

# A Data-Centric Approach To Generate Faithful and High Quality Patient Summaries with Large Language Models

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## Abstract

Patients often face difficulties in understanding their hospitalizations, while healthcare workers have limited resources to provide explanations. In this work, we investigate the potential of large language models to generate patient summaries based on doctors’ notes and study the effect of training data on the faithfulness and quality of the generated summaries. To this end, we release (i) a rigorous labeling protocol for errors in medical texts and (ii) a publicly available dataset of annotated hallucinations in 100 doctor-written and 100 generated summaries. We show that fine-tuning on hallucination-free data effectively reduces hallucinations from 2.60 to 1.55 per summary for Llama 2, while preserving relevant information. We observe a similar effect on GPT-4 (0.70 to 0.40), when the few-shot examples are hallucination-free. We also conduct a qualitative evaluation using hallucination-free and improved training data. We find that common quantitative metrics do not correlate well with faithfulness and quality. Finally, we test GPT-4 for automatic hallucination detection, which clearly outperforms common baselines.

**Data and Code Availability** We use MIMIC-IV-Note (Johnson et al., 2023; Goldberger et al., 2000). We create a dataset of discharge instructions (MIMIC-IV-Note-Ext-DI) and hallucination annotations for 100 doctor-written and 100 generated patient summaries (Hallucinations-{MIMIC,Generated}-DI). Our data and code: <https://doi.org/10.13026/m6hf-dq94> and [https://github.com/stefanhgm/patient\\_summaries\\_with\\_llms](https://github.com/stefanhgm/patient_summaries_with_llms).

**Institutional Review Board (IRB)** Our work did not require IRB approval. The two clinical annotators are authors of this paper, and both had credentialed access to the MIMIC-IV-Note dataset.

## 1. Introduction

Many patients do not understand the events that occurred during their hospitalization and the subsequent actions they need to take (Kebede et al., 2014). For instance, Horwitz et al. (2013) performed post-discharge interviews and found that only 59.6% of the patients were able to accurately describe their admission diagnosis and 43.9% could fully describe their scheduled follow-up appointments. Improved discharge communication is associated with lower hospital readmission rates and higher adherence to treatment regimens (Becker et al., 2021). A potential intervention to improve patient comprehension could be patient-oriented summaries that describe all relevant facts in layperson language (Federman et al., 2018). However, writing high-quality patient summaries is a difficult and time-consuming task (Mueller et al., 2015), and healthcare workers already face high workloads (Phillips, 2020; Watson et al., 2019).

Large language models (LLMs) have demonstrated strong capabilities on many natural language tasks including medical summarization (Van Veen et al., 2024). However, LLMs are prone to generating unsupported or erroneous facts also referred to as hallucinations (Maynez et al., 2020). In healthcare, this issue is further aggravated by the fragmented nature of healthcare data, as datasets often do not perfectly

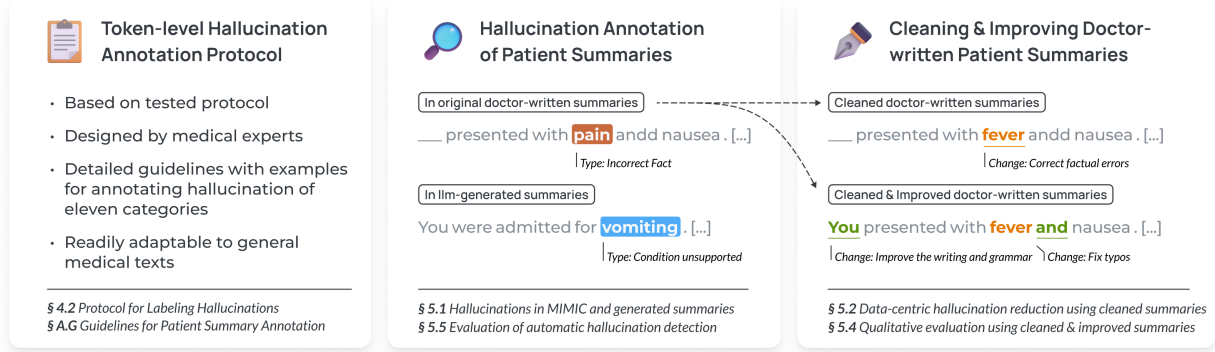


Figure 1: We developed a protocol for annotating hallucinations in medical text. Following this protocol, two medical experts labeled hallucinations in 100 doctor-written (**Hallucinations-MIMIC-DI**) and 100 LLM-generated patient summaries (**Hallucinations-Generated-DI**). We used the labeled hallucinations in the doctor-written summaries to derive two additional datasets by replacing or removing hallucinations (**Cleaned**) and by further improving the language (**Cleaned & Improved**). We used these two datasets for our data-centric hallucination reduction and qualitative experiments.

mimic the data available at the point of care. For example, radiologists often compare to previous images in their reports, even though many medical imaging datasets do not have the historical images available. Similarly, datasets for medical summarization may not include the full patient history to accompany the written summarization. As a result, there may be references in the summary to information that is not supported by the available context or patient history. Training or fine-tuning on this data replicates these artifacts leading to “hallucinations”. Several techniques for preventing hallucinations have been studied (Huang et al., 2023). However, hallucinations can vary highly in complexity, escaping automatic detection and making careful human annotation necessary (Thomson et al., 2023; Moramarco et al., 2022).

Recent work has emphasized the sample efficiency of LLMs. Zhou et al. (2023) showed that 1,000 carefully selected fine-tuning examples sufficed for the successful alignment of Llama 2 (Touvron et al., 2023). An additional set of 30 examples was found to enable multi-turn dialogues (Zhou et al., 2023). Also, GPT-4 achieved state-of-the-art performance on many benchmarks using at most 25 in-context examples (OpenAI et al., 2023). These findings open up opportunities for data-centric approaches that leverage data curated by human domain experts. In this study, we manually create 100 training examples without hallucinations and 100 training exam-

ples with improved quality to study their effect on the faithfulness and quality of LLMs. Our main contributions are:

1. We introduce a rigorous annotation protocol for token-level errors in medical texts.
2. We release two datasets of 100 doctor-written (MIMIC) and 100 generated patient summaries with hallucinations labeled by two trained medical experts requiring 70 hours per annotator.
3. For patient summaries, we demonstrate that fine-tuning on data with manually removed hallucinations can effectively reduce the hallucinations in LLMs while preserving key information.
4. We evaluate GPT-4 for automatic hallucination detection using our datasets, emphasizing its suitability for identifying unsupported evidence.

## 2. Related Work

Given the large burden of and repetition within clinical documentation, automated clinical summarization is of great interest across healthcare; generation targets include discharge summaries, radiology impression sections, patient-facing instructions, and problem lists (Van Veen et al., 2024; Adams et al.,

2022). Consequently, there has been significant research in the past few years exploring how the advent of LLMs can be leveraged to automate clinical summarization. Approaches for control have included both zero- and few-shot prompting (Van Veen et al., 2024) to fine-tuning (Adams et al., 2022, 2023; Moramarco et al., 2022; Cai et al., 2022; Van Veen et al., 2023). Results have been promising; for example, Van Veen et al. (2024) found that GPT-4 is often preferred over human-generated summaries in terms of correctness and completeness.

However, hallucinations – the generation of facts not grounded in the original text — are a recurring concern in text summarization, both across natural language processing (NLP) in general and specifically in the clinical domain (Zhang et al., 2020b; Kryscinski et al., 2020; Adams et al., 2022; Cai et al., 2022; Xie et al., 2023). Given the ubiquity of this issue, several taxonomies have sprung up in the wider NLP community for producing fine-grained annotations of the accuracy of generated text (Thomson and Reiter, 2020; Mishra et al., 2024). In the clinical domain, there have been similar efforts to annotate hallucinations in generated text, but this work has often occurred on proprietary data, with coarse buckets, or without the release of annotations (Adams et al., 2023; Cai et al., 2022; Van Veen et al., 2024). The closest public release was a set of edits clinicians made to summaries auto-generated from transcripts, but this did not target hallucinations specifically (Moramarco et al., 2022). To our knowledge, this work is the first to release a dataset highlighting hallucinations in clinical summarization. These are particularly important because automated metrics of summarization quality, while fast to compute, often do not correlate with manually evaluated performance, a finding also replicated in this work (Van Veen et al., 2024).

There have been three major strategies to mitigate the effect of hallucinations in auto-generated summaries. The first is to conduct post-hoc detection of hallucinations. This has largely involved learning a model of hallucinations from synthetically generated data (Cai et al., 2022; Zhou et al., 2021; Kryscinski et al., 2020) or identifying normalized concepts (e.g., UMLS concepts) that appear in the summary, but not the source (Nan et al., 2021; Adams et al., 2022). The second strategy is to minimize hallucinations by changing the underlying generation model, e.g., by grounding in Wikipedia, or first converting the source context as triples as an intermediary before generation (Zhang et al., 2020b; Tian et al., 2023; Semnani

et al., 2023; Aralikkatte et al., 2021; Cao et al., 2018; Cao and Wang, 2021). The final strategy is to improve the quality of the training data itself, either by removing poor training examples (Nan et al., 2021) or by improving the quality of the training examples. For example, to avoid decreasing sample size, Adams et al. (2022) revised the reference text via contrastive learning on synthetic data. In this work, we show that for sample-efficient LLMs, it is sufficient to revise only a small number of training examples that are feasible even manually.

### 3. Datasets

#### 3.1. MIMIC Discharge Instructions Datasets

For our experiments, we created a summarization dataset with clinical notes as context and patient summaries written by doctors as targets. We used the MIMIC-IV-Note v2.2 database, which includes 331,793 deidentified clinical notes from 145,915 patients admitted to Beth Israel Deaconess Medical Center in Boston, MA, USA. Each note consists of various sections that describe a patient’s hospital course. We selected the *Discharge Instructions* (DI) as summaries and the *Brief Hospital Course* (BHC) as contexts since the BHCs contain the most relevant information for medical professionals (see Figure 2). We chose this shorter context to reduce the effort for the human annotators and to better fit it into the models’ context windows. Many DIs contained irrelevant artifacts that could distort the downstream analysis. For instance, they consisted of static templates or started with a personal salutation. Hence, we designed a preprocessing pipeline selecting and cleaning 100,175 of the original 331,793 MIMIC-IV-Note examples (see Appendix A). The resulting dataset is named `MIMIC-IV-Note-Ext-DI-BHC` (see Table 1). We also release a version of the dataset with a longer context using all note sections before the DI, including the BHC (`MIMIC-IV-Note-Ext-DI`). Details for both summarization datasets can be found in Table 6 in the Appendix. To further facilitate human annotation, we considered a subset of the data with context lengths of at most 4,000 characters and summary lengths of at least 600 characters. This was done to reduce the amount of context to take into account for the annotators and to increase the information in the summaries. The resulting subset contained 26,178 entries (`MIMIC-IV-Note-Ext-DI-BHC-Anno`) and we used it to sample examples for human annotation.

Dataset	Size	Description
MIMIC Discharge Instructions Datasets		
MIMIC-IV-Note-Ext-DI	100,175	Summarization dataset derived from MIMIC-IV-Note with the section Discharge Instructions as summary and all prior notes as context
MIMIC-IV-Note-Ext-DI-BHC	100,175	MIMIC-IV-Note-Ext-DI with the Brief Hospital Course as context
MIMIC-IV-Note-Ext-DI-BHC-Anno	26,178	Subset of MIMIC-IV-Note-Ext-DI-BHC with contexts $\leq 4,000$ characters and summaries $\geq 600$ characters to facilitate human annotation
Hallucination Datasets Annotated by Two Medical Experts		
Hallucinations-MIMIC-DI	100	Random examples from MIMIC-IV-Note-Ext-DI-BHC-Anno
Hallucinations-Generated-DI	100	20 random contexts from M.-IV-Note-Ext-DI-BHC-Anno and summaries generated with five models during hallucination-reduction experiments
Derived Datasets from Hallucinations-MIMIC-DI		
Original	100	Context-summary pairs from Hallucinations-MIMIC-DI
Cleaned	100	Original with labeled hallucinations manually removed or replaced
Cleaned & Improved	100	Cleaned with mistakes and artifacts removed or corrected

Table 1: Overview of all datasets used in this work. All datasets are publicly available on PhysioNet.

### 3.2. Hallucination Datasets

We collected hallucination labels for 100 doctor-written and 100 LLM-generated patient summaries. The doctor-written summaries were selected at random from MIMIC-IV-Note-Ext-DI-BHC-Anno. For the LLM-generated summaries, we selected 20 held-out contexts from MIMIC-IV-Note-Ext-DI-BHC-Anno and used five models, which had been trained for the data-centric hallucination reduction experiments, to generate the summaries. Two medical experts labeled hallucinations in both datasets, following our annotation protocol. This resulted in two datasets: **Hallucinations-MIMIC-DI** for the doctor-written summaries and **Hallucinations-Generated-DI** for the LLM-generated summaries (see Table 1).

### 3.3. Derived Datasets

We define **Original** as a synonym for the data in **Hallucinations-MIMIC-DI** because it contains the original 100 doctor-written summaries that may include unsupported facts or errors, referred to as hallucinations. Based on the human labels of these hallucinations, we derived two additional datasets from **Hallucinations-MIMIC-DI** (see Table 1). The **Cleaned** dataset contains the same patient summaries with annotated hallucinations manually replaced or removed. We used the **Original** and **Cleaned** datasets to test the data-centric hallucination reduction approach (see Section 4.4). For the **Cleaned & Improved** data, we further manually cor-

rected mistakes and artifacts in the summaries. This dataset was used to fine-tune or prompt the models for our qualitative evaluation (see Section 4.6).

## 4. Methods

### 4.1. Generation of Patient Summaries

In this work, we generated patient summaries given the BHC as context. Formally, we have a set of contexts  $\mathcal{C} = \{C_1, \dots, C_n\}$  for which we predict the summaries  $\mathcal{S} = \{S_1, \dots, S_n\}$ . Note, however, that there is an additional translation step that simplifies the context into layperson language (Weng et al., 2019). On average, the context  $C$  was 552.0 words long, and the summary  $S$  was 113.2 words long (see Table 6 in the Appendix).

We included Llama 2 and GPT-4 in the data-centric hallucination reduction experiments since they are commonly used models that allow for sample-efficient alignment (Zhou et al., 2023; OpenAI et al., 2023). Since this experiment required expensive manual annotations of hallucinations, we could not test additional models. For the quantitative and qualitative evaluation, we also included the Longformer Encoder-Decoder (LED), which has shown good performance in medical summarization (Cai et al., 2022; Adams et al., 2022). Further details on parameter tuning for LED and Llama 2, and prompt tuning for GPT-4, are given in Appendices C and D.

- **LED:** The Longformer Encoder-Decoder was used as a baseline model (Beltagy et al., 2020).<sup>1</sup> The LED model was initialized by BART (Lewis et al., 2020) and can process 16K tokens. BART can only handle 1K tokens, which was insufficient. For training, we used full fine-tuning on 80% of MIMIC-IV-Note-Ext-DI-BHC(-Anno). The datasets with 100 examples were too small.
- **Llama:** Llama 2 (Touvron et al., 2023) has shown promising performance on clinical text summarization (Van Veen et al., 2024), and we used the versions with 7B and 70B parameters.<sup>2</sup> We always used 100 training examples for parameter-efficient fine-tuning with LoRA (Hu et al., 2021) and loaded the models in 8-bit to reduce the memory usage. Due to training time constraints, we did not train with all examples.
- **GPT-4:** GPT-4 (OpenAI et al., 2023) represents the state of the art in clinical summarization (Van Veen et al., 2024). We accessed the model via the Azure OpenAI service with opt-out for human review of the data to ensure data privacy. We tested the model with 5 in-context examples (5-shot) or no examples (0-shot).

#### 4.2. Protocol for Labeling Hallucinations

We developed a protocol for labeling token-level errors in medical texts based on (Thomson and Reiter, 2020, 2021).<sup>3</sup> Our main focus was to annotate hallucinations in patient summaries. However, we believe that with slight modifications, it could be applicable to other medical scenarios. We distinguished between unsupported, contradicted, and incorrect facts. Since most hallucinations were unsupported facts, we further distinguished them into nine subcategories (see Figure 2). Thomson and Reiter (2020) considered facts from all sources as given; that is, annotators could also use information from the internet to check facts in the summary. In contrast to that, we treated the context (BHC) as the only ground truth about the patient. We chose this approach to reduce the labeling burden, as annotators could not be expected to review all notes and structured information of a patient. However, since patient summaries contain not only patient-specific information, we did allow

*general medical knowledge* and *advice* even if not explicitly provided in the context (e.g., “Please take your medications as prescribed”). Clarifications that arose during the annotation process were added to the protocol. The final labeling protocol can be found in Appendix G.

#### 4.3. Hallucinations in MIMIC and Generated Patient Summaries

We used our developed protocol to annotate hallucinations in 100 doctor-written MIMIC summaries (Hallucinations-MIMIC-DI) and 100 LLM-generated summaries (Hallucinations-Generated-DI). It is important to note that “hallucinations” in doctor-written summaries are common in healthcare practice and usually should not be regarded as errors. Doctors may include information in the summary that was never documented, that was documented outside the considered context (in our case, only the BHC), or that was altered just prior to discharge. In this work, we considered the MIMIC data from a machine learning perspective and analyzed the effect of hallucinations in the training data on LLMs.

