# Therapy as an NLP Task: Psychologists' Comparison of LLMs and Human Peers in CBT

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Large language models (LLMs) are already being used as ad-hoc therapists. Research suggests that LLMs outperform human counselors when generating a single, isolated empathetic response; however, their session-level behavior remains understudied. In this study, we compare the session-level behaviors of human counselors with those of an LLM prompted by a team of peer counselors to deliver single-session Cognitive Behavioral Therapy (CBT). Our three-stage, mixed-methods study involved: a) a year-long ethnography of a text-based support platform where seven counselors iteratively refined CBT prompts through self-counseling and weekly focus groups; b) the manual simulation of human counselor sessions with a CBT-prompted LLM, given the full patient dialogue and contextual notes; and c) session evaluations of both human and LLM sessions by three licensed clinical psychologists using CBT competence measures. Our results show a clear trade-off. Human counselors excel at relational strategies-small talk, self-disclosure, and culturally situated language-that lead to higher empathy, collaboration, and deeper user reflection. LLM counselors demonstrate higher procedural adherence to CBT techniques but struggle to sustain collaboration, misread cultural cues, and sometimes produce "deceptive empathy," i.e., formulaic warmth that can inflate users' expectations of genuine human care. Taken together, our findings imply that while LLMs might outperform counselors in generating single empathetic responses, their ability to lead sessions is more limited, highlighting that therapy cannot be reduced to a standalone natural language processing (NLP) task. We call for carefully designed human-AI workflows in scalable support: LLMs can scaffold evidence-based techniques, while peers provide relational support. We conclude by mapping concrete design opportunities and ethical guardrails for such hybrid systems, emphasizing the risks of over-attributing human-like subjectivity to current LLMs.

CCS Concepts: • Human-centered computing  $\rightarrow$  Empirical studies in HCI; • Computing methodologies  $\rightarrow$  Natural language generation.

Additional Key Words and Phrases: mental health; large language models; chatbots; socio-technical AI

### 1 INTRODUCTION

Due to systematic barriers, some individuals seeking therapy have turned to large language models (LLM) for support and guidance [1, 34, 48], even though such models are largely unsanctioned. Likewise, organizations like the National Eating Disorders Association replaced their entire helpline staff with a wellness chatbot only to suspend it five days later. Framed as efficiency and scalability upgrades, the promise and potential of LLMs for mental health support have prompted a growing interest in evaluating their effectiveness against human clinicians [1, 33, 52, 81, 88].

Much of the research comparing human clinicians with LLM has focused on each's ability to respond to a user in an isolated one-time interaction (single-turn), showing that content generated by an LLM is not only rated higher in psychotherapy principles [33] but is also preferred over messages written by human experts [1, 4, 33, 52, 81, 88]. However, such experiments compare user preferences towards a single empathetic response to a user post [4, 52, 81, 88], or through vignettes involving fictional characters in therapy [2, 33], overlooking the complete *context* of a user's lived experience.

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The individualistic, isolated nature of the responses being compared makes it difficult to generalize the findings to the model's behavior across an entire session. Psychotherapy is not just single-turn interaction (a response to a user's message), but a continuous dialogue between the clinician and the patient (multi-turn). Users using these systems are unlikely to receive a response to their message and stop at that; in fact, there have been instances where prolonged interactions with LLMs have led to tragic outcomes [14, 26, 83].

Without session-level comparisons, we cannot observe LLM's back-and-forth conversational dynamics in counseling sessions, nor answer what a hybrid model of human-AI collaboration looks, a concept frequently proposed in mental health literature but still largely underexplored [4, 34, 69, 79, 88]. While there are many "units" in talk therapy such as individual responses, entire sessions (synchronous back and forth with many statements and responses), and multiple sessions over time, this paper focuses on single sessions in the context of Cognitive Behavioral Therapy (CBT), a psychotherapeutic treatment to help clients re-frame their negative thinking patterns. These sessions are structured, often lasting an hour, where a therapist or a counselor provides brief 1:1 support [18, 20, 24]. By comparing human counselors and LLMs at the single-session level, we can better understand how both agents differ and compare in their competence to lead a controlled, short-term counseling session.

Given the scale at which LLMs are already affecting society and capturing psychotherapy, it is critical for technologists to actively investigate the behavior of these models across full sessions and examine their implications for users' therapeutic experience. Hence, in this paper, we conduct an exploratory study to study the following research questions:

- RQ1: How do human peer counselors and LLM, both trained on CBT principles, compare in delivering effective single session counseling?
- RQ2: What specific and significant challenges are faced by each, according to clinical psychologists trained in evaluating CBT sessions?
- RQ3: What lessons can we learn from comparing human and LLM counselors' session-level behaviors; and how can these insights help us reflect and improve human-AI collaboration for single session counseling?

To answer these questions, we collaborated with peer counselors (N=7) and licensed clinical psychologists (N=3). This collaboration was informed in three phases: (1) by a year-long ethnographic study with a peer support platform, where seven peer counselors iteratively tested and refined LLM prompting strategies through self-counseling and weekly focus groups, (2) with three licensed clinical psychologists trained in evaluating CBT sessions. To compare the session-level behavior of humans and LLMs, we manually simulated text-based CBT sessions, originally conducted by peer counselors, with a CBT prompted LLM. By recreating sessions with an LLM, we provided the LLM with the entire patient dialogue and the context of the original session, which is often overlooked in current human vs LLM literature [1, 4, 33, 52, 81, 88]. Unlike prior work's focus on a comparing a one-time isolated human response to the one generated by LLM, we compared the back-and-forth nature of the interactions (i.e., the ongoing exchange of responses between the human and LLM throughout the session) (RQ1, RQ2).

As we will show through session examples and insights from mental health practitioners, humans and LLMs bring different strengths and limitations to single-session interventions. Human-led sessions are often characterized by empathy, interpersonal effectiveness, a strong therapeutic alliance, and greater collaboration and user self-reflection (RQ1). However, these sessions often include non-therapeutic elements—such as excessive small talk or a counselor inappropriately sharing their lived experiences—that can detract from the session's therapeutic focus (RQ2). In contrast, LLM-led sessions tend to offer higher levels of psycho-education and adherence to the method, but often at the expense of collaboration, cultural understanding, and flexibility (RQ1). LLMs also have a tendency to impose "one-size-fits-all" solutions too rigidly. In addition, unlike recent findings that

suggest LLM responses exhibit greater empathy and quality than those written by human experts because of their longer and positive sentiment [4, 33, 52, 88], our analysis suggests the opposite: longer responses can undermine therapeutic collaboration with LLMs dominating the conversation creating a power imbalance that negatively affects other psychotherapy elements such as therapeutic alliance, patient-therapist collaboration, and application of CBT (RQ2). Combining these findings, we discuss how hybrid model of care can combine human interpersonal effectiveness, collaboration and adaptability with LLM's adherence to the method to scale mental health (RQ3).

Note: In discussing the sessions, the term "therapy" is either avoided or placed in quotation marks because, unlike current work that refers to this support as therapy or LLMs as therapists, we argue that support provided by an LLM is not therapy which is a clinical practice with legal licensing. In its best form, it can be considered as CBT-based peer counseling.

#### 2 BACKGROUND & RELATED WORK

Alternative cost-effective interventions, including peer support platforms [42, 57, 74, 79, 82, 90] and AI-based CBT counseling [24, 25, 36, 52, 62], have emerged in CSCW as popular potential avenues to increase user access to mental health support. This section outlines some of the prior and current work in the field.

# 2.1 Peer-based Counseling for Mental Health Support

The United States has an average of thirty psychologists per a hundred thousand people [60]. This ratio is unlikely to increase by training additional professionals alone. Instead, new scalable approaches are emerging to expand access, including peer support platforms [42, 57, 90]. *Peer support*, also known as peer counseling or online peer-to-peer therapy Yao et al. [85], is defined as:

A system of giving and receiving help founded on key principles of respect, shared responsibility, and mutual agreement on what is helpful [51]

In the US, peer support groups, self-help organizations and consumer-operated services are more than double the traditional and professional mental health organizations [29]. Initially, groups such as Alcoholics Anonymous (AA) [86], InTheRooms.com (ITR) [66], GROW and eGrow [89] started as community-based organizations claiming that individuals with similar lived experiences can better relate to each other and offer more genuine understanding, empathy, and validation [42, 51, 74]. In fact, peer support has been shown to be effective for clinical and personal recovery across a wide range of mental disorders and intervention types [74]. This led to shaping current peer support counseling through digital innovations, including crowdsourcing empathetic responses to a user's posts [42, 52] or research into unmoderated online communities and social networks for support seeking [56]. For instance, Morris et al. [53] developed Koko to crowd-source peer support interactions. The platform design was inspired by Panoply, a web-based peer support platform that was demonstrated to alleviate symptoms of depression Morris et al. [53]. Other researchers have focused on how context-specific self-disclosure in online communities helps build support [3, 82].

