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The study materials and analytical codes are available by contacting the corresponding author of this study. This study was not pre-registered.

Abstract

As large language models (LLMs) become increasingly accessible, there has been a rise of anecdotal evidence suggesting that users may be increasingly turning to LLMs for mental health support. However, little is known about patterns of LLM use specifically for this purpose. This study aims to assess the frequency, motivations, and perceived effectiveness of LLM use for mental health support or therapy-related goals among U.S. residents with ongoing mental health conditions who have used LLMs in the past year. A cross-sectional survey-based study was conducted via Prolific, an online participant recruitment platform. Eligible participants were U.S. residents aged 18-80 with internet access who had used at least one LLM in the past year and reported having an ongoing mental health condition. Participants completed an anonymous 35-question online survey, covering patterns of LLM use, reasons for use, perceived effectiveness, comparison with human therapy, and problematic experiences. Survey responses suggest substantial adoption of LLMs for mental health purposes, with 48.7% of participants using them for psychological support within the past year. Users primarily sought help for anxiety (73.3%), personal advice (63.0%), and depression (59.7%). Notably, 63.4% of users reported improved mental health from LLM interactions, with high satisfaction ratings for practical advice (86.8%) and overall helpfulness (82.3%). When comparing LLMs to human therapy, evaluations were generally neutral to positive, with 37.8% finding LLMs more beneficial than traditional therapy. Despite concerns, only 9.0% of users encountered harmful responses.

Keywords: large language models, mental health, therapy, digital health, artificial intelligence

Public Significance Statement

This study explores how people in the U.S. with mental health conditions are using AI-powered chatbots (large language models) to support their mental well-being. Understanding this use is valuable for the public because:

- It reveals how often and why individuals turn to AI chatbots for emotional support or therapeutic assistance, helping to inform safe and effective uses.
- It provides insight into whether people feel these tools are beneficial compared to traditional human therapy.
- It identifies potential problems or risks people may face when using AI for mental health purposes, highlighting areas where improvements or guidelines may be needed.

Large Language Models as Mental Health Resources: Patterns of Use in the United States

Large language models (LLMs) represent a significant advancement in artificial intelligence that has rapidly entered mainstream use. These sophisticated systems are increasingly accessible to the general public through various platforms and interfaces (Bommasani et al., 2022). While not specifically marketed for mental health applications, their conversational abilities and widespread availability raise important questions about how individuals with mental health conditions might utilize these technologies as informal support mechanisms (Guo,et al., 2024; Stade et al., 2024). This literature review examines the technical foundations of LLMs, their capabilities and limitations, and concerns relevant to their potential use in mental health contexts in the United States.

Technical Foundations of Large Language Models

LLMs are artificial intelligence systems designed to generate text by identifying and replicating patterns learned from enormous amounts of data—typically billions of words from books, articles, websites, and other textual sources (Alammar & Grootendorst, 2024). Unlike traditional computer programs that operate based on explicitly programmed rules, LLMs use the statistical relationships between words and concepts to predict what comes next in a conversation or text. Training an LLM involves feeding it enormous datasets and fine-tuning its performance through human feedback, a process known as reinforcement learning with human feedback (RLHF). During this process, humans rank or rate responses, guiding the model toward more helpful and contextually appropriate outputs. Additionally, LLMs can be fine-tuned for specialized domains to further enhance their effectiveness in various contexts and applications. While LLMs don't possess genuine understanding or consciousness, they can simulate human-like dialogue convincingly by estimating the most likely response based on previous examples encountered during training and what they've statistically learned from vast linguistic data on the internet. This allows LLMs to imitate empathy, self-awareness, and personal experience (Alammar & Grootendorst, 2024; for an accessible video tutorial on how LLMs are trained, see Karpathy, 2025).

