MedPAIR: Measuring Physicians and AI Relevance Alignment in Medical Question Answering

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Abstract

Large Language Models (LLMs) have demonstrated remarkable performance on various medical question-answering (QA) benchmarks, including standardized medical exams. However, correct answers alone do not ensure correct logic, and models may reach accurate conclusions through flawed processes. In this study, we introduce the **MedPAIR** (Medical Dataset Comparing Physicians and AI Relevance Estimation and Question Answering) dataset to evaluate how physician trainees and LLMs prioritize relevant information when answering QA questions. We obtain annotations on 1,300 QA pairs from 36 physician trainees, labeling each sentence within the question components for relevance. We compare these relevance estimates to those for LLMs, and further evaluate the impact of these "relevant" subsets on downstream task performance for both physician trainees and LLMs. We find that LLMs are frequently not aligned with the content relevance estimates of physician trainees. After filtering out physician trainee-labeled irrelevant sentences, accuracy improves for both the trainees and the LLMs. All LLM and physician trainee-labeled data are available at: `http://medpair.csail.mit.edu/`.

1 Introduction

Large language models (LLMs) have shown strong performance across a range of medical tasks, with systems like GPT-4 and MedPaLM outperforming human averages on standardized medical examinations [9, 42]. However, many tasks do not reflect the complexity of real-world use cases [63], and high performance on exam-style datasets may overstate a LLM's generalizability [39]. In human-facing settings, it is crucial to understand how models filter and prioritize relevant information [47].

Estimation of contextual relevance is a critical aspect in many applications. Techniques such as semantic entropy [23], influence functions [14], context attribution [17, 40], and evidence inference [21] have been employed to assess which elements within a context hold the most importance. Despite these efforts, existing relevance estimations are often imprecise and noisy, with models sometimes producing misleading or overly confident assessments that deviate from human judgment [22]. Even when estimations appear less noisy, model-generated relevance labels may not concord with those of human experts. This gap is particularly concerning in human-facing domains where alignment with expert judgment is necessary [66, 52].

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We focus on the question-answering (QA) in clinical contexts, which reflect how physicians synthesize patient data to address specific concerns. Existing medical QA datasets have driven progress in evaluating LLM's performance on clinically relevant tasks [45, 65, 33, 57]. However, QA benchmarks and leader boards primarily assess final answers, providing limited visibility into the underlying rationale [59, 2].

In this work, we curate a Medical Dataset comparing Physician trainees and AI Relevance estimation and question answering - *MedPAIR*. We design *MedPAIR* to understand how physician trainees and LLMs select relevant information in structured QA. We collect sentence-level relevance labels on 2000 samples from the four QA benchmark datasets from 36 physician trainees. In parallel, we prompt LLMs to self-report sentence-level relevance [15] and apply ContextCite [18], a context attribution framework that maps model outputs to the input sentences most responsible for their generation. This approach allows us to quantify the degree of alignment between human and model assessments of contextual importance. Using these annotations, we evaluate how sentence-level relevance, estimated by either LLMs or humans, affects downstream QA performance. We release the **first benchmark and open-source dataset of physician trainee-annotated relevance for patient case QA tasks**, enabling direct comparison with LLM-assigned scores. Our full workflow can be found in Figure 1.

2 Related Work

2.1 Aligning Human and LLM Estimation

Previous work has shown that limiting input to relevant information can reduce distraction, streamline evidence integration, and reduce memory requirements [38, 16, 41, 8]. Ensuring Artificial Intelligence (AI) systems focus on the same input information that physician trainees identify as relevant is crucial to evaluating which clinical details informed each prediction [58, 37]. This alignment allows physicians to judge the reliability and explainability of AI suggestions and reduces the risk of mistakes caused by extraneous or misinterpreted inputs [13]. Demonstrating alignment between LLM-selected input context and expert judgment is increasingly recognized as fundamental to earning physician trust in diagnostic AI tools [68, 61, 5].

Effective clinical decision-making often relies on understanding nuanced input information that can reveal critical insights. In a systematic review, Schuler and colleagues identify 946 distinct contextual factors that influence clinical decisions, demonstrating the complexity of integrating these elements into evidence-based reasoning [52]. For AI systems to be trusted in clinical settings, they must reflect this contextual understanding, prioritizing information in a way that resonates with clinical judgment [26, 30, 64]. Transparent alignment between AI reasoning and clinician perspectives can reduce the risks of misleading correlations and enhance trust in AI-based clinical decision support [10, 50], where alignment improved confidence in AI-assisted diagnoses. Aligning AI models with physicians' nuanced contextual understanding is essential for their acceptance by the medical establishment and effective integration into clinical practice.

2.2 Challenges in Comparing LLM and Human Relevance Judgments

Recent work has questioned the reliability of LLMs in consistently judging the relevance of information [12]. Although models such as GPT-4 demonstrate high average performance across benchmark datasets, studies have documented significant variance in self-reported labels when identical prompts are issued multiple times [18, 25, 24]. This inconsistency is attributed to several factors: prompt sensitivity [60, 49, 51], stochastic decoding procedures, architectural idiosyncrasies of the model, and ambiguity in input data. Even in deterministic settings (e.g., temperature zero), LLMs can produce divergent responses due to underlying randomness or unstable decision boundaries [3]. Empirical evaluations confirm that model agreement across repeated prompts is rarely perfect, with accuracy fluctuations of up to 10% depending on task complexity and phrasing [4]. Further highlighting this gap, recent studies report that between 50% and 90% of LLM-generated medical answers are not fully supported by the cited references [62]. There are multiple ways to evaluate LLM's relevance judgments in the input context, for example semantic entropy using probabilistic approaches to detect hallucination [23].

These challenges are particularly pronounced in clinical contexts; widely used medical QA benchmarks provide limited visibility into *how* models interpret context. For example, PubMedQA [35] does not offer detailed annotations identifying which parts of the text are crucial for answering the question [55]. Similarly, MedQA [34] lacks expert-provided rationales or sentence-level relevance labels. Other datasets, including MedMCQA [45], MMLU's medical subsets [31], MetaMedQA [28], and MEDIQ [39], also prioritize answer correctness.

3 The MedPAIR Dataset

3.1 QA Dataset Setup

To examine the alignment between physician trainees' and LLMs' assessments of relevance, we deliberately concentrate on existing QA pairs grounded in specific patient case scenarios, rather than general evidence-based questions. This focus is intended to better simulate authentic clinical contexts. Therefore, we draw on our four datasets *Massive Multitask Language Understanding* (MMLU)-precision medicine (272 QAs) [31], *Medbullets* (298 QAs), *JAMA Clinical Challenge dataset* (1,034 QAs) [11], and *MedXpertQA* (2,450 QAs) [69]. The characteristics for each dataset are presented in Appendix section A. Each source provides multi-sentence patient case descriptions paired with questions (4-option or 10-option multiple-choice) and answers, offering a rich context for relevance annotation. Such patient vignettes are broadly recognized in the medical and social sciences, including health economics, and physician responses to clinical vignettes have been shown to predict realized billing behavior in the U.S. Medicare system [20].