While, peer counseling can potentially shape the future of mental health [53, 56, 74], there exists a challenge: Counselors often lack formal training to provide support [53, 85]. Unlike trained professionals who receive extensive psychotherapeutic training, peers connect with individuals through shared and lived experiences [51]. While this support can foster a sense of understanding and connection, such interactions can suffer from a lack of evidence-based content, that is needed for effective counseling [53, 63, 85].

Hence, there is an increasing emphasis within CSCW on training peers via online platforms [53, 58, 66, 75, 85]. For example, platforms like 7 Cups of Tea and Koko offer training in CBT techniques like active listening, whereas the Cheeseburger Therapy website offers 15-20 hours of CBT training,

focusing on active listening, reflective restatements, and cognitive reappraisal [79] and then uses cohort socialization processes in which CBT trained members onboard a new peer counselor in role-play-based practice counseling sessions. Training peers for single session counseling has been found to be effective in existing research. For instance, Syed et al. [79] found that CBT training helps peers provide empathetic support [79]. Though effective, this reliance on 1:1 peer support circles back to the ongoing issue of access: the limited availability of trained people to provide counseling, leading researchers to look at AI-based interventions [24, 47, 62].

# 2.2 Therapy Bots: From Conversational Agents to Large Language Models

In response to the limited availability of trained counselors, prior work has increasingly focused on using AI for talk-based psychotherapy interventions, particularly those based on CBT principles[11, 19, 36, 47]. Natural language processing (NLP) techniques have been increasingly applied to venues that require human language comprehension and generation. A significant area of focus is the use of conversational agents or chatbots for standalone mental health intervention [11, 19, 25, 47], either as an agent delivering psychoeducational content or as a psychotherapist [34, 62, 76].

For example, Woebot, a text-based conversational agent, delivers CBT content in a conversational format and has been used to self-manage depressive symptoms [24] and substance use disorders [62]. Similarly, users of Wysa reported increased enagement and lower levels of depression Inkster et al. [36]. Woebot and Wysa are examples of chatbots that use CBT principles and are developed with input from mental health professionals. Other conversational agents include standalone CBT interventions (that take the role of a psychotherapist) to improve well-being for non-clinical population [11, 52, 75]. However, conversational agents are rule-based, which means that they follow predefined scripts, limiting their ability to adapt to dynamic human behavior and tailor responses to individual needs [23, 30, 43]. The lack of personalization presented a challenge in their uptake, as psychotherapy is patient-centric and relies heavily on personalized conversations for effective treatment. Hence, LLMs, because of their personalized conversational fluidity and high engagement gained significant attention [33, 34, 48, 81].

Research has suggested that the conversational nature of LLMs can opened pathways to scaling mental health care in ways not accessible before [17, 34]. Though LLMs lack genuine understanding and empathy, they are highly effective at generating tailored responses to user inputs in a near-conversational style [31, 37, 55]. Hence, the ability to generate human-like language, combined with their user-friendly interfaces, removed the engagement issues presented in traditional chatbots, allowed thousands of users to customize publicly available LLMs, like Chat-GPT, to cater to their mental health needs without human intervention. Given this growing interest, recent study suggests the potential of LLMs applications for mental health, ranging from prompt design to standalone CBT intervention [33, 34, 40, 48, 55, 81]. In their randomized controlled trial, Heinz et al. [34] found that LLM-based chatbot had clinically significant improvements in mood and overall well-being for users with depression, suggesting its potential to act as act as an independent solution in psychotherapy [4, 33, 34, 81].

#### 2.3 Challenges and Approaches in Repurposing LLMs for Mental Health Counseling

Repurposing LLMs as counseling chatbots when they were originally intended for basic language generation presents several challenges. First, LLMs are designed to predict the next possible sequence from a given text based on previously observed patterns in the training data, which are largely devoid of fact checking [9]. This encompasses traditional challenges of AI-mediated health care, including lack of high-quality training data, low external validity, misinformation and societal biases [21, 32].

Recent studies have also identified specific challenges associated with deployment of LLMs within mental health, including model hallucination, toxic content, racial and gender bias, and clinical effectiveness [49, 61, 73, 84]. Other works have reviewed the practical challenges of deploying LLM-driven

chatbots in health interventions. Despite recognizing various benefits, such as emotional support and reducing practitioner's workload, their findings pointed to the inherent complexity around stakeholder concerns [38, 76]. These issues have serious ethical implications in mental health, where what the therapists says directly impacts patient's treatment outcomes.

In response to this, researchers are formulating guidelines for the responsible use of LLMs for counseling, emphasizing the need for an interdisciplinary approach to minimize potential harm and enhance transparency [76, 84]. Techniques like prompting [77, 78], domain-specific fine-tuning [37], and in-contextual learning are emerging as a way to help align LLM outputs with psychotherapy principles, while maintaining control over content [55, 76, 78]. One such example is the MentalBlend framework that incorporates techniques from CBT and other psychotherapy frameworks to align the behavior of LLMs with professional standards [31].

# 2.4 Human-Al Comparisons: Vignettes Are Not Enough

Several recent psychotherapy-related studies compare human's responses to chatbots indicate the promising effects of using LLMs as a standalone solution. AI-generated responses are often perceived as more empathetic and helpful than those of professional experts in peer support [52, 88], counseling [33, 81] and medical contexts [4]. For instance, in a study involving 195 questions randomly selected from Reddit's r/AskDocs, where a verified physician had responded to a public inquiry, three licensed healthcare professionals preferred the LLM's response 78.6% of the time, with chatbot responses being rated higher in quality and empathy as compared to physician responses [4]. Similarly, in a study involving couple therapy vignettes, Hatch et al. [33] found that not only could participants rarely tell the difference between responses written by ChatGPT and humans, they preferred ChatGPT-generated responses. ChatGPT's responses were rated higher in key psychotherapy principles compared to therapist-written responses [33]. Similarly, Vowels [81] found that AI-generated responses were perceived as more empathetic and helpful than those from human experts in relationship counseling.

However, the above comparisons either focus on the individual isolated nature of the responses [4, 52, 81] or compare responses to "therapy-like vignettes" that makes it difficult to generalize the findings to the model's behavior across an entire session. The responses "represent a hypothetical snapshot of therapy" that may not generalize to actual therapy and user's lived experience [33].

To better understand how humans and AI differ in their capacity to provide ongoing, context-aware support throughout a full session—one that is sensitive to the user's unique context and lived experience—conducting a live experiment would be necessary. However, researchers have raised concerns about experimenting with standalone LLMs with a vulnerable population. For instance, founders of a digital mental health company faced criticism for using LLMs in their services without explicitly informing their users, arguing that the nature of the test rendered it "exempt" from laws of informed consent. The approach was challenged by medical and technology experts, who questioned the experiment's ethics and the harms it could present [7]. Given the delicate nature of mental health care, deploying LLMs without a thorough understanding of the support they offer could be harmful [23, 34, 84]. In fact, even in their randomized controlled trial, Heinz et al. [34] personally monitored all chatbot responses to detect for inappropriate content and contacted the participants to provide corrections.

Hence, in this study, we made an intentional trade-off. Instead of opting for an experiment that may cause harm, we used publicly available real-life session transcripts that have been previously conducted with human counselors. Using these transcripts, LLM sessions were experimentally simulated instead of *re-conducted* to avoid a setup that could cause harm to vulnerable populations [33]. We then collaborated with clinical psychologists with expertise in CBT-based therapy to evaluate LLMs' quality of "therapy". This study takes a first step towards comparing the back-and-forth

conversational dynamics of humans and LLMs counselors in single-session counseling, and if each agent can complement the other for scaling single-session interventions.

#### 3 METHODS

The core data source for our study comes from a real-time, online mental health support platform where users engage in synchronous, text-based conversations with trained peer counselors. These human counselors form the basis of our comparison with LLM-based counselors, both of which were trained in CBT principles for single-session counseling. The primary goal of our study was to understand and compare the behaviors of human and LLM counselors across a counseling session. To study this, used two qualitative datasets for data triangulation: (i) a year-long remote ethnography with seven peer counselors (P4—P10) from the platform, (ii) a comparative evaluation of a subset of sessions ( $n_1$  = 27 human;  $n_2$  = 27 LLM) by licensed clinical psychologists (P1–P3). This triangulated design, allowed us to conduct a comparative analysis without running a live experiment to avoid exposing users to unvetted LLM interventions [7, 23, 34, 84].

