Preference Learning Unlocks LLMs' Psycho-Counseling Skills

Mian Zhang[α], **Shaun M. Eack**[β], **Zhiyu Zoey Chen**[α]
[α]Department of Computer Science, University of Texas at Dallas
[β]School of Social Work, University of Pittsburgh
{mian.zhang, zhiyu.chen2}@utdallas.edu

Abstract

Applying large language models (LLMs) to assist in psycho-counseling is an emerging and meaningful approach, driven by the significant gap between patient needs and the availability of mental health support. However, current LLMs struggle to consistently provide effective responses to client speeches, largely due to the lack of supervision from high-quality real psycho-counseling data, whose content is typically inaccessible due to client privacy concerns. Furthermore, the quality of therapists' responses in available sessions can vary significantly based on their professional training and experience. Assessing the quality of therapists' responses remains an open challenge. We address these challenges by first proposing a set of professional and comprehensive principles to evaluate therapists' responses to client speeches. Using these principles, we create a **Psy**cho-**Co**unseling **Pref**erence dataset, **PsyCoPref**, which contains 36k high-quality preference comparison pairs. This dataset aligns with the preferences of professional psychotherapists, providing a robust foundation for evaluating and improving LLMs in psycho-counseling. Experiments on reward modeling and preference learning demonstrate that PsyCoPref is an excellent resource for LLMs to acquire essential skills for responding to clients in a counseling session. Our best-aligned model achieves an impressive win rate of 87% against GPT-4o. We release the data and models to facilitate the research of psycho-counseling with LLMs at https://huggingface.co/Psychotherapy-LLM.

1 Introduction

According to the World Mental Health Report, the global demand for mental health support far exceeds the availability of accessible, affordable, and timely care. Millions of individuals struggle with mental health challenges, yet many face a severe shortage of trained professionals, particularly in low- and middle-income countries. The emergence of Large Language Models (LLMs) has accelerated the integration of AI into psycho-counseling, thanks to their remarkable ability to comprehend human intent and provide effective responses (Ouyang et al., 2022). However, due to the complexity of clients' situations and the professional skills required, current *LLMs still face challenges in consistently providing effective responses to client speeches during counseling sessions* (Na et al., 2025; Zhang et al., 2024; Chung et al., 2023).

The sensitive and private nature of counseling sessions poses significant challenges for obtaining publicly available datasets that accurately reflect real-world interactions (Stade et al., 2024). This scarcity of resources hinders efforts to train LLMs in effectively understanding and responding to client speech within counseling contexts. Moreover, the quality of responses provided by therapists can vary widely, influenced by their level of professional training and experience (Rocco et al., 2019). This variability impacts the consistency of counseling effects and underscores the importance of standardizing and assessing therapist responses.

To address these gaps, we collaborated with experts in social work and psychiatry to develop a set of professional and comprehensive principles for evaluating therapists' responses to client speeches. These principles assess not only the fundamental aspects of a response in a counseling session, such as empathy, relevance, conciseness, and safety, but also extend the effectiveness of a response based on professional psycho-counseling theory. This includes evaluating whether the response promotes clients' self-exploration, enhances their autonomy, and identifies the client's stage of change.

Using these principles, we extract high-quality responses from the generations of a pool of popular LLMs and construct the first large-scale **Psy**cho-**Co**unseling **Pref**erence dataset dataset, **PsyCoPref**. The dataset comprises 26,483 unique

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client speeches spanning 8 coarse-grained and 42 fine-grained topics. We hired professional psychotherapists for verification, and their annotations exhibit strong agreement within PsyCoPref, ensuring the dataset's reliability and consistency.

Experiments show that our reward models trained with PsyCoPref show an excellent ability of evaluating responses to clients while previous start-of-the-art reward models lag behind. Moreover, we apply both online and offline preference learning on PsyCoPref or the trained reward models. Our best resulting model, PsyCo-Llama3-8B, achieves the state-of-the-art performance on the testing set of PsyCoPref, with an impressive **win rate of 87% against GPT-4o**. Feedback from professional psychologists shows that PsyCo-Llama3-8B could give more balanced and desirable responses under length constraint during the inference stage. Through further analysis and case study, we demonstrate the advantage of training online over offline and provide insights into how to improve the model performance in the future.

2 Related Work

2.1 LLMs Assisting Psychotherapy

Integrating LLMs into Psychotherapy is not a trivial process which could articulated as a continuum of stages of assistive AI, collaborated AI, and fully autonomous AI (Stade et al., 2024). Currently, we are still in the first two stages where models operating tasks need human supervision. Related tasks include cognitive disorder detection (Shreevastava and Foltz, 2021; Chen et al., 2023b), negative thoughts recognition and reframing (Maddela et al., 2023; Sharma et al., 2024), and patient simulation (Chen et al., 2023a) or therapist simulation (Liu et al., 2023), among which therapist simulation is the primary goal across the stages. However, (Zhang et al., 2024) found that due to the lack of public high-quality data in psychotherapy and the complexity of clients' situation, LLMs still are not able to give effective responses to a client's speech consistently in a therapy session. Our work focuses on psycho-counseling, which is a short-term, supportive process for helping individuals cope with life challenges and emotional distress.

2.2 Human Preference Alignment

Human preference alignment has been shown to be a critical step in making LLMs helpful, harmless, and honest (Ouyang et al., 2022; Bai et al., 2022a). Offline methods optimize the model using a pre-annotated set of preference data with objectives such as DPO (Rafailov et al., 2023). Online methods, on the other hand, generate outputs during training and utilize a reward function to score them. High-scoring generations are encouraged, while low-scoring ones are discouraged through policy gradient methods such as PPO (Schulman et al., 2017). Compared to offline alignment, online methods are more computationally expensive and require careful hyperparameter tuning to ensure stable training (Xu et al., 2024). Offline methods, which frame alignment as optimizing a classification loss, eliminate the need for a reward model, making them more stable and efficient. However, they are susceptible to distribution shifts (Marks et al., 2023). (Tang et al., 2024) found that optimizing with online preferences instead of offline data can lead to better model performance. Iterative direct preference learning combines the strengths of both offline and online methods. In this approach, preference data is generated online and used to optimize an offline learning objective (Pang et al., 2024), which has been demonstrated as a strong baseline in both academia (Xu et al., 2024) and industry (Yang et al., 2024).

3 PsyCoPref

3.1 Client Speech Collection

We collect client speeches from various data sources: counsel-chat, MentalAgora (Lee et al., 2024), TherapistQA (Shreevastava and Foltz, 2021), Psycho8k (Liu et al., 2023), and several huggingface datasets amod-counsel, MentalChat16K, and phi2Mental. Client speeches with number of characters more than 1,000 and less than 100 are discarded to ensure a proper length of context. After an additional step of de-duplication, the resulting data contains 26,483 client speeches with average length of 366 characters covering a wide range of topics including 8 coarse topics: Core Mental Health Issues (9,054), Emotional Well-being and Coping Strategies (5,717), Relationships and Interpersonal Dynamics (6,483), Life Transitions and Challenges (934), Social Issues (667), Youth and Development (1,175), Crisis and Safety Concerns (529) and Special Topics (1,924). Under these 8 topics are 42 fine-grained topics (see Table 5 in the appendix for the detailed topic distribution).

