DocLens: Multi-aspect Fine-grained Evaluation for Medical Text Generation

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Abstract

Medical text generation aims to assist with administrative work and highlight salient information to support decision-making. To reflect the specific requirements of medical text, in this paper, we propose a set of metrics to evaluate the completeness, conciseness, and attribution of the generated text at a fine-grained level. The metrics can be computed by various types of evaluators including instruction-following (both proprietary and open-source) and supervised entailment models. We demonstrate the effectiveness of the resulting framework, DocLens, with three evaluators on three tasks: clinical note generation, radiology report summarization, and patient question summarization. A comprehensive human study shows that DocLens exhibits substantially higher agreement with the judgments of medical experts than existing metrics. The results also highlight the need to improve open-source evaluators and suggest potential directions.[1]

1 Introduction

Medical text generation has been widely applied to various scenarios, including clinical note generation (Yim et al., 2023; Ben Abacha et al., 2023a), report summarization (Adams et al., 2021; Van Veen et al., 2023), and patient question summarization (Abacha and Demner-Fushman, 2019). In report summarization, for example, text generation systems aim to assist medical experts by automatically summarizing the salient findings in a CT or MR report, which reduces the time on paperwork and supports decision-making (Zhou et al., 2023). To help medical experts decide whether to adopt text generation systems or which system to use, it is imperative to have a reliable evaluation methodology.

One line of work on medical evaluation conducts human evaluation under *multiple aspects*, reflecting different criteria of an ideal generation result (Ben Abacha et al., 2023b; Zhou et al., 2023; Zhang et al., 2021). To capture which exact information is inaccurate or omitted, other human evaluation methods conduct more *fine-grained* evaluations by examining each fact individually (Ben Abacha et al., 2023b). Due to the high cost and poor scalability of human evaluation, another line of work focuses on automatic evaluation. However, existing automatic medical evaluation methods typically assign a coarse-level score for the entire system output (Ben Abacha et al., 2023c; Zhou et al., 2023), without indicating the aspects or criteria the score reflects. Recent general-domain evaluation methods focus on more fine-grained units such as sentences (Gao et al., 2023b) or atomic facts (Min et al., 2023). However, existing methods neglect evaluation aspects critical to medical generation or require external knowledge sources in evaluation.

In this paper, we propose DocLens, which *automatically* conducts evaluation of medical text generation at a fine-grained level, including both reference-based and reference-free aspects. As shown in Figure 1, to evaluate the recall and precision of clinically significant information in the generation, we conduct a reference-based evaluation for the **completeness** and **conciseness** of the system-generated output. Specifically, we break down the system output (e.g., generated clinical note) and reference (e.g., human-written note) into subclaims and assign a binary score for each subclaim. In real-world scenarios, AI systems are typically used in an *assisting* role, where the medical experts need to judge the reliability of the generated information as part of their process using the AI systems. As a result, we evaluate **attribution**, which checks whether each piece of generated information is properly grounded in the input. Specifically, we conduct a reference-free evaluation and

[*]Work done as an intern at Microsoft Research.
[1]We released the code at https://github.com/yiqingxyq/DocLens.

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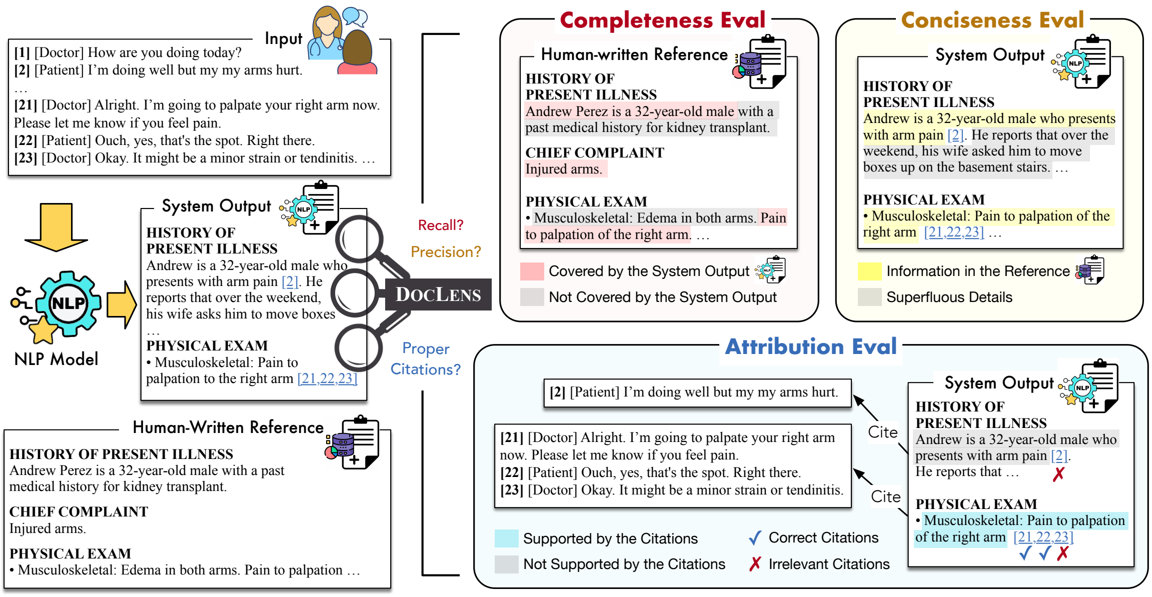


Figure 1: Evaluation aspects of DocLens for medical text generation. **Completeness** evaluates the amount of salient details in the system output. **Conciseness** evaluates the amount of information that is both accurate and salient. **Attribution** checks whether the generated information can be traced back and attributed from the input

check whether each generated sentence contains accurate references back to the input.

DocLens can be computed with various types of evaluator models and we experiment with three representatives: a proprietary model (GPT-4 (OpenAI, 2023)), an open-source instruction-following model (Mistral (Jiang et al., 2023)), and a supervised natural language inference (NLI) model (TRUE (Honovich et al., 2022)). We apply DocLens with the three evaluators to benchmark multiple medical generation systems on three tasks: clinical note generation, radiology report summarization, and patient question summarization. To compare the quality of DocLens with existing metrics and to compare different evaluators of DocLens, we conduct a human study to investigate how well each metric aligns with medical experts' judgment. Experiments show that DocLens exhibits substantially higher agreement with medical experts than existing metrics commonly used in the medical domain. The results also reveal the gap between open-source and proprietary evaluators. Our analyses further suggest potential directions to improve open-source evaluators.

Contributions. (1) We identify crucial aspects of medical text evaluation and design corresponding metrics for conducting a fine-grained evaluation. (2) We present an automatic evaluation framework, DocLens, based on the metrics, which can be computed by various types of evaluators. (3) We apply DocLens to three medical generation tasks. Human study results show that DocLens exhibits substantially higher agreement with human judgments than existing metrics.

2 Related Work

Evaluation in the Medical Domain. Existing approaches to medical text evaluation (Veen et al., 2023; Van Veen et al., 2023; Tu et al., 2023) have adopted traditional metrics from general NLP, including n-gram-based metrics (Lin, 2004; Papineni et al., 2002), embedding-based methods (Zhang et al., 2020a), and model-based methods (Sellam et al., 2020). Other existing approaches evaluate the overlap of medical concepts Zhang et al. (2020b); Miura et al. (2021); Delbrouck et al. (2022), which utilizes information extraction models (Jain et al., 2021) to extract clinical entities and relations from the system output and the reference and compute their overlap. Such metrics heavily rely on surface-level similarities and lack validity.

Factuality Evaluation in the General Domain. Factuality evaluation is the most relevant topic to our work, as it judges the factual alignment between input and output (Thorne et al., 2018; Wang, 2017; Augenstein et al., 2019). A common approach is to assign a single score for the entire system output (Liu et al., 2023b; Fu et al., 2023). This does not satisfy the needs of medical applications, where every piece of information is essential and

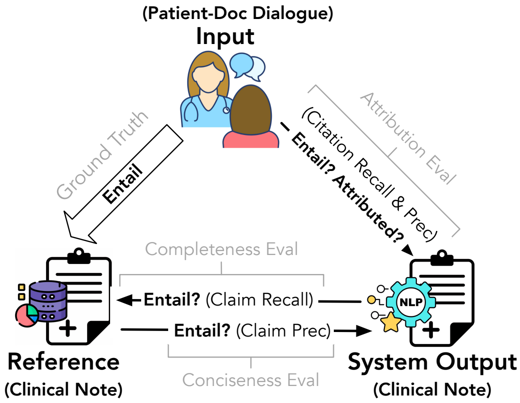


Figure 2: To conduct a multi-aspect evaluation, we verify the entailment relations among the input (e.g., patient-doctor dialogue), system output (e.g., generated clinical note), and reference (e.g., human-written clinical note).

requires careful examination. Another line of work decomposes the system output into fine-grained units, such as content units (Nenkova and Passonneau, 2004), short subclaims (Wright et al., 2022; Chen et al., 2022; Kamoi et al., 2023) or atomic facts that each convey only one piece of information (Min et al., 2023). Towards more transparent text generation, a strand of prior work further evaluates the attribution of generated facts by training or prompting the models to ground them with references back to the input (Gao et al., 2023a,b; Liu et al., 2023a; Yue et al., 2023).

To satisfy the specific requirements of the medical domain, our work extends past work by (1) evaluating the recall, precision, and attribution of the generated facts by conducting completeness, conciseness, and attribution evaluations at a fine-grained level, and (2) adapting a wider range of evaluator models to compute the metrics automatically and conducts empirical comparisons, providing a diverse range of selections.

3 Evaluation Framework of DocLens

There are two special characteristics of clinical text: (a) *Criticality*: every piece of information is essential. Medical documentation must be free from inaccuracies and omissions. (b) *Assistance*: the generated text will be examined by experts. As decisions can be life-critical, the generated text is positioned as a resource rather than a final product.

In line with these considerations, our proposed framework employs three evaluation aspects: completeness (§3.1), conciseness (§3.2), and attribution (§3.3) and design a set of corresponding metrics. The proposed metrics can be automatically computed using a variety of evaluator models (§3.5). As shown in Figure 2, we formulate the three evaluation aspects as verification of entailment relations between the input, system output, and human-written references. An illustrative example of each metric is shown in Figure 3.

3.1 Completeness Evaluation

We first evaluate completeness: the amount of clinically significant information in the system output, which corresponds to the relation *"System Output ⇒ Reference"* in Figure 2. This can be viewed as the recall of the system output. Based on the characteristic of *criticality*, unlike previous work (Veen et al., 2023) that assigns an overall score to the system output, we are also interested in which exact salient information is retained or omitted.

We introduce **claim recall** to evaluate completeness at a fine-grained level. As shown in Figure 3, we first break down the reference into a list of subclaims using GPT-4 (OpenAI, 2023), where each subclaim states only one fact in the reference. Let y be the reference, $\mathcal{L}_y$ be the list of reference subclaims, y' be the system output. We apply an evaluator model to judge whether each claim $l \in \mathcal{L}_y$ is entailed by the generated output y'. Claim recall is then formally defined as $\frac{1}{|\mathcal{L}_y|} \sum_{l \in \mathcal{L}_y} \mathbb{I}[y' \Rightarrow l]$.

The concept of claim recall parallels the definition provided in ALCE (Gao et al., 2023b), with the following difference: ALCE only requires the output to follow the key reasoning steps in the reference and hence restricts the extraction to three claims per instance. In contrast, since an ideal clinical note should cover all salient details, we prompt the model to generate claims that encapsulate all factual information in the reference.

3.2 Conciseness Evaluation

Following the characteristic of *assistance*, an ideal system output will allow medical experts to quickly capture salient information, without spending significant time on superfluous details. We thus evaluate conciseness: the amount of generated information that is both factually accurate and salient. Assuming that the reference only contains salient information, conciseness evaluation aligns with the *"Reference ⇒ System Output"* relation in Figure 2.

We define **claim precision** to evaluate conciseness. Similar to claim recall, we generate a list of

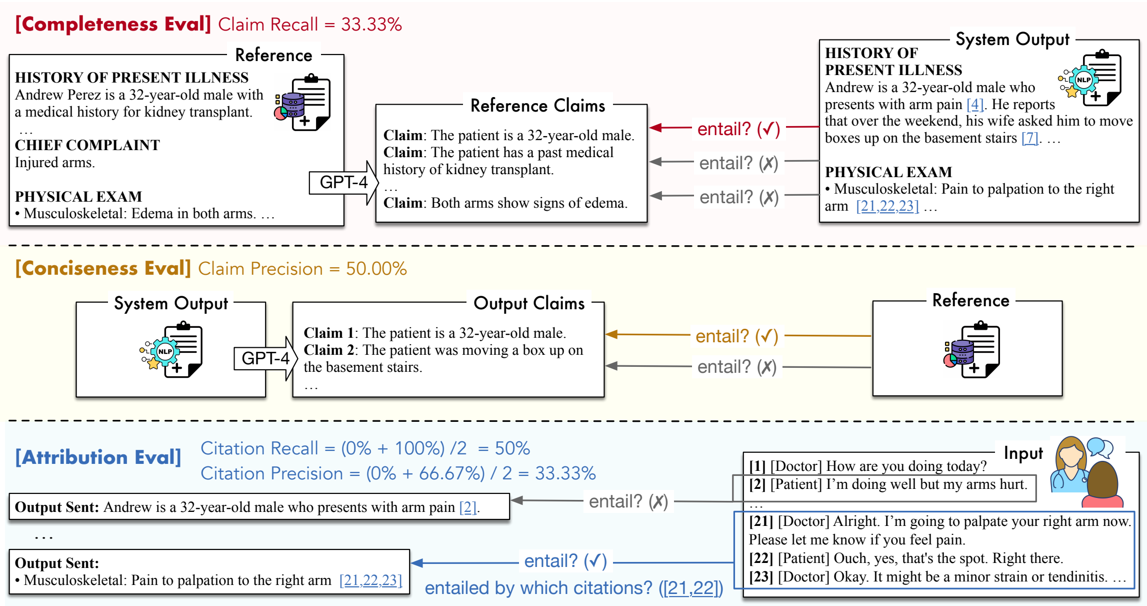


Figure 3: Illustration of the metrics of DocLens for medical evaluation: **Claim Recall** measures the proportion of claims from the human-written reference that can be entailed by the system output. **Claim Precision** measures the proportion of claims from the output that can be entailed by the reference. **Citation Recall** measures the proportion of output statements that can be entailed by their corresponding citations. **Citation Precision** measures the proportion of citations that factually support the associated statement.

claims for the system output and apply the evaluator to compute the proportion of claims that can be entailed by the reference. Formally, let y be the reference, y' be the system output, and $\mathcal{L}'_y$ be the list of output subclaims, we define claim precision as $\frac{1}{|\mathcal{L}_{y'}|}\sum_{l\in\mathcal{L}_{y'}}\mathbb{I}[y \Rightarrow l]$.