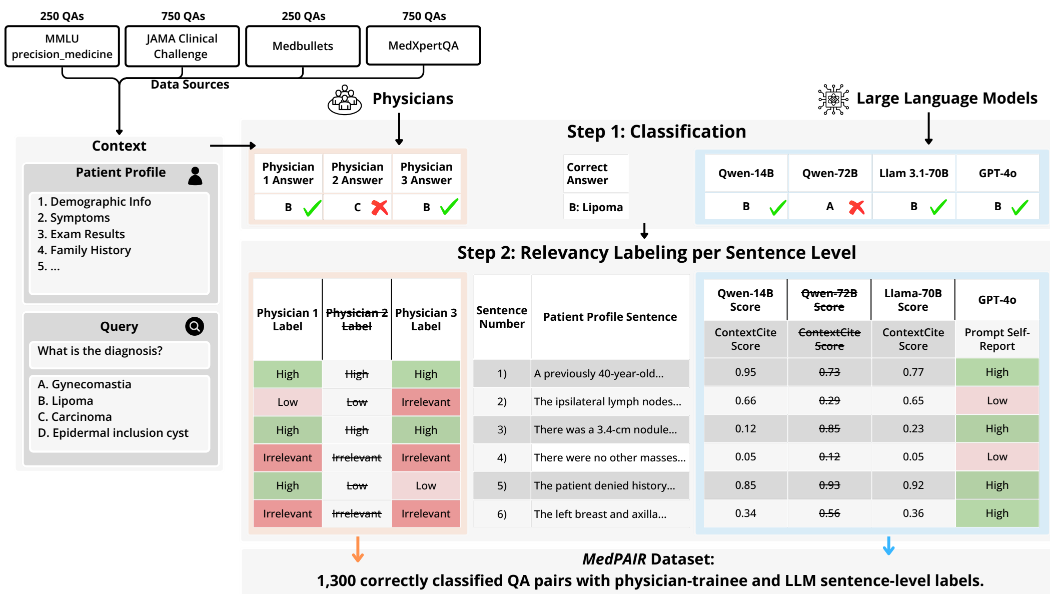


Figure 1: **Study Design.** We consolidated four QA data sources into two main components: the patient profile and the query. In the first step, 36 physician trainees and 4 LLMs independently selected the most appropriate answer. In the second step, physician trainees annotated the relevance of each sentence within the patient profile, excluding annotations linked to incorrect answers. Majority voting was used to produce binary relevance labels for physician trainees. Concurrently, we employed ContextCite with open-source LLMs (Qwen-14B, Qwen-72B, Llama-70B) to generate relevance scores, while GPT-4o was prompted to replicate the physician annotation process for each sentence following the same instructions.

To ensure diversity in patient scenarios, we include only those QAs in which the patient profile contained more than two sentences. Each QA presents a detailed vignette, which is often a long case description covering patient demographic information, symptoms, exam findings, family history, etc. From a combined pool of 4,052 QA pairs, we constructed the final dataset by randomly sampling 250 pairs each from MMLU and Medbullets, and 750 pairs each from JAMA and MedXpertQA, resulting in a curated dataset of 2,000 QA pairs. By pooling these sources, *MedPAIR* covers a wide spectrum of clinical topics and difficulty levels, ensuring that the evaluation is robust across various scenarios from routine to rare conditions. Figure 1 shows the *MedPAIR* data curation process.

3.1.1 Expert Data Annotation

We partnered with Centaur Labs[2] to employ physician trainees (medical students or higher qualifications) annotate the QA pairs. Physician trainees were chosen for their familiarity with medical exam preparation, as these questions are primarily designed for medical students. The demographic information is presented in the appendix table 9.

A total of 36 physician trainees participated (mean age: 26.4), with 77.3% at the advanced training level and 81.8% of the labelers had passed the United States Medical Licensing Examination Step 1 Exam. Notably, half of them reported familiarity with using LLMs in clinical contexts, such as integrating tools like ChatGPT into clinical queries or workflows. On average, each labeler spent an average of 3.28 minutes (SD 3.41 min) per QA. When participants arrived at the correct answer and provided sentence-level labeling, they spent on average 3.26 minutes (SD 3.18 min); for incorrect answers with labeling, the mean time was 3.30 minutes (SD 3.62 min). For each case, physician trainees first selected the most appropriate answer and then annotated the relevance of every sentence in the patient profile. A sample physician trainees' annotation is presented in Figure 1 (orange boxes). Full study instructions and the pre- and post-survey instruments are provided in the supplementary material. Data collection occurred between March 6 and May 5, 2025.

Each QA is annotated by at least three physician trainees and verified to contain at least one correct answer. For each sentence, annotators applied one of three labels: (1) **High Relevance:** Information that is critical and must be considered to answer the question correctly. These are the key clinical clues or data points that strongly point toward the correct diagnosis or decision. (2) **Low Relevance:** Information that provides some context or minor clues but is not essential. These details might help rule out alternatives, yet the question could still be answered correctly without them. (3) **Irrelevant:** Information that is not pertinent to determining the correct answer. These can be distractors or background details included in the vignette that do not impact the outcome in the given context.

This annotation process presents a fine-grained ground truth of relevance for every QA: a trinary label for each sentence in the context, representing the physician trainee consensus on whether that piece of information is pertinent to the question. While obtaining these annotations demanded expert effort, they serve as a gold standard for capturing what physicians deem significant. This level of detailed expert labeling is largely absent from existing medical QA benchmarks, which typically include only the question and answer, without explicit identification of supporting case details and their degree of relevance [11].

3.1.2 LLM Data Annotations

To directly compare physician trainees' majority-vote annotations with LLM-generated labels for each QA pair, we annotated the LLM outputs using both ContextCite and a self-reporting prompt. ContextCite scores approximate the model's attention distribution across sentences [7], while self-reported labels capture the model's own assessment of sentence relevance via prompting.

Then we performed a sentence-level analysis of their respective annotations to examine this divergence at the sentence level. We examined one closed-source model GPT-4o [44] and three open-source models: Qwen-14B, Llama 3.1 Instruct 70B [27], and Qwen 2.5-72B [48]. For GPT-4o, we structured the study the same as physician trainee labeling protocol: we fed the identical instruction prompt three times and determined each sentence's relevancy label by majority vote. For the open-source models, we applied ContextCite to quantify the relevance of each sentence within the QA contexts, as ContextCite provides a simple, scalable mechanism for tracing portions of a generated response back to specific input sentences [18]. Each model received the identical prompt used by the physician labelers to elicit sentence-level relevance judgments. The complete prompts for generating self-reported labels and ContextCite annotations are provided in Appendix section C.

[2] https://centaur.ai

3.2 Problem Formulation

Suppose that a particular question consists of a set of sentences $\mathcal{S} = \mathcal{S}^+ \cup \mathcal{S}^-$, where $\mathcal{S}^+$ is the set of relevant sentences (as labeled by a physician trainee), and $\mathcal{S}^-$ is the set of irrelevant sentences. Let $Y \in \{1, 2, ..., K\}$ be the true label. Suppose we have some LLM $f : 2^{\mathcal{S}} \to \{1, 2, ..., K\}$.

In order to probe whether f answers the question using the same information as a human, we compare $f(\mathcal{S})$ with $f(\mathcal{S}^+)$, under the assumption that the set $f(\mathcal{S}^+)$ is sufficient for a human to answer the question correctly. This gives us the following possible scenarios:

1. $f(\mathcal{S}) = f(\mathcal{S}^+) = Y$: The model is correct in both cases, suggesting that it relies on the same information as a human to solve the problem.
2. $f(\mathcal{S}) \neq Y, f(\mathcal{S}^+) \neq Y$: The model is incorrect in both cases, indicating that the problem is inherently difficult or f has poor capabilities.
3. $f(\mathcal{S}) = Y, f(\mathcal{S}^+) \neq Y$: By removing irrelevant sentences, we flip a correct prediction to an incorrect one. This indicates that the model may have been relying on spurious information in $\mathcal{S}^-$ (i.e. information for which a human deems irrelevant) to make its predictions.
4. $f(\mathcal{S}) \neq Y, f(\mathcal{S}^+) = Y$: The model improves when irrelevant information is removed, indicating that $\mathcal{S}^+$ contains sufficient information to answer the question as expected, and the presence of $\mathcal{S}^-$ introduces noise or distractions.

