# Extending Cognitive Reframing Therapy: Multimodal Support and Multi-hop Psychotherapeutic Reasoning

### Anonymous ACL submission

### Abstract

Previous studies have shown that Large Language Models (LLMs) have significant potential in supporting cognitive reframing therapy. However, these studies have primarily focused on uni-modal therapy, often overlooking the importance of the client's non-verbal cues. Identifying non-verbal emotions plays a crucial role in effective communication and is considered a central skill in psychotherapy. To alleviate this gap, we extend the concept of cognitive reframing conversation to multimodality. Specif-011 ically, we present a new dataset called Multi Modal-Cognitive Support Conversation (MM-CSConv), which pairs each dialogue with an image of the client's facial expression. Additionally, we introduce a multi-hop psychotherapeutic reasoning approach to enhance the capabilities of Vision-Language Models (VLMs) 018 019 as psychotherapists. This approach uses multihop reasoning over the conversations, incorporating implicit evidence crucial in psychotherapy. Our extensive experiments with both LLMs and VLMs show that the abilities of VLMs as psychotherapists are significantly enhanced through the MM-CSConv. Moreover, the multi-hop psychotherapeutic reasoning method allows VLMs to offer more ratio-027 nal and empathetic suggestions, outperforming standard prompting methods.

### 1 Introduction

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Many mental health issues are closely linked to deeply ingrained negative and distorted thoughts (Beck, 1970, 1979; Beck and Padesky, 1990; DiTomasso et al., 2000; Halamandaris and Power, 1997; Walen et al., 1992; Hofmann et al., 2012). These can be addressed through cognitive reframing therapy, a core technique in Cognitive Behavioral Therapy (CBT), provided by a skilled psychotherapist. Due to limitations in face-to-face CBT, such as time constraints, geographic barriers, a shortage of trained therapists, and concerns about the stigma of



Figure 1: Illustration of a multimodal conversational cognitive reframing. The therapist uses both verbal and non-verbal information to assess the client's status and then provides appropriate interventions.

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mental health referrals (Zisook and Downs, 1998; So et al., 2013), there has been active research into the use of AI in psychotherapy. Recent studies highlight the potential of Large Language Models (LLMs) in this field, emphasizing their knowledge and empathic counseling capabilities (Ziems et al., 2022; Maddela et al., 2023; Sharma et al., 2023; Qu et al., 2023; Yang et al., 2023, 2024; Xiao et al., 2024). These models could play a significant role in facilitating cognitive reframing. Research on cognitive reframing has focused on sentence rewriting, effectively transforming negative text by inducing a complementary positive viewpoint (Ziems et al., 2022; Maddela et al., 2023). Sharma et al. (2023) also explored cognitive reframing from the same perspective and proposed a methodology to enhance the actionability and specificity of the reframed thoughts generated by LLMs. However, there's a concern that when cognitive reframing is solely approached through sentence rewriting, clients may not feel ownership over the alternative thoughts and may perceive them as imposed rather than self-generated.



Figure 2: One example illustrating the construction of the MM-CSConv dataset. The left side shows the prompt provided to GPT-4 in the client role, while the right side shows the prompt provided to GPT-4 Vision in the therapist role. GPT-4 Vision is given an image of the client's face. The dialog history is a history of conversations accumulated during the role play. The yellow and blue boxes at the top are parts of the system messages provided to the client and counselor, respectively.

Xiao et al. (2024) studied cognitive reframing from a conversation perspective rather than a sentence rewriting perspective. They suggested that LLMs can induce the client's positive emotions by conducting three-stage conversational cognitive reframing therapy, which helps clients actively engage in the process and arrive at more positive viewpoints themselves.

Despite the promising results shown by LLMs in previous research, non-verbal aspects of psychotherapeutic theory are often overlooked, creating a significant gap between real face-to-face therapy and prior research. Real psychotherapy involves considering the client's non-verbal cues, such as facial expressions and gestures. Recognizing non-verbal emotions is crucial for effective communication and is a key skill in psychotherapy training, closely tied to the therapist's ability to provide effective therapy (Hutchison and Gerstein, 2012; Döllinger et al., 2021).

To alleviate this gap, we propose extending the concept of cognitive reframing into multimodality.