3.3 Attribution Evaluation

Based on the characteristic of *assistance*, to help medical experts quickly verify the output statements, we also evaluate attribution: the amount of generated information that can be traced back from the input, which corresponds to the *"Input ⇒ System Output"* relation in Figure 2. As shown in Figure 3, the system also generates citations to the input following each statement, which helps medical experts quickly locate the relevant context and verify the generated information.

Following existing work (Liu et al., 2023a; Gao et al., 2023b), we first compute **citation recall**, which evaluates whether each statement in the system output can be fully supported by the combination of its cited sentences. Formally, for each output statement s, let $\mathcal{C}$ be the set of input sentences it cites. The claim recall of s is 1 if and only if $\mathcal{C} \Rightarrow s$ and otherwise 0. The citation recall of the whole output is then defined as the percentage of statements that can be entailed by their citations.

We also evaluate **citation precision** to examine whether the system generates redundant citations. Intuitively, if a statement s can be supported by the combination of its citations $\mathcal{C}$, a citation $c \in \mathcal{C}$ is necessary if it independently supports the statement s, or if removing it leaves the statement unsupported. Formally, we define the citation precision of c as 1 if and only if:

(i) $\mathcal{C} \Rightarrow s$, and

(ii) $c \Rightarrow s$ or $\mathcal{C} \setminus \{c\} \not\Rightarrow s$.

For instance, in Figure 3, the output statement cites conversational turns "`[21][22][23]`" in the input, but only `[21]` and `[22]` are pertinent to the output. So `[21]` and `[22]` will have citation precision $= 1$ and `[23]` will have citation precision $= 0$. We define the citation precision of the whole output as the average precision of all its citations.

3.4 Discussion of Excluded Aspects

There are other evaluation aspects for text generation in general domains, such as **coherence** and **fluency** (Zhong et al., 2022; Gao et al., 2023b), where coherence evaluates whether the generated sentences form a coherent body and fluency evaluates whether each sentence is well-written and grammatical. These aspects are less emphasized in the medical domain since they do not directly impact treatment outcomes.

To ensure the accuracy of the generated text, many existing methods evaluate **factual consistency** (Thorne et al., 2018; Augenstein et al., 2019; Min et al., 2023), which compares the factual statements in the generated text and the input. Among our proposed aspects, conciseness and attribution both incorporate the need for factual consistency. In addition to the factuality of output statements, conciseness further evaluates whether the statements are salient and attribution judges whether they can be traced back from the input.

3.5 DocLens with Various Evaluators

In this section, we introduce how we compute the metrics of DocLens with various evaluator models, including NLI models and open-source and proprietary instruction-following models.

DocLens computed with NLI models. Let $\phi(p, h)$ be the output of the NLI model, which is 1 if the premise p entails the hypothesis h and 0 otherwise. The claim recall, claim precision, and citation recall can be computed by ϕ(system output, reference claim), ϕ(reference, output claim), and ϕ(combination of citations, output statement).

To compute citation precision for each citation $c \in \mathcal{C}$ in statement s, following our definition, c has citation precision $=1$ if and only if s has citation recall $=1$ and $\phi(c, s)||\phi(\mathcal{C} \setminus \{c\}, s) = 1$.

DocLens computed with instruction-following models. We also apply instruction-following models to compute the metrics, including proprietary and open-source models. To compute claim recall and claim precision, we prompt the evaluator to generate "1" or "0" for each claim based on whether they can be supported.

As for citation recall and precision, to reduce computation, we prompt the evaluator to predict if a statement is entailed by its citations and to identify the supporting citations in a single call. In the example of Figure 3, where the citations "`[21][22][23]`" support the output statement but `[23]` is irrelevant, the evaluator should output "1" for the entailment prediction and "`[21][22]`" as the supporting citations.

We further adopt two prompt styles to improve the quality of instruction-following evaluators, where the example prompts are shown in §A.2:

(1) **Generation with Structure**. Existing research has observed that models have better performance when they are prompted to generate in a structured format, such as logic representations, or pseudo code (Mishra et al., 2023). With the same high-level idea, we prompt the evaluator to generate the entailment prediction in a JSON dictionary.

Model	MedNLI	ANLI	Weight AVG
TRUE	81.9	71.5	74.3
GPT-4 (2-shot)	**<u>92.8</u>**	86.1	87.8
+ JSON	91.0	**<u>87.7</u>**	88.5
+ CoT	91.6	86.7	88.2
+ JSON + CoT	91.8	87.5	**<u>88.6</u>**
Mistral (2-shot)	84.8	69.6	73.4
+ JSON	<u>87.8</u>	67.8	72.8
+ CoT	87.2	<u>70.6</u>	<u>74.8</u>
+ JSON + CoT	87.3	70.0	74.3

Table 1: Classification accuracy on MedNLI and ANLI under the 2-way classification setting. "ANLI" is the average accuracy on ANLI (R1, R2, R3). We provide one in-context example from each of the 2 classes.

(2) **Chain-of-Thought**. Chain-of-thought (CoT) prompts the model to generate a series of intermediate reasoning steps, which has shown to be effective in various tasks (Wei et al., 2023). Following this idea, we prompt the evaluator to generate the explanation before the prediction.

We conduct experiments on two NLI datasets: MedNLI (Romanov and Shivade, 2018) and ANLI (Nie et al., 2020) to investigate the effectiveness of the two prompt styles on predicting entailment relationships. MedNLI evaluates reasoning with medical knowledge and ANLI focuses on commonsense reasoning. Both are reasoning abilities that an evaluator needs.

To align with our evaluation setting, we adopt a 2-way classification setting where "entailment" forms one class and both "neutral" and "contradiction" are merged into the other class. As shown in Table 1, the GPT-4 evaluator benefits the most from the combination of generation in JSON and CoT, and the Mistral evaluator only benefits from CoT. We observe that in many cases, Mistral fails to generate outputs in a valid JSON format, which leads to parsing error when reading the results. Detailed experiment results are shown in §A.1.

4 Experiments

In this section, we aim to answer three research questions: (**RQ1**) How do different medical generation models perform under our evaluation? (**RQ2**) How is the evaluation quality of DocLens compared to existing metrics? (**RQ3**) How is the eval-

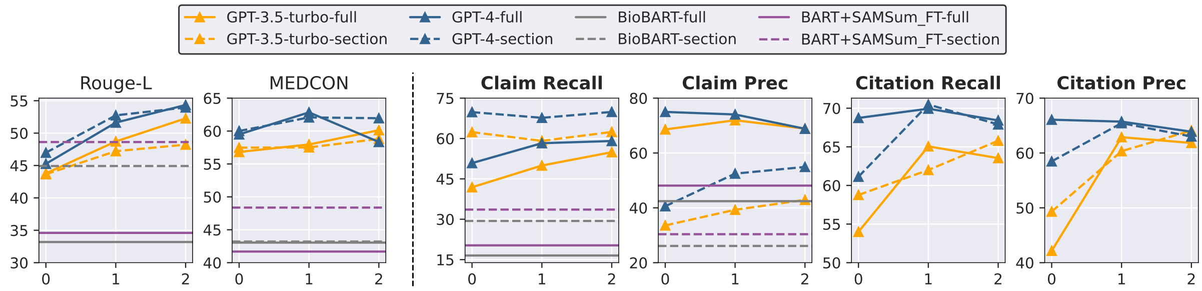


Figure 4: Clinical note generation results on ACI-BENCH (Yim et al., 2023). We split the results under existing metrics and DOCLENS computed with GPT-4. We evaluate open-source and proprietary note generation models with different numbers of in-context examples.

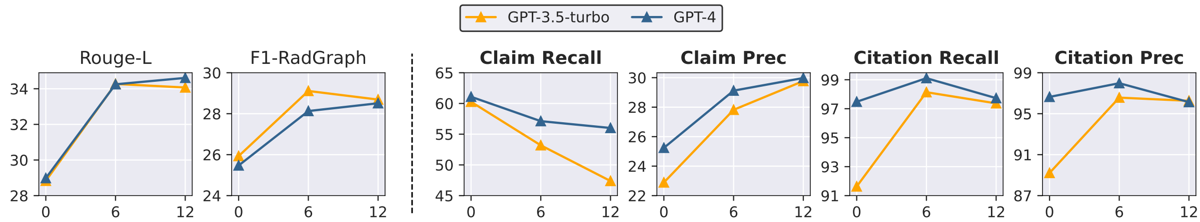


Figure 5: Radiology report summarization results on MIMIC-III (Van Veen et al., 2023) evaluated by existing metrics and DOCLENS computed with GPT-4.

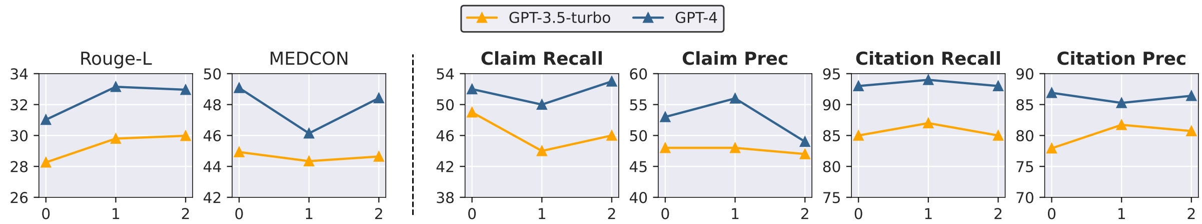


Figure 6: Patient question summarization results on MeQSum (Abacha and Demner-Fushman, 2019) evaluated by existing metrics and DOCLENS computed with GPT-4.

uation quality of DOCLENS computed with open-source evaluators compared to proprietary ones?

4.1 Evaluation tasks and metrics

To answer **RQ1**, we experiment with three types of evaluators for DOCLENS: proprietary and open-source instruction-following models, and NLI models, and evaluate three representative medical generation tasks: clinical note generation (Yim et al., 2023), medical report summarization (Van Veen et al., 2023), and patient question summarization (Abacha and Demner-Fushman, 2019).

Clinical note generation. Clinical note generation is defined as generating a "SOAP" note given a dialogue between a doctor and a patient (Yim et al., 2023; Ben Abacha et al., 2023a). A SOAP note consists of the subjective, objective Exam, objective results, and assessment and plan sections. We conduct experiments on the ACI-BENCH dataset (Yim et al., 2023). A test example is shown in Table 16.

Radiology report summarization. We follow the setting from Van Veen et al. (2023), where the input is the findings section of a radiology report, and the goal is to generate an impression section that contains key observations and conclusions. we utilize the public test set of MIMIC-III (Johnson et al., 2016). A test example is shown in Table 17.

Patient question summarization. Question summarization aims to generate a condensed question expressing the minimum information required to find correct answers to the original question (Abacha and Demner-Fushman, 2019). We utilize the MeQSum dataset, which consists of consumer health questions and their corresponding summaries authored by medical experts. A test example is shown in Table 18.

Evaluation methods. We evaluate the three tasks with DOCLENS computed with GPT-4 (OpenAI, 2023), Mistral (Jiang et al., 2023), and TRUE (Honovich et al., 2022), representing three types of mod-

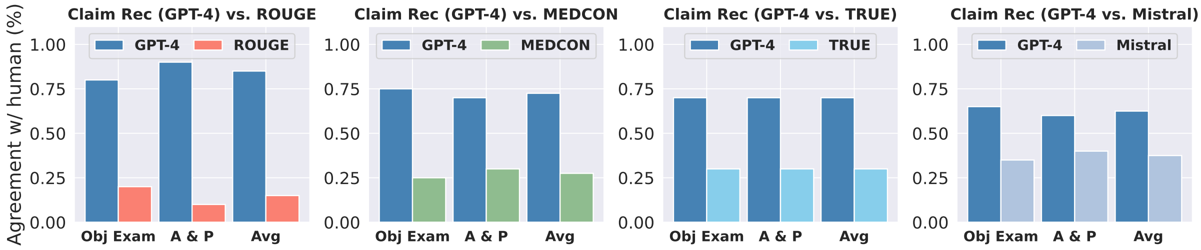


Figure 7: Agreement between each metric and the *subjective preferences* of medical experts over two system outputs. We only annotate the system outputs pairs *where the two metrics have different preferences*. The outputs are selected from the Objective Exam (O-Exam) and Assessment and Plan (A&P) section in note generation.

els. We also apply existing commonly-used metrics (Yim et al., 2023; Jain et al., 2021; Veen et al., 2023). We list the metrics for each task in Table 10.

Experimental details are provided in §A.4.