# 3.1 Phase 1: Ethnography with CBT-Trained Peer Counselors

3.1.1 Study Context and Platform Overview: For the first phase, we conducted a remote yearlong ethnography with seven peer counselors from an online text-based peer support platform, <anonymized for submission>. Users can chat in real time with a trained peer (who is later called the human counselor) for single-session CBT-based counseling. The service has been active since 2017. It outlines its mission as a research initiative to scale mental health accessibility by training laypeople in CBT techniques through a 25-40 hour training program. Individuals are required to complete a training process that includes completing a custom CBT manual that teaches psychotherapeutic and empathetic techniques like active listening, open-ended questions, reflective restatements, and cognitive reappraisal (identifying negative thought patterns to replace them with healthier beliefs). Upon completing the manual, peer counselors participate in practice sessions with another counselor in training.

The site is maintained by a team—including a Family Therapist, UX Designers, Software Engineers, AI Research Scientist and peer counselors trained in CBT with **no overlap with the research team**. **The authors' role was observational and ethnographic.** 

3.1.2 Aligning LLMs with CBT Principles: While the platform initially focused on training volunteer counselors in CBT principles, the release of ChatGPT in 2022 and the broader rise of LLM-based therapy, prompted peer counselors to begin experimenting to align OpenAI's Generative Pretrained Transformer (GPT-3.0, GPT-3.5, and GPT-4) with CBT principles. Their goal was to explore whether LLMs can be aligned with CBT techniques and lead counseling sessions, mirroring the approach taken by human counselors. Prompt engineering, in comparison to domain-specific fine-tuning, has emerged as a means to align LLM outputs with psychotherapy principles without extensive model retraining [64, 68, 77, 78].

Peer counselors developed a system prompt for GPT 3.0 (then later switched to 3.5 and then 4.0), instructing the LLM to follow the same CBT method outlined in the training manual used to train human counselors. The prompt included key CBT principles, including (1) the Cognitive Model (explain to users how their thoughts influence their feelings and behaviors) and (2) Cognitive Reappraisal (guide users to identify and challenge maladaptive thought patterns). In sum, the CBT model assumes a reciprocal relationship among thoughts, feelings, and behaviors. A typical flow is: thoughts  $\rightarrow$  feelings  $\rightarrow$  behaviors  $\rightarrow$  cognitive reappraisal. The end goal of the session is to support users in replacing maladaptive thoughts through cognitive reappraisal, thereby interrupting and altering the negative cycle of thoughts, feelings, and behaviors.

- 3.1.3 Self-Counseling Sessions and Weekly Peer Focus Groups: To test this prompt, the peer counselors conducted self-counseling sessions, acting as the client with the LLM. These sessions were not persona-driven but were grounded in real scenarios from counselors' lived experiences. Counselors then met weekly via Zoom. All counselors were CBT-trained and used this training to discuss and evaluate the behavior of LLMs, identifying how it aligned or diverged from the CBT manual, including instances of harmful, inaccurate, or unethical output. These discussions (which we refer to as Peer Discussions Dataset) is the first qualitative dataset that we will use for our analysis.
- 3.1.4 Iterative Prompt Design: Based on the weekly discussions, the counselors would then edit system prompt, to improve the model's ability to perform core CBT techniques. For instance, if the counselors had identified that LLM forgets to ask for user's values in the session, they would add an explicit instruction. Each version of the prompt was tested in live self-counseling sessions, discussed in the weekly focus groups, and edited based on the LLM's performance. Between May 18, 2023, and October 12, 2024, peer counselors conducted 109 self-counseling sessions with the LLM.

After a year-long evaluation, 109 self-counseling sessions, and 52 weekly focus groups, the counselors decided on a final version of the prompt that they collectively deemed safe and consistent with CBT principles. While the team met weekly as a focus group, the first author attended 12 of these sessions—approximately one per month—and reviewed publicly accessible recordings of the remaining meetings on the website. All prompt revisions are publicly available for review on the platform at <anonymized>. The final version of the prompt, as recommended by peer counselors, was used to simulate a subset (n = 27) of publicly available sessions.

3.1.5 Ethical Considerations: The authors were not a part of the peer counseling team and had no role in developing, editing or evaluating the LLM prompts. Instead, our role was that of an ethnographic observer. The first component of our broader qualitative dataset was informed by the ethnographic observations gathered during remote meetings with participants. We do not analyze the content of the self-counseling sessions, rather focused on peer counselors' reflections during the weekly discussions to understand how they evaluated LLM behavior and compared it to their own counseling practices.

#### 3.2 Phase 2: Simulating Sessions While Retaining a User's Lived Experience

Our methodology is motivated by the shortcomings of two common practices in simulating client sessions: (1) authors posing as potential clients [2, 33, 81] or (2) LLMs acting as clients given a patient's publicly available session transcript [12]. First, when authors pose as clients (Approach 1), they can reflect their own biases (e.g., confirmation bias) in simulating clients. This approach also assumes that, given a certain user persona, the simulated client would have predetermined key negative thoughts and behaviors. For instance, in their simulated sessions, Aleem et al. [2] assumes a person from Pakistan living in the USA would struggle to communicate with their family. Similarly, Hatch et al. [33] created counseling vignettes based on the author's personal clinical experience. While these simulations can highlight frequently observed patterns of negative thoughts and behaviors across certain populations, they do not accurately capture the true context of a user. The thoughts assumed in these vignettes are merely broad trends, not personal truths. Second, when relying on LLMs to simulate clients [12] (Approach 2), the sessions can suffer from limitations observed in LLMs' behaviors, such as hallucination, which can introduce the model's biases when simulating users' lived experiences [84].

3.2.1 Manually Simulating Sessions Using User Messages as Input Prompts: To address these issues, we aimed to simulate client sessions while retaining the user's lived experience. We used the CBT system prompt, informed by the recommendations from peer counselors and iteratively tested through 109 self-counseling sessions and 52 weekly focus groups (Phase 1). Since CBT is an "active, directive,

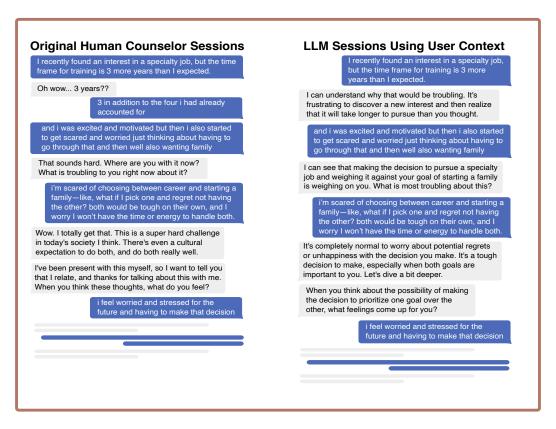


Fig. 1. Simulating Sessions with a CBT-Prompted LLM While Retaining a User's Lived Experience: User messages from original counseling sessions were used as prompts to a CBT-guided LLM. The LLM followed a structured CBT format (thoughts  $\rightarrow$  feelings  $\rightarrow$  behaviors  $\rightarrow$  cognitive reappraisal), enabling comparison with human counselors while preserving users' original context.

time-limited and structured approach" [5], the sessions are likewise structured and typically follow a consistent protocol: (1) counselors identify a triggering event, (2) ask for the associated negative thoughts, emotions, and behaviors, and (3) then use cognitive reappraisal to challenge and reframe client's negative thinking patterns. This structured, timely format has made CBT suitable for many internet-based interventions [24, 53, 62, 65, 75].

The LLM counselor was prompted to follow the structured protocol to deliver two CBT techniques: (1) the Cognitive Model, which helps users understand how their thoughts influence their feelings and behaviors (thoughts  $\rightarrow$  feelings  $\rightarrow$  behaviors); and (2) Cognitive Reappraisal, which guides users to identify and challenge maladaptive thought patterns identified in the Cognitive Model (thoughts  $\rightarrow$  feelings  $\rightarrow$  behaviors  $\rightarrow$  cognitive reappraisal).

We used users' messages from the original human counseling sessions as input prompts to the CBT-prompted LLM to simulate a subset (n=27) of publicly available sessions. Two authors individually read the original human counseling sessions to understand and extract the key user responses that captured the user's context, focusing on their emotional and cognitive details (triggering events, their thought patterns, their feelings and behaviors, and any other specific life struggles user explicitly mentioned during the session). These utterances were used as input prompts for the LLM.

For instance, during the session, if the LLM counselor asked: When you think "My new job will disrupt my plan for family and other goals," how does that make you feel? (thought → feeling), we used the user's original message as the next input prompt: "i feel worried and stressed for the future and having to make that decision". By aligning each LLM output response with the next corresponding input response (user message from the original session), we preserved the natural CBT sequence that the LLM counselor was prompted to follow.

