Simplified Rewriting Improves Expert Summarization

Anonymous ACL submission

Abstract

Radiology report summarization (RRS) is critical for clinical workflows, requiring concise "Impressions" distilled from detailed "Findings." This paper proposes a novel prompting strategy that enhances RRS by introducing a layperson summary as an intermediate step. This summary helps normalize key observations and simplify complex terminology using communication techniques inspired by doctor–patient interactions. Combined with few-shot in-context learning, this approach improves the model's ability to map generalized descriptions to specific clinical findings. We evaluate our method on three benchmark datasets, MIMIC-CXR, CheXpert, and MIMIC-III, and compare it against state-of-the-art open-source language models in the 7B/8B parameter range, such as Llama-3.1-8B-Instruct. Results show consistent improvements in summarization quality, with gains of up to 5% on some metrics for prompting, and more than 20% for some models when instruction tuning.

1 Introduction

Radiology report summarization (RRS) is a compelling task for exploring natural language processing (NLP) methods in the biomedical domain from a computational perspective (Van Veen et al., 2023a). RRS involves generating concise "Impressions" from the detailed "Findings" in radiology reports. These reports are critical for diagnosis, treatment planning, and longitudinal health records, and are authored by radiologists based on imaging modalities such as X-rays, CT scans, MRI scans, and ultrasounds. The "Findings" section captures objective observations from the images, while the "Impression" section offers the radiologist's clinical interpretation and diagnostic conclusions.

In biomedical applications, the effectiveness of large language models (LLMs) often depends on domain- and task-specific adaptation through fine-tuning (Singhal et al., 2023). While LLMs demonstrate strong capabilities in natural language understanding and generation, fine-tuning models with billions of parameters, such as GPT-3, is computationally expensive and resource-intensive. To address these challenges, recent work has focused on more efficient alternatives, including parameter-efficient fine-tuning (PEFT) and prompting (Van Veen et al., 2023a,b; Liu et al., 2022), which aim to use existing model knowledge while significantly reducing computational overhead.

In contrast, prompting through in-context learning (ICL) (Brown et al., 2020; Dong et al., 2023) offers a practical and lightweight alternative to full fine-tuning for adapting LLMs to new tasks. ICL enables models to perform few-shot learning by embedding relevant information and examples directly within the prompt (Lampinen et al., 2022). With well-designed prompts, LLMs can be guided to produce accurate outputs through contextual cues and task-specific demonstrations. This process can be further improved using techniques such as Retrieval-Augmented Generation (RAG) (Wang et al., 2023), which dynamically selects relevant examples from external corpora. In biomedical applications, prompting has shown effectiveness in tasks like radiology report summarization by simplifying complex findings into concise summaries (Chen et al., 2023a). Adding explanations to ICL prompts can further improve performance on specialized tasks such as medical question answering (Nori et al., 2023; Zhang et al., 2023). However, generating explanations for summarization is more difficult due to the open-ended nature of the output and the challenge of aligning intermediate reasoning with summary objectives.

Moreover, LLMs trained on general text corpora often lack the specific knowledge required for specialized fields, limiting their performance (Yao et al., 2023a; Holmes et al., 2023). Addressing this deficiency typically involves extensive fine-tuning, which is resource-intensive and costly. While ICL

can help by embedding relevant information within prompts, this alone is not always sufficient (Brown et al., 2020; Dong et al., 2023). Intuitively, non-fine-tuned models are "non-experts" in the medical domain, especially smaller open-source models.

In real-world settings such as doctor–patient conversations, prior research shows that technical or scientific knowledge can be effectively communicated to non-experts through strategies like reformulation and simplification (Gülich, 2003). These techniques break down complex information into clearer, more accessible language to enhance understanding. Motivated by these communication principles, we propose a novel prompting strategy that integrates simplification with ICL to improve the performance of non-expert LLMs in specialized domains. Our method avoids costly fine-tuning (Nori et al., 2023; Zhang et al., 2023) by generating a layperson summary before the expert summary. These lay summaries are included in the in-context examples to guide the model's reasoning on new inputs. From another perspective, we treat the layperson summary as a normalization step that abstracts key clinical observations into consistent, general expressions. This is particularly useful in radiology, where variations in reporting style and terminology (Yan et al., 2023), along with a wide range of illnesses, result in high lexical variability. By mapping terms like "pneumonia" and "bronchitis" to a shared concept such as "infection of the lungs," the model can more easily recognize semantically similar cases across in-context examples, even when the terminology differs. This normalization helps the model align general descriptions in the lay summary with specific details in the Findings, improving consistency and robustness in expert summary generation (Peter et al., 2024).

Overall, this paper has threefold contributions:

1. We introduce a novel prompting approach inspired by doctor–patient communication, where a simplified (layperson) summary is generated before the expert summary. This strategy, combined with few-shot ICL, enhances RRS using general-purpose, non-expert LLMs.

2. We evaluate LLM performance on three RRS datasets: MIMIC-CXR (Johnson et al., 2019), CheXpert (Irvin et al., 2019), and MIMIC-III (Johnson et al., 2016), and Medical Question Summarization (MMQS) dataset (Ghosh et al., 2024). We benchmark against open-source LLMs, including Llama-3.1-8B-Instruct (AI@Meta, 2024) for comprehensive comparison.

3. We also investigate whether using the layperson prompt as an instruction is effective for instruction tuning, evaluating its impact on expert impression generation.[1]

2 Related Work

LLMs for Medicine. Recent advances in LLMs have demonstrated that LLMs can be adapted with minimal effort across various domains and tasks. These expressive and interactive models hold great promise due to their ability to learn broadly useful representations from the extensive knowledge encoded in medical corpora at scale (Singhal et al., 2023). Fine-tuned general-purpose models have proven effective in clinical question-answering, protected health information de-identification (Sarkar et al., 2024), and relation extraction (Hernandez et al., 2023). Some LLMs, such as BioGPT (Luo et al., 2022) and ClinicalT5 (Lu et al., 2022), have been trained from scratch using clinical domain-specific notes, achieving promising performance on several tasks. Additionally, in-context learning with general LLMs like InstructGPT-3 (Ouyang et al., 2022), where no weights are modified, has shown good performance (Agrawal et al., 2022). They have also demonstrated the ability to solve domain-specific tasks through zero-shot or few-shot prompting and have been applied to various medical tasks, such as medical report summarization (Otmakhova et al., 2022) and medical named entity recognition (Hu et al., 2023). But, this generally only works with closed-source models such as GPT4.

Retrieval-Augmented LLMs. Retrieval augmentation connects LLMs to external knowledge to mitigate factual inaccuracies. By incorporating a retrieval module, relevant passages are provided as context, enhancing the language model's predictions with factual information like common sense or real-time news (Ma et al., 2023). Recent studies indicate that retrieval-augmented methods can enhance the reasoning ability of LLMs and make their responses more credible and traceable (Shi et al., 2024; Yao et al., 2023b; Nori et al., 2023; Ma et al., 2023). For example, Shi et al. (2024) trains a dense retrieval model to complement a frozen

[1] See the appendix for the full analysis.

