When and How to Integrate Multimodal Large Language Models in College Psychotherapy: Feedback from Psychotherapists in China

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As mental health issues rise among college students, there is an increasing interest and demand in leveraging Multimodal Language Models (MLLM) to enhance mental support services, yet integrating them into psychotherapy remains theoretical or non-user-centered. This study investigated the opportunities and challenges of using MLLMs during campus psychotherapy in China. Through a study involving 15 therapists with different levels of experience, we argue that the ideal role for MLLMs at this stage is an auxiliary tool to human therapists. Users widely expect features such as triage matching and real-time emotion recognition. At the same time, therapists still remain cautious about their role in providing deep emotional support and making complex decisions. Our findings further indicate that users' sense of social identity and perceived relative status of MLLMs significantly influence their acceptance. This study provides insights for future intelligent campus mental health care.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**; **User studies**; • **Applied computing → Consumer health**;

Additional Key Words and Phrases: mental health, college psychotherapy, multimodal large language model, interview study

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1 INTRODUCTION

Mental disorders remain among the top 10 causes of burden globally, with no evidence of a reduction globally since 1990 [52]. In 2019, the World Health Organization (WHO) reported that approximately 970 million people suffered from mental health disorders [47]. Particularly, as late adolescence or early adulthood (e.g., alcohol and substance abuse [65] are more sensitive to emotional stimuli [9, 31]), college students have an even higher incidence of mental disorders [21, 30, 34]. For example, in the U.S., depression affects 17.3% of undergraduates, and anxiety and depression often co-occur [20, 40]. In response to students' increasing mental health concerns, traditionally, face-to-face campus counseling and mental health services are considered an effective way [67]. However, many college students fail to seek timely help even when counseling centers are available on campus [30]. The reasons include social stigma [10, 11], personal emotional barriers, and financial challenges associated with face-to-face counseling [16]. Further, in some special periods, for example during the COVID-19 pandemic, physical isolation hinders college students from seeking and receiving help [13, 19].

With the rapid development of artificial intelligence (AI), researchers attempted to integrate AI into psychotherapy to support those in need. Particularly, as an effective information extraction tool, AI can also be used to accelerate the identification and treatment of mental disorders for both psychotherapists and users [4, 41]. For instance, text

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sentiment analysis can understand users' current state quicker, which can assist psychotherapists in making more accurate interventions, and allows users to identify their emotional problems earlier and seek mental health support in a timely manner [32]. Moreover, the use of chatbots driven by natural language processing (NLP) and machine learning (ML) complement the role of clinicians [27]. These chatbots mimic human conversations, allowing individuals to interact with them for support and guidance on their mental health needs at any time [64], and anywhere (e.g., at home via users' own mobile devices [42]). Additionally, being different from human counselor-patient therapy [7], some researchers [32, 38, 41] have also attempted to construct conversational AI agents that can provide autonomous therapy. This kind of agent is expected to have the ability to independently deliver complete psychotherapeutic services like a human expert. Despite these, limited by the technology, conversational chatbots or AI tools based on traditional NLP is difficult to perceive the client's shifts of engagement and emotion from information in other modalities; therefore the therapeutic effect would be significantly reduced if no human was involved [35]. Recently, the superior and impressive performance of the large language model (LLM) (e.g., GPT4-o[1]) in content generation [61, 62], sentiment analysis [66], and multi-modal perception [29] proved their great potential in mental health compared to tools or chatbots powered by traditional NLP [3]. Especially, based on the extremely high similarity obtained from a large number of studies comparing fine-tuned LLM-generated responses with human experts, researchers have begun to experiment with training LLM psychotherapists based on Cognitive behavioral therapy (CBT) [14, 46].

