VietMed-Sum: Real-time Speech Summarization for Medical Conversations

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Abstract

In doctor-patient conversations, identifying medically relevant information is crucial, posing the need for conversation summarization. We present VietMed-Sum which, to our knowledge, is the first speech summarization dataset for medical conversations. Secondly, we propose a novel real-time speech summarization design that generates a local summary after every N utterances within a conversation and a global summary for the entire conversation. Unlike previous works that continuously update the summary after each utterance generated by ASR systems which might be hard for users to follow, our design could improve user experience and lower computational costs. Thirdly, we are the first to utilize LLM and human annotators collaboratively to create gold standard and synthetic summaries for medical conversation summarization. Finally, we present baseline results of state-of-the-art models on VietMed-Sum. All code, data (English-translated and Vietnamese) and models are available here.

Index Terms: speech recognition, speech summarization, AI for healthcare

1. Introduction

In real-world conversations, the volume of information grows significantly in tandem with speaking rates, leading to information overload. Remembering every detail discussed, especially medical information, is beyond human capability. Yet, doctors and patients frequently make decisions by prioritizing crucial information and its significance. Consequently, the adoption of real-time speech summarization (RTSS) system is emerging as an effective approach to tackle this issue.

Compared to pre-recorded speech summarization, RTSS research has very little literature [1]. Besides, in industry settings, to the best of our knowledge, there is currently no RTSS system deployed for real-world applications[1].

In terms of medical domain, according to the latest survey by [2] and to the best of our knowledge, there is only one publicly available dataset for medical conversation summarization [3]. This dataset consists of written text in the Chinese language and was crawled from an online healthcare service provider. However, no speech summarization dataset for medical conversations is publicly available.

RTSS systems proposed by [1] constantly update and revise the current summary state in the course of a dialogue using additional components, such as flexible recognizer of utterance

units, utterance lookahead-er, and information overrider. While these additions increase inference and training time, they also contribute to increased deployment and maintenance complexity. Furthermore, from a business standpoint, these RTSS systems can degrade user experience as users are unaware of the exact moment when a comprehensive summary concludes.

To tackle all the problems above, we propose a new approach to a RTSS system for medical conversations. Our contribution are as follows:

- We introduce *VietMed-Sum* - the first speech summarization dataset for real-world medical conversations, to the best of our knowledge.
- We propose a novel design for a RTSS system.
- We conduct the first attempt to leverage ChatGPT and human annotators colaboratively to create gold standard and synthetic summaries for medical conversations.
- We present baseline results on our dataset using various state-of-the-art models.

All code, data (English-translated and Vietnamese) and models are published online[2].

2. Real-time Speech Summarization System

2.1. Previous Designs

RTSS system proposed by [1] has 3 major additional components: flexible recognizer of utterance units, utterance lookahead-er, and information overrider. Flexible recognizer of utterance units automatically split real-time Automatic Speech Recognition (ASR) transcript into segments with random lengths, while utterance lookahead-er seeks additional context from subsequent words generated by ASR, and information overrider continuously updates the summary in response to the latest contextual changes. We conducted surveys and gathered feedback from engineers and found that these extra components not only extend both inference and training time but also complicate RTSS systems, making it challenging for engineers to deploy and maintain them effectively. Furthermore, the summary is constantly updated after each utterance generated by the ASR system. This results in increased computational costs when compared to a scenario where a solid summary is generated after a set of utterances. The continuously updated summary creates confusion as users are unable to keep track, given the uncertainty of when a summary is completed.

2.2. Our Design

In contrast, our approach is much simpler. Our design generates a local summary after every N utterances of speech within a

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[2]https://github.com/leduckhai/MultiMed

conversation and a global summary after the end of a conversation. Every local summary is generated using the corresponding local context of N utterances, without the need to continuously update the new context generated by real-time ASR utterances. Meanwhile, the global summary serves as an "overrider" using the context of the entire conversation.