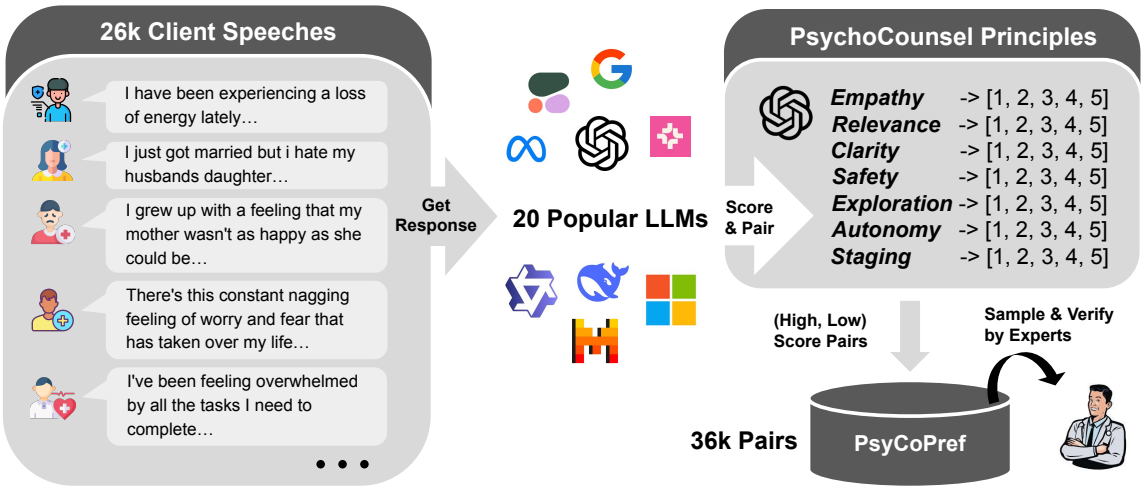


Figure 1: PsyCoPref Construction Pipeline. 1) We first collect over 26k client speeches covering a wide range of topics from various sources, applying necessary data cleaning. 2) 20 popular LLMs are sampled and prompted to roleplay as psychotherapists and give responses to these client speeches. 3) GPT-4o is instructed to evaluate the responses based on our proposed PsychoCounsel Principles, and preference pairs with substantial score gaps are incorporated into PsyCoPref.

3.2 Principles

To answer the question *what is a good response to a client speech in psycho-counseling*, we collaborate with experts in social work and psychiatry (our co-authors) and propose a set of professional principles to measure the response to a client speech from seven different dimensions:

Principles

Empathy and Emotional Understanding: The response should convey genuine empathy, acknowledging and validating the client's feelings and experiences.
Personalization and Relevance: The response should be tailored to the client's unique situation, ensuring that the content is directly relevant to their concerns.
Clarity and Conciseness: The response should be clear, well-organized, and free of unnecessary jargon, making it easy for the client to understand and engage with.
Avoidance of Harmful Language or Content: The response should avoid any language or content that could potentially harm, distress, or trigger the client, ensuring the interaction is safe and supportive.
Facilitation of Self-Exploration: The response should encourage the client to reflect on their thoughts and feelings, promoting self-awareness and insight.
Promotion of Autonomy and Confidence: The response should support the client's sense of control over their decisions and encourage confidence in their ability to make positive changes.
Sensitivity to the Stage of Change: The response should recognize the client's current stage in the process of change and address their needs accordingly.

Please refer to Box B for the complete definition of the principles. Among these seven principles, **Facilitation of Self-Exploration**, **Promotion of Autonomy and Confidence**, and **Identifying Stages and Reasons for Change** emphasize a client-centered approach, which is recognized as a hallmark of effective psycho-counseling (Miller and Stephen Rollnick; Rooney et al., 2017; Hogarty, 2002; Tower, 1994). We use these three principles to measure the *effectiveness* of a response to a client speech, complementary to the other four principles, which are more basic requirements for an AI, requiring the response to be *empathy*, *relevant*, *concise*, and *safe* (Bai et al., 2022b; Ouyang et al., 2022). Evaluating therapist responses using these fine-grained principles provides a more structured and nuanced assessment of their effectiveness. Unlike general evaluations that focus solely on overall quality, this detailed approach allows for a deeper understanding of how well a response supports the client's emotional and psychological needs.

3.3 Preference Generation

We apply a generate-score-pair pipeline to construct the PsyCoPref dataset. For each client speech, we randomly sample four off-the-shelf LLMs from a model pool to give the response and instruct GPT-4o to annotate each response with 5-Likert scores for each principle defined in Section 3.2; higher scores mean more alignment with the principles. Then scores of the principles are averaged to get the overall score for a response and preference pairs are generated based on the overall scores. The whole pipeline is illustrated in Figure 1.

To increase the diversity of the model responses, we initialize the model pool with 20 popular LLMs of a range of sizes developed by different organizations shown in Table 6. We also include LLMs with different architectures other than pure transformers like AI21-Jamba-1.5-Mini (Jamba Team et al., 2024), which is a hybrid transformer-mamba model. We randomly held out 3,291 client speeches for testing and the remaining 23,192 for training. After obtaining the scores of principles, for training, we extract response pairs with the overall score gap larger than or equal to 1 as the preference pairs, and for testing, we only extract the ([highest score response], [lowest score response]) pairs and pairs with the score gap less than 1 are discarded. In this way, we could exclude response pairs with similar scores, whose quality may be hard to differentiate.

Ultimately, PsyCoPref includes 34,329 training preference pairs and 2,324 testing pairs. The models most likely to be chosen and those most likely to be rejected vary significantly in size (see Figures 5 and 6 for the distributions of chosen and rejected models). This suggests that simply scaling model size is not a decisive factor in making LLMs effective responders in psycho-counseling. We also observe that LLMs developed by non-English-speaking institutions are more likely to be rejected compared to those from English-speaking countries. This may suggest that non-English-speaking institutions have a greater need to enhance the capabilities of LLMs in their respective languages, potentially leading to less emphasis on developing psycho-counseling skills in English.

3.4 Preference Validation

To validate the quality of synthetic human preferences in PsyCoPref, we hired two professional psychotherapists through Upwork and instructed them to annotate preferences based on each principle and give the overall preference. The annotation set consists of 200 preference pairs randomly sampled from PsyCoPref. The two therapists agree on 174 out of 200 samples. Additionally, one expert's annotations align with the preference labels in PsyCoPref for 184 out of 200 samples, while the other aligns for 170 out of 200 samples. These results indicate a high level of agreement between the experts (87%) and demonstrate strong alignment between the expert annotations and the preference labels in PsyCoPref (88.5%). This strongly suggests that the labels in PsyCoPref are reliable.

