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Retrieving Evidence from EHRs with LLMs: Possibilities and Challenges

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Abstract

Unstructured data in Electronic Health Records (EHRs) often contains critical information—complementary to imaging—that could inform radiologists' diagnoses. But the large volume of notes often associated with patients together with time constraints renders manually identifying relevant evidence practically infeasible. In this work we propose and evaluate a zero-shot strategy for using LLMs as a mechanism to efficiently retrieve and summarize unstructured evidence in patient EHR relevant to a given query. Our method entails tasking an LLM to infer whether a patient has, or is at risk of, a particular condition on the basis of associated notes; if so, we ask the model to summarize the supporting evidence. Under expert evaluation, we find that this LLM-based approach provides outputs consistently preferred to a pre-LLM information retrieval baseline. Manual evaluation is expensive, so we also propose and validate a method using an LLM to evaluate (other) LLM outputs for this task, allowing us to scale up evaluation. Our findings indicate the promise of LLMs as interfaces to EHR, but also highlight the outstanding challenge posed by "hallucinations". In this setting, however, we show that model confidence in outputs strongly correlates with faithful summaries, offering a practical means to limit confabulations.

Data and Code Availability We describe the data used for evaluation in §3. Briefly, we evaluate our approach using two datasets: (1) MIMIC-III dataset, (Johnson et al., 2016b), which is available on PhysioNet (Johnson et al., 2016a); and (2) EHR notes of patients admitted to the Emergency Room of Brigham and Women's Hospital (BWH) in Boston, MA, USA, between 2010 and 2015. Our code and data are available at https://github.com/hibaahsan/chil_diagnosis_evidence/.

Institutional Review Board (IRB) This retrospective medical records research was approved by the Mass General Brigham (MGB) IRB with a waiver of requirement for informed consent.

1. Introduction

We consider using LLMs as interfaces to unstructured data (notes) in patient Electronic Health Records (EHRs), ultimately to aid radiologists performing imaging diagnosis. The motivation is that unstructured evidence within EHR may support (or render less likely) particular diagnostic hypotheses radiologists come to based on imaging, but time constraints—combined with the often lengthy records associated with individual patients—make manually finding and drawing upon such evidence practically infeasible. Consequently, radiologists often perform diagnosis with comparatively little knowledge of patient history.

LLMs offer a flexible mechanism to interface with unstructured EHR data, e.g., recent work has shown that LLMs can capably perform *zero-shot* information extraction from clinical notes (Agrawal et al.,

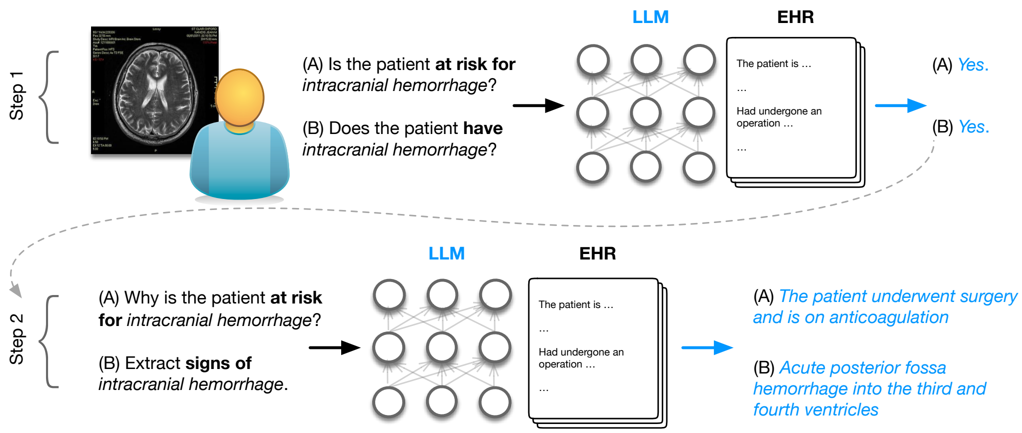


Figure 1: Proposed prompting strategy to identify and summarize evidence relevant to a given query diagnosis using LLMs. We first ask if the patient has (or is at risk of) a condition, then elicit a summary of supporting evidence if so.

2022; McInerney et al., 2023). In this work **we propose and evaluate an approach using LLMs to extract evidence from EHR notes to aid diagnosis**. We envision a clinician providing an initial suspected diagnosis as a query; the LLM should then confirm whether there is unstructured (textual) evidence in the patient record that might support this diagnosis, and—if so—summarize this for the clinician (Figure 1).

LLMs provide an attractive mechanism to permit such interactions given their established dexterity working with unstructured text, and their flexibility. Critically, they permit general question answering (e.g., "Is this patient at risk of *Atrial fibrillation*?") and can summarize supporting evidence. But with this flexibility comes challenges: Skillful as they are, LLMs are prone to "hallucinating" content (Azamfirei et al., 2023; Zhang et al., 2023), which is particularly concerning in healthcare.

We conduct an empirical evaluation with practicing radiologists to assess the use of LLMs as diagnostic aids. Our results show that LLMs are more capable than a representative "traditional" (pre-LLM) information retrieval system at surfacing and summarizing evidence relevant to a given diagnosis. However, manual evaluation by domain experts does not scale. Therefore, we propose and assess an automated evaluation approach using LLMs. Given a piece of evidence, we enlist an evaluator LLM to: (i) Extract the conditions stated as risk factors (or signs) in this snippet; (ii) Confirm the presence of each condition in the note independently; and then (iii) Validate whether each condition is a risk factor (or sign) of the query diagnosis. We find that this automated assessment strategy correlates with expert evaluations, and therefore use it to scale up our evaluation.

Our work shows the potential of LLMs as interfaces to EHRs, but also highlights challenges inherent to their use. How can we know that a generated summary of supporting evidence faithfully reflects an underlying patient record? We highlight troubling examples where the LLM fabricates plausible patient history that *would* support a condition of interest. At best this frustrates the provider (who must read through the record carefully to ascertain if there is in fact such evidence), and at worst it is dangerous. However, we find that model confidence in generations strongly correlates with accuracy in this domain, which mitigates this issue.