4.2 Exp-I: Medical Text Generation Results

Figures 4 to 6 show the results on the three representative tasks evaluated by existing metrics and DocLens computed with GPT-4. The detailed numbers are provided in Tables 20, 21, 28, 29, 32 and 33. We show the results of DocLens with the Mistral evaluator in Tables 26, 30 and 34 and the TRUE evaluator in Tables 27, 31 and 35.

Influence of in-context examples. We observe that the results under most metrics can be improved by adding in-context examples, but increasing the number of examples from 1 to 2 leads to diminishing returns. Intriguingly, when the prompt only contains the instruction with no examples, GPT-3.5-turbo often fails to generate any citations or produces all citations together at the end. In contrast, GPT-4 consistently generates citations in the correct format across the three datasets.

Proprietary vs. Open-source generation models. As shown in Figure 4, GPT-based models outperform open-source models in the majority of experiments. We also observe that open-source models typically generate much shorter outputs than GPT-based models with heavy omission. E.g., BART+SAMSum (full) generates 179.4 words on average and GPT-4 (full, 2-shot) generates 351.9.

Results under different evaluators. Comparing results computed by DocLens with different evaluators, we can observe that Mistral assigns overall higher scores than the other models, which in many cases misjudges "partially support" as "fully support". We can also observe that the correlation between TRUE and GPT-4 is much lower on MeQ-Sum than the other two datasets. The reason might be TRUE is mainly trained on declarative sentences and hence has unsatisfactory performance in judging the entailment relationships between questions.

Comparison	Corr w/ Medical Experts			
	O-Exam		A & P	
	ρ	τ	ρ	τ
Rouge-L Recall	0.326	0.267	-0.389	-0.307
Claim Recall (GPT-4)	**0.787**	**0.653**	**0.732**	**0.638**
MEDCON Recall	0.138	0.103	0.132	0.078
Claim Recall (GPT-4)	**0.752**	**0.621**	**0.820**	**0.652**
Claim Recall (TRUE)	0.710	0.526	0.251	0.168
Claim Recall (GPT-4)	**0.953**	**0.844**	**0.522**	**0.431**
Claim Recall (Mistral)	0.627	0.486	0.342	0.234
Claim Recall (GPT-4)	**0.682**	**0.612**	**0.702**	**0.546**

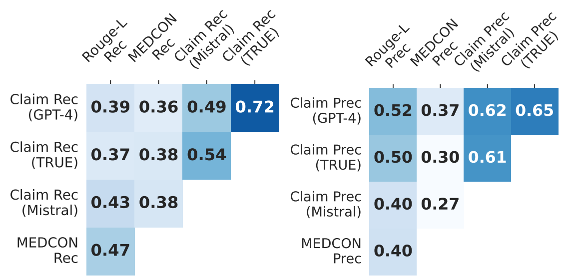
Table 2: Spearman (ρ) and Kendall-τ correlation between each recall-based metric and the completeness scores assigned by medical experts. When comparing two metrics, we only annotate the system outputs pairs *where the two metrics have different preferences*.

4.3 Exp-II: Agreement with Human

To answer (**RQ2**) and (**RQ3**), we conduct a human study to check the alignment of different evaluation methods with medical experts.

Setup. We focus on the completeness evaluation and compare claim recall computed by GPT-4 with other metrics, including (i) existing recall-based metrics: Rouge-L recall and MEDCON recall, and (ii) claim recall computed by Mistral and TRUE.

As shown in Table 11, we observe that the metrics have agreed preferences in most of the cases. As our primary goal is to compare pairs of metrics, to reduce the required amount of human annotation, we only annotate pairs of system outputs *where the two metrics disagree*: one metric ranks one system



(a) Recall-based metrics (b) Precision-based metrics

Figure 8: Kendall's τ coefficients between recall-based and precision-based metrics on note generation.

output higher, and the other metric ranks the other output higher. We select system outputs from the "Objective Exam" (O-Exam) and "Assessment and Plan" (A&P) sections in clinical note generation.

We invite five medical experts to the human study and assign three of them to label each pair of selected system outputs, without telling them which model generates which output Given the reference note and the reference subclaims, we ask the medical experts (1) what percent of the claims can be entailed by each output, and (2) which output they think is more complete (i.e., their *subjective preference*). We present the inter-annotator agreement when comparing each two metrics in Table 12. The average Spearman (ρ) coefficient is 0.763. More details are shown in §A.4.5.

DocLens vs. existing metrics. Table 2 shows the Spearman (ρ) and Kendal-τ correlations between metrics and medical experts and Figure 7 shows the agreement with human subjective preference. Results show that in both experiments, claim recall (GPT-4) has a substantially better alignment with human than Rouge-L and MEDCON, which typically misjudges the cases where the system output and the reference have little or no lexical overlap. An example is shown in Table 9.

Comparison among DocLens evaluators. We can also observe from Table 2 and Figure 7 that there is still a large gap between open-source models (Mistral and TRUE) and GPT-4. As shown in Table 3, we observe several patterns in the cases where GPT-4 and Mistral disagree: **[Case 1]** The judgment requires medical knowledge. In claim 1, a medical expert would know that "`lungs are clear`" already means there are "`no wheezes, rales, or rhonch`" and hence "`clear bilaterally`" fully support this claim. However, this is misjudged by Mistral, which suggests that continuous pretraining on medical corpus could be beneficial. **[Case 2]** The output only partially entails the subclaim. Although output 2 mentions the "`systolic ejection murmur`", it omits the fact that the murmur is unchanged, but Mistral does not capture the omission. **[Case 3]** Multiple facts are related to each other. Output 2 omits the fact of "`no masses`" in claim 3. However, Mistral wrongly predicts claim 3 as "supported" with the explanation: The notes states that there is no tenderness, which could potentially indicate that there is no masses. In both case 2 and 3, Mistral does not strictly follow the instruction of "judge whether the text fully supports the claim", which calls for instruction tuning for entailment.

Subclaims of the reference *(Used to compute claim recall)*
1. Lungs are clear bilaterally, with no wheezes, rales, or rhonchi. 2. The patient has a grade 2/6 systolic ejection murmur, unchanged. 3. Examination of the abdomen shows no masses or tenderness.
Output 1 *(Preferred by GPT-4 and human)*
PHYSICAL EXAMINATION The doctor performs a physical exam and finds the patient's lungs to be clear bilaterally and no tenderness or pain in the abdomen. The patient has a grade two out of six systolic ejection murmur in her heart, which has not changed since the previous visit. **Claim Recall (Mistral)**: 33.34 // Support Claim 2. **Claim Recall (GPT-4)**: 66.67 // Support Claim 1 and 2. **Human Judgment**: 66.67 // Support Claim 1 and 2.
Output 2 *(Preferred by Mistral)*
PHYSICAL EXAMINATION • Lungs: Clear bilaterally. No wheezes, rales, or rhonchi. • Heart: Grade 2/6 systolic ejection murmur. • Abdomen: No tenderness to palpation. **Claim Recall (Mistral)**: 100.00 // Support Claim 1, 2 and 3. **Claim Recall (GPT-4)**: 33.34 // Support Claim 1. **Human Judgment**: 33.34 // Support Claim 1.
Preference of Human & claim recall (GPT-4): *Output 1* **Preference of claim recall (Mistral)**: *Output 2*

Table 3: An example of disagreement between claim recall (GPT-4) and claim recall (Mistral) on the completeness over two system outputs.

4.4 Exp-III: Correlations between Metrics

§4.3 shows that DocLens (GPT-4) aligns better with human than existing metrics or open-source evaluators. To further study (**RQ2**) and (**RQ3**), we investigate to which extent these metrics diverge from each other. Specifically, we divide the metrics into two groups: recall-based metrics (including claim recall, ROUGE-L recall, etc.) and precision-based metrics (including claim precision, ROUGE-L precision, etc.). We then compute Kendall's τ

coefficient between each two metrics in each group.

Results in Figure 8 suggest that DocLens computed with various models exhibit relatively weak correlations with existing metrics, where the τ coefficients are lower than 0.5 in the majority of cases. Recall that DocLens (GPT-4) also has a better alignment with human when it disagrees with existing metrics, the results suggest that DocLens can highly improve current evaluation qualities.

We can also observe that although computing the same metrics, the correlations between DocLens computed with open-source evaluators and GPT-4 are not particularly high. For instance, there are only around 78% of the system output pairs where Mistral and GPT-4 have the same preference. This suggests that open-source evaluators exhibit significant divergence from proprietary models, which calls for future improvement.

5 Conclusions and Future Works

We present DocLens, a medical evaluation framework that judges three aspects with a set of fine-grained level metrics. DocLens can be computed with various types of evaluator models, including proprietary and open-source instruction-following models and NLI models. We apply DocLens to three tasks: clinical note generation, radiology report summarization, and patient question generation. Human study shows that DocLens exhibits substantially higher agreement with human judgments than existing metrics. The results also reveals the substantial gap between proprietary and open-source evaluators.

To close the gap, as suggested by our case study, future works could improve open-source evaluators by (1) continuous pretraining the model on medical corpora, and (2) instruction-tuning the model for entailment, where we can construct training data by adapting existing NLI datasets or leveraging the model itself to generate silver labels. Another potential direction is to train the evaluator to generate multiple forms of feedback, such as the explanation of its judgement used in this work. Then evaluator model can then be applied to further improve medical text generation models.

6 Acknowledgement

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7 Limitations

We have only tested DocLens on public datasets, and hence this work cannot be directly used in real-world clinical scenarios.

Self-bias of GPT-4. While recent work (Zheng et al., 2023) shows that there is no evidence that LLMs exhibit a self-enhancement bias, we agree that the GPT-4 evaluator may potentially have self-bias towards the text that is also generated by GPT-4. We use two ways in our paper to mitigate the potential bias; (1) implement two other evaluators: Mistral and TRUE, and (2) conduct a human study to verify the quality of the evaluators. As shown by our human study, GPT-4 still has a higher correlation with human judgment than the other two evaluators.

Improvement of open-source evaluators. In this work, we use the open-source evaluator models in a zero-shot or few-shot way, and observe that there is still a substantial gap between open-source evaluators and GPT-4. Given that GPT-4 is costly, inefficient, and potentially contains self-bias, future works could focus on further training open-source evaluators to bridge the gap.

Medical question-answering. Though we have evaluated our work on multiple medical summarization tasks, we have not conducted experiments on medical question-answering (QA), which is another crucial task in the medical domain. The major reason is that current medical QA datasets mainly focus on short answers or multiple-choice questions (Jin et al., 2019, 2020; Pal et al., 2022), where evaluation is simpler than with the tasks we have focused on because in this case, it is possible simply to evaluate the exact match between the generated output and the answer.

Multimodal medical generation. Another limitation is that we do not consider the evaluation of multimodal medical generation, including visual QA (Lin et al., 2023; He et al., 2020) and multimodal note/report generation. An interesting extension for future work may be to focus on the consistency between input and output in different modalities.

8 Ethics Statement

License. In our use of three public datasets, we have observed the highest ethical standards of conduct. The specific datasets include: ACI-BENCH (Yim et al., 2023), MIMIC-III (Johnson et al., 2016), and MeQSum (Abacha and Demner-Fushman, 2019). The ACI-BENCH data is published under a Creative Commons Attribution 4.0 International Licence (CC BY). MIMIC-III is under the PhysioNet Credentialed Health Data License 1.5.0. MeQSum is distributed under the apache-2.0 license.

Potential Risks. Our framework leverages GPT-4 to evaluate medical data, which could be highly sensitive. To prevent data leakage as we have done, the potential users of our framework may use Azure OpenAI services in a HIPAA-compliant manner, which sets the privacy rule, the security rule, and the breach notification rule to protect patient health information[2]. The privacy rule especially imposes restrictions on the use and disclosure of patient health information without patient authorization.

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[2]Details can be found in `https://learn.microsoft.com/en-us/azure/compliance/offerings/offering-hipaa-us`.

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A Appendix

A.1 Experiments on LLM Evaluators with Different Prompt Styles

In this section, we examine how different prompt styles affect the entailment ability of instruction-following evaluators.

Experiments on existing NLI datasets. We first conduct experiments on two prevalent natural language inference (NLI) datasets: ANLI (Nie et al., 2020) and MedNLI (Romanov and Shivade, 2018). We use GPT-4 as the base model. To evaluate binary factual consistency, we consider "*entailment*" as one class and merge two NLI labels "*neutral*" and "*contradiction*" into the other class, denoting inconsistency between a premise-hypothesis pair.

Table 4 compares supervised NLI and instruction-following models on ANLI and MedNLI under the 2-way classification setting. GPT-4 significantly outperforms open-source models on both datasets and both generating in JSON format and CoT improves its performance.

We further compare GPT-4 and Mistral with supervised state-of-the-art models on MedNLI in Table 5. With few-shot examples, GPT-4 outperforms supervised models, but Mistral does not have satisfactory performance.

Experiments on claim recall. We also compare different prompt styles for GPT-4 on the computation of claim recall.

We first randomly sample 20 (system output, reference claim) pairs from note generation where at least two evaluators make different entailment predictions. Then we ask 4 human annotators to annotate these examples. We use the majority vote of the first three annotators' answers as the ground truth and compute the accuracy of the fourth human annotator as well as the models. As shown in Table 6, we can observe that the fourth annotator achieves 0.85 accuracy, indicating high agreement among annotators. Results also show that the agreement among humans is still stronger than the agreement between models and human annotators.

To obtain annotations for more examples, we additionally sample 100 (system output, reference claim) pairs where at least two evaluators disagree, and assign them to 5 human annotators. Namely, each human evaluator is assigned 20 examples. We consider human evaluations as the ground truth and compute the accuracy of each evaluator. The results of note generation are shown in Table 7. We can observe that both CoT and JSON improve the evaluation quality of claim recall (GPT-4).

A.2 Examples of Different Prompt Styles

We show the prompt styles "CoT" in Table 14 and "JSON + CoT" in Table 15. Based on the experiment results in Table 1 and §A.1, we use the prompt style "CoT" for the Mistral evaluator and use the prompt style "JSON + CoT" for the GPT-4 evaluator.

