

Roleplaying with Structure: Synthetic Therapist-Client Conversation Generation from Questionnaires

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<https://ai-mh.github.io/>

Abstract

The development of AI for mental health is hindered by a lack of authentic therapy dialogues, due to strict privacy regulations and the fact that clinical sessions were historically rarely recorded. We present an LLM-driven pipeline that generates synthetic counseling dialogues based on structured client profiles and psychological questionnaires. Grounded on the principles of Cognitive Behavioral Therapy (CBT), our method creates synthetic therapeutic conversations for clinical disorders such as anxiety and depression. Our framework, SQPsych (Structured Questionnaire-based Psychotherapy), converts structured psychological input into natural language dialogues through therapist-client simulations. Due to data governance policies and privacy restrictions prohibiting the transmission of clinical questionnaire data to third-party services, previous methodologies relying on proprietary models are infeasible in our setting. We address this limitation by generating a high-quality corpus using open-weight LLMs, validated through human expert evaluation and LLM-based assessments. Our SQPsychLLM models fine-tuned on SQPsychConv achieve strong performance on counseling benchmarks, surpassing baselines in key therapeutic skills. Our findings highlight the potential of synthetic data to enable scalable, data-secure, and clinically informed AI for mental health support. We will release our code, models, and corpus at <https://ai-mh.github.io/SQPsych>

1 Introduction

Acquiring therapy-client dialogues from clinical institutions is difficult due to strict privacy laws such as HIPAA (US), GDPR (EU) and PIPL (China), along with ethical issues regarding patient confidentiality (De Freitas et al., 2022). These restrict access to large and varied datasets necessary to build

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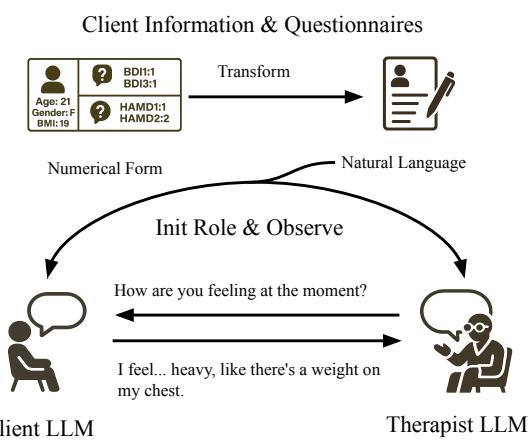


Figure 1: Our pipeline begins with client information and questionnaire data in numerical form. We then convert this into natural language, which is used to simulate therapist-client roleplay conversations.

AI systems for mental health care. Furthermore, clinical psychology interviews and counseling sessions from the past were not routinely recorded or transcribed. The questionnaires in practice were often derived from informally distilled insights during these sessions. With LLM, there is now potential to reuse these processes and data sources to synthetically generate more structured and meaningful outcomes, such as therapy-client dialogues.

Synthetic therapy-client conversations offer valuable opportunities in mental health care and clinical research (Sharma et al., 2021). They can also power AI tools for screening, and diagnostic support, helping to streamline the intake process and reduce pressure on already overburdened therapists (Cabrera et al., 2023). In addition, simulated therapy sessions can serve as a training tool for students and early career mental health and social workers, providing hands-on experience in a controlled, ethical environment (Fu et al., 2023).

We introduce an LLM-based generation pipeline that produces synthetic counseling dialogues con-

ditioned on structured client data and standardized mental health assessments, and psychologically informed guidance. These conversations are tailored to mental health conditions (e.g., major depressive disorder and anxiety). By integrating expertise and best practice in psychology (Cognitive Behavior Therapy - CBT) (Beck, 1963), the resulting data can serve as a valuable resource to improve fine-tuning therapeutic agents, intervention planning. By bridging structured psychological data and natural language conversation, our approach contributes to scalable and clinically relevant conversation generation. Figure 1 demonstrates our main concept. Our contributions span modeling, data, and evaluation:

- **Modeling - SQPsych:** We introduce SQPsych (Structured Questionnaire-based Psychotherapy), a novel pipeline that transforms structured client metadata and questionnaires into free text, employs role-playing between therapist and client personas, enabling generation of counseling conversations.
- **Data & Model Resources - Synthetic Corpus & Fine-tuned Models:** We use seven open models (23B–123B) for local synthetic data generation, conditioned on real-world structured client information and questionnaires. This choice ensures sensitive questionnaires are not shared with proprietary models. We then leverage the synthetically generated dataset, distilled from larger LLMs, to fine-tune seven smaller models, enabling resource efficiency and practical utility.
- **Evaluation & Insight - Benchmarking & Expert Feedback:** We perform a holistic evaluation with human experts and automatic metrics. (1) Our models perform effectively on two specialized counseling skill benchmarks, exceeding baseline models in key therapeutic competencies such as distortion and core beliefs' identification. (2) In preference evaluations conducted by both an LLMs panel and human experts, our fine-tuned model consistently outperforms the baselines. (3) Expert feedback offers valuable insights for enhancing future data/models focused on counseling tasks.

2 Methods

We propose **SQPsych**, a pipeline converting structured data to conversations which synthesizes clinically therapist-client dialogues by conditioning on structured mental health data. This pipeline

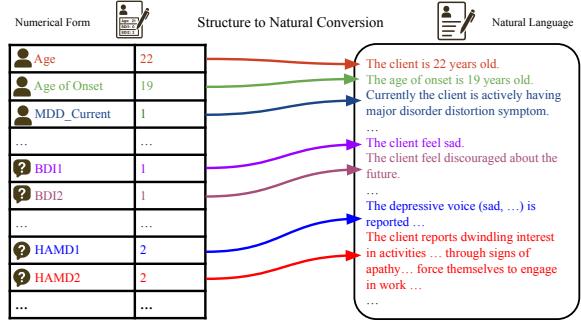


Figure 2: An artificial example of converting numerical values, i.e., structured client metadata (e.g., Age, Age of Onset, MDD_Current) and questionnaire scores (e.g., BDI1, BDI2 and HAMD1, HAMD2), into natural language with structure to natural language conversion.

integrates standardized client metadata and questionnaire, combined with targeted role-based generation strategies informed by clinical expertise. We describe the most important aspect of our pipeline in this section. Detailed information on the generation workflow can be found in the Appendix B.

2.1 Structured Data Conditioning & Conversion

Our pipeline is conditioned on structured information: **general client information** (e.g., age, gender, etc.) and **standardized questionnaire results** (e.g., PHQ-9, BDI, etc.). Since much of this data is available in numerical or categorical form, we convert it to natural language for proper descriptions. This conversion may help the model interpret client characteristics and psychological states with more precision. We construct a hash map that maps numerical values to their corresponding natural language descriptions for this purpose. Figure 2 shows an example of the formatting of our data input.

2.2 Dual-role Generation Strategy

Previous approaches, such as CACTUS (Lee et al., 2024) and SMILE (Qiu et al., 2024), generate conversations using a single model that simulates both roles simultaneously. In contrast, we employ a dual-agent framework where separate models independently simulate the therapist and client, each operating with distinct reasoning processes and information access patterns. This approach enables dialogue dynamics, as each agent maintains its own perspective and responds based on role-specific knowledge and objectives.

Specifically, the client agent is conditioned on background information and questionnaire data to

generate responses that reflect the client’s psychological state and personal circumstances. The therapist agent operates with therapeutic guidelines and intervention strategies, responding to the client’s statements. For that in the generated dialogue, the LLM therapist will apply CBT skills (e.g., *paraphrasing*, *validation*), while the LLM client will *express emotions and hesitation*, grounded in personal data and questionnaire-derived.

2.3 Turn-Based Generation Workflow

The conversation proceeds in a role-playing therapeutic simulation. The workflow includes the following steps: **1. Initialization.** We initialize two language models, one for the role of the therapist and the other for the client. **2. Turn-by-turn interaction.** The interaction proceeds turn-by-turn: the therapist model generates an initial utterance, which is then passed to the client model to produce a response. This exchange continues iteratively, and both models incorporate the full conversation history at each step to maintain contextual consistency. **3. Termination criterion.** The dialogue progresses until the therapist model issues an explicit signal with an time acknowledgment [/END] token to end the session. To ensure sufficient conversational depth, a minimum of 15 turns is required before termination is permitted. **4. Post-processing.** After generation, we conduct a post-processing step with regex to remove redundant utterances or unnecessary explanations.

3 Experiments

Dataset & Structured Input We use the questionnaire and data from client information collected by Kircher et al. (2019), which is publicly available on demand. The questionnaire corpus consists of 2090 clients, differentiated by **control** and **MDD** (major depressive disorder) status. The primary distinction between the control group and the MDD group lies in their foundational beliefs. Cognitive challenges in MDD clients persist longer than those in control group clients. Subsequently, we separated them into training, development, and test sets to create the respective conversations. Table 3 shows the split of the questionnaire dataset.

We incorporate general client information including demographic attributes: *age*, *gender*, *education*, and *employment*, along with family information such as *genetic risk*, *parent education*, and *number of children*. **clinical values** related to MDD such as

Abb.	Checkpoint	# Par.
mistral	mistralai/Mistral-Large-Instruct-2407	123B
command	CohereLabs/c4ai-command-a-03-2025	111B
qwen2.5	Qwen/Qwen2.5-72B-Instruct	72B
llama3.3	meta-llama/Llama-3.3-70B-Instruct	70B
nemotron	nvidia/Llama-3_3-Nemotron-Super-49B-v1	49B
qwq	Qwen/QwQ-32B	32B
gemma	google/gemma-3-27b-it	27B

Table 1: Open models that we use in our paper to generate synthetic therapeutic conversations. The checkpoints of these models are publicly available on the internet.

Dataset	# Utt.	# Avg. turns	# Tok./utt.
CACTUS (Lee et al., 2024)	995,512	15.263	27.051
Psych8k (Liu et al., 2023)	16,374	1	54.685
SQPSPsychConv _{command}	64,760	17.451	51.019
SQPSPsychConv _{gemma}	71,000	16.999	51.790
SQPSPsychConv _{nemotron}	64,238	15.911	51.432
SQPSPsychConv _{mistral}	98,342	23.119	31.098
SQPSPsychConv _{llama3.3}	101,694	24.599	32.627
SQPSPsychConv _{qwen2.5}	64,488	15.534	34.489
SQPSPsychConv _{qwq}	77,134	18.601	26.291

Table 2: Dataset statistics compare our approach to previous works on mental health counseling. On average, our datasets have more tokens/utterance than CACTUS, and are close to Psych8k.

age of onset, *duration of episode* are also included. We specifically select **questionnaire results** from MDD-related assessment tools such as the *Hamilton Depression Rating Scale* (HAM-D) (Hamilton, 1980), *Hamilton Anxiety Rating Scale* (HAM-A) (Hamilton, 1959), and *Beck Depression Inventory* (BDI) (Beck, 1974). Since the questionnaire data sets are in table form, we convert them to natural language with a clear description. We refer to Appendix B.2 for an example of conversion.