Our contributions are as follows. (1) We introduce an approach in which we task an LLM to infer patient risk of a given condition, and to produce a conditional summary of supporting evidence if so. We enlist experts to manually evaluate outputs from two LLMs—Flan-T5 XXL (Chung et al., 2022) and Mistral-Instruct (Jiang et al., 2023a)—and find they both outperform a representative baseline evidence retrieval approach. (2) We introduce a method to automate evaluation of retrieved evidence via an LLM, and show this enjoys good correlation with expert annotations. Larger scale evaluation using this approach confirms the advantage of LLMs over traditional methods. (3) We highlight examples that illustrate the issue of hallucinated content in this context, and report results indicating that LLM confidence may be sufficient to avoid this.

2. Retrieving and summarizing evidence with LLMs

For a given query (≡ condition), we attempt to retrieve two distinct types of evidence from patient history: (A) snippets that indicate a patient *may be at risk* of developing the condition in the future, and; (B) those that suggest the patient *currently has* the condition. For example, a patient on anticoagulants after a recent posterior fossa surgery may be at risk of an intracranial hemorrhage, but not experiencing one currently. By contrast, observing acute posterior fossa hemorrhage indicates the patient most likely has intracranial hemorrhage.

Extracting evidence for *risk* informs clinicians about occurrences in the patient's history (e.g., procedures, diagnoses) that make them more vulnerable to the condition. Extracting evidence for *signs* of a condition serves two purposes. Those that occur in the patient's immediate history indicate that they likely have the condition; those that occur earlier indicate the patient (may) have a history of the condition, which is also important.

We consider openly available "medium-scale" models, including Flan-T5 XXL (Chung et al., 2022) and Mistral-Instruct (Jiang et al., 2023a) as representative LLMs (11.3B and 7B parameters, respectively). While larger, proprietary models may offer superior results, we wanted to use an accessible LLM to ensure reproducibility. Moreover, protections for patient privacy mandated by the Health Insurance Portability and Accountability Act (HIPAA), and our institutional policy on use of LLM restrict us to using models that can be deployed "in-house", precluding hosted variants (e.g., those provided by OpenAI).

Zero-shot sequential prompting We adopt a sequential prompting approach to find and summarize evidence relevant to a query. We first ask the LLM whether a given note indicates that the corresponding patient is at risk for or has a given query diagnosis—prompting the LLM for a binary decision about this. If the answer is 'Yes', we prompt the model to provide support for this response.

More specifically, to query whether the patient is at risk for the given diagnosis, we use the prompts below for Flan-T5 and Mistral-Instruct.

> Read the following clinical note of a patient: `[NOTE]`.
>
> Question: Is the patient at risk of `[DIAGNOSIS]`?
> Choice -Yes -No.
>
> Answer:

To elicit supporting evidence from the model for these risk predictions, we use the following prompt for Flan-T5.

> Read the following clinical note of a patient: `[NOTE]`.
>
> Based on the note, why is the patient at risk of `[DIAGNOSIS]`?
>
> Answer step by step:

For Mistral-Instruct, we found that CoT prompting yielded very lengthy responses. We therefore instead used the following prompt:

> Read the following clinical note of a patient: `[NOTE]`.
>
> Based on the note, why is the patient at risk of `[DIAGNOSIS]`? Be concise.
>
> Answer:

Similarly, to query whether the patient *has* a given diagnosis, we ask "Question: Does the patient have `[DIAGNOSIS]`?" (asking for a binary response). And then to obtain evidence supporting this assessment (in the case of a positive response), we prompt with: "Question: Extract signs of `[DIAGNOSIS]` from the note.". In the above prompts, `[NOTE]` denotes a patient note, and `[DIAGNOSIS]` a potential diagnosis for which we would like to retrieve supporting evidence. We then combine and present the result for the two types of evidence (risks and signs) to the end user.

Why not a single prompt? It might seem more intuitive to simply ask the model to answer 'Yes' or 'No' *and explain its reasoning* in a single prompt. However, we found that this strategy yielded many false positives for both Flan-T5 and Mistral-Instruct. To quantify this, we randomly sampled 40 notes and used a single prompt to find evidence for conditions that the patient did *not* have. The single prompt produced ‘No’ for only 7.5% (Flan-T5) and 27.9% (Mistral-Instruct) of the notes. By contrast, sequential prompting yielded ‘No’ all 40 times for both models. We provide more details in §A.1. We also experimented with a single few-shot prompt to extract evidence (§A.2), but preliminary results were not promising so we did not pursue this further.

A retrieval baseline (CBERT) As a point of comparison for unsupervised evidence extraction (with pre-LLM methods), we use a simple ranking approach using neural embeddings.[1] Specifically, given a query `[DIAGNOSIS]`, we retrieve associated `[RISK FACTORS]` using GPT-3.5 and generate an embedding e_{rf} of the sentence: ‘Risk factors of `[DIAGNOSIS]` include `[RISK FACTORS]`’ using ClinicalBERT (Alsentzer et al., 2019).[2]

Table 7 shows examples of risk factors provided by GPT-3.5. The intuition is to generate n-grams that are likely to indicate risk of the corresponding diagnosis so that we can match these against notes in EHR. Then, for a patient and `[DIAGNOSIS]`, we retrieve the top 20 sentences in the patient notes most similar to e_{rf}. One downside of such a retrieval-based approach is the need to pre-specify the number of evidence snippets to retrieve (here, we arbitrarily set this to 20). By contrast, the LLM approach implicitly and dynamically adjusts this threshold. We refer to this baseline as CBERT.

3. Data

For evaluation, we collaborated with radiologists, specializing in neuroimaging, from the Brigham and Women’s Hospital (BWH) in Boston, MA, USA. Three radiologists with 25,15, and 8 years of experience, respectively, participated in the evaluation. One of them (25 years of experience) had prior experience with LLM projects while the other two did not. For experiments, we used a private dataset from BWH and the publicly available MIMIC-III (Johnson et al., 2016b) dataset, to ensure that our findings are robust and (partially) reproducible.

BWH dataset comprises patients admitted to the Emergency Room (ER) of BWH between 2010 and 2015 along with clinical notes including: cardiology, endoscopy, operative, pathology, pulmonary, radiology reports, and discharge summaries. We sampled patients who underwent brain imaging within 48 hours of their ER visit. It is typically in the ER that evidence can be beneficial as the initial diagnosis is undetermined in most ER cases. Clinicians attend to several patients in one shift and have to go through often previously unknown patient history to come up with a diagnosis (Murray et al., 2021). Without this constraint, the probability of the diagnosis already being determined in the past would be higher and would trivialize the problem. We are interested in scenarios where patients are associated with a large volume of EHR data, so we included patients with ≥10 EHR notes.