A.3 Case Studies for Human Evaluation

Table 8 presents a case where the medical experts assign the same score to both outputs, but still prefer one over the other. The reason is that *Output 2* contains the details about EKG, which supports "the heart rate is normal" with evidence. In comparison, *Output 1* only mentions the heart rate is normal without revealing how the heart rate is examined.

Table 9 presents an example where claim recall (GPT-4) disagrees with both ROUGE and MEDCON on preference over a pair of outputs.

We explain the human judgment of each claim as follows:

- *Output 1 supports Claim 1*: the output states "patient is not in any distress"
- *Output 1 supports Claim 2*: the output states "Carotid: No appreciable carotid bruits"
- *Output 1 supports Claim 3*: "Lungs: Clear to auscultation bilaterally" already means no wheezes, rales, or rhonchi.
- *Output 1 supports Claim 4*: the output states "Slight 2/6 systolic ejection murmur ".
- *Output 1 supports Claim 5*: the output states "1+ edema in lower extremities".
- *Output 2 does not support Claim 1*: no information about distress.
- *Output 2 does not support Claim 2*: no information about neck.
- *Output 2 supports Claim 3*: "clear lungs" already means no wheezes, rales, or rhonchi.
- *Output 2 supports Claim 4*: the output states "2/6 systolic ejection murmur".
- *Output 2 supports Claim 5*: the output states "1+ pitting edema in bilateral lower extremities".

A.4 Experimental details

A.4.1 Datasets

Clinical note generation experiments. We experiment on the ACI-BENCH (Yim et al., 2023)

Model / Prompt Style ↓	ANLI-R1	ANLI-R2	ANLI-R3	MedNLI	Average
|Test Set|	1000	1000	1200	1422	–
TRUE	78.8	69.1	67.3	81.9	74.3
Mistral (2-shot)	68.9	69.2	70.8	84.8	73.4
+ JSON	68.2	65.6	69.7	87.8	72.8
+ CoT	70.6	69.6	71.7	87.2	74.8
+ JSON + CoT	71.5	66.8	71.7	87.3	74.3
GPT-4 (2-shot)	88.7	84.5	85.1	**92.8**	87.8
+ JSON	**91.4**	**86.3**	85.4	91.0	88.5
+ CoT	90.0	84.9	85.2	91.6	88.2
+ JSON + CoT	90.6	86.2	**85.6**	91.8	**88.6**

Table 4: Accuracy on ANLI and MedNLI under the 2-way classification setting. We combine "neutral" and "contradiction" into one class. In the 2-shot prompt, we provide one example for each class.

Model / Prompt Style ↓	MedNLI
Supervised	
T5-large (Phan et al., 2021)	83.8
ClinicalT5-large (Lu et al., 2022)	85.9
BioBART-large (Yuan et al., 2022)	86.3
SciFive-large (Phan et al., 2021)	86.6
Few-shot, open-source	
Mistral (Jiang et al., 2023)	78.3
Mistral + JSON	83.0
Mistral + CoT	81.5
Mistral + JSON+CoT	82.4
Few-shot, proprietary	
GPT-4 (OpenAI, 2023)	87.6
GPT-4 + JSON	86.4
GPT-4 + CoT	87.6
GPT-4 + JSON+CoT	**87.8**

Table 5: Accuracy on MedNLI under the 3-way classification setting. For 3-shot models, we provide one example from each class in the prompt. We organize results into 3 groups: fully supervised, 3-shot open-source, and 3-shot proprietary models.

Claim Recall Evaluation (20 examples, three annotators per example)	
Model	**Accuracy**
TRUE	60.0
GPT-4 (0-shot)	40.0
+ JSON	50.0
+ JSON + CoT	80.0
GPT-4 (2-shot)	50.0
+ JSON	55.0
+ JSON + CoT	**80.0**
Human	**85.0**

Table 6: Accuracy of each evaluator (including human) on claim recall evaluation on 20 sentences of ACI-BENCH. We take the majority vote of three annotators as the ground truth and compute the accuracy of another annotator (denoted as "human").

dataset for note generation, which is a dataset of 207 pairs of dialogue and SOAP notes. We report results on the "test1" split, which contains 40 dialogue-note pairs. The definition of "SOAP note" is a widely used method of documentation for healthcare providers [3]. The original task setup only evaluates the generated SOAP note against the reference. To assess attribution, our task setup additionally requires each sentence in the generated note to cite at least one conversational turn in the input dialogue that supports the sentence.

Radiology report summarization experiments. We conduct report summarization experiments on MIMIC-III (Johnson et al., 2016). It contains 67K radiology reports spanning seven anatomies (head, abdomen, chest, spine, neck, sinus, and pelvis) and two modalities: magnetic resonance imaging (MRI) and computed tomography (CT). In our experiments, we randomly sample 200 examples following the proportion of each Modality/Anatomy category (e.g., CT head, MR spine) for evaluation. Similarly, we require each sentence to cite at least one sentence in the input.

Patient question summarization experiments. We conduct patient question summarization experiments on MeQSum (Abacha and Demner-Fushman, 2019). It contains (1) original patient health questions of varying verbosity and coherence selected from the U.S. National Library of Medicine, and (2) corresponding condensed questions created by

[3] ncbi.nlm.nih.gov/books/NBK482263/

Claim Recall Evaluation (100 examples, one annotator per example)	
Model	**Accuracy**
TRUE	58.0
GPT-4 (0-shot)	52.0
+ JSON	64.0
+ JSON + CoT	65.0
GPT-4 (2-shot)	48.0
+ JSON	62.0
+ JSON + CoT	**66.0**

Table 7: Accuracy of each evaluator on claim recall evaluation on ACI-BENCH. We select 100 sentences where at least two of these models have different predictions. We consider human annotations as the ground truth.

Reference subclaims
1. The patient's carotid arteries do not have audible bruits.
2. The patient's lungs are clear to auscultation on both sides, with no wheezes, rales, or rhonchi.
3. The patient exhibits a slight 2/6 systolic ejection murmur in the cardiovascular exam, which is stable.
4. The patient has a normal heart rate.
5. The patient has trace lower extremity edema in both legs.

Output 1

PHYSICAL EXAM: Heart rate is normal. On physical examination, there are no carotid bruits in the neck, but a slight 2/6 systolic ejection murmur is present on heart exam, which is stable. Lungs are clear, and there is trace lower extremity edema bilaterally.

Claim Recall (GPT-4): **100.00** // Support all claims.
Human Judgment: **100.00** // Support all claims.
Preferred by Subjective Preference?: **No.**

Output 2 *(Preferred by human)*

OBJECTIVE EXAM:
- Carotid: No appreciable carotid bruits
- Heart: 2/6 systolic ejection murmur, stable from previous exams
- Lungs: Clear to auscultation bilaterally
- Extremities: Trace lower extremity edema bilaterally

EKG: Within normal limits

Claim Recall (GPT-4): **100.00** // Support all claims.
Human Judgment: **100.00** // Support all claims.
Preferred by Subjective Preference?: **Yes.** // more details.

Table 8: An example where human and claim recall (GPT-4) give the same entailment score for both outputs, but human subjectively prefers one of them. In this case, Output 2 also contains the EKG results, which is not presented in the reference but should be included.

three medical experts such that the summary allows retrieving complete, correct answers to the original question without the potential for further condensation. We experiment on the subset of the test set selected by the MEDIQA 2021 challenge (Ben Abacha et al., 2021), which contains 100 examples and covers a wide range of topics and question types such as *Treatment, Information, Side effects, Cause, Effect, Person-Organization, Diet-Lifestyle, Complications, Contraindications, Diagnosis, Usage, Interaction, Ingredients, Prognosis, Susceptibility, Transmission, and Toxicity*.

Reference subclaims
1. The patient appears to be in no apparent distress.
2. No carotid bruits are present in the patient's neck.
3. The patient's lungs are clear upon auscultation, with no wheezes, rales, or rhonchi.
4. The patient has a grade 2/6 systolic ejection murmur.
5. There is 1+ edema in both lower extremities of the patient.

Output 1 *(Preferred by GPT-4 and human)*

OBJECTIVE EXAM:
Vital Signs:
- Blood pressure: within normal range
- Heart rate: within normal range
- Pulse ox: within normal range

Physical Exam:
- General: Patient is not in any distress
- Carotid: No appreciable carotid bruits
- Heart: Slight 2/6 systolic ejection murmur (previously noted)
- Lungs: Clear to auscultation bilaterally
- Extremities: 1+ edema in lower extremities

Labs:
- Blood glucose: 162 mg/dL (fasting)
- Hemoglobin A1c: 8%

ROUGE-L Recall: **27.66**
MEDCON Recall: **33.33**
Claim Recall (GPT-4): **100.00** // Support all claims.
Human Judgment: **100.00** // Support all claims.

Output 2 *(Preferred by ROUGE-L and MEDCON)*

PHYSICAL EXAMINATION
• Cardiovascular: 2/6 systolic ejection murmur, stable.
• Respiratory: Lungs clear to auscultation.
• Extremities: 1+ pitting edema in bilateral lower extremities.

ROUGE-L Recall: **40.43**
MEDCON Recall: **75.00**
Claim Recall (GPT-4): **60.00** // Support Claim 3, 4, 5.
Human Judgment: **60.00** // Support Claim 3, 4, 5.

Table 9: An example of disagreement between claim recall (GPT-4) and ROUGE/MEDCON on preferences over a pair of outputs. In this example, Output 1 has fewer medical terms overlapping with the reference, but covers more subclaims.

A.4.2 Examples for each Dataset

Table 16 is an example of clinical note generation under the full-note generation setting. The input is the dialogue between the doctor and the patient and the target output is the full clinical note based on the dialogue. We highlight the four sections in the reference clinical note, which is divided automatically by the name of each paragraph (e.g., "REVIEW OF SYSTEMS" belongs to the subjective section). As for per-section generation, the input is the same and the target output contains only one of the four sections.

Task	Commonly-Used Metrics	Reference
Clinical note generation	ROUGE, BERTScore, BLEURT, MEDCON	Yim et al. (2023); Ben Abacha et al. (2023a)
Radiology report summarization	ROUGE, BERTScore, BLEU, F1-RadGraph	Van Veen et al. (2023); Tu et al. (2023)
Patient question summarization	ROUGE, BERTScore, BLEU, MEDCON	Abacha and Demner-Fushman (2019); Veen et al. (2023)

Table 10: Evaluated tasks and their commonly used metrics. We list prior works that apply the corresponding metrics under "Reference".

Comparison	**# Disagreements**	
	O-Exam	**A & P**
Claim Recall (GPT-4) & ROUGE Recall	524 / 2460	635 / 2460
Claim Recall (GPT-4) & MEDCON Recall	251 / 2460	499 / 2460
Claim Recall (GPT-4) & Claim Recall (TRUE)	148 / 2460	268 / 2460
Claim Recall (GPT-4) & Claim Recall (Mistral)	121 / 2460	309 / 2460

Table 11: Number of disagreements between each two evaluation metrics among all 2460 pairs of generated outputs.

Table 17 is an example of radiology report summarization. The input is the findings section of the radiology report, containing experiment results and findings. The target output is the impression section of the report, which should summarize the important information in the findings section.

Table 18 shows an example of patient question summarization. The input is the patient question of varying verbosity and coherence, and the goal is to summarize the input into a short question that allows retrieving complete, correct answers to the original question.

A.4.3 Evaluation Metrics

To evaluate note generation, we compare DOCLENS with the following metrics that are commonly used in the existing research (Yim et al., 2023): **ROUGE** (Lin, 2004) computes the overlap of n-grams. **BERTScore** (Zhang et al., 2020a) compares the embeddings of matched tokens in the output and reference. **BLEURT** (Sellam et al., 2020) trains a model to compute output-reference similarity. **MEDCON** (Yim et al., 2023) computes the F1-score of the UMLS concepts in the output and the reference.

To evaluate report summarization, we follow previous work (Van Veen et al., 2023) and evaluate ROUGE, BERTScore, BLEU, and F1-RadGraph (Jain et al., 2021), where BLEU evaluates the overlap of 1- to 4-grams, and F1-RadGraph computes the F1 score of a predefined set of entities and relations present in radiology reports.

As for question summarization, we evaluate ROUGE, BERTScore, BLEU, and MEDCON following existing words (Veen et al., 2023; Abacha and Demner-Fushman, 2019).

A.4.4 Evaluated Methods

We evaluate both open-source models and proprietary models on note generation. For open-source models, we choose the best models reported by Yim et al. (2023): BART fine-tuned on SAMSum (Gliwa et al., 2019) (denoted as BART + SAMSum FT) and BioBART (Yuan et al., 2022). Since these models are not capable of generating citations, we do not report their citation metrics. For proprietary models, we experiment on GPT-3.5-turbo and GPT-4 with zero-shot and few-shot prompting.

As for report summarization, we compare GPT-3.5-turbo and GPT-4 with zero-shot and few-shot prompting. For few-shot prompts, we sample the same number of examples (1 or 2) from each of the six Modality/Anatomy categories in MIMIC that have a train set. Namely, we experiment on 0-shot, 6-shot, and 12-shot prompting.

Similarly, to evaluate question summarization, we compare 3.5-turbo and GPT-4 with 0-shot, 1-shot, and 2-shot prompting. The few-shot examples are selected from the validation set of MeQSum.

A.4.5 Human Evaluation Details

We only annotate the disagreement between two metrics to manage the required amount of human annotation. As shown in Table 11, the metrics have agreed preferences in most of the cases. For instance, if we randomly sample a set of output pairs for the objective exam section, GPT-4 and TRUE disagree in only 148 / 2640 = 5.6% of the output pairs. GPT-4 and Mistral disagree in only 121 / 2640 = 4.6% of the output pairs. As a result, randomly sampling from all output pairs would be inefficient, and we only focus on the disagreement.

