Investigating LLM Capabilities on Long Context Comprehension for Clinical Question Answering

Anonymous ACL submission

Abstract

Despite the impressive reported performance of Large Language Models (LLMs) on medical QA, evaluation still overrelies on multiple-choice and extractive settings primarily assessing textbook knowledge, with limited work on open-ended QA over patient records. We present a comprehensive study investigating LLM long-context (LC) comprehension on longitudinal, patient-centric EHRs across multiple datasets, models and metrics, covering extractive, multiple-choice, and open-ended generative QA under different context formulation and RAG settings. We reveal gains from larger and reasoning models with memorization in smaller ones. Hybrid RAG with reranking outperforms full EHR context across tasks, with chunk-based RAG benefiting single-note and hierarchical RAG complex multi-note reasoning. A question-category analysis further reveals where RAG and FC excel and struggle, with RAG falling behind in longitudinal reasoning. Our multi-faceted metric evaluation uncovers systematic failures pointing to the need for more reasoning-appropriate metrics.

1 Introduction

Large Language Models (LLMs) (Achiam et al., 2023; Grattafiori et al., 2024; Yang et al., 2024) perform impressively on medical tasks (Borgeaud et al., 2022; Nori et al., 2023), achieving superhuman scores on United States Medical Licensing Examination (USMLE)-style exam question-answering (QA) (Chen et al., 2023b; Tang et al., 2024; Pal and Sankarasubbu, 2024; Singhal et al., 2025). Yet evaluation is mostly based on multiple-choice QA (MCQA) (Liévin et al., 2024; Xiong et al., 2024; Chen et al., 2024b; Singhal et al., 2025) which doesn't reflect performance in complex tasks (Arias-Duart et al., 2025), such as open-ended medical QA (Sandeep Nachane et al., 2024). Furthermore, medical board exams designed to assess professional knowledge and decision-making rely primarily on textbook knowledge which is likely available during pre-training (Chen et al., 2025a). With the growing burden on clinicians (Martinez et al., 2024), LLM-based QA on patient EHRs offer a promising avenue, yet existing deployment studies rely on shallow, category-triggered context and narrow clinical evaluation (Garcia et al., 2024; Bootsma-Robroeks et al., 2025). Systematically assessing LLMs on expert-curated EHRs could provide crucial signals on how well models handle real-world clinical complexities, yet research largely focuses on dataset creation (Yang et al., 2022) or specialized model development (Fleming et al., 2024), rather than investigating LLM performance in realistic long-context clinical settings. Related work has examined LLMs for diagnostic prediction over EHRs (Pan et al., 2025; Albassam et al., 2025), but is limited to specific diagnoses or single datasets, short-form accuracy-based evaluation, with limited scope in addressing long-context comprehension.

Most EHR-based benchmarks consider single-document contexts (Pampari et al., 2018; Yue et al., 2021), yet in practice relevant information may span multiple documents. Reasoning over multiple long, temporally-dependent documents raises questions around LC limitations and evidence positioning sensitivity (Liu et al., 2024; Xiao et al., 2023; Adams et al., 2025), while existing LC medical QA work is either synthetic, MCQA-based and short (Adams et al., 2025) or small and not human-validated (Fan et al., 2025a).

We address this gap by investigating LLM capabilities on longitudinal, patient-centric EHRs with human-validated QA pairs. While recent LLMs push the frontiers of context size, performance does not scale with increased context (Levy et al., 2024; Modarressi et al., 2025). RAG (Lewis et al., 2020)

* Indicates equal contribution.

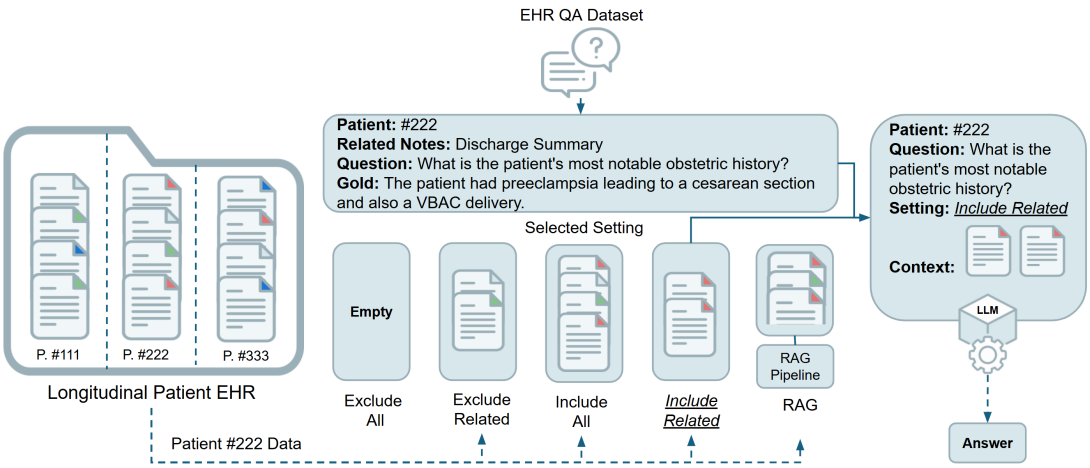

Figure 1: Overview of our Approach. Given a patient question grounded in EHR records, the corresponding most related note (by the original dataset), and an expert-verified gold answer (used only during evaluation), we augment the relevant note with the patient's full longitudinal EHR history from MIMIC (§3.1). We evaluate four prompting settings: (a) *Include Related*: only the most related note(s); (b) *Include All*: all longitudinal notes; (c) *Exclude Related*: supplementary notes only; (d) *Exclude All*: no notes. We additionally examine two RAG strategies over all longitudinal notes: (i) retrieved chunks (RAG) and (ii) their parent notes (RAG HIR) (§3.4, 4.2). Evaluation spans two extractive and two open-ended generative QA datasets.

offers a cost-efficient alternative by selecting relevant context on demand, with reported gains over LC across various settings (Zhang et al., 2024a; Xu et al., 2024a; Bai et al., 2025), though its advantage peaks at 32K for large LLMs (Leng et al., 2024) and models still struggle with specialized content such as EHRs (Fan et al., 2025b; Myers et al., 2025), leaving LC vs RAG superiority in long-form clinical EHR-based QA an open question. We make the following contributions:

- We assess how LLMs of different capabilities and sizes perform on long-context clinical QA given longitudinal EHR patient notes, covering three task formulations: 1) MCQA, 2) Extractive, and 3) Open-ended generative QA (§4.1, §4.2) across a variety of LC and RAG settings (Fig. 1).
- We perform comprehensive experiments evaluating different note inclusion strategies, examining their effect on performance and model memorization (§3.1).
- We design a hybrid RAG pipeline and evaluate it against Full-Context (FC) prompting over longitudinal EHR patient histories across task formulations and context sizes, demonstrating its superiority across tasks (§5.1, §5.2).
- Our multi-faceted evaluation methodology covers both single- and multi-document long-form reasoning settings, while a category-level quantitative analysis reveals where RAG and FC respectively excel and struggle, with RAG falling behind in longitudinal reasoning (§5.1, §5.2, §5.3).

2 Related Work

Leveraging Long Context: While increasing long-context window capabilities of LLMs, e.g. GPT-4o (Hurst et al., 2024) (128K), Claude 3 (Anthropic, 2023) (200K), Gemini 1.5 (Team et al., 2024a) (1 million), boost their long-context performance, they still struggle in general purpose open-form QA beyond short passage retrieval (Zhang et al., 2024b; Chen et al., 2025b). Despite positional embedding techniques like RoPE (Su et al., 2024), YaRN (Peng et al., 2023) and Position Interpolation (Chen et al., 2023a), QA task performance remains low even for 32K contexts (Chen et al., 2025b), with LLMs particularly challenged by long-range dependencies requiring reasoning (Li et al., 2024; Dong et al., 2024; Bai et al., 2024; Liu et al., 2024; Hsieh et al., 2024). The performance gap between open-source and closed-source models (Li et al., 2024) further raises concerns for patient-centric settings where privacy matters. Fan et al. (2025a) show notable performance drops in medical QA up to 200K tokens, yet despite the prominence of longitudinal context in real-world patient data, little work investigates long LLM capabilities.

