D4: a Chinese Dialogue Dataset for Depression-Diagnosis-Oriented Chat

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Abstract

In a depression-diagnosis-directed clinical session, doctors initiate a conversation with ample emotional support that guides the patients to expose their symptoms based on clinical diagnosis criteria. Such a dialogue system is distinguished from existing single-purpose human-machine dialog systems, as it combines task-oriented and chit-chats with uniqueness in dialogue topics and procedures. However, due to the social stigma associated with mental illness, the dialogue data related to depression consultation and diagnosis are rarely disclosed. Based on clinical depression diagnostic criteria ICD-11 and DSM-5, we designed a 3-phase procedure to construct D4: a Chinese Dialogue Dataset for Depression-Diagnosis-Oriented Chat1, which simulates the dialogue between doctors and patients during the diagnosis of depression, including diagnosis results and symptom summary given by professional psychiatrists for each conversation. Upon the newly-constructed dataset, four tasks mirroring the depression diagnosis process are established: response generation, topic prediction, dialog summary, and severity classification of depressive episode and suicide risk. Multi-scale evaluation results demonstrate that a more empathy-driven and diagnostic-accurate consultation dialogue system trained on our dataset can be achieved compared to rule-based bots.

1 Introduction

Given the increasing worldwide health threat brought by depression, researchers have been exploring effective methods for depression detection and diagnosis. Besides automatic depression detection from posts on social media (Orabi et al., 2018), speech (Zhang et al., 2021b) and multi-modality (Cummins et al., 2013), the dialogue system is considered an effective tool for large-scale depression detection (Pacheco-Lorenzo et al., 2021). It is believed that conversation agents could reduce the concealment of sensitive information such as suicidal thoughts caused by social expectations (Schuetzler et al., 2018) and the emotional hindrance due to the pressure of being judged in face-to-face conversation (Hart et al., 2017). In past research, chatbots initiated for depression diagnosis are generally implemented based on self-rating scales (Jaiswal et al., 2019; Arrabales, 2020) or diagnostic criteria (Philip et al., 2017). The final diagnosis results are obtained by asking fixed questions on the scale and corresponding the user’s answers to each question to the scale options. These chatbots present good sensitivity and specificity in diagnosis and are more attractive and acceptable (Vaidyam et al., 2019; Abd-Alrazaq et al., 2019) than the original self-rating scales. Nevertheless, the fixed dialogue flow limiting the user’s expressions to specific answers can not realize personalized consultation and give emotional support at an appropriate time, for which there still exists a big gap between the conversation experience current depression diagnosis agents provide and the face-to-face interview in the process of clinical diagnosis.

Interview-based clinical diagnosis in psychiatry is a complex procedure with the purpose of collecting and summarizing key symptom infor-
mation about one patient while providing a chat-like conversation experience. In clinical practice, psychiatrists communicate with patients and offer diagnosis results based on practical experience and multiple diagnostic criteria. The most clinically-adopted criteria involve ICD-11 (The World Health Organization, 2022), DSM-5 (American Psychiatric Association, 2013), etc., which define core symptoms for the depression diagnosis. At the same time, psychiatrists provide emotional support such as empathy and comfort during the consultation to better prompt patients’ self-expression. The practice of clinical depression diagnosis displays the possibility of the depression diagnosis dialogue system in further improving the accuracy of diagnosis and user engagement.

Accordingly, the depression diagnostic conversation belongs to a distinguished dialogue from previously defined dialogue typologies, which is a combination of task-oriented dialogue and chit-chat. Such a compound dialogue type could be defined as Task-Oriented Chat as shown in Figure 1. This type of dialogue requires multiple assessments regarding task completion and chit-chat experience, which are extremely challenging and still under-investigated. As a specific domain of Task-Oriented Chat, the depression diagnosis dialogue has a clear purpose of the task-oriented dialogue aiming at medical diagnosis: to collect the patient’s symptom information and draw a diagnosis conclusion while simultaneously bearing the needs of a chit-chat dialogue with emotional support: to start a user-oriented chat and provide emotional support from time to time. Currently, no datasets are specified for depression diagnosis, mainly due to the social stigma associated with clinical privacy and the complexity of the diagnosis process.

To construct a clinically sound and empathetic depression-diagnosis-oriented dialogue system close to clinical practice, we conduct dialogue collection through consultation dialogue simulation. We devise a three-phase approach to collect depression diagnostic dialogues (see Figure 2). P1: To simulate medical records, we collect actual patients’ portraits with a consultation chatbot web app that asks users fixed questions abstracted from clinical depression diagnosis criteria ICM-11 and DSM-5. P2: To restore psychiatric consultation conversations, we employ workers to conduct the consultation dialogue simulation based on the collected portraits. The workers are divided into patients and doctors for separate training by professionals. The doctor actor is required to obtain fixed symptom information involved in the diagnostic criteria in the chat, while the patient actor needs to express according to the symptoms in the portrait. P3: To reinforce the clinical setting, professional psychiatrists and psychotherapists supervise the whole process and filter out unqualified dialogues. In addition, they provide diagnosis summaries based on the portrait and dialogue history. We further annotate the conversation procedure with 10 topic tags and the symptom summaries with 13 symptom tags (grouped by core depressive symptoms listed in DSM-5 and ICD-11). In this way, we propose $D^4$: a Chinese Dialogue Dataset for Depression-Diagnosis-Oriented Chat. The key contribution of this paper is as follows:

- A close-to-clinical-practice depression diagnosis dataset with 1,339 conversations generated from actual populations’ portraits, accompanied by psychiatrists’ diagnosis summaries, under the framework of most applied clinical diagnosis criteria ICD-11 and DSM-5, with multi-dimensional analysis suggesting that our simulated diagnosis data are reliable and up to professional standards.
- Experimental validation on four tasks that mirror the real-life diagnosis process: response generation, topic prediction, dialog summary, and severity classification of depression and suicide risk;
- To the best of our knowledge, this is the first diagnosis dialogue dataset for mental health, aiming to advance the realization of an Avante-Garde clinical diagnosis-oriented dialogue system that combines characteristics of task-oriented dialogue and chit-chat.

