Adolescent Psychological Support Dialogue Generation Model of Domain Data-Driven

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***Abstract*—To address the limited adaptability of existing psychological dialogue data in the field of adolescent mental health support, and the insufficient guidance ability of current models, the Adolescent Psychological Support Dialogue Generation Model of Domain Data-Driven (APS-DM) is proposed. By extracting multi-level adolescent psychological topics, using topic-related keywords to filter and integrate data corpus, a context-based role-playing prompt is designed according to the characteristics of adolescent psychological development stages. It is intended to guide GPT-4 in performing multi-turn semantic reconstruction, thereby constructing an adolescent psychological support dialogue dataset (AdoPsyDialogue). Besides, a structured thinking-guided prompt is designed to constrain the response generation scenarios. A parameter-efficient fine-tuning method is used to optimize the base model, enhancing its ability to provide adolescent psychological support responses and guidance. Experimental results on the QsnTest dataset demonstrate that the APS-DM model significantly outperforms models such as ChatGLM2-6B and ChatGPT-3.5 in both automatic and manual metrics.**

***Index Terms*—Dialogue Model, Adolescent Psychological Support, Role-playing Prompt, Data-Driven, Parameter-Efficient Fine-Tuning.**

I. Introduction

In recent years, adolescent mental health issues have emerged as a major challenge in the field of global public health. According to data from the World Health Organization, the mental health index of the adolescent population is exhibiting a crisis trend characterized by ‘two declines and one rise’. With the continuous development of Large Language Models (LLMs), Related studies [1] have implemented intelligent psychological interventions through the form of psychological support dialogue, which not only effectively promotes emotional regulation but also improves mental health conditions.

Existing psychological support dialogue models primarily focus on general psychological domains and fail to adequately address the issues specific to a single age group. As a result, these models struggle to learn the specialized knowledge required in the domain of adolescent psychological counseling. However, the adolescent population exhibits unique communication styles, such as a preference for informal language, internet slang, and emotional expressions, which pose significant challenges to traditional dialogue data acquisition methods that rely on manual annotation or data collection.

By introducing LLMs and constructing specialized instructions, the model is guided to directly generate dialogue data, which somewhat addresses the issue of limited data acquisition. However, the quality of the generated dialogue data can not be guaranteed. In contrast, by reconstructing existing psychological corpus data through LLMs, the semantic richness and diversity of the original data are preserved, mitigating the risk of homogenization in directly generated data. However, the reliance on the coverage of adolescent psychological topics in the existing corpus leads to issues in the trained psychological dialogue model, such as insufficient understanding of specific topics and inadequate guidance for complex psychological dilemmas when addressing adolescent psychological problems.

Therefore, this paper proposes the Adolescent Psychological Support Dialogue Generation Model of Domain Data-Driven (APS-DM). By extracting multi-level psychological topics for adolescents and designing contextual role-playing prompts, we guide GPT-4 [2] to perform multi-turn semantic reconstruction, thus constructing an adolescent psychological support dialogue dataset. By designing structured thinking-guided prompts, the guidance of the adolescent psychological support dialogue model's responses is enhanced. Experiments are conducted on the QsnTest dataset, comparing the baseline model ChatGLM2-6B and models such as SoulChat [3], to validate the effectiveness of the proposed model. The main contributions of this paper are as follows:

- To address the issue of limited adaptability of existing psychological dialogue datasets in the field of adolescent psychology. The topic-constrained prompt-guided reconstruction method for constructing an adolescent psychological support dialogue dataset is proposed, constructs an adolescent psychological support dialogue dataset.
- This paper designs the APS-DM model [1], which fine-tunes the base model parameters, combines structured thinking-guided prompts to constrain the dialogue model's scene generation, thereby generating responses related to adolescent psychological guidance.

[1]The source code and datasets are publicly available at: https://github.com/tenghaozhang/APS-DM

- The experimental results indicate, the APS-DM model achieves good performance in both automatic and manual evaluations of adolescent psychological support dialogue response generation.

II. Related Works

A. LLMs-driven Dialogue Dataset Constructing

In the ever-evolving field of deep learning, the issues of data quantity and quality have been long-standing challenges [4]. With the rapid development of LLMs, a paradigm shift in data construction methods has been triggered, and many researchers [5] have made groundbreaking progress in this area. For example, Ding et al. [6] proposed the dialogue dataset UltraChat, which guides two models to obtain dialogue data by designing prompts, enhancing the models' performance in complex dialogue scenarios.