The labeling was carried out by two German medical students in their sixth year. They had completed their second state examination (USMLE Step 2 equivalent) and were working in the hospital. We utilized MedTator for annotation (He et al., 2022). For annotator training, we used twelve examples. Two examples were used to familiarize with the task and two times five examples were labeled separately and discussed for training. For the final labeling, the annotators worked independently and reached a consensus through discussion. To quantify the variability of the annotation, we determined manual and automatic statistics for agreement (see Appendix B).

#### 4.4. Data-Centric Hallucination Reduction

We evaluated whether manually removing hallucinations from the training data can reduce hallucinations of LLMs. To this end, we tested Llama 70B fine-tuned on 100 examples and GPT-4 5-shot prompted with 5 random examples from the **Original** and the hallucination-free **Cleaned** data. We also included GPT-4 0-shot, which did not require any training data. Figure 11 contains examples for all five models. Due to limited manual annotation capabilities, no further models were included in this analysis. To determine the number of generated hallucinations, we

1. Huggingface models `allenai/led-{base/large}-16384`

2. Huggingface models `meta-llama/Llama-2-{7,70}b-hf`

3. See the Word document on GitHub: [https://github.com/ehudreiter/accuracySharedTask/blob/main/example\\_exercise/Example\\_Annotation\\_Exercise.docx](https://github.com/ehudreiter/accuracySharedTask/blob/main/example_exercise/Example_Annotation_Exercise.docx)

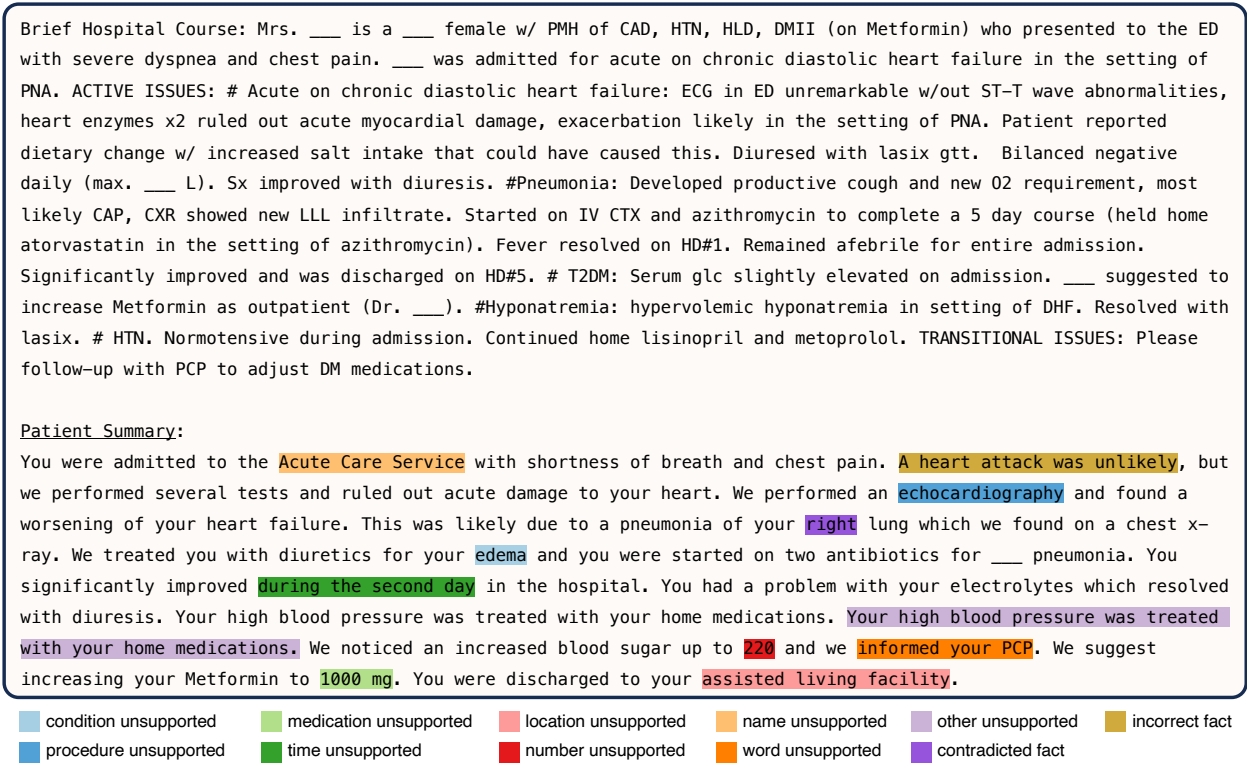


Figure 2: A synthetic MIMIC example labeled with the developed annotation protocol for hallucinations. The protocol was adapted from Thomson and Reiter (2020) and we used eleven different labels.

chose 20 random contexts from MIMIC-IV-Note-Ext-DI-BHC-Anno and generated summaries with each of the five models. We annotated the resulting 100 summaries with our protocol yielding the hallucination dataset Hallucinations-Generated-DI. We also determined the amount of missing key facts and medical jargon using the annotation procedures of the qualitative evaluation (see Appendix F). The summaries for each context were permuted during the annotation process to prevent model identification.

#### 4.5. Quantitative Evaluation

We evaluated the performance of all models to compare them to existing work. We used the MIMIC-IV-Note-Ext-DI-BHC dataset, which contains 100,175 context-summary pairs. For training, we used 80,140 examples (80% of the data) for LED, 100 examples for Llama, and 5 examples for GPT-4 5-shot. We performed parameter and prompt tuning for all models (see Appendices C and D) and used 100 examples

each for validation and testing from the remaining 20% of the held-out data.

To evaluate lexical overlap, we used the ROUGE F1 score (Lin, 2004). For similarity based on contextual embeddings, we reported BERTScore (Zhang et al., 2020a) for the default roberta-large (BERTScore) and microsoft/deberta-large-mnli (DeBERT) as recommended by the authors.<sup>4</sup> We did not utilize medical embeddings since the summaries should be written in layperson language. Lastly, we determined the SARI score for text simplification (Xu et al., 2016) and the number of generated words.

#### 4.6. Qualitative Evaluation

We evaluated the quality of patient summaries generated by LLMs aligned with the highest quality data (Cleaned & Improved). Llama 70B was fine-tuned on 100 examples and GPT-4 5-shot was prompted with 5 random examples. We also included the

4. See readme: [https://github.com/Tiiiger/bert\\_score](https://github.com/Tiiiger/bert_score)

Model (training data)	Mean (SD)			
	Hallucinations↓	Missing Key Facts↓	Medical Jargon↓	Length (Words)
Llama 70B (100 Original ex.)	2.60 (2.39)	3.77 (1.33)	1.05 (0.84)	97.90 (36.73)
Llama 70B (100 Cleaned ex.)	1.55 (1.99)	3.73 (1.45)	1.68 (1.23)	96.20 (31.82)
GPT-4 5-shot (5 Original ex.)	0.70 (0.86)	0.93 (0.80)	1.07 (0.99)	151.10 (19.42)
GPT-4 5-shot (5 Cleaned ex.)	0.40 (0.75)	0.97 (0.80)	1.25 (1.18)	158.80 (23.27)
GPT-4 0-shot (none)	0.45 (0.60)	0.82 (0.61)	0.70 (1.03)	165.05 (22.75)

Table 2: Results for data-centric hallucination-reduction showing mean number of hallucinations, missing key facts, medical jargon, and words generated by Llama 70B and GPT-4 5-shot trained or prompted on **Original** versus **Cleaned** summaries (hallucinations removed) and GPT-4 0-shot. Training Llama using hallucination-free summaries shows a strong hallucination reduction while keeping key facts.

Dataset / Model (training data)	Number of Annotated Hallucinations per Type											Total
	cond.	proc.	medic.	time	loc.	numb.	name	word	other	contrad.	incurr.	
Hallucinations-MIMIC-DI	52	19	34	35	29	7	18	76	1	15	0	286
Hallucinations-Generated-DI	27	4	10	2	12	3	5	44	0	7	0	114
Llama 70B (100 Original ex.)	16	2	9	1	4	3	3	11	0	3	0	52
Llama 70B (100 Cleaned ex.)	7	2	1	1	5	0	1	10	0	4	0	31
GPT-4 5-shot (5 Original ex.)	2	0	0	0	1	0	1	10	0	0	0	14
GPT-4 5-shot (5 Cleaned ex.)	1	0	0	0	2	0	0	5	0	0	0	8
GPT-4 0-shot (none)	1	0	0	0	0	0	0	8	0	0	0	9

Table 3: The first row shows the labeling results for 100 MIMIC summaries for which we found 286 hallucinations. The subsequent rows present the category breakdown for different types of hallucinations annotated in 20 summaries. It corresponds to the data in the *Hallucinations↓* column in Table 2.

original MIMIC summaries, LED-large fine-tuned on 20,942 MIMIC-IV-Note-Ext-DI-BHC-Anno examples, and GPT-4 0-shot (see examples in Figure 12). We generated summaries for the same 20 contexts from MIMIC-IV-Note-Ext-DI-BHC-Anno used for the hallucination-reduction experiments to reduce the annotation workload. Ratings were performed by the same two medical experts and the summaries were again permuted to prevent model identification. The annotators completed two training examples, and no agreement was sought as this was considered a subjective task. We combined both ratings for our analysis.

We evaluated the summaries for *Relevance*, *Consistency*, *Fluency*, and *Coherence* on a 1-5 Likert scale (Fabbri et al., 2021) following previous work on medical summarization (Adams et al., 2022). We added the dimension *Simplification*. To obtain more reliable results, we defined subtasks to be performed before rating *Relevance* (subtask: labeling key facts in con-

text and summary), *Consistency* (labeling hallucinations using our protocol), and *Simplification* (labeling medical jargon) and defined the meaning of each Likert rating based on these subtasks. Additional details on the subtasks and annotator instructions are given in Appendix F and Figures 8 and 9.

#### 4.7. Automatic Hallucination Detection

We performed an evaluation of automated hallucination detection on two annotated datasets: 100 doctor-written summaries (**Hallucinations-MIMIC-DI**) and 100 LLM-generated summaries (**Hallucinations-Generated-DI**). This method could serve for the automatic cleaning of training data or post-hoc editing to improve faithfulness. We framed the task of automatic hallucination detection as a span classification problem. Given a context  $C$  and a summary  $S$ , our objective was to identify all spans of hallucinations within the summary, denoted as  $\mathcal{H}_S = \{H_1, \dots, H_n\}$ .

Brief Hospital Course: Mrs. \_\_\_ is a \_\_\_ female w/ PMH of CAD, HTN, HLD, DMII (on Metformin) who presented to [...]

Llama 70B trained with 100 original examples:

You were admitted for shortness of breath and were found to have a mild pneumonia. You were started on antibiotics. You were also found to have some fluid build up in your lungs from heart failure. We gave you medications to help remove this fluid and your symptoms improved. You should continue the antibiotics you were started on for a total of 5 days. You should also increase your Metformin to 1000mg twice a day. You should also follow-up with your primary care physician to adjust your other diabetes medications.

Llama 70B trained with 100 cleaned examples:

You were admitted to the hospital for shortness of breath and chest pain. You were found to have a worsening of your heart failure in the setting of pneumonia. You were treated with antibiotics and diuretics. You were also found to have a low sodium level in your blood, likely due to the fluid retention. Your sodium level normalized after you were given diuretics. You were discharged on oral antibiotics for your pneumonia. You should continue taking your medications as you were before admission. Please follow-up with your primary care doctor to adjust your diabetes medications.

Figure 3: Patient summaries generated by Llama 70B fine-tuned on 100 Original and 100 Cleaned examples given the synthetic context in Figure 2 with annotated hallucinations according to our protocol. These are two of the five models included in the data-centric hallucination reduction experiments.

Each hallucination span  $H_i$  is defined by a tuple  $(s, e, c)$ , consisting of a start token, an end token, and a class (see Figure 2). We also explored class-agnostic hallucination detection without the class  $c$ .

We used a class-agnostic approach based on medical entities as a baseline (Cai et al., 2022; Adams et al., 2022). For entity recognition and linking, we utilized MedCat (Kraljevic et al., 2021) with UMLS semantic types from Adams et al. (2021). All entities that appeared in the summary but not in the context were considered hallucinations. We further enhanced this approach with SapBERT embeddings (Liu et al., 2021) to determine equivalent entities (Adams et al., 2023). The equivalence threshold for similarity was a hyperparameter for these methods and we determined its value based on ten additional examples labeled during annotator training. We tested GPT-4 for class-agnostic and class-aware hallucination detection. We designed a suitable prompt based on the aforementioned ten examples labeled during annotator training and utilized varying numbers of in-context examples and chain-of-thought (COT) prompting, detailed in Appendix E. Since our prompt design is based on the annotation protocol for general medical text, this approach might also prove useful for texts other than patient summaries. Evaluation was performed using partial matching with the `nervaluate` package (Segura-Bedmar et al., 2013).

## 5. Results

### 5.1. Hallucinations in MIMIC and Generated Patient Summaries

Two medical experts labeled 100 doctor-written patient summaries (Hallucinations-MIMIC-DI) and found 286 hallucinations (see Table 3). The most prevalent label was the generic *word unsupported* ( $n=76$ ) followed by *condition unsupported* ( $n=52$ ), and *time unsupported* ( $n=35$ ). Hence, there is a significant amount of unsupported data in MIMIC when using the BHC as context. For the 100 generated patient summaries (Hallucinations-Generated-DI), they found a total of 114 hallucinations and *word unsupported* was the most common label (see Table 3). Agreement statistics show that annotators agreed on 1.55 of 2.86 annotations for MIMIC and 0.67 of 1.14 annotations for the generated summaries (see Table 8) emphasizing some variability during labeling. The annotation of MIMIC summaries took 30 hours for each expert and 6 hours for the agreement. For the generated summaries, annotation took less time, with 20 hours for labeling and 4 hours for the agreement, since there were only 20 different patient contexts.

### 5.2. Data-Centric Hallucination Reduction

The results for GPT-4 5-shot prompted with Original data were significantly better than for Llama



Model (training data)	R-1↑	R-2↑	R-3↑	R-4↑	R-L↑	BERT↑	DeBERT↑	SARI↑	Words
MIMIC-IV-Note-Ext-DI-BHC (100,175 examples)									
LED-large (80,140 ex.)	43.82	17.33	8.85	4.92	29.89	88.11	64.12	46.71	76.99
Llama 2 7B (100 ex.)	38.36	12.66	5.13	2.24	24.73	85.68	60.23	44.12	73.13
Llama 2 70B (100 ex.)	40.58	14.31	6.09	2.74	26.19	86.30	61.89	45.16	76.90
GPT-4 5-shot (5 ex.)	38.80	10.78	3.55	1.12	21.98	86.67	61.30	42.88	131.86
GPT-4 0-shot (none)	38.26	10.81	3.70	1.49	21.49	86.37	60.75	42.04	165.78

Table 4: Quantitative evaluation of patient summary generation on MIMIC-IV-Note-Ext-DI-BHC dataset. We used the ROUGE F1-score for n-grams (R-n) and the longest common subsequence (R-L), BERTScore using `roberta-large` (BERT) and `deberta-large-mnli` (DeBERT), the SARI score, and the number of generated words. Additional performance results can be found in Table 11.

70B fine-tuned on `Original` with 0.70 versus 2.60 hallucinations and 0.93 versus 3.77 missing key facts per summary (see Table 2). Data-centric hallucination reduction (training on `Cleaned`), showed a substantial effect for Llama 70B, reducing hallucinations from 2.60 to 1.55 per summary while maintaining the same number of key facts. Figure 3 displays generations of both models with hallucination annotations. Llama 70B trained on `Original` introduced unsupported adjectives “mild” and “other”, as well as an unsupported metformin dosage. Both models incorrectly recommended continuing antibiotics at home. Apart from “mild”, all hallucinations can be considered reasonable advice and are commonly found in patient summaries. For GPT-4 5-shot, the difference of 0.70 (`Original`) to 0.40 (`Cleaned`) hallucinations is only marginal, while retaining key facts. The use of medical jargon and the length of the generations did not change substantially. GPT-4 0-shot exhibited a few hallucinations (0.45) and the lowest number of missing key facts (0.82) and medical jargon (0.70), although the generations were longer than for 5-shot. Table 3 shows the types of hallucination for each model. While Llama 70B occasionally generated unsupported conditions and locations, this was rare for GPT-4. The hallucinations produced by GPT-4 were mostly labeled as *unsupported word*.

### 5.3. Quantitative Evaluation

Table 4 contains the performance evaluation on the MIMIC-IV-Note-Ext-DI-BHC dataset. Overall, the LED model performed the best, followed by Llama and GPT-4. Only for BERT and DeBERT, Llama and GPT-4 achieved similar performance. This behavior is consistent with the amount of training data,

which is much less for Llama and GPT-4 5-shot. Notably, GPT-4 0-shot achieved considerable performance even without using any training data.

### 5.4. Qualitative Evaluation

The qualitative results are visualized in Figure 4. The *Consistency* results for doctor-written (MIMIC) summaries should be interpreted with caution because these summaries were artificially considered only with the restricted context of the BHC. The original MIMIC examples, LED-large trained on all data, and Llama 70B fine-tuned on 100 `Cleaned & Improved` examples showed similar results. For *Relevance*, around half of the examples received a rating of two or higher, indicating that at most three key points were missing. The *Simplification*, *Fluency*, and *Coherence* all received a median rating of four for all three approaches. Llama 70B performed better for *Consistency* with a median rating of four compared to three for the original MIMIC and LED-large summaries. GPT-4 performed significantly better across all five dimensions. The difference in *Consistency* compared to Llama 70B is in line with the lower hallucination rate of GPT-4 observed earlier (see Table 2). Also, GPT-4 achieved high *Relevance* with a median of four, indicating one missing key fact per summary, and a median of five for simplification, fluency, and coherence. There was only a slight difference between GPT-4 5-shot and GPT-4 0-shot. GPT-4 5-shot performed better for *Consistency*, i.e., including all key facts, while GPT-4 0-shot performed better for *Relevance* and *Simplification*.