As case (3) is the most salient, we propose a metric to evaluate f based on the prevalence of samples which fall into this case. Specifically, we define the SR (**S**purious **R**ate), which is computed as:

$$\texttt{SR}(f) = \frac{\sum_{i=1}^{N} \mathbf{1}[f(\mathcal{S}_i) = Y_i \wedge f(\mathcal{S}_i^+) \neq Y_i]}{\sum_{i=1}^{N} \mathbf{1}[f(\mathcal{S}_i) = Y_i]},$$

where N is the total number of questions. A higher SR indicates greater reliance on spurious or irrelevant information, while a lower value suggests the model's predictions are more robust to the removal of distractors and better aligned with human problem solving.

3.3 Evaluation Set-Up

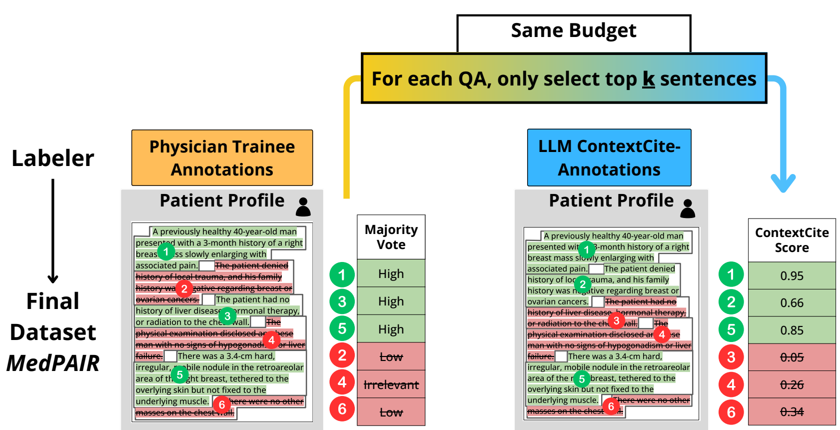


Figure 2: **Aligning Physician Trainee Annotations with LLM ContextCite Raw Scores Using an Identical Input Context Budget.**

To compare the LLM-generated ContextCite scores (numerical) with the relevance labels assigned by the physician trainee (three categories) for each sentence, we established a matching metrics between ternary labels and ContextCite scores to map the numerical scores to the categorical labels. For each QA pair, we let k equal the number of sentences marked relevant by majority vote. We then selected the k sentences with the highest raw ContextCite scores and labeled them "*high relevance*." The remaining sentences were ranked and assigned to "*low relevance*" or "*irrelevant*" based on their score order. This alignment creates a direct mapping between LLM attributions and human judgments, allowing us to assess how well the model's sentence rankings match expert annotations. Figure 2 illustrates this matching process, showing how trainee-provided labels are applied to ContextCite outputs.

4 Results

4.1 Dataset Characteristics

We received a total of 6,224 QA labels from 36 labelers and only 2,918 labels answer the step 1 classification correctly (Figure 1). There are 1,404 unique QAs with all correct physician trainees label, with 104 QAs which contain only highly relevant sentences and for which the QA would therefore be the same after low or irrelevant sentences removal. In the end, we curated 1,300 QAs which contained at least one removed low-relevance or irrelevant sentence.

The four QAs have different characteristics, as JAMA Clinical Challenge are usually long and have lots of details, with each sentence containing more words on average. The low relevance and irrelevant sentences also show the characteristics in perplexity that they are harder to predict as they are more complex, less structured, or diverge from typical language patterns the model has seen during training.

We compared the final 1300 QAs *MedPair* on their average of sentences, words per sentence, and perplexity. Across the four medical QA datasets, the highly relevant sentences are consistently longer and more uniform in structure, with lower perplexity values and thus greater linguistic predictability. In contrast, irrelevant or low-relevance sentences were shorter on average, displayed much higher variability in length, and proved more difficult for the language model to anticipate.

Dataset	**Total QA**	**Total Options**	**Avg Sentence**	**Avg Words Per Sentence**		**Perplexity**	
				High	**Low/Irr**	**High**	**Low/Irr**
MMLU **(Precision Medicine)**	193	4	15.9 (7.0)	18.7 (5.2)	12.8 (4.6)	46.4 (56.3)	58.7 (70.4)
JAMA Clinical Challenge	582	4	26.8 (8.5)	23.1 (5.6)	16.0 (5.4)	51.6 (69.3)	68.2 (92.4)
MedBullets	207	4	21.0 (4.6)	18.1 (4.2)	16.0 (4.3)	46.5 (51.1)	48.3 (65.8)
MedXpertQA	318	10	14.9 (5.6)	21.4 (6.8)	15.6 (4.9)	41.4 (43.8)	52.3 (71.0)
Overall	1300	4/10	21.3 (8.8)	21.2 (6.0)	15.4 (5.1)	48.7 (62.0)	61.0 (82.9)

Table 1: **Comparative Analysis of Physician Trainee–Annotated *MedPair* Dataset Characteristics.** Values in parentheses represent standard deviations.

4.2 Humans and LLMs Disagree on Information Relevance

Data Source	Qwen-72B	Llama-70B	Qwen-14B	GPT-4o
	CC	CC	CC	SR
MMLU	26.9 (0.2)	**70.7** (0.2)	56.9 (0.2)	50.5 (0.3)
JAMA	45.5 (0.2)	**62.1** (0.2)	59.1 (0.2)	45.2 (0.3)
MedBullets	49.8 (0.3)	**66.6** (0.2)	53.9 (0.2)	45.2 (0.3)
MedXpertQA	51.8 (0.3)	**69.3** (0.3)	51.9 (0.2)	52.1 (0.4)
Overall	44.9 (0.3)	**65.9** (0.2)	56.2 (0.2)	47.7 (0.3)

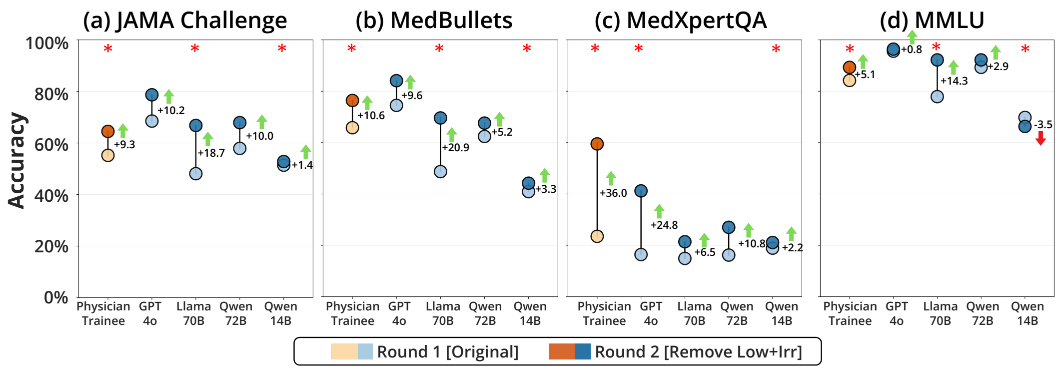
Table 2: **Relevance Label Concordance (%)** with Physician Trainee Labels. "CC" denotes ContextCite score; "SR" denotes Self-Reported labels. Standard deviations in parentheses.

