Retrieve, Reason, and Refine:
Generating Accurate and Faithful Patient Instructions

Fenglin Liu¹, Bang Yang², Chenyu You³, Xian Wu⁴, Shen Ge⁴, Zhangdaihong Liu¹,⁵
Xu Sun⁶, Yang Yang⁷, David A. Clifton¹,⁵

¹Department of Engineering Science, University of Oxford  ²School of ECE, Peking University
³Department of Electrical Engineering, Yale University  ⁴Tencent JARVIS Lab, China
⁵Oxford-Suzhou Centre for Advanced Research, China
⁶MOE Key Lab of Computational Linguistics, School of Computer Science, Peking University
⁷School of Public Health, Shanghai Jiao Tong University School of Medicine, China

{fenglin.liu, david.clifton}@eng.ox.ac.uk, {bangyang, xusun}@pku.edu.cn
chenyu.you@yale.edu, jessie.liu@oxford-oscar.cn
{kevinxwu, shenge}@tencent.com, emma002@sjtu.edu.cn

Abstract

The “Patient Instruction” (PI), which contains critical instructional information provided both to carers and to the patient at the time of discharge, is essential for the patient to manage their condition outside hospital. An accurate and easy-to-follow PI can improve the self-management of patients which can in turn reduce hospital readmission rates. However, writing an appropriate PI can be extremely time-consuming for physicians, and is subject to being incomplete or error-prone for (potentially overworked) physicians. Therefore, we propose a new task that can provide an objective means of avoiding incompleteness, while reducing clinical workload: the automatic generation of the PI, which is imagined as being a document that the clinician can review, modify, and approve as necessary (rather than taking the human “out of the loop”). We build a benchmark clinical dataset and propose the Re³Writer, which imitates the working patterns of physicians to first retrieve related working experience from historical PIs written by physicians, then reason related medical knowledge. Finally, it refines the retrieved working experience and reasoned medical knowledge to extract useful information, which is used to generate the PI for previously-unseen patient according to their health records during hospitalization. Our experiments show that, using our method, the performance of five different models can be substantially boosted across all metrics, with up to 20%, 11% and 19% relative improvements in BLEU-4, ROUGE-L and METEOR, respectively. Meanwhile, we show results from human evaluations to measure the effectiveness in terms of its usefulness for clinical practice.

1 Introduction

At the time of discharge to home, the Patient Instruction (PI), which is a rich paragraph of text containing multiple instructions, is provided by the attending clinician to the patient or guardian. PI

*Equal contribution.
†Corresponding authors.
3The code is available at [https://github.com/AI-in-Health/Patient-Instructions](https://github.com/AI-in-Health/Patient-Instructions)
Figure 1: Two examples of the Patient Instruction written by physicians which guide the patients how to manage their conditions after discharge based on their health records during hospitalization.

| Input (Patient's Health Records) | Output (Patient Instruction) |
|----------------------------------|-----------------------------|
| Admission Notes | Patient 1: Please shower daily including washing incisions gently with mild soap, no baths or swimming. [...] please no lotions, cream, powder, or ointments to incisions [...] females: please wear bra to reduce pulling on incision. avoid rubbing on lower edge. |
| Nursing Notes | Patient 2: You were admitted for bleeding from an ulcer in your stomach. This ulcer is at least partially caused by naproxen. You should stop taking naproxen and take only tylenol for pain. [...] you are scheduled to get a repeat endoscopy next week. Prior to the procedure do not have anything to drink or eat after midnight. |
| Radiology Notes | |
| Physician Notes | |
| Medications | |

is used for the purpose of facilitating safe and appropriate continuity of care [6, 37, 43]. As a result, the PI has significant implications for patient management and good medical care, lowering down the risks of hospital readmission, and improving the doctor-patient relationship. As shown in Figure 1, a PI typically contains the following three main components from patients’ perspective [16, 45]: (1) What is my main health condition? (i.e., why was I in the hospital?) (2) What do I need to do? (i.e., how do I manage at home, and how should I best care for myself?) (3) Why is it important for me to do this? Of the above, the second section is often considered to be the most important information. For example, when a patient has had surgery while in the hospital, the PI might tell the patient to keep the wound away from water to avoid infection.

Currently, the following skills are needed for physicians to write a PI [37, 43, 6]: (1) thorough medical knowledge for interpreting the patient’s clinical records, including diagnosis, medication, and procedure records; (2) skills for carefully analyzing the extensive and complex patient’s data acquired during hospitalization, e.g., admission notes, nursing notes, radiology notes, physician notes, medications, and laboratory results; (3) the ability of extracting key information and writing instructions appropriate for the lay reader. Therefore, writing PIs is a necessary but time-consuming task for physicians, exacerbating the workload of clinicians who would otherwise focus on patient care [50, 41]. Besides, physicians need to read lots of patient’s health records in their daily work, resulting in substantial opportunity for incompleteness or inappropriateness of wording [44, 51]. Statistically, countries with abundant healthcare resources, such as the United States, have up to 54% of physicians experiencing some sign of burnout in one year of study [42], which is further exacerbated in countries with more tightly resource-constrained healthcare resources.

The overloading of physicians is a well-documented phenomenon [44, 51], and AI-related support systems that can partly automate routine tasks, such as generation of PIs for modification/approval by clinicians is an important contribution to healthcare practice. To this end, we propose the novel task of automatic PI generation, which aims to generate an accurate and fluent textual PI given input health records of a previously-unseen patient during hospitalization. In this way, it is intended that physicians, given the health records of a new patient, need only review and modify the generated PI, rather than writing a new PI from scratch, significantly relieving the physicians from the heavy workload and increasing their time and energy spent in meaningful clinical interactions with patients. Such endeavors would be particularly useful in resource-limited countries [46].

In this paper, we build a dataset PI and propose a deep-learning approach named Re3Writer, which imitates the physicians’ working patterns to automatically generate a PI at the point of discharge from hospital. Specifically, when a patient discharges from the hospital, physicians will carefully analyze the patient’s health records in terms of diagnosis, medication, and procedure, then accurately write a corresponding PI based on their working experience and medical knowledge [3, 6]. In order to model clinicians’ text production, the Re3Writer, which introduces three components: Retrieve, Reason, and Refine, (1) first encodes working experience by mining historical PIs, i.e., retrieving instructions
of previous patients according to the similarity of diagnosis, medication and procedure; (2) then reasons medical knowledge into the current input patient data by learning a knowledge graph, which is constructed to model domain-specific knowledge structure; (3) at last, refines relevant information from the retrieved working experience and reasoned medical knowledge to generate final PIs.