2 Data Collection

To maximize doctor and patient authenticity in a diagnosis dialogue, we devise a 3-phase collection paradigm (see Figure 2) instead of the commonly-adopted vanilla crowdsourcing scheme: P1. We collected natural populations’ portraits (in particular actual depressive patients) to form pre-diagnosis records; P2. Simulated natural diagnostic consultation dialogues based on the portraits; P3. Psychiatrists proofread dialogue history and prescribed professional symptom summaries.
2.1 Human-to-Machine Portrait Collection

To overcome the impracticability in obtaining patients’ medical records covered by doctor-patient confidential protocol, we designed a consultation chatbot based on the state machine, which utilizes fixed questions from clinical criteria to document each user’s depression symptoms and demographic information such as age, gender, marital status and occupation. Depression symptoms are prompted accordingly, including mood, interest, mental status, sleep, appetite, social function, and suicidal tendency. Users are invited to respond concisely, e.g., yes/no answer and severity estimation. Combined, we obtained a voluntary and legitimate depression portrait. As of the submission of the paper, we have collected a total of 478 patient portraits. We estimate the severity of depressive episodes and suicide risk based on clinical criteria ICD-11 and DSM-5, we released the simulation tasks to crowdsourcing workers. The whole procedure is introduced accordingly: 1) Design and Training: the workers first go through specialized training and are then divided into doctor and patient roles; 2) Annotation: During the conversation, they are required to annotate topic transitions; 3) Peer Assessment: doctor and patient roles rate each other on multiple dimensions after the conversation.

| Risk     | Control | Mild  | Moderate | Severe |
|----------|---------|-------|----------|--------|
| Depression | 264     | 49    | 95       | 70     |
| Suicide   | 338     | 46    | 75       | 19     |

Table 1: Risk Estimation of Portraits: "control" represents no risk, "mild", "moderate", and "severe" represent the severity of the risk respectively

2.2 Human-to-Human Dialogue Collection

To guarantee the quantity, quality, and professionalism of our consultation dialogues, we conducted conversation simulations under the guidance of psychiatrists, following portraits collected in Phase 1. In particular, we first gathered a small number of dialogues between doctors and patients in real scenarios. Based on the prerequisites mentioned above and clinical depression diagnosis criteria ICD-11 and DSM-5, we released the simulation tasks to crowdsourcing workers. The whole procedure is introduced accordingly: 1) Design and Training: the workers first go through specialized training and are then divided into doctor and patient roles; 2) Annotation: During the conversation, they are required to annotate topic transitions; 3) Peer Assessment: doctor and patient roles rate each other on multiple dimensions after the conversation.

2.2.1 Design and Training

Acting Patients It should be noted that most of our patient actors are not depressive patients. To help them better interpret the symptoms in the patient portraits, we provide detailed explanations, including the severity and duration, and some patients’ self-reports to help them understand their inner feelings. Based on the accurately expressed
symptoms, they extend the natural expressions of each aspect following doctors’ inquiries in the conversation.

**Acting Doctors** Firstly, we invite licensed psychiatrists and clinical psychotherapists to initiate consultation conversations with actual depressive patients, from which we collect reference conversations. Then based on these essential histories, combined with ICD-11 and DSM-5, we compile 41 symptom items necessary when diagnosing depression and design the questioning logic between questions of symptoms from mild to severe. The inquiries weren’t set as specific expressions for data diversity. Thus, the acting doctors needed to use colloquial rhetoric to ask relevant information involved in these questions and obtain enough information from the patient. Meanwhile, to further improve the dialogue experience, we require the acting doctors to conduct a user-oriented dialogue and provide emotional support when necessary. All acting doctors start the dialogue simulation after completing the training process.

### 2.2.2 Topic Annotation

Considering that the depression diagnostic dialogue has ambiguity between the chat and task-oriented dialogue, it’s difficult to define a clear ontology as other task-oriented dialogues (Chen et al., 2022b). To facilitate dialogue generation, we conducted topic annotation on doctors’ utterances. According to core symptoms covered in the clinical criteria, we categorized the dialogue topics into mood, interest, mental status, sleep, appetite, somatic symptoms, social function, suicidal tendency, and screening. Notably, we included empathy as a special topic since it is an essential part of clinical practice. The doctor actors were asked to mark the topics for each utterance during the conversation.

### 2.2.3 Peer Assessment

After the conversation, both sides are required to rate each other in several dimensions for the need for quality control which will be detailed in 2.4.

### 2.3 Professional Diagnosis Collection

To ensure the accordance with clinical protocol, we further invite professional psychiatrists and clinical psychotherapists to screen the dialogues that meet the diagnostic standards and provide psychiatric diagnostic results and symptom summaries. At the same time, they score the acting doctors and patients separately with the real-scenario resemblance degree.

### 2.4 Quality Control

Hierarchical screenings are conducted to control the data quality: whether it is up to clinical standard and can satisfy our model training purpose. Besides psychiatrists’ clinical protocol screening mentioned in part 2.3, we adopt a variety of paradigms to conduct quality examinations for better training. We set minimum limits on the length of the dialogue, the average utterance length per dialogue of the doctor, the mutual scores, and the scores given by the psychiatrist shown in Table 2. The unqualified dialogues are excluded.

Ultimately, we collected a total of 4,428 conversations and finally retained 1,339 (30%) after our stringent up-to-clinical-standard quality screenings.

### 3 Data Characteristics

#### 3.1 Statistics

The overall statistics of the dataset are shown in Table 3. As seen in such a diagnosis scenario, sufficient dialogue turns are required: our diagnosis dialogue exhibit avg. 21.6 turns and avg. 877.6 tokens per dialogue, significantly longer than previous related datasets, suggesting the discrepancies of a diagnosis dialogue task and its distinguished data requirements. Meanwhile, our dataset has colloquial and diverse expressions shown by the number of n-grams and avg. 14.4 tokens per utterance.

#### 3.2 Depression Severity Analysis

To observe differences in patients with different depression severity, we analyzed conversational and summary symptom statistics by seriousness.

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| Aspects | Rating Content | Minimum |
|---------|----------------|---------|
| Patient | expression naturalness | 3(5) |
|         | narrative consistency | 3(5) |
|         | matching extent of symptom severity and expression* | 3(5) |
| Doctor  | degree of similarity to the doctor* | 3(5) |
|         | Avg.length of utterances | 8 |
| Total   | Avg. utterances per dialogue | 30 |

Table 2: Quality Control Criteria: Scores* is given by psychiatrists, the rest are obtained by peer assessment; Numbers in parentheses = the highest score
Figure 3: The Symptom Ratio of Summaries: the depressive episode severity increases from (a) to (d) with avg. number of symptoms in the center of each pie chart

| Category          | Total   | Patient | Doctor |
|-------------------|---------|---------|--------|
| Dialogues         | 1339    | -       | -      |
| Avg. turns        | 21.6    | -       | -      |
| Workers           | 201     | 127     | 74     |
| Avg. utterances   | 60.9    | 30.9    | 29.9   |
| Avg. tokens       | 877.6   | 381.8   | 495.8  |
| Distinct 3-grams | 245,553 | 148,269 | 128,203|
| Distinct 4-grams | 452,012 | 251,121 | 224,476|
| Distinct 5-grams | 617,233 | 324,738 | 304,128|
| Avg. tokens       | 84.4    | -       | -      |

Table 3: D^4 Statistics

**Distribution Feature** We present statistics on patients’ severity of depressive episodes in Table 4. As the degree of depression worsens, the turns and dialog lengths get longer due to doctors’ more in-depth questions on specific topics. The diagnostic summaries are also longer to include more symptoms. The most frequent topics are also subject to change with severity: suicidal tendency is more likely to be questioned among severer patients.