By examining cases in which physician trainees and LLMs produced differing relevance annotations, *MedPAIR* reveals fundamental differences in how each identifies and priorities clinically relevant input context. We quantified the agreement between sentences marked as highly relevant by physician trainees and those highlighted by the models, using ContextCite scores for Qwen-14B, Llama-70B and Qwen-72B alongside GPT-4o self reporting. Although Llama-70B achieved the highest agreement rate at 65.9 percent, the concordance did not exceed two thirds of all instances. More than thirty percent of sentences identified as *"highly relevant"* by clinicians were not recognized by the models as highly relevant. Such discrepancies in relevance annotation are likely to affect the QA accuracy. The results are shown in table 2.

A common pattern was overattention to superficial cues. For example, a model might latch onto a laboratory value that is extreme and assume it must be important, even if it is not relevant to the question at hand. Conversely, models sometimes missed subtle but crucial cues that humans tagged as relevant. These findings could be partially due to LLMs occasionally attribute incorrect answers on misinterpreted or irrelevant context, indicating flawed input context relevance estimates. ContextCite highlights cases where a model justifies its answer by citing a sentence it wrongly deems supportive, what researchers term contributive attribution.

4.3 Human Relevance Improves LLM Performance

After removing low-relevance and irrelevant sentences, LLM performance improved when limited to the physician trainee majority-vote labeled sentences marked as highly relevant. This filtering effectively constrained the model's attention to clinically pertinent information, reducing the noise introduced by less relevant context. Physician labeling instructions explicitly emphasized that QA tasks could be completed using only these highly relevant sentences, ensuring that models concentrated on the critical details necessary for accurate decision-making.



* denotes that statistical significance p < 0.001.

Figure 3: **Effect of Filtering Context on Final Performance.** GPT-4o outperforms all tested open-source language models. After removing irrelevant and low-relevance sentences, LLaMA 70B and Qwen 14B demonstrated the most substantial accuracy improvements. In contrast, Qwen 72B occasionally experiences performance drops following the removal process.

Figure 3 demonstrates that excising sentences deemed low-relevance by physician trainees yields substantial accuracy gains for most LLMs. Noted that in round 2, physician trainee only annotated 248 QAs (the same sampling ratio for each dataset as 1,300 QAs). Notably, Qwen-72B's accuracy increases from 89.3% to 92.2% on the MMLU Precision Medicine subset and from 35.1% to 62.2% overall, while GPT-4o improves from 95.6% to 96.4% and from 39.3% to 73.0%, respectively, preserving its position as the highest-performing model before and after filtering. Parallel improvements appear on the JAMA Clinical Challenge, MedBullets, and MedXpertQA datasets, with standard deviations remaining under 0.5 in nearly every case, indicating consistent benefits of relevance pruning. In contrast, Qwen-14B and Llama-70B exhibit modest declines on the MMLU subset—marked in

Models	MMLU	JAMA	MedBullets	MedXpertQA
Llama-70B	1.6	8.9	7.7	6.0
Qwen-72B	2.6	8.6	5.8	4.1
Qwen-14B	9.8	13.9	18.5	8.8
GPT-4o	2.1	6.5	4.8	4.1

Table 3: **The SR (%) of removing physician trainee-identified low-relevance and irrelevant sentences.** Each number denotes the proportion of questions that were answered correctly in Round 1 but became incorrect in Round 2 after those sentences were removed.

red—suggesting that less advanced models may sometimes rely on information classified as irrelevant. Overall, these findings underscore that expert-guided sentence removal can markedly enhance LLM performance in clinical QA, even surpassing the unfiltered accuracy of physician trainees (48.3%).

While the performance gains were modest, the results indicate that focusing on high-relevance input enables the models to avoid distractions from extraneous information that could otherwise skew their predictions. This targeted approach demonstrates the value of fine-grained relevance curation in enhancing LLM decision-making reliability in clinical contexts. As shown in Table 3, there are a subset of QAs (ranging from 1.6% - 18.5%) which LLM depend on sentences annotated as low-relevance or irrelevant to arrive at the correct answer. Among the models evaluated, Qwen-14B exhibits the highest SR, while the closed-source GPT-4o exhibits the lowest.

4.4 LLM Relevance Improves LLM Performance

The disagreement between physician trainees and LLMs on the input context relevancy reveals the differences in highly relevant sentences. To assess how these differences influence model accuracy, we pruned question contexts according to four criteria: the original unaltered text; sentences retained by physician trainees; sentences retained by Qwen-72B and Llama-70B via ContextCite scoring; and sentences self-reported as relevant by GPT-4o. We then re-evaluated GPT-4o on each reduced context, as it performs the best on the original data.

Datasets	**MMLU**	**JAMA**	**MedBullets**	**MedXpertQA**
Original	95.6	68.5	74.5	16.4
After **Physician Trainee** Labeled Low+Irr Removal	+0.8	+10.2	+9.6	+24.8
After **Qwen-72B** Low+Irr Removal	−1.8	+4.0	+2.3	+24.6
After **Llama-70B** Low+Irr Removal	−2.4	+0.7	+0.1	+22.4
After **GPT-4o** Self-Reported Low+Irr Removal	+1.8	+10.4	+8.6	+8.8

Table 4: **Heatmap of GPT-4o performance gains (%).** Red shades denote positive gains; blue shades denote losses.

In smaller benchmarks such as MMLU, pruning based on non–GPT-4o criteria sometimes led to modest accuracy declines. By contrast, every pruning strategy yielded dramatic gains on MedXpertQA—where shorter average contexts and a larger answer set amplify the benefit of removing irrelevant material—boosting accuracy by 22.4% to 24.8%. The largest improvement occurred with physician-curated pruning, while ContextCite-based selection from Qwen-72B and Llama-70B delivered moderate gains. GPT-4o's own self-reported labels proved the least reliable, occasionally degrading performance. These findings underscore the superior value of expert human judgments for relevance curation in clinical question answering.

4.5 Qualitative Results

A board-certified physician, HJ, reviewed the physician-annotated majority-vote outcomes. Analysis of high- and low-relevance labels reveals that text marked as highly relevant by the physician trainee contains more anatomical structures and comparative descriptions (e.g., progressive, increased), whereas low-relevance text includes more historical information (medication, allergy, travel, social (smoking, illicit drug), etc.) and negative findings (uncomplicated, noncontributory, etc.)(Table 8).

From the full dataset, 30 QA pairs were randomly selected and Dr. HJ compared original and edited versions after removing irrelevant sentences, then categorized these removed low relevance or irrelevant sentences into thematic groups such as *1) Redundant Clinical Details*, *2) Negative Result* that is not essential for current chief complaint, *3) Low relevant or Irrelevant Temporal Information*, *4) History (Medical, Surgical, Medication, Social) with No/Very Low Clinical Information*, etc. The validation exercise evaluated whether the remaining highly relevant sentences maintained the link to the correct answer and whether removing low-relevance content affected answer correctness. The sample case study is presented in Appendix section D and the validation sheet is available in the supplementary material.