2.3. Balance for System Delay

RTSS system by [1] generates a summary with a delay of one utterance. A large number of delayed utterances results in longer waiting time for users to receive the generated summary. Conversely, a low number of delayed utterances means that the context necessary for accurate summaries is missing, making summarization unnecessary. After analyzing the context within the *VietMed* corpus [4] and conducting our internal user survey, we found that setting N = {4, 5} (or a maximum of around 30 seconds) strikes a suitable balance. This ensures that each summary includes an adequate amount of context without keeping users waiting excessively.

3. Data

3.1. Labeling strategy

We used GPT-3.5 Turbo[3] (or ChatGPT) to generate summaries for every transcript in our dataset, which we refer to as GPT-annotated summaries. We then split the dataset into two subsets: **Gold standard (*GOLD*)** set and the **Synthetic (*SYN*)** set. On the *GOLD* set, we performed **human editing** where the human annotator edit the GPT summary according to the annotation guideline, while on the *SYN* set, we did not. More information on GPT annotation is on section 4.

3.2. Data Collection

Real-world dataset (REAL): We choose the *VietMed* dataset [4], a real-world medical ASR dataset in Vietnamese, for annotating summaries. This choice is driven by the fact that *VietMed* currently stands as the world's largest and most generalizable publicly-available medical ASR dataset.
Simulated dataset (SIM): To make the dataset more generalizable and to extend the scale of the existing *VietMed* dataset, we used extra medical text data[4]. We simulated real-world conversations by imitating the speaking style found in the *VietMed* corpus. This includes incorporating hesitations, disfluencies, and stuttering words at a rate similar to that of *VietMed* utterances. Pseudo Python code for simulation is in the Appendix.

Our *GOLD* set contains gold standard data from *REAL* and *SIM*, while *SYN* contains GPT summaries from the extra medical text mentioned above.

3.3. Annotation Process and Data Quality Control

We hosted meetings to discuss complex cases and create the annotation guideline with the help of a medical expert. Two developers with basic medical training independently edited GPT summaries based on the annotation guideline. For each human-edited summary, the medical expert decided which version as the gold standard and requested re-annotation if there were any deviations from the annotation guideline. For summaries not human-edited by the two developers, we called synthetic data. Final annotation guideline is in the Appendix.

3.4. Data Statistics

	Gold-standard Data			Synthethic	All
	Real-world		Simulated		
	Local	Global	Local	Local	
Train	837	382	560	18981	20760
Dev	874	624	70	0	1568
Test	1192	767	70	0	2029
Total	2903	1773	700	18981	24357

Table 1: *Data statistics for VietMed-Sum. Full table is in the Appendix.*

Table 1 shows the statistics of our dataset. To construct our *VietMed-Sum* dataset, we keep the original split of *REAL* by [4] as 5-5-6 hours for the corresponding train-dev-test set. We split our *SIM* set with a ratio of 8:1:1 for the corresponding train-dev-test, while the entire *SYN* is used for training.

Acquisition and annotation of medical dataset is challenging and costly, resulting in medical summarization datasets typically being smaller compared to those in the general domain. Compared to other public medical written text summarization dataset, such as MeQSum corpus of summarized consumer health questions [5], our dataset has 23 times more summaries. Besides, compared to the Chinese medical text summarization dataset by [3], ours is half the size.

3.5. English-translated *VietMed-Sum*

We also introduce *VietMed-Sum-en*, the English version of *VietMed-Sum* which was translated using Google Translate[5]. Results are in the Appendix.

4. GPT for Annotation

4.1. Motivation

To the best of our knowledge, existing prominent Vietnamese summarization datasets, such as VietNews [6] and FAQSum [7], utilize their titles and abstracts as summaries. Our dataset, however, lacks these pre-made summaries which would traditionally require human annotation. However, finding high-quality annotators for either low-resource languages like Vietnamese or medical domain is hard [8].

In recent year, there has been an increasing focus on utilizing Large Language Models (LLMs) for annotation [9, 10, 11]. Experimental results from [12] showed that fully GPT-3 labeling can ourperform fully human labeling in low-budget settings. GPT has shown to have adequate medical knowledge [13]. Furthermore, it achieves reasonable performance as an annotator in sequence generation tasks in Vietnamese [10].