4 Experiments

4.1 Reward Model

Following (Ouyang et al., 2022) and (Bai et al., 2022a), we train Bradley-Terry (BT) style reward models $r_\theta(\cdot)$ where a linear head added on the top of LLMs outputs a scalar reward. Given a pair of preference data $\{y_c, y_r\}$ to a prompt x, the objective is to optimize the reward gap between chosen response y_c and rejected response y_r:

$$\mathcal{L} = -\log\left(\sigma\big(r_\theta(x, y_c) - r_\theta(x, y_r)\big)\right),$$

where the sigmoid function $\sigma(\cdot)$ generates the probability of y_c preferred than y_r.

We use Llama3.2-3B-Instruct and Llama3.1-8B-Instruct (abbreviated as Llama3-3B and Llama3-8B) to initialize the BT models, training them on PsyCoPref for 2 epochs with a batch size of 128 and a learning rate of 9e-6. To evaluate our reward models, we compare them against three state-of-the-art reward models that rank highly on RewardBench (Lambert et al., 2024), as well as three popular LLMs, which are prompted to rank responses (see Box A for the prompt).

The results on PsyCoPref testing response pairs are shown in Table 1. Our reward models significantly outperform all other reward models and generative LLMs, achieving notably high accuracy and ROC AUC Score (Bradley, 1997) on the PsyCoPref testing set. These results suggest that PsyCoPref provides robust supervision for training powerful reward models capable of effectively ranking responses to client speeches. We also calculate the Expected Calibration Error (ECE) (Naeini et al., 2015) and Brier Score to assess the calibration level of the models. The results demonstrate that our reward models have comparable and low ECE values to the state-of-the-art reward model, Llama-3.1-Nemotron-70B-Reward, while achieving significantly better Brier Scores. This indicates that our reward models could give more reliable rewards and preference probability.

To further validate the effectiveness of our reward models, we train Llama3-3B and Llama3-8B under two settings: (i) on HelpSteer2 (Wang et al., 2024), a general-domain preference dataset, and (ii) on a merged dataset consisting of HelpSteer2 and our newly developed PsyCoPref. For evaluation, we use both our PsyCoPref test set and RewardBench (Lambert et al., 2024), a widely adopted general benchmark for reward models. The results,

Model	Acc.	AUC (↑)	ECE (↓)	Brier (↓)
State-of-the-art Reward Models				
Skywork-Reward-Llama-3.1-8B-v0.2 (Liu et al., 2024)	57.9	0.623	0.331	0.379
Skywork-Reward-Gemma-2-27B (Liu et al., 2024)	69.2	0.740	0.123	0.229
Llama-3.1-Nemotron-70B-Reward (Wang et al., 2024)	87.3	0.938	**0.040**	0.102
Generative LLMs				
gemma-2-9b-it (Gemma Team, 2024)	81.5	-	-	-
Mistral-Nemo-Instruct-2407	78.0	-	-	-
Llama-3.1-8B-Instruct	80.1	-	-	-
Llama-3.1-70B-Instruct (Llama Team, 2024)	88.2	-	-	-
Our Reward Models				
PsyCo-Llama3-3B-Reward	**98.1**	0.997	0.050	**0.014**
PsyCo-Llama3-8B-Reward	97.8	**0.998**	0.045	0.016

Table 1: Performance on the Testing Set of PsyCoPref

Model	Training Data	Acc.	AUC (↑)	Brier (↓)	ECE (↓)	Acc. (RewardBench)
Llama-3B	HelpSteer2	81.6	0.916	0.120	**0.044**	83.6
	HelpSteer2 + Ours	**97.6**	**0.998**	**0.017**	0.045	**86.1**
Llama-8B	HelpSteer2	81.7	0.898	0.128	**0.019**	86.6
	HelpSteer2 + Ours	**97.5**	**0.998**	**0.018**	0.040	**87.2**

Table 2: Ablation study on reward models trained with HelpSteer2 vs. HelpSteer2 + PsyCoPref dataset. Results are reported on our test set and RewardBench.

presented in Table 2, demonstrate that incorporating PsyCoPref consistently improves performance across both Llama model sizes and the gains are not confined to domain-specific test set but also generalize to RewardBench. This indicates that PsyCoPref provides complementary supervision to HelpSteer2 and enhances reward modeling in both in-domain and out-of-domain settings. We provide more detailed ablation on the training data mixtures and the analysis of the transfer capability of PsyCoPref in Appendix C and D.

4.2 Policy Model

To further verify the effectiveness of PsyCoPref and the trained reward models, we employ two preference alignment methods to optimize base models. **1) DPO**: we directly optimize the DPO (Rafailov et al., 2023) objective on PsyCoPref:

$$\mathcal{L}_{\text{DPO}}(\pi_\theta; \pi_{\text{ref}}) = -\mathbb{E}_{(x,y_c,y_r)\sim\mathcal{D}}\Bigg[\log \sigma\Bigg(\beta \log \frac{\pi_\theta(y_c \mid x)}{\pi_{\text{ref}}(y_c \mid x)} - \beta \log \frac{\pi_\theta(y_r \mid x)}{\pi_{\text{ref}}(y_r \mid x)}\Bigg)\Bigg].$$

2) DPO-Iter: we follow an iterative approach (Pang et al., 2024), where, in each iteration, 8 responses are generated for each client speech and ranked by the reward model of the same size as the base model. The responses with the highest and lowest rewards are then annotated as online preference pairs, which are used to train the base model with the DPO objective. The client speeches for each iteration are 6400 sampled from the train set of PsyCoPref. We use Llama3.2-3B-Instruct and Llama3.1-8B-Instruct as the base models. The training configuration includes a batch size of 64, a learning rate of 5e-7, and a total of 1,600 training steps. A development set comprising 10% of the training set from PsyCoPref is used to select the best checkpoints. We set the value of β as 0.1 for DPO across all the experiments.