Figure 1 illustrates the conversation involved in multimodal cognitive reframing that we are investigating. Building on previous research that emphasizes empowering the client rather than therapistdriven therapy, we adopt a conversational cognitive reframing approach. Our focus is on cognitive reframing within a multimodal context, taking into account clients' non-verbal information as well. To this end, we create a new synthetic benchmark called Multi Modal-Cognitive Support Conversation (MM-CSConv), which pairs each synthetic dialogue with an image of the client's facial expression. Leveraging the powerful roleplaying capability of LLMs and following Xiao et al. (2024), we employ role-play settings where two agents, GPT-4 Vision and GPT-4, simulate the roles of psychotherapist and client, respectively, as shown in Figure 2. In this task, multimodal psychotherapy models operate in four main stages, extending the three-stage model proposed by Xiao et al. (2024): Introduction, Problem Exploration, Brainstorming, and Suggestion. We present the

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109Introduction stage, where the therapist shows empathy to establish rapport with the client and encourages them to discuss issues directly impacting110courages them to discuss issues directly impacting112them. This stage is designed based on the 'Initial113Disclosure' stage in the five stages of counseling114(Krishnan, 2015).

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We also introduce multi-hop psychotherapeutic reasoning based on the principle that therapists provide guidance based on the client's status. By exploring the implicit evidence necessary for real cognitive reframing counseling and then generating responses based on this evidence, the AI therapist can offer guidance after identifying the client's status. For this task, we choose LLaVA-v1.5-7b (Liu et al., 2024), one of the strong Vision-Language Models (VLMs) for visual dialogue tasks.

To evaluate our approach, we conduct extensive experiments with two test scenarios: AI-simulation and MM-CSConv benchmark, using both LLMs and VLMs. The results show that through the MM-CSConv, the treatment ability of VLMs surpasses that of existing LLMs. Moreover, the multi-hop psychotherapeutic reasoning method allows VLMs to offer more rational and empathetic suggestions, outperforming standard prompting methods.

To sum up, our contributions are as follows:

- We explore cognitive reframing concepts extended to multimodality which reflects crucial properties in real psychotherapy.
- We propose a multi-hop psychotherapeutic reasoning approach to enhance the capabilities of VLMs in providing rational therapeutic interventions.

### 2 Problem Definition and Goals

In cognitive reframing therapy, a therapist must understand the client's status, including their problematic situations, distorted thoughts, and thinking traps. The therapist then encourages the client to consider alternative possibilities. Building rapport with the client by expressing empathy is also crucial. In real psychotherapy, these processes involve both verbal and non-verbal information, and the therapist has sufficient ability to understand the client's status.

Here, our goal is to enhance the abilities of an AI psychotherapist by leveraging non-verbal information, particularly focusing on facial expressions, and comprehending the client's status. Given the client's facial image and dialog history, we aim to empower AI therapists to offer empathetic, logically consistent, specific, and rational interventions based on this information.

To evaluate the abilities of the AI therapist, we adopt the three evaluation criteria from the prior research: empathy, logical coherence, and guidance (Xiao et al., 2024).

- Empathy signifies the therapist's ability to understand and resonate with the client's emotions, fostering connection, trust, and emotional support, which are essential for a therapeutic relationship.
- Logical coherence demonstrates the therapist's ability to organize thoughts and provide well-structured insights, enhancing the quality of the conversation.
- Guidance reflects the therapist's capacity to offer practical advice, solutions, and direction, helping the client navigate challenges, make informed decisions, and achieve positive outcomes.

We also compared overall scores encompassing all three items. (see Section A for details.)

# 3 Cognitive Support Conversation

### 3.1 Data Construction

We leverage existing resources to construct a multimodal conversational cognitive reframing dataset annotated with three different psychotherapeutic evidence. To create the dataset, we employ roleplay settings with two agents, GPT-4 Vision and GPT-4. As shown in Figure 2, to prompt GPT-4 in the client role and GPT-4 Vision in the therapist role, we use a quadruplet consisting of (image, facial expression, thinking traps, thought)<sup>1</sup>. The image represents the client's facial image, the facial expression denotes the client's facial expression, the *thought* reflects the client's thoughts, and the thinking traps capture cognitive distortions present in the thought. The image and facial expression are sourced from AffectNet, a facial expression recognition benchmark (Mollahosseini et al., 2019), while the thinking traps and thoughts come from a well-designed cognitive reframing dataset that is in English (Sharma et al., 2023).

<sup>&</sup>lt;sup>1</sup>We used version gpt-4-0613 of the GPT-4 API and version gpt-4-1106-vision-preview of the GPT-4 Vision API.



Figure 3: Comparison of standard prompt and multi-hop psychotherapeutic reasoning. In multi-hop psychotherapeutic reasoning, the client's status is included in the prompt for providing intervention at each stage. The client's status comprises facial expressions, thoughts, and thinking traps.

Each dialogue consists of four turns, corresponding to different stages of a psychotherapeutic conversation. The prompt for each step is shown in Figure 2. The action expected from the client is to follow the psychotherapist's instructions, and the actions required of the psychotherapist at each stage are as follows.