| Category            | Control | Mild    | Moderate | Severe |
|---------------------|---------|---------|----------|--------|
| Dialogues           | 430     | 342     | 368      | 199    |
| Avg. turns          | 17.9    | 21.3    | 23.7     | 26.0   |
| 1st frequent topic  | Emp.    | Emp.    | Emp.     | Emp.   |
| 2nd frequent topic  | MS      | MS      | MS       | Suicide|
| 3rd frequent topic  | Sleep   | Mood    | Suicide  | MS     |
| Avg. tokens         | 59.8    | 82.0    | 100.5    | 111.9  |

Table 4: Depression Severity Statistics in D^4

**Analysis of Symptom Summary** We annotated the 13 core symptoms in the symptom summary according to ICD-11. From Figure 3, we observe a difference in the symptom number and ratio from diagnosis summaries of varying severity. As shown in Chart (a), control participants have only a few symptoms, and most are superficial symptoms like sleep changes and worthlessness, commonly in healthy populations. As the condition worsens, the patient has more symptoms, the proportion of each symptom in the summary is gradually averaged, and suicide thoughts become more frequent. The moderate and severe patients share the same average symptom number, indicating that a more fine-grained classification of depression severity requires additional information besides the number of symptoms, such as the duration and severity of each symptom.

### 3.3 Topic Analysis

**Topic Distribution** To analyze the characteristics of the doctor’s consultation method, we provide perspectives on topic distribution, transition, and lexical features of empathy.

**Topic Distribution** To better analyze the proportion of different symptoms, we regrouped the 10 topics annotated by acting doctors. mood, interest, mental status, social function are grouped into core and sleep, appetite, somatic symptom are grouped into behavior. Figure 4 shows the proportion of regrouped topics. Core and behavior occupy 63.17% of the conversation, followed by empathy at 23.1%, indicating that empathy plays an important role in such a psychiatric diagnosis-oriented dialogue.
manner and provides emotional support from time to time.

Figure 5: Topic Transitions. Topics over every 3 turns are visualized. The height represents the absolute number of dialogues at this topic.

Lexical Analysis of Empathy  As shown in Figure 4, empathy accounts for a large proportion, indicating its importance and commonness. We extract its lexical features and observe that the empathy expressions in our dataset could mainly be divided into 4 aspects: 1) understanding: "will understand/is normal" to express understanding of the patient's situation; 2) encouragement: "is valuable" to help patients regain confidence; 3) suggestions: "you can try/try" to encourage patients to make changes and try; 4) blessings: "you will get well soon" to express blessings to the patient. In actual practice, providing empathetic and emotional support improves the medical experience and is a critical component of ensuring the success and completion of a diagnostic session (Hardy, 2019).

4  Comparison with Related Datasets

D^4 is compared with related datasets and manifested its characteristics as having more dialogue turns and utterances with a sufficient number of dialogues for model training (see Table 5). This again emphasizes that depression diagnosis is distinguished from current dialogue types and exhibits specific challenges with existing data.

Task-Oriented Dialogue Datasets Task-oriented dialogue dataset is one of the most essential components in dialogue systems study (Ni et al., 2021), consisting of various datasets for this purpose (Chen et al., 2022a), i.e. MultiWOZ (Budzianowski et al., 2018), MSR-E2E (Li et al., 2018), CamRest (Wen et al., 2016), Frames (Asri et al., 2017). However, these dialogue datasets mainly involve daily scenarios instead of clinical practice. Therefore, the number of dialogue turns is relatively small, with little attention paid to providing emotional support.

Emotional Support Datasets A few dialogue studies on mental health address users' emotions in the dialogue process and endeavor to motivate users suffering from a mood disorder. For example, Saha et al. (2021) presents the dialogue dataset MotiVAte to impart optimism, hope, and motivation for distressed people. Recently, works like ESConv (Liu et al., 2021) switch their attention to construct a professional emotional support dialog Systems. However, they are mainly concerned with providing encouragement and advice to patients instead of providing professional diagnoses for screening purposes.

Medical Diagnosis Dialogue Datasets Some medical dialogue datasets target at diagnosis, such as MedDG (Liu et al., 2020) and MedDialog (Zeng et al., 2020). Meanwhile, some datasets aim at biomedical language understanding such as CBLUE (Zhang et al., 2021a). However, these efforts focus mainly on somatic symptoms and physical diseases. MedDialog, although containing a small amount of psychiatric data, lacks professional psychiatric annotations, limiting its usage for a depression diagnosis dialogue system. It should be noted that the diagnosis process of depression essentially differs from that of somatic disorders. According to ICD-11 (The World Health Organization, 2022), in addition to somatic symptoms, patients often have multiple dimensions of symptoms such as mood, interest, mental status, and social function disorder. For this reason, psychiatrists need comprehensive information extracted from patients’ subjective statements to provide unbiased diagnoses, leading to a longer, multi-domain dialogue process.

Table 5: Comparison with Related Datasets
Depression-Related Dialogue Dataset Along with the worldwide attention on depression, a few dialogue datasets strongly related to depression are constructed, such as DAIC-WOZ (Gratch et al., 2014), a multi-modal dataset. The dataset consists of face-to-face counseling conversations between a wizard interviewer and patients who suffer from depression, anxiety, etc. However, DAIC-WOZ only includes 189 dialogues without specific annotations, which is insufficient for dialogue generation training.

5 Experiments

5.1 Tasks
Upon the construction of D4 with 1,339 well-annotated and up-to-clinical-standard depression diagnosis conversations, we can support an entire generation and diagnosis process mirroring the real-life clinical consultation scenario. We split the entire depression diagnosis dialogue procedure into 4 subtasks: Response Generation aims to generate doctors’ probable response based on the dialog context; Topic Prediction predicts the topic of the response based on the dialogue context. In our experiments, we jointly optimize the topic prediction model and the response generation model. We take the topic as a special first token of dialogue response; Dialogue Summary generates symptom summaries based on the entire dialog history; Severity Classification separately predicts the severity of depressive episodes and the suicide risk based on the dialogue context and dialogue summary. Binary (positive/negative) and fine-grained 4-class (positive further classed into mild, medium, and severe) classifications are both investigated.

5.2 Backbone Models
We use Transformer (Vaswani et al., 2017) pretrained on MedDialog (Zeng et al., 2020), BART (Lewis et al., 2019) pretrained on Chinese datasets (Shao et al., 2021), CPT (Shao et al., 2021) and BERT (Devlin et al., 2019) as backbone models to conduct the experiments.

5.3 Objective Evaluation

Generation and Summarization We evaluate the response generation task and dialog summary task with objective metrics including BLEU-2 (Papineni et al., 2002), Rouge-L (Lin, 2004), METEOR (Banerjee and Lavie, 2005) to measure the similarity between model generated responses and labels. To show the generation diversity, we also compute DIST-2 (Li et al., 2015). We implement jieba for tokenization and compute the metrics at the word level.