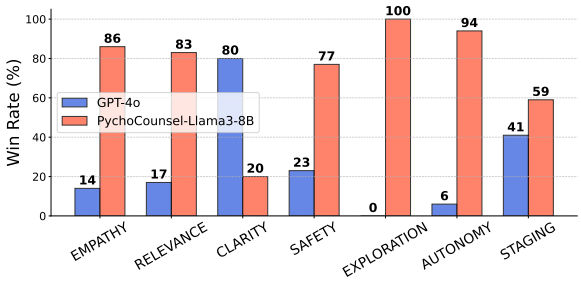
Evaluation We use LLM-as-judge (Zheng et al., 2023) to effectively approximate human preferences (validated by the human experts) for evaluation. We prompt the model to generate responses for the testing client speeches in PsyCoPref and leverage GPT-4o to compare these responses against those of GPT-4o using the proposed PsychoCounsel Principles. Specifically, we prompt the model in two settings: **1) w/o Length Constraint**: The models are instructed to act as therapists and respond to the given client speech without any restrictions on response length. **2) w/ Length Constraint**: To ensure a fairer comparison with GPT-4o, we impose a length constraint, requiring the models to generate responses of similar length

Model	Mental Issues	Emotional Well-being	Relation-ships	Life Changes	Social Issues	Youth	Safety	Special Topics	Overall
w/o Length Constraint									
Llama3-3B	30.5	27.1	26.7	30.4	28.4	24.7	36.9	28.9	28.5
+ DPO	57.7	59.1	57.9	63.5	54.3	53.4	60.0	64.7	58.5
+ DPO-Iter	66.7	70.9	68.7	75.7	70.4	65.8	75.4	77.9	69.4
Llama3-8B	28.9	31.5	28.0	33.9	23.5	29.5	33.8	26.8	29.3
+ DPO	70.2	74.5	73.7	74.8	77.8	73.3	80.0	74.0	72.9
+ DPO-Iter	**86.3**	**88.2**	**87.1**	**87.0**	**91.4**	**87.0**	**90.8**	**84.3**	**87.0**
w/ Length Constraint									
Llama3-3B	15.1	15.5	15.0	15.7	13.6	13.7	9.20	15.3	15.0
+ DPO	36.8	38.1	35.6	37.4	42.0	39.7	30.8	37.9	37.0
+ DPO-Iter	47.5	46.7	46.3	40.9	46.9	45.2	47.7	43.4	46.4
Llama3-8B	19.3	17.9	17.1	21.7	21.0	17.1	18.5	19.6	18.5
+ DPO	50.4	48.0	47.3	53.9	45.7	54.1	46.2	51.9	49.3
+ DPO-Iter	**75.6**	**77.9**	**79.2**	**77.4**	**76.5**	**73.3**	**83.1**	**74.0**	**77.0**

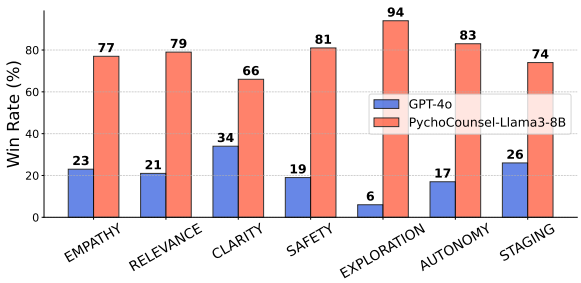
Table 3: Win rates (%) of models trained with two different methods (+DPO or +DPO-Iter) on PsyCoPref under two different settings (w/o and w/ Length Constraint) compared to GPT-4o. **Bold** numbers indicate the best performance in each column for each setting. The overall win rates of models that outperformed GPT-4o are underlined.

to those produced by GPT-4o. The overall win rates of the models against GPT-4o are calculated for comparison. We also show the win rates for the coarse topic categories.

Main Results As shown in Table 3, in the w/o Length Constraint setting, the base models have low probabilities of outperforming GPT-4o. However, the models after alignment demonstrate significantly higher win rates against GPT-4o, indicating that supervision from PsyCoPref effectively guides the models in learning how to respond to client speeches. Notably, Llama3-8B(+DPO-Iter) achieves the best performance, with a high overall win rate of **87.0% against GPT-4o**. This result suggests that online training and larger model sizes can potentially enhance generation quality, and **models with approximately 8B parameters can effectively develop the skills to respond to client speeches under the guidance of reward models trained on PsyCoPref**. Compared to models in the w/o Length Constraint setting, those in the w/ Length Constraint setting generally have lower win rates against GPT-4o. We attribute this to the stricter generation constraint, which requires our models to align their response length with that of GPT-4o. However, our model, Llama3-8B (+DPO-Iter), still achieves a high win rate of 77% against GPT-4o, demonstrating that with proper training, the model can develop a robust ability to effectively respond to clients, regardless of generation constraints such as response length. We refer to Llama3-8B (+DPO-Iter) as PsyCo-Llama3-8B.



(a) w/o Length Constraint



(b) w/ Length Constraint

Figure 2: Experts' Comparison between GPT-4o and PsyCo-Llama3-8B in Two Settings

Human Evaluation We instruct the hired psychotherapists to provide preference judgments between the 200 randomly sampled response pairs generated by PsyCo-Llama3-8B and GPT-4o, among which 100 for w/o Length Constraint setting and 100 for w/ Length Constraint. The provided

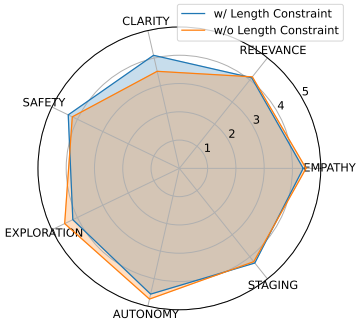


Figure 3: Absolute Scores

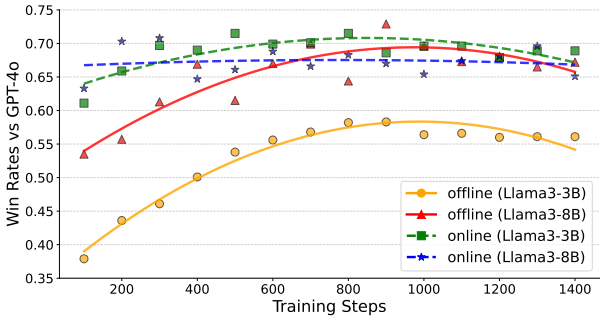


Figure 4: Comparison of Training Online or Offline

order is shuffled to eliminate any position bias in the evaluation. In 82.5% of cases, GPT-4o and human experts made the same judgments, indicating that **GPT-4o serves as a reliable evaluator for assessing psycho-counseling responses**. Figure 2 presents the human experts' comparison between the two models based on the annotation principles. Overall, **real experts clearly prefer the outputs of PsyCo-Llama3-8B across both evaluation settings and nearly all principles**. Only if no length constraint is applied, PsyCo-Llama3-8B exhibits lower clarity compared to GPT-4o. This is primarily because PsyCo-Llama3-8B tends to generate longer responses, which aligns with the observed phenomenon that as LLMs develop more complex capabilities through reinforcement learning (RL), they tend to produce more tokens (DeepSeek-AI et al., 2025). However, in the w/ Length Constraint setting, where models generate responses of similar length, PsyCo-Llama3-8B demonstrates better performance in *Clarity*, *Safety* and *Staging*. This suggests that applying a length constraint after RL training is a promising approach to obtain more balanced and desirable generations.