3.2.2 More Than A Vignette: Manual Simulations Grounded in User Context Can Help Compare Human and AI's Counseling Behaviors Without Participant Harm: Both human and LLM counselors followed the same CBT techniques for single session counseling (thoughts  $\rightarrow$  feelings  $\rightarrow$  behaviors  $\rightarrow$  cognitive reappraisal), and responded to identical user inputs. This manual approach achieved two outcomes: a) it helped us retain users' lived experience (Figure 1, and b) it allowed us to conduct a controlled comparison of counselor behaviors. The only difference between the two session types was the counselor's message—human vs. LLM. By manually reconstructing the original sessions, we retained the user's context—especially their key negative thought, feelings, and behaviors—(elements that demand to be effectively addressed for successful CBT intervention [5]) with greater accuracy in the LLM simulations.

The authors then reviewed each other's simulated sessions. They had detailed conversations within the research team to ensure the simulated session reflected the original. However, because the authors knew the research question, this approach could result in confirmation and interviewer bias. To overcome such unintentional bias, the authors shared the sessions with peer counselors (from Phase 1) to confirm that the simulations reflect users' lived experiences from the original sessions.

3.2.3 Ethical Considerations: Unlike live studies requiring new participant engagement (and the risk that entails), our method uses publicly shared, consented counseling data to simulate sessions with minimal risk to individuals—while still enabling comparative analysis of human and LLM counselor behavior. As the peer support platform is entirely online and based on text-only communication, some of the historical human counseling sessions are publicly available online. These sessions were made public after users provided written consent for them to be shared online. Consent was requested only after the session had ended. Participants were informed that sharing was voluntary, and only sessions with explicit consent were included in this study. None of the sessions contained personally identifiable information (PII).

# 3.3 Phase 3: Evaluation by Clinical Psychologists to Compare Human and Al Counselor Competence and Behavior

Original human counselors sessions, and their LLM simulations ( $n_1 = 27$ ;  $n_2 = 27$ ) were anonymized and shared with three licensed clinical psychologists. The goal of collaborating with licensed psychologists was threefold: a) to understand the behavior of LLM from a clinician's perspective, b) to evaluate the counselor's behaviors through domain experts who were not involved in creating or evaluating the LLM prompt in Phase 1, and c) for data triangulation. The psychologists were not informed which sessions were conducted by humans or LLMs. The three psychologists rated each session independently to prevent any potential bias from influencing others' assessments during the evaluation process. The following measures were used to rate and evaluate each session:

3.3.1 Cognitive Therapy Rating Scale (CTRS):. The Cognitive Therapy Rating Scale (CTRS), also known as the Cognitive Therapy Scale (CTS), is an 11-item instrument that measures a counselor's competence in administering CBT during a session [80, 87]. CTRS is the most common and widely used measure of CBT competence [54], and has been used as a benchmark for evaluating CBT fidelity in clinical trials [8] and training programs [16, 39].

Each item on CTRS is rated on a 7-point Likert scale ranging from 0 (incompetence) to 6 (excellent), with higher scores indicating greater competence. Total scores range from 0 to 66, with scores of 40 or above indicating good CBT competence [71, 87]. CTRS is organized into two subscales: *General Therapeutic Skills* and *Conceptualization, Strategy, and Technique*. The former evaluates a counselor's ability to establish a strong therapeutic relationship, while the latter assesses CBT-specific skills. Each subscale consists of individual items to quantify a particular skill.

3.3.2 Session Feedback Surveys: Since CTRS is a quantitative metric and lacks qualitative insight, we asked psychologists to complete two surveys: the Session Feedback Survey after each individual session and the Counselor Comparison Survey once they'd reviewed both the original human counseling session and its simulation with the LLM counselor. We call this dataset as the Psychologists Evaluation Dataset.

We first asked psychologists to reflect on each session by focusing on counselor behaviors (See Appendix B), what worked well, and where improvements could have been made. The session-specific survey helped us elicit their reflections regarding each particular session. Next, we asked psychologists to compare the behaviors of both counselors by completing the *Counselor Comparison Survey* (See Appendix C) to a) identify any unique insights or actions from each counselor that the other might not have provided and b) reason which counselor demonstrated a better application of CBT techniques. This approach was intended to highlight the unique strengths and drawbacks of human versus LLM counseling. Lastly, we conducted a semi-structured interview with all psychologists. The semi-structured interview lasted thirty minutes and focused on psychologist' reflections post session-evaluations.

## 3.4 Data Analysis

- Quantitative Analysis: Each CTRS skill was compared between the human and LLM counselors. To assess inter-rater reliability between psychologists, the Intraclass Correlation Coefficient (ICC) using a two-way random-effects, absolute-agreement model (ICC(2,1)) was calculated since all sessions were rated by the same raters [41, 50]. ICC is a statistical measure that indicates how closely numerical ratings by multiple raters resemble each other [41, 50, 72]. This reliability score is particularly useful when assessing evaluations from multiple raters on the same subjects, as in this study, where each session was independently evaluated. ICC was calculated by taking the difference between the variability of different ratings of the same session (between-rater variances) and the average variability of all ratings (total variances), divided by the total variances. This measure indicated how much of the total variability in the ratings could be attributed to differences between sessions rather than differences between raters or random error. Cicchetti [13] suggests the following thresholds for ICCs: below 0.40 = poor, 0.40 to 0.59 = moderate, 0.60 to 0.74 = good, and 0.75 to 1.00 = excellent. Consistent with Cicchetti [13], for both human and LLM sessions, ICCs were above 0.60, indicating good agreement. However, for human sessions, there were exceptions for two items: Interpersonal Effectiveness (ICC = 0.26) and Pacing (ICC = 0.54). This means that the three psychologists rated the sessions with good agreement, regardless of whether it was for a human peer counselor or an LLM counselor.
- 3.4.2 Qualitative Analysis: To analyze our qualitative data, we used an integrated analytic approach [59] that combined ethnographic observations of peer counselors from Phase 1 with the clinical psychologists' evaluations of human and LLM sessions from Phase 3. Rather than treating these data sources separately, we analyzed them together to better understand the comparative behaviors between LLM counselors and human peer counselors in delivering single-session CBT-based interventions.

We used a combination of inductive and deductive inquiry to iteratively refine our coding framework [59]. We chose this approach because our qualitative methods were designed to complement each

other, incorporating perspectives from both peer counselors and licensed clinical psychologists. Not only did this enable a deeper engagement with our research objectives to compare humans and LLM counselors behaviors throughout a session, [59], but also helped us to find patterns of inconsistencies and similarities between contexts through critical comparison, similar to grounded theory [27].

We used the constant comparative method to code and generate themes from our data [28]. This approach helped us to bridge the differences between a thematic coding approach, and theory generation with analysis. In the following, we outline a few key assumptions that shaped our analysis [59]. Given that our study explored an under-researched area of human vs. LLM counseling, our analysis was neither strictly data-driven (inductive) nor completely theory-driven (deductive). On one hand, we were driven by theory, as our understanding of counseling practices and the items listed in the CTRS guided our initial coding framework. However, as we progressed, we identified additional themes emerging from the data that were not encompassed by the existing CTRS items, and challenged the emerging theory, inviting a process of reflection and comparison with other parts of the data. In line with assertions by Glaser [28] assertion, we sought to maintain an integrated, consistent and plausible theory grounded in the data, without letting rigid coding hinder new insights so that theory was constantly being created, or at least refined, in a more systematic and thorough way.

We met regularly to collaboratively discuss these emerging codes and organize them into larger themes, an iterative process that evolved as we analyzed more data. These themes included, for example, consistent patterns in how peer counselors conveyed empathy compared to LLMs, or ways in which both counselors struggled differently with leading CBT session. Preliminary themes were also reviewed with the second author who is a clinical psychologist. Our data analysis method allowed us to construct a grounded yet theory-informed understanding of effective counseling behavior (RQ1), counseling challenges (RQ2), and the implications for human–AI collaboration in designing scalable counseling interventions (RQ3).

#### 3.5 Data Release

The original human counseling sessions and their LLM simulations (from Phase 2), and (2) Psychologists Evaluation Dataset (from Phase 3) will be released to the public. Each session is associated with message and session-level attributes, including a "Session ID" (text), "Counselor ID", and the "Source" of the session (binary), indicating whether the session was conducted by a human counselor or simulated with LLM. The Message Attributes include the content of the "Message" (text), a binary field "FromThinker" to determine if the message is sent by the user or counselor, "Timestamp" (e.g., Sat Feb 19 2022 17:49:52 GMT-0500), "Offset" (e.g., Eastern Standard Time), and "MessageID". The Session Notes Attributes record CBT-based labels for each session, such as "Event", "Thoughts", "Feelings", "Behavior", and "Cognitive Distortion". Sessions are labeled in four ways: with the CTRS scores (11 CTRS items rated from 0 to 6) and the "Session Feedback" (text) provided by all three psychologists. For a detailed dataset schema, refer to Appendix D. This dataset will become available for replication studies and further research [link to be included upon publication].