Retrieval-augmented Generation (RAG) has been leveraged in a prompt-based plug-in manner to address black-box long-context challenges (Yu et al., 2023). LLM-based retrievers like BGE M3

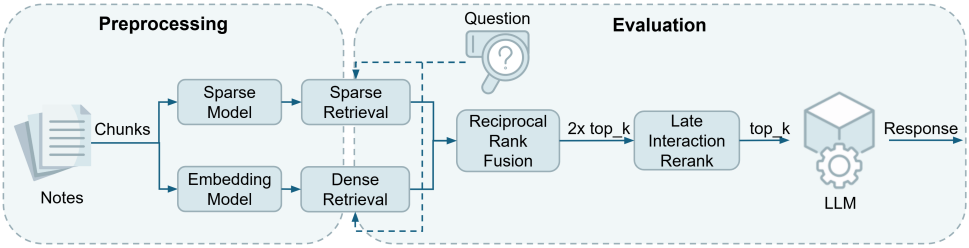

Figure 2: RAG Pipeline: Clinical notes are split into 512-token chunks and encoded using a dual embedding strategy (dense vector representations with Qwen3-Embedding-8B and sparse vectors with BM25) and then indexed in Qdrant during preprocessing. At evaluation time, the patient question retrieves $2\times$top-k candidate chunks independently from each retriever. Semantic and lexical signals are combined via Reciprocal Rank Fusion (RRF) selecting $2\times$top-k chunks and the resulting candidates are reranked using Late Interaction Reranking to yield the final top-k chunks, which are sorted chronologically before being passed as context to the LLM.

(Chen et al., 2024a) and self-reflective approaches like Self-RAG (Asai et al., 2024) have shown notable gains in open-domain QA. In the biomedical domain, MedCPT (Jin et al., 2023) and BMRETRIEVER (Xu et al., 2024b) achieve strong retrieval performance, while Med-RAG (Zhao et al., 2025) and Self-BioRAG (Jeong et al., 2024) further improve EHR-based diagnostics through knowledge graph reasoning and self-reflection respectively. Yet despite strong in-domain retrieval capabilities, models still struggle with specialized medical content such as EHRs (Fan et al., 2025b; Myers et al., 2025), motivating a thorough examination of RAG versus LC over realistic long-context patient-oriented QA.

3 Approach

Since strong medical QA performance offers the potential of LLM integration in clinical workflows we aim to uncover LLM limitations given complex patient-oriented scenarios. We focus on **content-comprehension** settings using longitudinal EHRs, thus emphasizing relevant patient-centric **long-context** across time and documents.

Our comprehensive approach spans across expert annotated datasets covering **three task formulations**: 1) MCQA, 2) Extractive, and 3) Open-ended QA. We assess each dataset across **four settings with varying note relevance** (§3.1).

3.1 Context Inclusion Formulation

While most of the datasets are based on a single note/report or up to few discharge summaries, there is a large amount of *longitudinal patient supplementary* content that remains unused in the EHR patient history. We aim to assess the significance of the patient's longitudinal Full-context (FC) as well to evaluate on a realistic clinical setting where there is no a-priori knowledge of the most relevant note. Therefore we leverage the MIMIC resources to augment the context with each patient's longitudinal notes[1], resulting in long context from the entire patient's note history (*Include All*). We then investigate how LLMs leverage long-form context to answer patient-specific questions.

We explore four data inclusion scenarios depicted in Fig. 1, allowing comprehensive analysis:

1. **Exclude All**: Exclusion of all notes - assessing model note memorization.
2. **Exclude Related**: Exclusion of relevant notes - assessing usefulness of supplementary material.
3. **Include All**: Inclusion of all patient notes - assessing LC processing of varying importance.
4. **Include Related**: Inclusion of only the most relevant note(s) (DS, CN or RR) as marked in each dataset - assessing model's ability to leverage the most relevant context information.

These settings enable direct comparison between memorization, supplementary context utility and full versus targeted context inclusion, spanning from no context to the full longitudinal patient history.

3.2 Dataset Selection Criteria

The following criteria were used for benchmark selection (full comparison in Table 11):
Beyond MCQA: Medical MCQA benchmarks i.e. PubMedQA (Jin et al., 2019), MedQA (Jin et al., 2021), MedMCQA (Pal et al., 2022) evaluate option selection instead of grounded synthesis and risk pretraining leakage from textbooks, which

[1]MIMIC preprocessing is described in Appendix C.2.

can inflate scores, providing little signal towards noisy clinical settings. Our evaluation goes beyond MCQA to both extractive and open-ended QA.

Long-context Documents: To address LLM capabilities in handling real-world LC we seek benchmarks extending well-beyond 8K, with inclusion of patient-specific content.

Expert Annotated QA pairs grounded on multi-document EHRs were our choice, to avoid clinical reliability issues like non-expert curation (Fan et al., 2025a) or synthetic data (Adams et al., 2025).

Patient-centric Longitudinal Content: Prioritizing clinically-relevant QA with reasoning, we focus on MIMIC-based EHR datasets (Johnson et al., 2016, 2023), offering timestamped notes across document types with consistent format.

3.3 RAG Approach

Retrievers are distinguished into *sparse* and *dense*. Sparse retrievers such as BM25 (Robertson and Zaragoza, 2009) and Splade (Formal et al., 2021) use overlapping terms to match queries with snippets, while dense retrievers encode them into embeddings and match them based on semantic similarity. Recently, using LLM-based embeddings for dense retrieval has become standard practice.

Research on biomedical MCQA (Wang et al., 2024) and biomedical document retrieval (Luo et al., 2022) has shown that hybrid approaches combining sparse and dense retrieval outperform single component counterparts. Recent work across biomedical QA shows that hybrid retrieval outperforms both sparse and dense retrievers alone (Stuhlmann et al., 2025), with sparse+dense+RRF specifically demonstrated to be superior on PubMedQA and MedQA (Ryan et al., 2026). Additionally, non-hybrid experiments on EHR subsets of varying granularity (Fan et al., 2025b) show no clear winner between sparse and dense retrievers. Finally, re-ranking of retrieved snippets also exhibits superior performance in biomedical applications (Jin et al., 2023; Wang et al., 2024; Sohn et al., 2025). Provided substantial evidence for the superiority of hybrid retrieval over single-component counterparts in this domain, we leverage a hybrid approach followed by re-ranking, presented in Figure 2, focusing on our primary goal on evaluating LLM capabilities under different context settings on long longitudinal EHR patient data.

Clinical notes are segmented into 512-token chunks, forming the document collections $D = \{d_1, d_2, \ldots, d_n\}$. The question respectively forms the query Q.

Sparse retrieval: we employ a lexical retriever as a ranking function of each chunk d_j [2]:

$$S_{\text{sparse}}(Q, d_j) = \sum_{i=1}^{n} \text{IDF}(q_i) \cdot \frac{f_{q_i,d_j}\,(k_1+1)}{f_{q_i,d_j} + k_1\left(1 - b + b \cdot \frac{|d_j|}{\text{avgdl}}\right)} \quad (1)$$

Dense retrieval: we use the same encoder, E, for the query and the chunks and capture semantic similarity of such pairs using the cosine similarity:

$$S_{\text{dense}}(Q, d_j) = \frac{E(Q) \cdot E(d_j)}{\|E(Q)\|\,\|E(d_j)\|} \quad (2)$$

Reciprocal Rank Fusion (RRF): combines the top-k chunks from each retriever, through $\text{rank}_s(d_j)$ denoting the rank assigned to document d_j by retriever $s \in \{\text{dense}, \text{sparse}\}$, using a smoothing constant k_{RRF}:

$$\text{RRF}(d_j) = \sum_{s \in \mathcal{S}} \frac{1}{k_{RRF} + \text{rank}_s(d_j)} \quad (3)$$

Late Interaction Reranking: measures how well every Q-token, $\mathbf{q}_i$, is supported by at least one document token, $\mathbf{d}_{j,r}$, to produce the top-k set:

$$S_{\text{MaxSim}}(Q, d_j) = \sum_{i=1}^{|Q|} \max_{1 \le r \le |d_j|} \langle \mathbf{q}_i, \mathbf{d}_{j,r} \rangle \quad (4)$$

Document Ordering: we sort retrieved chunks temporally rather than by retrieval score due to its superior long-context performance (Yu et al., 2024).

3.4 Evaluation Methodology

Evaluating medical QA systems has traditionally relied on automatic metrics and MCQA benchmarks (Jin et al., 2019, 2021; Pal et al., 2022), which probe memorized knowledge and underrepresent the complexity of clinical reasoning, and EHR-grounded context. Towards a clinically meaningful assessment, we adopt a multi-dimensional, reference-based scheme that complements lexical overlap with embedding-based semantic similarity and domain-adapted Natural Language Inference (NLI). In line with emerging clinical evaluation practices (e.g., MEDIC (Kanithi et al., 2024)) and the rise of LLM-as-a-judge, we employ a calibrated rubric and we prioritize widely available metrics while cross-checking signals for robustness. Our datasets comprise gold-standard QA pairs that are

[2] Here terms document and chunk are used interchangeably.