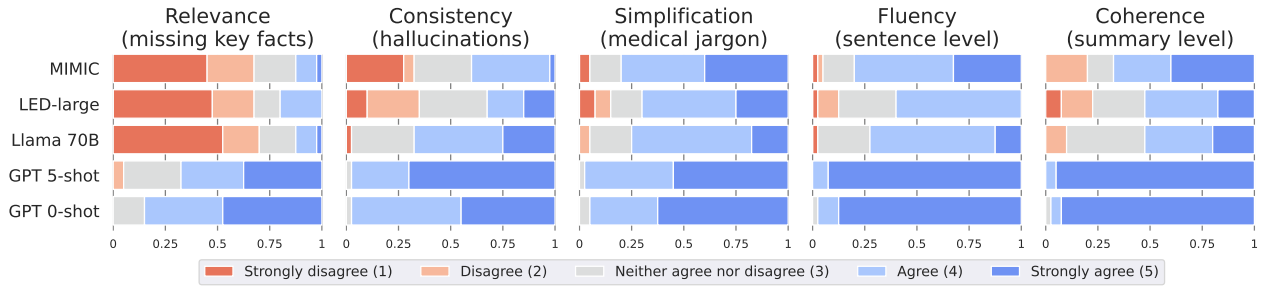


Figure 4: Qualitative evaluation of Llama 70B fine-tuned on all 100 examples of **Cleaned & Improved** and GPT-4 5-shot prompted with 5 random examples of **Cleaned & Improved**. We compared them to the original MIMIC summaries, LED-large fine-tuned on MIMIC-IV-Note-Ext-DI-BHC-Anno, and GPT-4 0-shot. Two medical experts evaluated 20 summaries from each of the five models.

Model	H.-MIMIC-DI			H.-Generated-DI		
	Prec.	Rec.	F1	Prec.	Rec.	F1
Class-agnostic recognition						
MedCat	7.4	16.4	10.2	3.4	20.3	5.8
MedCat + Em.	8.0	16.1	10.7	3.9	19.9	6.5
GPT-4 (class-ag.)	23.3	16.4	19.3	14.7	16.7	15.6
GPT-4 (class-aw.)	20.0	20.8	20.4	13.0	21.5	16.2
Class-aware recognition (11 classes)						
GPT-4 (no-cot)	21.3	4.5	7.5	13.4	7.9	9.9

Table 5: Results of automatic hallucination detection on 100 doctor-written (H.-MIMIC-DI) and 100 LLM-generated (H.-Generated-DI) patient summaries. GPT-4 clearly outperformed the baselines using medical UMLS entities recognized by MedCat.

### 5.5. Automatic Hallucination Detection

Using medical entities extracted by MedCat for class-agnostic hallucination detection performed poorly with an F1-Score of 10.2 for doctor-written (MIMIC) and 5.8 for generated summaries (see Table 5). Adding medical embeddings (MedCat + Em.) only resulted in marginal improvements. GPT-4 clearly outperformed this baseline on both datasets. The best prompting strategy used a class-aware prompt (detailed in Appendix E). GPT-4 exhibited low recall in class-aware hallucination detection highlighting the need for improved methods for automatic hallucination detection. Additional results for class-specific recall are presented in Table 13.

## 6. Discussion

Hallucinations in patient summaries are diverse and complex. We introduced a rigorous protocol for annotating hallucinations and considered a simplified experimental setting with the BHC as limited context. Still, it took medical experts between 12 and 18 minutes to annotate a single summary. For the generated patient summaries, only 59% of all annotations were identified by both annotators, with 56% of these being of the same type (see Table 8). Additionally, 39% of all hallucinations were classified as *unsupported word* which typically indicates more complex hallucination structures. The annotation of doctor-written (MIMIC) summaries yielded similar results, aligning with previous findings on consultation notes that reported medium inter-annotator agreement among clinicians (Moramarco et al., 2022). We attempted to automate hallucination detection based on our annotations. We tested UMLS concepts recognized by MedCat combined with embeddings, which showed very poor results on our datasets. Many annotations spans did not align with medical concepts, suggesting that medical entity-based approaches may be insufficient (Cai et al., 2022; Adams et al., 2022). Although GPT-4 demonstrated significantly better performance, we consider this only as an initial step. These results emphasize the importance of thorough evaluation with human domain experts and highlight the challenges for reliable hallucination detection in the healthcare domain.

The data used for LLM alignment is crucial for generating faithful and high-quality patient summaries. In a study on medical summarization, Adams

et al. (2022) demonstrated that automatic revisions of 45,000 training examples improved the hallucination rate and quality. In our work, we focused on more sample-efficient LLMs, where 100 human-curated training examples were sufficient. We evaluated Llama 2 and GPT-4 for data-centric hallucination reduction, as well as for quantitative and qualitative performance. Consistent with previous studies, we found that quantitative metrics do not correlate well with the hallucination rate (Moramarco et al., 2022; Adams et al., 2023) and quality (Van Veen et al., 2024). Quantitatively, LED-large outperformed both Llama 2 and GPT-4, but the ranking reversed when assessing quality, including hallucinations (*Consistency*). This behavior can be attributed to the qualitative shortcomings of the doctor-written (MIMIC) summaries. LED-large, which was extensively trained, most faithfully reproduced MIMIC, as confirmed by similar qualitative results. Llama 2, fine-tuned on 100 examples, showed moderate alignment to MIMIC, placing it midway in both quantitative and qualitative evaluations. The fine-tuning made Llama 2 more susceptible to data-centric hallucination reduction, which had a strong effect. GPT-4 5-shot, aligned with on only five examples, largely retained its pre-trained summarization style and was less susceptible to data-centric hallucination reduction. However, we observed that alignment with only five examples already led to slightly lower *Relevance*, *Simplification*, and length compared to GPT-4 without any examples (0-shot). Hence, this study emphasizes the importance of high-quality training data for fine-tuning and in-context learning of LLMs.

The clinical evidence regarding the effectiveness of high-quality patient summaries is not clear. Becker et al. (2021) conducted a systematic review of patient education interventions, which included 60 randomized controlled trials (RCTs). Out of these trials, only five primarily relied on text (Baker et al., 1991; Hayes, 1998; Giuse et al., 2012; Lin et al., 2014; Doyle et al., 2020). Closest to this work, Lin et al. (2014) evaluated manually created patient-directed discharge letters based on a template, which were discussed during discharge. They found that patient understanding improved in four domains after three and six months, but there was no significant reduction in 6-month readmission. In this study, we focused on generating patient after-visit summaries that have only weak evidence for usefulness (Pathak et al., 2020). We demonstrated that GPT-4, particularly in the 0-shot setting, deviated from the original

summarization style, resulting in higher quality summaries that could potentially lead to more effective interventions (Haver et al., 2024; Artsi et al., 2024). Further enhancements could involve adaptive methods (Fok et al., 2023) to cater to different information needs and interactive approaches. Ultimately, more clinical evidence is necessary to support the use of patient information automatically generated by LLMs.

This work has limitations. We relied on a single dataset for medical notes and focused on patient summaries, limiting the generalizability of our findings. We only considered the reduced context of the BHC, which likely led to an overestimation of hallucinations in doctor-written summaries. The labeling of hallucinations was conducted by only two annotators, leading to variability in the labels. The qualitative ratings were obtained from medical experts. Instead, it would have been preferable to include the patients’ perspectives. Lastly, we included only two LLMs in our data-centric hallucination-reduction experiments and qualitative evaluation due to the expensive annotation required by medical experts.

## 7. Conclusion

LLMs are sensitive to fine-tuning or prompting examples. We have demonstrated that data-centric interventions by domain experts can reduce hallucinations and improve the quality of generation. Specifically, GPT-4 showed few hallucinations and omitted key facts while receiving high-quality ratings making it a strong model for generating patient summaries. We have developed a protocol for labeling unsupported evidence in medical texts and have released two annotated datasets consisting of 100 doctor-written and 100 LLM-generated patient summaries. Future work should explore different summary formats and the application of other LLMs. The provided datasets could serve as a valuable resource for the advancement and assessment of automatic hallucination metrics. A crucial direction for future research is the collection of more clinical evidence for useful interventions to enhance patient health literacy.

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## References

- Griffin Adams, Emily Alsentzer, Mert Ketenci, Jason Zucker, and Noémie Elhadad. What’s in a Summary? Laying the Groundwork for Advances in Hospital-Course Summarization. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 4794–4811, Online, June 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.naacl-main.382. URL <https://aclanthology.org/2021.naacl-main.382>.
- Griffin Adams, Han-Chin Shing, Qing Sun, Christopher Winestock, Kathleen McKeown, and Noémie Elhadad. Learning to Revise References for Faithful Summarization. In Yoav Goldberg, Zornitsa Kozareva, and Yue Zhang, editors, *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 4009–4027, Abu Dhabi, United Arab Emirates, December 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.findings-emnlp.296. URL <https://aclanthology.org/2022.findings-emnlp.296>.
- Griffin Adams, Jason Zucker, and Noémie Elhadad. A Meta-Evaluation of Faithfulness Metrics for Long-Form Hospital-Course Summarization, March 2023. URL <http://arxiv.org/abs/2303.03948>. arXiv:2303.03948 [cs].
- Rahul Aralikkatte, Shashi Narayan, Joshua Maynez, Sascha Rothe, and Ryan McDonald. Focus Attention: Promoting Faithfulness and Diversity in Summarization. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 6078–6095, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.acl-long.474. URL <https://aclanthology.org/2021.acl-long.474>.
- Yaara Artsi, Vera Sorin, Eli Konen, Benjamin S. Glicksberg, Girish Nadkarni, and Eyal Klang. Large language models in simplifying radiological reports: systematic review. preprint, Radiology and Imaging, January 2024. URL <http://medrxiv.org/lookup/doi/10.1101/2024.01.05.24300884>.
- D. Baker, De Roberts, Rg Newcombe, and Ka Fox. Evaluation of drug information for cardiology patients. *British Journal of Clinical Pharmacology*, 31(5):525–531, 1991. ISSN 1365-2125. doi: 10.1111/j.1365-2125.1991.tb05574.x. URL <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1365-2125.1991.tb05574.x>.
- Christoph Becker, Samuel Zumbrunn, Katharina Beck, Alessia Vincent, Nina Loretz, Jonas Müller, Simon A. Amacher, Rainer Schaefer, and Sabina Hunziker. Interventions to Improve Communication at Hospital Discharge and Rates of Readmission: A Systematic Review and Meta-analysis. *JAMA Network Open*, 4(8):e2119346, August 2021. ISSN 2574-3805. doi: 10.1001/jamanetworkopen.2021.19346. URL <https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2783547>.
- Iz Beltagy, Matthew E. Peters, and Arman Cohan. Longformer: The Long-Document Transformer, December 2020. URL <http://arxiv.org/abs/2004.05150>. arXiv:2004.05150 [cs].
- Lukas Biewald. Experiment tracking with weights and biases. *Software available from wandb. com*, 2: 233, 2020.
- Pengshan Cai, Fei Liu, Adarsha Bajracharya, Joe Sills, Alok Kapoor, Weisong Liu, Dan Berlowitz, David Levy, Richeek Pradhan, and Hong Yu. Generation of Patient After-Visit Summaries to Support Physicians. In *Proceedings of the 29th International Conference on Computational Linguistics*, pages 6234–6247, Gyeongju, Republic of Korea, October 2022. International Committee on Computational Linguistics. URL <https://aclanthology.org/2022.coling-1.544>.
- Shuyang Cao and Lu Wang. CLIFF: Contrastive Learning for Improving Faithfulness and Factuality in Abstractive Summarization. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 6633–6649, Online and Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.emnlp-main.532. URL <https://aclanthology.org/2021.emnlp-main.532>.
- Ziqiang Cao, Furu Wei, Wenjie Li, and Sujian Li. Faithful to the original: fact-aware neural abstractive summarization. In *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence*

- and *Thirtieth Innovative Applications of Artificial Intelligence Conference and Eighth AAAI Symposium on Educational Advances in Artificial Intelligence*, AAAI'18/IAAI'18/EAAI'18, pages 4784–4791, New Orleans, Louisiana, USA, February 2018. AAAI Press. ISBN 978-1-57735-800-8.
- Sarah K Doyle, James C Rippey, Angela Jacques, Alethea M Rea, Bronwyn N Kaiser, Suzanne M Miller, and Matthew HR Anstey. Effect of personalised, mobile-accessible discharge instructions for patients leaving the emergency department: A randomised controlled trial. *Emergency Medicine Australasia*, 32(6):967–973, 2020. ISSN 1742-6723. doi: 10.1111/1742-6723.13516. URL <https://onlinelibrary.wiley.com/doi/abs/10.1111/1742-6723.13516>.
- Alexander R. Fabbri, Wojciech Kryściński, Bryan McCann, Caiming Xiong, Richard Socher, and Dragomir Radev. SummEval: Re-evaluating Summarization Evaluation, February 2021. URL <http://arxiv.org/abs/2007.12626>. arXiv:2007.12626 [cs].
- Alex Federman, Erin Sarzynski, Cindy Brach, Paul Francaviglia, Jessica Jacques, Lina Jandorf, Angela Sanchez Munoz, Michael Wolf, and Joseph Kanrny. Challenges optimizing the after visit summary. *International journal of medical informatics*, 120:14–19, December 2018. ISSN 1386-5056. doi: 10.1016/j.ijmedinf.2018.09.009. URL <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6326571/>.
- Raymond Fok, Joseph Chee Chang, Tal August, Amy X. Zhang, and Daniel S. Weld. Qlarify: Bridging Scholarly Abstracts and Papers with Recursively Expandable Summaries, October 2023. URL <http://arxiv.org/abs/2310.07581>. arXiv:2310.07581 [cs].
- Nunzia B. Giuse, Taneya Y. Koonce, Alan B. Storrow, Sheila V. Kusnoor, and Fei Ye. Using Health Literacy and Learning Style Preferences to Optimize the Delivery of Health Information. *Journal of Health Communication*, 17(sup3):122–140, October 2012. ISSN 1081-0730, 1087-0415. doi: 10.1080/10810730.2012.712610. URL <http://www.tandfonline.com/doi/abs/10.1080/10810730.2012.712610>.
- Ary L. Goldberger, Luis A. N. Amaral, Leon Glass, Jeffrey M. Hausdorff, Plamen Ch. Ivanov, Roger G. Mark, Joseph E. Mietus, George B. Moody, Chung-Kang Peng, and H. Eugene Stanley. PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals. *Circulation*, 101(23), June 2000. ISSN 0009-7322, 1524-4539. doi: 10.1161/01.CIR.101.23.e215. URL <https://www.ahajournals.org/doi/10.1161/01.CIR.101.23.e215>.
- Hana L. Haver, Anuj K. Gupta, Emily B. Ambinder, Manisha Bahl, Eniola T. Oluyemi, Jean Jeudy, and Paul H. Yi. Evaluating the Use of ChatGPT to Accurately Simplify Patient-centered Information about Breast Cancer Prevention and Screening. *Radiology: Imaging Cancer*, 6(2):e230086, March 2024. doi: 10.1148/rycan.230086. URL <https://pubs.rsna.org/doi/abs/10.1148/rycan.230086>. Publisher: Radiological Society of North America.
- Karen S. Hayes. Randomized Trial of Geragogy-Based Medication Instruction in the Emergency Department. *Nursing Research*, 47(4):211, August 1998. ISSN 0029-6562. URL [https://journals.lww.com/nursingresearchonline/fulltext/1998/07000/randomized\\_trial\\_of\\_geragogy\\_based\\_medication.6.aspx](https://journals.lww.com/nursingresearchonline/fulltext/1998/07000/randomized_trial_of_geragogy_based_medication.6.aspx).
- Huan He, Sunyang Fu, Liwei Wang, Sijia Liu, Andrew Wen, and Hongfang Liu. MedTator: a serverless annotation tool for corpus development. *Bioinformatics*, 38(6):1776–1778, March 2022. ISSN 1367-4803. doi: 10.1093/bioinformatics/btab880. URL <https://doi.org/10.1093/bioinformatics/btab880>.
- Karl Moritz Hermann, Tomas Kocisky, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. Teaching Machines to Read and Comprehend. In *Advances in Neural Information Processing Systems*, volume 28. Curran Associates, Inc., 2015. URL [https://proceedings.neurips.cc/paper\\_files/paper/2015/hash/afdec7005cc9f14302cd0474fd0f3c96-Abstract.html](https://proceedings.neurips.cc/paper_files/paper/2015/hash/afdec7005cc9f14302cd0474fd0f3c96-Abstract.html).
- Leora I. Horwitz, John P. Moriarty, Christine Chen, Robert L. Fogerty, Ursula C. Brewster, Sandhya Kanade, Boback Ziaieian, Grace Y. Jenq, and Harlan M. Krumholz. Quality of Discharge Practices and Patient Understanding