4.2. GPT Setup

We used GPT-3.5 Turbo to generate GPT summaries. Full setup details are in the Appendix.

4.3. Cost-Efficiency Evaluation

Following the design from [10, 12], we evaluated the performance difference of human-annotated summaries versus GPT-annotated summaries under a fixed budget. In particular, we evaluated ViT5 performance on FAQSum, a medical summarization dataset, trained with human-annotated summaries ver-

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Cost	Method	R-1	R-2	R-L
$2.5	250 Human Summaries	60.73	45.35	55.67
	6k GPT Summaries	56.69	40.13	50.61
$5	500 Human Summaries	62.85	47.19	57.50
	6k GPT → 250 Human-reuse	**62.88**	**47.81**	**57.67**
	6k GPT → 250 Human-new	63.45	47.65	57.49

Table 2: *ROUGE on FAQSum on two budgets: $2.5 and $5. ViT5 is trained on the data from each method. GPT → Human-reuse refers to two-step finetuning on the 250 human summaries from the $2.5-budget setting while GPT → Human-new refers to two-step finetuning on new 250 human summaries.*

sus with GPT summaries on fixed budgets of $2.5 and $5, corresponding to 250 and 500 human-annotated summaries accordingly[6]. At $2.5, GPT can generate around 6000 summaries[7].

The experimental results from the $2.5-budget setting in Table 2 demonstrate the importance of human annotation in the Vietnamese medical summarization task. Since summaries are heavily influenced by the annotators' medical knowledge and writing style, we hypothesize that GPT summaries still provide useful medical knowledge but require additional training on human summaries for writing style transfer.

To verify our hypothesis, we devise the the $5-budget setting where we fine-tuned ViT5 on GPT summaries, then on human summaries, and compared this two-step process with fine-tuning only on human summaries. We also doubled the number of human summaries for fair comparison. Experimental results show that the two-step process achieves slightly better results while costing significantly less time. We hypothesize that fine-tuning on GPT summaries helps provide medical knowledge and fine-tuning on human summaries helps the model aligns its output's text style.

Method	R-1	R-2	R-L
6k Human Summaries	65.80	50.82	60.83
6k GPT Summaries	56.69	40.13	50.61
6k GPT → 250 Human-reuse	62.88	47.81	57.67

Table 3: *ROUGE scores on FAQSum on 6k human summaries, 6k GPT summaries and the previously mentioned two-step fine-tuning process of ViT5.*

Table 3 further support our argument. When we perform two-step finetuning on ViT5, the performance gap between human summaries and GPT summaries is significantly closed. As such, our labeling strategy involves creating the *SYN* set and refining the *GOLD* set to balance between time-consumption, cost and performance.

4.4. Human Evaluation

We further investigate the characteristics of the GPT summaries empirically. In this experiment, we sample 50 arbitrary transcripts of varying lengths from *VietMed-Sum* and let two annotators independently summarize them, one with GPT summaries as references (human editing) and one without.

Human Editing Time-Efficiency: We quantify the overall improvement in time taken to annotate the transcripts between hu-

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[6]Based on the minimum fee of $0.01 per assignment on MTurk
[7]With an average of 700 input tokens and 20 output tokens per sample with rate $0.50 per 1M input tokens and $1.50 per 1M output tokens

man editing and manually writing the summary. We found that annotators who perform human editing is approximately 70% faster than those who perform manual summary writing. As such, we perform human editing on the *GOLD* set.

Hallucination: To make sure the GPT summary is factually aligned with the transcript, we further cross-check the GPT summaries with the transcripts. We found that (1) the GPT summaries sometimes contain details implied but not explicitly mentioned in the transcript and (2) GPT is easily confused by transcripts with a lot of spoken language characteristics (i.e. hesitations, disfluencies and stuttering words). This typically leads to hallucinate and we found that around 25% of our samples have hallucination. Furthermore, the GPT summaries are often more lengthy with an average compression rate of 30%, higher than required in the guideline. As such, we ask the annotators to strictly adhere to the annotation guideline when editing.

