

## SMILE: Single-turn to Multi-turn Inclusive Language Expansion via ChatGPT for Mental Health Support

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## Abstract

There has been an increasing research interest in developing specialized dialogue systems that can offer mental health support. However, gathering large-scale and real-life multi-turn conversations for mental health support poses challenges due to the sensitivity of personal information, as well as the time and cost involved. To address these issues, we introduce the SMILE approach, an inclusive language expansion technique that employs ChatGPT to extend public single-turn dialogues into multi-turn ones. Our research first presents a preliminary exploratory study that validates the effectiveness of the SMILE approach. Furthermore, we conduct a comprehensive and systematic contrastive analysis of datasets generated with and without the SMILE approach, demonstrating that the SMILE method results in a large-scale, diverse, and close-to-real-life multi-turn mental health support conversation corpus, including dialog topics, lexical and semantic features. Finally, we use the collected corpus (SMILECHAT) to develop a more effective dialogue system that offers emotional support and constructive suggestions in multi-turn conversations for mental health support.

*The code and data are released for research purposes only.<sup>1</sup>*

## 1 Introduction

Mental health issues (Kessler et al., 2005) have been a constant concern of human beings. In recent years, the rapid advancement of natural language processing (NLP) techniques (Vaswani et al., 2017; Ouyang et al., 2022; Ni et al., 2022) has made extraordinary conversational AI possible, such as ChatGPT and GPT-4 (OpenAI, 2023). It is imperative to focus on developing specialized dialog systems (Liu et al., 2022; Tu et al., 2022) that provide mental health support as an effective and practi-

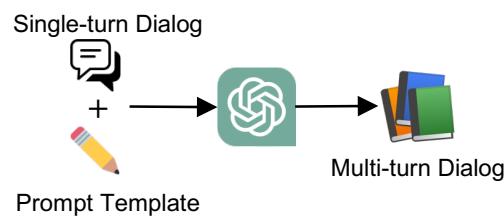


Figure 1: The pipeline of SMILE.

cal online counseling approach for people in need. However, the lack of publicly available, large-scale, high-quality, and real-life multi-turn chat datasets in the mental health support domain hinders the development of dialog agents.

Conversations related to mental health support often contain sensitive information and should be kept confidential (Lu et al., 2021) to protect the privacy of help-seekers. Making these conversations publicly available may discourage them from seeking support or negatively impact their personal and occupational lives once known by other people with whom they are familiar. To facilitate progress in the NLP community, some researchers have attempted to collect a large-scale dialog corpus (Liu et al., 2021; Sun et al., 2021; Zheng et al., 2022) via crowd-sourcing, data crawling or data augmentation to build a dialog agent that can provide emotional support and constructive suggestions.

Crowd-sourcing conversations (Liu et al., 2021) for emotional support has limitations due to the high cost and time required to train and manage annotators, as well as the difficulty in mimicking real-life interactions, that is, interlocutors may lack an understanding of the dilemma of living with mental disorders. An alternative is crawling QA (Sun et al., 2021) on a public mental health forum for training psychological support models. However, single-turn conversations may not be sufficient for resolving mental health issues, as multiple interaction ex-

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<sup>1</sup><https://github.com/qiuahuachuan/smile>

changes are often needed. Multi-turn conversations, which can better simulate real-world conversations, are therefore more practical for training psychological support models. While the post-triggered machine-augmented method (Zheng et al., 2022) can address the limitations of scale and topic diversity, it does not consider real-life supporters’ responses.

To this end, we propose SMILE, single-turn to multi-turn inclusive language expansion via ChatGPT, a large language model with chatting capability, which has shown remarkable performance on various natural language processing tasks. With the proposed method, we build a large-scale, diverse (including dialog topics, lexical and semantic aspects) and close to real-life multi-turn conversation dataset for mental health support. Specifically, we instruct ChatGPT to rewrite the QA, which can also be viewed as a single-turn dialog from the real world, into a multi-turn conversation.

Our main contributions in this paper are as follows:

- We propose SIMLE, single-turn to multi-turn inclusive language expansion via ChatGPT. We validate the effectiveness of the SMILE approach through explorative study.
- We conduct a comprehensive and systematic analysis to verify the dialog diversity of the SMILE method. Then, we use our proposed SMILE method to call ChatGPT (gpt-3.5-turbo) API for automatically generating a large-scale, diverse and close to real-world multi-turn conversation dataset, named SMILECHAT, for mental health support.
- We utilize the SMILECHAT corpus to further empower the chatting capability of mental health support for publicly available chat models.

## 2 Related Work

### 2.1 Applications of ChatGPT

ChatGPT has proven to be a powerful AI tool for various NLP tasks since its release. Currently, it is being utilized in several domains, such as conversational AI (Alessa and Al-Khalifa, 2023; ?; Chen et al., 2023), education (?Eshghie and Eshghie, 2023), code program (Dong et al., 2023; ?) and healthcare (Zhao et al., 2023; Yang et al., 2023).