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- 1. Introduction Stage: The AI psychotherapist expresses empathy and encourages the client to explore their problems.
- 2. Problem Exploration Stage: The AI psychotherapist guides the client to distinguish their thoughts from their situation.
- 3. Brainstorming Stage: The AI psychotherapist discusses other possibilities for the client's interpretation. This involves asking about the basis for the client's thoughts or considering the possibility of alternative interpretations.
- 4. Suggestion Stage: The AI psychotherapist first recognizes the client's effort to explore other possibilities and presents specific and rational suggestions for the client. 224

		Avg.		
	# of Dialog	Client	Therapist	Rounds
Train	329	24.93	63.64	4
Test	100	24.01	62.81	4

Table 1: Dataset statistics for MM-CSConv. # of Dialog indicates the total number of dialogues in the subset. *Avg.* Tokens represents the average number of tokens per utterance from the Client and the Therapist. Rounds denotes the number of turns per dialogue in the subset.

Reflecting the characteristics of cognitive reframing counseling, which often involves addressing negative emotions, we excluded the "happy" expression from the 8 facial expressions in AffectNet. The matching between (image, facial expression) and (thinking traps, client's thought) was performed randomly with uniform distribution.

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#### 3.2 Data Quality Assurance

To ensure the quality of the MM-CSConv dataset, we conducted manual data cleansing with the three native speakers, focusing on four aspects (see Section B for detailed criteria). To this cleansing, we hired three English native speakers through Up-

	Empathy	Logical Coherence	Guidance	Overall
Human	2.929	2.980	2.879	2.929
GPT-4	2.920	2.930	2.400	2.420

Table 2: Human and GPT-4 evaluation results on MM-CSConv test set.

# work<sup>2</sup>, a crowdsourcing platform.

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Additionally, we evaluated the test set of the MM-CSConv dataset based on three criteria: empathy, logical coherence, and guidance, along with an overall score. Each criterion was rated on a scale from 0 to 3 following the manual provided by Xiao et al. (2024). The test set evaluation was conducted using both human and GPT-4 assessments. We hired an English-fluent psychotherapist for this evaluation and engaged the psychotherapist to manually evaluate the test set according to the manual. We also employed GPT-4 for evaluation, feeding it the scorecard criteria and the dialogues from the test set.

The statistics of the MM-CSConv dataset are shown in Table 1 and the evaluation results for the test set are presented in Table 2. Our MM-CSConv dataset comprises 429 conversations, each comprising precisely 4 turns. Notably, both human and GPT-4 show similar score ranges, guaranteeing the quality of our dataset.

# 3.3 Multi-hop Psychotherapeutic Reasoning

In real psychotherapy, psychotherapists typically understand the client's state before providing interventions and then provide interventions based on that. To mimic the real therapy process, we introduce multi-hop psychotherapeutic reasoning. This approach identifies implicit evidence crucial for cognitive reframing and incorporates it into stepby-step instructions. It then generates a response based on the client's status detected by the AI therapist as illustrated in Figure 3. In this study, we focus on three major aspects of the client's status: facial expression, thought, and thinking traps. Each evidence is annotated at the appropriate stage. The detected evidence is included in the client's status and the status is fed AI therapist as the prompt for the next evidence detection.

# 4 Experiments and Results

# 4.1 Experimental Settings

**Baseline Models.** Our experimental setup leveraged two types of model: LLaMA2-chat-7b (Touvron et al., 2023)<sup>3</sup> and LLaVA-v1.5-7b<sup>4</sup>, renowned as benchmarks in the domains of LLMs and VLMs respectively. 276

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For simplicity, we will refer to LLaMA2chat-7b as LLaMA2 and LLaVA-v1.5-7b as LLaVA throughout this paper. Additionally, we denote the versions of LLaMA2 and LLaVA that were trained on the MM-CSConv dataset as CS-LLaMA2 and CS-LLaVA, respectively. When multi-hop psychotherapeutic reasoning using facial expressions, thoughts, and thinking traps evidence is applied, we add (FE+TH+THT) to their names.

Hyper-parameter Settings. Both LLaMA2 and LLaVA are fine-tuned with LoRA on the MM-CSConv dataset. For LLaMA2, we used the default parameter settings, except for the number of epochs, employing the official models for open-source LLMs available from Hugging Similarly, for LLaVA, we applied the Face. default parameter settings, except for the number of epochs, as specified in the official code<sup>5</sup>. To determine the best epoch, we randomly split the MM-CSConv train set into training and validation subsets with an 80/20 ratio. The optimal epoch for each model was selected based on performance on the validation subset. All models were trained using  $4 \times A100$ -80GB GPUs with a training batch size of 32 per GPU. In this paper, all experiments were run using a fixed random seed of 42.