5. Experimental Setup

5.1. Evaluation Metrics

We use ROUGE [14], a metric commonly used for summarization, to evaluate our models. More details are in the Appendix.

5.2. Baseline Summarization Models

We employed BARTpho$_{syllable}$ and BARTpho$_{word}$ [15], ViT5, ViT5-vietnews [16] (ViT5 fine-tuned on Vietnews summarization dataset [17]), and ViPubmedT5 [18] models in our experiments. More information about the models is in the Appendix.

5.3. Downstream Tasks

Summarization on Human Transcript: We train the models on the abstractive summarization task on VietMed-Sum. To evaluate their performance, we calculate their ROUGE scores on the local and global summaries in the test set.

Summarization on ASR Transcript: We also evaluated the models' performance from transcripts obtained from audio speech recognition (ASR). We employed the best ASR model on *VietMed* from [4] with a Word-Error-Rate (WER) of 28.8% to generate the ASR transcripts for summarization. This creates noisier text which is more challenging for the baseline models.

6. Experimental Results

We report the ROUGE of our baseline models on the Global summaries and Local summaries subset from *GOLD*.

6.1. Gold Standard Data Summarization

| Data | Global Summaries | | | Local Summaries | | |
GOLD	R-1	R-2	R-L	R-1	R-2	R-L
BARTpho$_{syllable}$	60.92	40.71	49.38	59.07	38.27	47.69
BARTpho$_{word}$	58.83	39.71	48.07	57.76	37.43	46.87
ViT5	61.65	40.56	49.62	59.95	38.66	48.66
ViT5-vietnews	61.90	41.07	49.61	59.94	38.69	48.25
ViPubmedT5	61.73	40.17	48.81	59.99	38.3	47.67

Table 4: *Experimental results on VietMed-Sum's GOLD test set of each model fine-tuned on local + global summaries of GOLD.*

Table 4 shows the ROUGE scores on our *GOLD* test set for the baseline models fine-tuned on the combination of *GOLD*

local and global summaries. ViT5, ViPubmedT5, and ViT5-vietnews consistently outperforms the BARTpho variants.

| Data | Global Summaries | | | Local Summaries | | |
Global	R-1	R-2	R-L	R-1	R-2	R-L
BARTpho$_{syllable}$	61.69	41.19	49.87	59.13	37.8	47.59
BARTpho$_{word}$	59.45	39.05	47.79	57.8	36.28	46.35
ViT5	58.89	37.2	46.76	56.79	34.97	45.31
ViT5-vietnews	60.67	39.20	48.17	58.64	36.83	46.61
ViPubmedT5	58.57	36.65	45.75	56.83	34.7	44.72
Local	**R-1**	**R-2**	**R-L**	**R-1**	**R-2**	**R-L**
BARTpho$_{syllable}$	58.33	39.62	47.49	57.37	37.43	46.41
BARTpho$_{word}$	56.46	38.62	46.20	55.65	36.36	45.13
ViT5	59.82	40.47	48.74	59.11	38.41	47.87
ViT5-vietnews	61.04	41.43	49.57	60.10	39.39	48.52
ViPubmedT5	59.00	38.27	47.36	58.99	37.38	47.11

Table 5: *Results on VietMed-Sum's Global and Local subset of GOLD test set. Each baseline model is fine-tuned on the global summaries (above) and the local summaries (below) of GOLD*

Results from Table 5 shows the models have a noticeable drop in performance. On the local summaries, the ROUGE scores from the BARTpho variants are much lower than that of the ViT5 variants. Conversely, when fine-tuned on the global summaries, both variants of BARTpho performs much better than the ViT5 variants except ViT5-vietnews, probably because ViT5-vietnews was previously fine-tuned on other Vietnamese abstractive summarization dataset.