Results for the response generation task are presented in Table 6. Five observations can be drawn: 1) BART and CPT exhibit similar generation performance on our dataset; 2) Both models vastly outperform Transformer, which is pretrained on the medical corpus, suggesting that, on the one hand, pretrained language models with more parameters could improve generation performance; on the other hand, depression diagnosis is different from traditional somatic-oriented medical dialogues; 3) Based on the topic of response predicted by the model itself, the model could generate a more accurate response, which is of great significance for the model to be applied in real human-machine interaction scenarios; 4) Based on more accurate topics predicted by BERT, response generation performance is enhanced, indicating that higher topic prediction accuracy can effectively improve generation accuracy. 5) Given golden topics, generation performance can be further enhanced.

Table 6: Evaluation Results of Response Generation and Topic Prediction

| Model  | BLEU-2  | ROUGE-L | METEOR | DIST-2  | Topic ACC. |
|--------|---------|---------|--------|---------|------------|
| Transformer | 7.28%  | 0.21    | 0.1570 | 0.29    | -          |
| BART   | 19.29%  | 0.35    | 0.2686 | 0.09    | -          |
| CPT    | 19.79%  | 0.36    | 0.2696 | 0.07    | -          |
| Transformer | 13.43% | 0.34    | 0.2620 | 0.04    | 56.82%     |
| BART   | 28.62%  | 0.48    | 0.4053 | 0.07    | 59.56%     |
| CPT    | 29.40%  | 0.48    | 0.4142 | 0.06    | 59.77%     |
| Transformer-BERT | 23.95% | 0.40    | 0.3758 | 0.22    | 61.32%     |
| BART-BERT | 33.73% | 0.50    | 0.4598 | 0.07    | 61.32%     |
| CPT-BERT | 34.64% | 0.51    | 0.4671 | 0.06    | 61.32%     |
| Transformer* | 25.73% | 0.44    | 0.3905 | 0.04    | -          |
| BART*   | 37.02%  | 0.54    | 0.4920 | 0.07    | -          |
| CPT*    | 37.45%  | 0.54    | 0.4943 | 0.06    | -          |

* means topics are excluded, BERT means topics predicted by BERT are given as prompt, + means golden topics are given as prompt

Table 7: F1 of Topics Predicted by BART

| Core | Behavior | Empathy | Suicide | Screening |
|------|----------|---------|---------|-----------|
| F1   | 0.63     | 0.69    | 0.24    | 0.49      | 0.35      |
Results for Dialog Summary are listed in Table 8, CPT is on par with BART regarding the N-gram overlap with human references. Nevertheless, CPT exhibits a higher DIST-2 score, suggesting its superiority in generation diversity. We manually annotated summaries by 13 symptoms from ICD-11 and calculated the summaries’ sample average F1 score on the multi-label classification task of symptoms, where CPT and BART perform the same. It shows that the summary generated by the model can accurately summarize most symptoms.

Severity Classification Binary and 4-class classification are evaluated by average weighted precision, recall, and F1 by sklearn\(^3\), and results of depression severity and suicide risk severity are shown in Table 9 and Table 10. For the classification of depression severity, we conducted experiments based on dialogue history and symptom summaries respectively. The evaluation results show that the accuracy of 2-classification and 4-classification based on summaries is significantly improved, indicating that symptom summaries have extracted vital information from the dialogue, being extremely helpful for diagnosis. Although the results of 4-classification tasks are relatively poor compared with the performance in 2-classification tasks, as a screening tool, the binary classification results are already sufficient in the practical application of the system.

| Task     | Model | Precision | Recall | F1  |
|----------|-------|-----------|--------|-----|
| 2-class dialog | BERT | 0.81±0.02 | 0.78±0.02 | 0.79±0.02 |
| CPT      | 0.77±0.02 | 0.75±0.02 | 0.75±0.02 |
| 4-class dialog | BERT | 0.72±0.03 | 0.64±0.04 | 0.66±0.03 |
| CPT      | 0.70±0.05 | 0.66±0.04 | 0.65±0.03 |

Table 9: Depression Severity Classification Results

5.4 Human Interactive Evaluation

To comprehensively evaluate the model’s conversation experience with the user, we include human interactive evaluation for CPT with a rule-based chatbot. Evaluators were invited to chat with both bots in a random order upon the provided patient portrait and rated on 4 aspects with a 1-5 scale: Fluency measures how fluently the conversation flows; Comforting measures how comforting the responses are; Doctor-likeness measures to what extent does the chatbot flexibly adjust the topic according to the patient’s description; Engagingness measures to what time could the chatbot maintain their attention to continue the chat.

| CPT vs Base Metric | Fluency | Comforting | Doctor-likeness | Engagingness |
|--------------------|---------|------------|-----------------|-------------|
| Win                | 19\(^†\) | 18\(^†\)   | 17\(^†\)        | 11          |
| Lose               | 14      | 13         | 14              | 11          |

\(^†\) means p-value < 0.05/0.5 respectively

Table 11: Human Evaluation Results

The interactive human evaluation results are illustrated in Table 11. The CPT-based chatbot outperforms rule-based bots on all four metrics, suggesting that dialogue models can help us build more human-like and user-friendly depression diagnosis systems. In particular, the discrepancy in engagingness indicates that users prefer chatbots that can better understand and comfort users in completing the depression screening process. We give some empathy examples of human interactive evaluation in Table 12, indicating that the model can generate diverse empathy representations from different aspects.

6 Conclusion

In this paper, we designed a 3-phase data collection and constructed a close-to-clinical-practice and up-to-clinical-standard depression diagnosis dataset with 1,339 conversations accompanied by psychiatrists’ diagnosis summaries. Further, we conduct experimental validation on multiple tasks with state-of-art models and compare the results
Understanding

I could understand you.
I could understand your feelings.

Encouragement

Everyone has their own value.
Everyone has their own characteristics.

Suggestion

It is suggested to seek professional medical help as soon as possible.

Blessing

Wish you a happy life!
Hope you get well soon!

Table 12: Empathy Examples in Human Evaluation

with objective and human evaluation. The evaluation results show that the model-based chatbot outperforms traditional rule-based dialogue bots in all metrics, indicating that a more user-friendly dialogue system can be built with our dataset. However, the model is still not effective enough in generating appropriate empathic responses suggesting that the model needs further improvement to generate more appropriate empathy during the consultation process.

Limitations

Our work has some limitations. The principal limit of our work is that our dataset D⁴ is in Chinese, which in line with Chinese culture and expression habits. Therefore, it may not be applicable to translate the conversations into another language directly, so further exploration is required for our work to transfer to other languages. However, considering that there are no similar datasets in other languages published before, we hope that our data collection method and data form (dialogue+summary+diagnosis) could inspire more research on this unique type of dialogue in the future.

Additionally, for patient privacy protection, our dialogue data is collected in a simulated manner, not from real scenarios. This approach helps construct a more secure and generalizable consultation dialogue system because we have defined the acting doctors’ behaviors during the data collection process, that is, the system behavior range. But it should be mentioned that our dataset cannot restore the expressions of actual patients and doctors. For this reason, the textual features of acting patients in our dataset are not sufficient for the classification of depression. Therefore, it is meaningful to explore the construction of a more empathy-driven and diagnostic-accurate consultation dialogue system based on our dataset rather than conduct textual depression classification.