5 Discussion

Our findings highlight a significant mismatch between LLM and human expert estimated relevance in the evaluation of clinical vignettes. This resonates with concerns raised in earlier work [6] that LLM performance can be overestimated if one only looks at accuracy [32]. Such discordance suggests that accuracy metrics alone may fail to capture how large language models derive answers from clinical context. Alignment between model-assigned and physician-assigned relevance is essential for developing clinically deployable AI, where safe and effective integration depends not only on producing accurate outputs but also on correct interpretation on the input context. Models that prioritize the same clinically meaningful information as human experts are more likely to support interpretable and actionable decision-making. Previous work has demonstrated that selectively pruning input contexts and retaining only the most relevant context can enhance QA performance in language models [43, 36]. Our experiments extend these findings by showing that context reduction guided by physician annotations, ContextCite scores from open-source models, or few-shot self-report prompting of GPT-4o each provides consistent performance gains across four medical QAs.

Additionally, the *MedPAIR* dataset contributes to understand whether LLM is able to automate the evaluation process as a judge. While our findings suggest that LLMs can enhance performance in this role, the substantial improvements observed with domain expert-generated datasets demonstrate the importance of human involvement in the evaluation process [54, 67]. The human and LLM disagreements on information relevance highlight the need for expert oversight in ensuring accuracy [56]. Although LLMs can provide ContextCite scores and self-report labels to explain the identification of input context, the quality and consistency of these outputs still require validation from human experts. This is particularly important in healthcare, where automating prediction and evaluation with LLMs could have serious consequences due to potential misalignments with human judgment in input information retrieval [1].

6 Limitation & Future Work

Interpreting LLM's input relevance scoring using ContextCite scores and self-reported labels may lack reliability [29, 46]. ContextCite scores do not always accurately capture the relevance of each sentence in decision-making for question answering, while self-reported labels are often inconsistent and may not align with actual annotations. It's critical to understand how LLMs evaluate sentence relevance within patient profiles and new evaluation metrics or measurement approaches may be necessary. Given that human interpretations are costly and time-consuming, we are limited to a small subset of data, which restricts the ability to ensure generalizability within a larger alignment framework. In addition, while removing irrelevant and low-relevance sentences improved accuracy, relying solely on human annotations for this task is impractical for real-time clinical scenarios [19, 53]. Moving forward, we aim to use physician-in-the-loop *MedPAIR* benchmark to fine-tune text-based LLMs (e.g., Llama-3 and Mistral), aligning their contextual relevance judgments more closely with physician reasoning. This enhanced alignment is expected to significantly improve LLM performance in medical QA tasks by enabling models to prioritize clinically relevant information effectively.

7 Conclusion

The *MedPAIR* benchmark establishes a rigorous pre-reasoning evaluation by quantifying sentence-level alignment between LLM relevance judgments and physician-trainee annotations across a comprehensive suite of medical QA scenarios. We introduce the notion of relevance pairs, highlighting which parts of a problem should be central to solving it, and used these maps to diagnose mismatches in how an AI approaches clinical reasoning. Our experiments with 1,300 annotated QA examples revealed that, although the LLM can arrive at correct answers, by solely focusing on the physician-labeled highly relevant input context, LLM performance can be improved. The *MedPAIR* benchmark lays the groundwork for developing LLMs whose performance meet the exacting demands of real-world medical practice.

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Raul Puri, Reah Miyara, Reimar Leike, Renaud Gaubert, Reza Zamani, Ricky Wang, Rob Donnelly, Rob Honsby, Rocky Smith, Rohan Sahai, Rohit Ramchandani, Romain Huet, Rory Carmichael, Rowan Zellers, Roy Chen, Ruby Chen, Ruslan Nigmatullin, Ryan Cheu, Saachi Jain, Sam Altman, Sam Schoenholz, Sam Toizer, Samuel Miserendino, Sandhini Agarwal, Sara Culver, Scott Ethersmith, Scott Gray, Sean Grove, Sean Metzger, Shamez Hermani, Shantanu Jain, Shengjia Zhao, Sherwin Wu, Shino Jomoto, Shirong Wu, Shuaiqi, Xia, Sonia Phene, Spencer Papay, Srinivas Narayanan, Steve Coffey, Steve Lee, Stewart Hall, Suchir Balaji, Tal Broda, Tal Stramer, Tao Xu, Tarun Gogineni, Taya Christianson, Ted Sanders, Tejal Patwardhan, Thomas Cunninghman, Thomas Degry, Thomas Dimson, Thomas Raoux, Thomas Shadwell, Tianhao Zheng, Todd Underwood, Todor Markov, Toki Sherbakov, Tom Rubin, Tom Stasi, Tomer Kaftan, Tristan Heywood, Troy Peterson, Tyce Walters, Tyna Eloundou, Valerie Qi, Veit Moeller, Vinnie Monaco, Vishal Kuo, Vlad Fomenko, Wayne Chang, Weiyi Zheng, Wenda Zhou, Wesam Manassra, Will Sheu, Wojciech Zaremba, Yash Patil, Yilei Qian, Yongjik Kim, Youlong Cheng, Yu Zhang, Yuchen He, Yuchen Zhang, Yujia Jin, Yunxing Dai, and Yury Malkov. GPT-4o System Card, October 2024. arXiv:2410.21276 [cs].

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A Dataset Explanation

Massive Multitask Language Understanding (MMLU) is a common benchmark which consists of multiple domains and tasks based on real-world exams [31]. It includes 57 subjects across STEM, the humanities, the social sciences. Here we only focused on medical related questions (precision_medicine), which has 272 multiple-choice medical questions.

The **JAMA Clinical Challenge dataset** includes 1,034 clinical cases sourced from the JAMA Network Clinical Challenge archive. Each entry summarizes a real and diagnostically complex clinical scenario, presented in the form of a question. These challenges feature an extended case vignette followed by a multiple-choice question with four answer options, accompanied by a detailed discussion explaining both the correct and incorrect responses. The questions span a broad spectrum of medical topics [11].

Medbullets consists of 298 United States Medical Licensing Examination (USMLE) Step 2 and Step 3–style questions curated from open-access posts beginning in April 2022. These questions aim to reflect common clinical scenarios encountered in medical education, with difficulty levels comparable to Step 2 and 3 exams. Each item includes a brief case description, five answer choices, and an explanation that clarifies the reasoning behind both correct and incorrect responses. Compared to JAMA, these cases tend to be shorter and potentially less complex [11].

MedXpertQA consists of 2450 questions for text evaluation. It is a highly challenging and comprehensive medical multiple-choice benchmark. MedXpertQA integrates specialty-specific assessments into medical benchmarking and challenging medical exam questions with real-world clinical information into medical multimodal benchmarking [69].

A.1 NLP Analysis

In order to investigate how sentence relevance shifts according to its position in the clinical vignette, we plotted the labels assigned by physician trainees and those self reported by LLMs (Figure 4 plots (a), (b)) and LLM ContextCite scores (Figure 4 plot (c)). Our objective was to determine whether trainees or the model demonstrate systematic attention to particular segments of the patient profile. All three plots indicate that sentences appearing at the beginning of the text receive the highest relevance ratings. GPT-4o marks slightly fewer sentences as highly relevant and more as irrelevant in the central region compared with physician trainees. In contrast, ContextCite scores decline from approximately 0.33 at the outset to 0.22 by the tenth percentile, then plateau between 0.20 and 0.25 with minimal variance. This flat, low-variance profile diverges sharply from the dynamic patterns of expert and self-reported labels, suggesting that ContextCite does not capture the nuanced, position-dependent relevance judgments.