6.2. Synthetic Data Summarization

| Data | Global Summaries | | | Local Summaries | | |
SYN	R-1	R-2	R-L	R-1	R-2	R-L
BARTpho$_{syllable}$	60.37	40.27	48.48	58.68	38.17	47.14
BARTpho$_{word}$	59.64	40.21	48.01	57.5	37.31	46.01
ViT5	61.71	42.36	50.17	59.74	39.83	48.65
ViT5-vietnews	60.78	40.79	49.07	58.18	38.21	47.01
ViPubmedT5	60.58	40.95	48.72	58.44	38.4	47.09
SYN + GOLD	**R-1**	**R-2**	**R-L**	**R-1**	**R-2**	**R-L**
BARTpho$_{syllable}$	61.13	41.55	49.83	59.1	39.1	48.06
BARTpho$_{word}$	61.11	42.08	49.66	59.16	39.36	48.12
ViT5	63.23	43.92	51.64	60.9	40.93	49.83
ViT5-vietnews	62.68	43.59	51.58	60.31	40.52	49.32
ViPubmedT5	62.15	42.92	50.45	59.96	40.22	48.82
SYN → GOLD	**R-1**	**R-2**	**R-L**	**R-1**	**R-2**	**R-L**
BARTpho$_{syllable}$	62.37	41.87	50.49	60.5	39.78	49.24
BARTpho$_{word}$	60.93	41.80	49.89	59.38	39.43	48.67
ViT5	**64.52**	**45.12**	**52.95**	**62.56**	**42.41**	**51.61**
ViT5-vietnews	**63.34**	**43.29**	**51.58**	**61.73**	**41.2**	**50.23**
ViPubmedT5	61.70	40.13	48.80	59.99	38.31	47.68

Table 6: *Experimental results on VietMed-Sum's GOLD test set of each baseline model fine-tuned on SYN, (SYN + GOLD) and SYN → GOLD. + refers to concatenating the datasets while → refers to two-step fine-tuning. Bolded text refers to two best performing models.*

Table 6 shows the ROUGE scores of each model fine-tuned on *SYN*-only and with *GOLD*. We found that fine-tuning only on *SYN* data did not improve the models' performance. However, when we incorporated *GOLD* into fine-tuning the models either by concatenating the *GOLD* and *SYN* data or by perform-

ing two-step fine-tuning *SYN → GOLD*, the performance of the models drastically improved compared to training only on *GOLD* on all metrics. This is consistent with our observations from Subsection 4.3.

6.3. ASR Transcript Summarization

| Model | Global Summaries | | | Local Summaries | | |
	R-1	R-2	R-L	R-1	R-2	R-L
ViT5	58.95	36.82	46.63	56.78	34.43	45.52
ViT5-vietnews	58.22	35.34	46.02	56.48	33.65	45.10

Table 7: *Experimental results on ASR transcripts of the two best performing models from Section 6.2. Full table with all results is in the Appendix.*

We report the results of our baseline models on the ASR transcripts on Table 7. The performance of the models is worse than that on *VietMed-Sum*, which we attribute to the noisy nature of the text generated by the ASR models. Nevertheless, the ROUGE scores remain fairly reasonable, which is proof to our model's robustness.

6.4. Human Evaluation

While ROUGE is commonly used to evaluate the performance of the models, does not measure the fluency and factual alignment of the summaries. As such, we adopt the human evaluation methodology from [19, 20] and report the results in Table 8. Details of experiments are in the Appendix.

7. Conclusion

We present *VietMed-Sum*, the first speech summarization dataset for medical conversations. Secondly, we propose a novel real-time speech summarization design that generates a local summary after every N speech utterances within a conversation and a global summary after the end of a conversation. Our design could enhance user experience from a business standpoint, while also reducing computational costs from a technical perspective. Thirdly, our proposed labeling strategy strikes a balance between performance of summarization models, annotation cost, and annotation time (approximately 70% time reduction). We report the use of our proposed synthetic data, which improves models' performance across all metrics. Notable is an average improvement of 2.74 in the R-1 score for ViT5.