Diagnosis	Notes	Evidence	
		Flan-T5	Mistral-Instruct
MIMIC-III			
intracranial hemorrhage*	95	29	26
stroke	16	4	2
small vessel disease	16	8	2
pneumocephalus	12	12	11
sinusitis	49	14	3
Total	**188**	**67**	**44**
BWH			
small vessel disease	13	8	2
chemoradiation necrosis	18	10	20
demyelination	21	12	9
brain tumor	21	20	17
intracranial hypotension	20	20	5
craniopharyngioma	20	18	10
cerebral infarction	14	14	20
sinusitis	17	15	8
Total	**144**	**117**	**91**

Table 1: **Evaluation dataset statistics**. *intracranial hemorrhage is the only diagnosis with more than one patient (it has 4).

MIMIC-III is a publicly available database of deidentified EHR from patients admitted to the Intensive Care Unit (ICU) of the Beth Israel Deaconess Medical Center between 2001 and 2012. As above, we sampled patients who underwent brain imaging within 48 hours of their ER or Urgent Care visit, whose EHR included ≥ 10 notes.

We sampled individual patient data, but evaluated models with respect to diagnoses. For example, if a patient report mentioned ‘stroke’ and ‘sinusitis’, radiologists evaluated the surfaced evidence for these conditions independently. To reduce annotation effort, we discarded diagnoses with ≥20 pieces of ev-

1. Other, even simpler, baselines are a possibility (e.g., BM25, TF-IDF), but the expensive expert time required for annotations limited our ability to evaluate additional baselines.
2. Note that this does not entail passing any sensitive data to OpenAI; we send only a condition name.

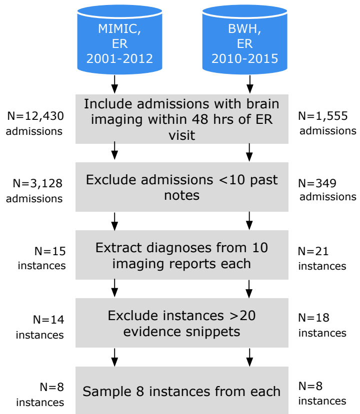


Figure 2: Data sampling flow-chart for our manual evaluation. An instance is a unique (patient, diagnosis) pair. In §5, we perform larger-scale evaluation, automatically.

idence and sampled 8 instances from each source to create our final evaluation dataset. Figure 2 shows a schematic of our data sampling procedure. Table 1 reports statistics about the set of examples used for manual evaluation.

For expert evaluation, one of the collaborating radiologists identified all diagnoses discussed in the *Findings* and *Impressions* sections of the radiology reports of 10 patients from each dataset (excluding MIMIC-III patients used in the pilot).[3] For each diagnosis, we retrieved supporting evidence from all patient notes using the zero-shot prompting strategy from §2. Three collaborating radiologists then manually assessed each retrieved piece of evidence.

Because the relevance of an evidence snippet inherently depends on the context, we ask radiologists to ground their assessments by assuming the following hypothetical setting: "You are a radiologist reviewing a scan of a patient in the ER. Based on the scan, you are concerned that the patient has the diagnosis stated below. Assess the relevance of the retrieved evidence to support your inference." (Figure 6 provides a screenshot of the interface.) For each piece of evidence surfaced by a model, radiologists answered two questions.

Is the evidence present in the note? LLMs can "hallucinate" evidence. Therefore, we first ask radiologists to confirm whether *all* of the model generated evidence is in fact supported by the note on the basis of which it was produced. To aid the radiologists in finding the corresponding sentences, we compute ClinicalBERT (Alsentzer et al., 2019) embeddings of sentences in the notes and highlight those with a cosine similarity of ≥ 0.9 with the ClinicalBERT embedding of the generated evidence. This heuristic approach realizes high precision but low recall. Therefore, if a highlighted sentence is incongruous with generated evidence, we ask radiologists to read through the entire note to try and manually identify support.

Note that the (non-generative) retrieval method to which we compare as a baseline is extractive, and so incapable of confabulating content; we nevertheless ask this question with regards to the baseline for consistency and to ensure blinding.

Is the evidence relevant? If generated evidence is supported by the note, we ask radiologists whether it is *relevant* to the query diagnosis. A piece of evidence can contain multiple reasons summarized from across the note. We collect assessments on the following scale (see Table 3 for examples).

Not Useful None of the evidence is useful; it is irrelevant to the query condition.

Weak Correlation Evidence produced has a plausible but weak correlation with the query condition.

Partially Useful Out of the multiple risks or signs in the evidence, only some are relevant.

Useful The evidence is relevant and may inform one's diagnostic assessment.

Very Useful The evidence is clearly relevant and would likely inform diagnosis.

4. Results

To first assess agreement between radiologists, we had each of them annotate evidence surfaced by Flan-T5 for one patient (selected at random from the BWH dataset). For this patient, the model generated 10 pieces of (potentially) relevant evidence for the query *chemoradiation necrosis*. On this shared set, the inter-annotator agreement score (average pairwise Cohen's κ) for relevance assessments between the three radiologists was 0.68.

Figure 3 shows our main results. Radiologists found evidence generated by Mistral-Instruct to be the most useful (MIMIC-47.7%, BWH-59.0%), followed by Flan-T5 (MIMIC-41.5%, BWH-48.4%) and

3. While this is a relatively small number of patients, we emphasize that manual evaluation is expensive: Radiologists on our team spent ∼16 hours manually assessing outputs.

FLAN-T5/Mistral-Instruct	CBERT
CAD (s/p stents x 2, > 2 MIs, on Coumadin INR=1.9) hx of > 3 TIAs in past 2.5 yrs multiple AAAs (largest last measured at 5.5 cm, surg intervention held 2/2 cardiac status	IMMUNIZATIONS: INFLUENZA VACCINE (INACTIVATED) IM Given [DATE] ALLERGY: AMOXICILLIN ADMIT DIAGNOSIS: Stroke PRINCIPAL DISCHARGE DIAGNOSIS ;Responsible After Study for Causing Admission) same OTHER DIAGNOSIS;Conditions,Infections,Complications,affecting Treatment/Stay CAD (s/p stents x 2, > 2 MIs, on Coumadin INR=1.9) hx of > 3 TIAs in past 2.5 yrs multiple AAAs (largest last measured at 5.5 cm, surg intervention held 2/2 cardiac status OPERATIONS AND PROCEDURES: None.OTHER TREATMENTS/PROCEDURES (NOT IN O.R.)
The patient has a TBI	A/P- S/P REPAIR [**Doctor Last Name **] & LL ORTHOPEDIC INJURIES STABLE TBI W/CLOSE MONITORING FOR CHANGES STABLE LIVER LAC AT PRESENT SUCCESSFULL WEAN/EXTUBATION POST-OP PAIN CONT TO MONITOR PER ORDERS- Q2/HR NEURO & PERIPHERAL VASCULAR CHECKS...?