# 4.2 Evaluator

**GPT-4.** Recent research has shown that the evaluation of natural language generation (NLG) models using GPT-4 closely aligns with human evaluations. As a result, GPT-4 is increasingly used as a judge for NLG tasks across various domains, including common applications, medical fields, and mathematics (Liu et al., 2023; Sottana et al., 2023; Hsu et al., 2023; Khondaker et al., 2023; Xiao et al., 2024). In a recent study, Zheng et al. (2023) showed that GPT-4 achieves high agreement with

<sup>&</sup>lt;sup>3</sup>https://huggingface.co/meta-llama/ Llama-2-7b-chat-hf

<sup>&</sup>lt;sup>4</sup>https://huggingface.co/liuhaotian/llava-v1. 5-7b

<sup>&</sup>lt;sup>2</sup>https://www.upwork.com/

<sup>&</sup>lt;sup>5</sup>We use default parameter settings in https://github. com/haotian-liu/LLaVA/tree/main

	Empathy	Logical Coherence	Guidance	Overall	Avg.
LLaMA2	2.665*	2.390*	1.600*	1.540*	2.218*
LLaVA	2.640*	2.570*	1.790*	1.740*	2.333*
CS-LLaMA2	2.690*	2.410*	1.640*	1.580*	2.247*
CS-LLaVA	2.915*	2.890	2.380	2.400	2.728
CS-LLaVA (FE+TH+THT)	2.980	2.960	2.510	2.490	2.817
GPT-4 Vision	2.920	2.930	2.400	2.420	2.750

Table 3: Manual scoring result assessed by GPT-4 on the AI simulation testbed. Since the same evaluation method was used (Section 3.2), we attached GPT-4 Vision scores for comparison. The values of each model show a significant difference compared to CS-LLaVA (FE+TH+THT), with a p-value < 0.05 (\*) as determined by the paired t-test.

human judgment in evaluating conversation models. They also released the corresponding judging prompt and code used in their study<sup>6</sup>.

Building on this research, we evaluated the AI therapists using GPT-4 (API version)<sup>7</sup> as a judge in two ways:

- Manual Scoring: We adopt a threedimensional scoring system for the AI therapists, evaluating them on empathy, logical coherence, and guidance.
- **Pairwise Comparison**: We compared the interventions of therapists to determine whether Model A is better than Model B, vice versa, or if it's a tie, for all possible pairs.<sup>8</sup>

**Human.** To enhance the reliability of the intervention evaluation, we conducted human evaluations by domain experts. We hired two fluent Englishspeaking psychotherapists through Upwork. The experts performed a pairwise comparison between our CS-LLaVA with multi-hop psychotherapeutic reasoning and others. (see Section C)

### 4.3 Test Scenarios

Toward reliable comparison, We compared the performance of both LLMs and VLMs with two test scenarios: AI-simulation and MM-CSConv benchmark. The AI simulation testbed, which has been used in prior research, allows us to observe how interventions are carried out throughout conversations. However, using only the AI



Figure 4: Win rates assessed by GPT-4 on the AI simulation testbed

simulation testbed makes it difficult to clearly compare the abilities of the AI therapist due to the subjectivity of the AI client. To achieve our goal of comparing therapists' interventions in terms of empathy, logic, and rationality, we also compared therapists' interventions when given the same context by observing turnlevel performance on the MM-CSConv benchmark. 350

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### 4.3.1 Scenario 1: AI-Simulation

**Settings.** In this scenario, we employ ChatGPT (API version)<sup>9</sup> as an AI client to test our approach in AI-to-AI scenarios. For prompting to AI client, we leverage 100 resources which are used as base resources to build the test set, from Sharma et al. (2023) and Mollahosseini et al. (2019). The role of

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<sup>&</sup>lt;sup>6</sup>We utilize prompts from https://github.com/lm-sys/ FastChat/tree/main/fastchat/llm\_judge

<sup>&</sup>lt;sup>7</sup>We used the gpt-4-0613 version of the GPT-4 API.

<sup>&</sup>lt;sup>8</sup>To ensure fairness and prevent position bias, we tested each case twice, swapping the positions each time.

<sup>&</sup>lt;sup>9</sup>We used the gpt-3.5-turbo-0125 version of the ChatGPT API.

	Introduction		<b>Problem Exploration</b>		Brainstorming		Suggestion					
	Emp.	Coh.	Gui.	Emp.	Coh.	Gui.	Emp.	Coh.	Gui.	Emp.	Coh.	Gui.
LLaMA2	1.58*	1.79*	$0.80^{*}$	2.16	$2.20^{*}$	1.03*	2.10*	2.18*	1.44*	2.17*	2.06*	0.97*
LLaVA	0.64*	0.98*	$0.05^{*}$	1.94*	1.96*	1.12*	1.86*	1.99*	1.39*	2.21*	2.37*	1.50*
CS-LLaVA	1.87*	1.99	0.92*	2.15	2.24*	1.64	2.11*	2.25*	1.68	2.54	2.61	1.71
CS-LLaVA (FE+TH+THT)	2.11	2.16	1.02	2.23	2.39	1.60	2.27	2.39	1.79	2.59	2.67	1.80

Table 4: Manual evaluation results as assessed by GPT-4 at each stage on the MM-CSConv benchmark. **Emp.**, **Coh.**, and **Gui.** represent Empathy, Logical Coherence, and Guidance, respectively. The values of each model show a significant difference compared to CS-LLaVA (FE+TH+THT), with a p-value < 0.05 (\*) as determined by the paired t-test.