8. Limitations

We acknowledge that our work relies on GPT which may contain hidden and unknown biases. As GPT is regularly updated, parts of our experiments may not be exactly emulated.

Summary	Fluency	Consistency	Relevance	Coherence
ChatGPT	3.8	3.3	5.0	4.2
GOLD	5.0	5.0	5.0	5.0
ViT5	4.0	4.2	4.3	4.2

Table 8: *Results for human evaluation on 50 samples. Scores range from 1 (worst) to 5 (best). GOLD is the baseline which has all scores of 5. ViT is the best model for ROUGE scores.*

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A. Additional Details about Experiments

A.1. Additional Details of Data Collection: Data Simulation Methods

Pseudo Python code for creating simulated data (*SIM*) using the extra medical text data, which is described in the subsection Data Collection 3.2.

```python
fillers = [List of Vietnamese filler words]

def simulate_speaking_style(words, fillers):
    new_words = []

    for word in words:
        # Randomly repeat a word with 0.01 probability
        if random.random() < 0.01:
            new_words.append(word)
        # Randomly insert a filler with 0.01 probability
        if random.random() < 0.01:
            new_words.append(random.choice(fillers))

    return ' '.join(new_words)
```

```python
def simulate_spoken_text(simulated_speaking_style_utterances, avg_lengths):

    chosen_len = random.choice(avg_lengths)

    # Randomly decide trimming strategy
    trim_strategy = random.choice(['back', 'front', 'both'])

    if trim_strategy == 'back':
        trimmed_words = words[:chosen_len]
    elif trim_strategy == 'front':
        trimmed_words = words[-chosen_len:]
    elif trim_strategy == 'both':
        trimmed_words = words[flexible_start:flexible_end]

    return trimmed_words
```

A.2. Additional Data Statistics

Table 9 shows the additional data statistics which extends the Table 1.

| | Gold-standard Data | | | Synthethic | |
| | Real-world | | Simulated | | |
	Local	Global	Local	Local	
Train	837	382	560	18981	
Dev	874	624	70	0	
Test	1192	767	70	0	
Total	2903	1773	700	18981	24357
Appendix					
#Summary words	46683	40465	18235	669900	775283
#Input words	202944	215229	77485	2074704	2570362
Avg summary length	16.08	22.82	26.05	35.29	
Avg input length	69.91	121.39	110.69	109.30	

Table 9: *Full data statistics for VietMed-Sum. Extention of Table 1.*

A.3. GPT Setup for Annotation

We used GPT-3.5 Turbo with hyperparameters *temperature*=0.7 and *top_p*=0.9 to generate GPT summaries. Our choice to use GPT 3.5 Turbo for generating GPT summaries is motivated by balancing between the annotation cost and the overall data-model performance. To improve the overall quality of these summaries, we used in-context learning with two examples. Figure 1 illustrates the prompt we used for in-context learning.

A.4. Summarization Evaluation Metrics

We used ROUGE [14], a metric commonly used for summarization, to evaluate our models. ROUGE measures the lexical overlap between the candidate and the reference summaries. We report the ROUGE-1, ROUGE-2, and ROUGE-L scores on the test set.

Generate vietnamese summaries of these passages. Do not use a third-person perspective. The length of the summary is at most 20% of that of the passage, except for passages that are too short. Retain as many entities as possible while be concise as much as possible. Two examples are provided. Follow the format of the summaries in the examples.
Examples:
Passage 1: ...
Summary 1: ...
Passage 2: ...
Summary 2: ...

Passage: {}
Summary:

Figure 1: *An example of prompt used for GPT summaries*

ROUGE-1 and ROUGE-2 measures the overlap between consecutive unigram and bigram, while ROUGE-L is based on the longest common subsequence.

A.5. Detailed Information of Baseline Summarization Models

Since some models lack the large version, our experiments were conducted on the base version. Fine-tuning was done using the Transformer library [21].