Ethics Statement

This research study has been approved by the Ethics Review Board at the researchers’ institution (Ethics Approval No. I2022158P). Different stages in data collection comply with corresponding ethical requirements and we endeavour to protect privacy and respect willingness of our data providers and annotators.

Specifically, our data collection falls under the Personal Information Protection Law of the People’s Republic of China. In the phase of portrait collection, the collection application was developed as a WeChat mini program⁴, which complied with the privacy protection agreement and passed the security and privacy check of WeChat mini program before releasing on the platform. Furthermore, all the portrait providers signed an informed consent form to give permission to collect their anonymous information for research purposes.

In the phase of the dialogue collection process, all the workers and annotators are informed about the purpose of our data collection and equally paid for their workload. In the phase of the dialogue examination process, the psychiatrists and psychotherapists are licensed to practice and paid equally for their workload.

To protect users’ privacy, we anonymized the portraits by storing them without a one-to-one correspondence between the identification information required for user login and the data we use in research. Therefore, all the information that could uniquely identify individual people is excluded from our dataset and research process. Regarding offensive content, we rigorously filtered the dataset manually to ensure that it did not contain any offensive content or words encouraging patients to self-harm and commit suicide. We will also require the users of D⁴ to comply with a data usage agreement to prevent the invasion of privacy or other potential misuses.

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⁴https://developers.weixin.qq.com/miniprogram/en/dev
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A Data Example

The portrait (Figure 6), the dialogue (Figure 8 and Figure 9), and diagnosis (Figure 10) belong to the same data example in our dataset. We marked the topic (if any) of the doctor’s responses in the conversation history. In this example, the doctor combined sleep and appetite into one question, so only one topic of appetite was marked. In addition, for the convenience of presentation, we have combined the doctor’s multiple utterances of the same turn into one sentence. To compare machine generation performance with humans, we provide data examples of the same portrait in this section and Section E - Human Interactive Example. Dialogues in D4 were simulated based on diverse portraits showed in Section B. More data examples can be found in website https://x-lance.github.io/D4.

B Data Characteristics

Statistics of Portraits’ Demographic Information The aggregated demographic information of 478 portraits is provide in Figure 7.

| Portrait | Demographic Information |
|----------|-------------------------|
| 年龄:21 | 性别:男 | 职业:学生 | 婚姻状态:未婚 |
| Age:21 | Gender: male | Occupation: student | Marital status: unmarried |

| Symptom Description |
|---------------------|
| 1. | 兴趣低下，对所有事情兴趣丧失 | Low interest in everything |
| 2. | 注意力难集中，疲倦 | Difficulty in concentrating and fatigue |
| 3. | 缺乏自信心，自我价值感低 | Low confidence, worthless |
| 4. | 精神运动性激越和迟滞 | Psychomotor agitation and retardation |
| 5. | 个人生活功能受损，人际关系不稳定，工作学习效率下降 | Difficulty functioning in personal life, social relationship and education |

Figure 6: A Portrait Example

Figure 7: Aggregated Demographic Information

C Backbone Model Introduction

Rule-based Model Without existing chatbots having the same function, we built the rule-based chatbot by state machine as the baseline. Based on ICD-11 (The World Health Organization, 2022), DSM-5 (American Psychiatric Association, 2013), the bot covers the same topics as the dialogue simulation process mentioned in 2.2.2. This robot has fixed question templates and recognizes the user’s answer based on regular matching, based on which it performs state jumps until all symptom information is acquired.

Transformer We use the classic sequence-to-sequence model (Vaswani et al., 2017) to conduct the response generation and topic prediction experiment. The implementation used is HuggingFace5. The parameters are loaded from the transformer pretrained on MedDialog (Zeng et al., 2020), a Chinese Medical Dialogue Dataset.

BART BART (Lewis et al., 2019) is a denoising sequence-to-sequence pre-trained model, which is a start-of-art model for both text generation and summary tasks. For this reason, we use Bart pretrained on Chinese datasets (Shao et al., 2021) to conduct the response generation and dialog summary task.

CPT CPT (Shao et al., 2021) is a novel Chinese pre-trained un-balanced transformer model, which is not only effective in generation tasks but also has powerful classification ability, so we choose it as our backbone model to conduct the generation task and also compare its performance of classification task with BART.

BERT Bert (Devlin et al., 2019) is effectively used for a wide range of language understanding tasks, such as question answering and language inference. Thus, we use the version6 which is pre-trained on eight popular Chinese NLP datasets, to conduct the classification task.

D Training Details

The division of train, validation, and test sets for all experiments is close to 8:1:1, and the data of

5https://github.com/huggingface/transformers
6https://huggingface.co/hfl/chinese-macbert-base
PART1

Doctor: 你好 Hello
Patient: 医生我最近觉得啥事情都没有意思，不知道怎么回事 I feel that nothing has been interesting recently, and I don't... 还是一个问题。
Patient: 你最近是大几？ What grade are you currently in?
Doctor: 大四了 I’m a senior student.
Doctor: 学生的压力大吗？ But you think the current situation will change or not? If you were given a month off and didn't need to take the exam. Do you think your current situation will change or not?
Patient: 我觉得可能会吧，但是我上大以来一直都很难受的 I think it might be, but I've been having a hard time since college.
Doctor: 情绪 你说上大学来一直挺难受什么意思？是从大一开始就感觉情绪不好吗？ Mood What do you mean? Did you feel bad from your first year?
Patient: 就是同学之间竞争压力很大，我一直不是很优秀的学生。 And you think the current situation will change or not? If you were given a month off and didn't need to take the exam. Do you think your current situation will change or not?
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Patient: 我觉得可能会吧，但是我上大学以来一直都很难受的 I think it might be, but I've been having a hard time since college.
Doctor: 情绪 你说上大学来一直挺难受什么意思？是从大一开始就感觉情绪不好吗？ Mood What do you mean? Did you feel bad from your first year?
Response Generation  For BART and CPT models, the initial parameters are pretrained on Chinese datasets (Shao et al., 2021). We use a cosine learning rate scheduler with the initial learning rate of 1e-5, 100 warm-up steps, and the AdamW optimizer (Loshchilov and Hutter, 2019). Beam search where the number of beams is 4 is used in response generation. Models are trained for 30 epochs. The one with the best BLEU-2 metric on the evaluation set is selected for the test.

For the Transformer, we use the implementation by HuggingFace7. We load the parameters of the Transformer pretrained on MedDialog (Zeng et al., 2020). The weight parameters were learned with Adam and a linear learning rate scheduler with the initial learning rate of 1.0e-4 and 100 warm-up steps. The batch size was set to 16. Top-k random sampling (Fan et al., 2018) is used in response generation. The model is trained for 20 epochs. The one with the highest BLEU-2 score on the evaluation set is chosen for the test.