Figure 5: Win rates assessed by GPT-4 at each stage of the MM-CSConv benchmark.

the AI client is the same as the data construction method, and the prompt used is also the same.

In this scenario, we also compared the results of CS-LLaMA2 to evaluate the performance difference between using only the text modality and using both text and image information. For CS-LLaMA2, only the text modality was used, without incorporating image information.

**Results.** Table 3 shows the manual scoring results in the AI simulation scenario. With our MM-CSConv, the LLaVA family demonstrates significant improvements across all aspects. Furthermore, incorporating reasoning with three types of implicit evidence - facial expressions, thoughts, and thinking traps - led to performance enhancements across all evaluation aspects, with a significant improvement on the empathy aspect. This is quite close to the GPT-4 evaluation score for the MM-CSConv test set, showing that it's on par with GPT-4. For LLaMA2, there is almost no noticeable change before and after training with MM-CSConv, mainly because image information is not provided during the Introduction stage, leading to training failure. Based on these results, we anticipate challenges in effectively training LLMs with MM-CSConv, so we decided not to assess CS-LLaMA2 on the MM-CSConv

benchmark except for human evaluation settings.

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In the pairwise comparison using GPT-4 as a judge, LLaVA shows a significant improvement in the win rate, as illustrated in Figure 4 (see Section D for numerical win rates). There is no significant difference between LLaMA2 and CS-LLaMA2, and LLaVA shows the lowest win rate. Additionally, multi-hop psychotherapeutic reasoning slightly improves win rates and reduces loss rates. We also conducted a case study using our approaches and LLaMA2 (see Section E).

### 4.3.2 Scenario 2: MM-CSConv benchmark

**Settings.** In this testbed, each AI therapist responds to the same dialogue history to directly compare their interventions. To ensure reliability, we conducted evaluations using both GPT-4 and two human psychotherapists. The evaluation is carried out at the turn level for each stage. Similar to the AI simulation testbed, we present win rate results alongside manual scores.

To further strengthen the reliability of the human evaluation results, we derived the win rate by comparing the proposed methodology with other approaches. Specifically, we compared CS-LLaVA with multi-hop psychotherapeutic reasoning to other baselines and to CS-LLaVA with standard prompting, as evaluated by two experts.



Figure 6: Win rates against CS-LLaVA (FE+TH+THT) assessed by two psychotherapists on the MM-CSConv benchmark. The domain experts are asked to choose which intervention is better at assessing the given intervention.

Table 4 shows the performance of **Results.** manual scoring evaluated by GPT-4 at different stages. The score distribution is lower than that of the AI simulation testbed because it evaluates intervention at the utterance level rather than the entire conversation. Figure 5 illustrates the result of pairwise comparison among the four models under the GPT-4 judge (see Section F for numerical win rates). The performance difference due to prompting is most evident in the Introduction and Suggestion stages, and the performance difference due to the use of MM-CSConv is clearly visible in all stages. In both cases, our approach consistently outperforms the baseline models at all stages except for the Problem Exploration stage. Similar to the manual scoring results, LLaVA shows the lowest win rate in the Introduction stage, supporting our hypothesis that LLaVA may lack the ability to express empathy using the client's non-verbal information.

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However, considering both manual scoring and pairwise comparison, standard prompting tends to slightly outperform multi-hop psychotherapy reasoning in the Problem Exploration stage. The Problem Exploration stage involves additional exploration of the client's situation using facial expression evidence, which seems to improve empathy but not other evaluation criteria.

Figure 6 shows the pairwise comparison results between CS-LLaVA (FE+TH+THT) and other baseline models. The effectiveness of our approach is strongly supported by the fact that all models have significantly fewer wins and significantly more losses. Table 5 presents the results of human evaluation at each stage. CS-

	Win Rate (%)				
	Intro.	Explo.	Brain.	Sugg.	
LLaMA2	10.0	25.5	32.0	10.0	
LLaVA	2.5	2.0	17.5	30.0	
CS-LLaMA2	12.0	22.5	29.5	12.0	
CS-LLaVA	29.0	54.0	39.0	43.0	

Table 5: Win rates against CS-LLaVA (FE+TH+THT) as evaluated by two psychotherapists at each stage of the MM-CSConv benchmark.