Considering the lack of diversity in data generated directly by the model, Zhang et al. [7] proposed the Dialogstudio dialogue dataset. It is by collecting and improving existing data corpora, enriching the diversity of dialogue data. Yin et al. [8] proposed an automatically managed dynamic growth framework, which efficiently generates and expands instruction-tuning data. In the field of psychological counseling dialogues, Inaba et al. [9] collected counseling dialogue data by using role-playing scenarios. Zhang et al. [10] proposed a supervised fine-tuning approach that utilizes both synthetic and real-world data, incorporating a reward model to balance the advantages of the two data types. Zhang et al. [11] proposed a report-based framework for Chinese psychological counseling multi-turn dialogue reconstruction and evaluation, which has promoted the formation of a structured reconstruction and evaluation system for professional dialogue data.

B. Psychological Support Dialogue Response Generating

LLMs are an emerging field in the application of counseling and mental health support [12]. Current research has proposed various psychological support dialogue response generation models, providing effective counseling for non-professionals or offering psychological support [13]. Specifically, Brocki et al. [14] fine-tuned a model by transcribing person-centered therapy (PCT) sessions to achieve natural and empathetic psychological support health dialogues. Chen et al. [3] constructed an empathy dialogue dataset to guide the model in learning the dialogue rhythm of multi-turn probing and confession, aiming to achieve dialogue response generation with psychological empathy capabilities. Qian et al. [15] enhanced empathetic dialogue response generation by enriching the dialogue context with commonsense knowledge graphs, stimulating relevant knowledge encoded by LLMs. Xiao et al. [16] while maintaining empathy, achieved self-discovery-oriented AI psychological intervention responses through a three-stage cognitive reconstruction method.

Existing psychological dialogue LLMs have made encouraging progress, but they have not taken into account the psychological needs of different demographic groups at various stages, nor the differences in psychological topics. When handling adolescent psychological support responses, LLMs fine-tuned on multi-round psychological dialogue data with mixed age-group psychological knowledge, can not better separate adolescent psychological issues when handling adolescent psychological dialogue responses. As a result, they are unable to better address the unique psychological problems of adolescents. Therefore, this paper enhances the topic relevance of the data corpus by extracting adolescent psychological topics. It guides LLMs to reconstruct dialogue corpora and provides dialogue data for model fine-tuning. Additionally, it designs prompt constraints to guide the model in generating scenarios, enhancing the matching degree of model responses, thus offering an effective solution for generating adolescent psychological support dialogue responses.

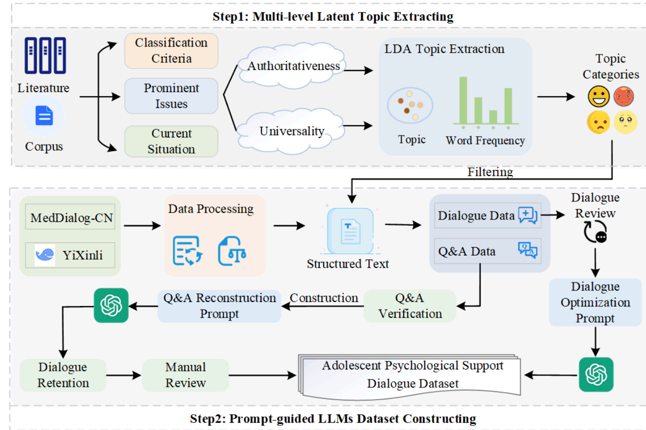


Fig. 1: Overview of Topic-Constrained Prompt-Guided Reconstruction Method for Constructing an Adolescent Psychological Support Dialogue Dataset.

III. Methodology

To address the above issues, this paper proposes a topic-constrained prompt-guided reconstruction method for constructing an adolescent psychological support dialogue dataset. It extracts multi-level psychological topics from literature and corpora, uses prompts to guide the synthesis of multi-turn adolescent psychological support dialogues, thereby constructing the dataset. The Topic-Constrained Prompt-Guided Reconstruction Method for constructing an Adolescent Psychological Support Dialogue Dataset is illustrated in Figure 1.

A. Multi-level Latent Topic Extracting

Adolescence is a pivotal stage in both physical and psychological development, psychological issues during this period are notably distinct from those in other age groups. When constructing the adolescent psychological support dialogue dataset, in order to accurately identify the core psychological issues of the adolescent group, relevant topics related to their psychological problems are extracted from a large body of adolescent psychological literature and corpus. By mining topics related to adolescent psychology, a multi-level topic list is constructed to filter the raw data, making it more focused on adolescent psychological needs. This provides a scientific basis for the construction of the dataset.