- at an Academic Medical Center. *JAMA Internal Medicine*, August 2013. ISSN 2168-6106. doi: 10.1001/jamainternmed.2013.9318. URL <http://archinte.jamanetwork.com/article.aspx?doi=10.1001/jamainternmed.2013.9318>.
- Edward J. Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. LoRA: Low-Rank Adaptation of Large Language Models, October 2021. URL <http://arxiv.org/abs/2106.09685>. arXiv:2106.09685 [cs].
- Yichong Huang, Xiachong Feng, Xiaocheng Feng, and Bing Qin. The Factual Inconsistency Problem in Abstractive Text Summarization: A Survey, April 2023. URL <http://arxiv.org/abs/2104.14839>. arXiv:2104.14839 [cs].
- Alistair Johnson, Tom Pollard, Steven Horng, Leo Anthony Celi, and Roger Mark. MIMIC-IV-Note: Deidentified free-text clinical notes, January 2023. URL <https://physionet.org/content/mimic-iv-note/2.2/>.
- Sosena Kebede, Hasan M. Shihab, Zackary D. Berger, Nina G. Shah, Hsin-Chieh Yeh, and Daniel J. Brotman. Patients’ Understanding of Their Hospitalizations and Association With Satisfaction. *JAMA Internal Medicine*, 174(10):1698–1700, October 2014. ISSN 2168-6106. doi: 10.1001/jamainternmed.2014.3765. URL <https://doi.org/10.1001/jamainternmed.2014.3765>.
- Zeljko Kraljevic, Thomas Searle, Anthony Shek, Lukasz Roguski, Kawsar Noor, Daniel Bean, Aurelie Mascio, Leilei Zhu, Amos A. Folarin, Angus Roberts, Rebecca Bendayan, Mark P. Richardson, Robert Stewart, Anoop D. Shah, Wai Keong Wong, Zina Ibrahim, James T. Teo, and Richard J. B. Dobson. Multi-domain clinical natural language processing with MedCAT: The Medical Concept Annotation Toolkit. *Artificial Intelligence in Medicine*, 117:102083, July 2021. ISSN 0933-3657. doi: 10.1016/j.artmed.2021.102083. URL <https://www.sciencedirect.com/science/article/pii/S0933365721000762>.
- Klaus Krippendorff. *Content Analysis: An Introduction to Its Methodology*. SAGE Publications, May 2018. ISBN 978-1-5063-9567-8. Google-Books-ID: nE1aDwAAQBAJ.
- Wojciech Kryscinski, Bryan McCann, Caiming Xiong, and Richard Socher. Evaluating the Factual Consistency of Abstractive Text Summarization. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 9332–9346, Online, November 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.emnlp-main.750. URL <https://aclanthology.org/2020.emnlp-main.750>.
- Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension. In Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel Tetreault, editors, *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7871–7880, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.703. URL <https://aclanthology.org/2020.acl-main.703>.
- Chin-Yew Lin. ROUGE: A Package for Automatic Evaluation of Summaries. In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain, July 2004. Association for Computational Linguistics. URL <https://aclanthology.org/W04-1013>.
- R. Lin, R. Gallagher, M. Spinaze, H. Najjounian, C. Dennis, R. Clifton-Bligh, and G. Tofler. Effect of a patient-directed discharge letter on patient understanding of their hospitalisation. *Internal Medicine Journal*, 44(9):851–857, 2014. ISSN 1445-5994. doi: 10.1111/imj.12482. URL <https://onlinelibrary.wiley.com/doi/abs/10.1111/imj.12482>.
- Fangyu Liu, Ehsan Shareghi, Zaiqiao Meng, Marco Basaldella, and Nigel Collier. Self-Alignment Pre-training for Biomedical Entity Representations. In Kristina Toutanova, Anna Rumshisky, Luke Zettlemoyer, Dilek Hakkani-Tur, Iz Beltagy, Steven Bethard, Ryan Cotterell, Tanmoy Chakraborty, and Yichao Zhou, editors, *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 4228–4238, Online, June 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.naacl-main.

334. URL <https://aclanthology.org/2021.naacl-main.334>.
- Laurens van der Maaten and Geoffrey Hinton. Visualizing Data using t-SNE. *Journal of Machine Learning Research*, 9(86):2579–2605, 2008. ISSN 1533-7928. URL <http://jmlr.org/papers/v9/vandermaaten08a.html>.
- Joshua Maynez, Shashi Narayan, Bernd Bohnet, and Ryan McDonald. On Faithfulness and Factuality in Abstractive Summarization. In Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel Tetreault, editors, *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 1906–1919, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.173. URL <https://aclanthology.org/2020.acl-main.173>.
- Abhika Mishra, Akari Asai, Vidhisha Balachandran, Yizhong Wang, Graham Neubig, Yulia Tsvetkov, and Hannaneh Hajishirzi. Fine-grained Hallucination Detection and Editing for Language Models, January 2024. URL <http://arxiv.org/abs/2401.06855>. arXiv:2401.06855 [cs].
- Francesco Moramarco, Alex Papadopoulos Korfiatis, Mark Perera, Damir Juric, Jack Flann, Ehud Reiter, Anya Belz, and Aleksandar Savkov. Human Evaluation and Correlation with Automatic Metrics in Consultation Note Generation. In Smaranda Muresan, Preslav Nakov, and Aline Villavicencio, editors, *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 5739–5754, Dublin, Ireland, May 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.acl-long.394. URL <https://aclanthology.org/2022.acl-long.394>.
- Stephanie K Mueller, Kyla Giannelli, Robert Boxer, and Jeffrey L Schnipper. Readability of patient discharge instructions with and without the use of electronically available disease-specific templates. *Journal of the American Medical Informatics Association*, 22(4):857–863, July 2015. ISSN 1527-974X, 1067-5027. doi: 10.1093/jamia/ocv005. URL <https://academic.oup.com/jamia/article/22/4/857/1746200>.
- Feng Nan, Ramesh Nallapati, Zhiguo Wang, Cicero Nogueira dos Santos, Henghui Zhu, De-  
jiao Zhang, Kathleen McKeown, and Bing Xiang. Entity-level Factual Consistency of Abstractive Text Summarization. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 2727–2733, Online, April 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.eacl-main.235. URL <https://aclanthology.org/2021.eacl-main.235>.
- OpenAI, Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altmenschmidt, Sam Altman, Shyamal Anadkat, Red Avila, Igor Babuschkin, Suchir Balaji, Valerie Balcom, Paul Baltescu, Haiming Bao, Mo Bavarian, Jeff Belgum, Irwan Bello, Jake Berdine, Gabriel Bernadett-Shapiro, Christopher Berner, Lenny Bogdonoff, Oleg Boiko, Madelaine Boyd, Anna-Luisa Brakman, Greg Brockman, Tim Brooks, Miles Brundage, Kevin Button, Trevor Cai, Rosie Campbell, Andrew Cann, Brittany Carey, Chelsea Carlson, Rory Carmichael, Brooke Chan, Che Chang, Fotis Chantzis, Derek Chen, Sully Chen, Ruby Chen, Jason Chen, Mark Chen, Ben Chess, Chester Cho, Casey Chu, Hyung Won Chung, Dave Cummings, Jeremiah Currier, Yunxing Dai, Cory Decareaux, Thomas Degry, Noah Deutsch, Damien Deville, Arka Dhar, David Dohan, Steve Dowling, Sheila Dunning, Adrien Ecoffet, Atty Eleti, Tyna Eloundou, David Farhi, Liam Fedus, Niko Felix, Simón Posada Fishman, Juston Forte, Isabella Fulford, Leo Gao, Elie Georges, Christian Gibson, Vik Goel, Tarun Gogineni, Gabriel Goh, Rapha Gontijo-Lopes, Jonathan Gordon, Morgan Grafstein, Scott Gray, Ryan Greene, Joshua Gross, Shixiang Shane Gu, Yufei Guo, Chris Hallacy, Jesse Han, Jeff Harris, Yuchen He, Mike Heaton, Johannes Heidecke, Chris Hesse, Alan Hickey, Wade Hickey, Peter Hoeschele, Brandon Houghton, Kenny Hsu, Shengli Hu, Xin Hu, Joost Huizinga, Shantanu Jain, Shawn Jain, Joanne Jang, Angela Jiang, Roger Jiang, Haozhun Jin, Denny Jin, Shino Jomoto, Billie Jonn, Heewoo Jun, Tomer Kaftan, Lukasz Kaiser, Ali Kamali, Ingmar Kanitscheider, Nitish Shirish Keskar, Tabarak Khan, Logan Kilpatrick, Jong Wook Kim, Christina Kim, Yongjik Kim, Hendrik Kirchner, Jamie Kiros, Matt Knight, Daniel Kokotajlo, Lukasz Kondraciuk, Andrew Kondrich, Aris Konstantinidis, Kyle Kopic, Gretchen Krueger, Vishal Kuo, Michael Lampe,

- Ikai Lan, Teddy Lee, Jan Leike, Jade Leung, Daniel Levy, Chak Ming Li, Rachel Lim, Molly Lin, Stephanie Lin, Mateusz Litwin, Theresa Lopez, Ryan Lowe, Patricia Lue, Anna Makanju, Kim Malfacini, Sam Manning, Todor Markov, Yaniv Markovski, Bianca Martin, Katie Mayer, Andrew Mayne, Bob McGrew, Scott Mayer McKinney, Christine McLeavey, Paul McMillan, Jake McNeil, David Medina, Aalok Mehta, Jacob Menick, Luke Metz, Andrey Mishchenko, Pamela Mishkin, Vinnie Monaco, Evan Morikawa, Daniel Mossing, Tong Mu, Mira Murati, Oleg Murk, David Mély, Ashvin Nair, Reiichiro Nakano, Rajeev Nayak, Arvind Neelakantan, Richard Ngo, Hyeonwoo Noh, Long Ouyang, Cullen O’Keefe, Jakub Pachocki, Alex Paino, Joe Palermo, Ashley Pantuliano, Giambattista Parascandolo, Joel Parish, Emy Parparita, Alex Passos, Mikhail Pavlov, Andrew Peng, Adam Perelman, Filipe de Avila Belbute Peres, Michael Petrov, Henrique Ponde de Oliveira Pinto, Michael, Pokorny, Michelle Pokrass, Vitchyr Pong, Tolly Powell, Alethea Power, Boris Power, Elizabeth Proehl, Raul Puri, Alec Radford, Jack Rae, Aditya Ramesh, Cameron Raymond, Francis Real, Kendra Rimbach, Carl Ross, Bob Rotsted, Henri Roussez, Nick Ryder, Mario Saltarelli, Ted Sanders, Shibani Santurkar, Girish Sastry, Heather Schmidt, David Schnurr, John Schulman, Daniel Selsam, Kyla Sheppard, Toki Sherbakov, Jessica Shieh, Sarah Shoker, Pranav Shyam, Szymon Sidor, Eric Sigler, Maddie Simens, Jordan Sitkin, Katarina Slama, Ian Sohl, Benjamin Sokolowsky, Yang Song, Natalie Staudacher, Felipe Petroski Such, Natalie Summers, Ilya Sutskever, Jie Tang, Nikolas Tezak, Madeleine Thompson, Phil Tillet, Amin Tootoonchian, Elizabeth Tseng, Preston Tuggle, Nick Turley, Jerry Tworek, Juan Felipe Cerón Uribe, Andrea Vallone, Arun Vijayvergiya, Chelsea Voss, Carroll Wainwright, Justin Jay Wang, Alvin Wang, Ben Wang, Jonathan Ward, Jason Wei, C. J. Weinmann, Akila Welihinda, Peter Welinder, Jiayi Weng, Lilian Weng, Matt Wiethoff, Dave Willner, Clemens Winter, Samuel Wolrich, Hannah Wong, Lauren Workman, Sherwin Wu, Jeff Wu, Michael Wu, Kai Xiao, Tao Xu, Sarah Yoo, Kevin Yu, Qiming Yuan, Wojciech Zaremba, Rowan Zellers, Chong Zhang, Marvin Zhang, Shengjia Zhao, Tianhao Zheng, Juntang Zhuang, William Zhuk, and Barret Zoph. GPT-4 Technical Report, December 2023. URL <http://arxiv.org/abs/2303.08774>. arXiv:2303.08774 [cs].
- Sarita Pathak, Gregory Summerville, Celia P Kaplan, Sarah S Nouri, and Leah S Karliner. Patient-Reported Use of the After Visit Summary in a Primary Care Internal Medicine Practice. *Journal of Patient Experience*, 7(5):703–707, October 2020. ISSN 2374-3735. doi: 10.1177/2374373519879286. URL <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7705830/>.
- Carswella Phillips. Relationships between workload perception, burnout, and intent to leave among medical–surgical nurses. *JBHI Evidence Implementation*, 18(2):265, June 2020. ISSN 2691-3321. doi: 10.1097/XEB.0000000000000220. URL [https://journals.lww.com/ijebh/abstract/2020/06000/relationships\\_between\\_workload\\_perception,.11.aspx](https://journals.lww.com/ijebh/abstract/2020/06000/relationships_between_workload_perception,.11.aspx).
- Isabel Segura-Bedmar, Paloma Martínez, and María Herrero-Zazo. SemEval-2013 Task 9 : Extraction of Drug-Drug Interactions from Biomedical Texts (DDIExtraction 2013). In Suresh Manandhar and Deniz Yuret, editors, *Second Joint Conference on Lexical and Computational Semantics (\*SEM), Volume 2: Proceedings of the Seventh International Workshop on Semantic Evaluation (SemEval 2013)*, pages 341–350, Atlanta, Georgia, USA, June 2013. Association for Computational Linguistics. URL <https://aclanthology.org/S13-2056>.
- Sina J. Semnani, Violet Z. Yao, Heidi C. Zhang, and Monica S. Lam. WikiChat: Stopping the Hallucination of Large Language Model Chatbots by Few-Shot Grounding on Wikipedia, October 2023. URL <http://arxiv.org/abs/2305.14292>. arXiv:2305.14292 [cs].
- Craig Thomson and Ehud Reiter. A Gold Standard Methodology for Evaluating Accuracy in Data-To-Text Systems. In Brian Davis, Yvette Graham, John Kelleher, and Yaji Sripada, editors, *Proceedings of the 13th International Conference on Natural Language Generation*, pages 158–168, Dublin, Ireland, December 2020. Association for Computational Linguistics. URL <https://aclanthology.org/2020.inlg-1.22>.
- Craig Thomson and Ehud Reiter. Generation Challenges: Results of the Accuracy Evaluation Shared Task, August 2021. URL <http://arxiv.org/abs/2108.05644>. arXiv:2108.05644 [cs].



- Craig Thomson, Ehud Reiter, and Barkavi Sundararajan. Evaluating factual accuracy in complex data-to-text. *Computer Speech & Language*, 80:101482, May 2023. ISSN 0885-2308. doi: 10.1016/j.csl.2023.101482. URL <https://www.sciencedirect.com/science/article/pii/S0885230823000013>.
- Katherine Tian, Eric Mitchell, Huaxiu Yao, Christopher D. Manning, and Chelsea Finn. Fine-tuning Language Models for Factuality, November 2023. URL <http://arxiv.org/abs/2311.08401>. arXiv:2311.08401 [cs].
- Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurelien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. Llama 2: Open Foundation and Fine-Tuned Chat Models, July 2023. URL <http://arxiv.org/abs/2307.09288>. arXiv:2307.09288 [cs].
- Dave Van Veen, Cara Van Uden, Maayane Attias, Anuj Pareek, Christian Bluethgen, Malgorzata Polacin, Wah Chiu, Jean-Benoit Delbrouck, Juan Manuel Zambrano Chaves, Curtis P. Langlotz, Akshay S. Chaudhari, and John Pauly. RadAdapt: Radiology Report Summarization via Lightweight Domain Adaptation of Large Language Models, May 2023. URL <http://arxiv.org/abs/2305.01146>. arXiv:2305.01146 [cs].
- Dave Van Veen, Cara Van Uden, Louis Blanke-meier, Jean-Benoit Delbrouck, Asad Aali, Christian Bluethgen, Anuj Pareek, Malgorzata Polacin, Eduardo Pontes Reis, Anna Seehofnerová, Nidhi Rohatgi, Poonam Hosamani, William Collins, Neera Ahuja, Curtis P. Langlotz, Jason Hom, Sergios Gatidis, John Pauly, and Akshay S. Chaudhari. Adapted large language models can outperform medical experts in clinical text summarization. *Nature Medicine*, pages 1–9, February 2024. ISSN 1546-170X. doi: 10.1038/s41591-024-02855-5. URL <https://www.nature.com/articles/s41591-024-02855-5>. Publisher: Nature Publishing Group.
- Alexander G. Watson, Jonathan V. McCoy, JoAnn Mathew, Daniel A. Gundersen, and Robert M. Eisenstein. Impact of physician workload on burnout in the emergency department. *Psychology, Health & Medicine*, 24(4): 414–428, April 2019. ISSN 1354-8506. doi: 10.1080/13548506.2018.1539236. URL <https://doi.org/10.1080/13548506.2018.1539236>. Publisher: Taylor & Francis eprint: <https://doi.org/10.1080/13548506.2018.1539236>.
- Wei-Hung Weng, Yu-An Chung, and Peter Szolovits. Unsupervised Clinical Language Translation. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, KDD '19, pages 3121–3131, New York, NY, USA, July 2019. Association for Computing Machinery. ISBN 978-1-4503-6201-6. doi: 10.1145/3292500.3330710. URL <https://dl.acm.org/doi/10.1145/3292500.3330710>.
- Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander M. Rush. HuggingFace’s Transformers: State-of-the-art Natural Language Processing, July 2020. URL <http://arxiv.org/abs/1910.03771>. arXiv:1910.03771 [cs].
- Qianqian Xie, Jiayu Zhou, Yifan Peng, and Fei Wang. FactReranker: Fact-guided Reranker for Faithful Radiology Report Summarization, March 2023. URL <http://arxiv.org/abs/2303.08335>. arXiv:2303.08335 [cs].