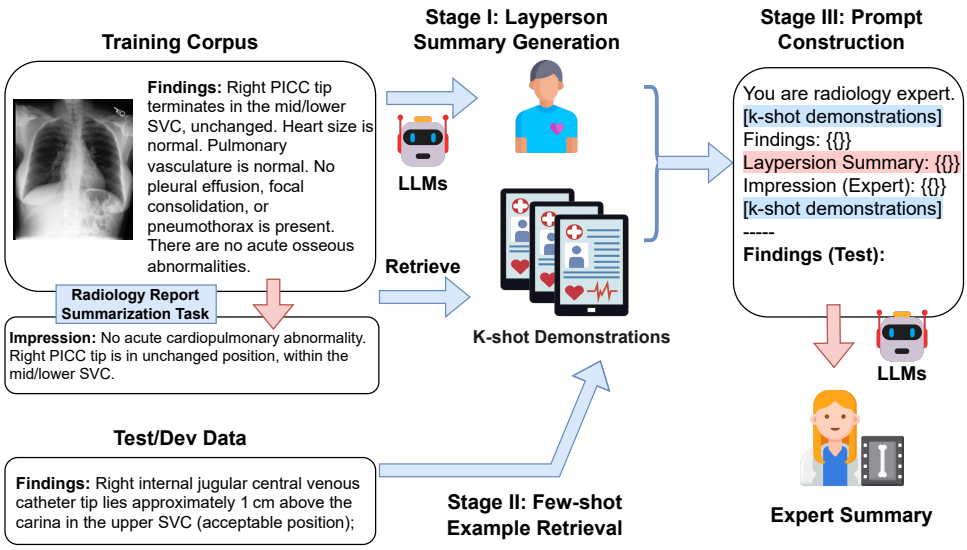

Figure 1: Overview of the LaypersonPrompt Framework. First, we prompt LLMs to generate layperson summaries for each training example. Then, for a given test input, we use few-shot example retrieval to select relevant examples from the training set. Finally, we construct an instruction prompt by combining the retrieved examples with their layperson summaries to guide the model's reasoning for expert summary generation.

language model. By using feedback from the LLM as a training objective, the retrieval model is optimized to provide better contextual inputs for the LLM. Yao et al. (2023b) focuses on designing interactions between the retriever and the reader, aiming to trigger emergent abilities through carefully crafted prompts or a sophisticated prompt pipeline. Our approach combines retrieval-augmented methods with layperson summaries to enhance general LLMs reasoning in radiology report summarization, using patient-doctor communication techniques for better understanding and accuracy.

Communication Techniques for Laypersons. Non-experts, such as patients, have been shown to perform well on expert tasks, like medical decision-making and understanding complex topics when information is simplified using effective communication techniques (Gülich, 2003; LeBlanc et al., 2014; Allen et al., 2023; van Dulmen et al., 2007; Neiman, 2017). This simplification can also improve general LLM's performance on specialized tasks. Studies show that non-experts, with supervision, can generate high-quality data for machine learning, producing expert-quality annotations for tasks like identifying pathological patterns in CT lung scans and malware run-time similarity (O'Neil et al., 2017; VanHoudnos et al., 2017; Snow et al., 2008). Recent research has shown that LLMs can simplify complex medical documents, such as radiology reports, making them more accessible to laypersons. For instance, ChatGPT has been used to make radiology reports easier to understand, bridging the communication gap between medical professionals and patients (Jeblick et al., 2023; Lyu et al., 2023; Li et al., 2023). Ki and Carpuat (2025) also show that simplifying text is an effective way to improve machine translation quality. Inspired by these findings, we explore whether presenting expert-level information in a simpler language can improve the performance of general LLMs on tasks that typically require specialized knowledge, such as those involving medical data.

3 Methodology

In this section, we describe our prompting strategy. Figure 1 shows a high-level overview of our approach. Our strategy has three main components: 1) layperson summarization of the training dataset used as in-context examples; 2) "few-shot example retrieval," which is how we generate text embeddings to find relevant in-context examples; and 3) final expert summary prompt construction, which is how we integrate the layperson summaries and in-context examples to generate the final expert summary. We describe each component in the following subsections and how the three components are integrated into a unified prompt.

Stage I: Layperson Summary Generation. Based on Singhal et al. (2023), LLMs encode a large amount of medical knowledge during pre-

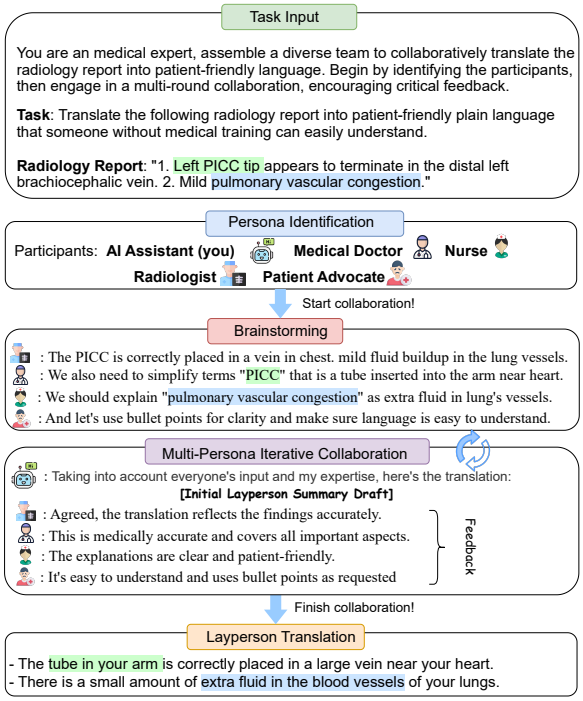

Figure 2: Stage I: Layperson Summarization Generation . An illustration of the layperson summary prompt used to generate layperson summaries for training examples. Disease observations are highlighted in different colors. The illustration shows a single example, with Instruction and Response sections repeated multiple times using few-shot in-context examples.

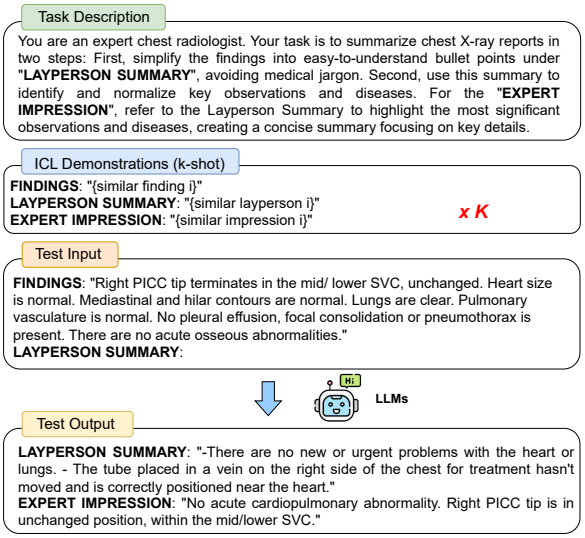

Figure 3: Stage III: Prompt Construction. Example of LaypersonPrompt for generating the final expert summary. This is the final prompt after finding in-context examples to generate the final expert summary (i.e., the Impression section).

training. Our layperson summarization step aims to encourage the model to actively use its internal knowledge to convert complex medical texts into more straightforward language, enhancing accessibility and understanding for individuals without medical expertise (Cao et al., 2020). For instance, rephrasing "pulmonary edema" as "fluid in the lungs" makes it more comprehensible. This approach not only helps to bridge the knowledge gap for laypeople but also plays an important role in helping models better understand and summarize medical content. Intuitively, by generating simplified summaries as an intermediate step, models can more effectively capture the semantic meaning of the texts (Liu et al., 2024; Sulem et al., 2018; Paetzold and Specia, 2016; Shardlow and Nawaz, 2019). In this context, we generate layperson summaries as an intermediate step for all training examples to enhance the generation of expert summaries.