We focus on completeness evaluation because

Inter-annotator Agreement			
Comparison	**Section**	**Spearman-ρ**	**Kendall-τ**
Claim Recall (GPT-4) vs. Rouge Recall	O-Exam A & P	0.744 0.881	0.641 0.767
Claim Recall (GPT-4) vs. MEDCON Recall	O-Exam A & P	0.688 0.785	0.594 0.667
Claim Recall (GPT-4) vs. Claim Recall (TRUE)	O-Exam A & P	0.765 0.686	0.644 0.554
Claim Recall (GPT-4) vs. Claim Recall (Mistral)	O-Exam A & P	0.690 0.861	0.561 0.709

Table 12: Inter-annotator agreement in the human study (§4.3). We compare the correlation between one annotator and the average score given by the other two annotators.

in medical scenarios, omission errors (i.e., important information is missed or excluded) are more critical than commission errors (Hayward et al., 2005) or hallucinations (Schumacher et al., 2023), in which information is fabricated and erroneously included. In the most common setting where we have human experts in the loop, detection of hallucinations is a much easier task as it can rely on comparisons against cited input or external sources. In contrast, detecting erroneous omissions is especially challenging as they are by definition not present in a system output, yet can mislead a reader by incorrectly portraying the source document.

We have five medical experts from two countries participating in our human evaluation, as introduced in §4.3. All of them are researchers in biomedical machine learning. We held a 1-hour meeting to briefly introduce our work and explain the purpose and setting of the human study.

We provide the instructions for the annotators in Table 19 and provide a screenshot of the interface in Figure 9. We provide the annotators with the reference note, the extracted subclaims of the reference note, and two notes generated by two models. We do not tell the annotators which model generates which note. The annotators are asked to judge (1) whether each claim is fully supported by the two notes, and (2) which note they subjectively think is more complete (i.e., covers more information in the reference note). To better understand the judgments of the annotators, they are free to leave any comments or thoughts when annotating the example, including but not limited to the explanations of their subjective preferences, and whether the claims extracted from the reference note are accurate and complete.

A.5 Detailed Evaluation Results

For DocLens computed with GPT-4, we provide the detailed evaluation results of note generation in Table 25, which corresponds to Figure 4. Evaluation results on report summarization are shown in Table 29, which corresponds to Figure 5. Evaluation results on question summarization are in Table 33, which corresponds to Figure 6.

Tables 27, 31 and 35 show the results evaluated by DocLens computed with TRUE.

Tables 22, 26, 30 and 34 show the results evaluated by DocLens computed with Mistral.

A.5.1 Generation With or Without Citations

We compare the performance with or without asking the model to generate citations. As shown in Table 36, there are no significant differences in the performances of generating with or without citations.

***Prompt style**: JSON*

Instruction:

Please act as an impartial judge and evaluate whether the clinical note provided by an AI assistant can fully entail each claim below. For each claim, please output '1' or '0' for each claim, where '1' means the claim can be fully entailed by the clinical note, and '0' means the claim contains information that cannot be entailed by the clinical note.
Generate the answer as a list of json dicts. Each dict should be in the format of {'claim': the original claim, 'entailment prediction': 1 or 0, whether the claim can be entailed}."

Example input:

```
{
  "clinical note": "PHYSICAL EXAM • Cardiovascular: 3/6 systolic ejection murmur, previously noted. • Extremities: 1+ pitting edema in lower extremities.",
  "claims": [
    "The patient's blood pressure is high.",
    "The patient has a grade 3/6 systolic ejection murmur.",
    "The patient exhibits 1+ pitting edema in both lower extremities."
  ]
}
```

Example output:

```
[
  {
    "claim": "The patient's blood pressure is high.",
    "entailment prediction": 0
  },
  {
    "claim": "The patient has a grade 3/6 systolic ejection murmur.",
    "entailment prediction": 1
  },
  {
    "claim": "The patient exhibits 1+ pitting edema in both lower extremities.",
    "entailment prediction": 0
  }
]
```

Table 13: Example of the prompt style "JSON" for claim recall and precision computation on ACI-BENCH. We format the input and output as a JSON dictionary.

***Prompt style**: CoT*

Instruction:

Please act as an impartial judge and evaluate whether the clinical note provided by an AI assistant can fully entail the claim below. Also generate an explanation for your answer. Please output '1' or '0' as your entailment prediction, where '1' means the claim can be fully entailed by the clinical note, and '0' means the claim contains information that cannot be entailed by the clinical note.
Generate the answer in the following format:
explanation: the reason why the entailment prediction is made.
entailment prediction: 1 or 0, whether the claim can be entailed.

Example input:

clinical note: PHYSICAL EXAM • Cardiovascular: 3/6 systolic ejection murmur, previously noted. • Extremities: 1+ pitting edema in lower extremities.
claim: The patient exhibits 1+ pitting edema in both lower extremities.

Example output:

explanation: the clinical note mentions 'Extremities: 1+ pitting edema', but does not specify whether it is in the upper or lower extremities.
entailment prediction: 0

Table 14: Example of the prompt style "CoT" for claim recall and precision computation on ACI-BENCH. We prompt the model to generate an explanation for its prediction.

***Prompt style**: JSON + CoT*

Instruction:

Please act as an impartial judge and evaluate whether the clinical note provided by an AI assistant can fully entail each claim below. **Also generate an explanation for your answer.** For each claim, please output '1' or '0' for each claim, where '1' means the claim can be fully entailed by the clinical note, and '0' means the claim contains information that cannot be entailed by the clinical note. Generate the answer as a list of json dicts. Each dict should be in the format of {'claim': the original claim, **'explanation': the reason why the entailment prediction is made,** 'entailment prediction': 1 or 0, whether the claim can be entailed}."

Example input:

```
{
  "clinical note": "PHYSICAL EXAM • Cardiovascular: 3/6 systolic ejection murmur, previously noted. • Extremities: 1+ pitting edema in lower extremities.",
  "claims": [
    "The patient's blood pressure is high.",
    "The patient has a grade 3/6 systolic ejection murmur.",
    "The patient exhibits 1+ pitting edema in both lower extremities."
  ]
}
```

Example output:

```
[
  {
    "claim": "The patient's blood pressure is high.",
    "explanation": "The clinical note does not mention anything about the blood pressure.",
    "entailment prediction": 0
  },
  {
    "claim": "The patient has a grade 3/6 systolic ejection murmur.",
    "explanation": "The PHYSICAL EXAM section mentions that 'Cardiovascular: 3/6 systolic ejection murmur', which supports the claim.",
    "entailment prediction": 1
  },
  {
    "claim": "The patient exhibits 1+ pitting edema in both lower extremities.",
    "explanation": "The clinical note mentions 'Extremities: 1+ pitting edema', but does not specify whether it is in the upper or lower extremities.",
    "entailment prediction": 0
  }
]
```

Table 15: Example of the prompt style "JSON + CoT" for claim recall and precision computation on ACI-BENCH. We format the input and output as a JSON dictionary and prompt the model to generate an explanation for its prediction. We highlight the difference between the "JSON" and "JSON + CoT" prompt styles in **bold**.

***Input**: Dialogue between the doctor and the patient*

[0] (doctor) hi, martha. how are you?
...
[4] (doctor) so, martha, it's been a year since i've seen you. how are you doing?
[5] (patient) i'm doing well. i've been traveling a lot recently since things have, have gotten a bit lighter. and i got my, my vaccine, so i feel safer about traveling. i've been doing a lot of hiking. uh, went to washington last weekend to hike in northern cascades, like around the mount baker area.
...
[28] (doctor) so, i'm just gon na check out your heart and your lungs. and you know, let you know what i find, okay?
[29] (patient) okay.
[30] (doctor) okay. so, on your physical examination, you know, everything looks good. on your heart exam, i do appreciate a three out of six systolic ejection murmur, which i've heard in the past, okay? and on your lower extremities, i do appreciate one plus pitting edema, so you do have a little bit of fluid in your legs, okay?
[31] (patient) okay.
...
[37] (doctor) i also wanna repeat another echocardiogram, okay?
[38] (patient) okay.
...
[46] (patient) can i take all my pills at the same time?
[47] (doctor) yeah.
...

***Reference**: Clinical note*

CHIEF COMPLAINT
Annual exam [4].

HISTORY OF PRESENT ILLNESS
Martha Collins is a 50-year-old female with a past medical history significant for congestive heart failure, depression, and hypertension who presents for her annual exam [4]. It has been a year since I last saw the patient [4].

The patient has been traveling a lot recently since things have gotten a bit better [5]. She reports that she got her COVID-19 vaccine so she feels safer about traveling [5]. She has been doing a lot of hiking [5].
...

REVIEW OF SYSTEMS
• Ears, Nose, Mouth and Throat: Endorses nasal congestion from allergies [22].
• Cardiovascular: Denies chest pain or dyspnea on exertion [12][13].
...

PHYSICAL EXAMINATION
• Cardiovascular: Grade 3/6 systolic ejection murmur [30].
1+ pitting edema of the bilateral lower extremities [30].

VITALS REVIEWED
• Blood Pressure: Elevated [26].

RESULTS
Echocardiogram demonstrates decreased ejection fraction of 45% [32]. Mitral regurgitation is present [32].
Lipid panel: Elevated cholesterol [33].

ASSESSMENT AND PLAN
Martha Collins is a 50-year-old female with a past medical history significant for congestive heart failure, depression, and hypertension who presents for her annual exam [4].

Congestive heart failure.
• Medical Reasoning: She has been compliant with her medication and dietary modifications [8][9][10][11]. Her previous year's echocardiogram demonstrated a reduced ejection fraction of 45%, as well as some mitral regurgitation [32]. Her cholesterol levels were slightly elevated on her lipid panel from last year [33].
• Additional Testing: We will order a repeat echocardiogram [37][38]. We will also repeat a lipid panel this year [33][34].
...

Table 16: An example of note generation, where the input is the dialogue between the doctor and the patient, and the goal is to generate a clinical note based on the dialogue. We highlight the four sections in the note: subjective, objective exam, objective results, and assessment and plan.

***Input**: The findings section of a radiology report*
[0] there are new areas of slow diffusion in left frontal and parietal lobes involving the precentral gyrus suggestive of acute infarcts. [1] areas of slow diffusion are noted in left corona radiata, left thalamus, left parieto-occipital regions and splenium of corpus callosum which are unchanged since the prior study. [2] areas of gliosis with flair and t2 hyperintensities are noted in bilateral occipital lobes which are sequelae of subacute/ chronic infarcts (left greater than right). [3] there is no evidence of hemorrhagic transformation of infarcts. [4] there is prominence of the cortical sulci, ventricular system and extra-axial csf spaces suggestive of generalized cerebral atrophy. [5] mucosal thickening is noted in the sphenoid sinus and bilateral ethmoid air cells. [6] orbits are unremarkable. [7] there is partial opacification of bilateral mastoid air cells.
***Reference**: The impression section, which summarizes the findings section*
1. new acute infarcts in left frontal and parietal lobes. [0] 2. subacute infarcts in splenium of corpus callosum, left thalamus and left parietal and frontal white matter. [0][1] 3. sequelae of subacute/chronic infarcts in bilateral occipital lobes. [2]

Table 17: An example of report summarization, where the input is the findings section of a radiology report, and the goal is to generate an impression section that summarizes important results in the findings section.

***Input**: The original patient health questions*
[0] Hello, I have been dealing with trimethylaminuria since I was a child. [1] I have done some of my own research and it looks like not much can be done for this condition. [2] I do not have it all over my body. [3] It's only in my armpits. [4] In the past I've gone to doctors and dermatologist they gave me no answers until I looked online today and finally found out what I have. [5] I don't know maybe I'm wrong. [6] But this disease isn't even consider common because no one has done anything about it. [7] I'm sure they're thousands of women with it... [8] Can I be tested for it and help in some kind of way to finding a cure or something? [9] What testing is done for this? [10] And where? [11] Thank you
***Output**: The summarized question*
How can I get tested and treated for trimethylaminuria? [0][8][9][10]

Table 18: An example of question summarization, where the input is the patient question of varying verbosity and coherence, and the goal is to summarize the input into a short question that allows retrieving complete, correct answers to the original question.

Instructions for the annotators
We are working on a project on medical text evaluation, and we need your help to evaluate the quality of clinical notes generated by different models. In this study, you will be presented with 20 (or 10) examples. Each example contains 2 clinical notes generated by different models, the reference clinical note written by human, and a list of subclaims we extracted from the reference clinical note. Your tasks are as follows: (1) Judge whether the information in each subclaim is fully covered by each of the generated clinical notes. (2) Judge which clinical note is more complete. Namely, which clinical note better captures the important information in the reference clinical note.