To prove the effectiveness of our Re³Writer, we incorporate it into 5 different language generation models: 1) recurrent neural network (RNN)-based model, 2) attention-based model, 3) hierarchical RNN-based model, 4) copy mechanism-based model, 5) fully-attentive model, i.e., the Transformer [47]. The extensive experiments show that our approach can substantially boost the performance of baselines across all metrics.

Overall, the main contributions of this paper are:

- We make the first attempt to automatically generate the Patient Instruction (PI), which can reduce the workload of physicians. As a result, it can increase their time and energy spent in meaningful interactions with patients, providing high-quality care for patients and improving doctor-patient relationships.

- To address the task, we build a dataset PI and propose an approach Re³Writer, which imitates physicians’ working patterns to retrieve working experience and reason medical knowledge, and finally refine them to generate accurate and faithful patient instructions.

- We prove the effectiveness and the generalization capabilities of our approach on the built PI dataset. After including our approach, performances of the baseline models improve significantly on all metrics, with up to 20%, 11%, and 19% relative improvements in BLEU-4, ROUGE-L, and METEOR, respectively. Moreover, we conduct human evaluations to the generated PI for its quality and usefulness in clinical practice.

2 Related Works

The related works are introduced from two aspects: 1) Natural Language Generation (NLG) and 2) Medical Text Generation.

Natural Language Generation (NLG) It aims to automatically generate coherent text in natural-language from given corresponding input data, which can be, e.g., text [11], images [49], video [48], and audio [8]. Commonly, approaches use an encoder-decoder framework, where the encoder computes intermediate representations for the input source data and the decoder adopts RNNs or CNNs [14, 9], to generate the target sentences given the intermediate representation. The attention mechanism [33, 47, 52, 27] and the copy mechanism [11] have been proposed to directly provide the decoder with the source information, enabling a more efficient use of the source data. In particular, fully-attentive models, such as the Transformer [47], in which no recurrence is required, have successfully achieved state-of-the-art performance for multiple natural language generation tasks. However, most existing work focuses on the natural text-related data, where research concerning the clinical domain remains relatively under-studied.

Medical Text Generation Recently, language generation in the medical domain has received growing research interest. For example, Jing et al. [18], Liu et al. [29, 30] proposed to generate radiology reports from chest X-ray images; Lee [23] proposed to generate the clinical notes of emergency department cases from discharge diagnosis codes; I ve et al. [17] proposed to generate mental health records. Meanwhile, some works treated the generation of medical text as a summarization task. For example, Zhang et al. [53] proposed to generate clinical impressions by summarizing radiology reports; Scott et al. [39] proposed to generate the patients’ histories by summarizing their respective health records; Several works [36, 12, 32, 10, 40], including HARVEST [13] - a medical summarization tool, proposed to summarize patients’ key conditions from their clinical health records, such as Hassanpour and Langlotz [12] and Shing et al. [40] which summarized important clinical entities from radiology reports and hospital health records, respectively.

Despite the encouraging performances of these methods in generating various types of medical text, to the best of our knowledge, none of them has attempted to generate the Patient Instructions, which has significant implications for supporting care delivery [6, 37, 43] as noted earlier. We here make the first attempt to generate the Patient Instructions, which is typically longer than existing NLG-related output in the medical domain and which covers more diverse topics than previous medical text generation tasks, such as clinical impressions [53], clinical notes [25], and radiology reports [28, 51].
3 Approach

We first define the PI generation problem; then, we describe the proposed Re³Writer in detail.

3.1 PI Generation Problem Definition

When a patient is discharged from the hospital, the PI generation system should generate a fluent and faithful instruction to help the patient or carer to manage their conditions at home. Therefore, the goal of the PI generation task is to generate a target instruction \( I = \{y_1, y_2, \ldots, y_{N_I}\} \) given the patient’s health records \( R = \{r_1, r_2, \ldots, r_{N_R}\} \) in terms of diagnoses, medications and procedures performed during hospitalization.

Since the input \( R \) including \( N_R \) words and the output \( I \) including \( N_I \) words are both textual sequences, we adopt the encoder-decoder framework, which is widely-used in natural language generation tasks, to perform the PI generation task. In particular, the encoder-decoder framework includes a health record encoder and a PI decoder, which can be formulated as:

\[
\text{Record Encoder} : R \rightarrow R' \quad \text{PI Decoder} : R' \rightarrow I,
\]

where \( R' \in \mathbb{R}^{N_R \times d} \) denotes the record embeddings encoded by the record encoder, e.g., LSTM [14] or Transformer [47]. Then, \( R' \) is fed into the PI decoder (which again could be an LSTM or Transformer), to generate the target PI \( I \). During training, given the ground truth PI for the input patient’s health records, we can train the model by minimizing the widely-used cross-entropy loss.

3.2 The Proposed Re³Writer

Our Re³Writer consists of three core components: Retrieve, Reason, and Refine.

Formulation of the Re³Writer As stated above, given the health records \( R \) encoded as \( R' \in \mathbb{R}^{N_R \times d} \), we aim to generate a desirable PI \( I \). Figure 2 shows the detail of our method, which is designed to retrieve related working experience \( W_{Pr} \) and reason related medical knowledge \( G_{Pr} \) from the training corpus for current input patient. Finally, Re³Writer refines the retrieved working
experience $W_{pr}$ and reasoned medical knowledge $G_{pr}$, to extract useful information to generate a proper PI:

\[
\text{Record Encoder} : R \rightarrow R'; \quad \text{Retrieve} : R \rightarrow W_{pr}; \quad \text{Reason} : R \rightarrow G_{pr};
\]

\[
\text{Refine + PI Decoder} : \{R', W_{pr}, G_{pr}\} \rightarrow I. \tag{2}
\]

Our method can be incorporated into existing encoder-decoder based models, to boost their performance with PI generation, as we will later demonstrate. We now describe how to retrieve related working experience and reasoned medical knowledge from the training corpus for PI generation.