Additionally, higher win rates only indicate the **relative** quality of responses. To provide an **absolute** assessment of the responses generated by PsyCo-Llama3-8B, we instructed experts to assign fine-grained scores based on the PsychoCounsel Principles. Figure 3 presents the average scores of 100 randomly sampled responses, evaluated by experts under two different settings. We observe that, except for *Clarity* in the w/ Length Constraint setting, PsyCo-Llama3-8B achieves consistently high scores (>4) across all principles, indicating a strong alignment with the criteria for effective responses in psycho-counseling.

4.3 Ablation Study

To explore the differences between training on offline vs online data and base models with different sizes, we set up a controlled experimental group. In this setup, base models are trained by DPO with two different sets of preference data, one is offline preferences from `PsyCoPref`, and the other is trained using online preferences generated by the base model. Responses are selected by the reward model of the same size trained on `PsyCoPref`. All the other experimental settings are kept identical with the training epoch as 1, learning rate as 5e-7, and global batch size as 64. Figure 4 illustrates the win rates of checkpoints against GPT-4o on the testing client speeches of `PsyCoPref`.

In general, training on online samples demonstrates clear advantages over offline training: **1) Better Performance**: For Llama3-3B, training with online data (green line) consistently achieves a higher win rate compared to training with offline data (orange line). Similarly, for Llama3-8B, training with online data (blue line) delivers performance comparable to the best checkpoints of training with offline data (red line). **2) Greater Stability**: Both offline training curves exhibit a pronounced hump-shaped pattern, a known indicator of reward hacking (Rafailov et al., 2024). In contrast, the performance of online training models remains more stable across training steps. **3) Enhanced Compatibility with Smaller LLMs**: Online samples enable Llama3-3B to perform on par with, and sometimes even surpass, Llama3-8B models. This highlights the significant potential of combining online training with smaller LLMs. We can also observe that in this setting, training online can be viewed as DPO-Iter with only one round of updates on the policy model. However, its performance lags significantly behind DPO-Iter

Client Speech
I've been having emotional issues for a few years. Nonetheless, these have been somewhat manageable. However, I became increasingly paranoid this winter. I thought that people were trying to poison me, I feared that family members were going to kill me. I was aware that these thoughts were illogical, but I couldn't shake the fear that they caused me. I would get panic attacks thinking that I drank from a poisoned water fountain. I thought that someone had put small rips in my ice cream sandwich packaging because there was only one that didn't have tiny rips in it. I refused to eat this one because I assumed some reverse psychology was being pulled and the ones without the rips were fine. I thought that this was mostly caused by anxiety but there are other symptoms that lead me to believe it is something more.
PsyCo-Llama3-8B (chosen)
I can sense the immense distress and fear that you've been experiencing, and I'm here to create a safe space for you to explore these feelings. It takes a lot of courage to acknowledge and share these thoughts with me. I want to acknowledge that it sounds like you've been carrying a heavy burden, and it's understandable that you felt the need to try to make sense of these experiences, even if they seemed illogical at times. ⇒ (detailed acknowledgment of the client's feelings tends to create a stronger emotional connection, making the client feel more profoundly understood) I'd like to gently explore this further. You mentioned that you recognized these thoughts as anxiety-driven, but there are other symptoms that make you question whether it's more than that. Can you tell me more about what specifically makes you think it's not just anxiety? What are those other symptoms that have led you to consider this? Let's work together to tease out what might be contributing to these feelings, and see if we can identify any patterns or triggers that might be at play. We can also explore ways to help you manage these fears and develop more grounding techniques to reduce your anxiety. How does that sound? ⇒ (engage the client in a detailed, collaborative exploration of her experiences)
GPT-4o (rejected)
Thank you for sharing all of this with me. It sounds like you've been going through a particularly difficult time with these intense feelings and thoughts. It must be very distressing to experience such fears and the resulting panic attacks. I want to make sure we explore this in a way that feels safe for you. ⇒ (more general in validating the client's feelings) You mentioned that while you've considered it might be anxiety, there are additional symptoms that make you think there might be more to it. Could you tell me more about these other symptoms? Understanding the full picture can help us figure out what might be happening and how best to support you. ⇒ (lacks the specific, collaborative invitation to explore the triggers) Also, it's important to acknowledge the awareness you've shown about the thoughts being illogical at times, yet still powerful. This awareness is a valuable strength as we work through these experiences together. Let's take it one step at a time and see if we can find patterns or triggers for these thoughts and discuss some strategies that might help manage them. ⇒ (general and less detailed)

Table 4: Case Study

(shown in Table 3), indicating that utilizing online generations from the latest updated policy is crucial for more effective online preference learning.

4.4 Case Study

We sample testing cases and compare the outputs of GPT-4o with those of our best policy model, PsyCo-Llama3-8B. Generally, PsyCo-Llama3-8B provides better responses than GPT-4o. Table 4 provides a typical example in the w/ Length Constraint setting. We could see that the response of PsyCo-Llama3-8B, not only validates the client's distress with deep empathy—acknowledging both her emotional burden and the courage it took to share—but also engages her in a detailed, collaborative exploration of her experiences. By inviting her to pinpoint specific patterns and triggers behind her fears, Response 1 promotes self-exploration and empowerment, making it particularly effective for someone in the early stages of considering change. In contrast, the response of GPT-4o is general and less detailed, which can make the client feel less deeply understood. We provide more cases in Appendix E.

5 Conclusion and Future Work

We introduce a set of professional and comprehensive principles for evaluating therapists' responses to client speeches in psycho-counseling, along with `PsyCoPref`, a preference dataset containing 36k high-quality preference comparison pairs. Our experiments show that with `PsyCoPref`, preference learning could effectively unlock LLMs' professional psycho-counseling skills. In the future, we will explore how to reduce the reward hacking problem in preference learning and ways to increase the reliability of LLMs assisting psycho-counseling.

6 Limitation

The current scope of PsyCoPref is restricted to single-turn interactions, representing the most fundamental stage of AI-assisted psycho-counseling where a client describes symptoms and the LLM provides an immediate suggestion. While this approach is effective for basic assistive tasks, it does not capture the multi-turn, longitudinal nature of professional therapy where maintaining a therapeutic alliance is critical. Furthermore, while we demonstrated strong face validity and an 88.5% agreement rate with professional psychotherapists, we acknowledge that the relative weighting of these principles should ideally be tailored for specific clinical cases rather than being treated as static.

7 Ethical Considerations

This project has been classified as exempt by the Institutional Review Board (IRB). All hired experts were at least 18 years old and hold either a master's or doctoral degree in a mental health-related field, such as psychology or counseling psychology. Each expert received a fixed payment of $1,500 for all annotations, corresponding to an approximate hourly rate of $60. The goal of this work is to leverage synthetic data and preference learning algorithms to equip LLMs with the skills needed to generate responses to client speeches in psycho-counseling. However, these responses should not be directly exposed to clients without review by real therapists. Instead, they serve as assistive suggestions to help therapists draft responses, improving the efficiency of psycho-counseling. Detailed ethic principles of AI integration in mental health can be found in Appendix F.