Wei Xu, Courtney Napoles, Ellie Pavlick, Quanze Chen, and Chris Callison-Burch. Optimizing Statistical Machine Translation for Text Simplification. *Transactions of the Association for Computational Linguistics*, 4:401–415, 2016. doi: 10.1162/tacl.a.00107. URL <https://aclanthology.org/Q16-1029>. Place: Cambridge, MA Publisher: MIT Press.

Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q. Weinberger, and Yoav Artzi. BERTScore: Evaluating Text Generation with BERT, February 2020a. URL <http://arxiv.org/abs/1904.09675>. arXiv:1904.09675 [cs].

Yuhao Zhang, Derek Merck, Emily Tsai, Christopher D. Manning, and Curtis Langlotz. Optimizing the Factual Correctness of a Summary: A Study of Summarizing Radiology Reports. In Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel Tetreault, editors, *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5108–5120, Online, July 2020b. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.458. URL <https://aclanthology.org/2020.acl-main.458>.

Chunting Zhou, Graham Neubig, Jiatao Gu, Mona Diab, Francisco Guzmán, Luke Zettlemoyer, and Marjan Ghazvininejad. Detecting Hallucinated Content in Conditional Neural Sequence Generation. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 1393–1404, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.findings-acl.120. URL <https://aclanthology.org/2021.findings-acl.120>.

Chunting Zhou, Pengfei Liu, Puxin Xu, Srinu Iyer, Jiao Sun, Yuning Mao, Xuezhe Ma, Avia Efrat, Ping Yu, Lili Yu, Susan Zhang, Gargi Ghosh, Mike Lewis, Luke Zettlemoyer, and Omer Levy. LIMA: Less Is More for Alignment. In *Thirty-seventh Conference on Neural Information Processing Systems*, November 2023. URL <https://openreview.net/forum?id=KBMOKmX2he>.

## Appendix A. Data Preprocessing

### A.1. Methods

Our goal for the preprocessing was to obtain fluent patient summaries with no artifacts. In general, we targeted for a higher precision, i.e., we considered removing low quality summaries as more important than keeping all summaries. We used two methods to iteratively build the dataset pipeline. First, we sampled 100 included and 100 excluded summaries and one author with medical expertise compared them with our preprocessing goals. Based on this analysis, we repeatedly refined the dataset pipeline. Second, we used the t-SNE method to analyze the BERT embeddings of the summaries to identify more systematic patterns. We mostly relied on static patterns and regular expressions to remove content since automatic approaches did not show a sufficient precision. The code for the preprocessing pipeline is available on GitHub.

### A.2. Results

The final dataset pipeline is shown in Figure 5. During preprocessing, we mostly focused on the summary. After steps changing the summary length, we filtered for summaries shorter than 350 character, which we considered as useful minimum length. To split the summary and the remaining hospital course, we simply used the *Discharge Instructions* section (Cai et al., 2022), which occurred in all but 2,690 notes. This led to a total of 296,697 candidate summaries. In step 2, we removed static prefixes that we encountered in our analysis that contained no specific and relevant content leading to 292,536 candidates. Next, we changed patterns in the summaries to make them more fluent. A typical approach to structure a summary is using headings like “Why were you in the hospital?”. To obtain fluent and homogeneous summaries, we removed those. Also, we replaced some simplistic deidentification patterns with the pronoun *you* to reduce the deidentified content. In step 4, we removed suffixes of the summaries, which often contained well wishes and general instructions. We also removed several static templates, e.g., that are used after a specific surgery, by filtering for key phrases. Hence, a large amount of summaries was removed leaving us with 119,260 notes. Lastly, we filtered for some additional quality criteria of the summaries and the brief hospital course (BHC), which is the sec-

	Quantity	Value (SD)
MIMIC-IV-Note-Ext-DI (100,175 context-summary ex.)		
Full context	# Sentences	118.2 (50.4)
	# Words	2088.8 (778.1)
	# Tokens	4367.1 (1625.3)
	# Characters	11343.6 (4377.8)
	# Deidentified	67.5 (39.1)
Short context (BHC) [used in this work]	# Sentences	33.0 (19.0)
	# Words	552.0 (314.0)
	# Tokens	858.6 (498.3)
	# Characters	3029.9 (1736.4)
	# Deidentified	11.5 (9.7)
Summaries (DI)	# Sentences	6.5 (2.6)
	# Words	113.2 (47.4)
	# Tokens	145.4 (61.4)
	# Characters	604.4 (251.0)
	# Deidentified	1.1 (1.7)

Table 6: Overview of MIMIC-IV-Note-Ext-DI with the full context and MIMIC-IV-Note-Ext-DI-BHC with the Brief Hospital Course (BHC) as context. The discharge summaries (DI) serve as patient summaries for both datasets.<sup>6</sup>

tion before the summary leading to a total of 100,175 context-summary pairs.

We performed a performance analysis on the original MIMIC-IV-Note dataset and MIMIC-IV-Note-Ext-DI for prediction of the discharge instructions with LED-large (see Table 7). We can observe that our preprocessing pipeline led to a significant decrease in performance, suggesting that instances that were easier to predict were removed.

### A.3. Analyzing 100 Included and Excluded Patient Summaries

For a qualitative analysis of the preprocessing, we also checked 100 examples that were processed and kept in the dataset (positive) and 100 examples that were removed (negative). One author with medical expertise looked at the original summaries and decided which part of the positive examples should be kept or whether a negative example should be removed. Among the 100 positive examples, nine were considered problematic due to removal of important

<sup>6</sup>. Sentences and words were determined with `nltk`. Tokens were determined with the Llama 2 tokenizer.

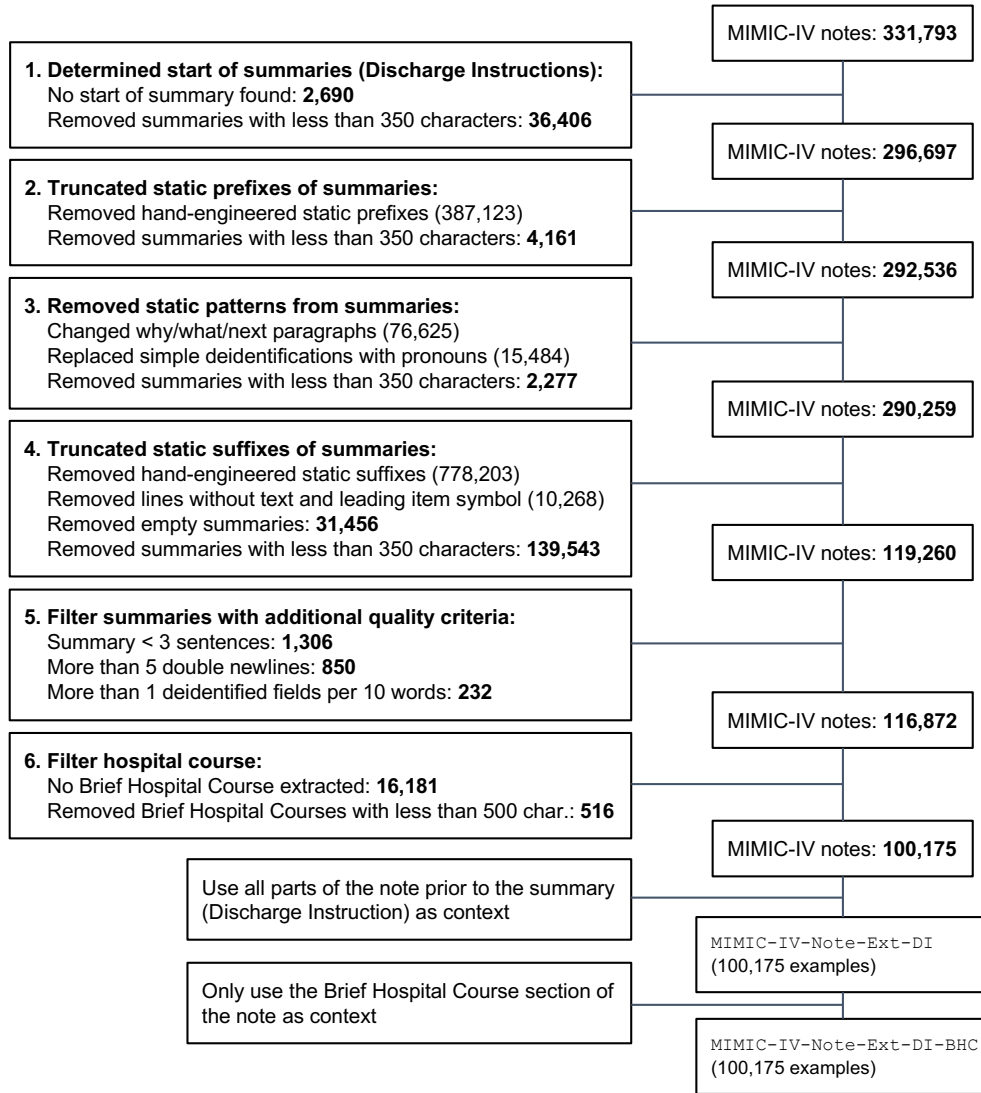


Figure 5: The preprocessing steps performed on MIMIC-IV-Note to obtain the datasets MIMIC-IV-Note-Ext-DI(-BHC). The goal was obtain diverse and free text discharge instructions (DI) as patient summaries.

content during preprocessing. Typically, the summary was cut at a closing statement, e.g., “Please follow up with your PCP”, but additional content was present after this. We also noted 33 positive examples with slight problems that did not affect the main summary. In two examples a greetings prefix was not removed, three examples still contained parts of a template after preprocessing, and in 28 examples some fluent text was removed that was not essential for the summary (11 follow-up, 11 medication, and

6 procedure statements). Of 100 negative examples, five were considered problematic. All of them contained statements or headings that lead to too early suffix pruning and, hence, were removed. Nine notes contained no or a too short brief hospital course. Another twelve examples showed useful summaries that contained summaries between 300-350 characters. However, we still consider this filtering useful to obtain longer summaries with more content.

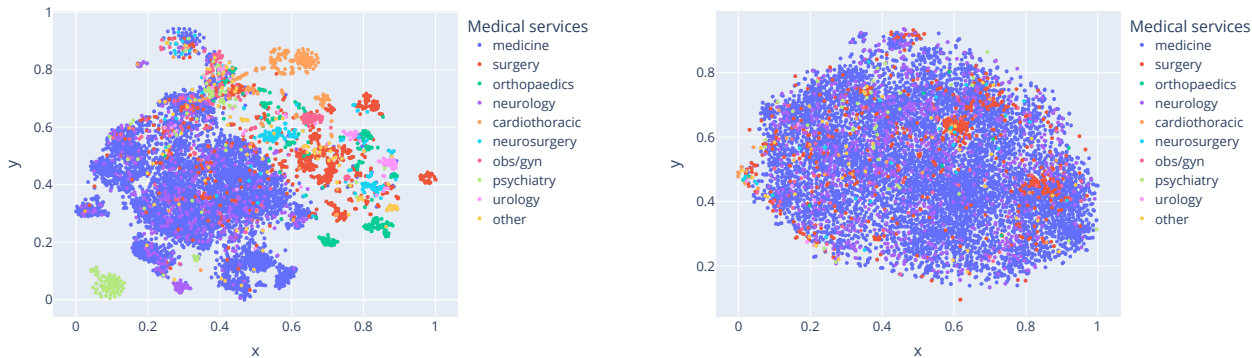


Figure 6: The t-SNE embeddings of 10,000 random patient summaries before and after the preprocessing labeled with the medical specialty mentioned in the note. We can observe outliers associated with medical specialties in the unprocessed data indicating the use of summary templates.

Dataset	R-1↑	R-2↑	R-3↑	R-4↑	R-L↑	BERT↑	DeBERT↑	SARI↑	Words
LED-large (allenai/led-large-16384)									
MIMIC-IV-Note (unprocessed)	51.17	31.28	24.06	20.08	39.85	89.10	70.48	60.62	162.49
MIMIC-IV-Note-Ext-DI	44.04	17.70	9.12	5.21	29.89	88.28	64.22	46.78	82.15

Table 7: Performance results for the LED-large model before and after preprocessing. A test set of 10,000 examples was used and the remaining data for training. The performance of the model decreased after preprocessing, suggesting that instances that were easier to predict were removed.

#### A.4. Analyzing Embeddings

We also inspected the t-SNE embeddings (Maaten and Hinton, 2008) of the patient summaries before and after preprocessing. Figure 6 shows the embeddings colored by the medical service mentioned in the note. The unprocessed summaries show several clusters that are often associated with a single medical service (same color). Inspection of those clusters revealed that these often represent static templates and copied content. We used these clusters to add filtering steps in our preprocessing pipeline. The processed summaries show a much more homogeneous distribution and medical services cannot easily be distinguished.

## Appendix B. Annotations Statistics

Both hallucination annotations were done completely separate by both annotators. Table 8 shows the results for MIMIC summaries and generated summaries split by annotators. After the annotation, there was an agreement process where annotators discussed their

labels and agreed on annotations. During this process, the annotators determined the number of labels with agreement for agreement statistics. We considered this approach more reliable than an automatic procedure since annotations of the same hallucination could differ a lot (e.g., labelling the negation instead of the subject). Results for annotations found by both annotators with the same and different labels are also given in Table 8.

We determined the inter-annotator agreement for hallucination labeling and the qualitative evaluation. For hallucination labeling, we calculated the agreement for annotated spans using the approach from Moramarco et al. (2022). To this end, we considered a simplification of the original task and calculated the interval Krippendorff’s alpha (Krippendorff, 2018) for the number of annotated hallucinations per summary. The agreement was 0.629 for the 100 MIMIC and 0.826 for the generated summaries indicating that annotating generated summaries was easier (see Table 9). Additionally, we computed F1-

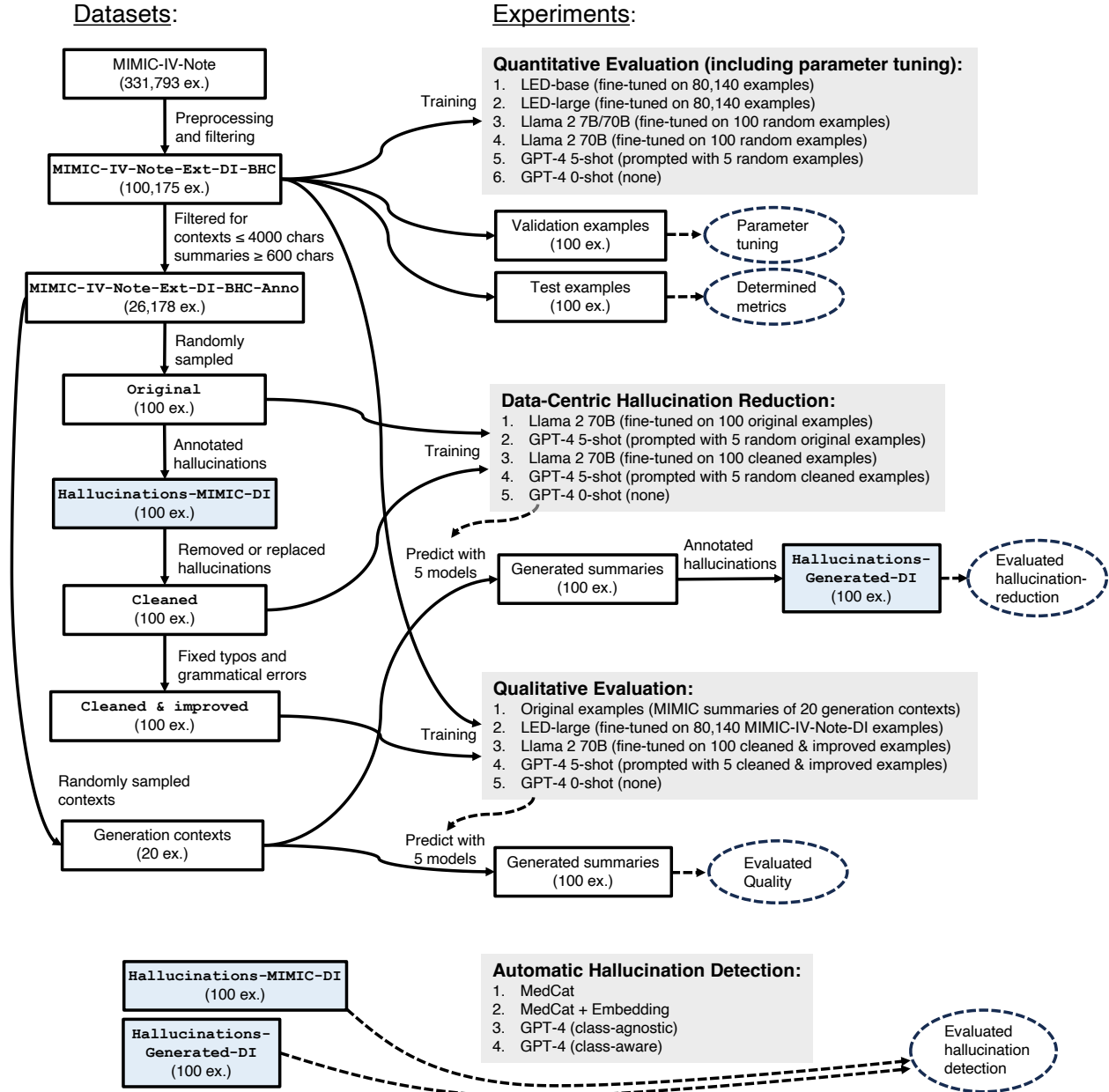


Figure 7: An overview flowchart of all datasets used in the experiments of this paper.

scores for the overlap of annotated spans between both annotators (Moramarco et al., 2022). The results showed similar scores for MIMIC and generated summaries with F1-scores of 0.479 and 0.440 when ignoring class labels and 0.245 and 0.271 when distinguishing classes (see Table 9). Although the results were slightly better than those reported in Moramarco et al. (2022), they underscore the difficulty

of the hallucination labeling task. To determine the inter-annotator agreement for the qualitative evaluation, we used the interval Krippendorff’s alpha (Krippendorff, 2018) for the Likert ratings (see Table 10). We distinguished the different qualitative dimensions and calculated the agreement for all ratings. The overall agreement was 0.586, with the highest agreement observed for consistency at 0.778. This is likely

Quantity	Mean (SD)	
	H-MIMIC-DI	H-Generated-DI
Annotations annotator 1	2.39 (2.06)	1.23 (1.52)
Removed in agreement	0.37 (0.66)	0.43 (0.67)
Annotations annotator 2	2.82 (2.05)	1.18 (1.58)
Removed in agreement	0.43 (0.64)	0.17 (0.40)
Annotations agreement	2.86 (2.12)	1.14 (1.70)
Both annot., same label	0.99 (1.16)	0.43 (0.78)
Both annot., diff. label	0.56 (0.73)	0.24 (0.62)
Only annotator 1	0.47 (0.80)	0.13 (0.37)
Only annotator 2	0.84 (1.13)	0.34 (0.59)

Table 8: Annotation statistics for 100 doctor-written (Hallucinations-MIMIC-DI) and 100 generated (Hallucinations-Generated-DI) patient summaries. Annotation were done separately and agreed on together.