**Retrieve** As shown in Figure [1], a hospitalization typically produces records of diagnoses given, medications used, and procedures performed; our dataset (described later) has 11,208 unique clinical codes, including 5,973 diagnosis codes, 3,435 medication codes, and 1,800 procedure codes. Therefore, we first extract the one-hot embeddings of all clinical codes. Given a new patient, we represent this patient’s hospitalization by averaging the associated one-hot embeddings of clinical codes produced during this hospitalization. Then, we collect a set of patients similar to the new patient according to the associated clinical codes. Taking the diagnosis codes as an example, we retrieve $N_P$ patients from the training corpus with the highest cosine similarity to the input diagnosis codes of the current patient. The PIs of the top-$N_P$ retrieved patients are returned and encoded by a BERT encoder [7][35], followed by a max-pooling layer over all output vectors, and projected to $d$ dimensions, generating the related working experience in terms of Diagnosis for the current patient: $\{I_1, I_2, \ldots, I_{N_p}\} \in \mathbb{R}^{N_p \times d}$. Similarly, we use the medication codes and procedure codes to acquire the working experience in terms of Medication and Procedure, respectively. At last, we concatenate these code-specific working experience representation (Diagnosis, Medication, Procedure) to obtain the final working experience related to current patient $W_{pr} = \{I_1, I_2, \ldots, I_{3+N_p}\} \in \mathbb{R}^{(3+N_p) \times d}$. We also attempted to incorporate age and gender information into our approach to match patients, please see Appendix C for details.

**Reason** To reason related medical knowledge from the training corpus, we construct an off-the-shelf global medical knowledge graph $G = (V, E)$ using all clinical codes, i.e., diagnosis, medication, and procedure codes, across all hospitalizations, where $V = \{v_1\}_{1=1}^{N_{kg}} \in \mathbb{R}^{N_{kg} \times d}$ is a set of $N_{kg}$ nodes and $E = \{e_{i,j}\}_{j=1}^{N_{kg}} \in \mathbb{R}^{N_{kg} \times d}$ is a set of edges. The $G$ models the domain-specific knowledge structure. In detail, we consider the clinical codes as nodes. The weights of the edges are calculated by normalizing the co-occurrence of pairs of nodes in the training corpus. After that, guided by current input patient’s health records, the knowledge graph is embedded by a graph convolution network (GCN) [34][24][22], acquiring a set of node embeddings $\{v'_1, v'_2, \ldots, v'_{N_{kg}}\}$, which is regarded as our reasoned medical knowledge $G_{pr} = \{v'_1, v'_2, \ldots, v'_{N_{kg}}\} \in \mathbb{R}^{N_{kg} \times d}$.

Please refer to Appendix A for the detailed description of our medical knowledge graph. We note that more complex graph structures could be constructed by using larger-scale well-defined medical ontologies. Therefore, our approach is not limited to the currently constructed graph and could provide a good basis for future research in this direction.

**Refine** As shown in Eq. (2), the PI decoder equipped with our method aims to generate the final PI based on the encoded patient’s health records $R' \in \mathbb{R}^{N_{kg} \times d}$, the retrieved working experience $W_{pr} \in \mathbb{R}^{(3+N_p) \times d}$ and the reasoned medical knowledge $G_{pr} \in \mathbb{R}^{N_{kg} \times d}$. In implementations, we can choose either the LSTM [14] or Transformer [47] as the decoder. Taking the Transformer decoder as an example: for each decoding step $t$, the decoder takes the embedding of the current input word $x_t = w_t + e_t \in \mathbb{R}^{d}$ as input, where $w_t$ and $e_t$ denote the word embedding and fixed position embedding, respectively; we then generate each word $y_t$ in the target instruction $I = \{y_1, y_2, \ldots, y_N\}$:

\[
h_t = \text{MHA}(x_{1:t}, x_{1:t}); \quad h'_t = \text{Refine}(h_t, R', W_{pr}, G_{pr}); \quad y_t \sim p_t = \text{softmax} (\text{FFN}(h'_t) W_p + b_p) \tag{3}
\]

where the MHA and FFN respectively stand for the Multi-Head Attention and Feed-Forward Network in the original Transformer (see Appendix D); $W_p \in \mathbb{R}^{d \times |D|}$ and $b_p$ are the learnable parameters ($|D|$; vocabulary size); the Refine component then refines the $W_{pr}$ and $G_{pr}$ to extract useful and correlated information to generate an accurate and faithful PI.

Intuitively, the PI generation task aims to produce an instruction based on the source patient’s health records $R'$, supported with appropriate working experience $W_{pr}$ and medical knowledge $G_{pr}$. Thus, $W_{pr}$ and $G_{pr}$ play an auxiliary role during the PI generation. To this end, the Refine component,
which makes the model adaptively learn to refine correlated information, is designed as follows:

\[
\text{Refine}(h_t, R^c, W_{Pr}, G_{Pr}) = \text{MHA}(h_t, R^c) + \lambda_1 \odot \text{MHA}(h_t, W_{Pr}) + \lambda_2 \odot \text{MHA}(h_t, G_{Pr})
\]

\[
\lambda_1 = \sigma ([h_t; \text{MHA}(h_t, W_{Pr})]W_{h_1} + b_{h_1}); \quad \lambda_2 = \sigma ([h_t; \text{MHA}(h_t, G_{Pr})]W_{h_2} + b_{h_2})
\]

where \(W_{h_1}, W_{h_2} \in \mathbb{R}^{2d \times d}\) and \(b_{h_1}, b_{h_2}\) are learnable parameters. \(\odot, \sigma, \text{and}[;;]\) denote the element-wise multiplication, the sigmoid function, and the concatenation operation, respectively. The computed \(\lambda_1, \lambda_2 \in [0, 1]\) weight the expected importance of \(W_{Pr}\) and \(G_{Pr}\) for each target word.

In particular, if LSTM is adopted as the PI decoder, we can directly replace the MHA with the LSTM unit and remove the FFN in Eq. (3). In the following sections, we will prove that our proposed Re3Writer can provide a solid basis for patient instruction generation.

4 Experiment

We first introduce our dataset used as the basis for our experiments, as well as the baseline models and settings. We subsequently show evaluations using both automatic and “human” approaches.

4.1 Dataset, Baselines, and Settings

Dataset We propose a benchmark clinical dataset Patient Instruction (PI) with around 35k pairs of input patient’s health records and output patient instructions. In detail, we collect the PI dataset from the publicly-accessible MIMIC-III v1.4 resource \(\text{[20, 19]}\), which integrates de-identified, comprehensive clinical data for patients admitted to the Intensive Care Unit of the Beth Israel Deaconess Medical Center in Boston, Massachusetts, USA. This resource is an important ‘benchmark’ dataset that promotes easy comparison between studies in the area. For each patient in the MIMIC-III v1.4 resource, the dataset includes various patient’s health records during hospitalization in terms of diagnoses, medications and procedures, e.g., demographics, laboratory results, admission notes, nursing notes, radiology notes, and physician notes. In our experiments, we found that the discharge summaries contain the abstractive information of patient’s health records. Therefore, for clarity, we adopt such abstractive information to generate the PI. We concatenate all available patients’ health records as the input of our model.