Table 19: Instructions for the annotators in our human study. We present the instructions in a meeting in which we briefly introduced them to the task of note generation, our project, and the purpose of the human study.

```
(py38) ~/Downloads/D2N_preference_annotations % python annotate.py objective_exam_GPT4_vs_TRUE.json NAME
Annotation progress 1/20
encounter_id: D2N107
section: objective_exam
claim_recall - Select the note that covers more subclaims of the reference note.

Reference note:
PHYSICAL EXAM

NEURO: Normal strength and sensation.
MSK: Examination of the lumbar spine: No pain on extension. Some pain with flexion. Pain with palpation around L5. Dorsiflexion is normal. Pulses
are equal in all extremities.

Reference subclaims:
  1. The patient has normal strength and sensation in the neurological exam.
  2. The patient experiences no pain on lumbar spine extension.
  3. The patient experiences some pain with lumbar spine flexion.
  4. The patient has pain on palpation around L5.
  5. The patient's dorsiflexion is normal.
  6. The patient has equal pulses in all extremities.

PHYSICAL EXAMINATION

• Musculoskeletal: Pain to palpation around the L5 area [15]. Pain on flexion [11], and reported pain on extension by the patient's partner [20].
• Neurological: Normal dorsiflexion [32].
• Extremities: Pulses equal in all extremities [32].
• Sensation: Tingling in the right leg [33].

Does the note entail subclaim 1? (1/0, default: 0) 1
Does the note entail subclaim 2? (1/0, default: 0) 0
Does the note entail subclaim 3? (1/0, default: 0) 0
Does the note entail subclaim 4? (1/0, default: 0) 1
Does the note entail subclaim 5? (1/0, default: 0) 1
Does the note entail subclaim 6? (1/0, default: 0) 0


Reference note:
PHYSICAL EXAM

NEURO: Normal strength and sensation.
MSK: Examination of the lumbar spine: No pain on extension. Some pain with flexion. Pain with palpation around L5. Dorsiflexion is normal. Pulses
are equal in all extremities.

Reference subclaims:
  1. The patient has normal strength and sensation in the neurological exam.
  2. The patient experiences no pain on lumbar spine extension.
  3. The patient experiences some pain with lumbar spine flexion.
  4. The patient has pain on palpation around L5.
  5. The patient's dorsiflexion is normal.
  6. The patient has equal pulses in all extremities.

Objective Exam:
- Patient reports onset of back pain after raking leaves in yard, with subsequent onset of pins and needles in right foot.
- Patient reports prior episode of similar back pain three years ago that resolved within a day.
- Patient tried icing and two Advils with no relief.
- Pain improves with hot shower and sitting, worsens with bending over and palpation at L5.
- Partner reports pain is worse when patient stands up.
- Dorsiflexion is normal, pulses are equal in all extremities, and there is tingling sensation in right leg.
- X-ray of low back shows no abnormalities.
- Diagnosis of low back sprain is made.
- Treatment plan includes rest, meloxicam prescription, and physical therapy.
- Follow-up in two weeks, with consideration of MRI if symptoms persist.

Does the note entail subclaim 1? (1/0, default: 0) 0
Does the note entail subclaim 2? (1/0, default: 0) 0
Does the note entail subclaim 3? (1/0, default: 0) 0
Does the note entail subclaim 4? (1/0, default: 0) 1
Does the note entail subclaim 5? (1/0, default: 0) 1
Does the note entail subclaim 6? (1/0, default: 0) 1

Subjective preference? (1/2, default: 1) 1
Any comments on this example?
```

Figure 9: The screenshot of the interface of our human study. Each annotator is asked to decide (1) whether each claim is fully supported by the two notes, and (2) which note they subjectively think is more complete (i.e., covers more information in the reference note). They are optionally asked to provide their comments for each example.

Evaluation Methods: Rouge, MEDCON				
Model	**Rouge-1**	**Rouge-2**	**Rouge-L**	**MEDCON**
BART + SAMSum FT (full)	40.87	18.96	34.60	41.69
BART + SAMSum FT (section)	53.46	25.08	48.62	48.37
BioBART (full)	39.09	17.24	33.19	43.05
BioBART (section)	49.53	22.47	44.92	43.21
GPT-3.5-turbo (full, 0-shot)	48.25	20.54	43.78	56.82
GPT-3.5-turbo (section, 0-shot)	47.61	20.80	43.65	57.48
GPT-4 (full, 0-shot)	48.74	22.93	45.26	59.49
GPT-4 (section, 0-shot)	51.16	23.33	46.98	60.01
GPT-3.5-turbo-16k (full, 1-shot)	53.08	24.16	48.71	57.96
GPT-3.5-turbo-16k (section, 1-shot)	50.56	23.85	47.21	57.52
GPT-4 (full, 1-shot)	56.34	27.04	51.62	62.84
GPT-4 (section, 1-shot)	56.99	28.10	52.74	62.07
GPT-3.5-turbo-16k (full, 2-shot)	56.50	27.38	52.27	60.13
GPT-3.5-turbo-16k (section, 2-shot)	51.99	25.52	48.22	58.80
GPT-4-32k (full, 2-shot)	**58.50**	29.44	**54.34**	**63.00**
GPT-4-32k (section, 2-shot)	58.25	**29.73**	53.96	61.95

Table 20: Note generation results on ACI-BENCH-test1 evaluated with existing metrics. We compute each metric over the full note.

Evaluation Method: DOCLENS computed with GPT-4				
Model	**Claim Recall**	**Claim Prec**	**Citation Recall**	**Citation Prec**
BART + SAMSum FT (full)	20.30	48.11	–	–
BART + SAMSum FT (section)	33.59	30.38	–	–
BioBART (full)	16.53	42.43	–	–
BioBART (section)	29.37	26.10	–	–
GPT-3.5-turbo (full, 0-shot)	46.80	69.74	53.99	42.16
GPT-3.5-turbo (section, 0-shot)	56.28	29.18	58.77	49.31
GPT-4 (full, 0-shot)	48.31	**75.67**	68.74	**66.07**
GPT-4 (section, 0-shot)	60.24	36.73	61.13	58.47
GPT-3.5-turbo-16k (full, 1-shot)	49.96	71.94	65.32	63.12
GPT-3.5-turbo-16k (section, 1-shot)	59.13	39.29	62.63	60.94
GPT-4 (full, 1-shot)	58.26	73.90	69.94	65.72
GPT-4 (section, 1-shot)	67.69	52.47	**70.81**	65.75
GPT-3.5-turbo-16k (full, 2-shot)	54.92	68.89	63.54	61.83
GPT-3.5-turbo-16k (section, 2-shot)	62.44	42.91	65.79	64.09
GPT-4-32k (full, 2-shot)	59.07	69.20	68.74	64.17
GPT-4-32k (section, 2-shot)	**69.88**	54.92	67.90	63.01

Table 21: Note generation results on ACI-BENCH-test1 evaluated with DOCLENS computed with GPT-4. We compute each metric over the full note.

Evaluation Method: DOCLENS computed with Mistral				
Model	**Claim Recall**	**Claim Prec**	**Citation Recall**	**Citation Prec**
BART + SAMSum FT (full)	24.76	52.42	–	–
BART + SAMSum FT (section)	43.03	36.08	–	–
BioBART (full)	18.77	47.63	–	–
BioBART (section)	36.84	32.95	–	–
GPT-3.5-turbo (full, 0-shot)	60.97	75.79	91.31	80.03
GPT-3.5-turbo (section, 0-shot)	67.30	36.44	83.34	64.20
GPT-4 (full, 0-shot)	62.13	**79.23**	**94.00**	**89.65**
GPT-4 (section, 0-shot)	72.31	42.33	89.47	80.58
GPT-3.5-turbo-16k (full, 1-shot)	61.50	75.58	85.68	82.79
GPT-3.5-turbo-16k (section, 1-shot)	65.20	46.91	88.64	80.19
GPT-4 (full, 1-shot)	69.53	78.56	89.01	82.90
GPT-4 (section, 1-shot)	72.59	57.32	91.34	82.18
GPT-3.5-turbo-16k (full, 2-shot)	66.05	74.04	84.60	79.10
GPT-3.5-turbo-16k (section, 2-shot)	66.30	50.82	88.32	81.90
GPT-4-32k (full, 2-shot)	67.89	73.17	87.86	80.06
GPT-4-32k (section, 2-shot)	**73.96**	59.24	86.15	77.57

Table 22: Note generation results on ACI-BENCH-test1 evaluated with DOCLENS computed with Mistral. We compute each metric over the full note.

Evaluation Method: DocLens computed with TRUE				
Model	**Claim Recall**	**Claim Prec**	**Citation Recall**	**Citation Prec**
BART + SAMSum FT (full)	19.95	47.62	–	–
BART + SAMSum FT (section)	32.23	29.42	–	–
BioBART (full)	15.74	40.45	–	–
BioBART (section)	27.84	24.05	–	–
GPT-3.5-turbo (full, 0-shot)	41.76	63.25	68.27	55.52
GPT-3.5-turbo (section, 0-shot)	53.54	27.14	56.20	34.52
GPT-4 (full, 0-shot)	45.21	**72.61**	**72.41**	**64.53**
GPT-4 (section, 0-shot)	57.79	34.53	49.38	38.59
GPT-3.5-turbo-16k (full, 1-shot)	47.40	66.28	56.51	52.23
GPT-3.5-turbo-16k (section, 1-shot)	56.39	37.57	58.45	48.03
GPT-4 (full, 1-shot)	56.61	69.49	60.95	51.92
GPT-4 (section, 1-shot)	67.13	49.81	60.99	49.13
GPT-3.5-turbo-16k (full, 2-shot)	53.04	65.19	54.99	49.50
GPT-3.5-turbo-16k (section, 2-shot)	60.71	41.00	59.59	52.18
GPT-4-32k (full, 2-shot)	57.90	63.83	54.41	46.42
GPT-4-32k (section, 2-shot)	**67.63**	50.78	55.33	45.99

Table 23: Note generation results on ACI-BENCH-test1 evaluated with DocLens computed with TRUE. We compute each metric over the full note.

Evaluation Methods: Rouge, BERTScore, BLEURT, MEDCON

Model	Rouge-1	Rouge-2	Rouge-L	BERTScore-F1	BLEURT	MEDCON
Subjective						
Reported GPT-3.5-turbo (full, 0-shot)	32.70	14.05	22.69	65.14	39.48	38.21
Reported GPT-4 (full, 0-shot)	41.20	19.02	26.56	63.34	43.18	44.25
BART + SAMSum FT (full)	46.33	25.52	29.88	68.68	45.00	43.02
BART + SAMSum FT (section)	52.44	**30.44**	35.83	72.41	44.51	47.68
BioBART (full)	45.79	23.65	28.96	68.49	41.09	41.10
BioBART (section)	46.29	25.99	32.43	70.30	42.98	41.21
GPT-3.5-turbo (full, 0-shot)	33.56	15.15	23.54	63.73	42.48	40.81
GPT-3.5-turbo (section, 0-shot)	36.30	13.27	20.30	59.69	43.55	35.95
GPT-4 (full, 0-shot)	35.09	16.49	25.56	65.12	42.11	41.15
GPT-4 (section, 0-shot)	43.32	19.03	27.04	63.70	46.30	48.54
GPT-3.5-turbo-16k (full, 1-shot)	43.02	21.97	31.15	70.37	45.62	48.50
GPT-3.5-turbo-16k (section, 1-shot)	40.95	18.15	29.21	62.37	43.57	38.02
GPT-4 (full, 1-shot)	47.63	24.71	33.07	71.51	46.58	**50.96**
GPT-4 (section, 1-shot)	48.16	23.23	34.08	65.04	47.86	44.97
GPT-3.5-turbo-16k (full, 2-shot)	50.44	27.18	35.55	73.68	**48.62**	49.18
GPT-3.5-turbo-16k (section, 2-shot)	40.95	18.76	29.80	63.27	44.52	35.92
GPT-4-32k (full, 2-shot)	**53.45**	30.12	**38.68**	**75.44**	48.03	49.65
GPT-4-32k (section, 2-shot)	49.58	24.71	34.86	65.81	47.55	45.95
Objective-Exam						
Reported GPT-3.5-turbo (full, 0-shot)	49.44	27.29	38.60	71.39	49.39	48.95
Reported GPT-4 (full, 0-shot)	50.11	28.20	40.43	71.79	51.11	42.59
BART + SAMSum FT (full)	6.22	3.74	5.21	44.33	14.83	4.14
BART + SAMSum FT (section)	47.73	29.51	36.98	73.41	42.86	35.91
BioBART (full)	2.57	1.04	1.68	42.10	12.40	1.22
BioBART (section)	42.51	26.15	32.19	71.57	42.18	29.55
GPT-3.5-turbo (full, 0-shot)	51.19	31.04	42.10	71.23	52.15	49.02
GPT-3.5-turbo (section, 0-shot)	32.21	17.87	26.44	60.11	45.57	31.60
GPT-4 (full, 0-shot)	62.41	40.44	52.82	77.04	55.40	55.69
GPT-4 (section, 0-shot)	39.58	22.91	35.11	62.70	45.55	38.33
GPT-3.5-turbo-16k (full, 1-shot)	55.67	32.25	45.85	76.74	51.77	44.25
GPT-3.5-turbo-16k (section, 1-shot)	39.07	22.02	34.52	60.45	37.69	36.29
GPT-4 (full, 1-shot)	63.18	40.99	53.14	80.52	**55.74**	**55.04**
GPT-4 (section, 1-shot)	52.45	30.10	46.81	66.45	44.42	49.54
GPT-3.5-turbo-16k (full, 2-shot)	61.13	37.93	51.84	79.40	52.18	48.14
GPT-3.5-turbo-16k (section, 2-shot)	46.46	27.29	42.44	64.02	41.24	44.97
GPT-4-32k (full, 2-shot)	**65.98**	**42.61**	**53.65**	**81.43**	51.50	53.80
GPT-4-32k (section, 2-shot)	55.58	32.45	49.69	68.54	47.29	50.50
Objective-Results						
Reported GPT-3.5-turbo (full, 0-shot)	34.50	17.75	30.84	66.68	48.51	22.28
Reported GPT-4 (full, 0-shot)	37.65	19.94	35.73	68.33	48.50	26.73
BART + SAMSum FT (full)	20.79	0.46	20.67	54.54	28.35	0.77
BART + SAMSum FT (section)	29.45	18.01	26.63	66.43	40.76	20.17
BioBART (full)	17.50	0.00	17.50	52.44	25.35	0.00
BioBART (section)	35.38	14.33	32.79	68.40	47.64	15.69
GPT-3.5-turbo (full, 0-shot)	36.01	20.57	33.45	66.06	51.00	22.27
GPT-3.5-turbo (section, 0-shot)	32.88	5.68	31.81	63.49	54.42	6.94
GPT-4 (full, 0-shot)	45.81	28.78	43.76	70.62	54.60	36.23
GPT-4 (section, 0-shot)	34.11	6.46	32.62	62.94	52.69	7.05
GPT-3.5-turbo-16k (full, 1-shot)	47.94	30.74	46.36	77.69	58.28	**36.64**
GPT-3.5-turbo-16k (section, 1-shot)	40.26	9.07	39.03	65.50	56.38	11.35
GPT-4 (full, 1-shot)	**64.59**	**33.67**	**63.26**	**86.09**	**68.34**	37.27
GPT-4 (section, 1-shot)	46.13	12.34	43.86	67.85	58.69	15.71
GPT-3.5-turbo-16k (full, 2-shot)	47.87	33.08	46.82	77.34	56.74	34.62
GPT-3.5-turbo-16k (section, 2-shot)	44.94	12.90	43.45	67.92	61.29	13.97
GPT-4-32k (full, 2-shot)	61.87	32.35	60.66	84.54	65.40	32.95
GPT-4-32k (section, 2-shot)	45.63	12.55	44.10	68.05	58.58	15.02
Assessment and Plan						
Reported GPT-3.5-turbo (full, 0-shot)	36.43	12.50	23.32	63.56	48.21	43.71
Reported GPT-4 (full, 0-shot)	38.16	14.12	24.90	64.26	49.41	42.36
BART + SAMSum FT (full)	1.52	0.49	0.87	35.38	19.80	1.00
BART + SAMSum FT (section)	43.89	21.37	27.56	68.09	41.95	31.65
BioBART (full)	0.00	0.00	0.00	0.00	29.05	0.00
BioBART (section)	42.44	19.44	26.42	67.57	43.88	31.07
GPT-3.5-turbo (full, 0-shot)	37.42	14.20	25.14	64.38	49.79	47.63
GPT-3.5-turbo (section, 0-shot)	38.17	14.10	26.80	62.41	51.16	43.75
GPT-4 (full, 0-shot)	39.25	16.12	27.71	68.13	50.91	47.03
GPT-4 (section, 0-shot)	41.68	16.52	30.14	63.47	**52.44**	43.20
GPT-3.5-turbo-16k (full, 1-shot)	48.20	23.16	33.58	71.79	51.31	50.00
GPT-3.5-turbo-16k (section, 1-shot)	43.93	17.98	31.81	63.98	48.44	43.61
GPT-4 (full, 1-shot)	49.32	23.50	33.74	72.14	50.26	50.07
GPT-4 (section, 1-shot)	46.48	20.38	34.18	65.57	47.39	44.80
GPT-3.5-turbo-16k (full, 2-shot)	52.18	26.99	35.83	73.25	48.47	47.82
GPT-3.5-turbo-16k (section, 2-shot)	44.68	19.38	32.34	64.68	47.19	43.99
GPT-4-32k (full, 2-shot)	**52.87**	**28.10**	**36.28**	**73.78**	49.39	**51.49**
GPT-4-32k (section, 2-shot)	46.64	22.11	34.36	65.72	47.54	46.13