Annotation Agreement Task	Class-agn. (Kripp.- $\alpha$ )	Class-aw. overlap (F1)	Class-aw. overlap (F1)
MIMIC	0.629	0.479	0.245
Generated	0.826	0.440	0.271

Table 9: Inter-annotator agreement for labeling hallucinations. We determined interval Krippendorff’s alpha on the number of hallucination per summary and the F1-score for overlap between annotators without (Class-agn.) and with classes (Class-aw.).

	Rel.	Con.	Sim.	Flu.	Coh.	Total
Agree. (Kr.- $\alpha$ )	0.457	0.778	0.633	0.431	0.218	0.586

Table 10: Inter-annotator agreement for qualitative evaluation. We determined interval Krippendorff’s alpha on the Likert ratings for each dimension separately and all ratings together (Total).

because the subtask for consistency required both annotators to label hallucinations using our protocol, which we considered the most rigorous instructions in the qualitative evaluation (see Appendix F). The agreement for fluency and coherence was relatively low, at 0.431 and 0.218, respectively, which can be attributed to the subjective nature of these ratings.

## Appendix C. Parameter Tuning

We performed parameter tuning for the LED (Beltagy et al., 2020) and the Llama 2 (Touvron et al., 2023) models. We used the full MIMIC-IV-Note-Ext-DI-BHC containing 100,175 examples and the subset MIMIC-IV-Note-Ext-DI-BHC-Anno of 26,178 examples used for labeling. We performed a separate parameter tuning on each dataset. For the LED model we performed full fine-tuning using 80% of the data for training. For Llama 2 we used LoRA for parameter-efficient fine-tuning (Hu et al., 2021) on 100 training examples and loaded the model in 8 bit. For both models, we used 100 examples for validation, and 100 examples for testing. The smaller number of validation and testing examples were chosen to reduce the runtime, however, we still consider them sufficient for representative results. We tracked our experiments with Weights & Biases (Biewald, 2020).

We used the LED models base and large (allenai/led-`{base,large}`-16384) from Huggingface (Wolf et al., 2020). We trained the model for 200,000 steps with a batch size of 1 and performed a validation every 20,000 steps to determine the best number of training steps. We used a `max_source_length` of 4,096 and `max_target_length` of 350, which sufficed for almost all examples based on a prior analysis. For the LED large model we had to use the fix described in <https://github.com/huggingface/transformers/issues/18190> for training. We tuned the LED model with a complete grid search for the following parameters:

- `dropout` in `{0.05, 0.1, 0.2}`
- `learning_rate` in `{5e-4, 1e-5, 5e-5, 1e-6, 5e-6}`

We could train both models on 24 GB GPUs and the training required approximately 8 hours for the base and 20 hours for the large model.

For Llama 2, we also used the 7B and 70B models (meta-llama/Llama-2-`{7,70}b-hf` from Huggingface (Wolf et al., 2020)). We trained the model for 100 steps with a batch size of 1 and gradient accumulation steps of 16. Hence, the model could encounter each training example at most 16 times during training. We performed a validation every 10 steps. The Llama 2 models have a context size of 4,096 and we truncated the context by removing the last sentences until there were at least 350 tokens for generation. However, the truncation was very rarely necessary. We tuned Llama 2 with a complete grid search for the following parameters:

Model	R-1↑	R-2↑	R-3↑	R-4↑	R-L↑	BERT↑	DeBERT↑	SARI↑	Words
MIMIC-IV-Note-Ext-DI-BHC (100,175 examples)									
LED-base (80,140 ex.)	43.32	17.05	8.26	4.30	29.21	87.98	63.52	46.39	74.36
LED-large (80,140 ex.)	43.82	17.33	8.85	4.92	29.89	88.11	64.12	46.71	76.99
Llama 2 7B (100 ex.)	38.36	12.66	5.13	2.24	24.73	85.68	60.23	44.12	73.13
Llama 2 70B (100 ex.)	40.58	14.31	6.09	2.74	26.19	86.30	61.89	45.16	76.90
GPT-4 5-shot (5 ex.)	38.80	10.78	3.55	1.12	21.98	86.67	61.30	42.88	131.86
GPT-4 0-shot (none)	38.26	10.81	3.70	1.49	21.49	86.37	60.75	42.04	165.78
MIMIC-IV-Note-Ext-DI-BHC-Anno (26,178 examples)									
LED-base (20,942 ex.)	42.30	14.98	7.04	3.87	26.50	86.71	60.85	44.38	117.81
LED-large (20,942 ex.)	46.21	17.38	8.72	5.14	28.87	87.50	63.52	45.84	117.59
Llama 2 7B (100 ex.)	36.95	11.92	5.12	2.53	22.73	82.44	57.07	42.41	100.54
Llama 2 70B (100 ex.)	41.82	13.63	5.77	2.66	24.83	86.43	61.34	43.86	114.08
GPT-4 5-shot (5 ex.)	43.07	12.91	4.79	2.13	23.91	86.80	62.08	43.40	159.68
GPT-4 0-shot (none)	41.76	11.39	3.96	1.75	22.34	86.42	61.12	42.25	164.59

Table 11: All performance results of patient summary generation. We tested all models on the full MIMIC-IV-Note-Ext-DI-BHC dataset and the subset MIMIC-IV-Note-Ext-DI-BHC-Anno used for labeling. Parameter or prompt tuning was performed for all models as described in Appendix C.

- `lora_rank` in  $\{8, 32\}$
- `lora_alpha` in  $\{8, 32\}$
- `lora_dropout` in  $\{0.050.1\}$
- `target_modules` in  $\{[q\_proj, v\_proj], [q\_proj, k\_proj, v\_proj, o\_proj]\}$
- `learning_rate` in  $\{2e-5, 2e-4\}$

For the Llama 2 7b model, we used a 24 GB GPU and the training required around 1,5 hours. For the Llama 2 70b model, we used two 80 GB GPUs and the training required approximately 8 hours.

## Appendix D. Prompt Tuning GPT-4

We performed prompt tuning for GPT-4 for generating patient summaries. We tried three different prompt formats (detailed in Table 14) and evaluated them qualitatively and quantitatively on ten held-out examples. The prompts used different settings of a general assistant, a medical resident assistant, and a patient assistant. We noticed that the results of the second prompt contained a lot of medical jargon leading to results targeted at medical experts. The results for the first prompt contained some simplifications but did not follow the style of the in-context examples. For instance, often a different start was used “During your hospitalization...”. Prompt three led

to generations with simplified language that followed the style of the in-context examples. Hence, qualitatively we considered the third prompt format the best. We tried two additional variations of prompt three using no in-context examples and using five in-context examples plus an instruction to start with “You were admitted”, which should help to guide the generation format. The second variant further improved the qualitative results.

This finding was supported by the quantitative analysis on ten held-out examples from the MIMIC-IV-Note-Ext-DI dataset. The results are shown in table 12. In general, prompt three lead to the best results and additional in-context example did not degrade the performance. Guiding the output with the instructions to start with “You were admitted” also lead to a quantitative improvement. Hence, we chose this prompt for all our GPT-4 summarization experiments.

## Appendix E. Hallucination Detection with GPT-4

Our GPT-4 hallucination detection pipeline consists two steps: (1) prompt GPT-4 to annotate hallucinated spans in the original summary text and (2) identify and extract the annotated span.



GPT-4 setting	R-1	R-2	R-3	R-4	R-L	BERTScore	Deberta	SARI	Words
Prompt 1: <i>You are a helpful assistant...</i>									
1 IC example	40.05	11.20	3.87	1.43	19.09	85.63	60.53	42.50	208.40
3 IC examples	40.64	9.99	3.51	1.14	19.64	85.51	59.94	41.90	189.60
5 IC examples	39.47	10.86	4.32	1.90	20.14	85.56	60.56	42.42	198.40
Prompt 2: <i>You are helping with a resident working at a large urban academic medical center...</i>									
1 IC example	27.93	5.43	1.18	0.05	13.66	83.43	55.69	38.54	192.70
3 IC examples	34.26	7.34	2.50	1.06	17.90	85.26	59.58	40.44	131.80
5 IC examples	32.92	7.28	2.41	0.63	17.40	85.12	59.33	38.65	127.70
Prompt 3: <i>You are a helpful assistant that helps patients understand their medical records...</i>									
0 IC examples	42.50	11.95	4.37	2.09	21.49	86.30	61.36	45.70	214.40
1 IC examples	36.05	8.97	3.28	1.53	18.32	85.84	60.20	43.10	191.80
3 IC examples	38.54	9.71	3.33	1.35	19.16	85.72	60.55	43.25	199.00
5 IC examples	39.22	10.73	3.95	1.69	20.73	85.65	60.06	42.39	206.30
5 IC examples + "You..."	41.99	12.83	5.22	2.26	22.67	86.95	62.35	43.55	138.70

Table 12: Performance results for GPT-4 for three different prompt formats with different numbers of in-context (IC) examples. The results were generated on ten held-out summaries.

Model	cond.	proc.	medic.	time	location	number	name	words	other	contrad.	incurr.
<b>Hallucinations-MIMIC-DI</b>											
MedCat	28.8	31.6	22.1	2.9	6.9	7.1	2.8	15.8	50.0	13.3	0.0
MedCat + Embedding	28.8	31.6	22.1	2.9	5.2	7.1	2.8	15.1	50.0	13.3	0.0
GPT-4 (class-ag.)	9.6	18.4	27.9	17.1	17.2	50.0	8.3	7.2	50.0	46.7	0.0
GPT-4 (class-aw.)	14.4	26.3	33.8	24.3	19.0	57.1	11.1	10.5	50.0	46.7	0.0
<b>Hallucinations-Generated-DI</b>											
MedCat	38.5	31.8	30.8	0.0	30.8	0.0	0.0	6.4	0.0	25.0	0.0
MedCat + Embedding	38.5	31.8	26.9	0.0	30.8	0.0	0.0	6.4	0.0	25.0	0.0
GPT-4 (class-ag.)	11.1	62.5	25.0	50.0	0.0	83.3	40.0	5.7	0.0	42.9	0.0
GPT-4 (class-aw.)	18.5	50.0	45.0	50.0	0.0	83.3	50.0	10.2	0.0	35.7	0.0

Table 13: Recall for different hallucination labels for hallucination detection on 100 doctor-written summaries (Hallucinations-MIMIC-DI) and 100 generated summaries (Hallucinations-Generated-DI) using partial matching.

As GPT-4 is a decoder-only model, we cannot directly use it to produce per-token predictions for potential spans of hallucination. One approach is to prompt it to “label” hallucination spans in the input text, i.e., to generate an HTML-like tag `<error class="hallucination type">` to indicate potential spans of hallucination in context. For example, for a sentence in the summary text, “Your pacemaker rate was increased to 50”, GPT-4 would generate the following annotated sentence: “Your pacemaker rate was increased to `<error class="unsupported_num-`

`ber">50</error>`” when the actual number is 40. This approach is similar to generate the relation or unverifiable labels in the pipeline by Mishra et al. (2024).

Given the generated annotations, we then extract the labeled spans from the annotated text and use them to identify potential hallucinations. Sometimes GPT-4 might produce text that is slightly different from the original text (e.g., correcting typos in the original sentences). Under such circumstances, we

first match the generations with the original sentence and then extract the labeled spans.

Table 15,16,17 show the prompt used to inform GPT-4 of potential error types and the format for annotating the hallucination spans. We can optionally turn off the hallucination class detection (i.e., generating only `<error>` rather than `<error class="hallucination type">`), and we compare the results as class-aware and class-agnostic hallucination detection.

One can also optionally prompt the LLM to reason about potential spans of hallucination before annotating the full text with chain-of-thought reasoning. In practice, we prompt GPT-4 to generate a list of labeled hallucination and explanations that mimics the examples in the prompt, i.e., generating bullet point lists like - "Your `<error>`red blood cell count`</error>` was followed and was stable." The BHC does not state that the red blood cell count was followed. Instead the hematocrit remained stable according to the BHC. with explanation before annotating the full summary with hallucination labels.

to ensure the quality of generated summaries in our hallucination-reduction experiments (see Table 2).

We did not develop a protocol for these labeling tasks. Instead, we used a more subjective procedure. For labeling key facts, annotators were asked to label key information that is important for the patient in the context. After that, they should label mentions of these facts in each summary (see dark blue annotations in Figure 2). Based on this, missing key facts in the summary could be determined. For medical jargon, annotators were asked to label span that they assumed would be difficult to be understood by the given patient (see green annotations in Figure 2). Every medical jargon term was only counted once for each summary. We also did not perform an agreement procedure between both annotators, since we did not develop a formal protocol and considered these labeling tasks more subjective.

## Appendix F. Qualitative Evaluation

For our qualitative evaluation of patient summaries we used the dimension introduced in Fabbri et al. (2021). They evaluated the quality of summaries for news articles in the CNN/DailyMail dataset (Hermann et al., 2015). The same taxonomy was already used for medical summaries (Adams et al., 2022). We adapted the instructions slightly by replacing “article“ with “brief hospital course“ to better suite our setting. We also added the dimension *Simplification* to measure the extent to which layperson language was used. We presented the annotators with the instructions shown in Figure 8. For step 2, we required the annotators to label hallucination. We used the developed protocol for this. For steps 1 and 3, annotators had to label key facts and medical jargon as described below.

### F.1. Labeling Key Facts and Medical Jargon

To improve the quality of the qualitative evaluation, we required annotators to label key facts and medical jargon for step 1 and 3. Based on this, they would then enter their rating on a Likert scale. We also used annotation for key facts and medical jargon

1. **Relevance:** The rating measures how well the summary captures the key points of the brief hospital course. Consider whether all and only the important aspects are contained in the summary. *To this end, please label key facts in the context and the summary.*
  - 5 = all key points included
  - 4 = 1 key point missing
  - 3 = 2 key point missing
  - 2 = 3 key point missing
  - 1 = more than 3 key points missing
  
2. **Consistency:** The rating measures whether the facts in the summary are consistent with the facts in the original brief hospital course. Consider whether the summary does reproduce all facts accurately and does not make up untrue information. *To this end, please label all hallucination in the summary according to the protocol.*
  - 5 = no finding
  - 4 = 1-2 minor findings
  - 3 = more than 2 minor or 1 major finding
  - 2 = 2 major findings
  - 1 = more than 2 major findings
  
3. **Simplification:** The rating measures whether the summary is written in plain language understandable for a patient. Consider medical terms and abbreviations. *To this end, please label medical jargon in the summary.*
  - 5 = no medical jargon
  - 4 = 1-2 minor unexplained medical term
  - 3 = more than 2 minor or 1 major medical term
  - 2 = 2 major medical terms
  - 1 = more than 2 major medical terms
  
4. **Fluency:** This rating measures the quality of individual sentences, are they well-written and grammatically correct. Consider the quality of individual sentences.
  - 5 = all sentences are well-written and correct
  - 4 = 1-2 sentences have minor errors or poor style
  - 3 = more than 2 sentences with minor errors or poor style or 1 sentence with severe error
  - 2 = 2 sentences with major errors
  - 1 = more than 3 major errors
  
5. **Coherence:** The rating measures the quality of all sentences collectively, to the fit together and sound naturally. Consider the quality of the summary as a whole.
  - 5 = the summary as a whole is well-written and clearly structured
  - 4 = the summary is mostly well-written and structured
  - 3 = the summary can be followed and has some structure
  - 2 = the summary is hard to follow and has no clear structure
  - 1 = the summary is very hard to follow and very unstructured

Figure 8: Instructions for qualitative evaluation. For step 1, 2, and 3 additional annotation were performed.