Table 2: Examples of evidence when generative models are more concise than CBERT, highlighting the benefits of abstractive summarization.

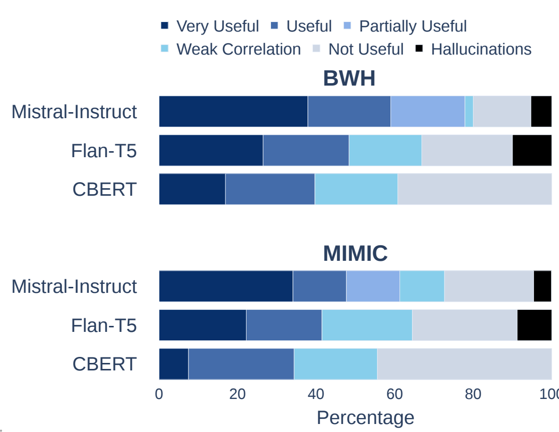


Figure 3: Evidence generated by the LLMs is more often deemed useful than that retrieved by CBERT. But on average, 9.4% and 4.9% of evidence by Flan-T5 and Mistral-Instruct respectively are hallucinated.

then CBERT (MIMIC-34.4%, BWH-39.7%). Flan-T5 and CBERT generated more weak correlations than Mistral-Instruct. Both generative models hallucinated evidence. We observed that unlike Mistral-Instruct, Flan-T5 did not summarize multiple reasons from *across* the note as evidence. Hence, none of its evidence was evaluated to be Partially Useful. Since CBERT is extractive, there is no clear indication of which condition is to be evaluated as evidence. For this reason, the evidence from CBERT was evaluated overall and Partially Useful was not used. The assessment of generated evidence implicitly measures precision. We also estimate model recall in §C.

4.1. Hallucinations

Concerningly, some model hallucinations flagged by radiologists include plausible risk factors. A few illustrative examples:

Example 1 For a patient with demyelination as the query diagnosis, Flan-T5 hallucinated the evidence 'axonal degeneration'. Demyelination is commonly viewed as the primary factor responsible for the deterioration of axons within multiple sclerosis lesions. The model also hallucinated signs of demyelination as evidence ('numbness and tingling in the arms and legs'). There was no evidence indicating axonal degeneration or the symptoms.

Example 2 For a patient with chemoradiation necrosis as the query diagnosis, Mistral-Instruct hallucinated that 'the patient had a history of chemoradia-

Evaluation	Diagnosis	Evidence	Explanation
Very Useful	intracranial hemorrhage	Recent fossa surgery and now on anticoagulants	Surgery in the brain inevitably leaves some hemorrhage. Anticoagulants increase the risk of hemorrhage. 'Recent surgery' and 'anticoagulants' make hemorrhage highly likely.
Useful	cerebral infarction	There is calcified thrombus obstructing the origins of the M2 branches	'Thrombus' is diagnostic of infarction, which is very useful information. But 'calcified thrombus' implies chronicity, so the thrombus could have been present for a long time and there may not be an acute infarction at this time.
Partially Useful	chemoradiation necrosis	The patient is at risk of chemoradiation necrosis due to her history of seizures and brain abscess, which may have caused damage to the brain tissue. Additionally, her use of concurrent Temodar and involved field radiation during her treatment may have further increased her risk.	History of seizures and brain abscess are not relevant to chemoradiation necrosis. Concurrent Temodar use and involved field radiation is useful information.
Weak Correlation	pneumocephalus	patient was involved in a motorcycle accident	A traumatic head injury is an important risk factor of pneumocephalus. A motorcycle accident increases the likelihood of a head injury.
Not Useful	small vessel disease (SVD)	patient is at risk of endocarditis	Not helpful in diagnosing SVD.
Hallucination	intracranial hemorrhage	patient has a brain tumor	Not present in the note.

Table 3: Examples of evidence surfaced by Flan-T5 and Mistral-Instruct for different evaluation categories. Snippet highlighted in red is irrelevant to the query diagnosis.

tion necrosis'. A history of chemoradiation necrosis would be very relevant to its diagnosis, but there was no such history in the EHR.

In other instances, the model hallucinated vague evidence, e.g., 'The patient is taking a lot of medications that can cause small vessel disease' for small vessel disease as the query diagnosis (a radiologist went through the note and was unable to find mention of any such medication).

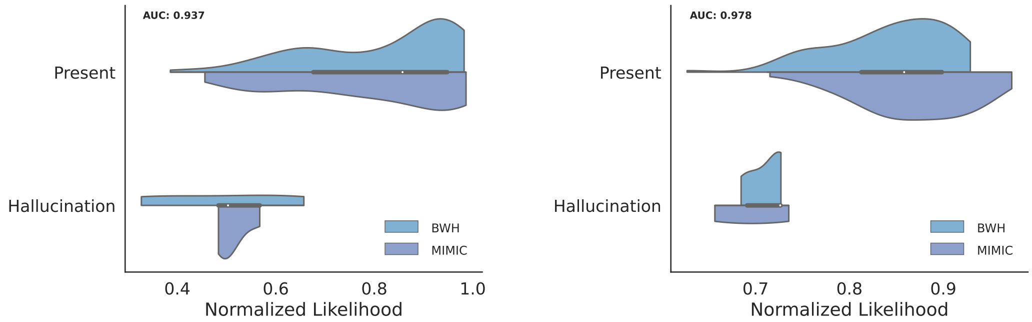
How certain is the model about such hallucinations? We evaluate the degree to which model uncertainty—normalized output likelihoods under the LM—suggests 'hallucinated' content (Figure 4). Both models considered yield confidence scores that are highly indicative of hallucinations. This is promising, as it suggests we can simply abstain from providing outputs in such cases.