Dataset	Context Data	QA Pairs	Patients	Mean/Max Context	Task Types	Answer Location	Reasoning	Question Generation	Answer Annotation
CliniQG4QA	MIMIC-III	1,287	36	4K / 7K	Extractive	Clinical Note	×	Experts	Clinical experts (3)
RadQA		3,509	80	6K / 14K		Radiology Report	Single-Note	Human-generated	Physicians (2)
EHR-DS-QA	MIMIC-IV	478	70	46K / 131K	Open-ended	Clinical Note/Dis. Summary	×	LLMs	Physician-verified (1)
EHRNoteQA		962	962	9K / 39K	MC,Open-ended	Dis. Summaries	Multi-Note	LLM	Clinician-refined (3)

Table 1: EHR QA Dataset Statistics. Mean/Max Context corresponds to the *Include All* setting.

either expert-verified or expert-generated enabling a clinically centric evaluation:

METEOR (Banerjee and Lavie, 2005) to capture *surface-level* and *lexical similarity*.

BERTScore (Zhang et al., 2019), computed with Clinical BioBERT embeddings (Alsentzer et al., 2019) to assess *semantic similarity*.

NLI Scores, to capture the logical relationship between reference and candidate answers. We use a domain-adapted NLI model (Deka et al., 2023) and then measure *Factual Consistency* using the probability of non-contradiction (Song et al., 2024) and *Factual Precision* using the entailment probability.

LLM-as-a-judge, employed with a 5-point scale rubric on three aspects: *Correctness* capturing factual consistency with respect to the gold answer, penalizing contradictions while allowing compatible additional information, *Completeness* capturing recall by assessing the predicted answer's coverage of information present in the reference, *Faithfulness* capturing precision assessing if the predicted answer only contains information that is supported by the reference.

Accuracy reported on the MCQA task.

4 Experiments

4.1 Datasets

We leverage MIMIC-III (Johnson et al., 2016) and MIMIC-IV (Johnson et al., 2023), comprising de-identified EHRs covering hospital admissions and ICU stays, as the underlying context. They support single- and multi-note settings and include: clinical notes (CN), discharge summaries (DS) and radiology reports (RR) per patient over time.

Our four selected QA datasets only use QA pairs curated or validated by clinical experts to ensure medical validity. We provide a brief dataset overview below, also summarized in Table 1:

CliniQG4QA (Yue et al., 2021): An extractive span benchmark on MIMIC-III comprising 1,287 QA pairs generated or verified by three clinical experts. We only use the expert-annotated set.

RadQA (Soni et al., 2022): An extractive dataset of 3,074 physician-crafted questions and 6,148 answer spans from Findings and Impressions sections of radiology reports in MIMIC-III, annotated by two human annotators. After filtering unanswerable pairs we retain 3,509 pairs.

EHR-DS-QA (Kotschenreuther, 2024): A synthetic QA corpus generated by two LLMs on discharge summaries and clinical notes from MIMIC-IV. Of 506 physician-verified pairs, we retain 478 marked as correct.

EHRNoteQA (Kweon et al., 2024): Built on MIMIC-IV, comprising 962 QA pairs authored by GPT-4 and iteratively refined by three clinicians, each corresponding to multiple discharge summaries (∼2.3 per patient) and supporting both open-ended and MCQA formats.

Context Bins: For *Include All* we report performance across four token bins: 0–8K, 8–16K, 16–32K, and 32–128K. As shown in Appendix C.3, both *Include Related* and *Exclude Related* yield shorter contexts across all bins, most notably in the 16–32K bin for *Include Related*.

4.2 Models and Experimental Setup

LLMs: To explore the effect of model size, domain specialization and reasoning capabilities we study four open Qwen2.5 (Team et al., 2024b) single-family models, ensuring a controlled comparison:

- *Qwen2.5-7B-Instruct*
- *HuatuoGPT-o1-Qwen-7B* (Chen et al., 2024b): medical LLM based on Qwen2.5-7B-Instruct
- *Qwen2.5-32B-Instruct-128K*
- *QwQ:32B*: reasoning model

Evaluation: Through comparisons against Selene-8B (Alexandru et al., 2025) and Prometheus-8x7B v2.0 (Kim et al., 2024), we finally selected QWEN-2.5-32B-INSTRUCT for the LLM-as-a-judge for stability and agreement (see Appendix D.2).

Retrieval Settings: Based on biomedical QA retrieval research that demonstrates the superiority of combining sparse and dense retrievers (see §3.3), we designed a hybrid retrieval approach to properly handle the semantic, lexical, and query complexity. The selected model components are enlisted below:

Model	Setting	EHRNoteQA				EHR-DS-QA			RadQA			CliniQG4QA		
		Open-ended			MC	Open-ended			Extractive			Extractive		
		LLM	NLI	F1	Acc.	LLM	NLI	F1	LLM	NLI	F1	LLM	NLI	F1
HuatuoGPT-o1 7B	Exclude All	7.85	**23.36**	**68.82**	51.08	**26.65**	**33.86**	72.21	25.06	27.90	63.78	15.96	23.01	64.44
Qwen2.5 7B		**9.73**	18.18	68.41	51.46	24.79	33.00	72.35	**39.08**	**29.24**	**70.73**	**27.02**	**26.30**	**74.06**
Qwen2.5 32B		0.71	11.30	66.56	58.34	20.16	20.23	**72.67**	3.86	2.88	10.35	0.11	0.19	2.16
QwQ 32B		2.68	12.23	66.98	**59.24**	24.16	23.80	71.70	1.51	6.44	15.29	0.93	5.62	14.77
HuatuoGPT-o1 7B	Exclude Related	26.62	**40.26**	72.57	58.35	28.49	**33.98**	71.84	24.39	28.28	63.33	15.70	24.13	64.15
Qwen2.5 7B		25.24	28.64	72.72	59.86	**29.90**	28.17	73.35	**38.86**	**29.07**	**70.72**	**27.01**	**25.95**	**74.09**
Qwen2.5 32B		25.59	23.67	73.01	58.72	22.16	22.35	73.15	3.77	2.78	10.02	0.13	0.20	2.17
QwQ 32B		**27.46**	23.01	**74.35**	**60.15**	27.19	23.98	**73.51**	1.14	7.11	17.48	0.99	4.84	15.75
HuatuoGPT-o1 7B	Include All	72.60	45.45	78.21	78.94	59.76	**63.66**	77.14	63.92	49.41	76.38	67.85	52.45	80.08
Qwen2.5 7B		70.49	38.11	79.95	78.81	**62.49**	61.00	79.14	62.56	50.13	76.65	68.89	54.13	81.27
Qwen2.5 32B		67.88	**55.33**	**81.50**	**90.97**	57.21	61.96	**79.59**	**67.74**	50.10	**77.55**	**80.49**	59.22	83.80
QwQ 32B		**75.52**	47.14	81.02	89.25	57.68	60.54	78.90	67.46	**53.26**	77.47	78.95	**66.00**	**83.94**
HuatuoGPT-o1 7B	Include Related	70.73	39.30	79.71	76.87	63.46	60.65	77.20	64.37	49.19	76.48	70.47	53.19	79.83
Qwen2.5 7B		74.44	39.15	80.78	80.9	**64.76**	**65.14**	80.28	63.01	50.25	76.71	69.06	54.87	81.29
Qwen2.5 32B		76.01	**61.41**	**82.48**	**90.33**	59.12	64.86	**80.70**	67.76	50.78	77.67	**79.81**	59.21	83.55
QwQ 32B		**82.03**	47.19	82.36	87.57	61.31	61.68	79.70	**67.79**	**55.48**	**77.69**	79.74	**65.86**	**84.35**

Table 2: Results for Full Context in each setting across datasets. **Bold** is best and underlined the second best model in each Setting and Metric. Red highlights the global best across all Settings per Metric. *LLM* corresponds to LLM Correctness, *NLI* to NLI Entailment and *F1* to BioBERT F1

- *Dense Retrieval* using the open embedding model Qwen3-Embedding-8B (Zhang et al., 2025).
- *Sparse Retrieval* using BM25, selected after ablating two sparse retrievers (see Table 10).
- *Late Interaction Reranking* with Reason-ModernColBERT, a ColBERT (Khattab and Zaharia, 2020) model finetuned on the ReasonIR dataset (Shao et al., 2025) demonstrating high performance on a reasoning-intensive retrieval benchmark (Su et al., 2025).

We explored two chunk inclusion strategies: i) direct chunk inclusion (*RAG*), ii) hierarchical parent note inclusion (*RAG HIR*).

Experimental Setup: LLM inference and prompt formulation specifics are in Appendices A and C.4.

5 Results and Discussion

5.1 Main Results

Performance for the different inclusion settings across datasets and models is shown in Table 2.