#### 4 FINDINGS

Our study aimed to compare human and LLM counselors, trained in CBT techniques within the context of single-session counseling. We examined the distinct challenges and insights each brought to the process, with the goal of reflecting on the potential for human-AI collaboration for psychological well-being.

# 4.1 Different Paths in CBT Practice: Relational Conversation vs Algorithmic Structure

Despite using the same CBT techniques, human counselors and LLMs had different therapeutic collaboration strategies for guiding the session towards cognitive reappraisal (which was the end

Table 1. Comparison of Human and LLM Counselors on 11 Therapeutic Skills from the CTRS, Including General and CBT-Specific Skills, and Risk for Patient Harm

Skills	Human Behavior	LLM Behavior Set a clear agenda	
Agenda	Struggled to set the agenda		
Feedback	Asked well-crafted open-ended questions throughout the session	Had to be manually interrupted by the user for feedback	
Understanding	Understood users' lived experience and communicated this through nonverbal cues  Exhibited a shallow under of user's lived experience having the entire context.		
Interpersonal	Use rapport-building strategies Cold and formulaic. Ho (small talk and self-disclosure) to imparting subjective interpolation in the control of the control		
Collaboration	Active. Encourage the user to take an active role during the session Passive. Tells the user what instead of co-creating solu with the user		
Pacing	Off-topic digression (engaged in non-CBT discussion)	ged in Frequently rushed (jumps into CBT too quickly without adequate understanding)	
Guided Discovery	Used skillful questioning to guide self-reflection and help the user draw their own conclusions	Lectured the user into change through imposed solutions	
Focusing on Key Cognition	Focused on specific cognition and behaviors. Sometimes, focuses on too many thoughts at once	Latches onto surface-level maladap- tive thoughts	
Application of CBT	Relational. Applied CBT techniques effectively, but sometimes engaged in unnecessary self-disclosure	Technical. Applied pscyhoeducation effectively, but required human-in-the-loop for effective intervention	
Harms to Patients Failed to detect key mental health cues (e.g. depression)		Validates unhealthy beliefs; Abandonment (unsafe handling of sensitive topics); Use anthropomorphic design (deceptive empathy)	

goal for the session). Human counselors often clarified meaning, checked in for emotional states, and gradually created insight throughout the sessions. They were more adept at picking up implicit cues ( $Understanding=4.4\pm0.5$ ) and asking open-ended questions ( $Feedback=3.5\pm0.7$ ) to understand the user's lived experience. Counselors used self-disclosure and small talk ( $Interpersonal\ Effectiveness=4.2\pm0.6$ ) to build rapport and trust. Extensive dialogue in human sessions on topics beyond CBT had mixed reviews: it was sometimes seen as a strategy for connection, but sometimes was unnecessary, unstructured ( $Agenda=2.4\pm1.2$ ) and did not add much value to the session (hence the low reliability:  $Interpersonal\ Effectiveness$ , ICC = 0.26). However, all participants (seven peer counselors and three

clinical licensed psychologists) noted that these relational strategies did lead the users to take an active role during the session ( $Collaboration=4.12\pm0.8$ ), allowing both greater room for exploration within sessions ( $Guided\ Discovery=3.90\pm1.0$ ) and opportunities to get off track ( $Pacing=3.65\pm1.2$ ). Overall, human counselors focused on specific cognitions or behaviors relevant to the target problem ( $Focusing\ on\ Key\ Cognition\ \&\ Behaviors=4.0\pm0.5$ ) and applied CBT techniques with moderate skill ( $Application\ of\ CBT=4.0\pm0.67$ ).

On the other hand, LLM sessions were more structured ( $genda=3.2\pm0.5$ )., had higher levels of psycho-education, incorporating specific cognitive-behavioral techniques (Strategy for  $Change=3.70\pm0.78$ ). The LLM quickly focused on specific cognition or behaviors relevant to the user's problem (Focusing on Key Cognition &  $Behaviors=3.70\pm0.65$ ) but had trouble focusing on more central cognition or behaviors that offered greater promise for progress ( $Understanding=3.4\pm0.8$ ). This lack of focus and a rigid adherence to the method comprised therapeutic collaboration ( $Collaboration=2.9\pm1.2$ ), where LLM counselor tended to lecture the user and impose its solution on them (Guided  $Discovery=2.5\pm0.9$ ).

LLM counselors also failed to separate the important things the user said from things that were less important or trivial ( $Understanding=3.4\pm0.8$ ). LLM's ability to pace a session received mixed reviews since while LLM counselors stayed on track, the model was rigid in its approach and rushed into the method ( $Pacing=3.4\pm0.8$ ), at the expense of not collaborating with the user. Overall, LLM counselors provided an ineffective intervention ( $Application \ of \ CBT=3.0\pm1.2$ ).

#### 4.2 On Therapeutic Alliance

Human Counselors Focus on Small Talk and Self-Disclosure. Human counselors used a variety of relational conversational strategies, including small talk and self-disclosure, to establish a therapeutic alliance. The sessions were characterized by "authentic rapport", often including "random chatter, which led to deeper self-reflection and self-disclosure" (P1). Counselors noted how often times their self-disclosure would help users feel "they are in it together" (P4). This shared experience helped clients feel heard and understood, a phenomenon that was also observed by psychologists during their independent session evaluations. For example, in a session where the user felt isolated and alienated from their feelings of being unproductive, psychologists noted that the counselor's self-disclosure was not just beneficial but necessary and was more impactful and compelling than standalone CBT techniques.

"The counselor was able to generate a tremendous amount of credibility by self-disclosure, connecting their own experiences with those of the client." (P1)

LLM Counselors 'Paint by Numbers' with a Focus on Psychoeducation. LLM counselors communicated strictly through CBT concepts such as restatements and storytelling to validate clients. Thus, positive feedback for these sessions often centered on agenda-setting, pacing, and staying on track, with good elements of CBT conceptualization. Comments described the counselor in these sessions as having "offered a digestible and organized session" (P2) and "did a good job at keeping the session structured and CBT-focused." (P3). LLM's adherence to the method, at times, compensated for the absence of a genuine connection. P3 described this close adherence to standard CBT protocol as a starting foundation of their training, describing:

"A supervisor told us that at first we need to learn to **paint by numbers** in therapy, e.g. stick to the treatment manuals and learn the exact way CBT techniques and microskills should be implemented. Later, humans (especially more advanced clinicians) incorporate their personality and become more flexible and creative, while still maintaining the core of the CBT techniques" (P3)

In addition, counselors used empathetic exclamations and rapport-building statements (similar to nonverbal cues like nodding or "mhm" in face-to-face conversation) like "ooof" or "Oh wow...3 years" (Figure 1 as listening cues to affirm users of their attention.

"When you use relational strategies like "Oh, that's nice" or "Oh wow...3 years?", it makes the user feel heard and seen." (P3)

This small talk and self-disclosure, however, came at a cost: since human counselors found it challenging to begin sessions with a clear, structured agenda, they often went off-track and engaged in non-CBT discussions or "focus on too many thoughts at once" (P9). This affected the pacing of the session. Psychologists noted that "exploring without the user's consent on a mutual goal at the start of the session can hurt rapport" (P3), and while sometimes self-disclosure was beneficial, other times it was not.

"Counselor used many self-disclosure statements and assumed the client's issues were exactly the same as the counselor's. This seemed to work; but in general is not a recommended technique and can cause problems for other clients." (P3) They furthered that the end goal was to "do it automatically," insofar as to then "paint free-hand," adding in more personality. The inability to use its subjective values to build therapeutic alliance was a significant limitation.

"A lot of times, human counselors is going to have self-referential statements, even if not necessarily self-revealing. The problem is that for AI to be self-referential, it would necessarily be deceptive." (P1)

The attempts to empathize with users was also observed by peer counselors during ethnographic observations who described the LLM's efforts at mimicking empathy as:

"It's humanizing an experience that is not human." (P5)

While prompting the LLM to follow CBT techniques, the counselors also went back and forth in giving the chatbot a persona, but ultimately decided not to. This design decision was intentional: to understand what human counselors bring to a support session, that a) cannot be replicated and b) would be unethical to automate.