For data preparation, we first exclude entries without a patient instruction and entries where the word-counts of patient instructions are less than five. This results in our PI dataset of 28,029 unique patients and 35,851 pairs of health records and patient instructions, as summarized in Table 1. We randomly partition the dataset into 80%-10%-10% train-validation-test partitions according to patients. Therefore, there is no overlap of patients between train, validation and test sets. Next, we pre-process the records and instructions by tokenizing and converting text to lower-case. Finally, we filter tokens that occur fewer than 20 times in the corpus, resulting in a vocabulary of approximately 19.9k tokens, which covers over 99.5% word occurrences in the dataset.

Baselines We choose five representative language generation models with different structures as baseline models, i.e., 1) RNN-based model (LSTM) [4], 2) attention-based model (Seq2Seq) [11][33], 3) hierarchical RNN-based model (HRNN) [26], 4) copy mechanism based model (CopyNet) [11], 5) fully-attentive model (Transformer) [47]. We prove the effectiveness of our Re3Writer by comparing the performance of the various baseline models with and without the Re3Writer.

Settings The model size \(d\) is set to 512. For a patient, we directly concatenate all available patient’s health records during hospitalization as input, e.g., admission notes, nursing notes, radiology notes, demographic information, and instructions. For example, if a patient only has admission notes, our model will just rely on the available admission notes to generate the PI. We adopt Transformer [47] as the record encoder. Based on the average performance on the validation set, the number of retrieved previous PIs, \(N_p\), is set to 20 for all three codes (see Appendix B). During training, we use the Adam optimizer [21] with a batch size of 128 and a learning rate of \(10^{-4}\) for parameter optimization. We perform early stopping based on BLEU-4 with a maximum 150 epochs. During testing, we apply beam search of size 2 and a repetition penalty

### Table 1: Statistics of the built Patient Instruction (PI) dataset.

| Statistics            | TRAIN | VAL  | TEST |
|-----------------------|-------|------|------|
| Number of Instructions| 28,673| 3,557| 3,621|
| Number of Patients    | 22,423| 2,803| 2,803|
| Avg. Instruction Length| 162.5 | 164.5| 162.8|
| Avg. Record Length    | 2147.1| 2144.9| 2124.3|

[1] https://physionet.org/content/mimiciii/
Table 2: Performance of automatic evaluation on our built benchmark dataset PI. Higher is better in all columns. We conducted 5 runs with different seeds for all experiments, the t-tests indicate that $p < 0.01$. The (+Number) denotes the absolute improvements. As we can see, all the baseline models with significantly different structures enjoy a comfortable improvement with our Re³Writer approach.

| Methods | METEOR | ROUGE-1 | ROUGE-2 | ROUGE-L | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 |
|---------|--------|---------|---------|---------|--------|--------|--------|--------|
| LSTM \[4\] | 16.5 | 35.9 | 17.9 | 33.2 | 34.4 | 26.3 | 23.1 | 21.0 |
| with Re³Writer | 19.6 (+3.1) | 39.4 (+3.5) | 20.5 (+2.6) | 37.0 (+3.8) | 40.8 (+6.4) | 31.5 (+5.2) | 27.6 (+4.5) | 25.3 (+4.3) |
| Seq2Seq \[1\] | 19.9 | 39.0 | 20.3 | 37.1 | 41.6 | 32.5 | 27.9 | 25.1 |
| with Re³Writer | 20.9 (+1.0) | 40.8 (+1.8) | 21.9 (+1.6) | 38.6 (+1.5) | 43.2 (+1.6) | 34.2 (+1.7) | 29.7 (+1.8) | 26.8 (+1.7) |
| HRNN \[26\] | 20.3 | 40.1 | 20.5 | 36.9 | 43.5 | 33.7 | 28.8 | 25.6 |
| with Re³Writer | 21.6 (+1.3) | 42.5 (+2.4) | 22.1 (+1.6) | 39.0 (+2.1) | 47.2 (+3.7) | 36.9 (+3.2) | 31.5 (+2.7) | 27.8 (+2.2) |
| CopyNet \[11\] | 20.6 (+1.1) | 39.9 (+1.6) | 20.9 (+1.0) | 37.8 (+1.3) | 42.7 (+2.3) | 33.6 (+2.0) | 28.7 (+1.7) | 26.0 (+1.6) |
| Transformer \[47\] | 23.7 (+1.9) | 45.8 (+3.7) | 24.4 (+2.8) | 42.2 (+3.3) | 52.4 (+5.3) | 41.2 (+4.4) | 35.0 (+3.6) | 30.5 (+3.2) |

Table 3: Performance of human evaluation for comparing our method (baselines with Re³Writer) with baselines in terms of the fluency of generated PIs, the comprehensiveness of the generated true PIs and the faithfulness to the ground truth PIs. All values are reported in percentage (%).

| Metrics | Seq2Seq \[1\] | Transformer \[47\] |
|---------|--------------|-----------------|
| Fluency | Baseline Win | Tied | Ours Win | Baseline Win | Tied | Ours Win |
| 10.5 | 69.5 | 20.0 | 27.0 | 40.5 | 32.5 |
| Faithfulness | 22.5 | 38.0 | 39.5 | 25.5 | 31.0 | 43.5 |
| Comprehensiveness | 17.5 | 48.0 | 34.5 | 21.0 | 24.0 | 55.0 |

Table 4: Evaluation of how many times physicians would have deemed the generated result as “helpful” vs. “unhelpful” in terms of assisting them in writing PIs. Baseline denotes the Transformer \[47\].

| Methods | Helpful ↑ | Unhelpful ↓ |
|---------|-----------|-------------|
| Baseline | 32% | 68% |
| Ours | 74% | 26% |

of 2.5. For all baselines, we keep the inner structure of baselines untouched and preserve the same training/testing settings for experiments.

4.2 Automatic Evaluation

**Metrics** We measure the performance by adopting widely-used natural language generation metrics, i.e., BLEU-1, -2, -3, -4 \[35\], METEOR \[2\] and ROUGE-1, -2, -L \[25\], which are calculated by the evaluation toolkit \[3\] and measure the match between the generated instructions and reference instructions annotated by professional clinicians.