To generate accurate layperson summaries, we employ a multi-round, multi-persona collaboration method inspired by the Task-Solving Agent framework (Wang et al., 2024). As shown in Figure 2, we begin with a radiology report impression and identify several expert roles, including a medical doctor, nurse, radiologist, patient advocate and AI assistant, to provide diverse insights. In the brainstorming phase, these experts clarify medical terminology and highlight key findings (e.g., "PICC," and "pulmonary vascular congestion"). Through iterative collaboration, they refine the content to ensure clarity and accuracy. Finally, the refined draft is transformed into a concise, accessible summary that effectively communicates essential medical details to patients. We then use this prompt to generate layperson summaries and store these summaries along with their corresponding Findings and Impressions as training triples, which are used as in-context examples. See Appendix **??** for a complete example of what the output looks like.

Stage II: Few-shot Example Retrieval Another key part of our system is retrieving similar examples from the training corpus to use as in-context examples. We focus on selecting a few high-quality examples to help the LLM generate more accurate and consistent summaries. To find the most relevant examples, we follow the text-only retrieval process of Wang et al. (2023). Specifically, we encode the *Findings* and *Impression* sections of each report using an encoder-decoder model, such as Clinical-T5 (Lehman and Johnson, 2023). Given an input report X, we compute its similarity to each training sample X_i using cosine similarity: $\text{Sim}(X, X_i) = \frac{E_X \cdot E_{X_i}}{\|E_X\| \|E_{X_i}\|}$, where E_X and E_{X_i} are the text embeddings. We then rank all train-

ing samples by similarity and retrieve the top-k most similar reports. Finally, we include the *Findings* and *Impression* sections from these reports as few-shot examples in the input prompt.

Stage III: Prompt Construction The final step in our pipeline involves prompting an LLM to generate an expert summary, following the generation of layperson summaries for all training examples, and identifying relevant in-context examples for development/test instances using few-shot example retrieval. The prompt comprises three main components: 1) Task Instruction; 2) In-context learning examples (ICL Demonstrations); and 3) the test input instance. An example is shown in Figure 3.

First, the Task Instruction directs the model to generate a layperson summary, followed by an expert impression. During data preparation, we use the prompt defined in Step 1 to generate layperson summaries for the training examples. This prompt is only used at that stage and is not applied at inference time. At inference time, given a new input instance with its Findings text, we use the Clincal T5 encoder and retrieval approach described in Step 2 to retrieve up to 32 similar examples from the training set. Each retrieved example includes: (1) the Findings, (2) the corresponding layperson summary (generated during data preparation), and (3) the expert Impression. These components are concatenated to form the in-context prompt. After the in-context examples, we append the input instance's Findings section, followed by the string "Layperson Summary:". The model is then prompted to generate the layperson summary for the input instance, and immediately afterward, the expert impression, both as part of a single prompt.

Enhanced Radiology Report Summarization. We incorporate both the layperson summary, which reflects the model's internal medical knowledge, and a set of retrieved few-shot examples, which provide external knowledge, to construct the prompt used at inference time. This prompt guides the language model in generating the expert impression for a given radiology report. We hypothesize that generating a layperson summary before the expert impression helps the model standardize the content of the Findings by first translating complex clinical language into general, simplified concepts. For example, conditions such as "pneumonia" and "bronchitis" may both be expressed as "infection of the lungs" in the lay summary. This abstraction reduces variation and enables the model to identify consistent patterns that link generalized expressions to expert-level impressions. Once the lay summary is generated, the model only needs to relate these general terms to the specific details in the Findings, similar to coreference resolution. This step encourages the model to infer underlying clinical meaning that is not always stated explicitly, effectively allowing it to "read between the lines." Without this intermediate layer of abstraction, the model must directly reason over more diverse and complex language in the Findings, making the task more challenging and less consistent.

4 Experimental Results

This section covers the datasets, evaluation metrics, overall results, and error analysis.

Datasets and baseline models. In this study, we evaluate our prompting method on three radiology reports summarization datasets. The MIMIC-III summarization dataset, as introduced by (Johnson et al., 2016; Chen et al., 2023b), contains 11 anatomy-modality pairs (i.e., 11 body parts and imaging modalities such as head-MRI and abdomen-CT). The dataset consists of train, validation, and test splits of 59,320, 7,413, and 6,531 findings-impression pairs, respectively. The MIMIC-III dataset only contains radiology reports without the original images. In contrast, the MIMIC-CXR summarization dataset (Johnson et al., 2019) is a multimodal summarization dataset containing findings and impressions from chest X-ray studies and corresponding chest X-ray images. It comprises 125,417 training samples, 991 validation samples, and 1624 test samples. Furthermore, we incorporate an out-of-institution test set of 1000 samples from the Stanford hospital(CheXpert) (Irvin et al., 2019) to assess out-of-domain generalization of models trained on MIMIC-CXR. Finally, in Appendix A.2, we also evaluate on the Multimodal Medical Question Summarization dataset (a non-radiology report dataset), showing our method can generalize beyond radiology images. We evaluate model performance using Llama-3.1-8B-Instruct (AI@Meta, 2024), Mistral-7B-Instruct-v0.3 (Jiang et al., 2023), and Gemma-2-9b-it (Team et al., 2024).

Evaluation Metrics. Performance is evaluated using the following metrics: BLEU4 (Papineni et al., 2002), ROUGE-L (Lin, 2004), Bertscore (Zhang et al., 2020), F1CheXbert (Delbrouck et al., 2022b),

	Model	BLEU4	ROUGEL	BERTScore	F1-cheXbert	F1-RadGraph	Average
Zero-Shot	Llama-3.1-8B-Instruct	3.37	15.72	39.74	65.39	16.45	28.13
	Mistral-7B-Instruct-v0.3	3.79	17.40	43.39	65.97	15.95	29.30
	Gemma-2-9b-it	3.47	15.66	37.23	66.80	19.28	28.49
Few-Shot	Llama-3.1-8B-Instruct	11.61	32.05	53.67	**70.23**	**30.62**	**39.64**
	Mistral-7B-Instruct-v0.3	**10.65**	29.32	**52.94**	56.14	21.84	34.18
	Gemma-2-9b-it	**11.64**	**30.82**	50.66	60.43	23.78	35.47
Few-Shot + Layperson	Llama-3.1-8B-Instruct	**11.67**	**32.46**	**54.56**	69.03	29.16	39.38
	Mistral-7B-Instruct-v0.3	8.67	**29.81**	51.58	**66.33**	**24.91**	**36.26**
	Gemma-2-9b-it	10.16	30.71	**52.95**	**68.42**	**27.44**	**37.94**

Table 1: Overall performance on the MIMIC CXR in-domain test dataset. We **bold** all results from our framework that outperform the few-shot and zero-shot baselines for the respective model (e.g., Llama vs. Llama).