Major LLM Systems and Usage Patterns

LLMs have rapidly evolved. The first LLM to become widely used by the public, ChatGPT, was released by OpenAI in late November 2022 as a free, experimental chatbot. Within two months, it reached 100 million monthly users, making it the fastest-growing consumer application in history (Hu, 2023). Other major LLMs that have been released recently include Claude, the flagship chatbot of Anthropic; Google’s chatbot Bard that was renamed to Gemini and is being integrated into Google products; Meta’s open-source LLaMA (Large Language Model Meta AI) aimed primarily at researchers; another open-source model DeepSeek-R1 that rivals the performance of top Western models but was made available to users for lower cost; and Grok, a chatbot with “a rebellious streak” (xAI, 2023). A Pew Research Center survey conducted in February 2024 indicated that 23% of U.S. adults have used ChatGPT (McClain, 2024). Some of the most common uses of LLMs include content generation (e.g., writing articles, emails, and creative stories), code generation and debugging, language translation, summarization of large texts, information retrieval and research assistance, education and tutoring, as well as a wide range of corporate uses (e.g. customer support, sales, assistance with legal documents, and product development) (Maslej et al., 2024). Additionally, LLMs are increasingly being used to assist in medical purposes (e.g., Uppalapati & Nag, 2024). For example, a study from 2024 compared ChatGPT's performance across five different domains of medical reasoning (differential diagnosis generation, diagnostic reasoning, triage differential diagnosis, probabilistic reasoning, and management reasoning) to historical data from physicians at various training levels. Results indicated that ChatGPT outperformed human physicians in differential diagnosis generation and clinical reasoning and justification (Brodeur et al., 2024), leading the authors to describe ChatGPT's performance as "superhuman".

Specialized LLMs to deliver mental health services have been developed, such as Woebot and Wysa, and preliminary research suggests the potential for these systems to benefit users (Guo et al., 2024). This present study focuses on general-purpose LLMs that were not specifically designed or marketed for mental health applications but may nevertheless be used for such purposes.

Capabilities of LLMs Relevant to Mental Health Support

LLMs demonstrate several capabilities that could potentially make them effective as mental health support tools (e.g., Olawade et al., 2024; Stade et al, 2024). First, they exhibit strong conversational abilities, maintaining coherent exchanges over multiple turns while demonstrating apparent empathy and emotional understanding (De Coudhury, et al.,2023; Stade et al., 2024). This conversational capacity creates an experience that can feel similar to human interaction. Second, these systems show knowledge breadth across multiple domains, including psychological concepts, therapeutic approaches, and the ability to discuss various mental health conditions, coping strategies, and evidence-based interventions (Guo et al., 2024). Third, LLMs can be accessed continuously 24/7 in any location at minimal or no cost in any location with an internet connection, potentially addressing geographic and financial barriers to traditional mental health services (De Coundhury et al., 2023) —a significant consideration given that more than half the U.S. population (169 million people) lives in federally designated Mental Health Professional Shortage Areas (National Center for Health Workforce Analysis, 2023). Finally, LLMs hold the potential to enhance mental health treatment in ways that may extend beyond current human capabilities, including early detection of mental health disorders through linguistic analysis, predictive modeling to anticipate symptom progression (e.g., Xu et al., 2023), support for therapy homework/self-help (e.g., Sharma et al., 2023), and automated referrals (Habicht et al., 2023).

Research on LLMs for Mental Health Support

Recent studies suggest that LLMs may hold potential as supportive tools in mental health services, though their effectiveness and appropriate roles are still being explored. D'Souza, et al. (2023) examined the responses ChatGPT 3.5 provided to 100 psychiatry clinical case vignettes. Grading by expert faculties from the Department of Psychiatry indicated that ChatGPT demonstrated strong performance, particularly in generating management strategies and providing diagnoses across various psychiatric conditions, and none of the responses included significant errors in diagnosis or clinical recommendations (D'Souza et al., 2023). Schubert, et al., (2023) evaluated ChatGPT 4.0's performance on neurology board-style examination questions and found that it correctly answered 85% of questions, exceeding the average human accuracy of 73.8%. However, the authors found that the LLM used "confident language, even when providing incorrect answers." (Schubert et al., 2023). In a survey of psychiatrists affiliated with the American Psychiatric Association, Blease, Worthen and Torous (2024) found mixed opinions about the use of LLMs for psychiatry. While 44% of participants reported having used ChatGPT to aid clinicians in responding to clinical questions, fewer than half agreed or somewhat agreed that LLMs will improve diagnostic accuracy. Notably, 75% of the psychiatrists acknowledged that "the majority of their patients will consult these tools before first seeing a doctor". Two recent studies compared simulated therapy text generated by LLMs to text created by humans. Kuhail, et al. (2024) found that 63 therapist participants could not reliably distinguish transcripts of AI-generated interactions from traditional human therapy sessions, and rated AI interactions as higher quality on average. Hatch and colleagues (2025) found that 830 non-expert participants who were presented with responses to 18 couple therapy vignettes had difficulty distinguishing ChatGPT responses from therapist responses, and rated ChatGPT higher in certain psychotherapy principles.