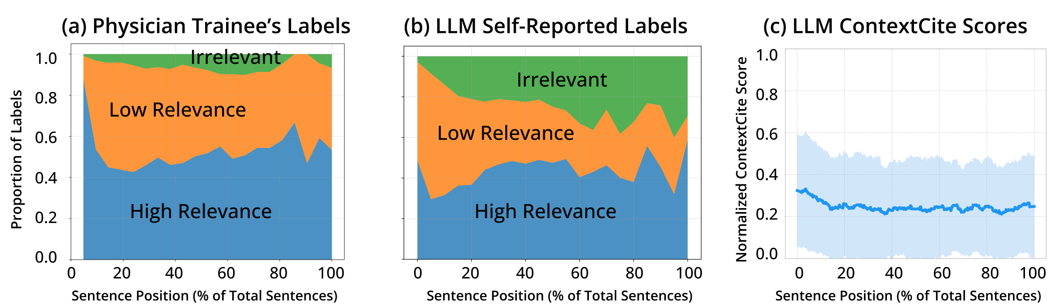

Figure 4: **Sentence Position Analysis.** Plot (a) Distribution of physician trainees' majority-vote relevance labels by sentence position. Plot (b) Distribution of GPT-4o self-reported relevance labels by sentence position. Plot (c) ContextCite scores across the context for three open-source models (Qwen-14B, Llama-70B, Qwen-72B).

B Expert Annotation Dataset Interpretation

We instructed each labeler to annotate every sentence as "high relevance," "low relevance," or "irrelevant." Depending on question difficulty and the exclusion of annotations from labelers whose answer classifications proved incorrect, each item received between one and three valid annotations. We then assigned numeric scores to those labels: high relevance was scored as 1.0, low relevance as 0.5, and irrelevant as 0.0. For sentences with more than one annotation, we calculated the average of those scores. If the average exceeded 0.66, we classified the sentence as high relevance; if it fell between 0.33 and 0.66, we classified it as low relevance; and if it was below 0.33, we classified it as irrelevant. The specific rules and combinations of relevance labels are displayed in Table D.

Labelers	High Relevance Labels	Low Relevance Labels	Irrelevant Labels
3 Correct Labels	High, High, High High, High, Low High, High, Irr High, Low, Low	Low, Low, Low High, Low, Irr	High, Irr, Irr Low, Low, Irr Low, Irr, Irr Irr, Irr, Irr
2 Correct Labels	High, High High, Low	High, Irr Low, Low Low, Irr	Irr, Irr
1 Correct Labels	High	Low	Irr

* “High” refers to high relevance; “Low” to low relevance; “Irr” to irrelevant.

Table 5: Rules based on majority label agreement across different label landscapes for each sentence-level analysis.

To structure the evaluation, we designed a framework distinguishing between accurate prediction and relevance agreement, summarized in the confusion matrix presented in Table 6. We evaluated the outcomes under both conditions in two ways: (a) *Answer correctness*: did the model get the question right or wrong? and (b) *Relevance agreement*: how well did the model align with the physician trainee's annotated relevant components?

We quantified alignment using metrics such as the proportion of the model's referenced high/low relevance components and the frequency of referencing irrelevant components, comparing these against the ground-truth annotations. Our goal is to ensure that relevance agreement aligns with both accurate prediction (true positives (TP) in Table 6) and correct relevance, using clinicians' relevance labels with correct predictions as ground truth. We seek to minimize cases where the model achieves correct predictions but relies on incorrect relevance (false positives (FP) in Table 6).

		Relevance Agreement	
		Yes	**No**
Accurate Prediction	**Yes**	TP (Relevance✓, Accurate ✓)	FP (Relevance✗, Accurate ✓)
	No	FN (Relevance✓, Accurate ✗)	TN (Relevance✗, Accurate ✗)

Table 6: **Confusion matrix of prediction accuracy and relevance agreement.** In our MedPAIR benchmark, we evaluated relevance labels from both physician trainee labelers and LLMs.

C Labeler Instructions & Prompts

We asked each physician trainee labeler to follow this instruction during sentence-level relevance labeling:

> You are given a list of sentences from a clinical vignette and a multiple-choice clinical question. Your task is twofold: (1) Select the most appropriate answer from the given options. (2) Label each sentence as either **[High Relevance]**, **[Low Relevance]**, or **[Irrelevant]**, based on its contribution to answering the question.
>
> **DEFINITIONS:**
>
> **[HIGH RELEVANCE]:** Give this label to sentences that directly answer the medical question with specific and essential information. If this part is missing or altered, the answer would be significantly affected.

- A sentence that explicitly states the primary cause or contributing factor (history, demographics, etc.) is considered high relevance.
- If the question is asking about the treatment plan, a sentence that clearly states the specific indication of the proposed treatment plan is considered high relevance.
- If the question is asking about the diagnosis, a sentence that includes diagnostic criteria for the condition is considered high relevance.
- If the question is asking about test results, a sentence that clearly reports the key findings that confirm or support the test outcome is considered high relevance.

[LOW RELEVANCE]: Give this label to sentences that offer background or contextually related or background information that may be helpful but do not directly answer the question.

- A sentence that includes a secondary or potential contributing factor (symptoms, history, etc.) of the main patient condition is considered low relevance.
- A negative history that contradicts or does not support the diagnosis (e.g., no prior epistaxis when the diagnosis is epistaxis) is considered low relevance.
- If the question is asking about the treatment plan, a sentence that includes the intervention or therapy that is not central to the gold standard treatment is considered low relevance.
- If the question is asking about the treatment plan, a sentence that describes the outcome of a previous intervention for the current chief complaint or diagnosis—particularly one that was unsuccessful—is considered low relevance.
- If the question is asking about the treatment plan, a sentence that does not indicate the treatment itself but instead rules out other conditions that would require different treatments is considered low relevance.
- If the question is asking about the diagnosis, a sentence that includes criteria that could rule out the current diagnosis (that provides differential diagnosis of the patient condition) is considered low relevance.
- If the question is asking about test results, a sentence that reports findings that correlate with or commonly co-occur with the expected result—but are not definitive—is considered low relevance.

[IRRELEVANT]: Give this label to sentences that do not fall under high or low relevance, or that seem completely unrelated or unhelpful to answering the question. Irrelevant sentences wouldn't affect anyone answering this QA even if this is removed.

- Sentence that adds no additional information on solving question and doesn't help in differentially diagnosing the condition
- General findings, not specific to the diagnosis or management decision.

Focus on identifying the information that directly contributes to answering the question. This task involves only text and does not include any images. If the text refers to figures or mentions 'from the image,' focus only on the information presented in the text. Please consider the following clinical question and answer options when labeling each sentence. Then, label each sentence.

To ensure both physician labelers and the LLM received identical instructions, we used the same prompt when eliciting self-reported sentence-level relevance annotations.

We also asked LLMs to output the answer while compiling the ContextCite score for each sentence.