Model Size, Tasks and Inclusion Settings: Consistent with general findings, larger models perform better across all tasks (Table 2), with the performance gap particularly pronounced in tasks requiring reasoning or information synthesis from multiple sources, namely EHRNoteQA and RadQA. However, smaller models perform better in settings excluding relevant information or completely removing the context, suggesting stronger memorization. Unlike the rest of the tasks, MC shows

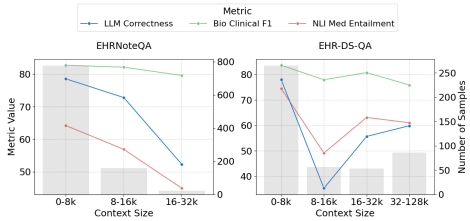

Figure 3: Metric performance over context size on *Include All* for Qwen2.5:32B-Instruct.

strong evidence of memorization with a performance of 59.24% in the *Exclude All* setting, while MC demonstrates 90%+ performance, open-ended and extractive tasks remain challenging for LLMs.

The *Exclude All* setting primarily assesses model memorization, with Qwen2.5-7B and HuatuoGPT-o1-7B outperforming Qwen2.5-32B further indicating stronger memorization in smaller models. The *Exclude Related* setting, which includes only supplementary patient history excluding the most relevant notes, yields near-identical performance to *Exclude All* across all models and sizes for the purely extractive RadQA and CliniQG4QA datasets, where the answer is contained within the single related note, rendering supplementary context uninformative. By contrast, for the open-ended generative datasets, *Exclude Related* outperforms *Exclude All* by a margin, demonstrating the usefulness of supplementary patient material. The *Include Related* setting outperforms *Include All* on most datasets and metrics except for MC, while the gap between the two suggests that LLMs strug-

Model	Setting	EHRNoteQA				EHR-DS-QA		
		Open-ended			MC	Open-ended		
		LLM	NLI	F1	Acc.	LLM	NLI	F1
HuatuoGPT-o1 7B	Include All	70.68	39.52	77.26	75.36	50.25	59.01	75.30
	Include Related	66.88	29.62	79.37	72.38	56.51	54.71	75.29
	RAG 5	59.94	**61.34**	78.44	75.67	57.57	61.53	78.22
	RAG 10	61.03	48.51	77.99	73.4	58.08	62.45	**78.61**
	RAG 15	60.84	52.53	77.92	74.97	**61.95**	**64.84**	77.68
	RAG HIR 3	70.13	56.91	77.99	70.81	50.06	53.82	76.17
	RAG HIR 5	**70.92**	57.51	**79.52**	72.38	48.46	55.21	76.66
	RAG HIR 7	70.80	54.61	79.35	**80.46**	55.99	57.12	77.35
Qwen2.5 7B	Include All	66.86	28.36	79.23	75.04	54.26	52.78	77.07
	Include Related	72.37	29.50	80.34	78.82	58.60	60.79	78.85
	RAG 5	59.54	40.33	78.82	75.67	54.17	56.11	**79.82**
	RAG 10	64.03	45.02	79.05	73.40	57.11	**62.76**	79.60
	RAG 15	58.07	52.08	79.20	75.60	**59.25**	60.32	79.65
	RAG HIR 3	65.54	46.34	80.37	76.93	50.73	53.12	78.65
	RAG HIR 5	**72.68**	**54.69**	80.17	79.76	53.59	52.56	77.66
	RAG HIR 7	67.55	46.41	**80.69**	**84.31**	52.10	52.39	78.26
Qwen2.5 32B	Include All	62.54	50.90	80.87	89.79	50.27	57.78	78.22
	Include Related	**74.16**	**59.11**	82.17	88.78	51.88	59.78	79.48
	RAG 5	60.35	46.36	80.28	80.46	58.02	58.91	80.29
	RAG 10	67.00	54.54	80.47	77.87	**60.52**	60.31	80.24
	RAG 15	73.45	53.94	80.84	81.02	55.68	61.39	**80.71**
	RAG HIR 3	67.48	57.17	**82.41**	83.36	55.13	**63.32**	80.55
	RAG HIR 5	68.86	54.87	81.59	90.74	51.20	60.73	80.12
	RAG HIR 7	72.00	47.33	81.84	**91.68**	52.82	57.27	80.21

Table 3: Open-ended and MCQA Results for Context of 8K+ tokens including LC and RAG Methods. **Bold** is best and underlined the second best performance per Model and Metric. Red highlights the global best across all models per Metric.

Model	Setting	RadQA			CliniQG4QA		
		LLM	NLI	F1	LLM	NLI	F1
HuatuoGPT-o1 7B	Include All	35.60	**48.81**	75.61	43.73	50.44	78.97
	RAG 5	**36.61**	29.51	**76.61**	**44.20**	**54.51**	**79.54**
Qwen2.5 7B	Include All	36.10	**48.59**	75.92	44.55	53.26	80.04
	RAG 5	**37.09**	28.39	**77.10**	**47.03**	**58.36**	**81.73**

Table 4: Extractive QA Results for Context of 4K+ tokens. **Bold** is best performing per Model and Metric and red highlights the global best per Metric.

gle to identify the most relevant information when processing the full *Include All* context.

Reasoning and Fine-tuning: The impact of reasoning-focused models and medical fine-tuning is mixed. *The QwQ:32B general reasoning model* showed improved results on Table 2 over other models overall on RadQA, EHRNoteQA (the reasoning datasets). This suggests that reasoning models can offer an advantage in tasks that demand complex inference across multiple sources of information, but this benefit may be more apparent in larger model sizes where reasoning capabilities can be effectively leveraged without compromising other essential skills. By contrast, *the medically fine-tuned reasoning model, HuatuoGPT-o1-Qwen2.5:7B*, did not show any improvement over its standard instruction-tuned base model Qwen2.5:7B-instruct, in line with studies revealing that biomedical LLMs often lead to reduced performance (Dorfner et al., 2024; Dada et al., 2025).

Context Size: Fig. 3 shows that performance decreases with increased context size on open-ended QA, particularly for multi-note reasoning (EHRNoteQA), with similar trends across models (see Appendix, Fig. 9). Notably, EHR-DS-QA exhibits a performance dip at 8-16K tokens across metrics and models, attributable to data noise and some ambiguous gold answers, consistent with observations by Fan et al. (2025a) and Ma et al. (2025).

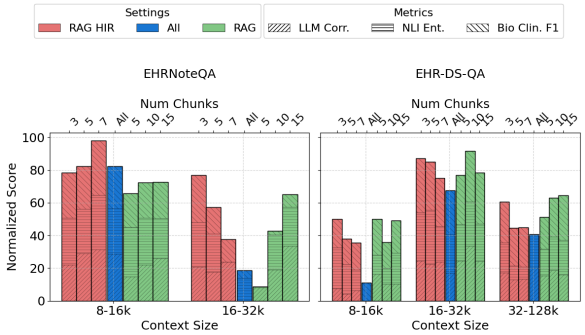

Figure 4: RAG performance across settings with Qwen2.5:32B-Instruct with min-max normalization across LLM Correctness, NLI Entailment and Bio F1.

RAG Performance: Table 3 shows two RAG settings: *RAG* x and *RAG HIR* x, corresponding to x 512-token chunks and x parent notes respectively[3]. RAG demonstrates clear improvement on the single-note EHR-DS-QA task, where direct chunk inclusion consistently performs best, while hierarchical RAG (RAG HIR) is superior for the more complex multi-note reasoning of EHRNoteQA, with similar gains observed on MC. Impressively, RAG surpasses *Include Related* performance across most settings, suggesting that effective retrieval can match or exceed having the most relevant note available a priori, with the exception of the multi-note reasoning dataset and larger models. Findings are consistent across 8K+ context sizes (Fig. 4), with smaller models benefiting most. The medically fine-tuned reasoning model HuatuoGPT-o1-Qwen2.5:7B scored the best results on multiple metrics across the open-ended datasets, showing that RAG could benefit even more to the smaller models that struggle in Full-context (FC) settings *Include All'* .In Table 4 we only evaluate 7B sized models using a single RAG setting, due to the task nature and limited context size of the extractive datasets. While the extractive datasets

[3]We excluded QwQ :32B due to time and budget constraints

have shorter contexts overall RAG still yields the best performance.

5.2 Quantitative Analysis: RAG vs FC

We first gathered challenging cases of disagreement between metrics (LLM Correctness, NLI Entailment, and Bio-F1) and manually analyzed these samples to form categorize the questions across QA types, showing results in Appendix G (Table 14). We then form the following rubric:

- **Specific Entity Extraction (SEE):** Requiring retrieval of high cardinality facts such as medications and lab values or surgical procedures.
- **Temporal & Longitudinal Reasoning (TLR):** Requiring tracking of changes over time, chronological event ordering or visit comparisons.
- **Clinical Nuance & Status (CNS):** Questions regarding discharge instructions, patient mental status or synthesized clinical course summaries.
- **Absence or Negative Information (ANI):** Requiring the identification of absent information.