- **BARTpho** [15] is the Vietnamese BART [22] pre-trained on 20GB of text from the Vietnamese Wikipedia and the Vietnamese news corpus. We used both BARTpho$_{syllable}$ and BARTpho$_{word}$, with number of parameters being 132M and 150M respectively.
- **ViT5** [16] is the Vietnamese T5 [23] pre-trained on 71GB of text from Vietnamese subset of CC100 [24]. We included ViT5-vietnews, ViT5 finetuned on Vietnews [17] for summarization, to observe if the previous fine-tuning knowledge could assist the model in our downstream task. The number of parameters is 310M.
- **ViPubmedT5** [18] is the ViT5 model pre-trained on 20GB of biomedical data from ViPubmed [18]. The number of parameters is 220M. To integrate into our pipeline, we converted its t5x [25] checkpoint to Flax [26].

A.6. Details of Human Evaluation Experiments

We used the human evaluation proposed by [19, 20], which evaluates summaries based on 4 metrics:

- Fluency: evaluates the quality of individual generated sentences
- Consistency: evaluates the factual alignment between the source text and generated summary
- Relevance: evaluates the importance of summary content
- Coherence: evaluates the collective quality of all sentences

We randomly picked 50 input text and their corresponding summaries in the test set, and ask a medical expert to give scores ranging from 1 to 5 based on 4 metrics mentioned above. To remove human bias and subjectivity, the medical expert did not know which summary was generated by human annotators or by models.

B. Additional Experimental Results

B.1. Additional Results for ASR Transcript Summarization

Table 10 shows the baseline results on ASR transcript for global summaries. Table 11 shows the baseline results on ASR transcript for local summaries. Both tables are the extention of Table 7.

B.2. Results for English-translated *VietMed-Sum*

To help international researchers, we translated our *VietMed-Sum* dataset, called *VietMed-Sum-en* and conducted experiments on it. Table 12 shows the results of fine-tuning on *VietMed-Sum-en* using some English pre-trained language models.

C. Annotation Guideline

We asked two annotators to follow the guideline described below:

1. Keep the summary as short as possible without losing key information. The length of the summary is at most 20% of that of the passage (except too short dialogues).
2. Retain as many medical named entities as possible as long as the limit is not exceeded.
3. Retain the purpose of the passage, e.g. questions should be preserved as question summaries.

Data	Model	R-1	R-2	R-L
Global + Local	BARTpho$_{syllable}$	57.19	34.27	44.97
	BARTpho$_{word}$	55.69	33.66	43.95
	ViT5-	57.44	34.61	45.33
	ViT5-vietnews	57.61	34.09	44.67
	ViPubmedT5	57.58	33.42	44.13
Local	BARTpho$_{syllable}$	56.75	33.27	44.42
	BARTpho$_{word}$	55.22	32.15	43.05
	ViT5	54.41	30.69	41.91
	ViT5-vietnews	56.39	32.6	43.35
	ViPubmedT5	54.21	30.15	41.04
Global	BARTpho$_{syllable}$	54.77	33.14	43.62
	BARTpho$_{word}$	52.96	32.22	42.02
	ViT5	55.92	34.11	44.57
	ViT5-vietnews	55.95	33.87	44.25
	ViPubmedT5	55.35	32.2	43.0
SYN	BARTpho$_{syllable}$	56.78	33.54	43.97
	BARTpho$_{word}$	56.08	32.92	43.19
	ViT5	57.32	34.7	44.71
	ViT5-vietnews	56.73	33.45	44.08
	ViPubmedT5	56.62	34.01	44.21
SYN + (Global + Local)	BARTpho$_{syllable}$	56.58	34.32	44.69
	BARTpho$_{word}$	56.44	34.28	44.72
	ViT5	58.51	36.26	46.4
	ViT5-vietnews	58.21	35.67	45.84
	ViPubmedT5	58.3	36.07	45.91
SYN → (Global + Local)	BARTpho$_{syllable}$	57.38	34.4	45.44
	BARTpho$_{word}$	56.42	34.24	44.65
	ViT5	58.95	36.82	46.63
	ViT5-vietnews	58.22	35.34	46.02
	ViPubmedT5	57.58	33.42	44.13