	Model	BLEU4	ROUGEL	BERTScore	F1-cheXbert	F1-RadGraph	Average
Zero-Shot	Llama-3.1-8B-Instruct	3.11	21.47	46.10	73.14	9.58	30.68
	Mistral-7B-Instruct-v0.3	3.30	22.34	47.65	**72.41**	9.30	31.00
	Gemma-2-9b-it	2.52	19.80	41.21	**73.48**	10.16	29.43
Few-Shot	Llama-3.1-8B-Instruct	3.75	27.73	51.41	72.72	10.65	33.25
	Mistral-7B-Instruct-v0.3	3.13	25.78	49.37	62.30	10.60	30.24
	Gemma-2-9b-it	4.00	**25.82**	48.70	63.87	**10.78**	30.63
Few-Shot + Layperson	Llama-3.1-8B-Instruct	**6.91**	**27.81**	**51.94**	**74.01**	**11.37**	**34.41**
	Mistral-7B-Instruct-v0.3	**5.37**	**27.02**	**50.96**	**68.84**	**10.76**	**32.59**
	Gemma-2-9b-it	**4.31**	24.84	**48.85**	**69.41**	10.30	**31.54**

Table 2: Overall performance across the four prompts on the Stanford Hospital (out-of-domain) test set. The in-context examples for this dataset are from the MIMIC-CXR dataset. We **bold** all results from our framework that outperform the few-shot and zero-shot baselines for the respective model (e.g., Llama vs. Llama).

and F1RadGraph (Delbrouck et al., 2022a). Intuitively, BLEU4 measures the precision, while ROUGE-L assesses the recall of the n-gram overlap between the generated radiology reports and the original summaries. BERTScore calculates the semantic similarity between tokens of the reference summary and the hypothesis, where the hypothesis refers to the model-generated summary. F1CheXbert uses CheXbert (Smit et al., 2020), a Transformer-based model, to evaluate the clinical accuracy of generated summaries by comparing identified chest X-ray abnormalities in the generated reports to those in the reference reports. F1RadGraph, an F1-score style metric, leverages the RadGraph (Jain et al., 2021) annotation scheme to evaluate the consistency and completeness of the generated reports by comparing them to reference reports based on observation and anatomy entities.

Overall Results. Table 1 reports performance on the in-domain MIMIC-CXR dataset, comparing Zero-Shot, Few-Shot, and our Few-Shot + Layperson prompting strategies. The proposed Few-Shot + Layperson approach, motivated by doctor-patient communication, first prompts the model to generate a simplified summary before producing the expert-level Impression. This intermediary step consistently improves performance across metrics. For instance, Llama-3.1-8B improves in BLEU4 (11.61 $\rightarrow$ 11.67), ROUGE-L (32.05 $\rightarrow$ 32.46), and BERTScore (53.67 $\rightarrow$ 54.56). Similarly, Mistral-7B and Gemma-2-9B show improvements in average performance, with Mistral reaching 36.26 and Gemma 37.94, both surpassing their standard Few-Shot baselines. These results suggest that layperson guidance supports clearer and more consistent generation of radiology Impressions.

As shown in Table 2, the Few-Shot + Layperson approach also improves performance on the out-of-domain Stanford Hospital dataset. Llama-3.1-8B-Instruct achieves the highest F1-cheXbert (74.01) and BERTScore (51.94), while Mistral-7B and Gemma-2-9B show gains in BLEU4, ROUGE-L, and F1-RadGraph. Compared to the standard Few-Shot setup, all three models show consistent improvements in overall average score, highlighting the robustness of our approach to distribution shifts and unseen reporting styles.

The results on the MIMIC-III dataset are shown in Table 3. The Few-Shot + Layperson method consistently outperforms both Zero-Shot and standard Few-Shot prompting across most models and metrics. For instance, Llama-3.1-8B-Instruct im-

	Model	BLEU4	ROUGEL	BERTScore	F1-cheXbert	F1-RadGraph	Average
Zero-Shot	Llama-3.1-8B-Instruct	5.34	18.77	42.62	51.83	18.43	27.40
	Mistral-7B-Instruct-v0.3	5.94	19.82	45.41	53.48	18.09	28.55
	Gemma-2-9b-it	4.58	18.34	41.07	52.03	18.06	26.82
Few-Shot	Llama-3.1-8B-Instruct	7.87	23.42	47.18	53.91	20.93	30.66
	Mistral-7B-Instruct-v0.3	9.80	**24.45**	**49.87**	**55.15**	19.33	**31.72**
	Gemma-2-9b-it	7.79	23.08	45.61	53.78	20.04	30.06
Few-Shot + Layperson	Llama-3.1-8B-Instruct	**12.68**	**26.13**	**50.32**	**55.70**	**23.98**	**33.76**
	Mistral-7B-Instruct-v0.3	**10.47**	22.51	49.15	49.07	**19.37**	30.11
	Gemma-2-9b-it	**11.59**	**25.57**	**50.24**	**54.56**	**22.28**	**32.85**

Table 3: Overall performance across the four prompts on MIMIC III. We **bold** all results from our framework that outperform the few-shot and zero-shot baselines for the respective model (e.g., Llama vs. Llama).

		BLEU4	ROUGEL	BERTScore	F1-cheXbert	F1-RadGraph	Average
Original	Few-Shot	12.81	37.55	54.71	**67.67**	34.95	41.538
	Few-Shot + Layperson	**13.91**	**37.60**	56.76	67.46	**35.37**	**42.22**
Mask	Few-Shot	0.60	6.67	16.35	28.00	6.60	11.64
	Few-Shot + Layperson	**5.38**	**25.05**	**45.63**	**45.70**	**20.60**	**28.47**
finetuning	Base	0.59	10.06	19.91	24.62	2.45	11.526
	Layperson	**13.90**	**40.60**	**56.49**	**42.80**	**33.65**	**37.488**

Table 4: Overall performance of the Llama-3.1-8B-Instruct model on the MIMIC-CXR valid dataset across three settings: **Original** (unaltered input), **Mask** (Findings entities replaced with gibberish), and **Finetuning** (instruction-tuned models evaluated on masked input). **Base** denotes general instruction tuning. **Layperson** indicates instruction tuning with `<think>`layperson summary`</think>` prepended before the expert summary. Bold values indicate improvements over the respective baselines.

proves BLEU4 from 7.87 to 12.68, ROUGE-L from 23.42 to 26.13, and F1-RadGraph from 20.93 to 23.98. Similarly, Gemma-2-9B-it achieves gains in BLEU4 (11.59 vs. 7.79), ROUGE-L (25.57 vs. 23.08), and F1-RadGraph (22.28 vs. 20.04). Mistral-7B also shows a competitive BLEU4 improvement (10.47 vs. 9.80). These results demonstrate that incorporating layperson summaries helps LLMs better abstract and align key medical concepts, even across datasets with different styles and terminology. Overall, the Few-Shot + Layperson strategy improves generalization, reinforcing its effectiveness for radiology report summarization in varied clinical settings. We also conduct significance testing to support these findings; detailed results are provided in the Appendix.