Although the latest multi-modal LLMs (MLLM) with improved capabilities bring new opportunities, there are still concerns when they are used in the field of mental health. As concluded by [23], there are still no mature clinically integrated solutions for AI-enabled psychotherapy. Although there have been some attempts to evaluate existing integration schemes of MLLMs, most of them have been limited to analyzing them in terms of technical-type metrics (e.g., coherence of model-generated content, similarity to human experts, etc.) or theoretical discussions [2, 28, 56]. However, psychotherapy always involves human interaction [23]. Given that the introduction of MLLM will have a huge impact on the existing therapy, the high prevalence of mental health problems in college students, and the greater acceptance of new technologies by young people [12], a comprehensive understanding of the attitudes, needs, and concerns of the stakeholders regarding the adoption of AI in psychotherapy is critical to designing psychotherapy tools. Such understanding can speed up the validation and dissemination of new MLLM-based psychotherapy solutions and thus benefit college mental health.

In this study, we conducted focus group interviews with 15 therapists specializing in college student mental health to answer the following research questions: (1) What are therapists' expectations of how to integrate current MLLMs into the psychotherapy workflow? (2) What functions should mental health MLLMs have to reach therapists' expectations? (3) What concerns do therapists have about applying MLLMs to psychotherapy? Our findings can provide insights into the function and application design of future MLLM-based mental health products for college psychotherapy.

2 RELATED WORKS

In the field of mental health, face-to-face campus counseling and mental health services are considered an effective solution to support students' increasing needs on mental health services [67]. With the rise of AI, researchers have explored the adaptation of AI in psychotherapy activities. For example, machine learning techniques have been used in mental health tools and the researches covered a variety of topics, including counselor adaptability and effectiveness [49], the distinction between personalized and standardized counseling language [5], shifts in psychological perspectives

[1] https://openai.com/index/hello-gpt-4o/

and topic adherence [5, 60], therapeutic interventions [37], empathy expression [55], transformative moments [51], counseling approaches [48, 53], and conversational involvement [54]. AI systems can analyze various types of behavioral data such as video, audio, and text from therapy sessions. This allows clinicians to receive immediate insight and feedback without relying on patients to complete extra self-report measures. Studies have shown that AI systems can accurately predict patient-reported alliance and symptom ratings based on behavioral markers extracted from video recordings of psychotherapy sessions. Verbal features [1, 22, 59], body and facial movements [15], have all been considered as directly associated with self-reported measures of the working alliance.

Recently, impressed by the outstanding performance of LLM in many fields [36, 50, 61], some studies tried to develop LLM-based tools to participate in traditional face-to-face psychotherapy. Particularly, in addition to classic functions like emotion recognition [44] and information retrieval [56], other advanced functions (e.g., LLM-based tools for counseling psychotherapists supervision [39], conversational topic recommendation in counseling [24], psychotherapists training [63]) are emerging.

However, although a small number of studies [23, 25] have mentioned the challenges of integrating large language models into traditional counseling modes, to the best of our knowledge, there is still a lack of user-centered (human psychotherapists and clients) research evaluating the current LLMs from the perspective of treating LLMs as supportive artificial intelligence systems in the context of human-computer interaction.

3 METHODOLOGY

In this study, we aimed to investigate proper ways of integrating MLLM into psychotherapy from the perspectives of college psychotherapists, and their demands and perceived barriers to applying MLLM for psychotherapy. Therefore, a focus group interview on psychotherapists was conducted to gather human therapists' comments and suggestions about current MLLM-based involvements in college mental health therapy. The whole experiment was approved by the Ethics Committee of the university.

Table 1. Demographic Information of the Interviewed Psychotherapists.