Table 24: Note generation results of each section on ACI-BENCH-test1, evaluated by existing metrics.

Evaluation Method: DocLens computed with GPT-4

Subjective

Model	Claim Recall	Claim Prec	Citation Recall	Citation Prec
BART + SAMSum FT (full)	46.98	49.50	–	–
BART + SAMSum FT (section)	42.94	55.90	–	–
BioBART (full)	39.92	44.00	–	–
BioBART (section)	33.69	50.68	–	–
GPT-3.5-turbo (full, 0-shot)	32.30	72.84	57.42	40.21
GPT-3.5-turbo (section, 0-shot)	48.82	37.90	56.29	38.71
GPT-4 (full, 0-shot)	32.22	75.85	76.21	68.90
GPT-4 (section, 0-shot)	51.02	66.36	71.96	65.77
GPT-3.5-turbo-16k (full, 1-shot)	41.06	71.63	69.65	64.04
GPT-3.5-turbo-16k (section, 1-shot)	58.55	44.76	68.72	54.94
GPT-4 (full, 1-shot)	47.39	**75.53**	**79.57**	**69.91**
GPT-4 (section, 1-shot)	63.76	64.50	74.05	65.96
GPT-3.5-turbo-16k (full, 2-shot)	50.65	67.65	71.16	63.85
GPT-3.5-turbo-16k (section, 2-shot)	62.47	41.71	67.19	63.74
GPT-4-32k (full, 2-shot)	52.42	72.29	75.78	68.13
GPT-4-32k (section, 2-shot)	**63.91**	67.57	73.77	66.06

Objective-Exam

Model	Claim Recall	Claim Prec	Citation Recall	Citation Prec
BART + SAMSum FT (full)	1.71	21.94	–	–
BART + SAMSum FT (section)	32.48	20.65	–	–
BioBART (full)	1.04	15.83	–	–
BioBART (section)	34.08	16.41	–	–
GPT-3.5-turbo (full, 0-shot)	61.30	68.88	57.25	47.07
GPT-3.5-turbo (section, 0-shot)	62.27	22.33	63.90	52.64
GPT-4 (full, 0-shot)	64.28	69.22	62.00	59.38
GPT-4 (section, 0-shot)	66.39	23.54	55.25	50.39
GPT-3.5-turbo-16k (full, 1-shot)	51.19	72.89	62.62	60.49
GPT-3.5-turbo-16k (section, 1-shot)	51.22	44.59	72.44	70.03
GPT-4 (full, 1-shot)	70.72	72.98	71.88	67.08
GPT-4 (section, 1-shot)	70.57	60.35	**78.48**	**71.51**
GPT-3.5-turbo-16k (full, 2-shot)	51.77	**77.97**	63.08	61.74
GPT-3.5-turbo-16k (section, 2-shot)	49.73	61.51	72.42	70.18
GPT-4-32k (full, 2-shot)	60.90	74.35	71.09	65.39
GPT-4-32k (section, 2-shot)	71.22	69.21	70.81	67.28

Objective-Results

Model	Claim Recall	Claim Prec	Citation Recall	Citation Prec
BART + SAMSum FT (full)	3.12	25.00	–	–
BART + SAMSum FT (section)	33.96	11.44	–	–
BioBART (full)	0.00	0.00	–	–
BioBART (section)	34.37	15.47	–	–
GPT-3.5-turbo (full, 0-shot)	64.24	48.21	49.33	47.74
GPT-3.5-turbo (section, 0-shot)	66.25	5.98	56.11	44.93
GPT-4 (full, 0-shot)	71.60	57.86	62.08	60.62
GPT-4 (section, 0-shot)	76.67	8.60	65.84	46.66
GPT-3.5-turbo-16k (full, 1-shot)	61.83	57.91	77.57	77.48
GPT-3.5-turbo-16k (section, 1-shot)	64.00	13.80	76.93	69.80
GPT-4 (full, 1-shot)	71.66	**75.44**	**80.88**	**78.68**
GPT-4 (section, 1-shot)	77.66	25.94	77.27	73.25
GPT-3.5-turbo-16k (full, 2-shot)	61.83	62.83	79.46	79.46
GPT-3.5-turbo-16k (section, 2-shot)	70.66	24.57	69.94	65.72
GPT-4-32k (full, 2-shot)	59.39	75.21	77.59	74.71
GPT-4-32k (section, 2-shot)	80.16	22.23	67.71	64.97

Assessment and Plan

Model	Claim Recall	Claim Prec	Citation Recall	Citation Prec
BART + SAMSum FT (full)	0.63	10.71	–	–
BART + SAMSum FT (section)	20.01	27.03	–	–
BioBART (full)	0.00	0.00	–	–
BioBART (section)	17.84	24.36	–	–
GPT-3.5-turbo (full, 0-shot)	52.47	73.10	55.53	41.54
GPT-3.5-turbo (section, 0-shot)	60.32	53.43	59.98	46.24
GPT-4 (full, 0-shot)	53.90	82.74	**67.77**	**65.43**
GPT-4 (section, 0-shot)	66.60	50.73	57.81	51.22
GPT-3.5-turbo-16k (full, 1-shot)	58.40	**74.43**	62.58	58.29
GPT-3.5-turbo-16k (section, 1-shot)	63.90	46.80	62.63	57.43
GPT-4 (full, 1-shot)	61.07	69.59	62.83	55.12
GPT-4 (section, 1-shot)	67.38	50.71	63.04	53.40
GPT-3.5-turbo-16k (full, 2-shot)	62.53	66.48	57.48	52.79
GPT-3.5-turbo-16k (section, 2-shot)	66.58	50.09	62.31	58.23
GPT-4-32k (full, 2-shot)	65.87	62.90	60.29	49.26
GPT-4-32k (section, 2-shot)	**72.11**	50.99	63.28	54.44

Table 25: Note generation results of each section on ACI-BENCH-test1, evaluated with DocLens (GPT-4).

Evaluation Method: DocLens computed with Mistral				
Subjective				
Model	**Claim Recall**	**Claim Prec**	**Citation Recall**	**Citation Prec**
BART + SAMSum FT (full)	55.52	53.92	–	–
BART + SAMSum FT (section)	51.05	58.00	–	–
BioBART (full)	44.33	48.37	–	–
BioBART (section)	40.21	57.67	–	–
GPT-3.5-turbo (full, 0-shot)	41.43	75.12	95.30	76.89
GPT-3.5-turbo (section, 0-shot)	57.64	45.27	86.02	61.57
GPT-4 (full, 0-shot)	41.36	**78.44**	**97.92**	**90.71**
GPT-4 (section, 0-shot)	**65.99**	69.35	93.05	85.15
GPT-3.5-turbo-16k (full, 1-shot)	49.52	74.05	94.60	88.57
GPT-3.5-turbo-16k (section, 1-shot)	59.74	51.08	85.45	79.70
GPT-4 (full, 1-shot)	58.96	76.46	97.82	86.50
GPT-4 (section, 1-shot)	63.35	65.57	95.42	83.76
GPT-3.5-turbo-16k (full, 2-shot)	61.44	72.30	93.14	82.31
GPT-3.5-turbo-16k (section, 2-shot)	62.42	49.08	89.06	80.16
GPT-4-32k (full, 2-shot)	59.61	73.09	96.11	83.89
GPT-4-32k (section, 2-shot)	65.39	67.61	95.12	83.54
Objective-Exam				
Model	**Claim Recall**	**Claim Prec**	**Citation Recall**	**Citation Prec**
BART + SAMSum FT (full)	5.18	42.41	–	–
BART + SAMSum FT (section)	45.81	31.56	–	–
BioBART (full)	2.50	30.00	–	–
BioBART (section)	44.91	24.69	–	–
GPT-3.5-turbo (full, 0-shot)	73.15	78.74	89.92	78.55
GPT-3.5-turbo (section, 0-shot)	71.14	34.50	82.07	68.32
GPT-4 (full, 0-shot)	74.20	74.68	90.79	87.10
GPT-4 (section, 0-shot)	76.97	30.21	84.59	76.08
GPT-3.5-turbo-16k (full, 1-shot)	64.38	78.41	82.09	79.79
GPT-3.5-turbo-16k (section, 1-shot)	61.78	48.42	89.92	83.38
GPT-4 (full, 1-shot)	80.37	**80.74**	84.08	80.37
GPT-4 (section, 1-shot)	78.66	64.75	91.50	86.53
GPT-3.5-turbo-16k (full, 2-shot)	71.24	82.35	79.46	75.82
GPT-3.5-turbo-16k (section, 2-shot)	62.78	65.96	**91.62**	**89.52**
GPT-4-32k (full, 2-shot)	70.77	72.77	87.52	83.83
GPT-4-32k (section, 2-shot)	**82.69**	70.04	85.33	81.19
Objective-Results				
Model	**Claim Recall**	**Claim Prec**	**Citation Recall**	**Citation Prec**
BART + SAMSum FT (full)	3.12	25.00	–	–
BART + SAMSum FT (section)	38.19	16.53	–	–
BioBART (full)	0.00	0.00	–	–
BioBART (section)	40.93	18.60	–	–
GPT-3.5-turbo (full, 0-shot)	81.53	62.38	91.03	85.56
GPT-3.5-turbo (section, 0-shot)	70.68	10.11	81.46	64.97
GPT-4 (full, 0-shot)	89.31	68.07	**95.00**	**93.54**
GPT-4 (section, 0-shot)	85.26	13.67	93.57	86.36
GPT-3.5-turbo-16k (full, 1-shot)	79.27	67.52	82.61	82.21
GPT-3.5-turbo-16k (section, 1-shot)	77.20	20.14	92.04	77.56
GPT-4 (full, 1-shot)	86.19	**85.29**	85.29	85.29
GPT-4 (section, 1-shot)	**90.78**	31.37	89.74	83.96
GPT-3.5-turbo-16k (full, 2-shot)	77.45	69.17	81.22	81.22
GPT-3.5-turbo-16k (section, 2-shot)	79.62	31.93	86.67	83.26
GPT-4-32k (full, 2-shot)	76.84	84.90	79.31	77.59
GPT-4-32k (section, 2-shot)	89.32	27.42	78.03	76.12
Assessment and Plan				
Model	**Claim Recall**	**Claim Prec**	**Citation Recall**	**Citation Prec**
BART + SAMSum FT (full)	1.63	23.21	–	–
BART + SAMSum FT (section)	30.72	33.83	–	–
BioBART (full)	0.00	0.00	–	–
BioBART (section)	26.23	31.96	–	–
GPT-3.5-turbo (full, 0-shot)	72.63	80.30	88.99	79.27
GPT-3.5-turbo (section, 0-shot)	76.39	60.97	83.82	61.93
GPT-4 (full, 0-shot)	74.00	**84.77**	**92.30**	**87.23**
GPT-4 (section, 0-shot)	77.24	58.16	86.66	74.76
GPT-3.5-turbo-16k (full, 1-shot)	71.30	77.53	83.17	80.53
GPT-3.5-turbo-16k (section, 1-shot)	71.82	58.50	87.16	80.12
GPT-4 (full, 1-shot)	74.05	78.01	88.29	79.82
GPT-4 (section, 1-shot)	76.12	59.77	88.70	74.45
GPT-3.5-turbo-16k (full, 2-shot)	70.17	73.26	84.16	77.29
GPT-3.5-turbo-16k (section, 2-shot)	69.48	60.30	85.91	74.66
GPT-4-32k (full, 2-shot)	74.89	70.89	86.16	74.26
GPT-4-32k (section, 2-shot)	**77.43**	60.72	86.11	69.43

Table 26: Note generation results on different sections of ACI-BENCH-test1 evaluated with DocLens (Mistral).