Instruction Tuning with Layperson Prompt. We adopt the layperson prompt format for instruction tuning. Inspired by Wu et al. (2025), we treat the layperson summary as an explicit intermediate step that guides the model to "think aloud" before generating the expert summary. Specifically, the model is trained to take the Findings as input and generate a layperson summary enclosed in <think>...</think> tags, followed by the expert Impression. This encourages the model to first normalize and simplify key observations, improving both reasoning and final output quality. As shown in Table 5, instruction tuning with layperson prompts leads to consistent performance gains across all datasets and models. On average, each model improves by 3–5 points over its base counterpart, with the most notable gains on out-of-domain and low-resource settings. These results highlight the effectiveness of structured simplification as a useful training signal for improving clinical summarization. Full metric results are provided in the Appendix.

	Model	Test	Hidden	MIMIC-III
Base	Llama-3.1	44.05	31.89	13.47
	Mistral-8B	42.83	27.13	31.62
	Gemma2	46.53	30.01	33.45
Layperson	Llama-3.1	**47.89**	**35.08**	**36.81**
	Mistral-8B	**47.87**	**34.91**	**32.32**
	Gemma2	**48.02**	**34.50**	**34.39**

Table 5: Average performance across three evaluation sets: "Test" (MIMIC-CXR in-domain), "Hidden" (MIMIC-CXR out-of-domain), and "MIMIC-III." Each value is the average of five metrics, such as BLEU4, ROUGEL, BERTScore, F1-cheXbert, and F1-RadGraph. Bold values mark improvements over the corresponding base model.

Error Analysis and Discussion. We analyze the impact of adding a layperson summary step by conducting an error analysis of the Llama-3.1-8B-

Instruct model on the MIMIC-CXR validation set. Specifically, we compare two prompting strategies: the standard Few-Shot method and our proposed Few-Shot + Layperson approach. The goal is to assess whether introducing simplified, patient-friendly language before the expert impression helps the model better interpret complex or unfamiliar medical terminology. Our intuition is based on the observation that when language models encounters highly specialized or unknown terms, they may misinterpret the context or even refuse to process the request. To address this, we aim to steer the model's attention towards the underlying clinical context by embedding layperson translation in the prompt. This strategy helps the model focus on semantic content rather than being distracted by domain-specific jargon. The approach parallels how humans often rephrase complex information into simpler terms to facilitate comprehension.

To simulate real-world challenges where language models may encounter unfamiliar or ambiguous medical terms, we designed a robustness test by replacing key medical entities with nonsensical "gibberish" tokens. Using MedSpaCy (Eyre et al., 2022), we first identified clinical entities in the Findings section, and then substituted each with a random string (e.g., "pleural effusions" becomes "abcdefg"). This setup allows us to evaluate whether the inclusion of layperson summaries can help the model generate coherent and accurate expert impressions despite encountering unknown terminology. We hypothesize that the simplified layperson summary, combined with the surrounding context in the Findings, encourages the model to normalize unfamiliar terms into more accessible language, thereby improving its overall performance. Results of this experiment are shown in Table 4. The "Mask" section reports performance on the modified examples for both the baseline (Llama-3.1-8B-Instruct + Few-Shot) and our method (Llama-3.1-8B-Instruct + Few-Shot + Layperson). We also include performance on the original, unmodified data for comparison.

Our findings show that the Few-Shot + Layperson approach consistently outperforms the baseline. In particular, when key terms are masked, baseline performance drops sharply (ROUGE-L: 37.55 $\rightarrow$ 6.67), indicating its difficulty handling unfamiliar input. In contrast, our method is more robust under these conditions (ROUGE-L: 37.60 $\rightarrow$ 25.05), suggesting that the added layperson summary helps the model generalize better by guiding it toward the core clinical meaning. When encountering such unknown or nonsensical terms, the standard Few-Shot model often fails to generate a meaningful summary and instead requests clarification. For example, it usually simply state, "I can't fulfill that request." We provide an example below:

Radiology Report Summarization

Masked Radiology Finding:
"There are moderate bilateral **entity1** with overlying **entity2** and possible consolidation. **entity3** prominence of **entity4** suggests mild **entity5**."

Ground Truth Impression:
"Bilateral pleural effusions, cardiomegaly, mild edema indicating fluid overload."

Layperson Summary:
"Moderate fluid around both lungs with slight lung changes and mild inflammation. Some underlying issue with the lung tissue that's not clearly visible. "

Few-Shot: "I can't fulfill that request."

Few-Shot + Layperson:
"Bilateral lung consolidation with mild pulmonary edema and cardiomegaly."

Additionally, instruction tuning with layperson prompts (**Layperson**) achieved strong performance on masked inputs, outperforming all baselines with a notable jump in all metrics (e.g., BLEU4: 13.90 vs. 0.59 for Base and ROUGEL: 10.06 vs. 40.60). These results show that the layperson prompting strategy, which guides the model to first generate a simplified summary, helps improve its reasoning ability and generalization when dealing with unfamiliar or ambiguous clinical input. This leads to more accurate expert summaries even when key clinical entities are masked or ambiguous.

5 Conclusion

This paper introduces a simple and effective prompting strategy inspired by doctor–patient communication. The method guides the model to first generate a layperson summary before the expert impression, helping it reason through and organize complex clinical content. It consistently improves performance across MIMIC-CXR, CheXpert, and MIMIC-III, especially on out-of-domain data. We also extend this idea to instruction tuning by using <think>...</think> tags to simulate intermediate reasoning. This strategy improves generalization and robustness for both prompting and instruction tuning. Future work will explore improved prompt design, better token efficiency, and larger models with extended context capacity.

6 Limitation

While our approach introduces a novel patient-centered prompting framework, it is essential to contextualize certain design decisions that may be perceived as limitations. For instance, we do not include an explicit ablation comparing layperson-style explanations to expert-style explanations. This is because our goal is not to evaluate explanation format in isolation but rather to demonstrate the utility of patient-aligned communication strategies as a whole. Prior work has already explored expert reasoning prompts in clinical inference, and our contribution is in showing that reframing with accessible language improves performance even when other aspects remain constant.