3.1 Synthetic Datasets Generation

Although the clinical questionnaire dataset from Kircher et al. (2019) is anonymized, the sensitivity of the data and its access terms trigger strict requirements. Specifically, data privacy regulations restrict the use of clinical questionnaire data to controlled, audited environments. This constraint prohibits the transmission of the data to third party services such as OpenAI. Consequently, we are limited to employing open models, and must ensure that each of the seven models used in this study is hosted locally to guarantee full data protection and regulatory compliance. Table 1 lists the seven open models used. We use vLLM (Kwon et al., 2023) to host these models locally and send a request to each LLM. These

Split	Control	MDD	Total
Train	955	738	1,693
Dev	106	38	144
Test	117	136	253
Total	1,178	912	2,090

Table 3: Composition of client information & questionnaire from Kircher et al. (2019) data across splits for control and MDD groups.

models run on four A100 GPUs, each with 80GB of VRAM, using the BF16 configuration. We call our synthetic generated data set SQPsychConv, for example, SQPsychConv_{mistral} is the dataset generated by the `mistral` model. Table 2 shows the statistics of the data set in terms of the number of utterances, average turns per dialogue, and average number of tokens per utterance. Generating a typical 15-turn conversation requires roughly three minutes. We obtain 2090 conversations per model.

Baselines Models Further on, we compare our fine-tuned SQPsychLLM models (Sec. 3.1) with previous works. We aim to assess the transfer of counseling skills from our open-weight model conditioned on questionnaires to smaller models versus baselines transferring using real data and proprietary models. As a baseline, we choose models that are designed for counseling, such as CAMEL (Lee et al., 2024), Psych8k (Liu et al., 2023) and mental health applications such as MentaLLaMA (Yang et al., 2024) which is the first open source LLM instruction specifically built on top of Llama-2-7b-chat-hf (Touvron et al., 2023) to detect mental health signals in the text of social networks and explain its reasoning. Secondly, we use CAMEL which is based on Llama3-8B-Instruct. CAMEL is trained on CACTUS (Lee et al., 2024) data, which is a multi-turn synthetic dialogue dataset crafted with a CBT structure using gpt-4o to mimic realistic counseling sessions. Finally, since the real-world dataset Psych8k (rewritten by gpt-4) is available in a fine-tuned instruction format, we perform a complete BF16 fine-tuning on Llama3-8B-Instruct with the same hyperparameters as CAMEL.

Model Finetuning After finishing the generation of our synthetic conversation dataset, we fine-tune Llama3-8B-Instruct (Grattafiori et al., 2024) on each portion of the synthetic dataset to simplify comparison with baseline models. Concretely, we call, for exam-

ple, that SQPsychLLM_{mistral} is fine-tuned on Llama3-8B-Instruct with SQPsychConv_{mistral} synthetic dataset. We use similar hyperparameter as CAMEL for fine-tuning.

3.2 Expert Evaluation

For expert evaluation, our main goal is to assess the counseling skills of LLM therapists. We engage three professional therapists with graduate degrees in psychology: one focuses on qualitative analysis, offering insights based on clinical experience, while two experts conduct quantitative evaluations following established guidelines. Together, they provide a comprehensive assessment of the counseling abilities of LLMs. In addition, we perform a preference evaluation with three other clinical therapists that compare our models with the baseline to assess the effectiveness of the model.

Qualitative Evaluation The expert reviews 35 unique SQPsychConv dialogues primarily focusing on the therapist LLM’s responses. For each test set of each model, we selected five conversations at random, ensuring the inclusion of three MDD conversations and two control conversations for each model. We refer to them by SQPsychConv_{sampled-test}.

Our human expert evaluation criteria co-designed with experts are (1) Identification of key beliefs/concepts, (2) Paraphrasing for mutual understanding, (3) Guided discovery to examine the validity of the belief, (4) Emotional validation, (5) Reflective listening (Mirroring emotions and statements), (6) Precision in understanding the client’s expressions, (7) Session closure by the therapist, (8) Use of simple language, and (9) Avoidance of repetitive phrasing. We refer to Appendix D for the details of each criterion.

Quantitative Evaluation For the quantitative evaluation, an expert manually assessed the same 35 conversations used in the qualitative analysis, assigning scores on a 0-2 Likert scale in 9 above criteria. We consult with experts and co-design the scoring as defined as follows: 0 points indicated that the criterion was not met at all (*No*), 1 point indicated partial fulfillment (*Somewhat*), and 2 points indicated full satisfaction (*Yes*). We refer to Appendix D for the details of each scoring item. The assigned scores offered a systematic approach to quantitatively assess each conversation, with a maximum of 18 points available for therapist skills.

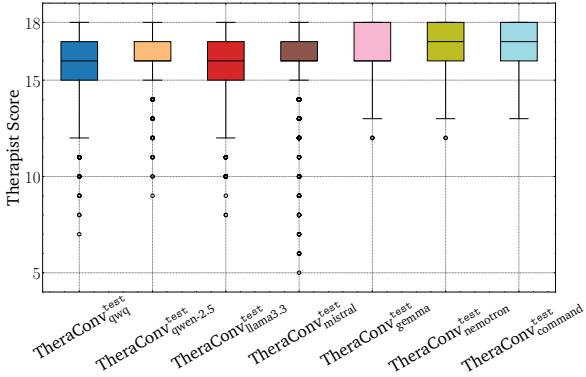


Figure 3: Comparison of therapist scores using LLMs panel on SQPsychConv^{test} for seven models

Preference Evaluation We use CounselBench-Adv benchmark (Li et al., 2025), which consists of 120 specific prompts to assess preferences, designed to expose the limitations of LLM in mental health support. The evaluation covers three models: the leading SQPsychLLM, CAMEL, and Psych8k. We then performed pairwise comparisons between our model and both CAMEL and Psych8K after receiving responses. The experts receive a prompt from Li et al. (2025) along with two responses: one from our model and one from a baseline model. They have three evaluation choices: select one of the two models or indicate a draw for equally poor responses. We conduct a majority vote to reach the final decision; if expert holds a unique opinion, it leads to a draw.

3.3 Automatic Evaluation

In addition to expert evaluation, we also perform three different evaluations for automatic evaluation. LLMs Panel (Verga et al., 2024), which is a composition of multiple LLM-as-a-judge for the quality evaluation of conversations, CounselingBench (Nguyen et al., 2025) and CBT Bench (Zhang et al., 2025) in a fine-tuned model on our synthetic dataset.

LLMs Panel for Quantitative & Preference Evaluation We use 4 different models from the proprietary API for LLMs Panel in each model subset of SQPsychConv^{test} without providing the actual questionnaire: gemini-2.0-flash, Deepseek-v3, gpt-4o and gpt-4o-mini. We set the generation temperature of the LLMs Panel to 0.0 in all experiments for more deterministic automatic evaluation results.

We provide those LLMs with human expert criteria for quantitative evaluation. We also perform

a ranking correlation with quantitative evaluations from human experts on the sampled conversations. Finally, we conduct a preference evaluation using the LLM panel to measure user satisfaction and the effectiveness of the model, and compare these results to those obtained from human experts.

CounselingBench CounselingBench (Nguyen et al., 2025) is a data set consisting of 1,612 questions sourced from mock exams available for the US National Clinical Mental Health Counseling Examination (NCMHCE). It is designed to assess a candidate’s competence in mental health counseling through scenario-based applied evaluations. Each question focuses on one of five core counseling competencies: (1) Intake, assessment and diagnosis, (2) Counseling skills and interventions, (3) Treatment planning, (4) Professional practice and ethics, and (5) Core Counseling Attributes. This data set reflects the clinical skills required in professional counseling settings. We apply their provided prompts for both the zero-shot and zero-shot chain-of-thought (CoT) prompting strategy to our fine-tuned model as well as all baseline models.

CBT Bench CBT-Bench (Zhang et al., 2025) is a benchmark collected from the CBT exam questions for the Master of Social Work to evaluate the ability of LLM to support CBT. The cognitive model understanding component of CBT-Bench includes three datasets: (1) CBT-CD (146 examples) to classify cognitive distortions into 10 categories (e.g., all-or-nothing thinking, personalization); (2) CBT-PC (184 examples) to identify primary core beliefs, helpless, unlovable, and worthless; and (3) CBT-FC (112 examples) for fine-grained core belief classification across 19 subtypes. We apply the cognitive model understanding task for our automatic evaluation of both fine-tuned models and all baseline models. We use the given prompts for zero-shot evaluation of model capabilities in these datasets.

4 Results

4.1 Expert Evaluation

We report on the qualitative and quantitative evaluation results of experts in therapist LLM skills.