Furthermore, ChatGPT’s efficiency and cost-

effectiveness have been well-documented, making it superior to human annotators (Gilardi et al., 2023; Zhu et al., 2023) even in zero-shot accuracy tasks. Xu et al. (2023) have proposed the use of self-chatting, where ChatGPT engages in a conversation with itself, resulting in 111.5k dialogs collected from Quora and Stack Overflow sources and 47k conversations from the medical domain.

Auto-GPT<sup>2</sup>, an AI agent, is capable of breaking down a natural language goal into sub-tasks and using various tools and the internet in an automated loop to achieve the objective. Shen et al. (2023) have suggested using ChatGPT for task planning when receiving user inquiries, selecting appropriate models based on function descriptions from Hugging Face, executing each subtask using the chosen AI model, and summarizing the response based on the execution’s outcomes.

In summary, ChatGPT has already demonstrated its enormous potential as an intelligent pipeline tool that can significantly advance NLP development, despite having only a restricted API available for researchers.

### 2.2 Datasets for Mental Health support

Research on mental health support has significantly depended on the availability of public available datasets (Sun et al., 2021; Liu et al., 2021; Zheng et al., 2022) in recent years. The large-scale conversational datasets have enabled researchers to investigate various aspects of mental health, including identifying mental health conditions (Liu et al., 2023; Srivastava et al., 2022), predicting support strategies (Sun et al., 2021), and deciding personalized interventions (Golden et al., 2023).

Liu et al. (2021) first define the emotional support conversation task and then, via crowd-sourcing, construct ESConv, an emotional support conversation dataset containing 1053 dialogs with rich support strategies. However, the collection of ESConv requires high cost and time yet leads to a small scale of dialog dataset. To this end, Zheng et al. (2022) present an approach for augmenting data scale with informative dialog posts and then constructing AugESC, a model-synthesized dataset with 102k dialogs. The previous two datasets are limited to English. In order to facilitate the research in Chinese, hence Sun et al. (2021) crawl QA posts

<sup>2</sup><https://github.com/Significant-Gravitas/Auto-GPT>

in a public mental health support platform compiling PsyQA, a high-quality Chinese dataset related to psychological health counseling in the form of one question mapping to multiple answers. The answers in PsyQA usually are very long, mimicking the whole counseling process.

### 3 Data Preprocessing for PsyQA

#### 3.1 Data Cleaning

This work aims to construct a large-scale and close to real-life multi-turn conversation corpus based on PsyQA with the proposed SMILE method. Although QA can be deemed as a single-turn conversation between a real seeker and a supporter, there are some differences in wording compared with actual multi-turn conversations. For example, the word "楼主" (literally *thread starter*) frequently appears in QA but rarely in conversation. Therefore, we suggest a two-stage data cleaning process for PsyQA to mitigate the linguistic discrepancies before rewriting QA to multi-turn conversations. This process involves both automatic and manual cleaning procedures.

**Automatic Cleaning** We employ a sequential data cleaning pipeline to swiftly replace words that are unsuitable to the conversation scenario. For example, both "楼主你" (literally *thread starter you*) and "楼主" (literally *thread starter*) should be replaced with "你" (you). However, it is necessary to perform the former replacement to avoid the repetition of "你" and the resulting "你你" (*you-you*). For detailed content, see Figure 11 in Appendix B.

**Manual Cleaning** Due to the specificity and complexity of language, manual cleaning remains an essential part of the process. To prevent virtual dialog systems from exhibiting overly frequent anthropomorphic behavior, we identify instances of the Chinese word for "hug" (抱抱) and manually delete sentence snippets containing this term.

#### 3.2 Length Control

After conducting a statistical analysis of the PsyQA dataset released by (Sun et al., 2021), we find that 757 QAs have a total length exceeding 1,800 characters. Additionally, we identify 9 QAs in which the total discourse length of helpers and supporters exceeds 4,000 characters. Furthermore, the ChatGPT model has a maximum context length of 4096 tokens. To ensure high-quality and smooth rewrites, we limit the length of the question and answer (QA)

```
'role': 'user',
'content': '"Generate a mental health support dialog in Chinese of 10 exchanges or more between a help-seeker and a supporter, where "求助者: utterance。 支持者: utterance。" is an exchange."
```

You should follow these requirements: 1. First, select a mental health problem by yourself. 2. Each sentence must begin with 求助者: or 支持者: . 3. The conversation must begin with 求助者: . 4. The supporter's response has just the right amount of emotional support and regulation. 5. The length of each speaker's utterance should be satisfied with the dialog scenario and not too long."

Figure 2: The plain prompt used to generate dialogs for mental health support.

```
'role': 'user',
'content': '"I want you to act as a text rewriter. You should follow these requirements: 1. Each sentence must begin with 求助者: or 支持者: . 2. The conversation must begin with 求助者: . 3. The supporter's response has just the right amount of emotional support and regulation. 4. The length of each speaker's utterance should be satisfied with the dialog scenario and not too long."
```

You need to rewrite the given single-turn dialog into a mental health support dialog in Chinese of 10 exchanges or more between a help-seeker and a supporter, where "求助者: utterance。 支持者: utterance。" is an exchange.