**Results** Table 2 shows that our Re³Writer can consistently boost all baselines across all metrics, with a relative improvement of 7%~20%, 4%~11%, and 5%~19% in BLEU-4, ROUGE-L, and METEOR, respectively. The improved performance proves the validity of our approach in retrieving working experience, reasoning medical knowledge, and refining them for PI generation. The performance gains over all of the five baseline models also indicate that our approach is less prone to the variations of model structures and hyper-parameters, proving that the generalization capabilities of our approach are robust over a wide range of models. In Section 4.5, we verify the robustness of our approach to various data/examples.

4.3 Human Evaluation

**Metrics** We further conduct human evaluation to verify the effectiveness of our approach Re³Writer in clinical practice. To successfully assist physicians and reduce their workloads, it is important to generate accurate patient instructions (faithfulness, precision), such that the model does not generate instructions that “do not exist” according to doctors. It is also necessary to provide comprehensive true instructions (comprehensiveness, recall), i.e., the model does not leave out the important instructions. For example, given the ground truth PI [Instruction_A, Instruction_B] written by physicians, the PI generated by Model_1 is [Instruction_A, Instruction_B, Instruction_C], and the PI generated by
Table 5: Ablation study of our Re³Writer, which includes three components: Retrieve, Reason, and Refine, on two representative baseline models, i.e., Seq2Seq [1] and Transformer [47]. Full Model denotes the baseline model with our Re³Writer.

| Settings | Retrieve | Reason | Refine | Dataset: Patient Instruction (PI) |
|----------|----------|--------|--------|-----------------------------------|
|          | Working Experience | Knowledge |        | METEOR | ROUGE-1 | ROUGE-2 | ROUGE-L | BLEU-3 | BLEU-4 |
| Seq2Seq  | (a) √     |         |        | 19.9  | 39.0    | 20.3    | 37.1    | 27.9   | 25.1   |
|          | (b) √     |         |        | 20.1  | 39.1    | 20.5    | 37.2    | 28.3   | 25.5   |
|          | (c)       |         |        | 20.7  | 39.8    | 21.2    | 37.8    | 29.0   | 26.1   |
|          | (d) √ √   |         |        | 20.6  | 40.1    | 21.1    | 38.0    | 29.2   | 26.3   |
|          | (e)       |         |        | 20.7  | 40.5    | 21.6    | 38.4    | 29.4   | 26.5   |
|          | (f) √ √ √ |         |        | 20.7  | 40.5    | 21.7    | 38.2    | 29.5   | 26.6   |
|          | Full Model|         |        | 20.9  | 40.8    | 21.9    | 38.6    | 29.7   | 26.8   |
| Transformer| (a) √ |        |        | 21.8  | 42.1    | 21.6    | 38.9    | 31.4   | 27.3   |
|          | (b) √     |         |        | 22.2  | 43.1    | 22.3    | 39.7    | 32.3   | 28.0   |
|          | (c)       |         |        | 22.7  | 44.2    | 23.0    | 40.7    | 33.4   | 28.9   |
|          | (d) √ √   |         |        | 22.5  | 43.6    | 22.7    | 40.1    | 32.7   | 28.4   |
|          | (e)       |         |        | 23.1  | 44.5    | 23.6    | 41.0    | 33.6   | 29.2   |
|          | (f) √ √ √ |         |        | 23.2  | 44.8    | 23.8    | 41.4    | 34.0   | 29.4   |
|          | Full Model|         |        | 23.7  | 45.8    | 24.4    | 42.2    | 35.0   | 30.5   |

Model_2 is [Instruction_A]. Model_1 is better than Model_2 in terms of comprehensiveness, while is worse than Model_2 in terms of faithfulness. Finally, it is unacceptable to generate repeated or otherwise unreadable instructions (fluency). Therefore, we randomly select 200 samples from our PI dataset. The human evaluation is conducted by two junior annotators (medical students) and a senior annotator (clinician). All three annotators have sufficient medical knowledge. By giving the ground-truth PIs, each junior annotator was asked to independently compare the outputs of our approach and that of the baseline models, in terms of the perceived quality of the outputs - including fluency, comprehensiveness, and faithfulness of outputs compared to the corresponding ground-truth instructions. The senior annotator re-evaluated those cases that junior annotators have difficulties deciding. The annotators were blinded to the model that generated the output instructions.

**Results**  We select a representative baseline, Seq2Seq, and a competitive baseline, Transformer, to show the human evaluation results (Table 5). As may be seen from the results, our Re³Writer is better than baselines with improved performance in terms of the three aspects, i.e., fluency, comprehensiveness and faithfulness. The human evaluation results show that the instructions generated by our approach are of higher clinical quality than the competitive baselines, which proves the advantage of our approach in clinical practice. In particular, by using our Re³Writer, the winning chances increased by a maximum of $43.5 - 25.5 = 18$ points and $55 - 21 = 34$ points in terms of the faithfulness metric (precision) and comprehensiveness metric (recall), respectively. At last, we further evaluate how many times physicians would have deemed the generated result as “helpful” vs. “unhelpful” in terms of assisting them in writing a PI. The results are reported in Table 4. As we can see, our approach can generate more accurate PIs than the baselines, improving the usefulness of AI systems in better assisting physicians in clinical decision-makings and reducing their workload.

### 4.4 Ablation Study

We conduct a quantitative analysis using the Seq2Seq and the Transformer for the purposes of evaluating the contribution of each proposed component: Retrieve, Reason, and Refine.

**Effect of the ‘Retrieve’ Component**  Table 5(a,b,c) shows that the Diagnosis, Medication, and Procedure elements of the model all contribute to a boost in performance, which proves the effectiveness of our approach in retrieving similar patient instructions from the available repository of historical PIs to aid in the generation of new patient instructions. Among these three elements, Medication leads to the best improvements, which may be explained by the fact that the PI is more relevant to medications from historical experience [45]. By combining the three elements (d), we observe an overall improvement. As a result, retrieving related working experience can boost the performance of baselines: $25.1 \rightarrow 26.3$ and $27.3 \rightarrow 29.2$ in BLEU-4 for Seq2Seq and Transformer, respectively.
Table 6: Performance of our approach on the three sub-datasets: Gender, Age, Disease.