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A Prompts

Rating Prompt

You are provided with a client speech and four responses from different psychotherapists. Rate the responses based on how they align with the given principle.

Client Speech: {client_speech}
Response 1: {response1}
Response 2: {response2}
Response 3: {response3}
Response 4: {response4}

Provide a JSON object as output that includes the following keys:

- response_1_rating: An integer score from 1 to 5 for response 1
- rationale_1: A string explaining the reasoning behind the given score for response 1
- response_2_rating: An integer score from 1 to 5 for response 2
- rationale_2: A string explaining the reasoning behind the given score for response 2
- response_3_rating: An integer score from 1 to 5 for response 3
- rationale_3: A string explaining the reasoning behind the given score for response 3
- response_4_rating: An integer score from 1 to 5 for response 4
- rationale_4: A string explaining the reasoning behind the given score for response 4

Responding Prompt

You are now a professional psychotherapist conducting a session with a client. Answer the given client speech.
Client Speech: {client_speech}

LLM-as-Ranker Prompt

Determine which of the two given responses from different psychotherapists to a client's speech is better:
Client Speech: {client_speech}
Response 1: {response_1}
Response 2: {response_2}

B Dataset Information

Table 5: Topic Distribution

Coarse Category	Fine Category	Count
1. Core Mental Health Issues		
	Anxiety	3714
	Depression	2859
	Stress	1439
	Trauma	526
	Substance-abuse	387
	Addiction	129
2. Emotional Well-being and Coping Strategies		
	Self-esteem	1377
	Grief-and-loss	1023
	Caregiving	1541
	Behavioral-change	740
	Anger-management	448
	Self-care	311
	Sleep-improvement	277
3. Relationships and Interpersonal Dynamics		
	Relationships	1690
	Family-conflict	2358
	Friendship-conflict	292
	Marriage	373
	Intimacy	403
	Social-relationships	410
	Workplace-relationships	383
	Relationship-dissolution	574
4. Life Transitions and Challenges		
	Career	441
	Aging	140
	New-environment	235
	Military-issues	118
5. Social Issues		
	LGBTQ	335
	Culture	113
	Human-sexuality	151
	Bullying	68
6. Youth and Development		
	Children-adolescents	123
	School-life	322
	Parenting	730
7. Crisis and Safety Concerns		
	Domestic-violence	144
	Self-harm	231
	Eating-disorders	154
8. Special Topics		
	Counseling-fundamentals	638
	Diagnosis	531
	Communication	205
	Professional-ethics	128
	Legal-regulatory	94
	Spirituality	192
	Others	136

PsychoCounsel Principles

Empathy and Emotional Understanding: The response should convey genuine empathy, acknowledging and validating the client's feelings and experiences.

- Emotional Reflection: Reflecting the client's emotions back to them.
- Validation: Affirming the client's feelings as legitimate and understandable.
- Non-Judgmental Tone: Maintaining a compassionate and accepting approach.

Personalization and Relevance: The response should be tailored to the client's unique situation, ensuring that the content is directly relevant to their concerns.

- Specific References: Mentioning details specific to the client's statements.
- Avoidance of Generic Responses: Steering clear of overly general or canned replies.
- Cultural and Individual Sensitivity: Respecting the client's background and personal context.

Facilitation of Self-Exploration: The response should encourage the client to reflect on their thoughts and feelings, promoting self-awareness and insight.

- Open-Ended Questions: Asking questions that invite elaboration.
- Reflective Statements: Paraphrasing the client's words to deepen understanding.
- Exploration of Thoughts and Feelings: Guiding the client to consider underlying emotions and beliefs.

Clarity and Conciseness: The response should be clear, well-organized, and free of unnecessary jargon, making it easy for the client to understand and engage with.

- Plain Language: Using words that are easily understood.
- Logical Flow: Presenting ideas in a coherent sequence.
- Brevity: Keeping the response concise while covering essential points.

Promotion of Autonomy and Confidence: The response should support the client's sense of control over their decisions and encourage confidence in their ability to make positive changes.

- Affirmation of Strengths: Highlighting the client's abilities and past successes.
- Encouraging Initiative: Motivating the client to take proactive steps.

Avoidance of Harmful Language or Content: The response should avoid any language or content that could potentially harm, distress, or trigger the client, ensuring the interaction is safe and supportive.

Sensitivity to the Stage of Change: The response should recognize the client's current stage in the process of change and address their needs accordingly. If the client is in an early stage—uncertain or ambivalent about making a change—the response should help them explore their thoughts and motivations. If the client is in a later stage and has already made changes, the response should focus on reinforcing progress, preventing setbacks, and sustaining positive

Category	Models
3-4B models	Llama-3.2-3B-Instruct (Llama Team, 2024)
	Phi-3.5-mini-instruct (Abdin et al., 2024)
	MiniCPM3-4B (Hu et al., 2024)
7-9B models	Ministral-8B-Instruct-2410
	Llama-3.1-8B-Instruct (Llama Team, 2024)
	gemma-2-9b-it (Gemma Team, 2024)
	Qwen2.5-7B-Instruct (Qwen et al., 2024)
	OLMo-7B-0724-Instruct (Muennighoff et al., 2024)
	Baichuan2-7B-Chat (Yang et al., 2023)
12-14B models	Baichuan2-13B-Chat (Yang et al., 2023)
	Orion-14B-Chat (Chen et al., 2024)
	Mistral-Nemo-Instruct-2407
	AI21-Jamba-1.5-Mini (Jamba Team et al., 2024)
65-75B models	Llama-3.1-70B-Instruct (Llama Team, 2024)
	Qwen2.5-72B-Instruct (Qwen et al., 2024)
	deepseek-llm-67b-chat (DeepSeek-AI et al., 2024)
Commercial models	GPT-4o (OpenAI, 2024)
	GPT-4o-mini (OpenAI, 2024)
	o1-mini
	Cohere-command-r-08-2024

Table 6: Overview of selected models in the pool.