Evaluation Method: DocLens computed with TRUE

Subjective				
Model	**Claim Recall**	**Claim Prec**	**Citation Recall**	**Citation Prec**
BART + SAMSum FT (full)	45.74	49.26	–	–
BART + SAMSum FT (section)	40.99	52.31	–	–
BioBART (full)	37.63	42.04	–	–
BioBART (section)	32.20	47.37	–	–
GPT-3.5-turbo (full, 0-shot)	28.40	**67.75**	61.31	40.40
GPT-3.5-turbo (section, 0-shot)	45.33	33.87	54.97	30.80
GPT-4 (full, 0-shot)	31.09	72.18	**66.95**	**45.98**
GPT-4 (section, 0-shot)	50.03	64.72	51.55	41.39
GPT-3.5-turbo-16k (full, 1-shot)	41.29	65.96	44.94	38.99
GPT-3.5-turbo-16k (section, 1-shot)	56.08	43.66	44.56	40.29
GPT-4 (full, 1-shot)	47.75	69.38	52.98	40.39
GPT-4 (section, 1-shot)	**64.72**	60.22	51.88	40.42
GPT-3.5-turbo-16k (full, 2-shot)	50.12	63.41	43.08	37.14
GPT-3.5-turbo-16k (section, 2-shot)	43.61	40.38	48.94	40.33
GPT-4-32k (full, 2-shot)	53.54	64.99	46.25	37.32
GPT-4-32k (section, 2-shot)	63.42	62.43	44.82	35.93

Objective-Exam				
Model	**Claim Recall**	**Claim Prec**	**Citation Recall**	**Citation Prec**
BART + SAMSum FT (full)	1.71	24.17	–	–
BART + SAMSum FT (section)	34.17	26.14	–	–
BioBART (full)	1.46	15.83	–	–
BioBART (section)	34.96	18.28	–	–
GPT-3.5-turbo (full, 0-shot)	61.82	62.06	69.54	55.63
GPT-3.5-turbo (section, 0-shot)	67.47	23.90	58.99	41.60
GPT-4 (full, 0-shot)	67.27	71.48	71.75	63.96
GPT-4 (section, 0-shot)	71.44	21.30	45.65	35.35
GPT-3.5-turbo-16k (full, 1-shot)	49.95	72.29	58.90	54.13
GPT-3.5-turbo-16k (section, 1-shot)	52.49	44.54	68.66	61.92
GPT-4 (full, 1-shot)	74.53	68.91	66.58	59.37
GPT-4 (section, 1-shot)	71.91	60.81	71.67	63.13
GPT-3.5-turbo-16k (full, 2-shot)	55.00	**79.64**	60.08	53.18
GPT-3.5-turbo-16k (section, 2-shot)	52.84	59.67	**72.72**	**69.34**
GPT-4-32k (full, 2-shot)	65.50	72.58	62.30	57.88
GPT-4-32k (section, 2-shot)	**75.61**	66.35	63.35	57.35

Objective-Results				
Model	**Claim Recall**	**Claim Prec**	**Citation Recall**	**Citation Prec**
BART + SAMSum FT (full)	3.12	25.00	–	–
BART + SAMSum FT (section)	35.89	12.81	–	–
BioBART (full)	0.00	0.00	–	–
BioBART (section)	35.90	15.71	–	–
GPT-3.5-turbo (full, 0-shot)	56.50	51.92	74.36	70.67
GPT-3.5-turbo (section, 0-shot)	64.42	4.86	54.98	34.51
GPT-4 (full, 0-shot)	63.87	60.15	**85.83**	**80.21**
GPT-4 (section, 0-shot)	**81.64**	8.73	55.91	44.80
GPT-3.5-turbo-16k (full, 1-shot)	51.31	61.32	72.97	72.07
GPT-3.5-turbo-16k (section, 1-shot)	66.27	14.49	73.43	53.60
GPT-4 (full, 1-shot)	65.17	**78.24**	72.06	69.85
GPT-4 (section, 1-shot)	78.07	27.31	70.31	62.20
GPT-3.5-turbo-16k (full, 2-shot)	52.34	65.83	71.36	71.36
GPT-3.5-turbo-16k (section, 2-shot)	71.36	28.26	66.54	62.16
GPT-4-32k (full, 2-shot)	52.95	77.40	62.07	59.77
GPT-4-32k (section, 2-shot)	81.51	22.96	64.12	61.07

Assessment and Plan				
Model	**Claim Recall**	**Claim Prec**	**Citation Recall**	**Citation Prec**
BART + SAMSum FT (full)	0.42	10.71	–	–
BART + SAMSum FT (section)	17.79	23.11	–	–
BioBART (full)	0.00	0.00	–	–
BioBART (section)	15.47	19.78	–	–
GPT-3.5-turbo (full, 0-shot)	44.92	63.23	**68.00**	55.74
GPT-3.5-turbo (section, 0-shot)	55.00	49.47	55.87	31.16
GPT-4 (full, 0-shot)	47.68	**74.80**	65.12	**57.98**
GPT-4 (section, 0-shot)	57.29	45.77	44.39	32.83
GPT-3.5-turbo-16k (full, 1-shot)	53.91	63.62	50.45	45.21
GPT-3.5-turbo-16k (section, 1-shot)	58.22	42.88	47.14	36.30
GPT-4 (full, 1-shot)	56.30	63.99	54.01	40.78
GPT-4 (section, 1-shot)	64.30	46.09	50.13	30.77
GPT-3.5-turbo-16k (full, 2-shot)	56.80	58.82	47.48	39.05
GPT-3.5-turbo-16k (section, 2-shot)	61.51	44.62	50.14	36.89
GPT-4-32k (full, 2-shot)	60.10	55.73	49.11	34.36
GPT-4-32k (section, 2-shot)	**67.65**	44.78	49.03	29.61

Table 27: Note generation results on different sections of ACI-BENCH-test1 evaluated with DocLens (TRUE).

Evaluation Methods: Rouge, BERTScore, BLEU, RadGraph				
Model/Prompt Style	**Rouge-L**	**BERTSore**	**BLEU**	**F1-RadGraph**
GPT-3.5-turbo (0-shot)	28.83	86.33	8.22	25.93
GPT-4 (0-shot)	28.98	86.39	7.81	25.47
GPT-3.5-turbo (6-shot)	34.27	87.46	13.10	**29.11**
GPT-4 (6-shot)	34.25	87.42	12.59	28.13
GPT-3.5-turbo-16k (12-shot)	34.07	**87.56**	**13.99**	28.69
GPT-4 (12-shot)	**34.61**	87.54	13.12	28.51

Table 28: Report summarization performance on 200 examples in MIMIC-III evaluated with existing metrics. The examples are proportionally sampled from each modality. We select one or two training example(s) from each of the 6 modality-anatomy pairs that contain a train set as the few-shot demos.

Evaluation Method: DOCLENS computed with GPT-4				
Model/Prompt Style	**Claim Recall**	**Claim Prec**	**Citation Recall**	**Citation Prec**
GPT-3.5-turbo (0-shot)	62.40	24.20	91.63	89.21
GPT-4 (0-shot)	**63.39**	25.38	97.48	96.64
GPT-3.5-turbo (6-shot)	53.19	27.82	98.14	96.57
GPT-4 (6-shot)	57.12	29.12	**99.11**	**97.98**
GPT-3.5-turbo-16k (12-shot)	47.38	29.77	97.37	96.26
GPT-4 (12-shot)	56.01	**29.98**	97.73	96.13

Table 29: Report summarization results on 200 examples in MIMIC-III evaluated with DOCLENS (GPT-4).

Evaluation Method: DOCLENS computed with Mistral				
Model	**Claim Recall**	**Claim Prec**	**Citation Recall**	**Citation Prec**
GPT-3.5-turbo (0-shot)	67.36	38.78	98.17	86.71
GPT-4 (0-shot)	**69.26**	39.47	99.79	**97.91**
GPT-3.5-turbo (6-shot)	59.60	43.09	99.50	96.26
GPT-4 (6-shot)	64.99	43.99	**99.93**	97.24
GPT-3.5-turbo-16k (12-shot)	59.79	44.28	99.59	95.94
GPT-4 (12-shot)	62.64	**45.72**	99.43	96.51

Table 30: Report summarization performance on 200 examples in MIMIC-III evaluated with DOCLENS (Mistral).

Evaluation Method: DOCLENS computed with TRUE				
Model	**Claim Recall**	**Claim Prec**	**Citation Recall**	**Citation Prec**
GPT-3.5-turbo (0-shot)	**47.55**	17.95	96.68	64.24
GPT-4 (0-shot)	46.00	17.96	97.54	**93.86**
GPT-3.5-turbo (6-shot)	38.60	21.49	96.67	92.43
GPT-4 (6-shot)	42.47	22.05	**97.69**	91.81
GPT-3.5-turbo-16k (12-shot)	35.12	23.54	95.42	89.00
GPT-4 (12-shot)	43.17	**23.70**	95.80	89.87

Table 31: Report summarization performance on 200 examples in MIMIC-III evaluated with DOCLENS (TRUE).

Evaluation Methods: Rouge, BERTScore, BLEU, MEDCON				
Model/Prompt Style	**Rouge-L**	**BERTSore**	**BLEU**	**MEDCON**
GPT-3.5-turbo (0-shot)	28.26	91.20	8.36	44.93
GPT-4 (0-shot)	31.02	91.41	6.69	**49.08**
GPT-3.5-turbo (1-shot)	29.80	91.56	**8.74**	44.34
GPT-4 (1-shot)	**33.15**	**91.85**	8.36	46.14
GPT-3.5-turbo-16k (2-shot)	29.98	91.34	8.57	44.64
GPT-4 (2-shot)	32.96	91.78	8.50	48.42

Table 32: Question summarization performance on MeQSum evaluated with existing metrics. We experiment on the test set provided by the MEDIQA 2021 challenge (Ben Abacha et al., 2021) with 100 examples.

Evaluation Method: DocLens computed with GPT-4				
Model/Prompt Style	**Claim Recall**	**Claim Prec**	**Citation Recall**	**Citation Prec**
GPT-3.5-turbo (0-shot)	49.00	48.00	85.00	77.93
GPT-4 (0-shot)	52.00	53.00	93.00	**86.90**
GPT-3.5-turbo (1-shot)	44.00	48.00	87.00	81.72
GPT-4 (1-shot)	50.00	**56.00**	**94.00**	85.27
GPT-3.5-turbo-16k (2-shot)	46.00	47.00	85.00	80.72
GPT-4 (2-shot)	**53.00**	49.00	93.00	86.42

Table 33: Question summarization performance on MeQSum evaluated with DocLens computed with GPT-4.

Evaluation Method: DocLens computed with Mistral				
Model	**Claim Recall**	**Claim Prec**	**Citation Recall**	**Citation Prec**
GPT-3.5-turbo (0-shot)	64.00	64.00	84.00	69.07
GPT-4 (0-shot)	71.00	72.00	86.00	69.20
GPT-3.5-turbo (1-shot)	71.00	64.00	**88.00**	66.77
GPT-4 (6-shot)	**79.00**	76.00	**88.00**	**69.58**
GPT-3.5-turbo-16k (2-shot)	74.00	**79.00**	82.00	72.37
GPT-4 (12-shot)	72.00	73.00	87.00	**69.58**

Table 34: Question summarization performance on MeQSum (MEDIQA 2021 test set) evaluated with DocLens (Mistral).

Evaluation Method: DocLens computed with TRUE				
Model	**Claim Recall**	**Claim Prec**	**Citation Recall**	**Citation Prec**
GPT-3.5-turbo (0-shot)	29.00	14.00	69.00	57.23
GPT-4 (0-shot)	**39.00**	10.00	82.00	66.22
GPT-3.5-turbo (1-shot)	30.00	12.00	68.00	55.49
GPT-4 (6-shot)	33.00	**16.00**	**86.00**	**67.08**
GPT-3.5-turbo-16k (2-shot)	33.00	14.00	69.00	58.19
GPT-4 (12-shot)	37.00	11.00	80.00	66.92

Table 35: Question summarization performance on MeQSum (MEDIQA 2021 test set) evaluated with DocLens (TRUE).

Model/Prompt Style	Rouge-L	BLEU	F1-RadGraph	Claim Recall (GPT-4)
GPT-4 (no citation, 6-shot)	33.95	<u>13.01</u>	<u>29.08</u>	55.24
GPT-4 (with citation, 6-shot)	<u>34.25</u>	12.59	28.13	<u>57.12</u>
GPT-4 (no citation, 12-shot)	<u>34.81</u>	<u>14.40</u>	<u>30.61</u>	55.43
GPT-4 (with citation, 12-shot)	34.54	13.12	28.51	<u>56.01</u>

Table 36: Report summarization results with or without asking the model to generate citations. We report the results on 200 examples in MIMIC-III evaluated with DocLens computed with GPT-4. The examples are proportionally sampled from each modality. We underline the better result in each block.