Brief Hospital Course: Mrs. \_\_\_ is a \_\_\_ female w/ PMH of CAD, HTN, HLD, DMII (on Metformin) who presented to the ED with severe dyspnea and chest pain. \_\_\_ was admitted for acute on chronic diastolic heart failure in the setting of PNA. ACTIVE ISSUES: # Acute on chronic diastolic heart failure: ECG in ED unremarkable w/out ST-T wave abnormalities, heart enzymes x2 ruled out acute myocardial damage, exacerbation likely in the setting of PNA. Patient reported dietary change w/ increased salt intake that could have caused this. Diuresed with lasix gtt. Balanced negative daily (max. \_\_\_ L). Sx improved with diuresis. #Pneumonia: Developed productive cough and new O2 requirement, most likely CAP, CXR showed new LLL infiltrate. Started on IV CTX and azithromycin to complete a 5 day course (held home atorvastatin in the setting of azithromycin). Fever resolved on HD#1. Remained afebrile for entire admission. Significantly improved and was discharged on HD#5. # T2DM: Serum glc slightly elevated on admission. \_\_\_ suggested to increase Metformin as outpatient (Dr. \_\_\_). #Hyponatremia: hypervolemic hyponatremia in setting of DHF. Resolved with lasix. # HTN. Normotensive during admission. Continued home lisinopril and metoprolol. TRANSITIONAL ISSUES: Please follow-up with PCP to adjust DM medications.

GPT-4 5-shot prompted with 5 cleaned & improved examples – modified:

You were admitted with severe shortness of breath and chest pain, which was found to be due to a worsening of your chronic heart failure, likely triggered by a lung infection (pneumonia) as seen on CXR and possibly by a recent increase in your salt intake. You were treated with medications to remove excess fluid from your body and antibiotics for the pneumonia. Your blood sugar levels were a bit high, and your doctor may adjust your diabetes medication after you leave the hospital. You also had low sodium levels in your blood likely due to a hypervolemic hyponatremia, which improved with the treatment for your heart failure. Your blood pressure was well controlled with your usual medications. You are feeling much better now and are ready to go home. Please make sure to see your primary care doctor to discuss any changes to your diabetes treatment.

Figure 9: Example for annotation of key facts and medical jargon based on the synthetic example and a modified output of GPT-4 5-shot. Annotators labeled key facts in the context and the summary (dark blue). The number of missing facts was determined based on the difference between key facts in the context and the respective summary. Medical jargon was labeled only in the summary (green). In the given summary, there are zero missing key facts and two uses of medical jargon.

Brief Hospital Course: Mrs. \_\_\_ is a \_\_\_ female w/ PMH of CAD, HTN, HLD, DMII (on Metformin) who presented to the ED with severe dyspnea and chest pain. \_\_\_ was admitted for acute on chronic diastolic heart failure in the setting of PNA. ACTIVE ISSUES: # Acute on chronic diastolic heart failure: ECG in ED unremarkable w/out ST-T wave abnormalities, heart enzymes x2 ruled out acute myocardial damage, exacerbation likely in the setting of PNA. Patient reported dietary change w/ increased salt intake that could have caused this. Diuresed with lasix gtt. Bilanced negative daily (max. \_\_\_ L). Sx improved with diuresis. #Pneumonia: Developed productive cough and new O2 requirement, most likely CAP, CXR showed new LLL infiltrate. Started on IV CTX and azithromycin to complete a 5 day course (held home atorvastatin in the setting of azithromycin). Fever resolved on HD#1. Remained afebrile for entire admission. Significantly improved and was discharged on HD#5. # T2DM: Serum glc slightly elevated on admission. \_\_\_ suggested to increase Metformin as outpatient (Dr. \_\_\_). #Hyponatremia: hypervolemic hyponatremia in setting of DHF. Resolved with lasix. # HTN. Normotensive during admission. Continued home lisinopril and metoprolol. TRANSITIONAL ISSUES: Please follow-up with PCP to adjust DM medications.

Original:

\_\_\_ were admitted to the **Acute Care Service** with shortness of breath and chest pain. **A heart attack was unlikely**, but we performed several tests and ruled out acute damage to your heart. \_\_\_ performed an **echocardiography** and found a worsening of your heart failure. This was likely due to a pneumonia of your **right** lung which we found on a chest x-ray. We treated you with diuretics for your **edema** and you were started on two antibiotics for \_\_\_ pneumonia. You significantly improved **during the second day** in the hospital. You had a problem with your electrolytes which resolved with diuresis. Your high blood pressure was treated with your home medications. **Your high blood pressure was treated with your home medications.** We noticed an increased blood sugar up to **226** and we **informed your PCP**. We suggest increasing your Metformin to **1000 mg**. You were discharged to your **assisted living facility**.

Cleaned:

\_\_\_ were admitted to the **hospital** with shortness of breath and chest pain. A heart attack was **likely and** we performed several tests and ruled out acute damage to your heart. \_\_\_ found a worsening of your heart failure. This was likely due to a pneumonia of your lung which we found on a chest x-ray. We treated you with diuretics and you were started on two antibiotics for \_\_\_ pneumonia. You significantly improved during **your stay** in the hospital. You had a problem with your electrolytes which resolved with diuresis. Your high blood pressure was treated with your home medications. We noticed an increased blood sugar. We suggest increasing your Metformin.

Cleaned & Improved:

**You** were admitted to the hospital with shortness of breath and chest pain. A heart attack was likely and we performed several tests and ruled out acute damage to your heart. **We** found a worsening of your heart failure. This was likely due to a pneumonia of your lung which we found on a chest x-ray. We treated you with diuretics and you were started on two antibiotics for **your** pneumonia. You significantly improved during your stay in the hospital. You had a problem with your electrolytes which resolved with diuresis. Your high blood pressure was treated with your home **medications**. We noticed an increased blood sugar. We suggest increasing your Metformin.

Figure 10: Example for the creation of the derived datasets **Cleaned** and **Cleaned & Improved**. The example is a slightly modified version of Figure 2. For **Cleaned**, we manually replaced hallucinations with useful facts in the context or removed them otherwise. For **Cleaned & Improved**, we further corrected mistakes and artifacts such as typos or deidentifications. We performed this process for all 100 examples in the **Original** dataset.

Brief Hospital Course: Mrs. \_\_\_ is a \_\_\_ female w/ PMH of CAD, HTN, HLD, DMII (on Metformin) who presented to [...]

Llama 70B trained with 100 original examples:

You were admitted for shortness of breath and were found to have a mild pneumonia. You were started on antibiotics. You were also found to have some fluid build up in your lungs from heart failure. We gave you medications to help remove this fluid and your symptoms improved. You should continue the antibiotics you were started on for a total of 5 days. You should also increase your Metformin to 1000mg twice a day. You should also follow-up with your primary care physician to adjust your other diabetes medications.

Llama 70B trained with 100 cleaned examples:

You were admitted to the hospital for shortness of breath and chest pain. You were found to have a worsening of your heart failure in the setting of pneumonia. You were treated with antibiotics and diuretics. You were also found to have a low sodium level in your blood, likely due to the fluid retention. Your sodium level normalized after you were given diuretics. You were discharged on oral antibiotics for your pneumonia. You should continue taking your medications as you were before admission. Please follow-up with your primary care doctor to adjust your diabetes medications.

GPT-4 5-shot prompted with 5 original examples:

You were admitted to the hospital with severe shortness of breath and chest pain. It was determined that you were experiencing heart failure due to fluid buildup, which was worsened by a lung infection (pneumonia) and possibly by eating too much salt. You were given medications to remove the excess fluid and antibiotics to treat the pneumonia. Your blood sugar levels were a bit high, and your doctor may adjust your diabetes medication after you leave the hospital. Your blood sodium levels were also low due to the excess fluid, but this improved with treatment. Your blood pressure was good throughout your stay. You were feeling much better by the time you were ready to go home. Please make sure to follow up with your primary care doctor to check on your diabetes medications.

GPT-4 5-shot prompted with 5 cleaned examples:

You were admitted to the hospital with severe shortness of breath and chest pain. It was determined that you were experiencing a worsening of your chronic heart condition, likely triggered by a lung infection and possibly by eating more salt than usual. You were given medication to remove excess fluid from your body, which improved your symptoms. The lung infection was treated with antibiotics, and you did not have a fever after the first day of treatment. Your blood sugar levels were a bit high, and your doctor may adjust your diabetes medication after you leave the hospital. You also had low sodium levels in your blood, which got better with the treatment for your heart condition. Your blood pressure was good throughout your stay. Please make sure to see your primary care doctor to discuss your diabetes treatment.

GPT-4 0-shot:

You were admitted to the hospital with severe shortness of breath and chest pain due to a worsening of your chronic heart failure, which was likely aggravated by a lung infection and an increase in salt intake. Your heart tests in the emergency room were normal, and there was no sign of a heart attack. You were treated with a medication to remove excess fluid from your body, which improved your symptoms. You also had pneumonia, for which you received antibiotics, and your fever went away after the first day of treatment. Your blood sugar was a bit high, and your doctor recommended adjusting your diabetes medication after leaving the hospital. Additionally, you had a low sodium level in your blood because of your heart condition, but this was resolved with treatment. Your blood pressure was stable, and you continued your usual blood pressure medications. You were feeling much better by the fifth day and were ready to go home, with instructions to see your primary care doctor to fine-tune your diabetes treatment.

Figure 11: Examples for the data-centric hallucination reduction. We generated a summary with all models included in the hallucination reduction experiment given the synthetic BHC as context (see Figure 2). Examples for Llama 70B are identical to Figure 3.

Brief Hospital Course: Mrs. \_\_\_ is a \_\_\_ female w/ PMH of CAD, HTN, HLD, DMII (on Metformin) who presented to the ED with severe dyspnea and chest pain. \_\_\_ was admitted for acute on chronic diastolic heart failure in the setting of PNA. ACTIVE ISSUES: # Acute on chronic diastolic heart failure: ECG in ED unremarkable w/out ST-T wave abnormalities, heart enzymes x2 ruled out acute myocardial damage, exacerbation likely in the setting of PNA. Patient reported dietary change w/ increased salt intake that could have caused this. Diuresed with lasix gtt. Bilanced negative daily (max. \_\_\_ L). Sx improved with diuresis. #Pneumonia: Developed productive cough and new O2 requirement, most likely CAP, CXR showed new LLL infiltrate. Started on IV CTX and azithromycin to complete a 5 day course (held home atorvastatin in the setting of azithromycin). Fever resolved on HD#1. Remained afebrile for entire admission. Significantly improved and was discharged on HD#5. # T2DM: Serum glc slightly elevated on admission. \_\_\_ suggested to increase Metformin as outpatient (Dr. \_\_\_). #Hyponatremia: hypervolemic hyponatremia in setting of DHF. Resolved with lasix. # HTN. Normotensive during admission. Continued home lisinopril and metoprolol. TRANSITIONAL ISSUES: Please follow-up with PCP to adjust DM medications.

LED-large trained with all MIMIC data:

You were admitted to the hospital because you were having chest pain and shortness of breath. You were found to have fluid in your lungs and in your legs. This was likely due to a condition called heart failure, where your heart does not pump hard enough and fluid backs up into your lungs. You were given a diuretic medication through the IV to help get the fluid out. You were also found to have a pneumonia and were started on antibiotics. You improved significantly and were ready to leave the hospital. Please continue to take the antibiotics (azithromycin and ceftriaxone) through \_\_\_. Please do not take your atorvastatin while you are taking the azithromycin.

Llama 70B trained with 100 cleaned & improved examples:

You were admitted with shortness of breath and cough. You had an infection in your lungs (pneumonia) and fluid in your lungs (heart failure). You were treated with antibiotics and a medication called Lasix to remove the fluid in your lungs. You improved with this treatment. You were also started on a new antibiotic called azithromycin. You were discharged on this antibiotic to complete a 5 day course. You were also started on a diuretic (Lasix) to remove the fluid from your lungs. Your primary care doctor will need to adjust your medications for your diabetes.

GPT-4 5-shot prompted with 5 cleaned & improved examples:

You were admitted with severe shortness of breath and chest pain, which was found to be due to a worsening of your chronic heart failure, likely triggered by a lung infection (pneumonia) and possibly by a recent increase in your salt intake. You were treated with medications to remove excess fluid from your body and antibiotics for the pneumonia. Your blood sugar levels were a bit high, and your doctor may adjust your diabetes medication after you leave the hospital. You also had low sodium levels in your blood, which improved with the treatment for your heart failure. Your blood pressure was well controlled with your usual medications. You are feeling much better now and are ready to go home. Please make sure to see your primary care doctor to discuss any changes to your diabetes treatment.

GPT-4 0-shot:

You were admitted to the hospital with severe shortness of breath and chest pain due to a worsening of your chronic heart failure, which was likely aggravated by a lung infection and an increase in salt intake. Your heart tests in the emergency room were normal, and there was no sign of a heart attack. You were treated with a medication to remove excess fluid from your body, which improved your symptoms. You also had pneumonia, for which you received antibiotics, and your fever went away after the first day of treatment. Your blood sugar was a bit high, and your doctor recommended adjusting your diabetes medication after leaving the hospital. Additionally, you had a low sodium level in your blood because of your heart condition, but this was resolved with treatment. Your blood pressure was stable, and you continued your usual blood pressure medications. You were feeling much better by the fifth day and were ready to go home, with instructions to see your primary care doctor to fine-tune your diabetes treatment.

Figure 12: Examples for the qualitative evaluation. We generated a summary with all models included in the qualitative evaluation given the synthetic BHC as context (see Figure 2).

PROMPT 1	
<b>System</b>	You are a helpful assistant.
<b>User</b>	<p>You will be given a doctor’s note and you will need to summarize the patient’s brief hospital course.                      Let’s do a practice round.                      {{#each icl_examples}}                      Here is the doctor’s note on a patient’s brief hospital course:                      {{this.document}}                      Summarize for the patient what happened during the hospital stay based on this doctor’s note. Please make it short and concise and only include key events and findings.                      {{this.summary}}                      {{/each}}</p> <p>Here is the doctor’s note on a patient’s brief hospital course:                      {{test.document}}                      Summarize for the patient what happened during the hospital stay based on this doctor’s note. Please make it short and concise and only include key events and findings.</p>
<b>Assistant</b>	{{generate_summary (max.tokens=600 temperature=0)}}
PROMPT 2	
<b>System</b>	You are helping with a resident working at a large urban academic medical center.
<b>User</b>	<p>Your task is to help summarize a patient’s brief hospital course based on the doctor’s note. Please make it short and concise and only include key events and findings.                      Here are some examples:                      {{#each icl_examples}}                      DOCUMENT:                      {{this.document}}                      SUMMARY:                      {{this.summary}}                      {{/each}}</p> <p>Here is another doctor note on a patient’s brief hospital course:                      DOCUMENT: {{test.document}}</p>
<b>Assistant</b>	{{generate_summary (max.tokens=600 temperature=0)}}
PROMPT 3	
<b>System</b>	You are a helpful assistant that helps patients understand their medical records.
<b>User</b>	<p>You will be given some doctor’s notes and you will need to summarize the patient’s brief hospital course in one paragraph. Please only include key events and findings and avoid using medical jargons, and you MUST start the summary with "You were admitted".                      Here are some examples: {{#foreach icl_examples}}</p> <p>DOCUMENT:                      {{this.document}}                      SUMMARY:                      {{this.summary}}                      {{/foreach}}</p> <p>DOCUMENT: {{test.document}}</p>
<b>Assistant</b>	{{generate_summary (max.tokens=600 temperature=0)}}

Table 14: Different prompts for using GPT-4 to generate patient summaries. In all examples, we can use a list of in-context learning examples (icl\_examples, whether cleaned or not) to guide the models for the final generation of the target summary, allowing 600 new tokens as well as using greedy decoding.



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We will present you with a pair of a brief hospital course (BHC) and a patient after visit summary (AVS). The AVS is also referred to as discharge summary. The BHC contains a detailed summary of the hospital stay written by medical service. It usually contains medical jargon, and it can follow different structures based on the hospital course and responsible medical specialty. The AVS summarizes the hospital stay for the patient in plain language. In practice, the BHC is not the only source of information to write the AVS. However, in our setting we treat the BHC as the only context for the summary.

### ## Instructions

For this labelling task, we are interested in errors in the AVS that are either unsupported by the BHC, contradict content in the BHC, or are wrong medical facts. We allow statements that contain general medical knowledge or advice that are often used in patient summaries. Most errors are due to unsupported facts, so we further distinguish those based on their specific content. This leads to the following error types or labels:

1. Unsupported facts, including condition/procedure/medication/time/location/number/name/word/other
2. Contradicted fact
3. Incorrect fact

And below is the detailed guideline, and we label error spans with the `<error>` tag (e.g. `<error class="error_type">incorrect fact</error>`).