ID	Age (years)	Gender	Work Experience (years)	Therapeutic Orientation
J1	28	Female	3-5	Humanistic Therapy
J2	27	Female	3-5	Cognitive Behavioral Therapy
J3	28	Female	3-5	Cognitive Behavioral Therapy
J4	29	Female	3-5	Family Systems Therapy
J5	27	Male	3-5	Humanistic Therapy
M1	34	Female	5-10	Humanistic Therapy
M2	38	Female	5-10	Psychoanalytic Therapy, Humanistic Therapy
M3	34	Female	5-10	Humanistic Therapy, Solution-Focused Therapy
M4	37	Male	5-10	Humanistic Therapy, Psychodynamic Therapy
M5	31	Female	5-10	Cognitive Behavioral Therapy
S1	60	Female	>10	Humanistic Therapy
S2	51	Male	>10	Psychodynamic Therapy
S3	44	Female	>10	Humanistic Therapy, Family Systems Therapy
S4	37	Male	>10	Psychoanalytic Therapy, Cognitive Behavioral Therapy
S5	47	Female	>10	Cognitive Behavioral Therapy, Mindfulness-Based Therapy

Notes: 'J' means the junior therapist group; 'M' stands for mid-career therapist; and 'S' is senior therapist group.

3.1 Participants

We recruited 15 psychotherapists (4 males and 11 females) who are currently working for different universities in mainland China and have MLLM usage experience. The description of each psychotherapist and the corresponding profile can be found in Table 1. Particularly, as previous studies pointed out that professional experience might contribute to varied attitudes to computerized psychotherapy [43], we expect to further compare and analyze the similarities and differences of views from groups of psychotherapists with different levels of working experience. Thus, we divided them into three groups according to their years of experience: 3-5 years (Junior therapist group, J), 5-10 years (Mid-career therapist group, M), and more than 10 years (Senior therapist group, S) [57]. Each group consisted of 5 participants. Moreover, referring to their self-reported therapeutic orientation, to eliminate the difference between therapy styles [8] and extract consensual within the group, we tried to balance the psychotherapists' distribution of therapeutic orientation within each group.

3.2 Procedures

Each focus group session lasted approximately 90 minutes and was moderated by two experienced researchers: one with a background in computer science and the other in psychology. The focus group study was held from April to May of 2024 via the online video meeting tool, the Tecent Meeting[2]. Upon entering the virtual meeting room, we notified them about the details of the interview, and obtained their consent and demographic information through an online questionnaire. Then, moderators introduced the purpose of the study, explained the discussion process, and emphasized confidentiality and their right to withdraw at any time. Next, a short video introducing MLLM and its functions that might be related to psychotherapy (e.g., multi-modal emotion perception, emotional soothing) was played before the interview.

After the interview began, each participant was asked to introduce themselves to others briefly. Then, participants were first asked about their attitudes toward using MLLMs in campus psychotherapy. This was followed by discussions about how to divide campus psychotherapy into different phases, and which specific phases the LLMs could be applied, particularly in addressing common mental health issues in universities. As there is no therapist in daily counseling and autonomous therapy theoretically, we did not design specific questions for these two types of MLLM. We then queried their opinions on essential features and functions that can make MLLMs effective in campus psychotherapy. Finally, participants gave their own opinions about potential challenges and concerns related to the use of MLLMs. The whole interview was audio-recorded, transcribed, and supplemented with field notes to capture non-verbal cues and group dynamics.

3.3 Analysis and Coding Methods

The data was analyzed using a rigorous thematic analysis procedure. The process began with transcribing audio recordings from Tencent Meeting into texts, ensuring accuracy through careful calibration with the original audio. Two researchers independently reviewed the transcripts and employed a combination of deductive and inductive coding techniques. Firstly, drawing on the research questions and interview guide, four overarching themes were established: attitude, scenario, function, and challenges. The researchers then independently coded segments of the interview data related to these themes. Simultaneously, we engaged in open coding, identifying key concepts and assigning descriptive labels to relevant text portions. Through iterative discussions, we reconciled the codings, merged frequently occurring