We apply the above rubric by prompting `Gemini-3-flash` with Chain-of-Thought reasoning to automatically categorize all 8K+ token instances in the multi-note reasoning EHRNoteQA dataset, computing FC versus RAG success rates via min-max normalization across LLM Correctness, NLI Entailment, and Bio F1. Human evaluation of 20 randomly sampled instances shows 85% categorization accuracy. In Table 5, we show that RAG has superior performance in the long-context categories of *CNS* and *ANI*, showing superior signals of consistency and factual grounding where clinical nuance, discharge status or absence of information must be identified. By contrast, FC has stronger performance in *TLR*, where tracking chronological events and longitudinal changes across the full context is more reliable over note fragmenting. FC and RAG are equally good in Specific Entity Extraction *SEE*.

		Favored by(%)		FC		RAG	
Category	Samples	FC	RAG	LLM Cor.	NLI Ent.	LLM Cor.	NLI Ent.
ANI	4	25.0%	**75.0%**	50.00	25.37	**100.00**	**74.77**
CNS	47	27.7%	**61.7%**	67.55	41.94	**72.87**	**53.58**
SEE	93	**45.2%**	**45.2%**	**75.54**	**61.76**	74.73	56.74
TLR	41	**53.7%**	36.6%	**63.41**	**63.80**	60.37	51.13
Total	185	42.2%	**48.1%**	70.27	**56.39**	**71.62**	55.08

Table 5: Performance comparison between FC and RAG across question categories, including metric breakdown on EHRNoteQA dataset 8K+.

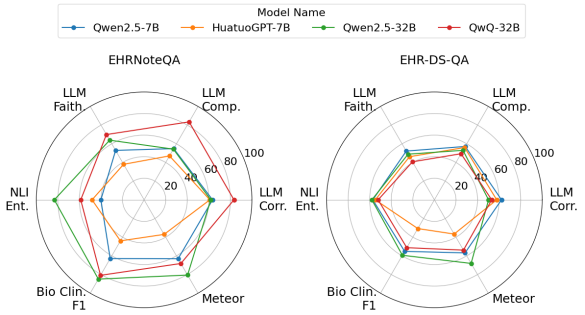

Figure 5: Model performance across metrics for open-ended QA, normalized with min-max per metric.

5.3 Metrics and Insights

Metric Comparisons: Fig. 5 of model performance across metrics shows that instruct models lead on the single-note task (EHR-DS-QA) across semantic and NLI metrics, while larger reasoning models lead on the multi-note reasoning task (EHRNoteQA) based on LLM-as-a-judge metrics[4].

Metric Insights: A qualitative analysis of metric disagreements reveals three common failure modes: models adding unsupported details inflating Correctness over Faithfulness, correct answers with low lexical overlap underscoring METEOR/BERTScore and clinically aligned answers flagged by NLI due to negation or phrasing differences. These point to the need for more reasoning-appropriate metrics (§Appendix E.2).

6 Conclusion

We comprehensively evaluate LLM long-context comprehension on longitudinal, patient-centric EHRs across multiple datasets and models and metrics under both Full-Context (FC) and RAG settings. Feeding only the most relevant content outperforms the full notes counterpart, showing that LLMs struggle to identify the most relevant information under long context, with reasoning models gaining on complex inference while smaller and medically fine-tuned models fall behind. Hybrid RAG with reranking outperforms FC, with chunk-based RAG benefiting single-note and hierarchical RAG complex multi-note reasoning, with smaller models benefiting most. A category-level analysis confirms RAG's advantage in clinical nuance and absence of information recognition, while FC retains an advantage in longitudinal reasoning.

[4] All- and long-context metric correlations in App.E.1

Limitations

Our work focuses on MIMIC-derived datasets, which represent English-only data from a single U.S. medical center. As such, performance may not generalize to other languages, populations, and healthcare systems. Furthermore, the de-identified nature of the data limits us from examining potential cultural and other biases of LLMs over long contexts. Importantly, although our work presents an early step towards benchmarking long-context LLM performance in longitudinal patient-centric settings, our findings are intended solely for research purposes. Results reflect model performance on question answering benchmarks and should not be interpreted as guarantees of clinical safety, equitable performance, or readiness for clinical deployment. Beyond the complexities of modeling clinical notes, real-world records comprise heterogeneous data from other sources and modalities. Our work is therefore limited in its assessment of long-context by focusing only on the textual modality, something we aim to address in future work. Our analysis also highlights limitations in current evaluation metrics, specifically regarding the assessment of reasoning, the lack of transparency in LLM-as-a-judge frameworks, and the difficulty of accurately measuring faithfulness when benchmarks are supplemented with additional information. Finally, while we focus on Qwen-based models due to their competitive performance, we acknowledge that an evaluation of a wider range of LLMs could offer a more complete picture of the LLM landscape in long-form medical QA.

Ethics Statement

This work uses MIMIC-III, MIMIC-IV, and four derivative datasets (EHRNoteQA, EHR-DS-QA, RadQA, CliniQG4QA) accessed under the PhysioNet Credentialed Health Data License 1.5.0. All datasets contain de-identified patient records in accordance with HIPAA Safe Harbor standards. We exclusively used open-weight LLMs to ensure no patient data were transmitted to third-party proprietary systems.

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A Inference Setup

- **Inference Engine:** Nvidia TensorRT.
- **Quantization:** FP8.
- **Hardware:** 7B parameter models: Deployed on single Nvidia H100 GPUs with 40GB VRAM. 32B parameter models with extended context: Deployed on dual Nvidia H100 GPUs, each equipped with 80GB VRAM. A total of 260 GPU hours was spent.
- **Libraries:** Qdrant, DSPy, Litellm, pandas, Evaluate, Fastembed, Pylate

B Hyperparameters

Hyperparameter		Value
LLM	temperature	inst: 0, reas: 1
	freq_penalty	0
	pres_penalty	0
	think tokens	QwQ: $20k$ HuatuoGPT: $8k$
RAG	top_k	$2\times$ num chunks
	k_{RRF}	60 (recommended by Qdrant)
	k_1	TF saturation
	b	length norm.
	avgdl	avg. doc length

Table 6: Hyperparameter Configuration

C Datasets

C.1 Context Data Distributions

Token-length distributions per dataset are shown in Figures 6 and 7.

C.2 Context Data Preparation

We performed minimal cleaning and standardization to support retrieval and prompting, including merging notes by patient and stay, normalizing timestamps, adding note-type metadata, computing token counts for context segmentation, and filtering to human-verified subsets where applicable.

We describe the cleaning and normalization steps applied prior to indexing and prompting:

- Cleaning and de-duplication of clinical notes; removal of template boilerplate where applicable.
- Merging notes by patient and hospital stay; preserving note-type and section headers for downstream retrieval.
- Datetime standardization and chronological ordering; normalization where timezones or partial timestamps occur.
- Metadata augmentation (e.g., note type, encounter identifiers) to support Include DS vs Include All settings.
- Tokenization and token-count computation at note- and patient-level for context segmentation.

These details enable reproducibility of sampling and retrieval segmentation.

C.3 Context Length per Formulation

We provide the Median token context length per original Full-Context (Include All) bin based on the combined EHR-DS-QA and EHRNoteQA datasets on which we evaluate the open-ended generative

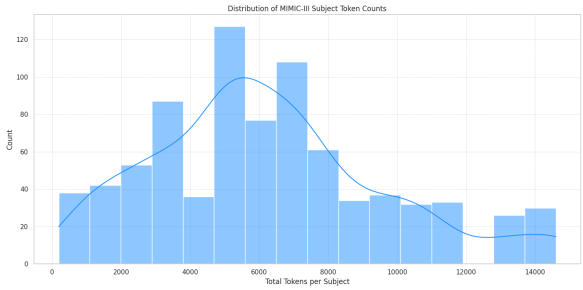

Figure 6: MIMIC-III Context Distributions

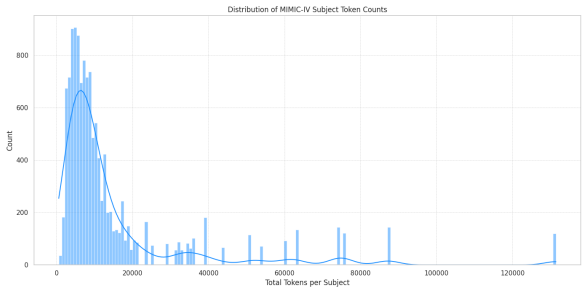

Figure 7: MIMIC-IV Context Distributions

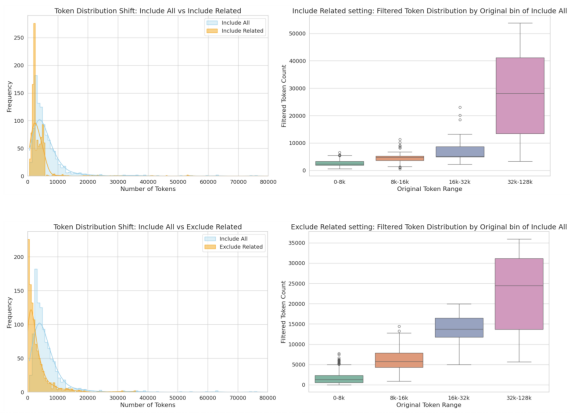

Figure 8: Distribution of tokens of Include Related versus Include All and Exclude Related versus Include All on the combined EHR-DS-QA and EHRNoteQA datasets.