Table 10: *Experimental results on ASR transcripts. We report the ROUGE on the GOLD test global summaries. Extention of Table 7.*

4. Summaries must sound natural.

D. Ethical Statements

D.1. Content Ownership

According to OpenAI terms of use[8], we have our ownership of the content generated by ChatGPT: "As between you and OpenAI, and to the extent permitted by applicable law, you (a) retain your ownership rights in Input and (b) own the Output. We hereby assign to you all our right, title, and interest, if any, in and to Output."

Also according to Fair Use[9], we and our work are protected under Fair Use policy to conduct and publicly release research data for research purposes. We state that we do not release data for commercial purposes, thus not rivaling any business parties.

D.2. Privacy

Understanding that medical data is sensitive, during the process of data generation and annotation, we carefully annonymized and removed any text that might reveal patient identities which might be incidently generated by LLMs.

E. Acknowledgement

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[8]https://openai.com/policies/terms-of-use
[9]https://www.copyright.gov/fair-use/

Data	Model	R-1	R-2	R-L
Gold	BARTpho$_{\text{syllable}}$	55.32	32.46	44.04
	BARTpho$_{\text{word}}$	53.22	30.98	42.12
	ViT5	54.86	31.70	43.76
	ViT5-vietnews	55.33	31.93	43.68
	ViPubmedT5	55.64	31.80	43.42
Local	BARTpho$_{\text{syllable}}$	54.44	31.41	43.16
	BARTpho$_{\text{word}}$	52.96	29.69	41.49
	ViT5	52.81	29.49	41.29
	ViT5-vietnews	54.34	31.03	42.61
	ViPubmedT5	52.34	28.09	39.97
Global	BARTpho$_{\text{syllable}}$	53.69	31.75	43.01
	BARTpho$_{\text{word}}$	51.62	30.11	40.64
	ViT5	55.09	32.55	43.88
	ViT5-vietnews	54.72	32.28	43.37
	ViPubmedT5	53.95	31.33	42.42
SYN + (Global + Local)	BARTpho$_{\text{syllable}}$	54.31	31.17	42.23
	BARTpho$_{\text{word}}$	53.76	31.18	41.92
	ViT5	55.21	32.47	43.29
	ViT5-vietnews	54.01	31.49	41.85
	ViPubmedT5	54.28	31.00	42.41
SYN	BARTpho$_{\text{syllable}}$	54.78	31.92	43.46
	BARTpho$_{\text{word}}$	54.06	31.58	42.56
	ViT5	56.52	34.30	45.15
	ViT5-vietnews	58.21	35.67	45.84
	ViPubmedT5	58.30	36.07	45.91
SYN → (Global + Local)	BARTpho$_{\text{syllable}}$	55.46	32.57	44.38
	BARTpho$_{\text{word}}$	54.22	32.07	43.27
	ViT5	56.78	34.43	45.52
	ViT5-vietnews	56.48	33.65	45.10
	ViPubmedT5-base	55.48	31.57	43.06

Table 11: *Experimental results on ASR transcripts. We report the ROUGE on the GOLD test local summaries. Extention of Table 7.*

Data	Model	Global Summaries			Local Summaries		
	Model	R-1	R-2	R-L	R-1	R-2	R-L
Gold	BART-base	34.26	16.19	29.85	35.87	17.69	31.23
	T5-base	33.49	14.73	28.89	34.67	15.93	29.88
Global	BART-base	33.87	15.70	29.62	35.93	17.45	31.50
	T5-base	30.69	13.49	26.29	31.65	14.47	27.04
Local	BART-base	34.01	15.72	29.56	35.42	17.16	30.80
	T5-base	33.05	14.59	28.18	34.37	15.77	29.33

Table 12: *ROUGE scores of T5 and BART on the GOLD set of VietMed-Sum-en*