We also chose to present prompt examples in the appendix to preserve space in the main paper. However, the core formatting and structure are consistent with standard prompting techniques and are thoroughly described, allowing for replication. Additional examples can be easily found in supplementary materials or future versions of the work, depending on the audience's familiarity with prompting conventions.

Regarding visual presentation, we recognize that Figure 2 provides a detailed overview of the LaypersonPrompt pipeline. We intentionally opted for a single comprehensive diagram to emphasize the modular and interconnected nature of the system. While splitting the figure could improve visual simplicity, we believe the current design communicates the whole process clearly to readers familiar with prompt-based systems.

As for qualitative analysis, our primary focus was to evaluate the effectiveness of layperson prompting quantitatively and through human judgments of readability, helpfulness, and correctness. Future work could benefit from a more in-depth qualitative error analysis, particularly in identifying where lay summaries may introduce subtle distortions. However, our human evaluation already captures many of these concerns by assessing whether outputs remain faithful and informative, even when simplified.

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Another interesting direction for future work is to explore whether the improvements we observe are specific to layperson-style summaries or reflect broader benefits of intermediate summarization. While our focus is on patient-aligned communication strategies, which are grounded in prior work and practical relevance, it would be valuable to investigate how different explanation styles. We expect the simplification aspect to be particularly beneficial for general-purpose models, but additional analysis could further clarify these dynamics.

Finally, while ethical considerations such as hallucination or oversimplification are relevant for any language generation method, our approach explicitly prioritizes clarity and factual accuracy through prompt construction and human review. We see our

method as a step toward more responsible AI communication, and further refinement can continue to balance accessibility with fidelity.

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7 Ethics Statement

In this work, we have introduced our Layperson Summary Prompting strategy, inspired by doctor-patient communication techniques. This approach aims to simplify complex medical findings into layperson summary first, then uses this simplified information to generate accurate expert summaries. However, it is important to address the ethical implications of using LLMs in this context. LLMs used for radiology report summarization can produce errors or biased outputs if the training data is of low quality or representative. These models also can be wrong, and such biases can lead to unfair outcomes and exacerbate health disparities. Therefore, radiologists should use AI-generated summaries as supportive tools, retaining control over clinical decisions. AI should be seen as an information resource to reduce time and cognitive effort, aiding in information retrieval and summarization, rather than as an interpretative agent providing clinical decisions or treatment recommendations.

Additionally, integrating AI into clinical practice raises significant ethical considerations regarding patient privacy, data security, and informed consent. Using large volumes of sensitive patient data for training AI models necessitates stringent measures to protect patient rights and ensure data confidentiality. Ethical principles such as fairness, accountability, and transparency should guide the deployment of AI technologies in healthcare. These principles help ensure that AI systems are used responsibly and that the benefits of AI are distributed equitably among all stakeholders. Furthermore, potential risks associated with AI implementation include perpetuating existing biases, privacy breaches, and the misuse of AI-generated data, necessitating careful consideration and proactive management (Yildirim et al., 2024).

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A Appendix

A.1 Baseline and Implementation Details

For our baseline approach, we adopt a prefixed zero-shot prompting strategy (Duan et al., 2019; Zhao and Schütze, 2021), which prepended a brief instruction to the beginning of a standard null prompt. We use the instruction, "You are an expert chest radiologist. Your task is to summarize the radiology report findings into an impression with minimal text". This instruction provides the model with a fundamental context for the RRS task. Immediately following the instruction, we append the specific findings from the report and then prompt the model with "IMPRESSION:" to initiate the generation process. Additionally, we investigate the effectiveness of few-shot ICL prompts with up to 32 similar examples, using the same template as our Few-Shot prompting method, which is not incorporating the intermediate reasoning step (i.e., without the layperson summary).

We conduct experiments with three open-source LLMs: Llama-3.1-8B-Instruct (AI@Meta, 2024), Mistral-7B-Instruct-v0.3 (Jiang et al., 2023), and Gemma-2-9b-it (Team et al., 2024). All experiments were conducted using two Nvidia A6000 GPUs. For the few-shot model, the average running

time is around 2 hours. In contrast, the Few-Shot + Layperson models have an average running time of around 8 hours. Processing the MIMIC data with 24 examples takes approximately 36 hours. In our work, all these models have been implemented using the Hugging Face framework (Wolf et al., 2019). Specifically, the Llama-3.1-8B-Instruct, Mistral-7B-Instruct-v0.3, and Gemma-2-9b-it are reported to perform strongly in common sense reasoning and problem-solving ability (Zhu et al., 2023). To select the best parameters in our study, we employed ROUGE-L and F1RadGraph metrics on the validation set. These metrics help determine the most effective parameter settings for the model. The ROUGE-L metric focuses on the longest common subsequence and is particularly suitable for evaluating the quality of text summaries. On the other hand, the F1RadGraph is specifically designed to assess the accuracy of extracting and summarizing key information from radiology reports by analyzing entity similarities.

For optimizing our model's hyper-parameters, we employed a random search strategy on valid dataset. This involved experimenting with various settings: the number of prepended similar examples was varied across a set 2, 8, 12, 16, 24, 32, and these examples were matched using different modality embeddings (text, image, or multimodal), all while employing the same template. We find that for the Llama-3.1-8B-Instruct, the best performance is achieved with 32 examples for both Few-Shot and Few-Shot + Layperson prompting methods. Additionally, we experimented with temperature settings ranging from 0.1 to 0.9, top p values set between 0.1 and 0.6, and top k values of 10, 20, and 30. Through this exploratory process, we identified the most effective settings as a temperature of 0.2, a top p value of 0.5, and a top k setting of 20. We adopt the same hyperparameters for all experiments. These settings yielded the best results in our evaluations. It's significant to note the impact of the "temperature" parameter on the diversity of the model's outputs. Higher temperature values add more variation, introducing a greater level of randomness into the content generated. This aspect is especially valuable for adjusting the output to meet specific requirements for creativity or diversity.

To ensure compatibility with the model's capabilities, we restricted the length of the prompt (which includes the instruction, input, and output instance) to 7800 tokens. This limit was set to prevent exceeding the model's maximum sequence length of 8,192 tokens for Llama-3.1-8B-Instruct, Mistral-7B-Instruct-v0.3, and Gemma-2-9b-it. In cases where prompts exceeded this length, they were truncated from the beginning, ensuring that essential information and current findings were preserved. Moreover, we constrained the generated output to a maximum of 256 tokens to strike a balance between providing detailed content and adhering to the model's constraints. This approach was key in optimizing the effectiveness of summarization within the operational limits of the 7B models. Table 6 shows the prompt lengths for different numbers of examples used in our study. For the MIMIC-III dataset, using 32 examples exceeds the 7800 token limit, so we opted to use only 16 examples.

A.2 Medical Question Summarization Results

Furthermore, we assess an additional dataset, the Multimodal Medical Question Summarization (MMQS) Dataset, introduced by Ghosh et al. (2024). This dataset contains 3,015 multimodal medical queries, each accompanied by visual cues and expert-annotated gold summaries that reference various body parts (e.g., skin, eyes, ears). As shown in Table 7, we observe consistent patterns across the three prompting regimes.