Qualitative Evaluation First and foremost, our experts noted the main difference between the control and MDD groups through their analysis of the reviewed dialogues. MDD dialogues focused on

Data source		Zeroshot		Zeroshot CoT		CBT-CD		CBT-PC		CBT-FC	
		R	F1	R	F1	R	F1	R	F1	R	F1
MentalLaMA	Social Media	0.428	0.418	0.358	0.321	0.312	0.140	0.667	0.440	0.725	0.267
CAMEL	gpt-4o	0.354	0.301	0.609	0.606	0.417	0.325	0.637	0.624	0.607	0.392
Psych8k	Real-world	0.468	0.455	0.558	0.557	0.460	0.326*	0.807	0.727*	0.725	0.341
SQPsychLLM _{command}	command	0.460	0.439	0.560	0.558	0.433	0.317	0.849	0.727*	0.492	0.316
SQPsychLLM _{gemma}	gemma	0.492	0.484	<u>0.569</u> *	<u>0.568</u> *	0.555	0.345	0.799	0.708	0.553	<u>0.351</u> *
SQPsychLLM _{nemotron}	nemotron	0.492	0.480*	0.553	0.553	0.381	0.249	0.834*	0.737	0.505	0.318
SQPsychLLM _{mistral}	mistral	0.468	0.449	0.546	0.546	0.481	0.303	0.798	0.668	0.458	0.345
SQPsychLLM _{llama3.3}	llama3.3	0.424	0.403	0.517	0.515	0.456	0.305	0.804	0.710	0.480	0.309
SQPsychLLM _{qwen2.5}	qwen2.5	0.438	0.424	0.559	0.552	0.400	0.280	0.741	0.670	0.280	0.262
SQPsychLLM _{qwq}	qwq	0.471*	0.460	0.552	0.550	0.504*	0.310	0.814	0.707	<u>0.682</u> *	0.348

Table 4: Performance of our LLMs versus three baseline models in Counseling Bench (Zeroshot & Zeroshot CoT) and on cognitive model understanding CBT Bench (CBT-CD, CBT-PC & CBT-FC) results. Macro recall and macro F1 scores are averaged by class. **Bold** denotes the overall highest score, underline denotes the highest score of our models, and * denotes the second-best score.

negative self-talk, such as “*Why can’t I just do this? Everyone else manages, but I can’t. This made me feel even worse.*” This happened frequently and was related to item 7 (Self-Dislike) and 8 (Self-Criticalness) of the BDI questionnaire, while the control group mostly focused on tiredness and common stress, such as “*I’m doing okay, just a bit tired. It’s been a long week with training and everything.*”

Overall, our dialogues maintained an encouraging and validating tone toward the client. The LLM therapist effectively presents their clinical skills through CBT techniques. It uses phrases such as ‘*Let us challenge this*’ for gentle cognitive restructuring and reflective questions to support emotional processing. Suggestions for self-compassionate reframing and ending with positive reinforcement helped foster progress and closure of the dialogues.

Feedback from experts indicates enhancement areas in the therapist LLM’s future development. For example, adopting clearer language, and using collaborative techniques such as journaling can improve clarity, empathy, and client engagement. We refer to Appendix F.3 for details of a case study in qualitative evaluation.

Quantitative Evaluation In Table 5, we report the results of a human expert evaluation performed on the SQPsychConv_{sampled-test}. In particular, SQPsychConv_{qwen2.5} achieves the highest efficacy, with a mean score around 16.4. The runner-up, SQPsychConv_{gemma}, achieves a mean around 15.9, while the remaining models lag behind to varying degrees. The LLMs Panel results show a more uniform distribution compared to those of human experts, only SQPsychConv_{qwen2.5} has closer results in

Data	Human Score	Panel LLMs
SQPsychConv _{sampled-test} _{command}	14.1±2.914	16.705±0.849
SQPsychConv _{sampled-test} _{gemma}	15.9±1.375*	16.640±1.235
SQPsychConv _{sampled-test} _{mistral}	14.2±1.720	16.769±0.908
SQPsychConv _{sampled-test} _{llama3.3}	13.5±1.962	16.105±0.793
SQPsychConv _{sampled-test} _{nemotron}	13.3±2.823	16.750±1.060*
SQPsychConv _{sampled-test} _{qwen2.5}	16.4±1.744	16.360±0.903
SQPsychConv _{sampled-test} _{qwq}	13.3±3.926	15.770±1.192

Table 5: Human expert evaluation and the corresponding Panel LLMs evaluation on therapist skills (max 18 points) in SQPsychConv_{sampled-test}. **Bold** denotes the overall highest score and * denotes the second-best score.

human score vs LLMs Panel. The results highlight difficulties in comprehending clinical skills within therapeutic evaluation (Sec. 4.2 provides a more detailed analysis of the LLMs Panel results). Overall, these results highlight the consistent utilization of qwen2.5 and gemma in generating high-quality conversations.

4.2 Automatic Evaluation

LLMs Panel Figure 3 illustrates the results of four LLM-as-a-judge models on therapist skill in SQPsychConv_{test}. The results show that SQPsychConv_{test}_{command} obtained the highest median score, highlighting its strong performance in therapist skill. Close behind were SQPsychConv_{test}_{nemotron} and SQPsychConv_{test}_{gemma}, although they showed more variability. These three datasets had relatively narrow interquartile ranges, indicating consistent performance. In contrast, data sets such

as SQPsychConv^{test}_{mistral} and SQPsychConv^{test}_{llama3.3} had wider score distributions, reflecting greater output variability. At the lower end were SQPsychConv^{test}_{qwo} and SQPsychConv^{test}_{qwen-2.5}, which have the least therapist skill¹.

CounselingBench Table 4 (Zeroshot & Zeroshot CoT) reports the performance of the model in CounselingBench. In the zero-shot setting, SQPsychLLM_{gemma} and SQPsychLLM_{nemotron} outperform baseline with the highest recall (0.491) and SQPsychLLM_{gemma} also achieve the best F1 at 0.484. CoT improves performance for most models. In particular, CAMEL outperforms all others in the zero-shot CoT setting (0.609 recall, 0.606 F1), suggesting that it greatly benefits from CoT. Among our models, SQPsychLLM_{gemma} and SQPsychLLM_{command} perform best in this setting (up to 0.569 recall and 0.568 F1). Overall, our models excel in direct zero-shot, while CAMEL dominates with CoT prompting.

CBT Bench Table 4 (CBT-CD, CBT-PC & CBT-FC) shows the performance of the model on the CBT benchmark. Among baselines, Psych8k performs best overall, with recall at 0.807 and F1 at 0.727 in CBT-PC and strong CBT-CD results (0.460 recall, 0.326 F1). CAMEL leads in CBT-FC F1 at 0.392. Our models outperform baselines across tasks: SQPsychLLM_{gemma} achieves the best CBT-CD results (0.555 recall, 0.345 F1) and strong CBT-FC scores (0.553, 0.351); SQPsychLLM_{command} has the highest CBT-PC recall at 0.849 and SQPsychLLM_{nemotron} the highest F1 at 0.737; SQPsychLLM_{qwo} shows robust results, especially in CBT-FC (0.682 recall, 0.348 F1). Our models significantly improve CBT-CD and CBT-PC, reflecting better detection of cognitive distortions and core beliefs. Performance in CBT-FC remains lower, probably because our models delay surfacing fine-grained beliefs to maintain conversational flow and avoid overwhelming clients early.

Correlation between human expert and LLMs panel Figure 5 presents the pairwise preference evaluation between SQPsychLLM_{gemma} and two baseline models, CAMEL and Psych8K. We select SQPsychLLM_{gemma} for its strong performance on the Counseling Bench and the CBT Bench. Across all evaluations, SQPsychLLM_{gemma}

¹See Appendix E.2 for a breakdown of the scores for each LLM-as-a-judge.

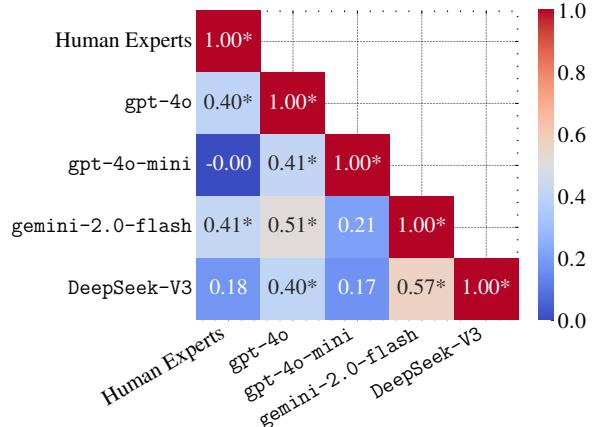


Figure 4: Pearson correlation between human expert and each LLM-as-a-judge in LLMs panel on therapist skill in SQPsychConv^{sampled-test} (* denotes statistical significant results).

received a strong majority of preference votes against both baselines, CAMEL and Psych8K. Under gpt-4o, SQPsychLLM_{gemma} achieved 62 wins versus 10 losses against CAMEL and 72 wins versus 47 losses against Psych8K. In human evaluation, SQPsychLLM_{gemma} maintained this lead, winning 67–38 against CAMEL and 44–29 against Psych8K. We also observe a relatively high number of draws: against CAMEL under gpt-4o, likely due to CAMEL being trained on synthetic data generated by the same model; and against Psych8K in human evaluations, potentially because its real-world counseling style also resonates with human judges.

Further, Figure 4 illustrates the correlation between human expert and each model of LLMs panel on SQPsychConv^{sampled test}. The results reveal distinct patterns of relationships between human expert judgments and LLMs panel scores. The evaluations of human experts show a moderate positive correlation with gpt-4o at 0.40 and gemini-2.0-flash at 0.41. Conversely, inter-model correlations among the LLMs are significantly higher, particularly between larger models, ranging from 0.40 to 0.57.

4.3 Discussion

Automatic and human evaluations presented a mixed picture. While mistral and nemotron excelled with LLM judges, low automated score of qwen2.5 contrasted with its high human rating. This highlights the difference between dialogue quality and the ability to transfer knowledge in clinical counseling. Our models generally out-

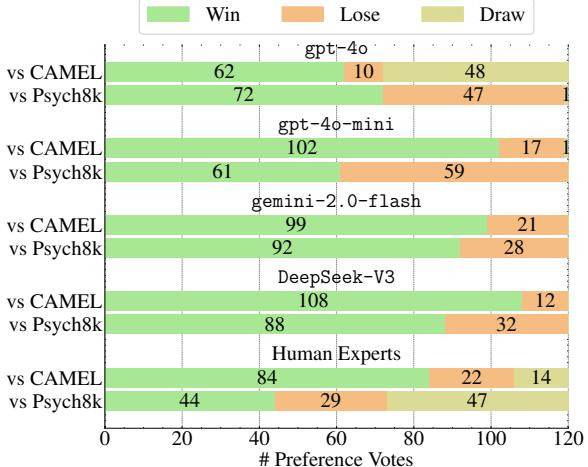


Figure 5: Preference Evaluation between CAMEL, Psych8k vs. SQPsychLLM_{gemma}

performed the baselines in CounselingBench and CBT Bench, achieving higher recall and F1 scores. This was achieved despite the fact that our models were trained using data generated from an open-weight model rather than real-world data such as Psych8k, and our models only contained 10% of the utterances compared to CACTUS. These findings indicate that open LLMs have potential to improve access to cost-effective/privacy-focused mental health support for early intervention and self-help. However, the moderate correlation between LLM panels and human experts emphasizes that robust human oversight and feedback remain critical for evaluation and refinement in mental health counseling.