| Gender | Female | Male | METEOR | ROUGE-L | BLEU-4 | METEOR | ROUGE-L | BLEU-4 |
|--------|--------|------|--------|---------|--------|--------|---------|--------|
|        |        |      | Seq2Seq with Re³|Writer  |        | Transformer with Re³|Writer  |        |
|        |        |      | 19.8   | 35.9    | 25.0   | 20.0   | 38.0    | 25.2   |
|        |        |      | 20.6   | 37.6    | 26.3   | 21.1   | 39.5    | 27.2   |
|        |        |      | 21.5   | 38.1    | 26.9   | 22.0   | 39.6    | 27.6   |
|        |        |      | 23.2   | 41.3    | 30.1   | 24.1   | 43.0    | 30.8   |

| Age Group | Age<55 | 55<=Age<70 | Age>=70 | METEOR | ROUGE-L | BLEU-4 | METEOR | ROUGE-L | BLEU-4 | METEOR | ROUGE-L | BLEU-4 |
|-----------|--------|------------|---------|--------|---------|--------|--------|---------|--------|--------|---------|--------|
|           |        |            | Seq2Seq with Re³|Writer  |        | Transformer with Re³|Writer  |        |
|           |        |            | 18.2    | 34.7    | 21.9   | 20.7   | 39.5    | 26.7   |
|           |        |            | 19.2    | 35.6    | 23.7   | 21.8   | 41.2    | 28.4   |
|           |        |            | 20.2    | 36.9    | 24.4   | 23.1   | 41.3    | 28.5   |
|           |        |            | 22.9    | 40.1    | 28.5   | 26.2   | 45.0    | 31.8   |
|           |        |            | 24.3    | 42.7    | 28.4   | 21.5   | 38.9    | 28.1   |

| Disease  | Hypertension | Hyperlipidemia | Anemia | METEOR | ROUGE-L | BLEU-4 | METEOR | ROUGE-L | BLEU-4 | METEOR | ROUGE-L | BLEU-4 |
|----------|--------------|----------------|--------|--------|---------|--------|--------|---------|--------|--------|---------|--------|
|          |              |                |        | Seq2Seq with Re³|Writer  |        | Transformer with Re³|Writer  |        |
|          |              |                |        | 21.3    | 39.8    | 27.9   | 21.3   | 41.7    | 27.2   | 18.0    | 36.4    | 20.7   |
|          |              |                |        | 22.6    | 41.4    | 30.4   | 22.5   | 43.9    | 29.5   | 18.8    | 37.6    | 22.3   |
|          |              |                |        | 22.8    | 42.5    | 30.7   | 23.0   | 44.7    | 30.3   | 19.6    | 38.2    | 23.4   |
|          |              |                |        | 24.6    | 45.1    | 33.5   | 24.9   | 46.4    | 33.8   | 21.8    | 41.3    | 27.4   |

**Effect of the ‘Reason’ Component** Table 5(e) shows that the Reason component can further improve the performance by learning the enriched medical knowledge. By comparing (d) and (e), we can observe that the reasoned medical knowledge leads to similar improvements as the retrieved working experience does. We attribute this to the fact that learning conventional and general writing styles for PIs in a deep learning-based approach is as important as incorporating accurate medical knowledge. In this way, the retrieved patient instructions of previous patients can be treated as templates, providing a solid basis to generate accurate PIs.

**Effect of the ‘Refine’ Component** As shown in Table 5(f and Full Model), it is clear that the model with our Refine component performs better than the model without it, which directly verifies the effectiveness of our approach. To further understand the ability of adaptively refining useful information, we summarize the average refining weight values $\bar{\lambda}_1$ and $\bar{\lambda}_2$ of Eq. (4). We can find that the average value of $\bar{\lambda}_2 = 0.42$ is larger than $\bar{\lambda}_1 = 0.26$. It indicates that the medical knowledge plays a prominent role in PI generation; it is in accordance with the results of (d) and (e). We conclude that our method is capable of learning to efficiently refine the most related useful information to generate accurate PIs. Overall, our three components improve the performance from different perspectives, and combining them can lead to an overall improvement.

### 4.5 Robustness Analysis

In this section, we evaluate the performance of our approach with more fine-grained datasets. Specifically, we further divide our PI dataset into three sub-datasets according to Gender, Age, and Disease. Specifically, to ensure an even distribution of the data, we divide the ages into three age-groups: Age < 55 (29.9%), 55 <= Age < 70 (30.5%), and Age >= 70 (39.7%). Table 6 shows the results of our approach on the three sub-datasets. As we can see, the proposed approach can consistently boost baselines across different genders, ages, and diseases on all evaluation metrics, proving the generalization capability and the effectiveness of our method to different datasets/examples.

### 4.6 Qualitative Analysis

Figure 3 shows that our approach is significantly better aligned with ground truth instructions than the baseline. For example, our approach correctly generates the key instructions (“you were found to have an infection in your gallbladder” and “you also had a urinary tract infection which was treated with antibiotics” (Blue-colored text)), and the personalised medication note (“start oxycodone 5 mg


Figure 3: An example of the PI generated by baseline and our approach (i.e., baseline with Re\textsuperscript{3}Writer). Underlined text denotes alignment between the ground truth text and the generated text. Red colored text denotes unfavorable results. The Blue and Green colored text respectively denote the retrieved working experience and reasoned medical knowledge when generating corresponding sentences.

every 6 hours as needed for pain” (Green-colored text), for the patient, who was admitted to the hospital with abdominal pain. The baseline can only generate the correct reason for the patient’s admission, however, it also generates a serious wrong instruction (Red-colored text). It proves the effectiveness of our approach in retrieving associated working experience and reasoning associated medical knowledge to aid PI generation. Meanwhile, we note that our method produces interpretable refining weight values that may help understand the contribution of working experience and medical knowledge towards PI generation: when generating words similar to those that appear in the retrieved working experience (Blue-colored text) and reasoned medical knowledge (Green-colored text), the corresponding $\lambda_1$ and the $\lambda_2$ would be significantly larger than their means, $\lambda_1$ and $\lambda_2$, to efficiently refine the relevant information from working experience and medical knowledge, respectively.

5 Conclusion

We propose a new task of Patient Instruction (PI) generation which attempts to generate accurate and faithful PIs. To address this task, we present an effective approach Re\textsuperscript{3}Writer: Retrieve, Reason, and Refine, which imitates the working patterns of physicians. The experiments on our built benchmark clinical dataset verify the effectiveness and the generalization capabilities of our approach. In particular, our approach not only consistently boosts the performance across all metrics for a wide range of baseline models with substantially different model structures, but also generates meaningful and desirable PIs regarded by clinicians. It shows that our approach has the potential to assist physicians and reduce their workload. In the future, it can be interesting to generate personalized PIs by taking into account the patient’s cognitive status, health literacy, and other barriers to self-care.