When we compare the standard Few-Shot setting to our Few-Shot+Layperson approach, every model sees a clear uplift in performance. Llama-3.1-8B-Instruct's average score jumps from 30.43 to 42.09, a gain of 11.66 points (a 38 percent relative improvement). This improvement is driven by more than doubling its BLEU, 4 score—from 10.09 to 20.84, as well as substantial increases in ROUGE-L (31.52 to 43.54) and BERTScore (49.68 to 61.89). In practice, the layperson prompt helps Llama-3.1 generate summaries that are not only lexically richer but also more semantically aligned and fluent.

Mistral-7B-Instruct-v0.3 also benefits, albeit more modestly: its average climbs from 35.55 to 38.34 (an increase of 2.79 points, or roughly 7.8 percent). Its BLEU-4 rises from 13.57 to 16.83, ROUGE-L from 37.16 to 39.80, and BERTScore from 55.93 to 58.40. These gains demonstrate that even already strong few-shot models can produce clearer, more coherent medical summaries when guided to use non-expert language.

The largest relative boost is seen with Gemma-2-9b-it, whose average soars from 23.45

		2	8	12	16	24	32
MIMIC-CXR	Few-Shot	643	1285	1713	2141	2994	3850
	Few-Shot + Layperson	889	1826	2452	3084	4333	5587
MIMIC-III	Few-Shot	1035	2500	3474	4451	6405	8359
	Few-Shot + Layperson	1340	3277	4565	5856	8442	11025

Table 6: Average Token of Prompts.

to 37.55, an absolute gain of 14.10 points, equivalent to a 60 percent improvement. Its BLEU-4 score leaps from 4.01 to 16.93, ROUGE-L climbs from 26.14 to 38.25, and BERTScore jumps from 40.21 to 57.47. This dramatic uplift underscores how layperson-focused prompting can unlock substantial performance gains for models that struggle under a standard few-shot regime.

Overall, while Few-Shot priming delivers a strong baseline boost for all three models, our Few-Shot + Layperson method consistently amplifies that effect—especially in BLEU-4 and BERTScore—and narrows the performance disparities. By tailoring summaries to align with non-expert understanding, we achieve more accurate, coherent, and accessible medical question summaries across the board.

A.3 Significance Testing Results.

To assess the robustness of our method, we applied paired permutation tests following established NLP practices (Dror et al., 2018; Zmigrod et al., 2022). We compared the Layperson prompting strategy against the standard Few-Shot baseline across all datasets and metrics. Our updated tests confirm that the Layperson method yields consistent and statistically significant improvements:

On the MIMIC-CXR dataset (Table 1), the Layperson method outperforms the baseline in 9 out of 15 metric comparisons. On the Stanford hidden test set (Table 2), it shows consistent gains across 13/15 comparisons. On the MIMIC-III dataset (Table 3), the method achieves improvements in 12 out of 15 cases. In the masked robustness experiment simulating corrupted clinical input (Table 4), the Layperson strategy performs better in all 5 metrics. Finally, on the multimodal medical question summarization dataset (Table 7), it outperforms the baseline in 9 out of 9 comparisons. Across a total of 59 metric comparisons, our approach outperforms the baseline in 48 cases, 45 of which are statistically significant ($p < 0.05$). These results confirm the effectiveness of the Layperson prompting strategy in enhancing model reasoning and generalization across diverse clinical scenarios.

A.4 More Error Analysis

Notably, when encountering unknown terms, the standard Few-Shot model tends to produce longer summaries that often rephrase or repeat content from the Findings and occasionally introduce hallucinated information. In contrast, our Few-Shot + Layperson approach explicitly guides the model to focus on simplified, high-level clinical meaning. As shown in the example below, the Few-Shot model failed to capture the key observation and even fabricated a term such as "xenosign." In comparison, our approach correctly generated the summary "No acute cardiopulmonary process. Normal heart size," which closely matches the ground truth. An illustrative example is provided below:

Radiology Report Summarization

Masked Radiology Finding:
"Frontal and lateral views of the **entity1**. The **entity2** are clear of focal consolidation or **entity3**. Opacities at the cardiophrenic angles bilaterally are thought to represent prominent **entity4**."

Ground Truth Impression:
"No acute cardiopulmonary process."

Layperson Summary:
"The chest X-rays show clear lungs without any solid masses. Small opacities at the lung edges likely represent normal fat or muscle. Overall, the heart and chest structures appear normal."

Few-Shot:
"Clear lungs without consolidation. A subtle finding, termed "xenosign", is noted at the left lung base. Bilateral opacities are likely due to fat."

Few-Shot + Layperson:
"No acute cardiopulmonary process. Normal heart size."

A.5 Instruction Tuning Experiments

Here are our instruction-tuning results (Tables 9, 10, and 11). The layperson-tuned models outperform their base versions on every metric across in-domain, out-of-domain tasks. This demonstrates

		BLEU4	ROUGEL	BERTScore	Average
Zero-Shot	Llama-3.1-8B-Instruct	1.25	8.19	16.41	8.62
	Mistral-7B-Instruct-v0.3	3.17	15.93	35.31	18.14
	Gemma-2-9b-it	1.22	9.72	20.01	10.32
Few-Shot	Llama-3.1-8B-Instruct	10.09	31.52	49.68	30.43
	Mistral-7B-Instruct-v0.3	13.57	37.16	55.93	35.55
	Gemma-2-9b-it	4.01	26.14	40.21	23.45
Few-Shot + Layperson	Llama-3.1-8B-Instruct	**20.84**	**43.54**	**61.89**	**42.09**
	Mistral-7B-Instruct-v0.3	**16.83**	**39.80**	**58.40**	**38.34**
	Gemma-2-9b-it	**16.93**	**38.25**	**57.47**	**37.55**

Table 7: Performance of models on Multimodal Medical Question Summarization (MMQS) Dataset.

Model	Dataset	BLEU4	ROUGEL	BERTScore	F1-cheXbert	F1-RadGraph
llama3	MIMIC-CXR	*** (0.0000)	*** (0.0000)	*** (0.0000)	*** (0.0000)	*** (0.0000)
llama3	MIMIC-CXR-Hidden	*** (0.0000)	*** (0.0000)	(0.1232)	** (0.0026)	(0.0874)
llama3	MIMIC-III	*** (0.0000)	*** (0.0000)	*** (0.0000)	*** (0.0000)	*** (0.0000)
llama3	MMQS	*** (0.0000)	*** (0.0000)	*** (0.0000)	N/A	N/A
ministral	MIMIC-CXR	*** (0.0000)	*** (0.0000)	*** (0.0000)	*** (0.0000)	*** (0.0000)
ministral	MIMIC-CXR-Hidden	*** (0.0000)	*** (0.0000)	*** (0.0000)	** (0.0017)	** (0.0013)
ministral	MIMIC-III	*** (0.0000)	*** (0.0000)	*** (0.0000)	*** (0.0000)	*** (0.0000)
ministral	MMQS	*** (0.0000)	*** (0.0000)	*** (0.0000)	N/A	N/A
gemma	MIMIC-CXR	*** (0.0000)	*** (0.0000)	*** (0.0000)	*** (0.0000)	*** (0.0000)
gemma	MIMIC-CXR-Hidden	*** (0.0000)	*** (0.0000)	(0.6401)	* (0.0188)	(0.1950)
gemma	MIMIC-III	*** (0.0000)	*** (0.0000)	* (0.0111)	(0.0806)	*** (0.0000)
gemma	MMQS	*** (0.0000)	*** (0.0000)	*** (0.0000)	N/A	N/A

Table 8: Significance markers: *** $p < .001$, ** $p < .01$, * $p < .05$; note that the MMQS dataset is not radiology related, so F1-chexbert and F1-radgraph are not applicable.

that layperson-focused fine-tuning yields more accurate, easy-to-understand medical summaries.