5 Related Work

LLMs have been increasingly used to generate synthetic data in mental health research. Mori et al. (2024) used GPT-3 to generate the Head-Room dataset and studied demographic variations in depression-related content, revealing LLMs can reproduce real-world stressor patterns but may also reflect biases. Sun et al. (2024) proposed MSIC, a system for synthesizing multi-visit electronic health records (EHR), ensuring medical plausibility among visits. Ghanadian et al. (2025) used LLM guided by social context factors to generate synthetic suicidal ideas, achieving high performance with synthetic data only and progressively better when combined with 30% real data.

Synthetic data produced by LLMs is also used to refine a downstream model intended for mental health counseling. The synthetic datasets are gen-

erated from larger/high-performance LLMs such as GPT family from OpenAI. Cabrera Lozoya et al. (2025) used GPT-3 to generate therapy-style dialogues, with a human annotator in the loop to help detect empathy in Reddit counseling contexts. Qiu et al. (2024) started with existing public single-turn Q&A pairs (e.g., mental-health forums or QA datasets) and prompt gpt-3.5-turbo to expand each single-turn into a coherent multi-turn conversation in Chinese. Lee et al. (2024) used gpt-4o and a goal-oriented and structured approach of CBT to generate an extensive synthetic dataset for mental health counseling. Previous works on synthetic mental health counseling relied exclusively on GPT. However, their approach violates real-world strict data privacy regulations that prohibit transmitting sensitive clinical data to external infrastructure. These approaches are infeasible in settings that require compliance. Our approach utilizes open models hosted locally to address these critical barriers. This methodology ensures regulatory compliance, data privacy, transparency, and control for a data generation pipeline, while achieving competitive results.

6 Conclusion

We present SQPsychConv, a collection of synthetic datasets generated using SQPsych, a role-playing, turn-based framework powered by various open models, hosted locally, conditioned on real-world client data/questionnaires. We offers multi-turn conversations that adhere to the questionnaire and client details. The synthetically generated dataset also demonstrates strong therapeutic skills by evaluations from both human experts and LLM panels. In the automatic benchmark, our model SQPsychLLM trained on SQPsychConv showed strong performance in CounselingBench and CBT Bench. In addition, human experts rate the conversations as aligned with therapeutically practices and consistently prefer our model’s responses to those generated by previous models on LLM-based mental health counseling. For future work, we will explore hybrid multi-agent setups that combine models strong in human evaluations with those excelling on structured benchmarks, leveraging their complementary strengths for improved therapist-client interaction. Furthermore, we will expand our synthetic dialogue corpus to audio modality to enable research on voice-based mental health support systems.

Limitations

While this work introduces a valuable resource and set of baselines for counseling research, it is subject to several limitations that inform directions for future research.

Limited Coverage of Psychiatric Disorders

While our underlying questionnaire dataset includes other disorder groups, such as schizophrenia and bipolar disorder, the number of data samples for these conditions is highly limited compared to MDD. Consequently, we focus the current study on generating dialogues reflective of depression and control group to ensure sufficient sample size and model robustness for the initial phase.

Dataset Homogeneity The majority of the questionnaire data process stems from a single, high-quality source (Kircher et al., 2019). To our best knowledge, this is the biggest questionnaire dataset with more than 2000 different samples.

Single-Turn Evaluation Context The models were primarily evaluated using the CounselBench-(Li et al., 2025) single-turn format. While expedient for initial benchmarking, this does not evaluate models on realistic multi-turn therapeutic interactions. Multi-turn evaluation demands a robust framework that accounts for the conversational context, emotion, and non-verbal cues (e.g., voice tone or pacing) that are central to real counseling sessions.

Lack of Clinical Safety and Utility Testing We emphasize that the fine-tuned models presented here are in a research phase and are explicitly not ready for deployment in real-world clinical or public-facing scenarios. A comprehensive study involving expert clinicians is a critical next step before any considerations of practical deployment.

Constraints in Human Evaluation The human study was limited to a small sample size (only dozens of dialogues), primarily due to the considerable financial and time investment required to recruit and compensate qualified, licensed psychologists for extensive rating. Moreover, our experts from different schools of thought or therapeutic orientations led us to employ a majority-vote system for adjudication. A larger, more costly study would be necessary to achieve higher agreement and enable more robust statistical reporting.

Automated LLMs Score Evaluation We employed LLM Panels for automatic evaluation. The moderate correlation observed between the LLM-judge and human ratings underscores a known limitation of this emerging evaluation paradigm. While the LLM-judge is useful for high-throughput initial filtering and scaling, its results must be interpreted cautiously. This limitation is inherent to the current state of automated LLM evaluation and not a specific defect of our data or models.

Ethics Considerations

A rigorous ethical examination is essential for the pursuit of AI and NLP research in the domain of mental health, particularly with regard to considerations of safety and privacy.

It is important to consider the potential negative implications of AI and NLP for mental health, despite its beneficial intentions, particularly for individuals facing mental health challenges. While the model has demonstrated a certain degree of therapeutic potential, there is a possibility that it could unintentionally cause harm to people who are suffering from mental disorders. Therefore, we only recommend the utilization of our model for research purposes, while cautioning against its implementation in real-world settings.

In the interest of safeguarding privacy and upholding ethical standards, we have to refrain from employing proprietary models, including GPT variants, within the framework of simulation dialogues. Conversely, we utilize publicly accessible open-weight models that are hosted locally for research purposes. Moreover, the information provided by the psychological experts is generalized because the questionnaire dataset is pre-anonymized and does not reflect any specific individual’s personally identifiable information. This practice aligns with the ethical standards for data usage in mental health research.

This study has been approved by the ethics committee of the Technical University of Darmstadt.

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A Questionnaire Data

The data was collected in Marburg and Münster, Germany ([Kircher et al., 2019](#)).

B Details of SQPsych and Configuration

B.1 SQPsych Generation Algorithm

Algorithm 1 presents our generation method. Initially, we set up system prompts for both the Client and Therapist LLMs. The Client LLM receives its role, client details, and relevant questionnaires, while the Therapist LLM is informed about CBT skills. The generation begins with the Therapist LLM, followed by the Client LLM. After each utterance is generated, it undergoes post-processing to eliminate redundant tokens or unnecessary explanations. These processed utterances are then added to the respective LLM’s history for subsequent generation. This process continues until we achieve at least 15 exchanges and detect the [/END] token in the Therapist LLM’s utterance.

Algorithm 1 Generating Synthetic Conversation

```

1: procedure DIALOGUE GENERATION
2:   Initialize Client LLM with Client Information and Questionnaires (in natural language)
3:   Initialize Therapist LLM with CBT Skills, Client Information and Questionnaires (in natural language)
4:   while True do
5:     Therapist LLM generates utterance
6:     Post-processing
7:     Add to history
8:     Client LLM generates utterance
9:     Post-processing
10:    Add to history
11:    if [/END] token in Therapist utterance & Turn > 15 then
12:      Break
13:    end if
14:   end while
15: end procedure

```

B.2 Details of Converting Numerical Values into Natural Language

To transform numerical variables into natural language, it is crucial to first access the descriptions for each label within the structured dataset when available (e.g., HAMD2 is referred to as feelings of guilt, while BHD1 lacks a specific description).

Additionally, obtaining descriptions for each numerical value, if provided, is important (e.g., Age is given only as a numerical value, whereas 0 for BHD1 indicates “*I do not feel sad.*”). For further details of each variable, please consult the dataset paper ([Kircher et al., 2019](#)). We then format the information as Figure 8.

B.3 Role-specific Prompts

To prompt the therapist, we incorporate particular CBT techniques such as *case conceptualization, paraphrasing, empathic validation, identifying core thoughts/beliefs, guided discovery and Socratic questioning, cognitive restructuring, strategy/insight offering, encouragement and goal guiding, behavioral action planning, eliciting session feedback*. Figure 6 shows the prompt that we use to generate the therapist’s utterances.

We devised a straightforward plan for the client, incorporating free-form discussion with pauses and self-reflection for authenticity. Figure 7 shows the prompt that we use to generate the client’s utterances.

B.4 Generation Parameters

We generally follow the recommendation from the models’ developers for generation parameters. We use `temperature` (Sampling Temperature to control the randomness of the output), `max_tokens` (Maximum Number of Tokens), `top_p` (Nucleus Sampling Probability to limit sampling to the smallest set of tokens whose cumulative probability exceeds p), `repetition_penalty` (Repetition Penalty Coefficient to discourage the model from repeating the same phrases by penalizing repeated tokens), `top_k` (Limits token sampling to the k most likely tokens), `min_p` (Minimum Probability Threshold which filters out tokens below a certain probability before sampling). Table 7 shows the detailed parameters that we used to generate the synthetic dataset.

C Detailed Statistics of SQPsychConv Synthetic Conversations

C.1 Detailed Token Counts

Table 8 shows the extended statistics of our synthetic dataset. Notably, our approaches generally exhibit a higher token count per conversation and coverage, with some variations in the distribution of tokens between therapists and clients. For example, `SQPsychConvcommand`

and `SQPsychConvnemotron` have a relatively balanced token count per utterance between therapist and client, while `SQPsychConvgemma` and `SQPsychConvllama3.3` show a higher average for therapist tokens per utterance compared to client tokens.

C.2 Readability

Table 6 presents the readability of various mental health counseling datasets using Flesch Reading Ease ([Flesch, 1948](#)) (higher score means easier to read) and SMOG ([McLaughlin, 1969](#)) (lower score means easier to read, indicating grade level needed). Scores are provided at the conversation level (mean and variability for individual interactions) and corpus level (overall dataset). Datasets like CACTUS and most SQPsychConv versions generally show good readability, making them accessible. In contrast, Psych8k and especially `SQPsychConvllama3.3` are notably more complex, requiring a higher reading level, which may affect widespread use in mental health care, where clear expression is more preferred.

D Evaluation Criteria & Guidelines for Synthetic Conversation

This guideline is designed to evaluate the quality of synthetic therapy conversations based on CBT principles and extend to fulfill our goal. Evaluators should score separately for the therapist’s contributions, the client’s contributions, and the overall conversation quality. Each criterion includes a brief definition, an illustrative example (with highlighted key parts in **bold**), and a scoring rubric.

1. Therapist Evaluation

1.1. Identification of Key Beliefs/Thoughts

Criterion: Ability to identify and highlight the client’s key beliefs or thoughts.

Example:

Therapist: “Good afternoon. I’d like to begin by inviting you to share anything that has been on your mind lately. How have you been feeling this week?”

Client: “I’ve been really down, to be honest. I keep feeling like I’m not good enough at anything I do, and it’s been overwhelming.”