Single-turn dialog: \${dialog}

**Let's analyze and rewrite it step by step.**  
Your rewritten multi-turn dialog is:"

Figure 3: The prompt with the SMILE method used to generate dialogs for mental health support.

pairs, maximizing the number of rewritten dialog turns. Specifically, we cap the length of the QA pairs at 1800 characters, truncating any excess text. This ensures that the generated text is limited to approximately 2000 tokens. It is worth noting that the PsyQA data we used for this study undergo a data preprocessing process.

## 4 Methodology

In this section, aiming to interpret the mechanism of the SMILE approach, we mainly focus on detailing our methodology. To establish some conventions regarding certain terms, we define the "help-seeker" and "supporter" as "求助者" and "支持者" in Chinese, respectively. A single-turn dialog is defined as "求助者:  $u^H$  支持者:  $u^S$ ", where  $u^H$  and  $u^S$  represent the utterances of the help-seeker and supporter, respectively, and  $H$  and  $S$  refer to the help-seeker and supporter.

### 4.1 Prompt Template

Our study focuses on two primary types of prompt templates, with and without single-turn dialog, de-

signed to guide ChatGPT in generating multi-turn conversations.

#### 4.1.1 Plain Prompt

As its name suggests, the plain prompt lacks a single-turn dialogue and instead uses only the initial prompt to generate multi-turn dialogues. The specifics of the plain prompt are illustrated in Figure 2. As the baseline, we present a multi-turn dialog example generated with the plain method, as illustrated in Figure 12 in Appendix C.

#### 4.1.2 Prompt with SMILE Method

Our proposed method, referred to as the SMILE method, expands language inclusively from single-turn to multi-turn dialogues. The specific prompt template is depicted in Figure 3. To evaluate the effectiveness of the chain-of-thought (CoT) prompting in the SMILE method (highlighted in red in Figure 3), we further divide it into two sub-methods: SMILE and SMILE<sub>cot</sub>.

Overall, we establish three prompt methods in this paper. For each prompting method, we instruct ChatGPT to generate 5000 conversations for preliminary exploratory analysis. We automatically filter out conversations that do not meet our requirements, and we regenerate any dialogue where the turn-taking falls below 3.

### 5 Explorative Study

This section primarily addresses three research questions for exploratory analysis.

- 1 Are the utterance lengths from the help-seeker and supporter in ChatGPT-generated conversations consistent with those found in real-world conversations?
- 2 Does the introduction of a single-turn dialog (QA) affect the number of dialog turns, and can the chain of thought improve this?
- 3 How effective is the SMILE method, and can the chain of thought improve its impact?

#### 5.1 Variations in Utterance Length Distribution

**Motivation** In conversation, there is typically no fixed limit on the length of words used by each speaker. Help-seekers and supporters may express themselves differently and have varying word usage habits, resulting in variations in vocabulary and sentence length during the conversation.

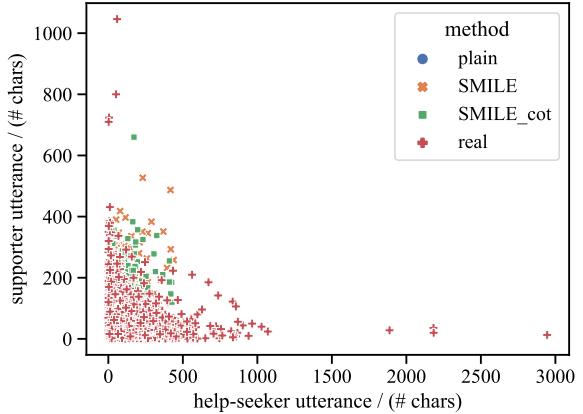


Figure 4: Relationship of utterance length variation between help-seekers and supporters in each turn, comparing real-life counseling conversations with conversations generated by the three proposed methods.

**Dataset** To investigate this phenomenon, we collected a small dataset of mental health support conversations between actual help-seekers and experienced supporters from a Chinese online text-based counseling platform. This real-life corpus contains 2000 multi-turn conversations, which serves as our reference. Each of the three methods proposed in this paper also contains 2000 conversations.

**Results** Figure 4 illustrates the relationship of utterance length variation between the help-seeker and supporter in each turn, comparing the conversations generated by the three methods proposed in this paper with real-life counseling conversations. Notably, the length of utterances generated by ChatGPT for both the help-seeker and supporter falls within the expected distribution observed in real-life settings, validating the rationality of the generated utterance length.

**Key takeaways** Our findings demonstrate that there is no correlation in utterance length between help-seekers and supporters in real-life counseling conversations. Additionally, the generated length of utterances by ChatGPT aligns with the distribution observed in real-life settings, indicating the effectiveness of our proposed methods.

#### 5.2 Distribution of Dialog Turns

**Motivation** Similar to humans, we expect ChatGPT to generate a comparable distribution of dialogue turns by specifying turn requirements across the three prompting methods.