	0–8K (Include All)	8–16K (Include All)	16–32K (Include All)	32–128K (Include All)
Include Related	2,247	4,767	5,149	28,131
Exclude Related	1,284	5,712	13,733	24,472
Include All	3,934	9,851	18,909	41,409

Table 7: Context Length per Formulation on the combined EHR-DS-QA and EHRNoteQA datasets.

Dataset	LLM-as-a-judge	QA Pairs
EHR-DS-QA	Selene-8B	113
	Prometheus-8x7B-v2.0	98
	Qwen2.5-32B-Instruct	71
EHRNoteQA	Selene-8B	180
	Prometheus-8x7B-v2.0	220
	Qwen2.5-32B-Instruct	42

Table 8: Disagreement instances where NLI Med Contradiction is high (> 0.7) and LLM Correctness is also high (> 0.7).

QA capabilities. Table 7 shows that as expected for each of the original bins the median lengths fall compared to the *Include All* setting in both the *Include Related* and *Exclude Related* settings, with the most drastic change being in the *Include Related* setting context-bin of 16-32K tokens from a median of $\sim$19K to a median of around $\sim$5K tokens. Additionally,in Figure 8 we also provide the distribution of tokens of *Include Related* versus *Include All* and *Exclude Related* versus *Include All*.

C.4 Prompt Formulations

We used a simple zero-shot prompt structure and tailored it explicitly for each task formulation:

- **Extractive**: Request the model to answer by extracting the most relevant answer from the context.
- **Multiple-choice**: Standard multiple choice prompt.
- **Open-ended**: Focusing on open ended question answering favoring short, single sentence answers.

Below is the sample prompt for extractive tasks:

```
System message:

Your input fields are:
1. `medical_record` (list[str]): List of patient notes (chronological order).
2. `question` (str): A question about the patient's record.
Your output fields are:
1. `answer` (str): Short single-sentence answer to the question.

All interactions will be structured in the following way, with the appropriate values filled in.

[[ ## medical_record ## ]]
{medical_record}

[[ ## question ## ]]
{question}

[[ ## answer ## ]]
{answer}

[[ ## completed ## ]]

In adhering to this structure, your objective is:
Given a patient's medical record and a question, answer the question correctly and shortly.
```

Dataset	LLM-as-a-judge 1	LLM-as-a-judge 2	QA Pairs
EHR-DS-QA	Prometheus	Qwen2.5-32B-Instruct	520
	Prometheus	Selene-8B	363
	Qwen2.5-32B-Instruct	Selene-8B	664
EHRNoteQA	Prometheus	Qwen2.5-32B-Instruct	690
	Prometheus	Selene-8B	236
	Qwen2.5-32B-Instruct	Selene-8B	519

Table 9: Judge-pair disagreements where the absolute difference in LLM Correctness ≥ 0.5.

Metric	Splade	BM25
LLM Correctness	67.30	**69.34**
LLM Completeness	65.41	**67.14**
LLM Faithfulness	**47.64**	46.23
NLI Med Entailment	52.68	**54.35**
NLI Med Contradiction	16.98	**16.94**
Bio BERTScore F1	**79.75**	79.67
METEOR	**43.93**	43.63

Table 10: Comparison of Different Sparse Retrievers

C.5 Dataset Comparisons

Aiming to stress-test LLM capabilities under real patient-centric scenarios, our dataset selection process was based on a extensive grid of datasets. Table 11 summarizes the QA datasets we analyzed in our selection process, including the EHR candidates. The chosen EHR-based, human-verified datasets provide diverse but comparable settings across generative, extractive, and MC formulations. While some exceed 8K tokens, supporting our long-context evaluation, they all provide strong augmentation potential towards a multi-note longer evaluation setting that allows content extension up to 128K for each patient (§3.1), enabling a realistic comparison of Full-context and RAG pipelines. We provide citations of each considered dataset from Table 11 in Table 12.

D Model Comparisons

D.1 Sparse Retrievers

On Table 10 we provide a sparse retriever comparison on the EHR-DS-QA dataset using the Qwen2.5-7B-Instruct-1M LLM and Qwen3-Embedding-8B as the dense retriever. BM25 has better performance across LLM Correctness, LLM Completeness and NLI-based metrics while showcasing slightly inferior performance on BioClinical BERTScore F1, METEOR and LLM Faithfulness.

D.2 LLM-as-a-judge

In Table 8 we examine the number of QA cases for each dataset that the different Judges cause disagreement with the NLI Med Contradiction metric. We observe that Qwen2.5-32B-Instruct [5] has far less such disagreement compared to more specialized judges. Table 9 also provides direct comparisons of LLM-as-a-judge models, demonstrating cases where LLM Correctness between such pairs is more than 0.5 and therefore high. Selene-8B [6] and Prometheus-8x7B-v2.0 [7] comparisons show that these two models are consistently more in agreement between them while Qwen2.5-32B-Instruct shows more independent judging abilities.

D.3 Context Size Performance

Figure 9 presents the performance of each model on open-ended generative QA across three different metrics.

E Metrics

E.1 Correlations

We examine correlations between evaluation metrics to identify metric independence. On EHRNoteQA and EHR-DS-QA across all non-exclude settings (Figure 10) as well as across long-context high LLM Correctness non-exclude settings (Figure 11), LLM-as-a-judge evaluation metrics exhibit strong inter-correlations while METEOR and BERTScore are highly correlated. Although the above correlations remain high, they are less pronounced for the long-context high LLM Correctness setting of Figure 11. In general all metrics are less correlated for the long-context high LLM Correctness setting.

E.2 Blind Spots

Table 13 showcases a qualitative view of what our metrics are capturing vs missing, based on an analysis of disagreement on the open-ended generative benchmarks.

F Case Studies

Here we show some sample studies of our error analysis.

[5] https://huggingface.co/Qwen/Qwen2.5-32B-Instruct
[6] https://huggingface.co/AtlaAI/Selene-1-Mini-Llama-3.1-8B
[7] https://huggingface.co/prometheus-eval/prometheus-8x7b-v2.0

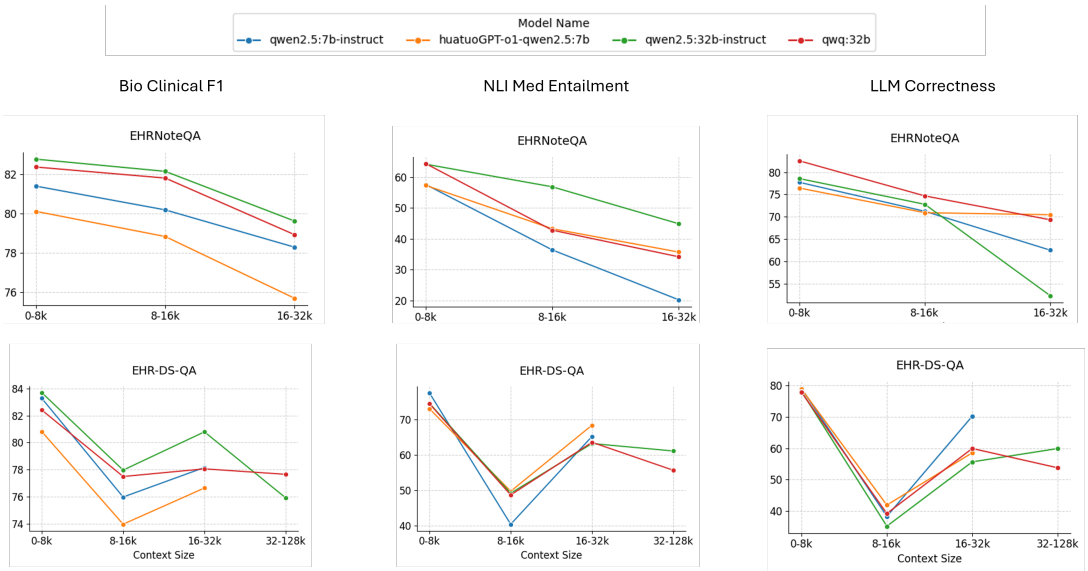

Figure 9: Model performance over context size across datasets and metrics.