4.2. Weakly correlating evidence

A factor complicating evaluation is that LLMs often yield evidence which has plausible but weak correlation with a query condition. One could argue that the model was 'correct' in retrieving such evidence from an epidemiology perspective, but incorrect (or at least not useful) from an individual patient, clinical perspective. In other words, evidence may be so weakly correlated with a condition that it is of small value, even if technically 'correct'. See Tables 3 and 8 for examples.

4.3. Qualitative Evaluation

We summarize the comments offered by radiologists during evaluation. Radiologists found outputs of Mistral-Instruct and FLAN-T5 to be more precise and concise compared to CBERT. Abstractive evidence was considered better than the extractive snippets from CBERT, which often chunked useful evidence with neighboring irrelevant sentences (notes are usually poorly formatted, making sentence-parsing difficult). See Table 2 for examples. CBERT was preferred in three cases, when both Mistral-Instruct and FLAN-T5 had poor precision or recall. For instance, both models had a precision of $\sim 50\%$ for pneumocephalus. Interestingly, our radiologist preferred CBERT for the case of demyelination because it helped confirm that the patient did *not* have demyelination, but in fact had a glioma (tumor). Demyelinating lesions and glioma present similar imaging characteristics and can be difficult to diagnose based on conventional MR imaging (Toh et al., 2012). A brain biopsy is often conducted to differen-



(a) Flan-T5 (b) Mistral-Instruct

Figure 4: Distributions of normalized likelihood, for present and hallucinated evidence. The score provides good discrimination of "hallucinated" evidence from present evidence (yielding AUCs of >0.9).

tiate between the two. All the evidence evaluated as (very) useful were snippets from the pathology report discussing the tests and related results that indicated that demyelination was less likely and that the findings were most consistent with glioma.

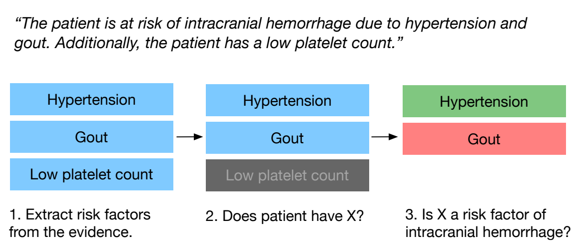


Figure 5: Automatic LLM-based evaluation of retrieved evidence. The evaluator LLM: (1) extracts risk factors from the evidence; (2) verifies the presence of each in the note; and (3) validates each present risk factor. The same approach is adopted for evaluating signs of the query diagnosis.

Model	MIMIC		BWH	
2. Verify presence of each risk factor/sign				
	H	P	H	P
Flan-T5	75.0(4)	90.0	83.3(6)	86.1
Mistral-Inst.	100.0(3)	88.2	60.0(5)	95.1
3. Check validity of present risk factors/signs				
	F1	PCC	F1	PCC
Flan-T5	75.6	79.2	74.2	37.8
Mistral-Inst.	81.4	92.0	77.5	34.2
CBERT	55.0	41.1	63.9	68.1

Table 4: Evaluating automatic evaluation. We first compute the accuracy for hallucinated (H) and present (P) evidence (Step 2 in Figure 5). We then compute micro-F1 and PCC for present evidence (Step 3 in Figure 5).

5. Automatic Evaluation

Manually evaluating evidence requires a considerable amount of scarce (expensive) expert time, meaning it does not scale. This limited our evaluation above to a small set of patients. To expand our evaluation we now also consider the use of LLMs as evaluators. Prior work has established that LLM-based evaluation can provide meaningful signal in general (Chiang and Lee, 2023; Min et al., 2023; Chang et al., 2023; Kim et al., 2023), but there has been limited work investigating such evaluation in healthcare; it is important to assess automatic evaluation in this domain due to the high cost of manual annotation.

In this section, we first verify the degree to which LLM-based automatic evaluations correlate with manual (expert) assessments (§5.1). Finding evidence of meaningful (if noisy) correlation, we then use this automated approach to increase the scale of our evaluation (§5.2).

Figure 5 provides an overview of our approach. Given a piece of evidence generated by an LLM to evaluate, we use an evaluator LLM to: (1) Extract the risk factors it contains; (2) Verify the presence of each risk factor in the note; (3) Check if each present risk factor is a valid risk factor of the query diagnosis. We execute these steps sequentially by one-shot prompting the evaluator LLM for (1) and zero-shot prompting it for (2) and (3). We provide more details in §B. Note that steps (2) and (3) are performed separately for each extracted risk factor. Recall that in addition to risk factors, we prompt for signs of diagnosis; we follow the same approach to evaluate these.

5.1. Evaluating automatic evaluation

We first validate this automated (LLM-based) evaluation approach for our task by comparing it to the expert evaluations described in §3. Given its superior performance according to expert evaluations, we use Mistral-Instruct as the LLM evaluator. We compute micro-F1 and Pearson's Correlation Coefficient (PCC), using expert evaluations on the set of instances manually annotated as the ground truth. Micro-F1 measures how well the LLM evaluates each extracted risk or sign individually (irrespective of which instance these are associated with). PCC is computed at the *instance-level* by calculating the average relevance over extracted risks and signs from all pieces of evidence; this is therefore an aggregate measure of how well the LLM evaluates an instance.

Because automatic evaluation yields binary predictions (whether a risk factor/sign is relevant to the diagnosis or not), we map expert *relevance* scale to binary labels: Not Useful $\rightarrow$ 0 and {Weak Correlation, Useful, Very Useful} $\rightarrow$ 1. For *evidence*, we assign 1 to pieces marked as (Very) Useful or Weak Correlations, and 0 to the rest. As discussed in §4.2, Weak Correlations fall into a grey area. Therefore, we also perform a *strict* evaluation where Weak Correlations $\rightarrow$ 0. We report results in Table 4, and offer the following observations.

Hallucinations can be automatically detected. As seen in Table 4 (top), prompting to confirm whether a patient has a condition based on the note permits discrimination of "hallucinated" and actually present conditions.

Micro-F1 scores are high for generative evidence. The evaluator LLM is able to extract and validate risk factors and signs of diagnoses in a way that agrees reasonably well with human experts. The micro-F1 scores are high for both Flan-T5 and Mistral-Instruct across the datasets.