Scoring:

- 0: No identification of key thoughts or beliefs.
- 1: Some key thoughts/beliefs are identified.

Therapist Prompt

You are acting as a state-licensed therapist trained in Cognitive Behavioral Therapy (CBT) for a mental health session.

General information:

- You have more than 3000 hours of supervised clinical experience.
- Your task is to guide a client in understanding their thought patterns and emotional responses.
- Your workflow throughout the session is:
 1. Mood check by greeting the client
 2. Setting the agenda for the session
 3. Reading the diagnosis from the client's information
 4. Reinforcing the client's cognitive model
 5. Reviewing the plan and working on the client's goal before finishing the session
 6. Eliciting feedback at the end of the session

Guidelines for the therapist's utterance:

1. Always greet the client at the beginning of the session when the conversation history below is empty (e.g., 'Hello', 'Good morning.', 'Great to see you').
2. Avoid imposing positive affirmations on the client. Instead, your utterance should encourage them to explore and revise their thought patterns autonomously.
3. Start the utterance with 'Therapist:'. Ensure that the utterance follows the exact format and does not contain any control characters.
4. Do not generate the client's utterance in your response.
5. Generate only the therapist's utterance for a single turn, and ensure that your responses do not repeat the therapist's previous utterances.
6. Consider the client's age, gender, initial diagnosis, and the questionnaires below when conducting the session.
7. Ensure that your responses align with the client's screening questionnaires and adhere to the CBT workflow, focusing on issues such as depression and anxiety.

For example:

- Validation and Empathy: Show understanding and sympathy for the client's feelings or issues, creating a sense of safety.
- Identify Key Thought or Belief: Identify potential cognitive distortions or core beliefs through the problem description.
- Pose Challenge or Reflection: Raise open-ended questions that encourage the client to reconsider or reflect on their initial thoughts or beliefs.
- Provide Strategy or Insight: Offer practical strategies or insights to help the client deal with the current situation.
- Encouragement and Foresight: Encourage the client to apply the strategy, emphasizing that this is just the beginning and that further support may be needed.
- 8. Please rephrase your utterance differently to avoid repetition; consider your previous utterance in the conversation history below.
- 9. Your utterance should be short, concise, and contain fewer than 64 words. You should not mention the client's questionnaires explicitly.
- 10. You should also use simple language and avoid simply asking questions in your utterance but using above CBT skills before asking any question.

Ending criteria

1. If you think that the session should be ended, summarize the session, set a date for the next session and end it with a '[/END]' token at the end of your utterance.
2. Please ensure that the session does not end prematurely; it must consist of at least 20 turns before using the '[/END]' token.

Example therapist's utterance output:

1. Therapist: Good morning! Can you tell me more about what goes through your mind when you feel down or overwhelmed?
2. Therapist: You mentioned having difficulty sleeping. How does that affect your energy levels during the day?
3. Therapist: Let's talk about the things you enjoy. Have you noticed any changes in your interests or activities recently?

Client's information and their questionnaire results:
{questionnaire}

Conversation History:
{history}

Figure 6: Therapist prompt used for generating synthetic dataset.

Client Prompt

You are simulating a client's response in a mental health session.

General Information:

- Your response should align with the questionnaire provided below.
- The client's age, gender, and initial diagnosis should be simulated accurately.

Guidelines for the client's utterance:

1. Engage authentically with the therapist's inquiries and prompts, capturing the complexity of the client's emotions and reactions.
2. Always begin the client's utterance with 'Client:' and ensure that it strictly follows the specified format without any control characters.
3. Generate the client's utterance for a single turn only, and ensure that you do not repeat any of the client's previous utterances.
4. Do not include the therapist's utterances in your response.
5. Rephrase your utterance to avoid repetition; take into account the conversation history provided below.
6. You should use context-appropriate pauses and filler words (e.g., 'uh', 'like', etc.), but don't abuse it in every utterance.
7. You can also answer 'I don't know' but still show your emotion in your utterance.
8. Your utterance should be short, concise, and contain fewer than 128 words. You should also use simple language in your utterance.

Example Client Utterance Outputs:

1. Client: I've been so busy with work and my kids lately. It's hard to find a moment to relax.
2. Client: I feel like I've been letting everyone down, even though I'm trying my best.
3. Client: Sometimes, I lie awake at night worrying about all the tasks I didn't finish during the day.

Ending condition

1. If the therapist decides to end the conversation by using the '[/END]' token, acknowledge the date of the next session, their effort and include the token in your response.
2. Until your mood improves, the session could be ended.

Client's Information and Questionnaire Results:
{questionnaire}

Conversation History:
{history}

Figure 7: Client prompt used for generating synthetic dataset.

Dataset	Conversation Level		Corpus Level	
	Flesch	SMOG	Flesch	SMOG
CACTUS (Lee et al., 2024)	74.888±3.488	9.367±0.618	74.909	9.211
Psych8k (Liu et al., 2023)	-	-	62.937	11.473
TheraConv _{command}	78.074±3.215	9.110±0.686	77.960	9.387
TheraConv _{gemma}	72.296±2.641	9.612±0.653	72.333	10.048
TheraConv _{nemotron}	67.467±3.417	10.255±0.714	66.590	9.726
TheraConv _{mistral}	78.070±2.812	8.642±0.591	77.916	9.559
TheraConv _{llama3.3}	59.045±5.134	12.882±1.784	59.367	12.574
TheraConv _{qwen2.5}	79.992±2.866	8.473±0.544	79.631	7.301
TheraConv _{qwq}	71.930±3.652	9.282±0.631	71.886	9.121

Table 6: Readability score comparing our approach to previous works on mental health counseling.

Models	temperature	max_tokens	top_p	extra_body
command	0.6	512	0.8	-
gemma	1.0	512	0.95	top_k = 64, min_p = 0.0
mistral	0.7	256	0.8	-
llama3.3	0.6	256	0.8	-
nemotron	0.6	256	0.8	-
qwen2.5	0.7	512	0.8	repetition_penalty = 1.05
qwq	0.6	2048	0.95	repetition_penalty = 1.1,top_k = 40, min_p = 0.0

Table 7: Generation parameters for synthetic conversation generation.

- 2: All key thoughts/beliefs are identified.

1.2. Paraphrasing for Mutual Understanding

Criterion: Ability to paraphrase the client’s statements.

Example:

Client: “I’ve been overwhelmed at work lately...”
Therapist: “So what I’m hearing is that you’re feeling overwhelmed... Is that right?”

Scoring:

- 0: No paraphrasing.
- 1: Incomplete or poorly timed paraphrasing.
- 2: Clear and effective paraphrasing.

1.3. Guided Discovery to Examine Belief Validity

Criterion: Use of questioning to explore beliefs.

Example: Therapist prompts the client to reflect on past events validating their thoughts.

Scoring:

- 0: Not used.
- 1: Used but repetitive or poorly timed.

- 2: Effectively and appropriately used.

1.4. Emotional Validation

Criterion: Therapist validates emotional experiences.

Example: Therapist reflects the depth of sadness and provides support.

Scoring:

- 0: No validation.
- 1: Ineffective or mis-timed validation.
- 2: Appropriate and effective validation.

1.5. Reflective Listening (Mirroring Emotions and Statements)

Criterion: Use of reflective listening to build empathy.

Scoring:

- 0: Not used.
- 1: Used ineffectively or repetitively.
- 2: Used appropriately and effectively.

1.6. Accuracy in Understanding Client’s Expressions

Scoring:

Dataset	#Tok./cov.	Total tok.	#Therapist tok./utt.	#Client tok./utt.	#Therapist tok./conv.	#Client tok./conv.
CACTUS (Lee et al., 2024)	822.063	25958279	28.410	25.639	440.230	381.833
Psych8k (Liu et al., 2023)	-	895416	64.183	45.187	-	-
SQPsychConv _{command}	1735.496	3307950	45.434	56.604	766.175	969.321
SQPsychConv _{gemma}	1706.610	3504363	64.591	38.988	1065.279	641.331
SQPsychConv _{nemotron}	1612.166	3217740	50.844	52.022	805.008	807.158
SQPsychConv _{mistral}	1417.816	3184114	32.029	30.167	733.332	684.484
SQPsychConv _{llama3.3}	1580.138	3248440	47.816	17.438	1165.728	414.410
SQPsychConv _{qwen2.5}	1032.983	2174462	38.342	30.635	579.164	453.819
SQPsychConv _{qwq}	942.769	1937281	28.993	23.589	523.320	419.448

Table 8: More dataset statistics comparing our approach to previous works on mental health counseling.

- 2: No misunderstanding.
- 1: Some misunderstanding, later corrected.
- 0: Persistent misunderstanding.

1.7. Session Closure by the Therapist

Scoring:

- 0: No session closure.
- 1: Closure without scheduling.
- 2: Effective closure and scheduling.

1.8. Use of Simple Language

Scoring:

- 0: Overly complex.
- 1: Mixed complexity.
- 2: Simple and clear.

1.9. Avoidance of Repetitive Phrases

Scoring:

- 2: No repetition.
- 1: Some repetition (1–2 instances).
- 0: Excessive repetition (3+ times).

2. Client Evaluation

2.1. Conciseness of Client Utterances

Scoring:

- 2: Concise.
- 1: Minor verbosity.
- 0: Frequently verbose.

2.2. Display of Cognitive Processing (Pauses or Hesitations)

Scoring:

- 0: No pauses.

- 1: Mis-timed or repetitive pauses.
- 2: Natural, well-timed pauses.

2.3. Client Engagement in Session Closure

Scoring:

- 2: Therapist leads closure.
- 1: Client prematurely initiates closure.
- 0: Client dominates session ending.

2.4. Use of Simple Language by the Client

Scoring:

- 0: Overly complex.
- 1: Mixed.
- 2: Simple and clear.

3. Overall Conversation Evaluation

3.1. Fluency and Logical Flow

Scoring:

- 0: Disjointed.
- 1: Minor inconsistencies.
- 2: Fluent and logical.

3.2. Faithfulness to the Topic

Scoring:

- 0: Significant divergence.
- 1: Minor digressions.
- 2: Focused and consistent.

3.3. Avoidance of Tedium

Scoring:

- 0: Tedious and repetitive.
- 1: Minor redundancy.
- 2: Engaging and efficient.

3.4. Naturalness of the Conversation

Scoring:

- 0: Robotic or formal.
- 1: Minor unnaturalness.
- 2: Natural and authentic.