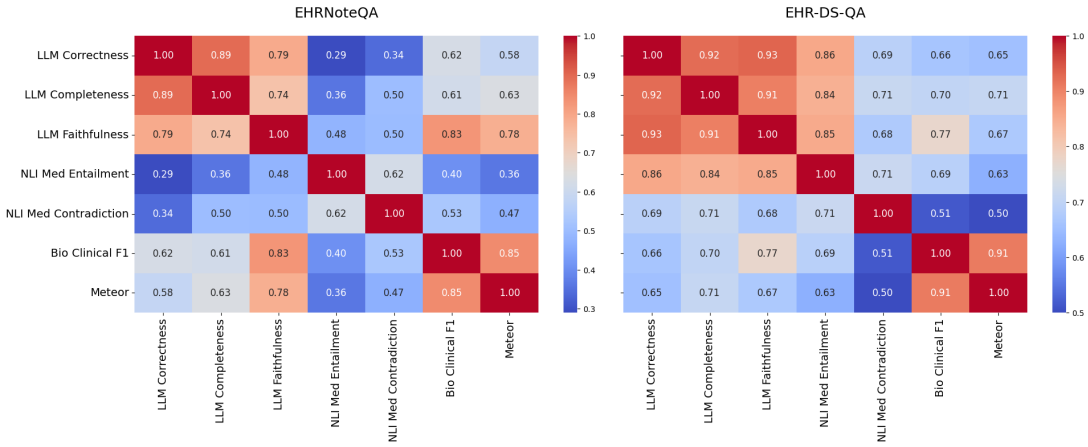

Figure 10: Metric correlations across all non-exclude settings.

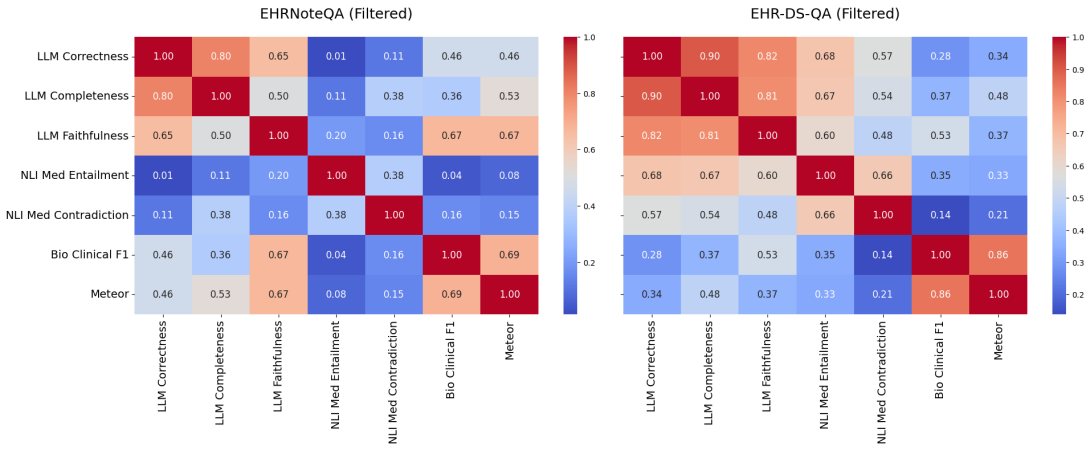

Figure 11: Metric correlations across all non-exclude settings filtered by LLM Correctness > 50 and Context $>= 16$K.

Dataset	# QA Pairs	Token Len. (max)	Task Types	Synthetic	Annotation	Reasoning
Medical Textbooks, Websites, Knowledge Bases						
MedQuAD	47,457	< 2K	extractive		automatic	✗
MashQA	34,808	< 2K	extractive (multi-span)		experts	✓
MedOdyssey (En.KG)	100	< 128K	extrative (graph)		model&human	✓
MedQA (USMLE)	12,723	> 1M	MC		experts	✓
Biomedical Literature						
BioMRC (LARGE)	812,707	< 2K	MC, extractive		automatic	✗
BioASQ (b)	5,729	< 8K	extractive, generative		experts	✓
PubMedQA	1,000	< 2K	MC, generative		experts	✓
Clinical Case Reports						
CliCR	104,919	< 8K	extractive (cloze)		automatic	✓
Patient Notes						
LongHealth	400	< 8K	MC	✓	experts	✓
DiSCQ	2,029	< 2K	extractive, generative		experts	✓
RadQA	6,148	< 16K	extractive		experts	✓
CliniQG4QA	8,824/1,287	< 8K	extractive		model/experts	✗
EHR-DS-QA	156,599/478	< 8K	generative	✓	model/experts	✗
EHRNoteQA	962	< 8K	MC, generative		experts	✓

Table 11: Biomedical Datasets Comparison. References for each dataset are in Table 12.

Dataset	Source
MedQA	Jin et al. (2021)
MedQuAD	Abacha and Demner-Fushman (2019)
MashQA	Zhu et al. (2020)
MedOdyssey	Fan et al. (2025a)
BioMRC	Pappas et al. (2020)
BioASQ	Nentidis et al. (2025)
PubMedQA	Jin et al. (2019)
CliCR	Suster and Daelemans (2018)
LongHealth	Adams et al. (2025)
MediNote	Leong et al. (2024)
DiSCQ	Lehman et al. (2022)
RadQA	Soni et al. (2022)
CliniQG4QA	Yue et al. (2021)
EHR-DS-QA	Kotschenreuther (2024)
EHRNoteQA	Kweon et al. (2024)

Table 12: Corresponding Citations for Datasets considered in Dataset Selection of Table 11

EHR-DS-QA: Case 10083814 (final diagnoses). Three discharge summaries exist across distinct admissions; each lists diagnoses. The correct target for "final diagnoses" is the most recent summary. Earlier summaries contain different diagnoses that are no longer *final* at discharge, explaining prediction–gold divergence without model hallucination.

EHRNoteQA: Case 15877599 (cause of AKI). The note supports a causal chain: gastroenteritis → increased ostomy output → severe dehydration (prerenal) → acute kidney injury. The gold captures the underlying illness; a model response may describe the immediate mechanism. Both are clinically coherent parts of the same sequence.

EHR-DS-QA: Case 10023117 (blood pressure at discharge). Predictions expressed as exact values versus ranges produce different behaviors across metrics. Ranges can be faithful to notes yet fail entailment or completeness thresholds defined against a single gold value.

G Quantitative Challenging Cases Analysis: RAG vs FC

In our analysis we gathered and manually categorized challenging cases of disagreement between metrics (LLM Correctness, NLI Entailment, and Bio-F1) across EHRNoteQA and EHR-DS-QA. Metrics were first z-score standardized and samples were gathered for cases were some metrics belonged to the top 60th percentile while another metric fell within the bottom 40th percentile. The 41 examples gathered were then manually examined in order to categorize them across QA types and determine which answer between RAG and FC is more reliable. We form the following rubric based on the manual analysis: *Specific Entity Extraction* (SEE), *Temporal & Longitudinal Reasoning* (TLR),

What they capture well	What they miss	Typical pattern	Examples (dataset #subject)
LLM Correctness			
Whether the main claim is right.	Unsupported add-ons that don't change the core fact.	Correctness high; Faithfulness low (adds extra).	EHRNoteQA #10043423 (core claim right, adds recommendation); EHRDSQA #10094318 (chief complaint right, extra symptom).
LLM Completeness			
Coverage of the requested pieces/elements.	Penalizes omissions but not ungrounded embellishments.	Completeness high; Faithfulness low (fully covers, then embellishes).	EHRNoteQA #10043423 (covers requested items + extras); EHRDSQA #19796003 (lists largely complete; minor extras elsewhere reduce faithfulness/F1).
LLM Faithfulness			
Grounding to evidence/gold; flags hallucinated or embellished content.	Can be over-strict on benign context or plausible but unsupported expansions.	Correct/Complete high; Faithfulness low (ungrounded detail).	EHRNoteQA #10043423 (extra recommendation not supported); EHRDSQA #10131388 (adds follow-up/psychiatric context not explicit).
NLI Med Entailment / Contradiction			
Sentence-level logical relation to gold (entailed vs. contradicted).	Sensitive to negation, hedging (*"low risk"* vs *"no risk"*), and phrasing templates.	Correctness high; Entailment low or Contradiction high (wording/negation mismatch).	EHRNoteQA #10494486 (mechanism phrasing hurts entailment); EHRDSQA #10010655 (*"no risk"* vs *"low acute risk"* triggers contradiction).
Meteor			
Surface-form overlap, good for close paraphrases.	Under-rewards long phrases, synonyms, and re-phrasings with low lexical overlap. Incorrectly rewards inaccuracies with lexical overlap.	Correctness high; Meteor low (semantic match, low surface match).	EHRDSQA #10076958 (concise "diffuse ischemic bowel" vs long gold narrative); #19796003 correct single word answer but low score; EHRNoteQA #10404814 (correct causal link, different wording/structure).
BioClinical F1			
Token/span overlap for clinical entities; good checklist signal for missing/extra items.	Under-rewards clinically acceptable reformulations (class vs. specific drug),. Incorrectly rewards inaccuracies with lexical overlap.	Correctness high; F1 moderate/low (one entity missing or formatted differently).	EHRNoteQA #10043423 (right ideas, entity list/format differences lower F1); EHRDSQA #19796003 (near-exact meds but lower F1 for small misses).