We spliced multiple sentences of the doctor in the same round into the dialogue history, and selected the last topic as the topic of the new sentence. Due to the limitation of models’ positional embedding, we intercepted data with a length over 512. In the response generation task, we try to keep the most recent conversations as they are more instructive to the current response.

Figure 10: A Diagnosis Example

different depression severity are also internally distributed according to the above ratio.

Social Function
会和朋友们倾诉自己的问题吗？
Will you talk to your friends about your problems?

Appetite
那体重跟饮食方面最近有什么变化吗？
Has there been any recent change in weight and appetite?

Suicide
你感到绝望的时候有没有想过伤害自己吗?
Have you ever wanted to hurt yourself when you're desperate?

Empathy
要知道，选择抑郁症很多人都会很痛苦。
Well, a lot of people have a choice of difficulties, don't worry too much.

Somatic Symptom
你会觉得头晕冒冷汗什么呢？
Do you feel dizzy and sweating or something?

Figure 11: Samples of Doctors’ Topic

Figure 12: Lexical Feature of Empathy

7https://github.com/huggingface/transformers
Dialog Summary Both BART and CPT models are trained for 50 epochs. We use a cosine learning rate scheduler with the initial learning rate of 1e-5 and 100 warm-up steps and the AdamW optimizer. The one with the highest rouge-1 metric on the evaluation set is selected for the test.

If the input dialog history is longer than the model’s input size, we retain the 512 tokens in the middle of the dialog.

Severity Classification For BERT, BART, and CPT models, we use a cosine learning rate scheduler with the initial learning rate of 1e-5, 100 warm-up steps, and the AdamW optimizer (Loshchilov and Hutter, 2019). Models are trained for 30 epochs. The one with the best F1-score metric on the evaluation set is selected for the test.

For the classification based on dialog history, we retain 512 tokens in the middle of the dialog. For the classification based on dialog summary, we retain 128 tokens in the middle of the summary.

E Generation Examples

Response Generation As shown in Figure 13, we selected one representative example of the generated responses by different models. The examples in the figure show us that the correct topic helps the model generate more reliable and secure replies.

Dialog Summary Generation In Figure 14, we present an example of the generated summary by different models. The models list most symptoms of the patient.

Human Interactive Example We give a dialogue example with dialog summary and depressive severity generated by CPT during human evaluation in Figure 15 and human evaluation in Figure 16. In parentheses before the chatbot’s sentence, we marked the topic predicted by the model. To clarify the correspondence between dialogue and summary, We have identified the correct symptom in the symptom summary with the same color as its location in the conversation. It can be seen that the model completed the entire consultation dialogue task and gave a dialogue summary covering almost all symptoms accurately.

F Worker Training Method

Acting Patients To help acting patients better interpret the symptoms in the patient portraits, we
The patient has difficulty concentrating; psychomotor agitation and retardation, with somatic symptoms: dizziness, worthless, poor sleep quality and shallow sleep.

The patient has recently been depressed, unable to concentrate in class, decreased learning efficiency, sleep disturbance, difficulty falling asleep, physical discomfort, slow thinking.

In the past month, the patient experienced: decreased concentration, decreased self-evaluation, impaired cognitive function, decreased interest, lack of energy, sleep disturbance, somatization symptoms, dizziness.

| Reason for Removing          | Sum |
|------------------------------|-----|
| Total                         | 4,457 |
| Unfinished                    | 961  |
| Dropped by Quality Control Criteria | 1,814 |
| Dropped by Doctor             | 342  |
| Our Dataset                   | 1,339 |

Table 13: Statistics of Removed Dialogues

**Figure 21** is screenshot of doctors’ user interface, and **Figure 22** is screenshot of the patients’.

**Acting Doctors** We compile the 41 symptom items in Figure 19 and Figure 20 that doctors need to know when diagnosing depression, and design the questioning logic between questions of asking symptoms from mild to severe. The basic requirement is to obtain enough information from the patient during the conversation. At the same time, in order to further improve the dialogue experience, we require the acting doctors to: 1) Conduct the dialogue centered on the patient’s complaint, that is, give priority to asking the patient’s initiative symptom-related questions; 2) Ask further questions based on the patient’s experience to elicit additional disclosure; 3) Give the patient certain feedback, e.g., empathy or comfort words when the patient talks about what they are going through.

**G Quality Control**

To create transparency about quality control, the statistics of dialogues removed is provided in Table 13. We have collected 4,457 dialogues, and 961 dialogues are removed because they haven’t completed the entire diagnosis dialogues. 1,814 dialogues are automatically dropped by the stringent quality control criteria in Table 2. Professional psychiatrists and clinical psychotherapists screening the dialogues dropped 342 dialogues which unsuccessfully meet clinical standards. Eventually, we selected 1,339 dialogues into D.4.

**H The Data Collection Platform**

...
PART1
Patient: 医生，我最近觉得啥事情都没有意思，不知道怎么回事
Doctor, I feel nothing has been interesting recently, and I don't know what happened to me.
Chatbot: [自杀倾向]这种状态持续多久了呢？[Core] How long have you been in this state?
Patient: 从上个月开始吧，就今年开学以来变成这样的。Since last month, probably since the beginning of this semester.
Chatbot: 最近生活中有发生什么事情吗？Has anything happened in your life recently?
Patient: 学习压力很大，尤其是最近同学们都保研了，只有我还得考，每天都很焦虑。I've been under a lot of pressure from studying recently, especially since my classmates have all been admitted to a graduate program but me, which makes me very anxious.
Chatbot: [自杀倾向]每天大部分时间都是这种状态吗？[Core] Are you in this state most of the day?
Patient: 是的差不多每天都是很焦虑很低落。Yes, almost every day. I'm very anxious and down.
Chatbot: [自杀倾向]会不会在早上或者晚上的时候觉得更难过呢？[Core] Do you feel sadder in the morning or at night?
Patient: 早上起来的时候会觉得尤其难过 I feel especially sad when I wake up in the morning.
Chatbot: [自杀倾向]你最近有没有觉得对以前喜欢的事情不感兴趣了呢？[Core] Have you recently felt disinterested in things you used to enjoy?
Patient: 有的，我不光是觉得以前喜欢的事情没有意思，我觉得什么事情都没有意思。Yes, I don't just think the things I used to like are boring, I don't think anything is interesting.
Chatbot: [自杀倾向]那你只是感觉不到快乐了，还是其它的一些感觉，例如悲伤、愤怒的感觉也没有了？[Core] Then you just can't feel happiness, or are some other feelings, such as sadness and anger, gone too?
Patient: 这倒是没有，我觉得难过得很。No, I feel very sad.
Chatbot: [自杀倾向]嗯嗯，那能正常清理个人卫生、做家务吗？[Core] Well, can you clean up your personal hygiene and do housework normally?
Patient: 可以的。但是我现在不喜欢出门，很少和人来往，以前的朋友都不一起玩了。Yes, but I don't like going out now, and I rarely interact with people. I don't play with my old friends anymore.
Chatbot: [自杀倾向]是有意识回避社交不想和人往来吗？[Core] Do you intentionally avoid social interaction and not want to interact with people?
Patient: 有这样的想法吧，我觉得自己很没用，和别人待在一起也不知道该说什么干什么。越来越自闭。Kind of. I think I am useless, don't know what to say or do when I stay with others and am increasingly autistic.

