https://radiopaedia.org/articles/breast-imaging-reporting-and-data-system-bi-rads-2, https://radiopaedia.org/articles/breast-imaging-reporting-and-data-system-bi-rads-2, https://radiopaedia.org/articles/oil-cyst-breast
RSNA-RadioQA-Q2	A: Low-grade fibrosarcoma: Low-grade fibrosarcoma is a rare malignant mesenchymal tumor characterized by spindle cell morphology with a herringbone pattern. Immunohistochemical markers for fibrosarcoma often include vimentin positivity, but specific markers can vary. Betacatenin nuclear staining is typically absent in fibrosarcomas, which helps differentiate them from other entities. The absence of nuclear beta-catenin staining in the presented case suggests low-grade fibrosarcoma is less likely. B: Phyllodes tumor: Phyllodes tumors are rare fibroepithelial breast tumors with a biphasic pattern of epithelial and spindle cell stromal components. Betacatenin staining may show nuclear positivity in some cases, reflecting Wnt pathway activation. The clinical presentation of a rapidly growing breast mass in adult women aligns with the patient's characteristics. The presence of spindle cells with nuclear beta-catenin staining in the presented case supports the possibility of a phyllodes tumor. C: Metaplastic carcinoma: Metaplastic carcinoma is a rare primary breast malignancy with both epithelial and mesenchymal components. Beta-catenin expression patterns may show aberrant nuclear localization, associated with Wnt signaling pathway activation. The patient's history of prior radiation exposure aligns with a potential risk factor for metaplastic carcinoma.\( \text{Nn-} \) The spindle cell morphology and nuclear beta-catenin staining in the presented case could be consistent with metaplastic carcinoma. D: Breast fibromatosis: Breast fibromatosis is a rare benign but locally aggressive tumor characterized by spindle cell proliferation and strong nuclear beta-catenin staining. Clinical association with prior radiation exposure matches the patient's history. The spindle cell morphology and nuclear beta-catenin staining in the presented case are in line with breast fibromatosis. Final Answer: D: Breast fibromatosis. Summary of Reasoning: Considering the patient's high risk of breast malignancy due to BRIP1 mutation and pri	https://radiopaedia.org/articles/fibrosarcoma-of-the-breast, https://radiopaedia.org/cases/breast-sarcoma-2?lang=gb, https://radiopaedia.org/articles/phyllodes-tumour-1, https://radiopaedia.org/articles/metaplastic-breast-carcinoma, https://radiopaedia.org/cases/metaplastic-carcinoma-breast, https://radiopaedia.org/articles/fibromatosis-of-the-breast, https://radiopaedia.org/cases/desmoid-fibromatosis-of-the-breast

Supplementary Table 3: Zero-shot responses from GPT-3.5-turbo on the first 20 questions of the RSNA-RadioQA dataset. Model-generated answers are shown without retrieval augmentation or agentic reasoning. Responses reflect zero-shot inference using only the question text as input.

Question identifier	LLM's (GPT-3.5-turbo) answer
RSNA-RadioQA-Q1	The most likely diagnosis is a benign breast lesion, such as a lipoma or fibroadenoma, with associated calcifications.
RSNA-RadioQA-Q2	The most likely diagnosis is desmoid tumor (also known as aggressive fibromatosis).
RSNA-RadioQA-Q3	The most likely diagnosis is Cat Scratch Disease (CSD) with suppurative granulomatous lymphadenitis.
RSNA-RadioQA-Q4	The most likely diagnosis is bilateral invasive ductal carcinoma of the breast, ER positive, PR positive, and HER2 negative, with no lymph node involvement.
RSNA-RadioQA-Q5	The most likely diagnosis is pulmonary rhabdomyosarcoma.
RSNA-RadioQA-Q6	The most likely diagnosis is severe COVID-19 pneumonia.
RSNA-RadioQA-Q7	The most likely diagnosis is pulmonary lymphangioleiomyomatosis (LAM), a characteristic manifestation of Tuberous Sclerosis Complex (TSC).
RSNA-RadioQA-Q8	The most likely diagnosis is a patellar fracture.
RSNA-RadioQA-Q9	The most likely diagnosis is diverticulitis with associated pericolic inflammation and phlegmon formation.
RSNA-RadioQA-Q10	The most likely diagnosis is Hashimoto's thyroiditis.
RSNA-RadioQA-Q11	The most likely diagnosis is orbital sarcoidosis.
RSNA-RadioQA-Q12	The most likely diagnosis is epidural spinal hemangioma.
RSNA-RadioQA-Q13	The most likely diagnosis is a stress fracture of the left femoral neck.
RSNA-RadioQA-Q14	The most likely diagnosis is Kienböck's disease.
RSNA-RadioQA-Q15	The most likely diagnosis is a benign simple cyst of the liver.
RSNA-RadioQA-Q16	The most likely diagnosis is Giant Cell Tumor of Tendon Sheath (GCTTS).
RSNA-RadioQA-Q17	The most likely diagnosis is Alveolar soft part sarcoma (ASPS).
RSNA-RadioQA-Q18	The most likely diagnosis is patellar tendon avulsion fracture.
RSNA-RadioQA-Q19	The most likely diagnosis is benign complicated cysts, given the resolution of the mass with aspiration and the benign nature of the identified cysts on imaging.
RSNA-RadioQA-Q20	The most likely diagnosis is a retroperitoneal teratoma.