Micro-F1 scores are relatively low for the baseline retrieval approach. CBERT fares comparatively poorly here. Prompting for risk factors and signs from extractive evidence is difficult because these are not as explicitly stated (as opposed to generative outputs of the format 'The patient is at risk of X because of Y') and are buried in irrelevant information. (This issue was observed during expert evaluation as well.) The result is noisy outputs (e.g., 'intubation', 'worsening respiratory status', 'age') that generate false positives for valid risk factors and signs. This highlights the relative advantage of LLMs for flexible evidence retrieval.

PCC varies from moderate to high. While PCC is high for both Flan-T5 and Mistral-Instruct for MIMIC, the correlation is moderate for BWH. This is apparently due to poor evaluative performance for one diagnosis (chemoradiation necrosis for Flan-T5 and intracranial hypotension for Mistral-Instruct). In both cases, a unique risk factor was incorrectly validated by the evaluator LLM. But multiple occurrences of the risk factor across notes, resulting in repeated retrieval as evidence, significantly brought down PCC. Removing the diagnoses out increases PCC to 82.3 and 51.3 for Flan-T5 and Mistral-Instruct, respectively.

Correlation drops significantly in strict evaluation. Table 5 shows the *change* in micro-F1 and PCC when strict evaluation is performed (compared to when Weak Correlations $\rightarrow$ 1, shown in Table 4). With the exception of PCC for CBERT (MIMIC), there is a drop in micro-F1 and PCC across all model-dataset combinations when Weak Correlations $\rightarrow$ 0. This owes to the inherent complexity of evaluating clinical evidence (automatically or otherwise). What constitutes 'Useful' evidence for supporting diagnosis is, to a degree, inherently subjective.

Model	MIMIC		BWH	
	Δ F1	Δ PCC	Δ F1	Δ PCC
Flan-T5	9.9↓	9.8↓	6.3↓	9.7↓
Mistral-Instruct	15.3↓	14.8↓	1.9↓	13.5↓
CBERT	14.1↓	18.7↑	13.5↓	13.7↓

Table 5: Evaluating **strict** automatic evaluation metrics. The figures here indicate the *change* in micro-F1 and PCC compared to when Weak Correlations $\rightarrow$ 1 (shown in Table 4). Correlation with expert evaluation drops when Weak Correlations $\rightarrow$ 0.

Overall, automatic evaluation using an LLM has a meaningful correlation (micro-F1) with expert eval-

Model	Useful	Not Useful	Hallucinations
Flan-T5			
MIMIC	48.5	42.1	9.4
BWH	47.0	38.4	14.6
Mistral-Instruct			
MIMIC	55.0	35.9	9.1
BWH	59.8	32.0	8.2
CBERT			
MIMIC	29.7	70.3	-
BWH	28.7	71.3	-

Table 6: Results of large-scale evaluation performed by using Mistral-Instruct as an evaluator. LLMs outperform the retrieval baseline. Mistral-Instruct generates more useful evidence compared to Flan-T5.

uation when measured at risk factor (sign)-level. At the instance-level, the correlation (PCC) is moderate (BWH) to high (MIMIC). The variance may owe to the small number of instances evaluated.

5.2. Scaling our Evaluation

Having verified that automatic evaluation provides an imperfect but meaningful assessment of outputs, we now scale our evaluation using this approach. Specifically, we complement our manual analysis with an automatic evaluation of the three models at a larger scale. We evaluate 100 and 50 instances (patient-diagnosis combinations) for MIMIC and BWH respectively. As discussed in §3, a collaborating radiologist identified the query diagnoses in the radiology reports during manual evaluation. For this automatic evaluation, we follow prior work Tang et al. (2023), and consider conditions following *likely indicators* (such as 'concerning for', 'diagnosis include'. Details in §D) as diagnoses.

Table 6 shows results of the scaled up evaluation (see Table 9 for data statistics). Both Flan-T5 and Mistral-Instruct significantly outperform CBERT, consistent with the findings from our manual evaluation. Mistral-Instruct appears to generate more useful evidence compared to Flan-T5 (again consistent with the manual evaluation). Both models have comparable rates of hallucination for MIMIC but Flan-T5 has a higher rate for BWH.

6. Related Work

NLP for EHR. Navigating EHRs is cumbersome, motivating efforts in summarization of and information extraction from EHR (Pivovarov and Elhadad, 2015). For example, in recent related work, Jiang et al. (2023b) created a proactive note retrieval system based on the current clinical context to aid note-writing. Adams et al. (2021) considered "hospital-course summarization", condensing the notes of a patient visit into a paragraph. Other work Liang et al. (2019) has sought to produce disease-specific summaries from notes.

LLMs for healthcare. There has been a flurry of work on the capabilities of LLMs for healthcare *generally*, i.e., in terms of ability to answer general questions and take medical exams, e.g., Singhal et al. (2023); Lehman et al. (2023); Nori et al. (2023); Yang et al. (2022). Our work, however, is focused on a grounded, specific task.

NLP in Radiology. Previous works regarding NLP in radiology primarily focus on processing radiology reports. Some work has sought to automatically generate the Impression section of reports (Van Veen et al., 2023; Zhang et al., 2019; Sotudeh et al., 2020). Other efforts have focused on extracting specific observations (Smit et al., 2020; Jaiswal et al., 2021), and modeling disease progression (Di Noto et al., 2021; Khanna et al., 2023).

NLP to aid diagnosis. The prior work most relevant to this effort concern aiding radiologists in diagnosis. McInerney *et al.* (2020) propose a distantly supervised model (trained to predict ICD codes) to perform extractive summarization conditioned on a diagnoses; our work addresses this problem with LLMs, *zero-shot*. Tang et al. 2023 address diagnostic uncertainty by suggesting less likely diagnosis to radiologists, learnt by differentiating between likely and less likely diagnoses via contrastive learning.

7. Discussion and Limitations

We proposed an approach for using LLMs to retrieve and summarize evidence from patient records which might be relevant to a particular diagnosis of interest, with the aim of aiding radiologists performing imaging diagnosis. Expert evaluations of model outputs performed by radiologists show that this is a promising approach, as compared to pre-LLM techniques. We also established that automated (LLM-based) evaluation is feasible, and confirmed our findings using this approach.

There are important **limitations** to the approach and to our evaluation. We found that LLMs are prone to hallucinating (plausible) evidence, potentially hindering their utility for the envisioned use. However, our results also indicate that model confidence might allow one to pro-actively identify hallucinations, and abstain from providing (generative) summaries in such cases; extending this is an interesting direction for future work.