PART2
Chatbot: [自杀倾向]你会觉得在生活中是自己在拖累别人吗？[Suicide Tendency] Do you feel like you are a burden to others?
Patient: 有时候会这么想。I sometimes have such thinking, and I am terrified that I will not be able to get into graduate school, and become a burden to my parents.
Chatbot: [自杀倾向]有没有自杀的念头？[Suicide Tendency] Do you have any plans for the next?
Patient: 我想专注于学习，好好准备考试，但是我最近感觉自己学习效率很低。I want to study hard and prepare well for exams, but I recently feel that my study efficiency is very low, and I can't concentrate all the time.
Chatbot: [行为]最近睡眠怎么样？[Behavior] How about your sleep?
Patient: 睡眠一般。Normally
Chatbot: [行为]吃饭怎么样呢？[Behavior] And how's your appetite?
Patient: 吃饭还行。Also Normally
Chatbot: [行为]身体上有没有不舒服感？[Behavior] Is there any physical discomfort?
Patient: 有时候会头疼恶心。Occasionally feel dizzy and nauseous.
Chatbot: [自杀倾向]你有伤害自己的想法吗？[Suicide Tendency] Do you have thoughts of hurting yourself?
Patient: 没有。No
Chatbot: [自杀倾向]你会觉得死了更好吗？[Suicide Tendency] would you feel better dead?
Patient: 不会。No
Chatbot: 还有其他想和我聊聊的吗？Is there anything else you want to talk to me about?
Patient: 我该怎么办，我好无助。What should I do? I'm so helpless.
Chatbot: [共情安慰]建议你尽快到专科医院进行诊断。[Empathy] It is recommended that you go to a specialist hospital for diagnosis as soon as possible. Please don't put too much pressure on yourself.
Patient: 谢谢你的帮助，谢谢医生。Well, thank you.
Chatbot: 那我们诊查结束了，谢谢你的信任。Then our consultation is over. Thanks for your trust.

Symptom Summary: 病人最近情绪低落，兴趣减退，精力缺失，自责自罪感，无望无助，有过轻生的念头，躯体不适感，头晕恶心，思维迟缓。The patient has recently suffered from low mood, loss of interest, lack of energy, self-blame, guilt, hopelessness, suicidal thoughts, physical discomfort, dizziness, nausea, and slow thinking.
Depression Risk Prediction: 中度。Moderate

Figure 15: Human Interactive Example-part1
Figure 16: Human Interactive Example-part2
| 症状                  | 解释                                      |
|----------------------|-------------------------------------------|
| 持续的情绪低落       | Persistent low mood                       |
|                      | 连续两周以上几乎每天或者大部分时间都心情不好 |
|                      | In a bad mood almost every day or most of the time, for more than two weeks |
| 早重夜轻             | Morning depression                        |
|                      | 早上或者晚上的时候觉得更难过             |
|                      | Feel more sad in the morning or at night   |
| 对过去的爱好兴趣丧失 | Loss of interest in past hobbies           |
|                      | 连续两周以上以前很喜欢某事，现在不喜欢了，觉得没意思 |
|                      | Do not like or feel boring about past hobbies, which are liked more than two weeks |
| 对所有事情兴趣丧失  | Loss of interest in all things             |
|                      | 连续两周以上所有事情都觉得没有意思     |
|                      | Feel bored of all things for more than two weeks |
| 缺乏情感体验         | Lack of emotional experience               |
|                      | 连续两周以上没有快乐的感觉，同时也有了悲伤和愤怒的感觉 |
|                      | There is no feeling of happiness, sadness and anger for more than two weeks |
| 疲倦                 | Tired                                     |
|                      | 没做什么事情就觉得很累，不想上班/上学只想躺在床上 |
|                      | Feel tired after doing nothing, don’t want to go to work/school, just want to lie in bed |
| 决断困难             | Difficulty to decide                      |
|                      | 在思考问题时会感觉反应不过来，无法思考，脑中一片空白，或在做本不需要思考的事情时犹豫不决，难以做决定 |
|                      | Can’t think and react when thinking about problems, or hesitate when facing things |
| 自我价值感低         | Low sense of self-worth                   |
|                      | 觉得自己没用                             |
|                      | Feel useless                             |
| 自罪感               | A sense of self-guilt                     |
|                      | 觉得自己在拖累别人                       |
|                      | Feel that you are dragging others down     |
| 无望感               | Hopelessness                              |
|                      | 觉得生活失去希望，无助                   |
|                      | Feel hopeless and helpless in life         |
| 睡眠浅               | Light sleep                               |
|                      | 除了起床上厕所，每天晚上醒来的次数超过两次 |
|                      | In addition to getting up to the toilet, wake up more than twice every night |
| 入眠困难             | Difficulty Falling-asleep                 |
|                      | 闭上眼睛之后需要半个小时以上才能睡着   |
|                      | It takes more than half an hour to fall asleep after closing your eyes |
| 早醒                 | Wake up early                             |
|                      | 早上比平时早醒了两个小时以上           |
|                      | Wake up more than two hours earlier in the morning than usual |
| 睡眠时间过短         | Short sleep time                          |
|                      | 睡眠时间比过去少了两个小时以上          |
|                      | Sleep more than two hours less than in the past |
| 多噩梦               | Nightmare                                 |
|                      | 和以前比，现在更频繁地做噩梦             |
|                      | Have nightmares more often than before     |
| 睡眠时间过长         | Sleep too long                            |
|                      | 睡眠时间比过去多了两个小时以上          |
|                      | Sleep time is more than two hours longer than in the past |
| 食欲不佳             | Poor appetite                             |
|                      | 不想吃饭/懒得吃饭                       |
|                      | Don't want to eat or is too lazy to eat    |