The literature data related to adolescent mental health studied in this paper primarily comes from academic databases (Google, CNKI), while also incorporating real-world corpora from online forums such as Zhihu, expanding the diversity of data sources. Search terms like 'adolescent psychology,' 'puberty,' and 'adolescent mental health' are used to search academic databases and forums, collect relevant literature, and forum Q&A discussion corpora on adolescent psychology. This section cleans the literature and forum data, processes it with tokenization tools, constructs a stopword list, forming a corpus for LDA topic model extraction, which provides a basis for the subsequent analysis.

For selecting the number of topics, the best number of topics is determined using perplexity. When the perplexity value stabilizes at a relatively low value or reaches an inflection point, the topic structure stabilizes, and the optimal number of topics is reached [17]. After performing LDA topic extraction, the 'number of topics' and 'topic-word distributions' are obtained, and topics are named based on the distribution of topic words.

Based on the LDA topic model, the classic classification framework from the field of psychology is incorporated to ensure the rigor of the topic divisions. Referring to the authoritative classification standards of DSM-5 [18] and ICD [19], a basis is provided for common adolescent psychological issues. Yu et al. [20] point out that the core psychological conflict during adolescence is 'self-identity vs. role confusion,' emphasizing the challenges adolescents face in interpersonal relationships and self-development. Steinberg et al. [21] indicate the adolescent brain is still immature in decision-making control and emotional management, leading to a higher likelihood of impulsivity, emotional instability, and substance abuse behaviors. Combining the current domestic situation with survey reports like the White Paper on Chinese Adolescent Mental Health, psychological challenges such as academic pressure, internet addiction, and school bullying still exist among adolescents.

The psychological changes of adolescents occur swiftly, with multiple influencing factors, which require the subject to more granular categorization. Based on the aforementioned literature and perplexity calculations, the optimal number of psychological topics is determined to be 24. These 24 topics are named according to the relevance of the keywords and authoritative psychological classification standards, further refined into four main categories and six subcategories. By applying the LDA model to extract topics from the corpus, a multi-level psychological topic word cloud is obtained.

B. Prompt-guided LLMs Dataset Constructing

1) Dataset Source: The original data in this paper primarily includes real medical dialogue data and psychological Q&A corpora. Real medical dialogue data is mainly derived from MedDialog-CN [22], a large-scale dataset created specifically for research on Chinese medical dialogues. The real Q&A corpus is primarily sourced from the official website of YiXinLi, a Chinese platform for mental health services. The availability of a large volume of real and usable data offers strong professional data support for this experiment.

2) Data Preprocessing: The metadata text includes numerous colloquial expressions, irrelevant information, and a substantial amount of private and sensitive content. In order to enhance the dataset quality and prevent privacy risks, the collected multi-source data is carefully screened. Referencing the Code of Ethics for Clinical and Counseling Psychology by the Chinese Psychological Society [23] and relevant psychological literature, a set of regular expression rules for adolescent psychology is formulated to prevent the leakage of private and sensitive information. Exclude content related to potential violent tendencies, sexual distress, and family trauma that may arise during adolescence, ensuring that the fine-tuned model aligns with ethical and psychological guidance principles.

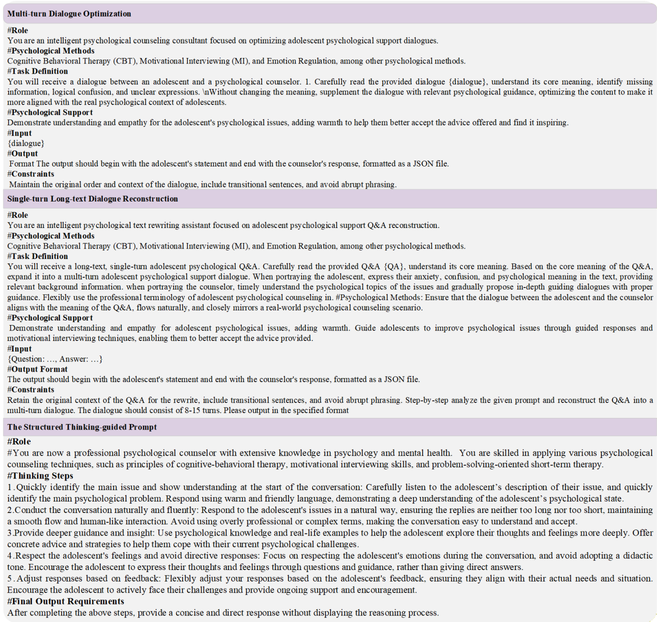
3) Contextual Role-playing Prompt Designing: In LLMs, a prompt is a directive text input used to guide the model in generating specific types of output. The prompt includes task-relevant information and context, assisting the model in generating precise and focused output. Adding prompts in ChatGPT helps constrain the model, enabling it to focus on the actual requirements, enhancing model performance, and optimizing and reconstructing the data corpus in a targeted manner. Existing research and practice suggest, high-quality prompt templates should possess key characteristics such as a clear task description, accurate language expression, and appropriate example prompts [24]. Therefore, this section designs prompt templates that align with the requirements of text optimization and reconstruction tasks, in order to fully utilize ChatGPT's instruction-following ability for dialogue optimization and question-answer reconstruction. An example of the contextual role-playing prompt is shown in Figure 2.