**Dataset** For each method, we generate 5000 con-

Turns	plain	SMILE	SMILE <sub>cot</sub>
3	2	26	10
4	118	197	163
5	1107	1018	976
6	2062	1652	1856
7	1048	1277	1238
8	344	548	513
9	163	212	175
10	135	64	65
11	19	6	2
12	2	0	1
16	0	0	1
Avg. Turns	6.30	6.36	6.35

Table 1: Distribution of dialog turns in 5000 conversations across three prompting methods. Results show no significant differences between any two methods (p-value > 0.05, Student’s t-test).

versations and calculate the number of dialogue turns and their corresponding distributions, as shown in Table 1.

**Results** Our results indicate that the average number of turns across all three prompting methods is approximately 6.3. ChatGPT struggles to satisfy our requirements, even when requiring generating dialogs with 10 turns or more in the plain prompt method. Notably, the average number of turns in the SMILE method is superior to that of the SMILE<sub>cot</sub> method.

**Key takeaways** The number of dialogue turns generated by ChatGPT is primarily concentrated between 4 and 10 turns across all prompting methods, indicating the feasibility of the SMILE method and suggesting that the introduction of a single-turn dialogue does not significantly impact the number of turns. Additionally, our findings suggest that the chain-of-thought technique does not help improve dialogue turns.

### 5.3 Extent of Rewriting with Role-based Analysis

**Motivation** Extending a single-turn dialog to a multi-turn one is a challenging task. Since QA is a single-turn and lengthy textual dialog, we meticulously analyze it from the perspectives of both the help-seeker and supporter to explore whether the rewrites are more influenced by the help-seeker or the supporter.

**Formulation** For each method, we generate 5000 conversations and split each dialog into two parts, one from the help-seeker and another from the

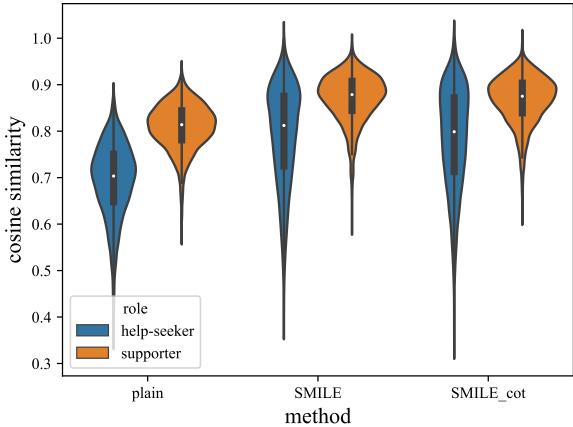


Figure 5: Cosine similarity values obtained using the plain method, SMILE, and SMILE<sub>cot</sub> from the perspectives of both the help-seeker and supporter roles, with all computations anchored to PsyQA.

supporter. We then compute the cosine similarity from the role perspective. We represent a conversation between a help-seeker and supporter as  $d = \{u_1^H, u_1^S, u_2^H, u_2^S, \dots, u_t^H, u_t^S, \dots, u_n^H, u_n^S\}$ , where  $u_t^H$  and  $u_t^S$  represent the respective utterances of  $t$ -th turn in a conversation. We concatenate all utterances of the help-seeker to a string  $Str^H = (u_1^H, u_2^H, \dots, u_t^H, \dots, u_n^H)$ , and vice versa for the supporter. The utterance strings of help-seeker and supporter in PsyQA are represented as  $Str_Q^H$  and  $Str_S^H$ , and are viewed as anchors. For example, in the SMILE method setting, to compute the cosine similarity for the help-seeker, we can obtain

$$\text{cosine}(Str_Q^H, Str_S^H) = \frac{E_Q^H \times E_S^H}{\|E_Q^H\| \times \|E_S^H\|} \quad (1)$$

where  $E_Q^H$  and  $E_S^H$  denote the mean pooling embeddings with 768 dimensions for texts in PsyQA and SMILE, respectively.

In this work, we utilize Sentence-BERT (Reimers and Gurevych, 2019) to calculate the text embeddings. We use the implementation available on Hugging Face <sup>3</sup> to map each dialog to a 768-dimensional dense vector. The maximum context length is 512, and consequently, the dialog text is automatically truncated when it exceeds this length.

<sup>3</sup><https://huggingface.co/shibing624/text2vec-base-chinese>

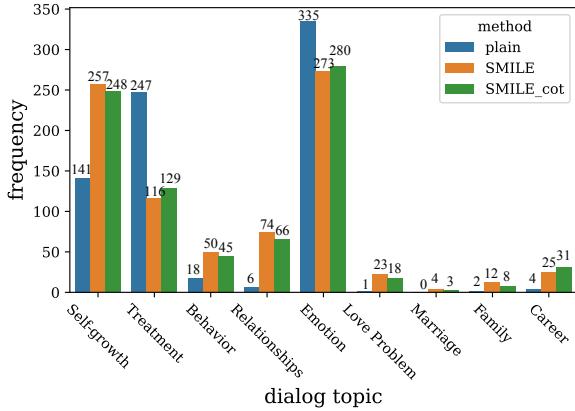


Figure 6: Distribution of dialog topics in three methods.