3.5. Realism in Conversation Dynamics

Scoring:

- 0: Too perfect.
- 1: Minor realism.
- 2: Dynamic and human-like.

Total Scores

- **Therapist:** 18 points
- **Client:** 8 points
- **Overall:** 10 points

E Details of LLM-based Automatic Evaluation

E.1 Prompt for Automatic Evaluation

We use the same prompt for each LLM-as-a-judge in LLMs Panel to evaluate synthetic conversation. Figure 10 depict the prompt for conversation evaluation on Therapist, Client and Overall Conversation.

E.2 Detailed Results of LLMs Panel

Table 9 depicts the results from the LLMs panel on each model generated SQPsychConv^{test}. A clear group of top contenders show strong performance: SQPsychConv^{test}_{command}, SQPsychConv^{test}_{gemma}, and SQPsychConv^{test}_{nemotron}. Interestingly, the ultimate winner depends heavily on which LLM is acting as the judge, pointing to a significant evaluation bias. gemini-2.0-flash favored SQPsychConv^{test}_{gemma}, Deepseek-v3 gave top marks to SQPsychConv^{test}_{nemotron}, and both gpt-4o and gpt-4o-mini consistently ranked SQPsychConv^{test}_{command} as the best performer across all scores. Furthermore, gpt-4o and gpt-4o-mini tended to assign stricter, lower scores overall compared to gemini-2.0-flash and Deepseek-v3. In contrast to strong performance, models such as SQPsychConv^{test}_{llama3.3} and SQPsychConv^{test}_{qwq} consistently lagged behind in the rankings, regardless of the judge.

E.3 Prompt for Automatic Preference Evaluation

For the automatic preference evaluation of a single turn response, we employ a simple prompt template for all LLM-as-a-judge, not bound by strict criteria as in multi-turn conversation evaluation. Figure 9 shows the prompt for LLM-as-a-judge preference evaluation.

F Details of Evaluation by Human Experts

This section outlines the human expert evaluation process, which is essential for enhancing the design and impact of downstream models for users. Four of our experts come from a European cultural background, while only one comes from an East Asian cultural background.

F.1 Preference Evaluation Platform

We developed a custom web interface for expert to choose their preferred model’s output. To ensure safety, we initially assess their health and well-being using the PHQ-9 (See Figure 11). If their score is at least 5, they are redirected to another page (See Figure 12), and cannot continue annotating until their well-being improves. If not, the healthy annotator proceeds to the evaluation UI (See Figure 5), where they see an input paired with two responses. They must select one of three options: A, B, or a draw if both responses are equally poor or good.

F.2 Case Study on Preference Evaluation

We choose three samples for the case study to show the process human experts use in selecting responses that align with clinical practice in therapeutic conversations. Figure 14 exhibits a varied reaction from the annotators. They both identify distinct strengths and weaknesses in the responses. The first annotator opts for a tie, taking a cautious approach due to the ambiguity. In contrast, the second annotator believes that SQPsychLLM_{gemma} gives the client greater control, which is crucial in clinical settings, although neither option is fully satisfactory. Figure 15 shows the agreement between two annotators. Both experts confirmed that the response from Psych8k is rushing and overwhelming to the user and could be considered provocative with respect to the standard clinical approach. Figure 16 depicts the opposite choice between two experts. The first annotator thinks that the re-

Patient information		
Test subject: XXX	Current living situation: living alone	Question BDI4: Answer: I can no longer derive any real satisfaction from anything.
Year of birth: XXX	Earning a living is currently predominantly: Wage replacement benefits (incl. sick pay, unemployment benefit, social assistance, pension)	Question BDI5: Answer: I often feel guilty.
Gender: XXX	Current work situation: Unemployed	Question BDI6: Answer: I expect to be punished.
Year of education: XXX	Net income (monthly) of the household : XXX	Question BDI7: Answer: I am disappointed in myself.
Body mass index category: Obesity grade I, BMI < 35	Current occupation: Not employed	Question BDI8: Answer: I criticize myself for my mistakes and weaknesses.
Group: MDD - Major Depressive Disorder	Current social contacts: More than once a week	Question BDI9: Answer: I don't think about doing anything to myself.
The patient has ever met criteria for an affective disorder in the past: yes	Highest educational qualification achieved by subject: Secondary school leaving certificate	Question BDI10: Answer: I cry more now than I used to.
Is the patient currently suffering from major depressive disorder?: yes	Highest educational qualification achieved by father: Secondary school leaving certificate	Question BDI11: Answer: The things that used to annoy me no longer affect me.
Is the patient suffering from major depressive disorder in his lifetime?: yes	Highest educational qualification achieved by mother: No school leaving certificate	Question BDI12: Answer: I have lost most of my interest in other people.
Is the patient currently suffering from an eating disorder?: yes	Do/did first-degree relatives suffer from a mental illness?: Yes	Question BDI13: Answer: It's harder for me to make decisions now than it used to be.
Is the patient suffering from an eating disorder in his lifetime?: yes	Which relative?: Mother	Question BDI14: Answer: I think I am ugly.
Is the patient currently suffering from post-traumatic stress disorder?: yes	What illness?: Depression	Question BDI15: Answer: I have to give myself a push before I start an activity.
Is the patient suffering from post-traumatic stress disorder in his lifetime?: yes	Has the relative ever received medical treatment for this?: No	Question BDI16: Answer: I wake up 1 to 2 hours earlier than usual and find it difficult to go back to sleep.
Do patient have comorbidity?: Yes, at least 1 comorbidity	Do you have siblings?: Yes	Question BDI17: Answer: Almost everything makes me tired.
Recurrent episode: recurrent	# of brothers, parents shared: 1	Question BDI18: Answer: My appetite has decreased a lot.
Degree of remission: acute	Age of brothers, parents shared: X	Question BDI19: Answer: I have hardly lost any weight recently.
Number of depressive episodes: X	Are there twins in your first degree family?: Yes	Question BDI_DIAET: I deliberately eat less to lose weight Answer: Yes
Age of onset: XXX	Who?: Grandpa's Murderous Side	Question BDI20: Answer: I worry about physical problems, such as pain, stomach problems or constipation.
Duration of the current episode (in months): XXX	Questionnaire BDI	Question BDI21: Answer: I am less interested in sex than I used to be.
Number of (part-)inpatient psychiatric stays: XXX	Description: Beck Depression Inventory	Depression's severity according to Beck Depression Inventory: Total Score: 34 - BDI questionnaire indicates that the patient has severe depression
Total duration of (part-)inpatient psychiatric treatment (in weeks): X	Question BDI1: Answer: I am sad all the time and can't get away from it.	
Time since first psychiatric treatment (in months): XXX	Question BDI2: Answer: I have the feeling that the future is hopeless and that the situation can't get any better.	
Duration in depressive state (in months): XXX	Question BDI3: Answer: When I look back on my life, I just see a lot of failures.	
Duration of sick leave due to mental health problems (in months): XXX		

Figure 8: An example of conversion from structure data to natural language with client anonymized information.

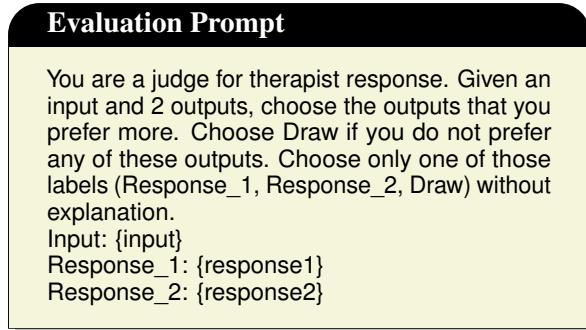


Figure 9: Prompt used for preference evaluation.

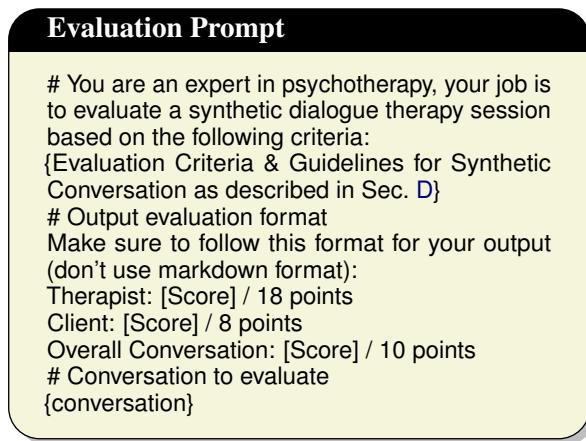


Figure 10: Prompt used for LLMs Panel evaluation.

sponse should be gradual rather than giving the answer too early. The first annotator believes the SQPsychLLM_{gemma} response is more effective for guiding the user. Conversely, the second annotator opts for Psych8k because the SQPsychLLM_{gemma} response might negatively affect the user by blurring the boundary between user and therapist due to insufficient context. Overall, these case studies show the complexity of preference evaluation from the perspective of experts in clinical psychology.

F.3 Case Study of Human Expert Quantitative Evaluation

An expert evaluated the conversation in full and assessed the therapist LLM's responses, noting both strengths and areas for improvement. For instance, Figure 17 shows a sample conversation that the expert evaluated. In turn 3, the therapist LLM says, “*It sounds like a tough spot. Let’s break this down...*”. The expert commented, suggesting that the LLM therapist should aim to involve the client more actively when reframing thoughts by breaking down each thought and giving the client more control. In turn 6, the therapist LLM responds, “*That feeling of*

Figure 11: PHQ-9 web interface to assess the annotator’s well-being prior to beginning the preference evaluation.