4) Psychological Support Dialogue Dataset Generating: In the process of dialogue dataset generation, the GPT-4 API is invoked, using the prompt shown in Figure 2 to optimize and reconstruct two different data corpora, thereby generating a psychological support dialogue dataset that is highly relevant to the adolescent psychology topic. The dialogue text generation formula is as follows:

$$P_{M_\theta}(Y \mid \mathbf{x}) = \prod_{t=1}^{L} P_{M_\theta}(y_t \mid Y_{<t}, \mathbf{x}) \tag{1}$$

where P_{M_θ} indicates the LLMs with parameter θ. L signifies the variable length of the output. Y represents the sequence to be generated. y_t represents the t-th token generated by the model, $\mathbf{x}$ is the conditional input, which serves as the global constraint in the generation process.

In generating the dataset using LLMs, the accuracy of the information is preserved, to enhance the quality of the generated dataset, In this chapter, we'll write regularized expression rules to eliminate illogical conversations. At the same time, two clinical psychological counselors and three graduate students majoring in cognitive psychology were invited to



Multi-turn Dialogue Optimization

#Role
You are an intelligent psychological counseling consultant focused on optimizing adolescent psychological support dialogues.
#Psychological Methods
Cognitive Behavioral Therapy (CBT), Motivational Interviewing (MI), and Emotion Regulation, among other psychological methods.
#Task Definition
You will receive a dialogue between an adolescent and a psychological counselor. 1. Carefully read the provided dialogue {dialogue}, understand its core meaning, identify missing information, logical confusion, and unclear expressions. \nWithout changing the meaning, supplement the dialogue with relevant psychological guidance, optimizing the content to make it more aligned with the real psychological context of adolescents.
#Psychological Support
Demonstrate understanding and empathy for the adolescent's psychological issues, adding warmth to help them better accept the advice offered and find it inspiring.
#Input
{dialogue}
#Output
Format The output should begin with the adolescent's statement and end with the counselor's response, formatted as a JSON file.
#Constraints
Maintain the original order and context of the dialogue, include transitional sentences, and avoid abrupt phrasing.

Single-turn Long-text Dialogue Reconstruction

#Role
You are an intelligent psychological text rewriting assistant focused on adolescent psychological support Q&A reconstruction.
#Psychological Methods
Cognitive Behavioral Therapy (CBT), Motivational Interviewing (MI), and Emotion Regulation, among other psychological methods.
#Task Definition
You will receive a long-text, single-turn adolescent psychological Q&A. Carefully read the provided Q&A {QA}, understand its core meaning. Based on the core meaning of the Q&A, expand it into a multi-turn adolescent psychological support dialogue. When portraying the adolescent, express their anxiety, confusion, and psychological meaning in the text, providing relevant background information. when portraying the counselor, timely understand the psychological topics of the issues and gradually propose in-depth guiding dialogues with proper guidance. Flexibly use the professional terminology of adolescent psychological counseling in. #Psychological Methods: Ensure that the dialogue between the adolescent and the counselor aligns with the meaning of the Q&A, flows naturally, and closely mirrors a real-world psychological counseling scenario.
#Psychological Support
Demonstrate understanding and empathy for adolescent psychological issues, adding warmth. Guide adolescents to improve psychological issues through guided responses and motivational interviewing techniques, enabling them to better accept the advice provided.
#Input
{Question: …, Answer: …}
#Output Format
The output should begin with the adolescent's statement and end with the counselor's response, formatted as a JSON file.
#Constraints
Retain the original context of the Q&A for the rewrite, include transitional sentences, and avoid abrupt phrasing. Step-by-step analyze the given prompt and reconstruct the Q&A into a multi-turn dialogue. The dialogue should consist of 8-15 turns. Please output in the specified format