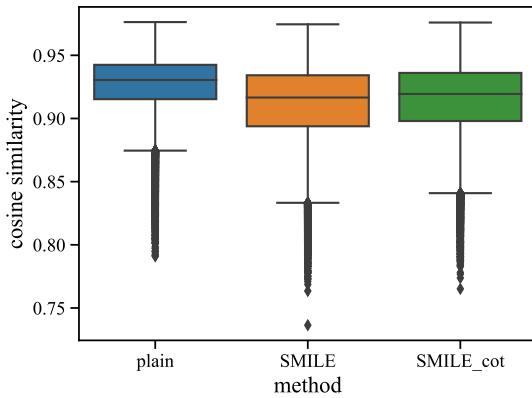


Figure 7: Difference of cosine similarity between three methods.

**Results** As depicted in Figure 5, our findings indicate that both SMILE and SMILE<sub>cot</sub> perform better than the plain method, with no significant difference between the two. From the perspective of the help-seeker, we observed that there are 1262 instances where cosine values in SMILE exceed the highest value in the plain method, while in SMILE<sub>cot</sub>, there are 1192 such instances. Conversely, from the viewpoint of the supporter, we found that 356 SMILE cosine values surpass the maximum value in the plain method, whereas there are 304 such instances in SMILE<sub>cot</sub>.

**Key takeaways** Our analysis reveals that the SMILE method can significantly extend the single-dialog to multi-turn dialog. Additionally, both SMILE and SMILE<sub>cot</sub> perform better than the plain method. However, there is no significant difference between them, suggesting that the chain-of-thought technique does not improve the method’s efficacy.

## 6 Dialog Diversity Analysis

To explore corpus diversity, we conduct a fundamental contrastive statistical analysis from three perspectives: dialog topic, lexical features, and semantic features. Firstly, we analyze the distribution of dialog topics for all three methods. Secondly, to evaluate lexical diversity, we use distinct- $n$  to calculate lexical features. Finally, we quantitatively study the dialog semantic feature using Sentence-BERT (Reimers and Gurevych, 2019) to compare discourse similarity at the dialog level.

### 6.1 Dialog Topics

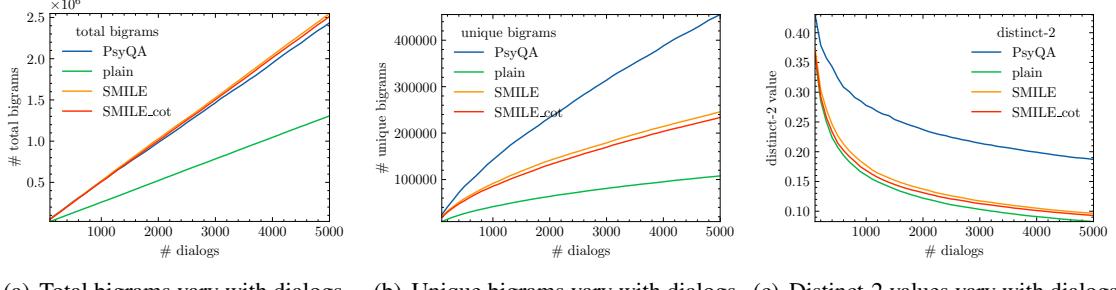
We sample 2000 distinct conversations from each method and design a prompt to automatically label dialog topics provided by Sun et al. (2021) for each conversation. Figure 6 demonstrates that the conversations generated using the SMILE method are substantially more diverse than those generated using the plain method.

When using the plain prompt approach, the conversational topics of the generated dialogues mostly revolve around three categories: Self-growth, Treatment, and Emotion. However, other categories are almost entirely ignored, except for Behavior, which occurs 18 times. Among the two categories, Treatment, and Emotion, the number of dialogue corpus generated using the plain prompt method is higher than those generated using the SMILE method.

In contrast, with the same number of conversations, the corpus generated with the SMILE method contains significantly richer dialog topics than that obtained using the plain prompt method in the six categories of Behavior, Relationships, Love Problem, Marriage, Family, and Career, where the frequency of conversation topics is below 100.

### 6.2 Lexical Feature

Lexical diversity is a measure of the richness and variety of the vocabulary used in a conversation corpus. In this study, we utilize the distinct- $n$  metric (Li et al., 2015) to analyze the lexical diversity between different methods. The number of total bigrams and unique bigrams, as well as distinct-2 values, vary with the number of dialogs, as shown in Figure 8. In the meantime, we offer statistics on 5000 conversations for each prompt setting, which also includes PsyQA as a reference point. Additionally, for a more comprehensive examination of unigrams, we present the analysis in Figure 10 in



(a) Total bigrams vary with dialogs. (b) Unique bigrams vary with dialogs (c) Distinct-2 values vary with dialogs.

Figure 8: The number of total bigrams and unique bigrams, distinct-2 values vary with the number of dialogs.

Metrics	Avg. Turns	Total Turns	Avg. Length	# unique unigrams	# total unigrams	distinct-1	# unique bigrams	# total bigrams	distinct-2
PsyQA	1.00	5000	377.9	38107	2439828	0.0156	455299	2434828	0.1870
plain	6.30	31523	32.4	9801	1310756	0.0075	107863	1305756	0.0826
SMILE	6.36	31805	63.4	18434	2552948	0.0072	245777	2547948	0.0965
SMILE <sub>cot</sub>	6.35	31743	62.8	17697	2517419	0.0070	233740	2512419	0.0930

Table 2: Statistics of 5000 conversations in every prompt setting, including PsyQA.