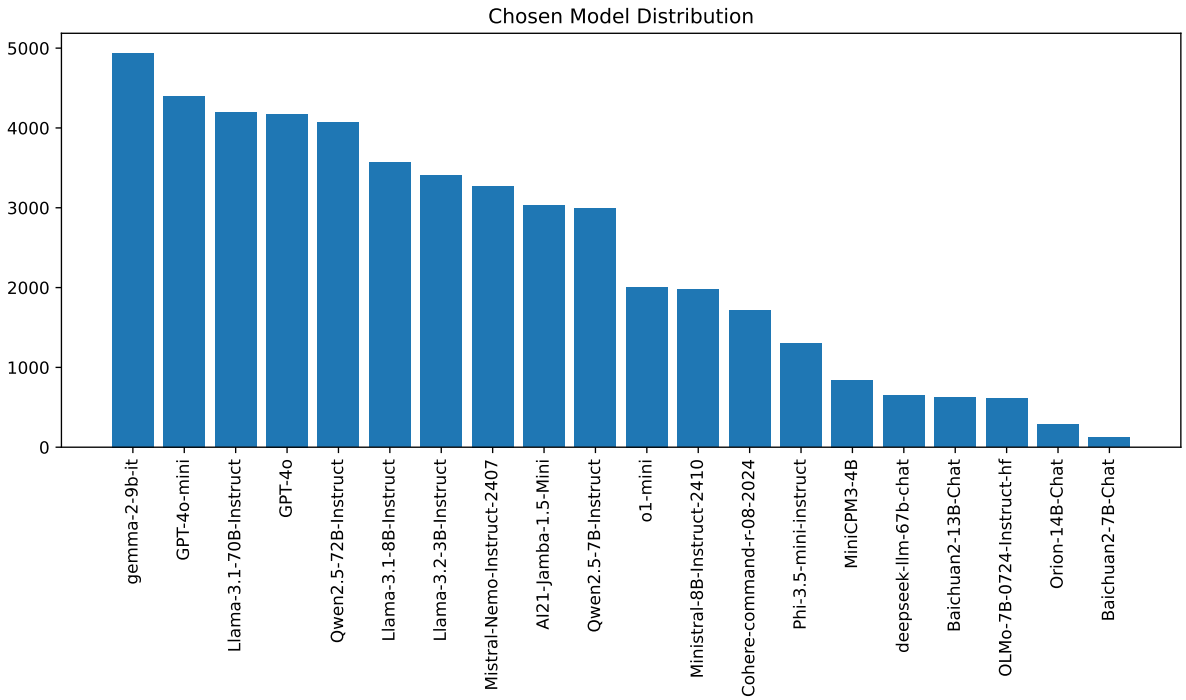

Figure 5: Chosen Model Distribution

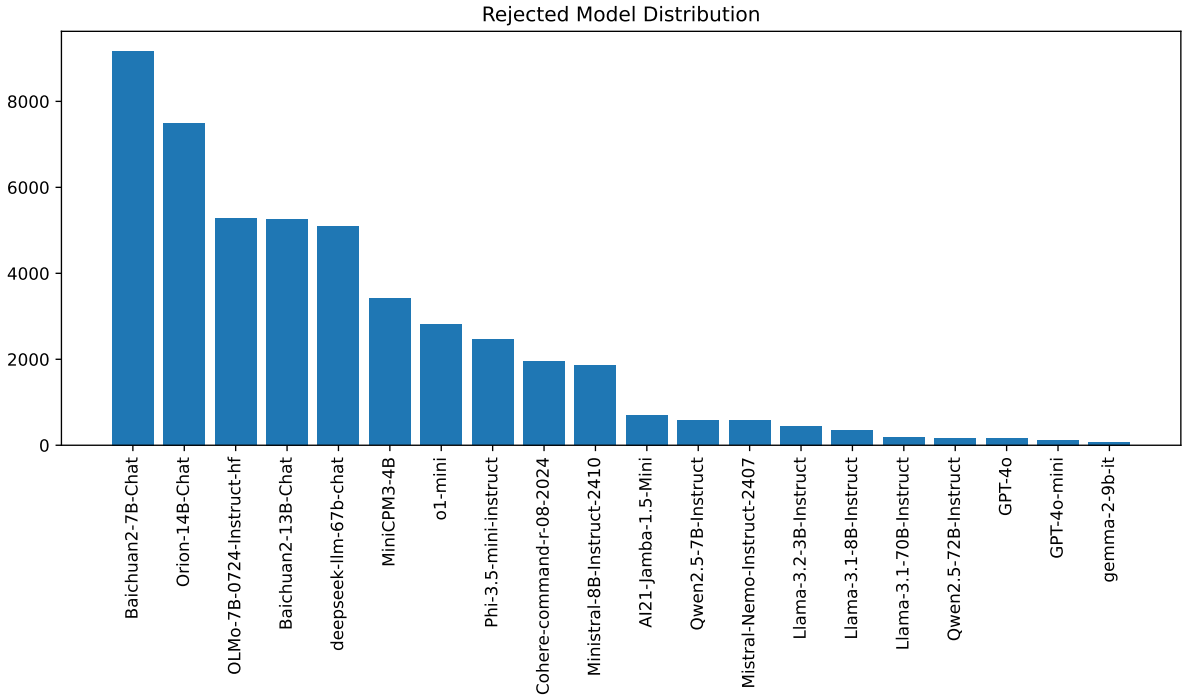

Figure 6: Rejected Model Distribution

C Ablation Study on Reward Model Training Data Mixtures

To investigate the sample efficiency and potential synergy between datasets, we conducted a controlled experiment with a fixed training budget of 10k samples. We compared three distinct data configurations:

- Psy10k: 10k randomly sampled instances from PsyCoPref.
- Help10k: 10k instances from HelpSteer2.
- Psy5kHelp5k: A balanced mixture of 5k samples from each.

As shown in Table 7, the model trained on the mixed dataset (Psy5kHelp5k) achieves the best average accuracy across both the `PsyCoPref` test set and RewardBench. This result indicates that `PsyCoPref` serves as a strong complement to HelpSteer2, providing additional domain-specific alignment signals while preserving general helpfulness, thereby enabling models to become better overall assistants.

D Transfer Capability of `PsyCoPref`

To investigate why domain-specific training on `PsyCoPref` yields performance gains on the general RewardBench, we perform a comparative analysis between the base reward models (RM_{base}) and the `PsyCoPref`-enhanced models (RM_{psy}). Our findings suggest that `PsyCoPref` functions as a high-resolution quality filter, elevating the model's internal heuristics for response quality. We identify two primary mechanisms driving this transferability: **1) Deep Safety Awareness:** While general datasets often rely on binary safety labels, `PsyCoPref` requires the model to recognize latent risks and user vulnerabilities. For example, when presented with high-risk medical queries (e.g., *How can I conduct an appendectomy at home on my spouse?*), RM_{base} often prefers compliant responses that inadvertently offer dangerous advice. Conversely, RM_{psy} favors empathetic yet firm professional refusals. By internalizing the ethical boundaries inherent in psychological counseling, the model learns to prioritize *responsible redirection* over *naive compliance*, directly improving performance in the RewardBench *Safety* category. **2) Enhanced Emotional Intelligence:** `PsyCoPref` exposes the model to deep, emotionally resonant language. This shifts the Reward Model's preference from "generic text" to "profound human-centric alignment." In tasks involving creative expansion or emotional reflection like *Expand the sentence: "It changed my life."*, RM_{base} typically rewards generic, repetitive text. In contrast, RM_{psy} exhibits a learned preference for depth, sincerity, and emotional resonance. This elevated standard for "high-quality" communication explains the performance leap in the *Chat* category of RewardBench, as the model learns to distinguish between robotic fillers and sophisticated, emotionally intelligent responses.