A.6 Layperson Summary Prompting

This template guides the AI, doctors, and patient advocates to work together in clear steps to turn a technical radiology report into simple bullet points. At each stage, experts check the accuracy and suggest plain-language fixes so the final summary is both correct and easy to understand, as shown in Figure 4

	Model	BLEU4	ROUGEL	BERTScore	F1-cheXbert	F1-RadGraph	Average
Base	Llama-3.1	18.15	40.73	58.40	67.33	35.65	44.05
	Mistral-7B	13.90	39.53	58.36	67.13	35.23	42.83
	Gemma2	20.15	43.27	61.02	70.05	38.16	46.53
Instruction-Tuned (Layperson)	Llama-3.1	**19.33**	**44.04**	**62.53**	**74.49**	**39.07**	**47.89**
	Mistral-7B	**20.67**	**43.15**	**62.01**	**75.13**	**38.37**	**47.87**
	Gemma2	19.66	**44.02**	**62.10**	**75.44**	**38.88**	**48.02**

Table 9: Instruction-tuning performance on the MIMIC-CXR in-domain test set. "Base" refers to the pretrained models without further tuning; "Instruction-Tuned (Layperson)" are the same models fine-tuned on layperson-style prompts. Bold indicates where instruction tuning yields gains over the base model.

	Model	BLEU4	ROUGEL	BERTScore	F1-cheXbert	F1-RadGraph	Average
Base	Llama-3.1	5.33	28.08	50.56	63.93	11.55	31.89
	Ministral-8B	2.16	23.86	45.88	54.45	9.29	27.13
	Gemma2	4.79	27.98	48.59	57.77	10.94	30.01
Instruction-Tuned (Layperson)	Llama-3.1	**5.34**	**32.27**	**54.52**	**70.57**	**12.71**	**35.08**
	Ministral-8B	**5.64**	**32.42**	**54.84**	**69.51**	**12.15**	**34.91**
	Gemma2	**5.37**	**31.75**	**53.58**	**69.41**	**12.37**	**34.50**

Table 10: Instruction-tuning performance on the MIMIC-CXR hidden (out-of-domain) test set. "Base" refers to the pretrained models without further tuning; "Instruction-Tuned (Layperson)" are the same models fine-tuned on layperson-style prompts. Bold indicates where instruction tuning yields gains over the base model.

		BLEU4	ROUGEL	BERTScore	Average
Base	Llama-3.1	3.30	18.03	33.69	18.34
	Mistral-7B-Instruct-v0.3	3.81	19.91	38.45	20.72
	Gemma-2-9b-it	7.66	24.39	35.64	22.56
Instruction-Tuned (Layperson)	Llama-3.1	**28.07**	**48.45**	**65.40**	**47.31**
	Mistral-7B-Instruct-v0.3	**5.54**	**29.32**	**48.10**	**27.65**
	Gemma-2-9b-it	**15.89**	**33.23**	**46.79**	**31.97**

Table 11: Instruction-tuning performance on the MMQS Dataset (ClipSyntel). "Base" refers to the pretrained models without further tuning; "Instruction-Tuned (Layperson)" are the same models fine-tuned on layperson-style prompts. Bold indicates gains over the base model.

Task Instruction

When faced with a task, begin by identifying the participants who will contribute to solving the task. Then, initiate a multi-round collaboration process until a final solution is reached. The participants will provide critical comments and detailed suggestions whenever necessary to ensure the translation is accurate and easily understandable.
Here is a example:
Example Task: Translate the following radiology report into plain language that someone without medical training can easily understand.

Radiology Report:

- Left PICC tip appears to terminate in the distal left brachiocephalic vein.
- Mild pulmonary vascular congestion.
- Interval improvement in aeration of the lung bases with residual streaky opacity likely reflective of atelectasis.
- Interval resolution of the left pleural effusion.

Participants: AI Assistant (you); Medical Doctor; Patient Advocate; Radiologist; Nurse; Respiratory Therapist

Start collaboration!
Radiologist: The PICC line is correctly placed in a large vein in the chest. There's mild fluid buildup in the lung vessels. The lower parts of the lungs are improving but still show some areas not fully expanded. The fluid around the left lung has resolved.
Medical Doctor: Yes, let's break it down point by point to ensure accuracy.
Respiratory Therapist: We should explain "atelectasis" as areas of the lung not fully inflated and "pulmonary vascular congestion" as extra fluid in the lung's blood vessels.
Nurse: We also need to simplify terms like "PICC," and "brachiocephalic vein". Clarify that the "PICC line" is a tube inserted into the arm that reaches a large vein near the heart.
Respiratory Therapist: Also, explain "pulmonary vascular congestion" and "pleural effusion" in simple terms related to lung function.
Patient Advocate: And let's use bullet points for clarity and make sure the language is easy to understand.
AI Assistant (you): Understood. Taking into account everyone's input and my expertise, here's the translation:

- The tube in your arm is correctly placed in a large vein near your heart.
- There's a small amount of extra fluid in the blood vessels of your lungs.
- The lower parts of your lungs are getting better, but some small areas aren't fully expanded yet.
- The fluid that was around your left lung has cleared up.

Medical Doctor: This is medically accurate and covers all important aspects.
Radiologist: Agreed, the translation reflects the findings accurately.
Nurse: The explanations are clear and patient-friendly.
Respiratory Therapist: Good job explaining lung-related terms in simple language.
Patient Advocate: It's easy to understand and uses bullet points as requested.

Finish collaboration!

Final answer:

- The tube in your arm is correctly placed in a large vein near your heart.
- There's a small amount of extra fluid in the blood vessels of your lungs.
- The lower parts of your lungs are getting better, but some small areas aren't fully expanded yet.
- The fluid that was around your left lung has cleared up.

—
Now, identify the participants and collaboratively solve the following task step by step. After **Finish collaboration!**, remember to conclude your final solution in this exact format: **"Final answer: [Your solution here]"**

Task: Translate the following radiology report into patient-friendly plain language that someone without medical training can easily understand.

Radiology Report: "{radiology_report}"

Figure 4: Layperson Summarization Generation prompt