## Appendix A.

### 6.3 Semantic Feature

In the PsyQA dataset, a specific question may have one or more answers. To ensure fairness and avoid duplicate occurrences of the same question with different answers, we sample 500 non-duplicate questions from the first 5000 QA in PsyQA and select the first answer to the corresponding question. Thus, we obtain 500 distinct indices and corresponding generated dialogs, as well as those obtained using the plain prompt method. We then compute the pairwise cosine similarity.

Figure 7 demonstrates that the medians in both the SMILE and SMILE<sub>cot</sub> methods are lower than that of the plain method, and the median in the SMILE method is lower than in the SMILE<sub>cot</sub> method. Regarding the interquartile ranges, the SMILE method has the largest width, the SMILE<sub>cot</sub> method has the second largest, and the plain method has the smallest. From the perspective of the median and interquartile ranges, we conclude that the corpus generated by the SMILE method leads to the most extensive semantic diversity. However, adding the chain-of-thought prompt has yet to yield any improvement.

Dialogs	Avg. Turns	Avg. Length	Avg. Length (help-seeker)	Avg. Length (supporter)
56032	6.3	62.1	35.3	88.9

Table 3: Statistics of the number of dialogs, average number of turns, average length of each turn, average length in help-seeker and supporter perspective.

## 7 SMILECHAT

### 7.1 Data Statistics

We observe that the SMILE method with the chain-of-thought technique does not show significant improvement compared with the SMILE method alone. Therefore, we utilize the SMILE method to guide the ChatGPT in generating all multi-turn conversations based on PsyQA. We collect a collection of 56,031 conversations, which we call SMILECHAT produced with the SMILE method. Table 3 presents the statistics of the SMILECHAT corpus, where role tokens such as "求助者：" and "支持者：" have been excluded.

### 7.2 Case Analysis

An example of multi-turn dialog generated by SMILE method without chain-of-thought technique, as shown in Figure 9.

### 7.3 Dialogue system construction

Given our synthesized dataset  $D = \{d_1, d_2, \dots, d_n\}$ , where every  $d_j$  is a single multi-turn dialog, we aim to build a dialog system.

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求助者：最近总是和妈妈闹矛盾，但是又不知道该怎么办，能帮我想办法吗？

Help-seeker: Recently, I've been constantly having conflicts with my mom, but I don't know what to do. Can you help me come up with some solutions?

支持者：我了解你的情况，跟亲人之间经常会产生矛盾是很常见的现象。你不妨试试和妈妈沟通一下，平静地提出自己的疑惑和不满，看看能否解决矛盾。

Supporter: I understand your situation. Having conflicts with family members is a common phenomenon. You can try talking to your mom calmly and express your doubts and dissatisfaction to see if you can resolve the conflicts.

求助者：但是每次我和妈妈说话，总会起争端，她总是让我感觉她不信任我，我该怎么办呢？

Help-seeker: But every time I talk to my mom, we always end up arguing. She always makes me feel like she doesn't trust me. What should I do?

支持者：听起来你和妈妈之间的交流很困难，你可以试试换个方式和她沟通，比如写信或者找一个更加中立的人一起协调谈话，让大家都有更好的表达机会。

Supporter: It sounds like communication with your mom is difficult. You can try changing the way you communicate with her, such as writing a letter or finding a more neutral person to mediate the conversation, so that everyone has a better chance to express themselves.

求助者：我特别讨厌和她吵架，可是我有时候就是自制力不够，很难抑制自己的情绪。

Help-seeker: I really hate arguing with her, but sometimes I just can't control my emotions.

支持者：青春期的年轻人情绪波动很大很正常，但是你可以试试找些方法来缓解情绪，比如听听音乐、看看书等等，使自己情绪更稳定。

Supporter: It's normal for young people in adolescence to have emotional fluctuations. However, you can try finding ways to relieve your emotions, such as listening to music or reading, to make yourself more emotionally stable.

求助者：妈妈总是很为我担心，但是我感觉她的表达方式让我很不舒服，怎么办？

Help-seeker: My mom always worries about me, but I feel uncomfortable with the way she expresses it. What should I do?

支持者：你可以试着跟妈妈提出你的感受，说出你觉得她的表达方式不太适合你，看看一起可以找到一个更好的沟通方式。

Supporter: You can try expressing your feelings to your mom and tell her that her way of expressing her concerns may not be suitable for you. See if you can find a better way to communicate together.

求助者：近期我迷上了游戏，可是妈妈总是担心我的学业，会经常跟我谈中考和未来，我也很焦虑。

Help-seeker: I've recently become obsessed with playing games, but my mom is always worried about my academic performance and often talks to me about the high school entrance exam and the future, which makes me very anxious.