Figure 17: Explanation of Symptoms - 1
| 症状 Symptoms | 解释 Explanation |
|-------------|----------------|
| 有被动进食行为 Passive eating behavior | 需要强迫自己去吃或者需要别人督促 Need to force yourself to eat or need to be urged by others |
| 暴饮暴食 Overeating | 在情绪影响下短时间内大量进食 Eating a lot in a short period of time under the influence of emotions |
| 精神运动性迟滞 Psychomotor retardation | 感觉自己讲话比平时慢，有时反应迟缓，有时甚至就像在糖浆或者泥泞中行走一样 Feel yourself speaking or responding slower, sometimes like walking in syrup or mud |
| 精神运动性激越 Psychomotor agitation | 经常感到烦躁不安，坐立难安 Often feel irritable and restless |
| 躯体症状 Somatic symptom | 身体上有一些反应，比如头晕、呼吸困难、出冷汗 Some physical reactions, such as dizziness, difficulty breathing, cold sweats |
| 个人生活功能受损 Impaired personal life function | 处理生活中的小事的功能受到影响，比如清理个人卫生做家务等，可以举更详细的例子 The function of dealing with small things in life is affected, such as cleaning up personal hygiene, doing housework, etc. More detailed examples can be given |
| 人际关系不稳定 Interpersonal relationship is unstable | 觉得与某些生活中比较重要的人的关系变差，不想与人交往 Feel that the relationship with others is getting worse, and don’t want to associate. |
| 自杀风险高 High suicide-risk | 有自杀计划 Have suicide plan |
| 自杀史 Have history of suicide | 曾经尝试过自杀 Have tried suicide |
| 躯体疾病相关 Physical disease related | 大脑或内分泌系统相关疾病包括了神经系统疾病，如癫痫、神经梅毒或脑卒中、脑肿瘤等；内科疾病，如甲状腺功能减退等 Diseases related to the brain or endocrine system include neurological diseases, such as epilepsy, neurosyphilis or stroke, brain tumors, etc.; medical diseases, such as hypothyroidism, etc. |
| 精神活性物质的依赖或者戒断 Psychoactive substance dependence or withdrawal | 长期服用精神活性物质：可卡因、酒精、毒品或其他致幻剂等或最近突然戒断 Long-term use of psychoactive substances: cocaine, alcohol, drugs or other hallucinogens, etc. or a sudden withdrawal recently |
| 延长哀伤 Prolonged grief | 有亲人去世，长期处于悲伤自责状态，超过六个月以上 Be grieve and self-blaming for more than six months when a loved one passes away |
| 月经周期相关 Menstrual cycle related | 每个月经周期都会出现类似症状 Similar symptoms appear every menstrual cycle |
| 双相情感障碍 bipolar disorder | 和过去相比，最近两周有超过四五天以上有异常兴奋、话多、想法多、做事冲动和即使不睡觉也觉得精力充沛的情况 Compared with the past, in the last two weeks, there have been more than four days of unusual excitement, talking, thinking, impulsiveness, energy even when not sleeping |
| 工作学习效率下降 Decrease in work and study efficiency | 无法正常完成工作学习任务，这种异常有被周围人觉察到，比如被领导批评/被老师约谈 Unable to complete work and study tasks normally, this kind of abnormality is noticed by people around, such as being criticized by the leader or interviewed by the teacher |
| 自残想法 Thought of self-harm | 想要伤害自己 Want to hurt yourself |

Figure 18: Explanation of Symptoms - 2
| 症状版块       | 询问主题         | 备注                                      |
|---------------|-----------------|-------------------------------------------|
| **导语** Lead | 病人主要诉求   | 病人有情绪低落/兴趣低下/疲倦的问题之后提问 |
| **持续时间** Duration | 持续时间 Duration | Ask if the patient has problems with depression/low interest/tiredness |
| **原因** Cause | 病因 Cause       | 病人有情绪低落或兴趣低下问题时提问       |

| 情绪低落 Upset | 是否有情绪低落 Whether patients are upset | 是否在某些特定时段会尤为心情不好 Are you in a particularly bad mood at certain times |
|---------------|------------------------------------------|-----------------------------------------------|
|               | 持续时间 Duration                       |                                               |
|               | 早晚差异 The difference between morning and evening |                                               |

| 兴趣低下 Low interest | 是否兴趣低下 Does the patient has low interest | 是否有兴趣的范围 Range for not being interested | 是否有兴趣的原因 Reasons for not being interested | 是否情感淡漠 Is it emotionally indifferent |
|-----------------------|-----------------------------------------------|-----------------------------------------------|------------------------------------------------|-----------------------------------------------|

| 社会功能 Social function | 个人生活事务 Personal life affairs | 根据不同年龄段提问一些基本的生活事务是否正常 According to different age groups, ask whether some basic life affairs are normal |
|--------------------------|-----------------------------------|--------------------------------------------------------------------------------------------------|
|                          | 学习工作 Study and Work           |                                                                                                  |
|                          | 社交 Social contact                | 是否和家人朋友联系/倾诉，是否获得他们的支持 Whether to contact/talk to family and friends, to get their support |
|                          | 社交 Social contact                | 病人是否有意回避社交 Does the patient deliberately avoid social interaction |

| 精神状态 Mental state | 注意力下降 Decreased concentration | 记忆力变差 Memory loss | 疲倦 Tired | 决断困难 Difficulty in decision | 自信心下降 Decline in self-confidence |
|---------------------|-----------------------------------|------------------------|-----------|-------------------------------|------------------------------------|

Figure 19: Doctors’ questions - 1

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| Symptoms section | Consultation topic | Remark |
|------------------|-------------------|--------|
| **睡眠问题** (Sleep problems) | **Does the patient have sleep problems** | 有睡眠问题逐个问 |
| 入睡困难 | Difficulty falling asleep | 有睡眠问题逐个问 |
| 睡眠浅 | Light sleep | 有睡眠问题逐个问 |
| 早醒 | Wake up early | 有睡眠问题逐个问 |
| 睡眠时间过短 | Sleep too short | 有睡眠问题逐个问 |
| 多梦 | Dreamy | 有睡眠问题逐个问 |
| **食欲问题** (Appetite problems) | **Does the patient have appetite problems** | 无上述食欲问题时提问 |
| 食欲不振 | Loss of appetite | 无上述食欲问题时提问 |
| 暴饮暴食 | Overeating | 无上述食欲问题时提问 |
| 体重变化 | Weight change | 无上述食欲问题时提问 |
| **躯体症状** (Ask when patients have serious emotional and interest issues) | **Psychomotor agitation or retardation** | 精神运动性激越或迟滞 |
| **躯体不适** | **Physical discomfort** | 烦躁不安或反应迟缓 |
| 自残倾向 | Self-harm tendency | 无上述食欲问题时提问 |
| 自杀倾向 | Suicidal tendency | 无上述食欲问题时提问 |
| 无望感 | Hopelessness | 无上述食欲问题时提问 |
| 未来的规划 | Future plan | 无上述食欲问题时提问 |
| 内疚感/自卑感 | Guilt/inferiority complex | 无上述食欲问题时提问 |
| 自我价值感低 | Low self-worth | 无上述食欲问题时提问 |
| **筛查** (Need to ask when mentioned in the patient description) | **The death of a loved one causes long-term grief** | 病人描述中提到时需问 |
| **躁狂** | **Mania** | 是否易怒、易发生争执 |
| **遗传史** (If the patient has emotional or interest symptoms or suicidal tendencies) | **Genetic** | 是否易怒、易发生争执 |
| **结束之前** (Before the end) | **Does the patient have other problems** | 无上述食欲问题时提问 |

Figure 20: Doctors’ questions - 2

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Figure 21: Page of doctor

Figure 22: Page of patient