LLaVA (FE+TH+THT) shows the most superior performance. While LLaMA2 and LLaVA had significantly lower win rates against CS-LLaVA (FE+TH+THT) in all stages, CS-LLaVA outperformed CS-LLaVA (FE+TH+THT) in the Problem Exploration stage. 457

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# 5 Conclusion

In this paper, we explored cognitive reframing therapy within a multimodal context. Recognizing the gap between real face-to-face cognitive reframing therapy and prior research, as well as the potential benefits of AI in psychotherapy, we aimed to enhance the therapeutic capabilities of AI therapists by incorporating non-verbal cues, particularly facial expressions, into the intervention process.

Our extensive experiments across two test scenarios, AI Simulation and the MM-CSConv benchmark, indicate significant improvements in the therapeutic capabilities of VLMs when using MM-CSConv. The multi-hop psychotherapeutic reasoning approach, which integrates facial expressions, thoughts, and thinking traps, demonstrated superior performance in providing empathetic, logically coherent, and specific rational suggestions to clients.

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# 6 Limitations

We expanded the concept of cognitive reframing 482 into multimodality, demonstrating that incorporat-483 ing multimodal evidence and multi-hop psychother-484 apeutic reasoning significantly enhances the thera-485 pist's abilities. However, these results were limited 486 487 to virtual clients whose facial images and dialogues were consistent. This controlled setting may not 488 fully capture the complexities of real-world interac-489 tions. We used benchmark images for facial expres-491 sion recognition, but capturing the facial expres-492 sions of real clients can be challenging and might affect the consultation's content. Moreover, our 493 study only utilized facial images as the source of 494 495 non-verbal information, which presents a limitation in comparison to actual face-to-face cognitive 496 reframing therapy. Real-life therapy involves a 497 broader spectrum of non-verbal cues, such as body 498 language, tone of voice, and other contextual fac-499 tors, which were not accounted for in our research.

For future work, we plan to expand the modalities to include a wider range of non-verbal information. By incorporating diverse non-verbal cues, we aim to further enhance the model's ability to mimic real-life therapy scenarios. This will help bridge the gap between virtual and actual consultations, ultimately enabling the model to learn how to effectively utilize non-verbal information in a more realistic setting.

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### **Overall Trait** Α

We introduced the Overall score as a metric to assess the therapist's overall ability, with the calculation method illustrated in Algorithm 1. e, c, g stand for empathy, logical coherence, and guidance.

Algorithm 1 Overall Score Calculation

**function** GETOVERALLSCORE(*e*, *c*, *g*) if  $e \leq 1$  or  $c \leq 1$  then return 0 end if if  $(e \ge 2$  and  $c \ge 2)$  and  $g \le 1$  then return 1 end if if  $(e \ge 2$  and  $c \ge 2$  and q == 2) then return 2 end if if  $e \ge 2$  and  $c \ge 2$  and g == 3 then return 3 end if end function

### B **Data Cleansing Manual**

Data cleansing guidelines are shown in Table 7. Image-Dialog Consistency is a criterion that evaluates whether the client's visual information and dialogue are consistent. If any of the four criteria received a score of 0, the corresponding data was deleted, and the Image-Dialog Consistency of the MM-CSConv is shown in Table 6.

	Image-Dialog Consistency
Train	1.472
Test	1.667

Table 6: Image-Dialog Consistency on the MM-CSConv dataset.

### С **Details for Human evaluator**

# C.1 Hiring and Payment

We hired a total of three psychotherapists, and paid \$0.8 per conversation for dataset evaluation and \$0.0625 per data entry for pairwise comparison.

### C.2 Instructions for MM-CSConv evaluation

We provided domain experts with instructions for evaluating the MM-CSConv test set, as illustrated in Figure 10.

### **C.3 Instructions for Human pairwise** comparison

We provided the other two experts with instructions for conducting human pairwise comparisons, as shown in Figure 11. The evaluation sheet provided to them included only Dialog history, Response A, Response B, and Question ID, without revealing information about Model A and Model B. Additionally, to prevent bias based on position, Model A and Model B were randomly assigned for each data entry.

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### D Numerical results of pairwise comparison on AI-simulation assessed by GPT-4.

In Table 8, we have provided the numeric results as additional data for Figure 4. When comparing the comparison results for each model pair, CS-LLaVA (FE+TH+THT) showed a win rate exceeding 50%, outperforming all models.

#### Ε **Case Study in AI-Simulation**

We conducted additional analysis on test cases to compare our approaches with the LLaMA2, one of the baseline models. Figure 7 displays the full conversation between LLaMA2 and an AI client, while Figure 8 shows the complete conversation between CS-LLaVA and an AI client. Additionally, Figure 9 presents the entire conversation between CS-LLaVA (FE+TH+THT) and an AI client. These three conversations were generated using the same base resource in the AI simulation testbed.