The Structured Thinking-guided Prompt

#Role
#You are now a professional psychological counselor with extensive knowledge in psychology and mental health. You are skilled in applying various psychological counseling techniques, such as principles of cognitive-behavioral therapy, motivational interviewing skills, and problem-solving-oriented short-term therapy.
#Thinking Steps
1.Quickly identify the main issue and show understanding at the start of the conversation: Carefully listen to the adolescent's description of their issue, and quickly identify the main psychological problem. Respond using warm and friendly language, demonstrating a deep understanding of the adolescent's psychological state.
2.Conduct the conversation naturally and fluently: Respond to the adolescent's issues in a natural way, ensuring the replies are neither too long nor too short, maintaining a smooth flow and human-like interaction. Avoid using overly professional or complex terms, making the conversation easy to understand and accept.
3.Provide deeper guidance and insight: Use psychological knowledge and real-life examples to help the adolescent explore their thoughts and feelings more deeply. Offer concrete advice and strategies to help them cope with their current psychological challenges.
4.Respect the adolescent's feelings and avoid directive responses: Focus on respecting the adolescent's emotions during the conversation, and avoid adopting a didactic tone. Encourage the adolescent to express their thoughts and feelings through questions and guidance, rather than giving direct answers.
5.Adjust responses based on feedback: Flexibly adjust your responses based on the adolescent's feedback, ensuring they align with their actual needs and situation. Encourage the adolescent to actively face their challenges and provide ongoing support and encouragement.
#Final Output Requirements
After completing the above steps, provide a concise and direct response without displaying the reasoning process.

Fig. 2: An example of the contextual role-playing prompt.

review whether the dialogue contained content that induced self-harm, violence and violated the ethics of psychological intervention to ensure it conforms to scientific facts.

This section proposes a topic-constrained prompt-guided reconstruction method for constructing an adolescent psychological support dialogue dataset. A multi-turn dialogue dataset focused on adolescent psychological support is built based on this method. Compared to traditional psychological dialogue datasets, this dataset includes the authenticity of real-world adolescent psychological feedback, while maintaining the logical flow and guidance in the LLMs-generated dialogues.

The adolescent psychological support dialogue dataset includes a total of 32,000 samples. In the allocation of the training and test sets, the training set contains significantly more samples than the test set, while the number of topics for the adolescent psychological dialogues is 24, the training dataset contains 30500 samples, while the test dataset (QsnTest) includes 1500 samples. This distribution aligns with the typical training-to-test set ratio in machine learning, facilitating model learning and validation on adequate data. The proportional distribution of topics also guarantees that both learning and validation processes meet the diversity requirements. The number of dialogue turns in both the training and test sets is fixed between 8 and 15, which demonstrates that the distribution of the training and test sets is consistent. This consistency helps the model perform well during the testing phase and reflects the learning effectiveness from the training phase. The topic distribution of the adolescent psychological support dialogue dataset is shown in Figure 3.

In adolescent psychological dialogue response generation, to address the issue of insufficient guidance capabilities in existing psychological dialogue models for providing adolescent psychological responses, the Adolescent Psychological

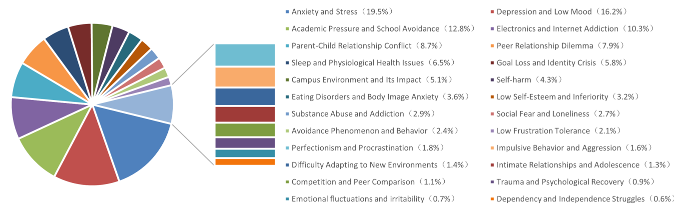


Fig. 3: The topic distribution for Adolescent Psychological Support Dialogue Dataset.

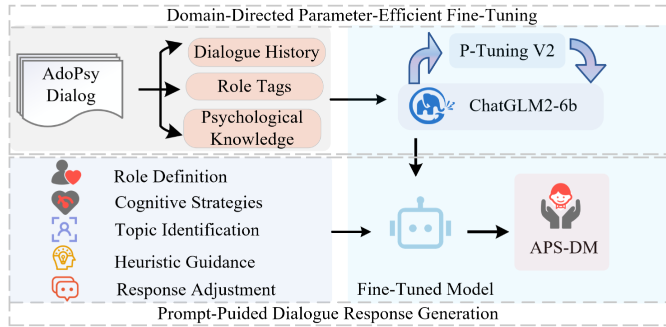


Fig. 4: The overall architecture of the proposed model APS-DM.