Table 13: What each metric captures vs. misses, with typical disagreement patterns and representative examples from EHRNoteQA and EHRDSQA.

Category	Total	Favored by RAG	Favored by FC
SEE	18	12 (66.7%)	6 (33.3%)
TLR	10	3 (30.0%)	7 (70.0%)
CNS	10	6 (60.0%)	4 (40.0%)
ANI	3	2 (66.7%)	1 (33.3%)
Total	**41**	**23 (56.1%)**	**18 (43.9%)**

Table 14: Breakdown of sampled favored by RAG vs FC across four categories in open-ended QA.

Clinical Nuance & Status (CNS), *Absence or Negative Information* (ANI) and show results in Table 14.

RAG shows higher performance across the *SEE*, *CNS* and *ANI* categories, while FC leads in the *TLR* one, demonstrating that while RAG effectively preserves the relevant information for challenging cases, it falls behind when temporal reasoning is required. A further qualitative analysis providing insights on cases where RAG or FC perform better (§H) showcases findings on par with the quantitative ones, with the exception of *ANI* where FC has more promising although inconsistent performance.

H Qualitative Analysis: RAG vs FC

In Table 15 we summarize our insights about case categories where either RAG or FC tend to be more beneficial, providing specific use cases by open-ended generative dataset. We also provide examples along each of our main findings below:

- *FC performs better for questions requiring comprehensive understanding* of the entire document or when answers are located in structured sections (i.e. lists) or temporal sequences.

  Examples include:

  - Questions like "What is the patient's discharge condition?" or "What were the patient's discharge diagnoses?".
  - Temporal sequence questions, such as "What surgeries has the patient undergone and in what order?".

- *RAG outperforms FC for questions that require retrieving specific details or synthesizing scattered information* across multiple parts of the document.

  Examples include:

  - Questions like "What family history does the patient have?" or "How many tablets of dilaudid did the patient receive?".
  - Synthesis tasks, such as "What were the patient's postoperative course details?".
  - Asking about specific dates like "What was the outcome of the patient's

colonoscopy as described in the discharge summary from the stay starting on 2113-09-30?" or "What was the patient's diagnosis for the hospital admission on 2154-01-28…" and other examples.

- *RAG tends to perform better overall in datasets where specific information is required from complex or lengthy documents*.

  For example:

  - In the EHRNoteQA dataset, RAG consistently outperformed FC for questions needing specific details from notes or summaries, such as "What was the outcome of the patient's colonoscopy?"

- *There is mixed evidence suggesting FC might perform better for tasks involving inferential reasoning* or identifying the absence of information.

  For example:

  - Questions like "Were there any complications during the procedure?" where RAG retrieves statements like "No complications," potentially diminishing FC's advantage.
  - Subtle inference tasks, such as "Does the patient have any psychological issues?" where FC occasionally performs better, though inconsistently.

Insight	Favored	Explanation	Supporting Examples
Specific Fact Retrieval	RAG	RAG excels at extracting precise, well-defined medical facts (dates, medications, lab values, procedures) that are typically documented in structured sections of medical records.	**EHRNoteQA:** *Subject 15036658:* Colonoscopy outcome from specific date (RAG: 0.632 vs. FC: 0.399) *Subject 11049732:* Medication changes (RAG: 0.829 vs. FC: 0.352) *Subject 17818938:* Surgical procedure for erectile dysfunction (RAG: 0.918 vs. FC: 0.479) **EHR-DS-QA:** *Subject 10131388:* Dilaudid tablet count (RAG: 0.982 vs. FC: 0.778) *Subject 19926045:* DVT medication (RAG: 0.901 vs. FC: 0.564) *Subject 10090787:* Discharge medications (RAG: 0.425 vs. FC: 0.190)
Temporal Information Processing	Mixed	RAG excels at explicit temporal facts (specific dates, temporal relationships) while FC is better at temporal reasoning (sequencing, duration calculation, recognizing absence of temporal information).	**RAG Advantage:** *EHRNoteQA 15036658:* Specific date anchoring *EHRNoteQA 18467824:* Temporal relationship between admissions *EHR-DS-QA 10264949:* Nausea/vomiting timing **FC Advantage:** *EHRNoteQA 11552479:* Temporal sequencing (FC: 0.696 vs. RAG: 0.236) *EHR-DS-QA 10751849:* Duration calculation (FC: 0.541 vs. RAG: 0.320) *EHR-DS-QA 19397212:* Absence of temporal information (FC: 0.426 vs. RAG: 0.180)
Medical Terminology and Technical Content	RAG	RAG performs better with specialized medical terminology, complex procedures, and technical test results due to its ability to locate and interpret specific sections containing this information.	**EHRNoteQA:** *Subject 17445067:* Diagnosis and surgical procedure details (RAG: 0.708 vs. FC: 0.328) *Subject 18122852:* MRI and EMG test findings (RAG: 0.750 vs. FC: 0.454) *Subject 16313269:* Brain mass pathological diagnosis (RAG: 0.915 vs. FC: 0.372) **EHR-DS-QA:** *Subject 10044189:* Necrotic ulcer treatment (RAG: 0.762 vs. FC: 0.465) *Subject 19401508:* Treatment for hyponatremia (RAG: 0.479 vs. FC: 0.262)
Discharge Planning and Instructions	RAG	RAG performs better on Discharge information (instructions, medications, condition) that is usually well-structured in specific sections.	**EHRNoteQA:** *Subject 11690633:* Discharge condition and instructions (RAG: 0.762 vs. FC: 0.349) *Subject 11863782:* Discharge disposition and medications (RAG: 0.749 vs. FC: 0.327) **EHR-DS-QA:** *Subject 10921250:* Discharge condition (RAG: 0.856 vs. FC: 0.466) *Subject 10940920:* Discharge instructions (RAG: 0.650 vs. FC: 0.253) *Subject 10064678:* Discharge instructions (RAG: 0.352 vs. FC: 0.094)
Cause–Effect and Relationship Understanding	RAG	RAG is better at understanding relationships (symptom–procedure, medication–outcome, test result–action).	**EHRNoteQA:** *Subject 13032648:* Causes of leg pain and surgical procedure (RAG: 0.730 vs. FC: 0.293) *Subject 15748482:* Flomax usage reason and outcome (RAG: 0.819 vs. FC: 0.495) *Subject 17436366:* Blood/urine culture results and actions (RAG: 0.718 vs. FC: 0.445) **EHR-DS-QA:** *Subject 19926045:* Lovenox symptom management (RAG: 0.545 vs. FC: 0.334) *Subject 19401508:* Admission cause and treatment (RAG: 0.372 vs. FC: 0.108)
Holistic Patient Understanding	FC	FC excels when questions require synthesis of information across multiple document sections to build a complete picture of the patient's status, multiple diagnoses.	**EHRNoteQA:** *Subject 18753609:* Therapeutic interventions for leg pain (FC: 0.675 vs. RAG: 0.450) **EHR-DS-QA:** *Subject 10262565:* Discharge condition (FC: 0.882 vs. RAG: 0.681) *Subject 10049941:* Discharge diagnoses (FC: 0.579 vs. RAG: 0.188) *Subject 10978236:* Discharge condition — unusual circumstance (FC: 0.321 vs. RAG: 0.093)
Absence or Negative Information Recognition	Mixed/FC	While findings remain inconsistent with both RAG and FC demonstrating mostly low scores, FC seems more promising at recognizing when information is absent or when negative findings are documented as it can assess the entire document context.	**EHR-DS-QA:** *Subject 19397212:* Absence of symptom presentation timing (FC: 0.426 vs. RAG: 0.180) *Subject 10751849:* Absence of major procedures (FC: 0.243 vs. RAG: 0.037) *Subject 10264949:* Absence of social factors (FC: 0.497 vs. RAG: 0.149) *Subject 19397212:* Absence of age information (FC: 0.725 vs. RAG: 0.452)

Table 15: RAG vs FC Qualitative Analysis.