LLaMA2 offers unconditional consolation, as it lacks the capability to utilize client information in the initial stage. In contrast, both CS-LLaVA and CS-LLaVA (FE+TH+THT) demonstrate more specific empathy. The client in these scenarios exhibits cognitive distortions of the overgeneralization type. With LLaMA2, the response involves merely engaging in conversation. However, CS-LLaVA and CS-LLaVA (FE+TH+THT) go further by encouraging the client to explore alternative ideas. Furthermore, CS-LLaVA (FE+TH+THT) not only promotes alternative thinking but also prompts the client to reflect on whether they have made similar misjudgments in the past.

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# F Numerical results of pairwise comparison on MM-CSConv assessed by GPT-4.

718In Table 9 and Table 10, we have provided the719numeric results as additional data for Figure 5.720When comparing each model pair, CS-LLaVA721(FE+TH+THT) showed a win rate that surpassed722other models, similar to the AI-simulation testbed723results.

Metric	Description	Scale
Client-clarity	The client expresses his or her situation clearly in the conversation	1/0
Client-role	The client adheres to the role of the client throughout the conversation.	1/0
Therapist-role	The therapist adheres to the role of the therapist in all conversations.	1/0
Image-Dialog Consistency	There is no consistency between the client's facial image and the client's utterances or situation. The client's facial image is relevant to neither the client's utterances nor the client's situation.	0
	There is acceptable consistency between the client's facial image and the client's utterances or situation.	1
	There is strong consistency between the client's facial image and the client's utterances or situation.	2

Table 7: Guideline for data cleansing in MM-CSConv. *Client-clarity*, *Client-role*, and *Therapist-role* are assigned 1 if they match the description, and 0 otherwise.

	LLaMA2	LLAVA-7b	CS-LLAMA2	CS-LLAVA	CS-LLAVA (FE+TH+THT)	Win Rate
LLAMA2	-	52.551	49.495	9.694	9.794	30.485
LLAVA-7b	47.449	-	49.485	6.566	7.071	27.481
CS-LLAMA2	50.505	50.516	-	10.309	7.071	29.592
CS-LLAVA	90.306	93.434	89.691	-	47.959	80.357
CS-LLAVA (FE+TH+THT)	90.206	92.929	92.929	52.041	-	82.061

Table 8: Numerical results of pairwise comparison of five models on the AI-simulation testbed, evaluated using GPT-4.

	Win Rate (%)				
	Introduction	<b>Problem Exploration</b>	Brainstorming	Suggestion	
LLaMA2	44.767	22.222	42.701	29.740	
LLaVA	3.529	37.770	35.907	46.539	
CS-LLaVA	69.336	72.119	60.256	57.617	
CS-LLaVA (FE+TH+THT)	82.101	68.978	60.478	67.671	

Table 9: Win rates at each stage on the MM-CSConv benchmark, evaluated using GPT-4.

	LLaMA2	LLAVA-7b	CS-LLAVA	CS-LLAVA (FE+TH+THT)	Win Rate
LLAMA2	-	54.096	27.562	22.877	34.676
LLAVA-7b	45.904	-	25.710	21.676	31.179
CS-LLAVA	72.438	74.290	-	47.067	64.848
CS-LLAVA (FE+TH+THT)	77.123	78.324	52.933	-	69.677

Table 10: Numerical results of pairwise comparison of four models on the MM-CSConv benchmark, evaluated using GPT-4.



Figure 7: A case study between an AI Client (ChatGPT) and LLaMA2. The red shading highlights the client's distorted thoughts, while the yellow shading emphasizes the key components of the therapist's intervention.

Client Therapist Client Therapist	Hello. I notice there's a hint of sadness in your expression. Whenever you feel ready, let's talk about what's been troubling you. I'm here to listen and support you. I feel like she doesn't respect me. It seems like no matter what I do, she always dismisses my opinions and never takes me seriously. I start to think that maybe I'm not worthy of respect at all. I see that you're feeling quite down about this situation. It's important to recognize that your feelings are valid, but let's try to look at the situation separately from the thoughts it's bringing up. Can you tell me more about the specific instances where you felt disrespected?
Client	I can't shake off the feeling of being unworthy.
Therapist	I understand that feeling unworthy can be really tough. Let's explore other perspectives. Could it be possible that she's dealing with her own stress or challenges that are affecting her behavior? Or maybe she's not aware of how her actions are coming across. What are some other reasons she might be dismissing your opinions that aren't about your worth?
Client	It's hard for me to consider other reasons for her behavior towards me, but I suppose it's possible that she might be under a lot of stress or facing her own challenges that are impacting how she interacts with me. Maybe she's not intentionally trying to disrespect me.
Therapist	I'm really impressed with your willingness to consider alternative explanations for her behavior. It's a significant step to recognize that her actions might not be a reflection of your worth. It's also important to remember that everyone has their own struggles, and it's possible that she's dealing with her own challenges that are affecting her interactions with you. Let's continue to explore these perspectives and see if they help you feel more understood and respected.