支持者：我能理解你的压力，但是你的妈妈对你的学业担忧也是很正常的。你可以试着和妈妈沟通一下，表明自己的压力和困惑，寻求她的理解和支持。

Supporter: I understand the pressure you're under, but your mom's concerns about your academic performance are also normal. You can try communicating with your mom and expressing your pressure and confusion, seeking her understanding and support.

求助者：妈妈总是说是我顶嘴顶的不好，可是我并没有说过什么不好的话，这些误解让我很难受。

Help-seeker: My mom always says that I talk back to her, but I haven't said anything wrong. These misunderstandings make me very upset.

支持者：很抱歉听到这些误解带给你的困扰，你可以试着和妈妈沟通，表明你没有说过不好的话，避免误解的发生。

Supporter: I'm sorry to hear that these misunderstandings are causing you trouble. You can try communicating with your mom and telling her that you haven't said anything wrong, to avoid misunderstandings.

求助者：有时候我觉得妈妈很不公平，总是让我做家务和学习，而她却不怎么做，这让我很不满意。

Help-seeker: Sometimes I feel that my mom is very unfair, always making me do household chores and study, while she doesn't do much herself, which makes me very dissatisfied.

支持者：家务和学习的确是每个人都需要承担的责任，但是你可以跟妈妈商量一下，建立更合理的分工方式，让家的负担更加均衡。

Supporter: Doing household chores and studying are responsibilities that everyone needs to bear. However, you can talk to your mom and work out a more reasonable division of labor to make everyone's burden more balanced.

求助者：我有时候会想，如果我不在妈妈身边，她就不会那么疲惫与辛苦了，是不是我应该离开她，这样她就会开心一些。

Help-seeker: Sometimes I think that if I'm not around my mom, she won't be so tired and exhausted. Should I leave her so that she can be happier?

支持者：不要把这些想法一直压在心里，试着跟她好好沟通，说说你的担心和顾虑，寻求她的支持和理解。离开并不会解决问题，关心和照顾妈妈也是你的责任之一。

Supporter: Don't keep these thoughts to yourself. Try to communicate with her and express your concerns and worries, seeking her support and understanding. Leaving will not solve the problem, and caring for and taking care of your mom is also one of your responsibilities.

求助者：非常感谢你的耐心倾听和建议，我会好好尝试和妈妈沟通，解决我们之间的矛盾。

Help-seeker: Thank you very much for your patient listening and advice. I will try to communicate with my mom and resolve the conflicts between us.

支持者：很高兴能帮助你，你已经迈出了寻求帮助的第一步，接下来只要继续坚持下去，相信问题一定会得到好的解决。

Supporter: I'm glad to have been able to help. You've taken the first step in seeking help, and as long as you continue to persevere, I believe the problem will be resolved.

---

Figure 9: An example of multi-turn dialog generated by SMILE method.

Specifically, for a sampled  $T_d$  turn dialog  $d = \{u_1^H, u_1^S, u_2^H, u_2^S, \dots, u_t^H, u_t^S, \dots, u_{T_d}^H, u_{T_d}^S\} \sim D$ , where  $u_t^H, u_t^S$  is an  $t$ -th utterance spoken by the help-seeker and supporter respectively, we build a model that can predict the supporter utterance  $u_{T_d}^S$  given the context  $c_{T_d} = \{u_1^H, u_1^S, u_2^H, u_2^S, \dots, u_{T_d}^H\}$ . Our objective is to maximize the likelihood probability, i.e.  $\mathbb{E}_{d \sim D} \prod_{t=1}^{T_d} \mathbb{P}(u_{T_d}^S | c_{T_d})$ .

## 8 Interactive Evaluation

Despite the existence of several automatic metrics, such as Perplexity, BLEU (Papineni et al., 2002), and ROUGE (Lin, 2004), for evaluating the performance of dialog systems, human evaluation is more reliable and practical for assessing model responses, particularly in the context of mental health support. As such, we will conduct a comprehen-

sive and dependable evaluation and incorporate the findings in the next version of this paper.

## 9 Conclusion

We utilize the SMILE (Single-turn to Multi-turn Inclusive Language Extension) approach to generate a diverse and close to realistic multi-turn conversation dataset for mental health support using ChatGPT. This method is simple and widely applicable.

We perform experiments analyzing utterance length, dialog turns, and rewrite degree to verify the effectiveness of the SMILE method. Additionally, we conduct a detailed analysis of dialog diversity, considering factors such as dialog topic and lexical and semantic features. Our observations reveal that the SMILE method alone is significantly more effective than the plain method. Ultimately, we employ the collected data to enhance the emotional support capability of publicly available chat models.

## Ethics Statement

Following the data copyright formulated by [Sun et al. \(2021\)](#), we release the multi-turn dialog corpus publicly available for research purposes only. Because of the complexity of the natural world, any suggestions generated by the neural models may exist inappropriately for anyone seeking help. The corpus is rewritten under the context of QA from an online mental health support forum, so we believe there are more advantages than disadvantages in the quality and practicality of answers from online supporters. Suppose the help-seeker does not gain any improvement after interacting with the dialog system trained with multi-turn conversations, SMILECHAT. In that case, we recommend that the help-seeker should seek help from a professional counselor or psychiatrist promptly. After all, a virtual dialog agent may not be a substitute for real-world therapy.