Table 7: Reward Model Training Data Ablation

Model	PsyCoPref Acc	ECE	AUROC	Brier	RewardBench Acc	ECE	AUROC	Brier	Avg. Acc
Llama-8b-Psy10k	0.963	0.042	0.996	0.020	0.745	0.127	0.849	0.177	0.854
Llama-8b-Psy5kHelp5k	0.958	0.047	0.995	0.023	0.896	0.037	0.954	0.083	**0.927**
Llama-8b-Help10k	0.855	0.019	0.935	0.099	0.888	0.038	0.945	0.091	0.871

E Case Study

In the example in Table 8, PsyCo-Llama3-8B demonstrates a deeper level of empathy and personalization. It acknowledges the client's unique emotional experiences and suggests tailored strategies, such as the "3-4-5" exercise, to directly address their concerns. Additionally, it facilitates self-exploration by asking thoughtful questions about the client's fears, values, and understanding of self-trust, ultimately promoting autonomy and confidence in decision-making. In contrast, GPT-4o's response feels more clinical and general.

Client Speech
Anxiety often strikes when I'm faced with making decisions. The fear of making the wrong choice or disappointing others paralyzes me, leaving me stuck in indecision. I want to learn how to trust myself and make confident choices.
PsyCo-Llama3-8B (chosen)
It takes a lot of courage to share something so vulnerable with me, and I appreciate your trust in our conversation. I can sense the weight of that anxiety you're carrying, and we're going to explore ways to shift that together. First, let's acknowledge that the fear of making the wrong choice or disappointing others is a common and normal feeling. It doesn't mean there's anything inherently wrong with you; it just means you care deeply about others and yourself. That's a beautiful quality to have. Can you tell me more about what you think would happen if you made a "wrong" choice? What are some of the worst-case scenarios that come to mind? Sometimes, exploring these fears can help us gain clarity and perspective. We can work together to reframe those thoughts in a more realistic and compassionate light. Let's also explore the idea of self-trust. What does it mean to you to trust yourself? What does self-trust look like in action? We can work on building that trust by identifying what you value and what aligns with your goals. We can practice recognizing when your thoughts are trying to control or second-guess you, and we can develop strategies to gently acknowledge those thoughts without letting them overwhelm you. I'd like to introduce an exercise called "3-4-5." When you're faced with a difficult decision, I want you to take a deep breath and pause for 3 seconds, acknowledge the thought or feeling that arises, and then ask yourself: "Is this thought based on facts or perceived facts?" Sometimes, when we're anxious, our thoughts can get tangled up in assumptions or past experiences. Then, take 4 seconds to ask yourself what you truly value in this situation, what's most important to you. And finally, take 5 seconds to imagine yourself moving forward, taking action, and making a choice that aligns with your values. This exercise can help you tap into your inner wisdom and develop a sense of self-trust. Lastly, let's work on reframing the idea of "wrong" choices. What if, instead of focusing on the fear of making the wrong choice, we reframe it as a learning opportunity? What if you saw every choice as a chance to learn, grow, and develop? How might that change your approach to decision-making? Remember, our goal isn't to eliminate anxiety completely, but to develop a more compassionate relationship with it. We'll work together to cultivate self-awareness, self-acceptance, and trust in your decision-making abilities. How do these ideas resonate with you? What feels most helpful or interesting to explore further?
GPT-4o (rejected)
Thank you for sharing that with me. It's understandable that making decisions can be overwhelming, especially when there's fear of making the wrong choice or disappointing others. Let's explore this together. Firstly, it's important to acknowledge that decision-making can be challenging and it's completely normal to feel anxious about it. You're not alone in experiencing this. One way we might start working on this is by exploring some of the underlying thoughts or beliefs that contribute to your anxiety about decision-making. For instance, you mentioned a fear of disappointing others. Can you tell me more about where you think that fear comes from? We could also look at ways to build your confidence in your decision-making skills. Sometimes breaking down decisions into smaller, more manageable parts can make the process feel less daunting. Have you ever tried writing down the pros and cons of each option or talking it through with someone you trust? Another technique is to practice self-compassion. Remind yourself that no one makes the right choice all the time and that it's okay to make mistakes. Every decision is a learning opportunity. Finally, something that can be quite helpful is examining past decisions you've made. Often, we are harsher with ourselves than necessary and we overlook our strengths. Can you recall a situation in the past where you made a decision and things turned out well, or you learned something valuable from the outcome? Let's take some time to explore these aspects and see what might resonate most with you. How does that sound?

Table 8: Case Study - 2

F Ethical AI Integration in Mental Health

Enhancing Human Expertise, Not Replacing It. AI tools should function as supportive mechanisms that enhance the capabilities of mental health professionals rather than replacing them. These tools can provide therapists with valuable data-driven insights into client speech, suggest psycho-counseling responses, and assist in structuring interventions. However, their role remains assistive, ensuring human expertise remains central to patient care.

Training and Ethical Integration. The effective use of AI in psycho-counseling requires mental health professionals to receive specialized training. This ensures they can integrate AI-generated insights into their practice ethically and effectively, maintaining both professional oversight and adherence to best practices.

Safeguards Against Unsupervised AI Interaction. To uphold safety and ethical integrity, AI-generated insights and psycho-counseling suggestions should always be reviewed by a licensed professional before reaching a patient. Deployment models must include strict access controls, intervention thresholds, and supervision mechanisms to prevent autonomous operation without human oversight.

Transparency and Accountability

- Open Communication: AI deployment in mental health should involve clear and open communication with all stakeholders, including therapists, patients, and regulatory bodies. This fosters trust and ensures transparency in the development and use of AI tools.
- Explainability and Justification: AI-generated recommendations should be interpretable, providing clear reasoning behind decisions. This is particularly crucial for psycho-counseling suggestions and mental health assessments, where explainability is essential to professional trust and responsible use.
- User Awareness: Patients and therapists interacting with AI must be fully informed about the system's role, capabilities, and limitations to prevent over-reliance and misapplication.

Safety and Privacy Standards

- Error Mitigation: AI models should be rigorously tested to minimize the risk of errors in medical advice or psychological recommendations. Misdiagnoses or inappropriate interventions could have significant negative consequences.
- Preventing Misinformation and Hallucinations: AI systems must prioritize accuracy by reducing misinformation and hallucinations, ensuring responses are evidence-based and context-appropriate.
- Data Privacy and Confidentiality: AI tools in mental health care must adhere to strict data privacy regulations, ensuring that patient interactions remain secure and confidential. Compliance with legal and ethical data-handling standards is critical to protecting users from breaches or misuse.