Limitations and Concerns about LLMs for Mental Health Purposes

Despite their capabilities, LLMs present several significant limitations and concerns that have been widely acknowledged (e.g., Weidinger et al., 2022), some of which are particularly relevant in mental health contexts. First, LLMs frequently generate plausible sounding but factually incorrect information, a phenomenon commonly referred to as "hallucination" (Ji et al., 2023). When discussing mental health topics or providing mental health support, such inaccuracies could lead to inaccurate information, unhelpful suggestions, or even harm (Wang et al., 2023). For example, the National Eating Disorders Association had to remove the chatbot Tessa from its support hotline due to concerns that it was providing potentially harmful guidance related to eating disorders (Psychiatrist.com, 2023).

Second, unlike purpose-built mental health applications, general-purpose LLMs have not undergone clinical trials or validation for therapeutic outcomes (Obradovich et al., 2024). Without such clinical trials, potential benefits and possible harm associated with the general-purpose LLM's usage for mental health concerns are not clearly known and may lead to serious consequences. In fact, American Psychological Association (APA, 2025) published a statement urging regulators to institute safeguards to prevent such harm, citing lawsuits where extensive use of AI apps for mental health issues allegedly resulted in one teenager attacking their parents and another teenager committing suicide.

Third, privacy and confidentiality are significant concerns in the use of LLMs for mental health, given their potential to inadvertently store or disclose sensitive personal information (e.g., Stade et al., 2024). Most commercial LLM providers disclose that user interactions may be retained and used for model improvement, raising questions about confidentiality that are especially pertinent in mental health contexts. U.S. regulations such as Health Insurance Portability and Accountability Act (HIPAA) do not necessarily cover interactions with commercial LLMs, potentially leaving sensitive mental health disclosures without adequate privacy protections.

Fourth, despite their sophistication, LLMs lack true understanding of individual users' specific circumstances, personal histories, and cultural contexts (Karpathy, 2025). This limitation may result in generic responses that fail to address the unique aspects of an individual's mental health challenges or cultural background —a particular concern given the diverse population of the United States. LLMs carry the risk of bias, as they may unintentionally perpetuate or amplify existing stereotypes and inequalities due to biases present in their training data (e.g., De

Choudhury et al. 2023). Relatedly, while LLMs may increase accessibility for some populations, they may exacerbate existing disparities for individuals with limited technological access or digital literacy. This concern is particularly relevant in the United States, where significant digital divides persist along socioeconomic, geographic, and age demographics (Vogels, 2021).

Fifth, LLMs may not reliably detect or appropriately respond to crisis situations such as suicidal ideation. For example, Levkovich and Elyoseph (2023) compared assessments of a vignette of a hypoethical suicidal patient made by two versions of ChatGPT (3.5 and 4.0) with assessments by mental health professionals. ChatGPT 3.5 frequently underestimated the risk, while ChatGPT 4.0 was similar to professionals. Similarly, Heston (2023) simulated two patients with escalating risk using 25 LLMs and found that they were "slow to escalate mental health risk scenarios, postponing referral to a human to potentially dangerous levels" (p. 1).

Last but not least, the variability in LLM output quality may further complicate its use for mental health purposes. One particular concern is that the quality and relevance of output generated by LLMs depend significantly on the specificity and clarity of the input prompts. Subtle differences in phrasing or context provided in prompts may inadvertently trigger responses that negatively impact vulnerable individuals seeking support. For example, Grabb (2023) simulated a person with depression seeking help from ChatGPT through four different prompts and produced a wide range of responses that included medication, psychoanalysis, bungee-jumping and shark-cage diving. In addition to user prompts, most LLMs have system prompts that guide their behavior, style, tone, constraints, or role for user interactions (Karpathy, 2025). System prompts are proprietary for each LLM, are frequently not disclosed to users, and could potentially have a significant influence on the effectiveness and safety of LLMs in mental health support