Limitations and Societal Impacts: The training of our approach relies on a large volume of existing PIs. The current model performance may be limited by the size of the built dataset. This might be alleviated in the future by using techniques such as knowledge distillations from publicly-available pre-trained models, e.g., ClinicalBERT \textsuperscript{15}. Although our approach has the potential of alleviating the heavy workload of physicians, it is possible that some physicians directly give the generated PI to the patients or guardians without quality check. Also for less experienced physicians, they may not be able to correct the errors in the machine-generated PI. To best assist the physicians via our approach, it is required to add process control to avoid unintended usage.

Acknowledgments

This work was supported in part by the National Institute for Health Research (NIHR) Oxford Biomedical Research Centre; an InnoHK Project at the Hong Kong Centre for Cerebro-cardiovascular Health Engineering; and the Pandemic Sciences Institute, University of Oxford, Oxford, UK. Fenglin Liu gratefully acknowledges funding from the Clarendon Fund and the Magdalen Graduate Scholarship.
References

[1] D. Bahdanau, K. Cho, and Y. Bengio. Neural machine translation by jointly learning to align and translate. In ICLR, 2015.

[2] S. Banerjee and A. Lavie. METEOR: an automatic metric for MT evaluation with improved correlation with human judgments. In IEEEvaluation@ACL, pages 65–72, 2005.

[3] X. Chen, H. Fang, T. Lin, R. Vedantam, S. Gupta, P. Dollár, and C. L. Zitnick. Microsoft COCO captions: Data collection and evaluation server. arXiv preprint arXiv:1504.00325, 2015.

[4] K. Cho, B. van Merrienboer, Ç. Gülçehre, D. Bahdanau, F. Bougares, H. Schwenk, and Y. Bengio. Learning phrase representations using RNN encoder-decoder for statistical machine translation. In EMNLP, pages 1724–1734, 2014.

[5] A. Chugh, M. V. Williams, J. Grigsby, and E. A. Coleman. Better transitions: improving comprehension of discharge instructions. Frontiers of Health Services Management, 25(3):11, 2009.

[6] E. A. Coleman, A. Chugh, M. V. Williams, J. Grigsby, J. J. Glasheen, M. McKenzie, and S.-J. Min. Understanding and execution of discharge instructions. American Journal of Medical Quality, 28(5):383–391, 2013.

[7] J. Devlin, M. Chang, K. Lee, and K. Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. In NAACL-HLT, pages 4171–4186, 2019.

[8] K. Drossos, S. Adavanne, and T. Virtanen. Automated audio captioning with recurrent neural networks. In WASPAA, pages 374–378, 2017.

[9] J. Gehring, M. Auli, D. Grangier, D. Yarats, and Y. N. Dauphin. Convolutional sequence to sequence learning. In ICML, pages 1243–1252, 2017.

[10] D. J. Goff and T. W. Loehfelm. Automated radiology report summarization using an open-source natural language processing pipeline. Journal of Digital Imaging, 31(2):185–192, 2018.

[11] J. Gu, Z. Lu, H. Li, and V. O. K. Li. Incorporating copying mechanism in sequence-to-sequence learning. In ACL, 2016.

[12] S. Hassanpour and C. P. Langlotz. Information extraction from multi-institutional radiology reports. Artificial Intelligence in Medicine, 66:29–39, 2016.

[13] J. S. Hirsch, J. S. Tanenbaum, S. Lipsky Gorman, C. Liu, E. Schmitz, D. Hashorva, A. Ervits, D. Vawdrey, M. Sturm, and N. Elhadad. Harvest, a longitudinal patient record summarizer. Journal of the American Medical Informatics Association, 22(2):263–274, 2015.

[14] S. Hochreiter and J. Schmidhuber. Long short-term memory. Neural Comput., 9(8):1735–1780, 1997.

[15] K. Huang, J. Altosaar, and R. Ranganath. Clinicalbert: Modeling clinical notes and predicting hospital readmission. arXiv preprint arXiv:1904.05342, 2019.

[16] Institute for Healthcare Improvement. Ask me 3: Good questions for your good health. National Patient Safety Foundation, 2016.

[17] J. Ive, N. Viani, J. Kam, L. Yin, S. Verma, S. Puntis, R. N. Cardinal, A. Roberts, R. Stewart, and S. Velupillai. Generation and evaluation of artificial mental health records for natural language processing. NPJ Digital Medicine, 3(1):1–9, 2020.

[18] B. Jing, P. Xie, and E. P. Xing. On the automatic generation of medical imaging reports. In ACL, pages 2577–2586, 2018.

[19] A. E. W. Johnson, T. J. Pollard, and R. G. Mark. MIMIC-III clinical database (version 1.4). PhysioNet, 2016. URL https://doi.org/10.13026/C2XW26
[20] A. E. W. Johnson, T. J. Pollard, L. Shen, L. wei H. Lehman, M. Feng, M. M. Ghassemi, B. Moody, P. Szolovits, L. A. Celi, and R. G. Mark. MIMIC-III, a freely accessible critical care database. *Scientific Data*, 3, 2016.

[21] D. P. Kingma and J. Ba. Adam: A method for stochastic optimization. In *ICLR*, 2014.

[22] T. N. Kipf and M. Welling. Semi-supervised classification with graph convolutional networks. In *ICLR*, 2017.

[23] S. Lee. Natural language generation for electronic health records. *arXiv preprint arXiv:1806.01353*, 2018.

[24] Y. Li, D. Tarlow, M. Brockschmidt, and R. S. Zemel. Gated graph sequence neural networks. In *ICLR*, 2016.

[25] C.-Y. Lin. ROUGE: A package for automatic evaluation of summaries. In *ACL*, pages 74–81, 2004.

[26] R. Lin, S. Liu, M. Yang, M. Li, M. Zhou, and S. Li. Hierarchical recurrent neural network for document modeling. In *EMNLP*, pages 899–907, 2015.

[27] F. Liu, Y. Liu, X. Ren, X. He, and X. Sun. Aligning visual regions and textual concepts for semantic-grounded image representations. In *NeurIPS*, 2019.

[28] F. Liu, S. Ge, and X. Wu. Competence-based multimodal curriculum learning for medical report generation. In *ACL/ICNLP*, 2021.

[29] F. Liu, X. Wu, S. Ge, W. Fan, and Y. Zou. Exploring and distilling posterior and prior knowledge for radiology report generation. In *CVPR*, 2021.

[30] F. Liu, C. You, X. Wu, S. Ge, S. Wang, and X. Sun. Auto-encoding knowledge graph for unsupervised medical report generation. In *NeurIPS*, 2021.

[31] G. Liu, T. H. Hsu, M. B. A. McDermott, W. Boag, W. Weng, P. Szolovits, and M. Ghassemi. Clinically accurate chest x-ray report generation. In *MLHC*, pages 249–269, 2019.