[2]https://voovmeeting.com/

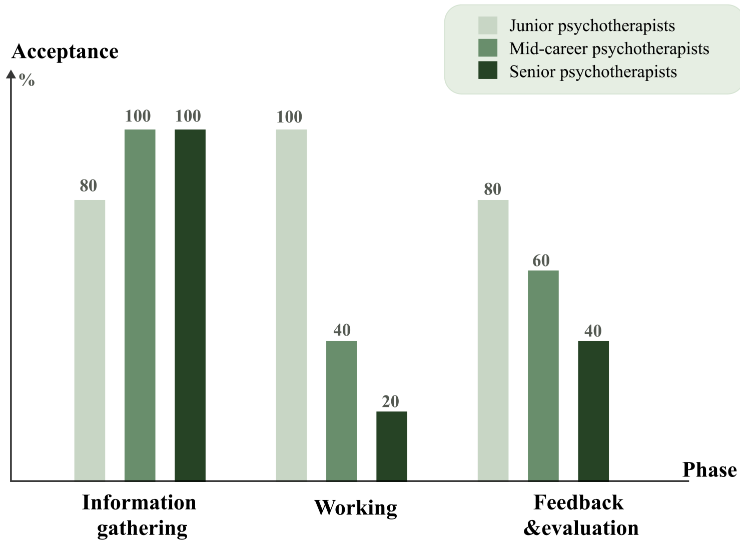

Fig. 1. Statistics about psychotherapists' views of MLLM application scenarios in campus psychotherapy.

labels, and developed a comprehensive codebook. This codebook was further refined through discussions with the broader research team. To further guarantee the quality of the analysis, a third researcher independently reviewed the coding framework. Quantitative results were also concluded to examine the frequency, distribution, and relationships between codes. Finally, the research team synthesized findings from both the qualitative and quantitative analyses, drawing connections between the themes and exploring key patterns. It is important to note that the semi-structured nature of the interviews allowed for flexibility in questioning. Consequently, not all participants responded to the same set of questions. Therefore, the analysis focused on the specific subset of participants who provided relevant data for each code and theme, rather than the entire pool of 30 interviewees.

4 RESULTS

4.1 Application phases

As shown in Figure 1, in the information gathering phase of psychotherapy, most junior psychotherapists recognized the potential of MLLMs. Junior therapist J4 remarked, *"The first step in information gathering is to understand the client's family background and developmental history... I personally think this step can be supported by MLLMs."* Mid-career and senior psychotherapists also agreed on the suitability of MLLMs for this phase. Mid-career therapist M5 noted, *"After collecting the basic questions and information, MLLMs can match the client with a suitable psychotherapist... I think this approach can significantly reduce the initial investment of manpower and resources."* Senior therapist S1 suggested, *"When students are waiting for an appointment, they might fill out a form... they could be guided to download and complete an assessment themselves while in the waiting room."*

During the working phase, junior psychotherapists agreed on the applicability of MLLMs. J4 suggested, *"During the working phase, I think MLLMs can help with the unidirectional collection of repeated information… The second aspect is providing prompts... MLLMs might help enhance the completeness or fluency of my output."* However, fewer psychotherapists in mid-career and senior groups recognized the applicability of MLLMs in this phase. For example, senior therapist S3 highlighted, *"If MLLMs could be employed in crisis assessment, it would significantly reduce the pressure on psychotherapists."*

In the feedback and evaluation phase, most junior therapists indicated they would use MLLMs for support. Junior therapist L3 remarked, *"During the termination phase, clients might also provide MLLMs with feedback on their progress... I think it's important to observe from multiple perspectives to understand how well their action plan has been executed."* Among mid-career therapists, more than half believed MLLMs are helpful, with mid-career therapist M2 stating, *"In the final termination phase, dealing with common termination procedures and evaluating and providing feedback (with MLLMs) ... is, in my opinion, appropriate."* However, only a few senior therapists discussed the applicability of MLLMs in this phase.