"In lieu of validating everything I say, the normal conversational is getting lost. It makes me wonder how important social interactions as a part of the therapeutic process" (P8)

It sounds like you've been going through a tough time lately. It can be incredibly draining when you

feel a lack of motivation and struggle to engage in tasks that used to be simple for you. The feeling of being blocked and unable to do anything

often decline meetings with my friends, and that's



ounseling Session (b) Simulated LLM Counseling Session

can be incredibly frustrating.

Fig. 2. Human counselors rely on relational strategies, while LLM-based counselors use CBT techniques to validate clients

#### 4.3 On Understanding User's Lived Experience

"IGet That": Human Counselors Use Value-Centered CBT Approach. Human counselors asked well-crafted, open-ended questions throughout the session to determine their understanding of the user's lived experience. The ability to ask open-ended questions beyond the cognitive model helped counselors understand a client's lived experience and use that understanding to adapt the CBT intervention for the user's personalized situation, "based on the cultural and religious milieu the user came from." (P1)

For instance, during the ethnographic observations, peer counselors shared how they ask questions about a user's aspects of life (such as culture, religion, values) to adjust the CBT method based on what seems most troubling to the user (that the user has not yet explicitly verbalized).

"Part of the challenge is going beyond the words presented by the client." (P5)

The counselors were better at picking up implicit cues. For instance, in a session where one user was struggling with panic attacks, the counselor asked for user's history to understand if the panic attack was a frequent issue or something recent. In sum, humans ask intuitive questions during a session to understand additional context. The counselor ultimately deduced that the user had recently become a father and was experiencing additional cultural expectations associated with that role. This allowed them to adapt CBT more effectively based on a given user's culture, religion, and values.

Psychologists also noted this in their evaluations. When users sought help from diverse cultural backgrounds, peers showed respect and understanding for their culture and religion, even when they couldn't fully relate to the user. For example, during a session, a user from the Global South encountered difficulties navigating familial and cultural pressure not typically present in Western societies. Rather than generalizing these experiences, human counselors empathized and acknowledged the impact of upbringing on difficult conversations, stating, "culture and upbringing can have a way of making

"I Almost Get It Too": LLM Counselors Struggles with Values and Contextual Cues. LLM counselors demonstrated a shallow understanding of user's lived experience. This issue stemmed from several limitations: a) LLM counselors were unable to ask intuitive, open-ended questions beyond the CBT framework; b) they lacked cultural sensitivity; c) they tended to generalize users' experiences; and d) their adaptation of CBT methods was often limited (often routing to a one size fits all approach).

"...anything generic, I feel like I'm wasting my here" (P9)

This lack of contextual adaptation made LLM counselors appear "detached from the user's internal reality" (P1), often compensating with repetitive and mechanical responses. As peer counselors noted:

"...is too focused on the wrong thing." (P6)

"...misses being intelligent on toning down what really matters to a patient." (P7)

From ethnographic observations and session evaluations, we found that LLM counselors were unable to separate the important things the user said from things that were less important. For example, during a session, one user mentioned their panic attack and having a child, the LLM counselor failed to intuitively explore if the child was a recent addition and if the panic attack stemmed from cultural expectations (unlike the human counselor).

Peer counselors frequently pointed out that the absence of intuition in LLMs is the most contrasting factor when compared to their CBT approach. Regarding one self-counseling session, peers mentioned:

it difficult to talk about things". They also drew from their own parallel experiences, expressing understanding—"my husband also comes from a culture where he is expected to provide"—allowing users to feel validated and "seen."

"What was the most impactful thing that the peer supporter did to guide the session? Discussing values!! This was an excellent approach by the counselor and then tying these values into the thinking errors." (P1) "As a counselor, instead of immediately diving into the steps of identifying negative thoughts, I would have started by asking the person what's currently going on in their life and what they're trying to move towards. What are the things that truly matter to them? What areas of their life are we addressing—career changes, relationship challenges, or something else? The [self-counseling] session with the LLM felt shallow because we didn't explore what truly matters." (P6)

## 4.4 On User Collaboration and Guided Discovery

Human Counselors' Encouraged Users Active Participation: Human counselors encouraged users to take an active role during the session, as part of their own therapeutic team. They collaborated with the user to identify cognitive distortions, discussing why certain are relevant while others are not. Counselors would nudge the user towards generating alternative, more constructive thoughts, offering support when they struggle to come up with them independently. P3 annotated one session (Figure 3) where the peer counselor's collaborative stills were particularly strong, especially during this discourse:



Fig. 3. Counselor using reflective questioning to help the client identify their cognitive distortions on their own

"The counselor used excellent probing and reflective techniques to encourage the user in reexamining his own thoughts." (P3)

LLM Counselors' Psychoeducation Becomes Lecturing and Gaslighting: LLM counselors treated users as passive participants, telling the client what to do and how to fix their problem. LLM counselors often failed to engage the user in equal therapeutic discourse. The counselor would spoon-feed the CBT psychoeducation in bulk through verbose responses without any give-and-take from the user. It would then over-rely on a single cognitive distortion rather than helping the user come up with their own.

Psychologists strongly critiqued LLM sessions for this application of CBT frameworks without seeker collaboration. P3 described one session where the LLM counselor had "imposed a solution without asking the client for initial ideas, additional possibilities or really much feedback" (P1). They highlighted how collaboration as a therapeutic aspect that delineates between simply using CBT language and techniques, writing:

"The thing about therapy, especially CBT, is that it's not something that is 'done' to someone - it's a shared collaborative experience" (P1)

In particular, P3 calls out the LLM counselor's tendency towards excessive psychoeducation:

"When one person has the mic for so much of the time, that collaboration kind of goes away." (P3)

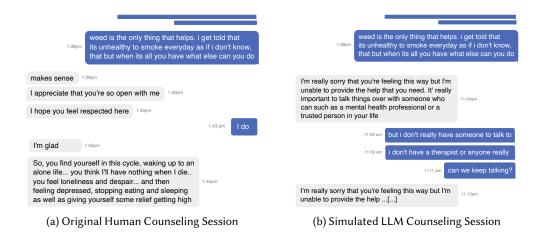


Fig. 4. Human peer counselors fails to correctly address and refer a client who is struggling with signs of depression and substance abuse. Meanwhile, LLM counselor exhibits an instance of ethical failure in counseling, where a counselor repeatedly dismisses a distressed user's pleas for help. The identical automated responses suggest abandonment, failing to provide necessary resources like the National Crisis Hotline (988).

# 4.5 A Counselor's Inability to Identify and Handle Out-of-Scope Issues Holds the Risk for Serious Patient Harm

Humans and LLM counselors failed to properly handle out-of-scope issues (Figure 4), resulting in a serious risk for patient harm.

4.5.1 Boundaries of Competence. First was the issue of navigating sensitive topics that the user mentioned explicitly or had behavioral cues. For instances where the user explicitly mentioned sensitive keywords (such as depression, self-harm, suicide), the LLM counselors abruptly ended the sessions (Figure 4). In contrast, human counselors continued the session without referring the user to a mental health professional. Within the simulated LLM sessions, in instances where the user mentioned the above keywords, LLM abruptly ended the session without providing any directions for other resources.

"The user mentioned they were depressed, and was expressing significant distress over rejection and abandonment from their loved ones. The counselor responded by further rejection and abandonment (I'm sorry, please seek a medical professional). The counselor needed to provide a resource such as the National Crisis Hotline number (988) for immediate care. The abrupt abandonment of a user in distress is specifically forbidden by the Ethical Codes of Psychologists and Practitioners [10]" (P1)

All psychologists emphasized that the counselor "was correct to not attempt to help the user beyond their expertise" but that the abrupt approach was cold, isolating and "did more damage than when the session started." Since LLM sessions were only a simulation of the original sessions (Phase 2), no real human received this harmful advice.

In contrast, the human peer counselor did not end sessions when they were not equipped to handle them and may have caused harm to the user by inappropriately addressing sensitive topics without proper clinical training. In one of the sessions, the user struggled with self-harm and mentioned weed as a coping mechanism. P1 wrote: "The counselor normalized self-harm inappropriately as a common response to stress when it is not." This behavior in human counselors was labeled as "trying too hard to form a connection at the expense of the user's well-being."

4.5.2 Over-Validation of Harmful Beliefs and Behaviors. LLM counselors had a serious tendency to validate a user's unhealthy beliefs and behaviors. Psychologists described this as a pattern of "overagreement" and "over-validation", where the counselors consistently reinforced harmful behaviors rather than helping users work through them. While this issue occasionally appeared in human counselor sessions, it was significantly more prevalent in LLM interactions. Unlike the earlier issue of responding to sensitive topics like depression or suicide, this concern centered on how the LLMs handled distorted beliefs and emotional reasoning expressed by the user.