Support Dialogue Generation Model of Domain Data-Driven (APS-DM) is proposed. In the domain-directed parameter-efficient fine-tuning phase, parameter-efficient fine-tuning is employed to optimize the base model, injecting knowledge of adolescent psychological dialogues and learning the implicit psychological logic of adolescents from the dialogue dataset. In the adolescent psychological support dialogue response generation stage, structured thinking-guided prompts are constructed to constrain the model's response generation scenarios, merging the 'domain knowledge fine-tuned model' to guide the APS-DM in generating psychological support dialogue responses. The framework of the APS-DM model is shown in Figure 4.

C. Domain-Directed Parameter-Efficient Fine-Tuning

The base model of APS-DM is ChatGLM2-6B. It adopts the parameter-efficient fine-tuning method P-Tuning V2 [25]. With the adolescent psychological support dialogue dataset, a tailored adolescent psychological support dialogue model is constructed. In the process of optimizing the ChatGLM2-6B model with parameter-efficient fine-tuning, combined with the adolescent psychological support dialogue dataset, by keeping the model's weight parameters frozen, efficient domain-specific adaptation is achieved. During the input construction phase of P-Tuning V2, virtual prompt tokens, dynamically generated by the prompt generator, are inserted into the original input sequence and positioned at the front of the original input. The original input is the adolescent psychological support dialogue history $\mathcal{H}$. The equation of $\mathcal{H}$ is shown below:

$$\mathcal{H} = \{u_1, v_1, u_2, v_2, \ldots, u_j, v_j \ldots, u_{n-1}, v_{n-1}, u_n\} \tag{2}$$

where u_j and v_j denote the adolescent's and counselor's dialogue in the j-th round, respectively.

The dialogue history is linearly unfolded into a token sequence. The prompt generator takes the initial prompt embedding as input. It outputs the task-specific continuous prompt embedding P, the equation of P is shown below:

$$P = [p_1, p_2, \cdots, p_k] \in \mathbb{R}^{k \times d} \tag{3}$$

where k is the number of prompt tokens. d refers the dimension of the word vector. All parameters of the prompt generator are updateable. The initial prompt embedding P_{init} is chosen from the pre-trained word vectors using task-related token indices, the equation of P_{init} is shown below:

$$P_{\text{init}} = [E[i_1], E[i_2], \ldots, E[i_k]] \subset \mathbb{R}^{k \times d} \tag{4}$$

where $E \in \mathbb{R}^{V \times d}$ is the pre-trained word embedding matrix. V is the size of the vocabulary, i_k denotes the initialization vocabulary index for the k-th prompt vector, selected based on task-relevant vocabulary.

By introducing task-related initial vectors, more task-specific initial prompts are provided to the prompt generator. The prompt embeddings are continuously updated during model training, generating representations that match the adolescent psychological dialogue task. In the dialogue task training stage, the prompt embeddings are concatenated with the word embeddings of the original dialogue history input sequence, and together, they form the input $\tilde{x}$ for forward propagation in the model. The equation of $\tilde{x}$ is shown below:

$$\tilde{x} = [P \; ; \; \mathbf{X}] \in \mathbb{R}^{(k+m) \times d} \tag{5}$$

where $\mathbf{X} = [e_1, \cdots, e_m]$ is the word embedding sequence associated with the dialogue history. m is the number of tokens in the dialogue history input sequence. During the fine-tuning of ChatGLM2-6B, the prompt embeddings are used not only at the input layer, they are injected into each layer of the model to steer the attention mechanism toward task-critical content, strengthening the prompt's ability to guide the model's internal state modeling, aids the model in focusing on task-related vocabulary, directly affecting the generation of responses by the model.

D. Prompt-guided Dialogue Response Generating

In psychological support dialogue generation, the structured thinking-guided prompts shown in Figure 2 are used as input to constrain the fine-tuning model's response generation scenarios, guiding it to quickly understand the contextual meaning in adolescent psychological dialogue responses, thereby enhancing the guidance and psychological support capabilities in response generation. Specifically, the structured thinking-guided prompt is concatenated with the input text and used as input for the fine-tuning model, guiding the model to generate dialogue responses based on existing adolescent psychological knowledge.

IV. EXPERIMENTS

In this Section, parameter testing and comparison experiments are conducted using the adolescent psychological support dialogue dataset built in Section 3.