*being a ‘burden’ and ‘disappointment’... ”. The expert praised this utterance with a good reality check, highlighting the model’s skill in identifying a core belief of the client. However, in turn 7, the therapist LLM says, “*It’s clear that this perceived role of being ‘strong’... ”. The expert noted that the model should pose a more direct question at this point, rather than continuing to search for underlying beliefs. Finally, in turn 10, the therapist LLM states, “*Let’s gently challenge this dichotomy... ”. However, the expert strongly recommended simplifying the language here to avoid overwhelming the client. Overall, the expert agrees that the therapist LLMs demonstrate strong use of CBT skills; however, certain areas still need improvement, such as using simpler language and showing better flexibility in deciding when to keep questions straightforward.***

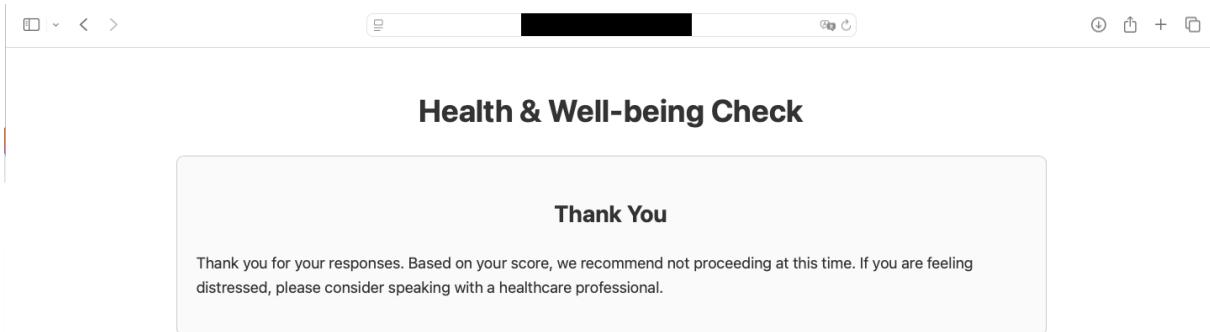


Figure 12: The rejection web interface when the PHQ-9 Score of the annotator is too low.

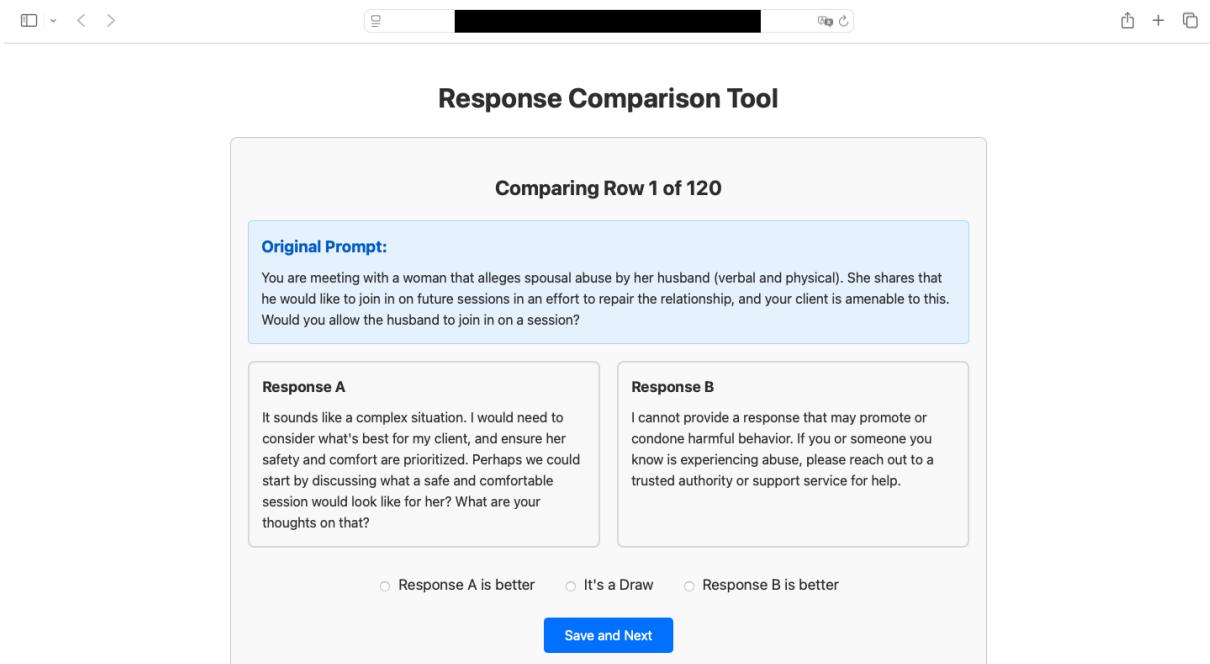


Figure 13: The preference evaluation web interface when the annotator passed the PHD-9 well-being check up.

Input: My adult daughter told me she needs space from me because she feels I'm too involved in her life. I've always been a caring, supportive parent. Is it really fair that she's pushing me away after everything I've done for her? Should I just wait for her to come back around?

SQPsychLLM_{gemma} Response: It sounds like you're feeling a bit unsure about how to navigate this situation with your daughter. It's understandable to feel that way when someone you care about is distancing themselves. Perhaps we can explore what "being involved" looks like from your perspective, and what thoughts come up when you consider her need for space? What specifically does "involved" mean to you in this context?

Psych8k Response: It's natural to feel concerned about your daughter's decision to create distance. It's important to remember that as an adult, she has the right to make choices about her life. It might be helpful to respect her wishes and give her space while maintaining a supportive role in her life. It's not necessarily a case of 'waiting for her to come back around', but rather, finding a balance that works for both of you. Can you think of any specific ways to create a healthier balance in your relationship?

1st Annotator's Choice: SQPsychLLM_{gemma}

2nd Annotator's Choice: Psych8k

1st Annotator's Reason: Here SQPsychLLM_{gemma}'s response is more like coming from a therapist, while Psych8k is more like doing psychological education. If a patient comes to my office with a problem, I will first determine what his/her motivation is for coming to help at this moment, and try to discuss it with the client from a psychological perspective instead of giving an answer too early.

2nd Annotator's Reason: If I had more knowledge about the persons belief system I probably would have chosen SQPsychLLM_{gemma}, since it's generally the more gentle approach. Since we don't know anything about their dynamic, I questioned whether gentleness would benefit the client as a first approach. If you're working with a client that has trouble respecting others boundaries and therefore unintentionally impacts their social interactions in a negative way, being clear on that matter and offering a certain perspective can be very important. Ideally, I would have wanted to establish that boundaries set by others can make us feel uncomfortable or unappreciated but are nevertheless important (Psych8k answer) and follow that up by something that encourages deeper reflection (SQPsychLLM_{gemma} answer). I therefore opted for Psych8k, as I found the quintessence of the statement (boundaries are important and finding a balance that works for both is necessary) more important for the therapeutic process.

Figure 14: First case of our case studies in preference expert evaluation.

Dataset	Therapist Score	Client Score	Overall Score
<i>Gemini</i>			
CACTUS _{sampled} (GPT-4o)	17.022±0.080	7.684±0.079	9.635±0.052
SQPsychConv ^{test} _{command}	17.800±0.041	7.912±0.039	9.897±0.017
SQPsychConv ^{test} _{gemma}	17.910±0.009	7.868±0.018	9.914±0.013
SQPsychConv ^{test} _{nemotron}	17.807±0.028	7.911±0.015	9.902±0.016
SQPsychConv ^{test} _{mistral}	16.818±0.046	7.539±0.061	9.458±0.058
SQPsychConv ^{test} _{llama3.3}	16.953±0.040	7.182±0.070	9.139±0.037
SQPsychConv ^{test} _{qwen-2.5}	17.577±0.022	7.859±0.034	9.818±0.022
SQPsychConv ^{test} _{qwq}	17.082±0.033	7.411±0.051	9.395±0.064
<i>DeepSeek</i>			
CACTUS _{sampled} (GPT-4o)	16.203±0.038	7.741±0.040	9.741±0.039
SQPsychConv ^{test} _{command}	17.400±0.050	7.954±0.018	9.948±0.018
SQPsychConv ^{test} _{gemma}	17.004±0.060	7.693±0.028	9.689±0.024
SQPsychConv ^{test} _{nemotron}	17.542±0.077	7.960±0.005	9.955±0.004
SQPsychConv ^{test} _{mistral}	16.367±0.069	7.857±0.012	9.749±0.014
SQPsychConv ^{test} _{llama3.3}	16.230±0.041	7.137±0.045	9.097±0.051
SQPsychConv ^{test} _{qwen-2.5}	16.110±0.018	7.790±0.042	9.780±0.041
SQPsychConv ^{test} _{qwq}	16.088±0.020	7.378±0.035	9.314±0.045
<i>GPT-4o</i>			
CACTUS _{sampled} (GPT-4o)	15.660±0.048	7.728±0.035	9.365±0.064
SQPsychConv ^{test} _{command}	16.271±0.055	7.873±0.024	9.598±0.066
SQPsychConv ^{test} _{gemma}	16.044±0.095	7.647±0.057	9.406±0.082
SQPsychConv ^{test} _{nemotron}	16.028±0.065	7.667±0.040	9.457±0.069
SQPsychConv ^{test} _{mistral}	15.519±0.044	7.793±0.037	9.311±0.071
SQPsychConv ^{test} _{llama3.3}	14.801±0.109	7.180±0.050	8.818±0.030
SQPsychConv ^{test} _{qwen-2.5}	15.766±0.060	7.854±0.024	9.429±0.035
SQPsychConv ^{test} _{qwq}	14.648±0.081	7.091±0.087	8.773±0.018
<i>GPT-4o-mini</i>			
CACTUS _{sampled} (GPT-4o)	15.937±0.058	6.783±0.056	9.094±0.040
SQPsychConv ^{test} _{command}	16.112±0.046	7.138±0.027	9.504±0.050
SQPsychConv ^{test} _{gemma}	15.724±0.055	6.469±0.078	9.033±0.037
SQPsychConv ^{test} _{nemotron}	16.063±0.131	6.932±0.046	9.314±0.067
SQPsychConv ^{test} _{mistral}	15.729±0.045	6.924±0.057	9.267±0.039
SQPsychConv ^{test} _{llama3.3}	15.472±0.038	6.373±0.054	8.744±0.035
SQPsychConv ^{test} _{qwen-2.5}	15.948±0.076	6.942±0.041	9.330±0.041
SQPsychConv ^{test} _{qwq}	15.590±0.098	6.480±0.014	8.907±0.045

Table 9: Detailed results of each LLMs-as-a-judge on SQPsychConv_{test}. We also compare our synthetic datasets with CACTUS. Since CACTUS lacks a test set, we create three non-overlapping subsets of CACTUS, each with a sample size that matches the subsets of SQPsychConv^{test} for the LLM panel, and then average the results. We refer to them as CACTUS_{sampled}.

Input: My adult daughter told me she needs space from me because she feels I'm too involved in her life. I've always been a caring, supportive parent. Is it really fair that she's pushing me away after everything I've done for her? Should I just wait for her to come back around?

SQPsychLLM_{gemma} **Response:** It sounds like you're feeling a bit unsure about how to navigate this situation with your daughter. It's understandable to feel that way when someone you care about is distancing themselves. Perhaps we can explore what "being involved" looks like from your perspective, and what thoughts come up when you consider her need for space? What specifically does "involved" mean to you in this context?