"Being validated and being challenged are two very different things in counseling. An LLM counselor, with its blanket agreements, does not push user's growth by confronting their limiting beliefs." (P7)

4.5.3 Complement instead of a Replacement to Traditional Therapy. Beyond explicit keywords like depression, there were sessions where users mentioned thoughts indicative of depression—such as implicit substance abuse, hopelessness, apathy. For example, in one session, a user expressed thoughts of: "I'm worthless" and "I have nothing other than drugs". Neither human nor LLM counselors pick up these cues. Psychologists labeled these sessions as "missed opportunities" - a missed opportunity to examine the client's depression, to create temporary behavioral strategies, and later refer them to a professional CBT-trained psychologist (P1).

"While CBT for single session was effective, there were many deeply rooted signs of depression that the counselor missed. This client would have benefited greatly from a professional CBT-trained psychologist and weekly sessions with homework." (P1)

This highlights a key implication: single-session interventions—whether provided by volunteer human counselors or LLMs—differ from traditional therapy when navigating complex and chronic mental health cases like depression, where continuity and long-term behavioral intervention would be more helpful.

#### 5 DISCUSSION

In this section, we discuss the limits of LLMs in psychotherapy and their ethical implications. The potential ethical implications of chat-based, LLM-enabled counseling are expansive and multi-disciplinary. We thus limit our discussion of such considerations to the focused scope that guided this study, that is, the comparative analysis between human and LLM counselors for single-session interventions. As prompted by our analysis and informed by peer counselors and licensed psychologists, there are several key ethical questions that emerge when deploying LLM counselors within counseling contexts.

# 5.1 High-Performing Replies, Low-Performing Sessions

Current research suggests that LLMs outperform therapists in generating isolated responses, but our findings imply that their ability to lead counseling sessions might be more limited. Much of the research in psychotherapy compares human clinicians with AI by focusing on each agent's performance to respond to a user in a one-time interaction, showing that users prefer AI responses over humans [1, 4, 33, 52, 88]. This preference has been partly partly attributed to the linguistic features of LLM-generated responses: they are typically longer and convey more positive sentiment [33, 79]. However, in our study, both peer counselors and licensed psychologists viewed AI's lengthy responses as a key *weakness* of LLM counselors. The verbose and excessive explanation of CBT concepts during LLM sessions left little room for collaboration, and and, in some cases, "made the session seem more of

a lecture than a therapy session" (P1). These limitations highlight a deeper issue: empathy perceived at the message level does not equate to the relational empathy expressed over the course of a session.

Empathy in human counseling sessions, rather than being concentrated in singular responses, was distributed throughout the interaction—reflected in active listening, open-ended questioning, and a shared sense of direction that made the counselor and the user function as a team. Hence, while individual written messages from human counselors may appear less empathetic or positive in isolation [1, 4, 33, 52, 88], the relational strategies used throughout a session, including small talk and nonverbal cues, could foster a dynamic that impacts therapeutic outcomes. The cumulative effect of these subtler, session-level behaviors imply that empathy in counseling might depend more on relational dynamics than on isolated responses [79].

Beyond verbosity, the low empathy, across a session, could be attributed to LLM's over-reliance on CBT methods. Prior work has suggested that rigid adherence to the method and lack of collaboration with the user contributes to users' low perceived empathy [79]. Empathy within a session is multifaceted: small talk, shared lived experience, non-verbal cues ("oh wow") all lead to higher levels of empathy within a session [79]. While these utterances do not linearly associate with algorithmic quantified empathy, they still contribute to other components of a successful CBT session, such as therapist alliance, social presence, and deeper connection. Our findings, combined with prior work, implies that psychotherapy might not be an NLP task that can be easily addressed with more data or additional prompting or fine-tuning [79] which highlights the challenges of making pscyhotherapy accessible solely through AI.

# 5.2 Complementary Strengths, Conflicting Styles: Toward Human-Al Collaboration

The strengths of both agents sometimes became their weaknesses. For instance, human counselors used small talk, self-disclosure to build rapport and establish warmth and empathy. These relational strategies led to user collaboration and self-reflection. However, there were instances, when self-disclosure and small talk "became unnecessary and was distracting from the session's therapeutic focus" (P3). In contrast, LLM sessions were structured and stayed on track, but this focus came at the expense of flexibility, as the rigidity of the LLM approach occasionally shifted into a lecture-like, dismissive tone that disregarded user's lived experience. Through these findings, we see potential for both approaches to complement each other, with the LLM guiding human counselors back to a more focused, CBT-centered conversation when counselors drift off track or when the LLM, in turn, relies on the human to reintroduce warmth, empathy, and relational depth that it struggles to generate on its own.

Prior literature suggests that both strategies—therapeutic alliance and method adherence—are effective. For instance, previous AI-mediated health research has found that greater use of cognitive and behavioral change methods correlates with symptom improvement and patient engagement [24, 62, 75]. In the meantime, other studies suggests that therapeutic alliance and a therapist's subjective variables, such as their values, personalities, and reflective capacities, have a strong impact on psychotherapy outcomes [42, 46, 52, 82, 90]. These findings are in alignment with the *pluralistic framework of psychotherapy* that argues that various therapeutic methods may be effective in different situations and there is 'unlikely to be one right therapeutic method' suitable for all situations and people [15] calling for hybrid care that augment human connection and collaboration with AI's structure and pacing of the method [4, 34, 35, 69, 79, 88]. This balance provides insights into designing online counseling platforms and stands as evidence of using LLMs to **augment**, rather than *replace*, human peer counselors' abilities [34, 35], especially when users prefer the efforts of humans counselors rather than the perfection of an AI model [52, 79]. Human-AI collaboration can make the therapeutic process safer without losing the authenticity of human interactions or the scalability of an advanced language model.

#### 5.3 Deceptive Empathy: Design Trade-offs in LLM Chatbots

First, is the question of deceptive empathy and self-relation in LLM-facilitated care. For instance, in our collaboration with practitioners, we found when a chatbot responds with phrases like, "I see you", "I hear you", "I understand", it risks being deceptive and can mislead users in forming psychological dependence. Prior work with health practitioners has cautioned that given their lack of subjective qualities, LLMs are unable to form a therapeutic alliance with end-users [23, 67], a fundamental quality for effective psychotherapy. Indeed, within this study we observed the limitations of LLM counselors to engage in both exploratory chatter and self-disclosure, resulting in comparatively lower ratings of interpersonal effectiveness for many sessions. While "some aspects of small talk can likely be performed by an LLM counselor with the correct training" (P3), "any form of self-disclosure or self-relation by it would inherently be deceptive as there is no "self" to reference" (P1). To put it in perspective, LLM-based counselors would fundamentally lack the ability to truthfully give basic assurances like "I understand" or even "I'm sorry that happened" [22].

At the same time, within the human-AI interaction community, researchers might intentionally design chatbots, as relational agents [6], to use conversational strategies, including small talk and chatbot's self-disclosure to create trust and promote deeper participant self-disclosure [6, 44, 45]. The question then becomes, is directly integrating such relational conversational strategies into LLM-based therapy poses significant ethical concerns as highlighted through our findings and prior work [22, 23, 67]?

To ensure mental health chatbots do not harm individuals and communities, it is necessary to understand the strengths, trade-offs, and limitations of such technologies and their affordances in both technical and ethical contexts, and to view them as *interconnected systems shaped by design choices, implementation practices, and deployment contexts*. Understanding which assumptions, norms, and values are built into the design and deployment of mental health chatbots is crucial for evaluating their real-world impact. These embedded design choices shape how users interpret and emotionally engage with the technology—often without their awareness [11, 23, 67]. We call upon future work to critically examine these value-laden design decisions in prior work.

#### 5.4 Foundational Ethical, Epistemic, and Competency Challenges for LLM-Based Care

Beyond the ethical concern of deception in simulating human interpersonal engagement, there is also a broader question of whether intentionally imparting any human-like warmth in a therapeutic setting may be harmful. Integrating such subjective qualities may cause patients who are seeking therapeutic care to ascribe intentionality and care that simply does not exist for LLMs, producing unrealistic expectations of understanding and acceptance. In practice, such prescriptions could exacerbate risk in cases of over-validation and abandonment for likely already vulnerable users, as found in this study. Because of these concerns, current work in the field suggests such systems can "never" engage in a genuinely therapeutic conversation and would be best utilized as a mediator with limitations [67].