4.2 Expected Function

In general, psychotherapists emphasized the importance of robust triage functionalities in MLLMs, which involves initial assessment and categorization of a client's symptoms. Junior therapist J2 noted, *"I believe that for MLLMs to effectively identify such situations, they must classify the clients accordingly... If the client suffers from conditions that might blur their subjective awareness and objective reality, an additional follow-up questioning phase is required."* Additionally, the triage function can assist psychotherapists by providing initial recommendations for further inquiry or intervention, helping to ensure that clients receive the most appropriate care based on their specific needs. S4 further elaborated, *"When a client is unable to distinguish between subjective and objective aspects of a particular issue... it would be beneficial to ask additional questions regarding general knowledge."*

Besides, therapists with different experience levels all expressed a strong desire for MLLMs to incorporate emotional support functionalities. Junior therapist J3 suggested, *"I believe that more precise and varied forms of emotional support could better assist the counseling process, making it more akin to emotional exchanges between individuals."* Similarly, in the Mid-Career group, M4 mentioned, *"For example, turning on a camera could provide a sense of interaction."* Additionally, there were two therapists expressed a preference for music options. For instance, S2 remarked, *" When a client is excessively anxious and tense... MLLMs could employ relaxation training techniques to substitute the psychotherapist... These techniques could include small methods for emotional stabilization."*

Psychotherapists highlighted the need for MLLMs to include monitoring and suggestion functions to assist in the therapeutic process. J1 stated, *"MLLMs can assist psychotherapists by monitoring the counseling process, recording the content of sessions, and capturing various non-verbal cues... such as gestures, tone, and facial expressions."* M3 also emphasized the importance of enabling MLLMs to assess whether the current situation is suitable for further intervention and determine the severity of the issue. She noted, *"As a psychotherapist if I wish to delegate some tasks... it would be very helpful if MLLMs could accurately record the key points of each session and even provide suggestions for the next stage."* They also mentioned that theoretical guidance could be provided in these suggestions. For example, M2 mentioned, *"I hope MLLMs can offer robust models to guide the counseling process."* This perspective was also supported by more than half of senior psychotherapists, with S2 stating, *"The ideal tool would offer a wealth of theoretical frameworks... This would provide valuable reference material for me. I hope it has a retrieval function."* The other two therapists also expressed their support for this functionality.

4.3 Concerns

Psychotherapists widely expressed concerns about potential breaches of client data confidentiality when using MLLMs, especially in online therapy environments where the risk of data leakage is higher. Across all three groups, half of psychotherapists highlighted this issue. For example, in the senior group, S3 stated, *"This violates the ethical principles of psychotherapy... Our confidentiality protocols, including recording sessions, require the client's explicit consent."* They were also concerned about whether MLLMs could effectively manage transference (i.e., a psychological phenomenon where an individual unconsciously redirects feelings and expectations from past relationships onto a current relationship, often seen in therapy). In the junior group, some therapists questioned this ability, and in the mid-career group, a few therapists expressed similar concerns. As junior therapist J2 questioned, *"If an MLLM is used to provide psychotherapy through an app, and the client develops transference towards the MLLM, how should this be addressed? ... MLLMs may not necessarily recognize when transference occurs."*

Furthermore, therapists believe that MLLMs may struggle to establish deep emotional connections with clients. Junior therapist J1 stated, *"My concern is that humans will never be able to establish a true emotional connection with machines."* Most of the interviewees in the mid and senior-career groups mentioned this concern. S3 mentioned, *"In psychotherapy, much of what we do involves the warm emotional flow between humans. An MLLM may not be able to provide such an emotional flow..."* Concerns were also raised about the lack of flexibility in MLLMs, as junior therapist J3 expressed, *"I am concerned that MLLMs may offer similar advice to many clients, lacking the ability to provide more individualized and targeted guidance."* S1 in the senior group also noted, *"The advice provided by MLLMs may not always be as precisely targeted as needed."*