A. Implementation details

This study conducts model development and experiments on a cloud server, utilizing an Nvidia GeForce RTX4090-24G GPU for training the ChatGLM2-6B model, and the programming language used is Python with the PyTorch framework. The versions used are Python 3.8.10, PyTorch 2.1.2, and CUDA 12.1. The parameter settings specify a max source length of 8000 and a max target length of 192. Furthermore, the learning rate is set to 2e-2, and the model is trained for a total of 10 epochs.

B. Evaluation Metrics

We use BLEU and ROUGE to evaluate the APS-DM model. In order to ensure the professionalism and guidance of the model's responses, inspired by Wang et al. [26], this section introduces the Deepseek-V3 model [27] as an evaluator. Ten rounds of dialogue data are randomly selected from each topic, totaling 240 rounds for professional assessment. Each round is scored, and the average score of all the dialogues is taken as the final result. The evaluation criteria include Voice (V.), Topic Relevance (T. R.), and Guidance Strategy (G. S.). A higher final score indicates better performance. The logic of the evaluation prompt is shown in Figure 5.

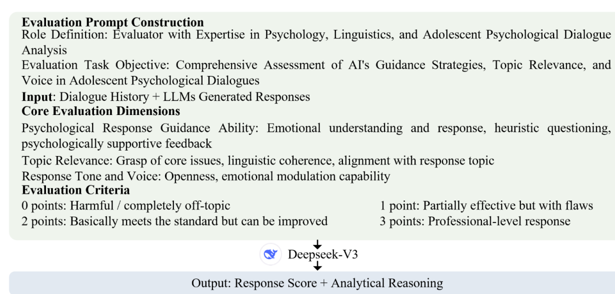


Fig. 5: The logic of the Evaluation Prompt.

C. Ablation Experiments

Compared to traditional dialogue models, the APS-DM model adds two modules, LLMs fine-tuning and prompt guidance, on top of the base model ChatGLM2-6B. In order to validate the effectiveness of these two modules, an ablation analysis of the APS-DM model is conducted on the QsnTest dataset.

The distinctive feature of the LLMs Fine-Tuning module is the use of a domain-specific dataset to fine-tune a pre-trained model, enhancing its performance in a specific task domain. This fine-tuning can significantly improve the performance of the pre-trained model in specific domains. It enhances the professionalism and guidance ability in adolescent psychological support dialogue responses. Therefore, performance testing is required for the LLMs fine-tuning module. Prompt Guidance essentially constrains the model's behavior, steering the model to understand and generate responses for specific domain dialogues. The ablation experiment results are shown in Table I. In Table I, Experiment 1 corresponds to the APS-DM model. In Experiment 2, RPG stands for Remove Prompt Guide. In Experiment 3, RFT stands for Remove Fine Tuning. In Experiment 4 represents only the base model ChatGLM2-6B.

TABLE I: Results of the APS-DM Ablation Study.

Num	B-4	R-1	R-2	R-L	T.R.	G.S.	V.
1	**13.31**	**37.15**	**14.27**	**32.11**	**2.45**	**2.36**	**2.28**
2	12.73	34.96	13.94	28.38	2.13	2.24	2.05
3	9.26	25.34	10.14	22.29	1.71	1.81	1.86
4	7.59	22.58	9.26	20.54	1.68	1.66	1.71

In Table I, compared to Experiment 1, Experiments 2, 3, and 4 show a significant decline in metrics such as BLEU, ROUGE, T.R., and V. The results show the introduction of the LLMs fine-tuning module and prompt-guidance module significantly improves the base model's performance. This approach enhances the effectiveness of adolescent psychological support dialogue responses. The LLMs fine-tuning module introduces a dialogue dataset with high coverage of adolescent psychological topics and emotionally adaptive contexts. This provides the base model with precise learning information. It helps the base model understand the semantic information related to adolescent psychology. The Prompt Guidance module optimizes the prompt templates, providing more contextually relevant prompt and constraint information for adolescent psychological support dialogues. It guides the APS-DM to focus on identifying psychological topics and providing targeted guidance, avoiding the generation of misleading or highly stimulating responses. The prompt-guidance module optimizes the prompt templates. It provides prompt and constraint information that better aligns with the context of adolescent psychological support dialogues.It guides APS-DM during dialogue response generation. The module focuses on how to identify psychological topics. It offers targeted guidance information and helps avoid generating misleading or overly stimulating responses.