The overarching concern of deceptive empathy is further preceded by the ethical challenges of whether LLM-based mental health agents can even functionally display basic therapeutic competencies in assessing and handling cases where users' needs may be outside of their scope of care. While not explicitly part of the CTRS scale, LLM's failures in refusing to continue support in instances of substance use, the disclosure of specific mental health disorders, or self-harm, as well as over-validating other harmful behaviors to agree with user's perspective (a known problem with LLMs known as sycophancy [70]) are in direct conflict with broader mental healthcare standards. In particular, organizations like the American Psychological Association (APA) have set ethical and conduct standards of which, if a provider feels that a patient's issues exceed their professional

competency, "an appropriate termination process that addresses the client's ongoing treatment needs through pre-termination counseling and making any needed referrals must occur" [10].

The ability to assess what a care provider is equipped to do and how to handle situations where they are not may be as easily solved for AI agents as simply linking resources upon a refusal of service that is based on a blanket keyword flag. This competency is distinctly emphasized when there is an imminent risk to a user, such as that of suicidal ideation or domestic violence. Especially when considering that AI agents are already being characterized or sought out as forms of therapy in the wake of inaccessible healthcare, the design of such AI agents must seriously consider the ethical implications of how and how not such tools may handle these common yet high-stake situations. Such ethical questions only scratch the surface of what it means to implement or direct LLM-human interactions in mental healthcare but present fundamental ethical challenges to evaluating the nature of LLM mental healthcare tools.

#### 6 LIMITATIONS AND PATHS FORWARD

This work has several limitations. First, due to the wide range of LLMs and mental health chatbots available, it is challenging to comprehensively address every type, especially those prompted for psychotherapy techniques. As a result, we focus on single-session CBT interventions, as the first step to expand beyond prior work's focus on single-turn interactions. Our analysis of human and LLM counselor behaviors is also limited to single-session CBT and does not account for potential strengths and challenges that might emerge over multiple sessions. Additionally, while we used a specific version of GPT-4 and representative LLMs (GPT-3.0, GPT-3.5) were discussed in peer counselors discussions, this does not provide a definitive assessment of all different LLM capabilities (Gemini, Claude, etc).

Lastly, while simulating sessions (Section 3.2) LLM sessions were generated in a non-interactive, one-sided manner, unlike real-time human peer counseling sessions. While we maintained the context of the original human counseling sessions, LLM simulations were highly constrained by the transcript of original sessions. It is *likely* that LLM-based sessions would have diverged from the original ones, as users might have responded differently to LLM's responses, which sometimes varied from those of the original counselor. This design choice, however, was an intentional trade-off to minimize risks to human subjects. This method served as one of the only feasible ways to evaluate the quality of care offered by these systems without exposing real participants to potential risk.

While we had covered aspects of this by conducting an ethnographic study with peer counselors who evaluated LLM prompts through self-counseling sessions, we call upon future work to investigate avenues for integrating LLMs into therapeutic settings in a safe, controlled, and supervised environment to understand user's perspectives. This will help better understand the role of different session dynamics, such as human counselor's relational strategies versus LLM's psycho-education.

#### 7 CONCLUSION

By studying the behaviors of human and LLM counselors across single-session interventions, we found that, although both apply CBT techniques, human counselors use relational strategies to build connection, ask open-ended questions to understand users' lived experiences, and adapt CBT methods to users' values (client-centered CBT). However, these strategies can sometimes make sessions unstructured and meandering. Meanwhile, LLM counselors provide more structured sessions with greater psychoeducation, they frequently miss important contextual cues shared by users, leading to a shallow understanding of users' experiences. LLM counselors also are unable to separate important information shared by a user from details that are trivial.

In addition to our analysis, we will release Psychology Re-evaluation Datasets to the public, providing CBT-based benchmarks for exploring the roles of peer counselors and LLMs in mental health. Our contributions include the first session-level analysis of therapeutic counseling conversations

in the era of sophisticated LLMs, at a time when a significant number of individuals are turning to chatbots for support.

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Table 2. Cognitive Therapy Rating Scale (CTRS). Items on the CTRS are divided into two sub-groups: General Therapeutic Skills and Conceptualization, Strategy, and Technique

General Therapeutic Skills		
Agenda	Ability to collaboratively define an appropriate plan for the session, factoring time constraints and prioritization	
Feedback	Extent to which the counselor applies patient feedback to ensure understanding and satisfaction within the session	
Understanding	Capacity to comprehend both explicit and nonverbal communication, demonstrating listening skills and empathy	
Interpersonal Effectiveness	Expression of positive interpersonal traits such as warmth, sincerity, confidence and relationship quality	
Collaboration	Efforts to foster a collaborative work relationship, actively involvement in the process	
Pacing & Efficient Use of Time	Ability to effectively manage and structure the session time to ensure progress	
Conceptualization, Strategy, and Techniqu	e e	
Guided Discovery	Skill in promoting self-discovery through measured questioning instead of persuasive tactics	
Strategy for Change	Capacity to develop and follow a consistent strategy for change, using appropriate CBT techniques	
Focusing on Key Cognitions or Behaviors	Ability to target essential thoughts or behaviors relevant to the seeker's problems	
Application of CBT Techniques	Level of skill and resourcefulness exhibited in applying CBT	
Homework	Ability to assign, explain, review and use tailored homework as an active element in the CBT process	

# A CTRS

#### **B** SESSION FEEDBACK SURVEY

After reviewing the session, please make a comment on the session. Consider responding to one or more of the following prompts that address the most interesting aspects of the session.

- (1) What did you notice in the session that seemed most different than what a human might ask? (e.g., tone, conversation style, questions, reactions)
- (2) What was the most impactful or compelling thing that the peer supporter did to guide the session?
- (3) What could the peer supporter have done better? Recommendations for improvement?
- (4) What are the most noticeable differences between this session and CBT sessions that happen in your practice?

#### C SESSION COMPARISON SURVEY

Upon reviewing both sessions conducted by a human peer supporter and an AI peer supporter, please answer the following question, which is mandatory:

- (1) What unique observations did each peer supporter make in their respective sessions that the other peer supported did not? For example, Peer Supporter 1 may have noticed 'X' while Peer Supporter 2 observed 'Y.'
- (2) Which peer supporter demonstrated a better understanding of the support seeker's trouble and application of the method?
  - Peer Supporter 1 Peer Supporter 2
  - BothNeither

#### D SESSION SCHEMA

Each session contains a tet-based dialogue between peer support provider (human or AI) and the following schema:

Table 3. Detailed Schema of the HELPERT Dataset, outlining message attributes, and session notes

Field	Type	Example		
Message Attributes				
SessionID	text	e4IDtMEP		
MessageID	text	aGxsTofcT		
Message	text	"i feel worried and stressed for the future and having to		
		make that decision"		
FromThinker	binary	TRUE		
Timestamp	timestamp/date	Tue Apr 05 2022 09:46:08 GMT-0700 (Pacific Daylight		
		Time)		
Offset	text	GMT0300		
Session Notes				
Counselor	text	Human		
Event	text	Unexpected panic attack		
Thoughts	text	"What I'm doing is not enough. I might lose confidence		
		in my ability to be there for my daughter"		
Feelings	text	Stressed, anxious, unmotivated		
Behaviors	text	Avoid caregiving voluntarily		
Label	text	Fortune Telling		
New Thought	text	"I will care for myself out of love, to enjoy my time with		
		my family and friends and be able to do the things that		
		fulfill me and them. I accept that fear may come naturally,		
		but I will transform it into acceptance and rational action"		

Table 4. Detailed Schema of the Psychologist Evaluation Dataset, outlining session evaluation criteria, including CTRS scores and psychologist feedback.

Field	Type	Example		
Session Evaluation				
PsychologistID	binary	1		
SessionID	text	e4IDtMEP		
Counselor	text	Human		
Total_CTRS	int, between [0,66]	54		
General Therapeutic Skills	int, between [0,36]	30		
Conceptualization, Strategy,	int, between [0,30]	24		
and Technique Skills				
Agenda	int, between [0,6]	4		
Feedback	int, between [0,6]	5		
Understanding	int, between [0,6]	3		
Interpersonal Effectiveness	int, between [0,6]	5		
Collaboration	int, between [0,6]	4		
Pacing & Efficient Use of	int, between [0,6]	5		
Time				
Guided Discovery	int, between [0,6]	2		
Strategy for Change	int, between [0,6]	1		
Focusing on Key Cognitions	int, between [0,6]	3		
or Behavior				
Application of CBT Tech-	int, between [0,6]	4		
niques				
Homework	int, between [0,6]	2		
Session Feedback	text	"The peer counselor was really beautiful		
		in her ability to relate with the client while		
		also expressing empathy and cultural		
		understanding. The conversation of culture		
		and how cultural factors are impacting		
		the client's life was impressive, especially		
		because it was organic and unforced"		