Our evaluation was limited in a few key ways. We enlisted radiologists to perform in-depth evaluation of a small number of instances, because evaluation is time consuming: We emphasize that this exercise required substantial allocation (∼16 hours) of scarce expert time. We attempted to mitigate this via LLM-based automatic evaluation, performed at larger scale. However, our assessment of this strategy also relied on this relatively small annotated set and so may not generalize. Another limitation here is that we considered only two LLMs (specifically, FLAN-T5 and Mistral-Instruct): Other LLMs might, naturally, perform better or worse. In addition, we did not investigate the fairness implications of our work. However, the small size of our expert-annotated sample and the inherently small samples of underrepresented groups limits our ability to meaningfully assess this. We leave the detailed analysis needed to determine if there are significant differences to future work. Finally, we did not extensively iterate on the prompts used, and this too could substantially affect results.

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Appendix A. Prompting for Evidence

A.1. Single prompt

For the single prompt setting (§2), we followed McInerney et al. (2020)'s approach of using 'future' ICD codes as the patient's diagnoses. To select a diagnosis that the patient did *not* have, we randomly sampled an ICD code, excluding the patient's diagnoses.

For Flan-T5, we use the following Chain of Thought (CoT) prompt :

> Read the following clinical note of a patient: `[NOTE]`
>
> Question: Is the patient at risk of `[DIAGNOSIS]`?
>
> Answer: Let's think step by step.

Some examples of incorrect reasoning by Flan-T5:

1. **Diagnosis:** Diabetes insipidus

   The patient has a Swan-Ganz catheter in place. The Swan-Ganz catheter is a device that is used to measure the amount of blood circulating to the brain. The higher the blood flow to the brain, the higher the risk of diabetes insipidus. The answer: yes.

2. **Diagnosis:** Extradural and subdural abscess

   The patient has asymmetrically distributed airspace opacities affecting the left lung more than the right with coexisting bilateral septal thickening is most suggestive of widespread pulmonary edema. Superimposed aspiration is also possible, particularly in the left lung. The heart *remains enlarged. Small pleural effusions are new. The patient is at risk of extradural and subdural abscess.*

For Mistral-Instruct, again we found that CoT prompting yielded very lengthy responses which were harder to parse. We thus used the following prompt:

> Read the following clinical note of a patient: `[NOTE]`
>
> Question: Is the patient at risk of `[DIAGNOSIS]`? Answer Yes or No and explain your answer. Be concise.
>
> Answer:

Some examples of incorrect reasoning by Mistral-Instruct:

1. **Diagnosis:** Pneumocephalus

   The patient has a history of taking Tylenol PR and has a cool bath, ice packs, and a fan to cool down, which may increase the risk of pneumocephalus.

2. **Diagnosis:** Stroke

   The patient has an endotracheal tube in place, which can increase the risk of stroke if not properly positioned and secured.

A.2. Few-shot prompting

We provide additional details on our preliminary experiments with few-shot prompting. As done in §A.1, we followed McInerney et al. (2020)'s approach of using 'future' ICD codes as the patient's diagnoses. To select a diagnosis that the patient did *not* have, we randomly sampled an ICD code, excluding the patient's diagnoses. We used the following prompt:

> Read the following clinical note of a patient: `[RANDOM NOTE SNIPPET]`.
>
> Answer step by step: can the patient possibly have cardioembolic strokes in the future?
>
> Answer: There is no evidence. Final answer: No.
>
> Read the following clinical note of a patient: patient stopped taking a blood thinning medication required for a heart valve due to side effects.
>
> Answer step by step: can the patient possibly have cardioembolic strokes in the future?
>
> Answer: The patient stopped taking a blood thinning medication required for a heart valve. The medication thins the blood and prevents blood clots. Blood clots can lead to strokes. Final answer: Yes.
>
> Read the following clinical note of a patient: `[NOTE]`.
>
> Answer step by step: based on the note, why is the patient at risk of `[DIAGNOSIS]`?
>
> Answer:

We observed that with few-shot prompting the model surfaced evidence for almost every diagnosis that the patient did not have. For example, for a patient with *'with g/j tube in place for gastroparesis'*, the model's output for the diagnosis, encephalitis, was *'The patient has a jejunostomy tube in place. The jejunostomy tube can be pulled out. The jejunostomy tube can be pulled out of the body. The jejunostomy tube can be pulled out of the body and into the brain. Final answer: Yes'*.

We suspect the prompt biases the model to support the query diagnosis which then makes the model generate incorrect explanations as evidence (Turpin et al., 2023). We also experimented with prompts such as *'Extract evidence for `[DIAGNOSIS]`. Output N/A if no evidence exists'* but the model then mostly generated *'N/A'*. Given these results, we carried the rest of the evaluation with the zero-shot prompting approach.

Appendix B. Automatic Evaluation

Our proposed LLM-based automatic evaluation (Section 5) consists of three steps, each realized as a single prompt. We use a one-shot prompt for the first step and zero-shot prompts for the subsequent steps, as shown below.

1. Extract risk factors from the evidence.

   > Read the following statement: The patient is at risk of intracranial hemorrhage due to presence of an endotracheal tube (ETT) in the patient's trachea which may increase the risk of complications such as aspiration and airway obstruction.

Diagnosis	Risk Factors
pneumocephalus	head injury, skull fracture, neurosurgical procedures, sinus or mastoid surgery, meningitis, cerebrospinal fluid leak, barotrauma, diving or scuba diving accidents, iatrogenic causes, such as lumbar puncture or spinal anesthesia
stroke	hypertension, smoking, diabetes, obesity, sedentary lifestyle, high cholesterol levels, atrial fibrillation, family history of stroke, previous history of stroke, excessive alcohol consumption, drug abuse.
intracranial hemorrhage	hypertension, aneurysms, arteriovenous malformations, blood clotting disorders, trauma, drug abuse, liver disease, brain tumor, stroke, coagulopathy
brain tumor	progression genetics, exposure to ionizing radiation, family history of brain tumors, certain hereditary conditions, weakened immune system, previous history of brain tumor.
intracranial hypotension	obesity, connective tissue disorders, previous spinal or cranial surgery, leaking cerebrospinal fluid, spinal epidural anesthesia, lumbar puncture or spinal tap

Table 7: Examples of risk factors provided by GPT-3.5

Diagnosis	Evidence	Explanation
intracranial hemorrhage	patient had multiple cardiac surgeries	Multiple cardiac surgeries may suggest anticoagulation or underlying cardiac dysfunction which could in turn predispose the patient to intracranial hemorrhage.
intracranial hypotension	The patient has a ventriculoperitoneal shunt.	A ventriculoperitoneal shunt (VPS) is a surgical device used to relieve intracranial pressure by draining excessive cerebrospinal fluid. Having a VPS catheter may increase the risk of intracranial hypotension due to over drainage.
craniopharyngioma	s/p resection X2, s/p VPS and panhypopitutiarism with second resection	Panhypopituitarism and the fact that something was removed through surgery suggests there was a tumor involving the sella which may or may not have been craniopharyngioma.