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## A Dialog Diversity

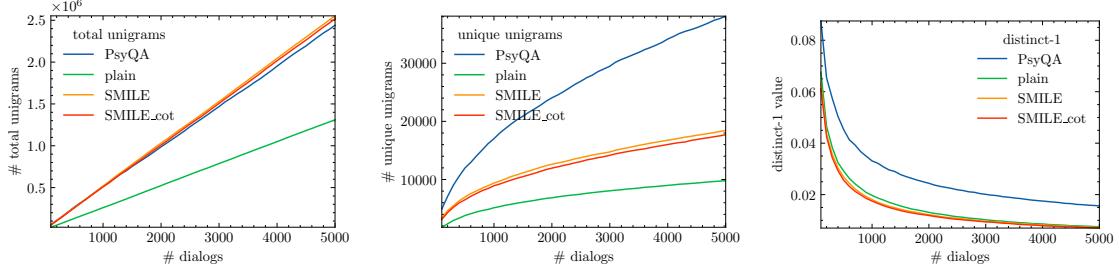
This section presents the details of the total number of unigrams and unique unigrams, as well as the distinct-1 values that vary with the number of dialogs for the three methods, as illustrated in Figure 10.

## B Word List for Data Cleaning

Figure 11 shows the word list for automatic cleaning.

## C A Dialog in the Plain Method

We present a dialog example generated with the plain method, as illustrated in Figure 12.



(a) Total unigrams vary with dialogs. (b) Unique unigrams vary with dialogs (c) Distinct-1 values vary with dialogs.

Figure 10: The number of total unigrams and unique unigrams, distinct-1 values vary with the number of dialogs.

Old String (ZH)	Old String (EN)	New String (ZH)	New String (EN)
'嗨，'	Hi,	"	/
'楼主你'	thread starter you	'你'	you
'题主你'	thread starter you	'你'	you
'楼主你'	thread starter you	'你'	you
'楼主'	thread starter	'你'	you
'题主'	thread starter	'你'	you
'楼主'	thread starter	'你'	you
'阿凉'	A Liang (a name)	'我'	me
'答主'	respondent	'人'	others

Figure 11: Word list for automatic cleaning.

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求助者：我最近有些情绪低落，感觉总是想哭。  
Help-seeker: I have been feeling a bit down recently, and I always feel like crying.  
支持者：听起来你感觉很难过。你想跟我分享一下你的感受吗？  
Supporter: It sounds like you are feeling very sad. Would you like to share your feelings with me?  
求助者：其实我也不知道自己为什么会情绪低落，但是总觉得一切都很无助。  
Help-seeker: Actually, I don't know why I feel so down, but I just feel like everything is hopeless.  
支持者：那是很难受的感觉。但是你知道，这种情绪是可以改变的。你想和我一起探讨一些方法吗？  
Supporter: That is a very difficult feeling. But you know, this emotion can be changed. Would you like to explore some ways with me?  
求助者：我感觉自己不想跟任何人说话，也不想做其他的事情了。  
Help-seeker: I don't feel like talking to anyone or doing anything.  
支持者：对于这种情况，有时候我们需要给予自己时间和空间。但是也不能太孤单，你可以试着和身边的人沟通或者外出走走。  
Supporter: Sometimes in situations like this, we need to give ourselves time and space. But we also shouldn't be too isolated. You can try communicating with people around you or going for a walk.  
求助者：我曾经试过很多方法，但是都没有效果。  
Help-seeker: I have tried many methods before, but they didn't work.  
支持者：那些方法或许只是不适合你。我们可以一起尝试一些新的方式，找到适合你的方法。  
Supporter: Those methods may not have been suitable for you. We can try some new ways together and find the ones that work best for you.  
求助者：我感觉自己很害怕，无法面对一些事情。  
Help-seeker: I feel very scared and unable to face some things.  
支持者：害怕是很正常的感觉。但我们可以学习如何面对和克服这种恐惧。你需要寻求帮助来处理这个问题吗？  
Supporter: It's normal to feel scared. But we can learn how to face and overcome these fears. Do you need help dealing with this issue?  
求助者：其实我很想去看看心理医生，但是我害怕别人会认为我很奇怪。  
Help-seeker: Actually, I really want to see a psychologist, but I'm afraid others will think I'm weird.  
支持者：寻求帮助是很勇敢的行为，它可以帮助我们更快的走出困境。别人的看法不能左右你的决定，你可以在我的陪伴下去找到心理医生。  
Supporter: Seeking help is a brave act, and it can help us get out of difficult situations faster. Other people's opinions should not influence your decisions. You can find a psychologist with my support.  
求助者：谢谢你一直在我的身边，听我倾诉。  
Help-seeker: Thank you for being by my side and listening to me.  
支持者：无论何时，我都会支持你。不要忘记，你不是一个人在战斗。  
Supporter: I will always support you no matter what. Don't forget, you are not alone in this fight.

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Figure 12: A dialog example generated with the plain method.