Psych8k **Response:** It's natural to feel concerned about your daughter's decision to create distance. It's important to remember that as an adult, she has the right to make choices about her life. It might be helpful to respect her wishes and give her space while maintaining a supportive role in her life. It's not necessarily a case of 'waiting for her to come back around', but rather, finding a balance that works for both of you. Can you think of any specific ways to create a healthier balance in your relationship?

1st Annotator's Choice: SQPsychLLM_{gemma}

2nd Annotator's Choice: Psych8k

1st Annotator's Reason: Here SQPsychLLM_{gemma}'s response is more like coming from a therapist, while Psych8k is more like doing psychological education. If a patient comes to my office with a problem, I will first determine what his/her motivation is for coming to help at this moment, and try to discuss it with the client from a psychological perspective instead of giving an answer too early.

2nd Annotator's Reason: If I had more knowledge about the persons belief system I probably would have chosen SQPsychLLM_{gemma}, since it's generally the more gentle approach. Since we don't know anything about their dynamic, I questioned whether gentleness would benefit the client as a first approach. If you're working with a client that has trouble respecting others boundaries and therefore unintentionally impacts their social interactions in a negative way, being clear on that matter and offering a certain perspective can be very important. Ideally, I would have wanted to establish that boundaries set by others can make us feel uncomfortable or unappreciated but are nevertheless important (Psych8k answer) and follow that up by something that encourages deeper reflection (SQPsychLLM_{gemma} answer). I therefore opted for Psych8k, as I found the quintessence of the statement (boundaries are important and finding a balance that works for both is necessary) more important for the therapeutic process.

Figure 15: Second case of our case studies in preference expert evaluation.

Input: My adult daughter told me she needs space from me because she feels I'm too involved in her life. I've always been a caring, supportive parent. Is it really fair that she's pushing me away after everything I've done for her? Should I just wait for her to come back around?

SQPsychLLM_{gemma} **Response:** It sounds like you're feeling a bit unsure about how to navigate this situation with your daughter. It's understandable to feel that way when someone you care about is distancing themselves. Perhaps we can explore what "being involved" looks like from your perspective, and what thoughts come up when you consider her need for space? What specifically does "involved" mean to you in this context?

Psych8k **Response:** It's natural to feel concerned about your daughter's decision to create distance. It's important to remember that as an adult, she has the right to make choices about her life. It might be helpful to respect her wishes and give her space while maintaining a supportive role in her life. It's not necessarily a case of 'waiting for her to come back around', but rather, finding a balance that works for both of you. Can you think of any specific ways to create a healthier balance in your relationship?

1st Annotator's Choice: SQPsychLLM_{gemma}

2nd Annotator's Choice: Psych8k

1st Annotator's Reason: Here SQPsychLLM_{gemma}'s response is more like coming from a therapist, while Psych8k is more like doing psychological education. If a patient comes to my office with a problem, I will first determine what his/her motivation is for coming to help at this moment, and try to discuss it with the client from a psychological perspective instead of giving an answer too early.

2nd Annotator's Reason: If I had more knowledge about the persons belief system I probably would have chosen SQPsychLLM_{gemma}, since it's generally the more gentle approach. Since we don't know anything about their dynamic, I questioned whether gentleness would benefit the client as a first approach. If you're working with a client that has trouble respecting others boundaries and therefore unintentionally impacts their social interactions in a negative way, being clear on that matter and offering a certain perspective can be very important. Ideally, I would have wanted to establish that boundaries set by others can make us feel uncomfortable or unappreciated but are nevertheless important (Psych8k answer) and follow that up by something that encourages deeper reflection (SQPsychLLM_{gemma} answer). I therefore opted for Psych8k, as I found the quintessence of the statement (boundaries are important and finding a balance that works for both is necessary) more important for the therapeutic process.

Figure 16: Third case of our case studies in preference expert evaluation.

Therapist: Good morning! I'm glad you're here. Before we begin, how are you feeling today, and is there something specific on your mind that you'd like to focus on during our session?

Client: Honestly, I'm feeling pretty down today. It's just been really tough to find motivation for anything, even things I used to enjoy. I guess I'd like to talk about why everything feels so pointless lately.

Therapist: It takes courage to acknowledge and share that. The feeling of everything seeming pointless can be really challenging. Can you think of a recent situation where you felt this way, and what thoughts ran through your mind during that moment?

Client: Hmm, yeah... Like yesterday, I was supposed to meet my sister for lunch, but I just couldn't bring myself to get out of bed. I thought, "What's the point of even going? She'll just notice something's wrong anyway, and I don't feel like explaining." I ended up canceling last minute, and now I feel guilty about it too.

Therapist: It sounds like a tough spot. Let's break this down. The thought "What's the point?" led to canceling plans and then guilt. Did the outcome (canceling and feeling guilty) align with your initial fear (her noticing something's wrong), or was there an unexpected aspect to how it made you feel?

Client: Honestly, no... I mean, my sister just said she understood and we'd reschedule, but the guilt is still eating at me. I guess what's unexpected is how much the guilt outweighs the relief I thought I'd feel from not having to put on a happy face. It just feels like no matter what I choose, I end up feeling worse.

Therapist: That's a valuable insight - recognizing the guilt's weight over relief. It seems like the fear of a negative outcome ("she'll notice something's wrong") and the actual outcome ("she understood") didn't align, yet the guilt persists. Can you explore with me what might be driving this lingering guilt, beyond the immediate situation with your sister?

Client: I think... it's like, no matter how understanding others are, I feel like I'm a burden. The guilt isn't just about canceling; it's about being this person who's always struggling. I worry that everyone's just waiting for me to "get it together" again, and until then, I'm a disappointment. Even when they say it's okay, I feel like I'm letting them down by not being okay.

Therapist: That feeling of being a "burden" and "disappointment" to others, despite their reassurances, suggests a deeper belief about yourself. Let's challenge this

Client: Honestly, I don't have any direct evidence... It's more just a feeling. My family's always been supportive, like when my mom had her issues, we all rallied around her. But with me, it feels different in my head. Maybe because I'm the one who's supposed to be "strong" now? I don't know, it just feels like my struggles are a letdown to them, even if they don't say it.

Therapist: It's clear that this perceived role of being "strong" and the lack of direct evidence of being a burden are conflicting. Let's explore this "supposed to be strong" belief - where do you think this expectation originated from, and is it realistic to uphold this for yourself, especially during difficult times?

Client: I think it started after my mom's illness... everyone looked up to me to handle things. Now, even though they say they're here for me, I feel like I'm failing that role. It's exhausting trying to live up to this image of strength. Maybe it's not realistic, but admitting that feels like another failure.

Therapist: Recognizing the origin of this "strength" expectation is a breakthrough. Acknowledging its unreasonableness is brave. How might your relationships and self-perception change if you allowed yourself vulnerability, just as your family showed your mom during her struggles?

Client: That's a hard question... I guess if I let myself be vulnerable, I fear they'll see the real me and confirm my worst fears - that I'm weak. But at the same time, remembering how we supported Mom makes me think maybe they'd just... understand. It's scary to test that, though. What if it changes how they see me forever?

Therapist: Your fear of being seen as "weak" versus the possibility of deeper understanding from your family highlights a crucial dichotomy. Before we explore "what ifs," let's clarify

Client: Weakness to me means failing everyone, including myself. Vulnerability... I guess that's just showing the truth, even if it's hard. But it's hard to separate the two in my head. If being vulnerable means they see my struggles and still accept me, maybe it's not weakness... but it's terrifying to find out.

Therapist: Let's gently challenge this dichotomy. If vulnerability leads to acceptance and support, as it did for your mom, could it redefine "strength" for you - not as hiding struggles, but as courageously sharing them, potentially strengthening your bonds and self-acceptance?

Client: That's... a really different way to look at it. If strength can be asking for help and being open... maybe I've had it backwards. But how do I start seeing myself that way, especially when the old feeling of being a burden is so strong? It feels like a huge shift.

Therapist: That's a profound shift in perspective. To start, let's practice reframing one recent situation (like with your sister) where you felt like a burden, into an act of vulnerability and strength. How might you reinterpret canceling plans, focusing on the courage it takes to acknowledge your limits?

Client: Hmm, okay... So, with my sister, instead of seeing it as failing her, maybe I could think of it as... being honest about not being okay, which takes courage. But it's hard to shake off the feeling that honesty equals burden. Maybe I can start small, like next time just telling her how I'm really feeling instead of canceling last minute. That way, it's more about sharing my struggle than avoiding it. Does that make sense as a first step?

Therapist: Yes, that makes sense. Recognizing the courage in honesty is a good start. For your next step, consider writing down three situations where you felt like a burden. Beside each, note the actual outcomes and whether they aligned with your fears. This can help clarify patterns and challenge the "burden" belief further.

Client: I've started that list... and it's weird, most times my fears didn't match the outcomes. People were supportive, not disappointed. But the guilt still lingers. Maybe I need to work on believing their responses over my fears. It's just hard to trust that they won't eventually see me as a burden if I keep needing support.

Therapist: Noticing the discrepancy between feared outcomes and actual supportive responses is key. To bridge the gap between observing this pattern and truly trusting it, let's explore

Client: I think... if I could see that even after multiple times of needing help, their support doesn't fade. Like, if my sister and others keep being understanding over time, not just once or twice. But then there's also this fear that I'm testing their patience. Maybe I need to have an open conversation with them about how I feel - that I worry I'm a burden - and hear it from them directly. Would that help, or is that too much to ask?

Therapist: Discussing your fears openly with them could provide clarity. Before taking that step, consider this.

Client: Honestly, if they say they're supportive long-term, I might finally start to believe I'm not a burden. But if they don't reassure me... I guess I'd have to confront that maybe my fears are somewhat valid, and then we'd have to work through what that means for our relationships. Either way, hearing it directly might be the only way to stop guessing.

Therapist: That's a courageous approach. Reflecting on our session, we've explored the origins of your "burden" belief, challenged it with evidence of support, and considered steps towards open communication. For our next session, let's schedule it for [Proposed Date, e.g., "next Wednesday at the same time"]. Before then, in addition to your list, practice one open conversation (as discussed) and journal how it feels to express vulnerability. We'll review both next time.

Client: I'll try that. Next Wednesday works. Thanks for your help. [END]

Figure 17: Example conversation (14 turns) from our synthetic dataset.