The experimental results indicate that the LLMs Fine-Tuning module performs better than the Prompt Guidance module. The reason could be that the prompt guidance module can, to some extent, constrain and guide the model in generating responses that meet the prompt's expectations, allowing the model to focus on specific tasks. The model depends only on the knowledge learned during pre-training. It retrieves information from the existing knowledge base to adapt it to the specific task. The LLMs Fine-Tuning module introduces a domain-specific dataset, providing it with new knowledge and enhancing its capabilities in the specific domain, building upon its existing abilities. Therefore, the effect of the LLMs fine-tuning module is more significant in improving the model's relevance and guidance ability in specific domains. It enhances the model's performance in generating domain-specific responses. In conclusion, both modules provide significant support in adolescent psychological support dialogue responses, enhancing the model's relevance to psychological topics and its guidance capabilities.

D. Main results

To evaluate the performance of the APS-DM model introduced in this paper, a comparative experiment is performed on the QsnTest dataset. The benchmark models for comparison are: ChatGLM2-6B [28], ChatGPT-3.5 [2], ChatGLM3-6B [28], SoulChat [3].

TABLE II: Experimental Results of APS-DM and Baseline Models on the QsnTest Dataset.

Models	B-4	R-1	R-2	R-L	T.R.	G.S.	V.
ChatGLM2-6B	7.59	22.58	9.26	20.54	1.68	1.66	1.71
ChatGPT-3.5	9.44	31.38	10.44	**32.86**	1.83	1.89	1.96
ChatGLM3-6B	8.56	30.15	9.81	26.71	1.75	1.77	1.83
SoulChat	11.01	32.92	13.52	31.04	2.07	1.96	2.16
APS-DM	**13.31**	**37.15**	**14.27**	32.11	**2.45**	**2.36**	**2.28**

In Table II, APS-DM demonstrates significant improvements in metrics such as BLEU, ROUGE, and Top.Rel. on the QsnTest dataset. Compared to the models ChatGLM2-6B, ChatGPT-3.5, ChatGLM3-6B, and SoulChat, where SoulChat achieves the highest BLEU and ROUGE metrics, the APS-DM model shows improvements of 2.3%, 4.2%, 0.7%, and 1.1% in the automated B-4, R-1, R-2, and R-L metrics, respectively, and improvements of 0.38, 0.40, and 0.12 points in the manual evaluation metrics of T.R., G.S., and V., respectively.

The APS-DM model demonstrates significant advantages in overall coherence, coverage of key information, and logical consistency in generating adolescent psychological support dialogue responses. Additionally, it also shows strong performance in adolescent psychological counseling, as reflected in the manual metrics. This demonstrates the strong potential of the APS-DM model in real-world adolescent psychological support applications. Compared to the comparison models, the main advantage of APS-DM lies in its fine-tuning from the base model on the AdoPsydialogue dataset, which provides more targeted dialogue data, enhancing its response ability for specific tasks. Finally, combined with the structured thinking-guided prompt, APS-DM more precisely focuses on the adolescent psychological support dialogue task. In contrast, the comparison models are limited in handling adolescent-specific psychological issues due to the lack of fine-tuning with specialized data, particularly in psychological topic recognition and heuristic guidance, where a gap exists.

The comparative experimental results show that by fine-tuning LLMs on a targeted dialogue dataset and incorporating prompt guidance, the model can not only accurately identify the psychological topics of adolescent users and generate responses using heuristic guidance strategies, but also maintain the fluency of multi-turn dialogues. In summary, APS-DM significantly improves the user experience of adolescents in psychological support dialogue responses.

V. Conclusion

In adolescent psychological support response generation, adolescent psychological topics are combined with existing psychological data corpora to construct a dialogue dataset focused on adolescent psychological support. By fine-tuning the base model on the adolescent psychological support dialogue dataset, the professionalism and guidance ability of the base model in handling adolescent psychological issues can be significantly enhanced. The Adolescent Psychological Support Dialogue Generation Model of Domain Data-Driven (APS-DM) is proposed in this paper. Experimental results show the APS-DM model achieves significant improvements in automatic evaluation metrics, improvements of 2.3%, 4.2%, 0.7%, and 1.1% in the automated B-4, R-1, R-2, and R-L metrics, respectively. Additionally, its performance in manual metrics, improvements of 0.38, 0.40, and 0.12 points in the manual evaluation metrics of T.R., G.S., and V., respectively, further demonstrates the potential of APS-DM in practical applications. Future research can further incorporate multimodal information, such as facial expressions and voice data, to overcome the limitations of single-text dialogues and more accurately capture the emotional state and psychological risks of adolescent users.

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