You are a clinical reasoning assistant. You will receive a patient case summary and a multiple-choice question.
Read the question and state your answer.
Patient Context: [*patient profile text*]
Question and Options: [*question and options*]

Please select the single most appropriate answer. Respond only in the following format:
Answer: <LETTER>

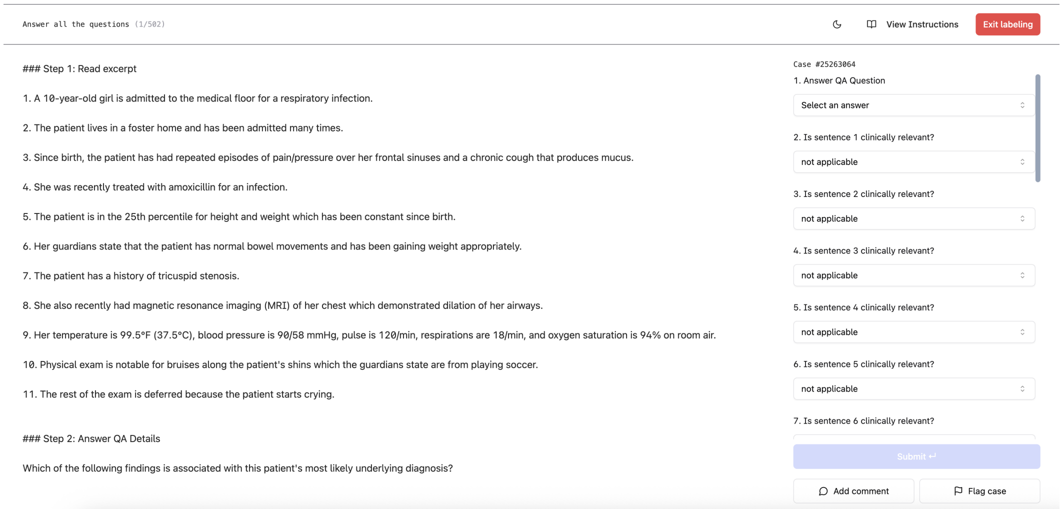

Figure 5: **Centaur Labs Labeling Interface.** The physician trainee labelers first answer the classification question, then provide high relevance, low relevant, and not relevant labels to each sentence.

	MMLU Precision Medicine (193 QAs)		JAMA Clinical Challenge (582 QAs)		Med Bullets (207 QAs)		MedXpertQA (318 QAs)		**Overall (1,300 QAs)**	
	Before	After	Before	After	Before	After	Before	After	Before	After
Physician Trainees	84.2 (0.4)	[31 QAs] 89.3 (0.2)	55.2 (0.5)	[93 QAs] 64.5 (0.2)	65.8 (0.5)	[31 QAs] 76.4 (0.2)	**23.5** (0.4)	[93 QAs] 59.5 (0.2)	**48.3** (0.5)	[248 QAs] 67.2 (0.2)
Qwen-14B	69.8 (0.5)	66.3 (0.5)	51.4 (0.5)	52.8 (0.5)	40.9 (0.5)	44.2 (0.5)	18.9 (0.4)	21.1 (0.4)	45.0 (0.5)	45.7 (0.5)
LLaMA-70B	77.9 (0.42)	92.2 (0.3)	48.1 (0.5)	66.8 (0.47)	48.7 (0.5)	69.6 (0.5)	14.9 (0.4)	21.4 (0.4)	30.0 (0.5)	62.2 (0.5)
Qwen-72B	89.3 (0.3)	92.2 (0.3)	57.9 (0.5)	67.9 (0.5)	62.4 (0.49)	67.6 (0.5)	16.2 (0.4)	27.0 (0.4)	35.1 (0.5)	61.5 (0.5)
GPT-4o	**95.6** (0.2)	96.4 (0.2)	**68.5** (0.5)	78.7 (0.4)	**74.5** (0.44)	84.1 (0.4)	16.4 (0.4)	41.2 (0.5)	39.3 (0.3)	73.0 (0.2)

Table 7: **Comparison of accuracy (%) across datasets before and after removing sentences that physician trainees labeled as low relevance or irrelevant.** Values in parentheses represent the corresponding standard deviations. **Bold** denotes the best performance across all physician trainee labelers and LLMs. Red highlighting denotes a drop relative to the baseline.

D Sample QA Case Study

Example of QA Data

Patient Profile:

1. A 29-year-old female presents with low back pain of five days' duration.
2. Her new job involves walking several miles daily across a large facility.
3. The pain is localized without radiation; no traumatic history.
4. Medications: only oral contraceptives.

Question: What is the most likely diagnosis?

Options:

A. bilateral sacral extension
B. bilateral sacral flexion
C. sacral base posterior
D. right-on-right sacral torsion
E. sacral base anterior

F. right-on-left sacral torsion
G. unilateral sacral flexion on the right
H. left-on-left sacral torsion
I. left-on-right sacral torsion
J. unilateral sacral extension on the left

Correct Answer: (D) right-on-right sacral torsion.

Sentence #	Physician Labels	GPT4o Self-Reported Labels	Llama70B ContextCite Labels
1	High	High	High
2	Low	Low	High
3	Low	High	High
4	Irr	Irr	Low

In this case study, we observe notable disagreement in informativeness assessments across sentence 2 and sentence 3 among physicians, GPT-4o, and LLaMA-70B ContextCite. Sentence 2 ("Her new job involves walking several miles daily across a large facility") was labeled as *Low* by both physicians and GPT-4o, yet *High* by LLaMA-70B ContextCite. This sentence describes the patient's lifestyle, specifically her physical activity level related to her job. This information is of limited relevance

Dataset	Readability		Top Keywords Frequency	
	High	Low/Irr	High	Low/Irr
MMLU (Precision Medicine)	62.0 (15.3)	67.4 (26.3)	days, emergency, department, shortness leukocyte, urine, previously	unremarkable, currently, smoke, controlled, illicit, bmi, illness, oral, kgm, weighs
JAMA Clinical Challenge	34.5 (15.3)	40.1 (18.3)	foveal, hyperreflective, spots, girl, progressively, hypopyon, cytoplasm, punctate, ventricular, man	swab, travel, procedures, order, allergic, noncontributory, pertinent, digital, empirically, animals
MedBullets	67.0 (12.2)	71.9 (16.4)	extremity, increased, meq/L, developed, flexion, bright, right, lateral, poor, progressively	metformin, sexually, active, clear, medications, uncomplicated, known, cervical, nonfocal, albuterol
MedXpertQA	49.8 (16.0)	54.9 (21.5)	progressive, severe, levels, low, urea, spine, nitrogen, labor, iliac, mmoll	trauma, allergies, appropriately, murmurs, vitamin, beers, personal, resuscitation, ordered, taking
Overall	47.5 (19.9)	52.9 (23.9)	spots, foveal, hyperreflective, progressive, hypopyon, watery, cytoplasm, punctate, particularly, wrist	organomegaly, smoke, walks, comfortable, noncontributory, personal, nonfocal, antihypertensive, weekends, case

Table 8: **Comparison of dataset characteristics focusing on Readability and Top Keywords Frequency.** Values in parentheses represent standard deviations. The readability is calculated through Flesch Reading Ease score, which typically ranges from 0 to 100, where a higher score indicates that the text is easier to read, and a lower score suggests the text is more difficult. We highlighted each clinical term using different colors based on the type of information it conveys: symptoms, severity, description on findings, demographics / history, medicine, medical test, anatomical structure/term, negative findings or suggestive of good patient status, timeline, comparative.

to sacral torsion. While one cannot entirely rule out its contribution—since prolonged walking with an asymmetric posture could potentially predispose a patient to sacral dysfunction—it is not a direct cause or a diagnostically decisive factor. As such, it offers minimal value in determining the correct answer to this question. LLaMA-70B may have overemphasized contextual lifestyle clues, interpreting the exertion from walking as highly indicative of a mechanical sacral dysfunction, whereas clinicians likely viewed it as a nonspecific background factor without clear diagnostic utility.

The sentence 3 (“The pain is localized without radiation; no traumatic history”) received a Low label from physicians but High from GPT-4o and LLaMA-70B. This discrepancy may reflect differing heuristics: while clinicians might not prioritize localization and absence of trauma due to their non-specificity or commonality in musculoskeletal complaints, models may have heuristically linked "localized pain without radiation" to mechanical causes, interpreting it as informative. These examples illustrate how LLMs may misattribute diagnostic weight to surface-level patterns.