[32] H. Liu and C. Friedman. Cliniviewer: a tool for viewing electronic medical records based on natural language processing and xml. In *MEDINFO 2004*, pages 639–643. IOS Press, 2004.

[33] T. Luong, H. Pham, and C. D. Manning. Effective approaches to attention-based neural machine translation. In *EMNLP*, pages 1412–1421, 2015.

[34] D. Marcheggiani and I. Titov. Encoding sentences with graph convolutional networks for semantic role labeling. In *EMNLP*, pages 1506–1515, 2017.

[35] K. Papineni, S. Roukos, T. Ward, and W. Zhu. BLEU: a Method for automatic evaluation of machine translation. In *ACL*, pages 311–318, 2002.

[36] R. Pivovarov and N. Elhadad. Automated methods for the summarization of electronic health records. *Journal of the American Medical Informatics Association*, 22(5):938–947, 2015.

[37] R. D. Powers. Emergency department patient literacy and the readability of patient-directed materials. *Annals of Emergency Medicine*, 17(2):124–126, 1988.

[38] N. Reimers and I. Gurevych. Sentence-bert: Sentence embeddings using siamese bert-networks. In *EMNLP/ICNLP*, pages 3980–3990, 2019.

[39] D. Scott, C. Hallett, and R. Fettiplace. Data-to-text summarisation of patient records: Using computer-generated summaries to access patient histories. *Patient Education and Counseling*, 92(2):153–159, 2013.

[40] H. Shing, C. Shivade, N. Pourdamghani, F. Nan, P. Resnik, D. W. Oard, and P. Bhatia. Towards clinical encounter summarization: Learning to compose discharge summaries from prior notes. *arXiv preprint arXiv:2104.13498*, 2021.
[41] C. Sinsky, L. Colligan, L. Li, M. Prgomet, S. Reynolds, L. Goeders, J. Westbrook, M. Tutty, and G. Blike. Allocation of physician time in ambulatory practice: a time and motion study in 4 specialties. *Annals of Internal Medicine*, 165(11):753–760, 2016.

[42] C. Sinsky, M. Tutty, and L. Colligan. Allocation of physician time in ambulatory practice. *Annals of Internal Medicine*, 166(9):683–684, 2017.

[43] J. M. Spandorfer, D. J. Karras, L. A. Hughes, and C. Caputo. Comprehension of discharge instructions by patients in an urban emergency department. *Annals of Emergency Medicine*, 25(1):71–74, 1995.

[44] D. S. Tawfik, J. Profit, T. I. Morgenthaler, D. V. Satele, C. A. Sinsky, L. N. Dyrbye, M. A. Tutty, C. P. West, and T. D. Shanafelt. Physician burnout, well-being, and work unit safety grades in relationship to reported medical errors. In *Mayo Clinic Proceedings*, pages 1571–1580, 2018.

[45] D. M. Taylor and P. A. Cameron. Discharge instructions for emergency department patients: what should we provide? *Emergency Medicine Journal*, 17(2):86–90, 2000.

[46] The World Bank. Physicians per 1,000 people. 2018. URL [https://data.worldbank.org/indicator/SH.MED.PHYS.ZS](https://data.worldbank.org/indicator/SH.MED.PHYS.ZS).

[47] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin. Attention is all you need. In *NIPS*, pages 5998–6008, 2017.

[48] S. Venugopalan, H. Xu, J. Donahue, M. Rohrbach, R. J. Mooney, and K. Saenko. Translating videos to natural language using deep recurrent neural networks. In *HLT-NAACL*, pages 1494–1504, 2015.

[49] O. Vinyals, A. Toshev, S. Bengio, and D. Erhan. Show and tell: A neural image caption generator. In *CVPR*, pages 3156–3164, 2015.

[50] M. Weiner and P. Biondich. The influence of information technology on patient-physician relationships. *Journal of General Internal Medicine*, 21(1):35–39, 2006.

[51] C. P. West, L. N. Dyrbye, and T. D. Shanafelt. Physician burnout: contributors, consequences and solutions. *Journal of Internal Medicine*, 283(6):516–529, 2018.

[52] K. Xu, J. Ba, R. Kiros, K. Cho, A. C. Courville, R. Salakhutdinov, R. S. Zemel, and Y. Bengio. Show, attend and tell: Neural image caption generation with visual attention. In *ICML*, pages 2048–2057, 2015.

[53] Y. Zhang, D. Y. Ding, T. Qian, C. D. Manning, and C. P. Langlotz. Learning to summarize radiology findings. In *Proceedings of the Ninth International Workshop on Health Text Mining and Information Analysis, Louhi@EMNLP 2018*, pages 204–213, 2018.

**Checklist**

1. For all authors...
   
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope? [Yes]

   (b) Did you describe the limitations of your work? [Yes]

   (c) Did you discuss any potential negative societal impacts of your work? [Yes]

   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]

   We have read the ethics review guidelines and ensured that our paper conforms to them.

2. If you are including theoretical results...

   (a) Did you state the full set of assumptions of all theoretical results? [N/A]

   (b) Did you include complete proofs of all theoretical results? [N/A]

3. If you ran experiments...

   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [N/A]

   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen) and reporting (e.g., number of trials, how many times the code was run)?? [N/A]
(a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] The code is available at https://github.com/AI-in-Health/Patient-Instructions

(b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Section 4.1.

(c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] We conducted 5 runs with different seeds for all experiments.

(d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] See Section 4.1.

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...

(a) If your work uses existing assets, did you cite the creators? [Yes]

(b) Did you mention the license of the assets? [Yes] PhysioNet Credentialed Health Data License 1.5.0 (https://physionet.org/content/mimic-cxr/view-license/2.0.0/) is used.

(c) Did you include any new assets either in the supplemental material or as a URL? [Yes] The code is available at https://github.com/AI-in-Health/Patient-Instructions

(d) Did you discuss whether and how consent was obtained from people whose data you’re using/curating? [Yes] All necessary patient/participant consent has been obtained and the appropriate institutional forms have been archived.

(e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes] All protected health information was de-identified. De-identification was performed in compliance with Health Insurance Portability and Accountability Act (HIPAA) standards in order to facilitate public access to the datasets. Deletion of protected health information (PHI) from structured data sources (e.g., database fields that provide patient name or date of birth) was straightforward. All necessary patient/participant consent has been obtained and the appropriate institutional forms have been archived.

5. If you used crowdsourcing or conducted research with human subjects...

(a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]

(b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]

(c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]