Figure 8: A case study between an AI Client (ChatGPT) and CS-LLaVA.



Figure 9: A case study between an AI Client (ChatGPT) and CS-LLaVA (FE+TH+THT).

### Overview

We built a multimodal cognitive reframing conversation dataset using LLMs for research purpose As this is a conversation created by LLM, data verification is required.

### **Job Description**

- You will be provided with 100 conversations, each accompanied by a corresponding facial image. :
- The conversation focuses on CBT, with the therapist working to reframe the client's distribution that in the provided manual.

### Evaluation traits

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lease ra	te the items below:
	Empathy
0 points:	The therapist disregards the content and feelings expressed by the client.
1 point:	The therapist may rephrase the client's content but remain oblivious to the emotions.
2 points:	The therapist provides responses that involve rephrasing both the content and feelings.
3 points:	The therapist can gather all signals and respond in a different way effectively.
	Logical Coherence
0 points:	Lack of logic and coherence, with a conversation that fails to focus on the client's issues, containing severe logical errors, contradictory viewpoints, or excessive subjectivity.
1 point:	The conversation shows some reasoning, but overall coherence is weak, with some logical errors, insufficient capturing of evidence from the client's statements, or unclear expressions.
2 points:	Good logical coherence, relatively clear and consistent conversation based on sufficient evidence and reasonable assumptions. While there may be minor logical issues, the overall argument is convincing.
3 points:	The therapist demonstrates strong logical coherence, with rigorous, coherent, and reasonable reasoning based on ample evidence and clearly defined premises. The conversation contains no logical errors or contradictory viewpoints, with a clear, powerful, and persuasive conclusion.
	Guidance
0 points:	Suggestions lack specificity and practicality, with no clear goals, implementation plans, or consideration of relevant factors and real-world situations.
1 point:	Suggestions are somewhat specific and practical, offering basic guidance. However, they may lack detail o specificity.
2 points:	Suggestions are highly targeted and practical, providing detailed and feasible implementation plans and recom- mendations tailored to the client's specific problems or needs

Intensions universe on the current's spectra proventies on necess. Suggestions are extremely targeted and practical, considering various factors and real-world situations, demon-strating high feasibility and operability. Additionally, the therapist offers guidance and insights into the client's future development and improvement.

### One example of the conversation

and. I will try to separate my thoughts about being judged from the actual event of char uve taken. Now, can you think of other ou re the change or see you as bold for trying win lives to notice much, meaning the jud ves before. It's possible that p



### **Output File**

Once the contract is signed, we will provide a Google spreadsheet for grading.

1	dialog_id	Empathy	Logical Coherence	Guidance	
2	dialog_7				
3	dialog_16				
4	dialog_17				
5	dialog_19				
6	dialog_23				
7	dialog_24				
8	dialog_25				
9	dialog_26				
10	dialog_30				
11	dialog_33				
12	dialog_41				
13	dialog_42				
14	dialog_43				
15	dialog_48				
16	dialog_51				
17	dialog 66				

### Figure 10: Instruction for human dataset evaluation.

### Overview

We would like to build an AI model that performs cognitive reframing. We hire experts to compare and evaluate multiple AI models that perform cognitive reframing conversations. The evaluation results will be used for research purpose.

You are given 1600 triplet (guestion id, response A, response B). If you check the pdf file with the same question\_id (to be provided), there is a record of the previous dialogue history. (Each AI model responded according to its previous dialogue history.) As an expert, please choose which of the two responses is better (A, B, or Tie)

### Job Description

- The conversation focuses on CBT, with the therapist working to reframe the client's
- The conversation rouses on OS1, must are uncoper money a conversation rouse of OS1, must are uncoper money a conversation of the distorted thinking. We will provide 1600 pairs of AI model responses. If you look at the Google Spreadsheet, each entry has **question\_id**, **response A**,
- and response B.
- There is a pdf file corresponding to question\_id (e.g. dialog;7-tum.0 and dialog\_7-tum.0.pdf ), and the pdf file contains the context of the previous conversation and the client's face image. Please select the response that best suits the conversation context and the client's
- facial expression contained in the pdf file. (A, B, or Tie)

### Evaluation traits

There is no exact evaluation trait, but please mainly observe empathy, logical coherence, and rationality.





### Output File

Once the contract is signed, we will provide a Google spreadsheet for grading



Figure 11: Instruction for human pairwise comparison.