Table 8: Examples of weakly correlated evidence surfaced by the model for different diagnosis queries. All have plausible but somewhat removed (or weak) connections.

> Question: Extract the risk factors from the statement as a list. Be concise.
>
> Answer: 1. presence of endotracheal tube (ETT) in the trachea.
>
> Read the following statement: `[EVIDENCE]`
>
> Question: Extract the risk factors from the statement as a list. Be concise.
>
> Answer: "

2. Verify the presence of each risk factor in the note.

> Read the following clinical note of a patient: `[NOTE]`
>
> Question: Does the patient have `[RISK FACTOR]`? Answer Yes or No.

3. Validate if each present risk factor is a valid risk factor of query diagnosis.

> Is `[RISK FACTOR]` a risk factor of `[DIAGNOSIS]`? Choice: -Yes -No. Be concise.
>
> Answer:

We used the following prompts for signs:

1. Extract signs from the evidence.

> Read the following statement: A patient may have intracranial hemorrhage because of the following report - Large left subdural hematoma, extensive subarachnoid hemorrhage, right temporal effacement, left uncal herniation, and effacement of the sulci.
>
> Question: Extract the signs from the statement as a list. Be concise.
>
> Answer: 1. Large left subdural hematoma 2. Extensive subarachnoid hemorrhage 3. Right temporal effacement 4. Left uncal herniation 5. Effacement of the sulci
>
> Read the following statement: A patient may have `[DIAGNOSIS]` because of the following report - `[EVIDENCE]`.
>
> Question: Extract the signs from the statement as a list. Be concise.

Answer: "

2. Verify the presence of each sign in the note.

   Read the following clinical note of a patient: `[NOTE]`

   Question: Does the patient have `[SIGN]`? Answer Yes or No.

3. Validate if each present sign is a valid sign of query diagnosis.

   A patient is showing the following sign: `[SIGN]`.

   Question: Can the sign indicate `[DIAGNOSIS]`? Choice: -Yes -No. Be concise.

   Answer:

Appendix C. Binary decision recall

Recall that we first ask the LLM whether a note indicates that the corresponding patient is at risk for, or has, a given query diagnosis. The precision of this LLM inference is implicitly measured by the assessment of generated evidence; if the patient does not have (is not at risk for) a condition, generated evidence will necessarily be irrelevant. But this does not capture model recall, i.e., recognizing when a patient indeed has (is at risk of) a condition.

To also estimate model *recall*, we sampled 20 patients from BWH and followed prior work (McInerney et al., 2020) in our evaluation. Specifically, we asked radiologists to browse reports from up to one year following a reference radiology report and tag relevant diagnoses; these constitute "future" diagnoses with respect to the reference report. Radiologists then flagged past notes containing supporting evidence for these diagnoses. Of the 200 notes marked as containing evidence, Mistral-Instruct, Flan-T5, and CBERT had a recall of 58.2, 70.0, and 80.4 respectively.

Appendix D. Likely Indicators

For the *likely indicators* in §5.2, we used 'likely represent', 'concerning for', and 'diagnosis include'. We did not consider diagnoses such as 'old infarction', which came up often for 'likely represent'. An infarction can be myocardial or cerebral. Since our dataset comprises of radiology reports concerning brain scans, we added 'cerebral' as prefix to 'infarction' to ensure specificity. Similarly, we added 'brain' as a prefix to 'metastasis'.

Model	% instances with evidence	# evidence	# risks (signs)
Flan-T5			
MIMIC	91.0	1,077	2,817
BWH	88.0	701	2,027
Mistral-Instruct			
MIMIC	84.0	968	2,894
BWH	90.0	614	1,799
CBERT			
MIMIC	100.0	2,000	7,467
BWH	100.0	1,000	3,336

Table 9: Data statistics of large-scale evaluation performed in §5.2. We evaluated 100 and 50 instances from MIMIC and BWH datasets respectively.

Appendix E. Implementation Details

We used the `HuggingFace` (Wolf et al., 2020) library to run inference using Mistral-Instruct (7B), Flan-T5 XXL (11B) and ClinicalBERT (110 million parameters). We split notes into sentences using the `spaCy` (en_core_web_sm) library (Honnibal and Montani, 2017). We processed notes in chunks of size 750 tokens (including the prompt text) for Flan-T5 and Mistral-Instruct. We used a single NVIDIA Tesla V100 (32G) GPU.

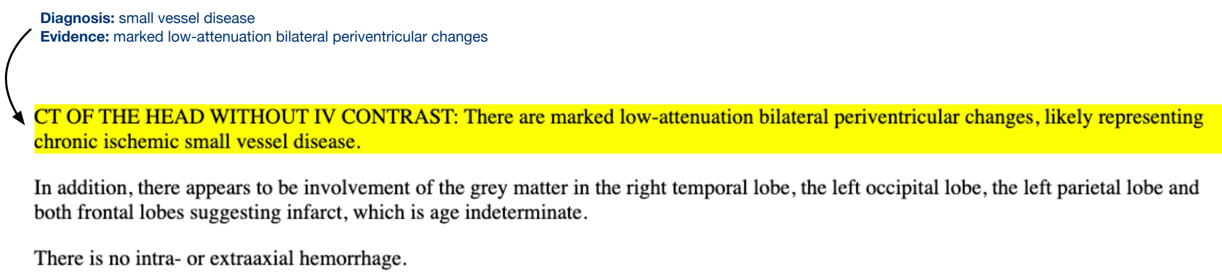

Figure 6: Screenshot of the evaluation interface showing highlighted evidence.