### ### Determining Span of Errors

We label the smallest possible consecutive span that specifies the error given the BHC as a context. Removing further parts from the span would remove important information. A useful heuristic is to identify the minimal span that must be replaced to obtain a correct statement that is grammatically correct. For example

- "We performed an `<error>`esophageal-gastro-duodenoscopy (EGD).`</error>`" when no such procedure is reported in the BHC. The article "an" is not labeled as an error. When no procedure at all was performed "performed an esophageal-gastro-duodenoscopy (EGD)" should be labeled as error because there is no suitable substitute for "esophageal-gastro-duodenoscopy (EGD)".
- "After the surgery, we `<error>`transitioned you to oral oxycodone`</error>`." when the BHC contains no information for such a transition. If another medication transition is mentioned in the BHC and makes sense in this sentence only "oral oxycodone" should be labeled. If another oral medication transition is mentioned in the BHC only "oxycodone" should be labeled.
- "`<error>`Your symptoms responded well`</error>`." when no part of the sentence makes sense in the given context of the AVS.

We allow general medical knowledge and advice that is often part of the AVS. Usually, these are information that are not specific for the hospital course given in the BHC. For example

- "Please take your medications as prescribed" contains no error even though the BHC does not contain this instruction because this is general medical advice.
- "If the symptoms get worse, please contact your doctor" contains no error even when the BHC does not contain this fact, since it is general medical knowledge that a doctor should be seen for worsening symptoms.

We try to ignore grammatical errors in the BHC and AVS. If the original meaning can still be inferred (e.g. "medictaions" instead of "medications"), the most likely corrected form can be used. If the meaning cannot be inferred, they can be ignored in the BHC or labeled as Unsupported Other in the AVS.

If a sentence or phrase is repeated, then please treat it as you would any other sentence and highlight all errors (even if you did so in a previous sentence). For example

- "Please take Tylenol. Please take Tylenol" when Tylenol was prescribed in the BHC.
  - "Limit your `<error>`use of stairs`</error>`. Please limit `<error>`use of stairs`</error>`" when movement was encouraged.
- 

Table 15: Prompts for using GPT-4 to detect hallucinations (Part 1). We only show the user message as the system prompt is the same as in Table 14.

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*Continued from Table 15*

To get reliable error counts a span should only contain a single error.

- "You received `<error>Tylenol</error>` and `<error>Ciprofloxacin</error>`" when there is no evidence in the BHC that the two medications were administered to the patient.
- "You have a `<error>follow-up appointment with your PCP</error>` and `<error>your cardiologist</error>`" when no such follow up is mentioned in the BHC. Both errors are labeled separately.

### ### Dealing with Deidentified Information

The data contains deidentified information shown with "\_\_\_" in the text. We always treat this as non-existent information. So, the annotators should not infer what the deidentified information could be. In general, deidentified fields in the AVS should not be labeled as errors. However, sometimes they belong to a wrong statement or clearly contain unsupported information (e.g., a doctor's name or phone numbers) that are not given in the BHC. In these cases, deidentified fields should be included in the error span. For example

- "Take \_\_\_ `<error>200mg daily</error>` and try to rest" when no such dosage information is provided in the BHC, but the statement to rest. The deidentified medication name is excluded from the error span.
- "Please avoid going up `<error>more than ___ stairs</error>` at a time" when restrictions for the number of stairs taken at a time are not mentioned in the BHC.
- "`<error>Dr. ___ will follow up with you</error>`" when no follow-up is mentioned in the BHC.
- "Please stop taking Aspirin `<error>on ___</error>`" when no stopping date is given in the BHC.
- "Your RBC peaked `<error>at ___ million</error>`" if there is no hint of a specific red blood cell count given in the BHC.

### ### Error Types

In general, we ask for the most specific error that is applicable. If there is uncertainty which type applies, prefer the one mentioned first in the enumeration of all error types shown earlier. For instance, if the error contains an unsupported medication name, the Unsupported medication type should be used instead of the Unsupported name type. Here is a detailed description of the error types:

- 'Unsupported Condition': includes unsupported symptoms, diseases, or findings of the patient. For example
    - "You were found to have a `<error class="unsupported.condition">left clavicle fracture</error>`" when no information was given for this condition in the BHC.
  - 'Unsupported Procedure': includes any unsupported medical procedures. For example
    - "You had a `<error class="unsupported.procedure">filter placed in your vein</error>`" when no intervention with a filter was mentioned.
  - 'Unsupported Medication': contains all errors related to unsupported medications. This includes medication classes, substances, routes, frequencies, and dosages. For example
    - "You were placed on `<error class="unsupported.medication">antibiotics</error>`" when only blood thinners were prescribed.
  - 'Unsupported Time': includes all errors for unsupported time or interval statements. For example
    - "Keep your arm in a sling for the `<error class="unsupported.time">next 6 weeks</error>`" when no specific duration is given.
  - 'Unsupported Location': Locations include both unsupported physical places as well as regions of the patient. For example
    - "The patient was admitted to the `<error class="unsupported.location">Acute Surgery Service</error>`" when no admission location was provided in the BHC.
  - 'Unsupported Number': any number either as digits or written that are unsupported. This also includes words such as "a" and "an". For example
    - "Your pacemaker rate was increased to `<error class="unsupported.number">50</error>`" when the rate of 50 is not given in the BHC.
- 

Table 16: Prompts for using GPT-4 to detect hallucinations (Part 2).

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*Continued from Table 16*

- ‘Unsupported Name’: named entities that are not supported by the BHC. For example
  - "You were seen by the <error class="unsupported\_name">interventional pulmonary service</error>" when no consult with this service was mentioned in the BHC.
- ‘Unsupported Word’: incorrect or inappropriate words or phrases which do not fit in any of the above types. For example
  - "We will send you home with a <error class="unsupported\_word">drain</error> in place" when drain not mentioned in the BHC.
- ‘Unsupported Other’: If there is a mistake which clearly does not belong to any of the above categories, you may use this category as a last resort. We cannot give precise instructions because the "other" category is very broad.
- ‘Contradicted Fact’: This error type is independent of the content and contains all facts that clearly contradict information provided in the BHC. For example
  - "Your pacemaker rate was increased to <error class="contradicted\_fact">50</error>" when the context state a pacemaker rate of 40.
- ‘Incorrect Fact’: This error type is independent of the content and contains all facts that clearly contradict general medical knowledge or advice. For example
  - "We diagnosed a seizure, and you <error class="incorrect\_fact">can continue driving your car</error>" when no reason for allowing driving after a seizure is provided this contradict common medical knowledge.

## Examples

```

{{#each icl_examples}}
### Example {{this.index}}

BHC:
{{this.document}}

AVS:
{{this.summary}}

ERRORS:
{{this.cot.description}}

AVS WITH ERRORS LABELED:
{{this.summary_with_errors}}
{{/each}}

### Example {{n_shot+1}}

BHC:
{{test_document}}

AVS:
{{test_summary}}

ERROR:

```

---

Table 17: Prompts for using GPT-4 to detect hallucinations (Part 3).

## Appendix G. Guidelines for Patient Summary Annotation

### Guidelines for Annotating Errors in Patient Summaries

We will present you with a pair of a brief hospital course (BHC) and a patient after visit summary (AVS). The AVS is also referred to as discharge summary. The BHC contains a detailed summary of the hospital stay written by medical service. It usually contains medical jargon, and it can follow different structures based on the hospital course and responsible medical specialty. The AVS summarizes the hospital stay for the patient in plain language. In practice, the BHC is not the only source of information to write the AVS. However, in our setting we treat the BHC as the only context for the summary.

For this labelling task, we are interested in errors in the AVS that are either unsupported by the BHC, contradict content in the BHC, or are wrong medical facts. We allow statements that contain general medical knowledge or advice that are often used in patient summaries. Most errors are due to unsupported facts, so we further distinguish those based on their specific content. This leads to the following error types or labels:

1. Unsupported condition
2. Unsupported procedure
3. Unsupported medication
4. Unsupported time
5. Unsupported location
6. Unsupported number
7. Unsupported name
8. Unsupported word
9. Unsupported other
10. Contradicted fact
11. Incorrect fact

#### Allowed General Medical Knowledge and Medical Advice

We allow general medical knowledge and advice that is often part of the AVS. Usually, these are information that are not specific for the hospital course given in the BHC. For example

- “Please take your medications as prescribed” contains no error even though the BHC does not contain this instruction because this is general medical advice.
- “If the symptoms get worse, please contact your doctor” contains no error even when the BHC does not contain this fact, since it is general medical knowledge that a doctor should be seen for worsening symptoms.

#### Determining Span of Errors

We label the smallest possible consecutive span that specifies the error given the BHC as a context. Removing further parts from the span would remove important information. A useful heuristic is to identify the minimal span that must be replaced to obtain a correct statement that is grammatically correct. For example

- “We performed an esophageal-gastro-duodenoscopy (EGD).” when no such procedure is reported in the BHC. The article “an” is not labeled as an error. When no procedure at all was performed “performed an esophageal-gastro-duodenoscopy (EGD)” should be labeled as error because there is no suitable substitute for “esophageal-gastro-duodenoscopy (EGD)”.
- “After the surgery, we transitioned you to oral oxycodone.” when the BHC contains no information for such a transition. If another medication transition is mentioned in the BHC and makes sense in this sentence only “oral oxycodone” should be labeled. If another oral medication transition is mentioned in the BHC only “oxycodone” should be labeled.
- “Your symptoms responded well.” when no part of the sentence makes sense in the given context of the AVS.

Also, to get reliable error counts a span should only contain a single error.

- “You received Tylenol and Ciprofloxacin” when there is no evidence in the BHC that the two medications were administered to the patient.
- “You have a follow-up appointment with your PCP and your cardiologist” when no such follow up is mentioned in the BHC. Both errors are labeled separately.

### Dealing with Deidentified Information

The data contains deidentified information shown with “\_\_\_” in the text. We always treat this as non-existent information. So, the annotators should not infer what the deidentified information could be. In general, deidentified fields in the AVS should not be labeled as errors. However, sometimes they belong to a wrong statement or clearly contain unsupported information (e.g., a doctor’s name or phone numbers) that are not given in the BHC. In these cases, deidentified fields should be included in the error span. For example

- “Take \_\_\_ 200mg daily and try to rest” when no such dosage information is provided in the BHC, but the statement to rest. The deidentified medication name is excluded from the error span.
- “Please avoid going up more than \_\_\_ stairs at a time” when restrictions for the number of stairs taken at a time are not mentioned in the BHC.
- “Dr. \_\_\_ will follow up with you” when no follow-up is mentioned in the BHC.
- “Please stop taking Aspirin on \_\_\_” when no stopping date is given in the BHC.
- “Your RBC peaked at \_\_\_ million” if there is no hint of a specific red blood cell count given in the BHC.

### Error Types

We distinguish different error types. In general, we ask for the most specific error that is applicable. If there is uncertainty which type applies, prefer the one mentioned first in the enumeration of all error types shown earlier.

For instance, if the error contains an unsupported medication name, the *Unsupported medication* type should be used instead of the *Unsupported name* type.

#### Unsupported Condition

Unsupported conditions include unsupported symptoms, diseases, or findings of the patient.

For example

- “You were found to have a left clavicle fracture” when no information was given for this condition in the BHC.
- “The ultrasound showed no blood clots in your leg” when the ultrasound showed a deep vein thrombosis in the right leg.

#### Unsupported Procedure

Unsupported procedures include any unsupported medical procedures. For example

- “You had a filter placed in your vein” when no intervention with a filter was mentioned.
- “You underwent a left clavicle repair” when the humerus was repaired.

#### Unsupported Medication

This type contains all errors related to unsupported medications. This includes medication classes, substances, routes, frequencies, and dosages. For example

- “You were placed on antibiotics” when only blood thinners were prescribed.
- “We gave you blood thinners by mouth” when blood thinners were administered by IV.
- “You received IV antibiotics” when no route was specified in the BHC.
- “Please take amitriptyline daily” when no interval for amitriptyline is given.
- “We started you on Coumadin 5 mg” when no dosage for the Coumadin is provided.

#### Unsupported Time

Unsupported time includes all errors for unsupported time or interval statements. For example

- “Keep your arm in a sling for the next 6 weeks” when no specific duration is given.
- “Your family arranges home care while you are getting discharged” when the family was instructed to establish home care before the patient gets discharged.

#### Unsupported Location

Locations include both unsupported physical places as well as regions of the patient. For example

- “The patient was admitted to the Acute Surgery Service” when no admission location was provided in the BHC.
- “There was concern for a thrombus in the right leg” when no side of the thrombus was specified.

#### Unsupported Number

Unsupported numbers are any number either as digits or written that are unsupported. This also includes words such as “a” and “an”. For example

- “Your pacemaker rate was increased to 50” when the rate of 50 is not given in the BHC.
- “You had a fracture of your second metacarpal” when no information about which metacarpal bone was fractured is given in the context.
- “If you have another episode” when the context asks for at least two more episodes.
- “You can take one more of this pill” if two additional pills are allowed according to the BHC.

#### Unsupported Name

Named entities that are not supported by the BHC. For example

- “You were seen by the interventional pulmonary service” when no consult with this service was mentioned in the BHC.
- “We discharged you the Gold Housing assisted living” when the name of the assisted living facility is not provided in the context.

#### Unsupported Word

Word mistakes are incorrect or inappropriate words or phrases which do not fit in any of the above types. For example

- “We will send you home with a drain in place” when drain not mentioned in the BHC.
- “Limit your use of stairs” when movement is encouraged.

#### Unsupported Other

If there is a mistake which clearly does not belong to any of the above categories, you may use this category as a last resort. We cannot give precise instructions because the “other” category is very broad.

#### Contradicted Fact

This error type is independent of the content and contains all facts that clearly contradict information provided in the BHC. For example

- “Your pacemaker rate was increased to 50” when the context state a pacemaker rate of 40.
- “We started you on ASS 81 mg” when the BHC contains a dosage of 300 mg for ASS.

#### Incorrect Fact

This error type is independent of the content and contains all facts that clearly contradict general medical knowledge or advice. For example

- “We diagnosed a seizure, and you can continue driving your car” when no reason for allowing driving after a seizure is provided this contradict common medical knowledge.

#### Special Situations

##### Grammatical Errors

We try to ignore grammatical errors in the BHC and AVS. If the original meaning can still be inferred (e.g. “medictaions” instead of “medications”), the most likely corrected form can be

used. If the meaning cannot be inferred, they can be ignored in the BHC or labeled as *Unsupported Other* in the AVS.

#### Repeated Content

If a sentence or phrase is repeated, then please treat it as you would any other sentence and highlight all errors (even if you did so in a previous sentence). For example

- “Please take Tylenol. Please take Tylenol” when Tylenol was prescribed in the BHC.
- “Limit your use of stairs. Please limit use of stairs” when movement was encouraged.

#### Complex Mistakes

If there are multiple ways in which you can annotate a sentence, follow the following rules:

1. Choose the alternative with fewest total mistakes.
2. Choose the alternative with the smallest error spans.
3. If both annotations would lead to the same number of mistakes with the same span sizes, prefer the error mentioned first in the enumeration of all error types above.

#### Additional Clarifications

##### Clarifications from first batch of 5 test examples

- If a condition is a consequence of another condition, it is not labeled as an error even if it is not directly mentioned.
  - For example, “You had pain during your admission” if a severe trauma is mentioned in the BHC.
- If another doctor takes over the treatment, it can be assumed that they re-evaluate the patient and can decide the following treatment.
  - For example, “Please continue your medications until your PCP appointment” if no stopping time for the medications was mentioned in the BHC.
- Facts classified as general medical knowledge are considered from a doctor’s perspective. The doctors write the AVS; hence, this general knowledge needs no support in the BHC but can be assumed to be known by any doctor.
  - For example, “After we placed a drug-eluting stent you will receive two blood thinning medications” if the BHC mentions the placement of a drug-eluting stent, the antiplatelet therapy can be assumed as general knowledge.
- If a medical specialty commonly treats a condition or performs a procedure, this is considered general knowledge and not considered as an unsupported fact.
  - For example, “Neurology evaluated your EEG” if the EEG evaluation was mentioned in the BHC but though no specialty was given.

##### Clarifications from second batch of 5 test examples

- Specific names of departments are not treated as general knowledge even though it is likely that they treat a condition or perform a procedure. We require those to be explicitly named in the BHC.



- For example, “[Neuro Epilepsy Service](#) evaluated your EEG” if the EEG evaluation was mentioned in the BHC but no responsible department was given.
- The main condition for admission named in the summary (“You were admitted for …”) cannot only be derived from the main condition named in the BHC. Sometimes another major reason relevant to the patient is mentioned later in the BHC, so it is also acceptable to use this.
  - For example, “You were admitted for abdominal pain.” If the BHC states an ileus as the main reason but also mentions the abdominal pain.

#### Clarifications from agreement procedures of 100 examples

- A reference to additional material or information that are not part of the AVS (e.g., medication plan or phone number) are considered as unsupported facts.
  - For example, “[Your medication plan is attached.](#)” If no medication plan is mentioned in the BHC.
- Generalizations and simplifications of medical conditions or procedures that are still close to the information in the BHC and aid patient understanding are not considered as unsupported facts.
  - For example, “You WBC was low” when the BHC mentions a neutropenia.
- If a span contains different error types, it is labeled as “unsupported word”.
  - For example, “The [lab test showed an increased risk of bleeding.](#)” when no lab test or increased risk of bleeding is mentioned in BHC. The error is labeled with one span since logically they belong together.
- If a common daily dosage of a medication is given, we treat instructions for daily intake in the AVS as general knowledge.
  - For example, “You therapy was changed to Plavix 75 mg daily.” If the BHC only contains the therapy change to Plavix 75 mg.
- If unsupported entities are clearly referred to in the next sentence, they are again labeled as an error.
  - For example, “[Vascular Surgery](#) was consulted. [They](#) recommended no surgery.” if the vascular surgery team is not mentioned in the BHC.