5 DISCUSSION

5.1 Attitudes from Human Therapists

The qualitative analysis reveals a nuanced perspective among therapists regarding the application of MLLMs in psychotherapy. Generally, therapists recognize the potential of MLLMs to support certain aspects of psychological counseling, such as information gathering and feedback analysis. However, as therapists' experience levels increase, their attitudes become more cautious. This caution is likely influenced by their accumulated experience and understanding of the complexities involved in psychotherapy [17]. Senior therapists, in particular, express concerns about MLLMs' ability to handle tasks requiring deep emotional support and complex decision-making, areas where human intuition and empathy are crucial. This aligns with the Computers Are Social Actors theory, which suggests that the perceived social status of MLLMs can influence acceptance [45]. However, in tasks requiring emotional intelligence and autonomous decision-making, therapists remain skeptical of MLLMs' capabilities [58].

5.2 Functionality Demands from Therapists

Therapists across different experience levels express a consistent demand for MLLMs to enhance their capabilities in specific therapeutic phases. In the information gathering phase, therapists expect MLLMs to assist in efficiently collecting and analyzing client data. During the working phase, there is a demand for MLLMs to support tasks such as real-time emotion detection and emergency management, though senior therapists are more reserved about this application. In the feedback and evaluation phase, therapists emphasize the need for MLLMs to aid in summarizing treatment processes and consolidating results. These functions require MLLMs to demonstrate robust content comprehension and generation capabilities, which are already prevalent in other domains [61].

Therapists also highlight the importance of customizing treatment plans based on client heterogeneity, with a particular emphasis on intelligent triage [33, 68]. Future MLLMs could improve the quality of psychotherapy services by integrating information from therapists and clients to facilitate two-way matching.

5.3 Concerns Regarding Current MLLMs

Therapists express significant concerns about the current MLLMs' ability to provide emotional support and ensure privacy and ethical security. These concerns are consistent with previous studies on AI tools [18, 23]. Establishing deep emotional connections and managing transference are critical in psychotherapy, and therapists doubt MLLMs can handle these independently. Despite the potential of MLLMs to perceive multimodal information, therapists believe there is room for improvement in emotional intelligence and conversational depth. Future MLLMs could benefit from incorporating real human experiences and case studies to enhance empathy and persuasiveness.

Privacy and ethical considerations are paramount, as psychotherapy involves sensitive personal information [6]. Ensuring data security and building trust in MLLMs' privacy protection mechanisms remain significant challenges. While technical solutions like privacy claims and federated learning exist, user skepticism persists [26].

6 LIMITATIONS

In this paper we have attempted to gain perspective from the therapist's point of view, however, there are other stakeholders in the therapeutic process, i.e. the student clients. Therefore, in the future, we plan to conduct a larger scale survey and interviews from the student clients's perspective in order to evaluate the MLLM intervention from the perspective of a complete existing human therapeutic alliance. Finally, the research methodology of this paper is interviews. Empirical experiments are still needed to evaluate the existing treatment workflow with integrated AI. Future empirical studies could consider conducting experiments based on the scenarios/phases defined in this paper, then quantifying and giving different priorities to the different needs of users.

7 CONCLUSION

In this paper, we explored the potential applications and current challenges of MLLMs in psychotherapy based on the feedback from human psychotherapists. Through qualitative analysis, we found that therapists generally recognize the supportive role of MLLMs in information gathering and feedback analysis phases, which can make better use of MLLM's multimodal perception, strong content understanding, and generation capabilities to enhance the efficiency and effectiveness of the treatment. Nonetheless, they remain cautious about their capabilities in handling tasks that require deep emotional support and complex decision-making. Although MLLMs demonstrate strong capabilities in content comprehension and generation, improvements are still needed in emotional intelligence and privacy protection. For now, MLLMs should be regarded as adjunct tools in psychotherapy, with a focus on developing functions like information collection and intelligent triage to enhance therapeutic efficiency. Furthermore, strengthening privacy protection mechanisms and enhancing anthropomorphic features will aid in increasing user acceptance. Future work could further expand the existing technology acceptance model from a psychosocial perspective, to facilitate the digital and intelligent campus mental health care.

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