Age	Gender	Year of med school?	USMLE Step 1 passed?	Medical school	Familiarity with clinical challenges? (i.e. JAMA Clinical Challenge, NEJM Image Challenge, NEJM Resident 360.)	If you are familiar with any of the clinical challenges, how regularly do you follow these challenges?	Familiarity with MedBullets	How often do you follow clinical challenges such as JAMA/NEJM Challenge?	Familiarity with LLMs in healthcare	Percentage (%) LLM Clinical deployment readiness percentage
N/A	Female	M3	No	Case Western	Some familiarity	Not at all	High familiarity	Not at all	High familiarity	30
28	Male	G3 (MD/PhD)	Yes	UC San Diego	Some familiarity	Not at all	Not familiar	N/A	High familiarity	30
24	Male	M3	Yes	Columbia VP&S	Not familiar	N/A	Not familiar	N/A	High familiarity	20
N/A	Male	M2	Yes	NYU Grossman School of Medicine	Some familiarity	Not at all	Not familiar	Not at all	Some familiarity	70
25	Male	M3	Yes	UNC School of Medicine	Not familiar	N/A	Not familiar	N/A	High familiarity	80
26	Male	M4	Yes	Dell Medical school	Some familiarity	Not at all	Not familiar	Not at all	Some familiarity	30
27	Queer	M3	Yes	KPSOM	Some familiarity	Not at all	Some familiarity	Not at all	Not familiar	N/A
25	Male	M4	Yes	University of Toledo	Some familiarity	Not at all	High familiarity	Not at all	Some familiarity	25
N/A	Male	M2	Yes	Harvard	High familiarity	Occasionally	High familiarity	Occasionally	High familiarity	25
26	Female	M4	Yes	George Washington University SOM	High familiarity	Occasionally	High familiarity	Occasionally	High familiarity	90
27	Female	M3	Yes	UNC Chapel Hill SOM	Not familiar	N/A	Some familiarity	Not at all	Some familiarity	30
26	Male	M4	Yes	UNC Chapel Hill	Not familiar	Not at all	Not familiar	Not at all	Some familiarity	30
28	Female	M3	Yes	KPSOM	Some familiarity	Occasionally	High familiarity	Occasionally	High familiarity	40
25	Male	M3	No	WUSM	Not familiar	Not at all	Some familiarity	Not at all	High familiarity	70
26	Female	M3	Yes	Tufts University School of Medicine	Not familiar	Not at all	Not familiar	Not at all	Some familiarity	40
26	Female	M3	No	Tufts University School of Medicine	Not familiar	Not at all	Not familiar	N/A	Not familiar	70
22	Male	M1	No	Dartmouth Geisel School of Medicine	Some familiarity	Not at all	High familiarity	Occasionally	High familiarity	80
25	Male	M4	Yes	University of Toledo	Some familiarity	Occasionally	Some familiarity	Occasionally	High familiarity	80
26	Female	M4	Yes	Medical College of Georgia	Not familiar	N/A	Some familiarity	Not at all	Some familiarity	45
28	Male	M4	Yes	Alabama College of Osteopathic Medicine	Some familiarity	Occasionally	Not familiar	Not at all	Some familiarity	60
25	Male	M3	Yes	Warren Alpert Medical School of Brown University	Some familiarity	Occasionally	High familiarity	Not at all	Some familiarity	45
32	Male	M4	Yes	Northwestern	Not familiar	Not at all	Some familiarity	Not at all	Some familiarity	5
27	Female	M4	Yes	Alabama College of Osteopathic Medicine	Not familiar	N/A	Not familiar	N/A	Some familiarity	50
23	Male	M1	No	University of Maryland School of medicine	Some familiarity	Occasionally	Some familiarity	Not at all	Some familiarity	45
N/A	Male	M4	Yes	Harvard	High familiarity	Occasionally	Not familiar	Not at all	High familiarity	60
28	Female	M4	Yes	Dartmouth	Not familiar	N/A	Some familiarity	Not at all	High familiarity	80
25	Male	M3	Yes	Indiana University School of Medicine	Some familiarity	Not at all	Some familiarity	Not at all	High familiarity	20
29	Male	M4	Yes	Emory University	Some familiarity	Occasionally	Not familiar	Not at all	High familiarity	60
23	Male	M1	No	UC Irvine	Not familiar	Not at all	Not familiar	Not at all	High familiarity	50
33	Female	M4	Yes	Touro College of Osteopathic Medicine Middletown NY	Not familiar	N/A	Not familiar	N/A	Some familiarity	70
26	Male	M4	Yes	UNC School of Medicine	Some familiarity	Occasionally	High familiarity	Occasionally	High familiarity	75
25	Male	M1	No	University of Texas Medical Branch	Some familiarity	Occasionally	Not familiar	Not at all	Some familiarity	50
N/A	Male	M4	Yes	Dell Medical School	Not familiar	N/A	Some familiarity	Not at all	Not familiar	20
26	Male	M3	No	Rush Medical College	Some familiarity	Occasionally	Some familiarity	Occasionally	High familiarity	25

Table 9: **Pre-Survey Demographics and Educational Background of Medical Student Participants, Including Self-Reported Familiarity with Clinical Challenges and LLMs in Healthcare.** "N/A" denotes that the labeler chose not to disclose this information. The complete list of pre-survey questions is available in the supplementary material.

NeurIPS Paper Checklist

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   Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

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2. **Limitations**

   Question: Does the paper discuss the limitations of the work performed by the authors?

   Answer: Yes

   Justification: A dedicated limitations section can be found at the end of the paper. This highlights key methodological limitations and explains attempts to address robustness, particularly with respect to template variation.

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   Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

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   Justification: No theoretical results are presented in this piece. Any calculations have associated equations in-line and are referenced as such.

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   Answer: Yes

   Justification: All code is available in a public repository that enables the running the context reduction guided by physician annotations and ContextCite scores from open-source LLMs.

5. **Open access to data and code**

   Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

   Answer: Yes

   Justification: A detailed README has been provided within each repository folder describing the steps required to reproduce or extend the current work.

6. **Experimental Setting/Details**

   Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

   Answer:Yes

   Justification: No training or tuning was conducted.

7. **Experiment Statistical Significance**

   Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

   Answer: Yes.

   Justification: The paper reports the statistical significance of the experiments, providing error bars and appropriate analysis of performance across multiple methods. The use of statistical measures enhances the credibility of the findings, demonstrating that the improvements in performance are meaningful and not due to random chance.

8. **Experiments Compute Resources**

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: Yes

Justification: We used 2 A100 GPUs for open-source LLM ContextCite Score generation. Other experiments used 2 CPUs or 1 A6000 GPU.

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13. **New Assets**

    Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

    Answer: Yes

    Justification: Details of the datasets, counts, code, and findings are all available on Github/Huggingface. We will also provide a blog on this website with a more user-friendly explanation of the approach and findings. We aim to increase accessibility of the results to a broader audience.

14. **Crowdsourcing and Research with Human Subjects**

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    Answer: Yes

    Justification:The detailed instructions are attached in supplementary material. The compensation details are mentioned in the manuscript.

15. **Institutional Review Board (IRB) Approvals or Equivalent for Research with Human Subjects**

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: Yes

Justification: We received an IRB2411001474 exempt for our project titled "Towards Digital Sustainability in Health Care: Developing Digital Health Products through Data-Driven User Insights".