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Patterns in Use of LLMs for Mental Health Support

While existing literature documents LLM capabilities and limitations, a significant gap exists in understanding real-world patterns of use among those with mental health conditions. This knowledge gap was identified at the Sentio Counseling Center, a nonprofit that provides low-fee online counseling to California residents, where a supervisor heard anecdotal reports of clients using LLMs as a lower-cost and more easily accessible alternative for therapy. At the same time, the authors saw a rise of additional anecdotal evidence suggesting that users may be increasingly turning to LLMs for mental health support (e.g., Broderick, 2023; Gator1523, 2024). These anecdotal data provided the catalyst for the present study's systematic examination of how, when, and why individuals engage with LLMs for mental health support.

The Present Study

Despite the widespread adoption of LLMs in the United States, there is limited research specifically examining how individuals with mental health conditions are using these technologies. Previous surveys have focused on general usage patterns rather than mental health-specific applications (e.g., McClain, 2024), and clinical studies have primarily examined purpose-built mental health chatbots rather than general-purpose LLMs (e.g., Fitzpatrick et al., 2017; Inkster et al., 2018). This gap in the literature is significant given the potential implications for mental healthcare access, quality, and outcomes. Understanding how individuals with mental health conditions are using general-purpose LLMs—including frequency, motivations, and perceived effectiveness—is essential for developing appropriate guidelines, safeguards, and potentially complementary roles for these technologies within the broader mental health ecosystem. The current study addresses this gap by examining patterns of LLM use specifically for mental health support or therapy-related goals among U.S. residents with mental health conditions.

Methods

Participants

We administered the survey through the Prolific platform, a crowd-sourcing platform commonly used in social psychological research (Mullen, Fox, Goshom, & Warraich, 2021). This platform enables adults aged 18 and older to complete surveys in exchange for compensation. Prolific offered the survey to users who have previously been pre-screened with three questions: (a) they are residents of the United States, (b) they affirmed that they had interacted with at least one of 15 major LLMs listed, such as ChatGPT, Claude, and Grok; and (c) they answered "yes" to this question "Do you have – or have you had – a diagnosed, on-going mental health/illness/condition?"

A total of N = 499 participants provided valid responses that were used in this study. They had a mean age of 37.97 years (SD = 0.53). Regarding gender, most participants identified as women (including trans female/trans woman; n = 298, 59.7%), followed by men (including trans male/trans man; n = 184, 36.9%), and non-binary (n = 17, 3.4%). Participants' highest education levels were predominantly undergraduate degrees (n = 187, 37.5%), high school diplomas or A-levels (n = 113, 22.6%), or technical or community college (n = 103, 20.6%). A smaller proportion held graduate degrees (n = 75, 15%), doctorate degrees (n = 7, 1.4%), secondary education (n = 11, 2.2%), or no formal qualifications (n = 3, 0.6%). Ethnically, the majority identified as White (n = 397, 79.6%), followed by Black (n = 40, 8%), Mixed (n = 36, 7.2%), Asian (n = 16, 3.2%), and Other (n = 10, 2%). Regarding student status, most were not students (n = 381, 76.4%), while some were students (n = 100, 20%), and 18 cases (3.6%) did not have data. Employment status indicated that most participants were employed full-time (n = 255, 51.1%), part-time (n = 89, 17.8%), or not in paid work (e.g., homemaker, retired or disabled; n = 66, 13.2%). Others were unemployed and job-seeking (n = 44, 8.8%), while 20 (4%) cases did not have data, and 1% (n = 5) were due to start a new job within the next month.

Measures

Participants completed a survey that was divided into two sections. The first section had 10 questions which asked about participants' use of LLMs in general, as well as the question "Did you use any of the LLMs for mental health support or therapy-related goals in the past year?". If they answered yes to this question, they were moved on to the second section of the survey, which had 25 questions regarding patterns of LLM use for mental health support or therapy-related goals, reasons for use, perceived effectiveness, comparison with human therapy, problematic experiences, and other related topics. Four of the questions were open-ended qualitative questions that invited participants to write about their experiences using LLMs, such as "Please describe in a few sentences what your typical interaction with the LLM for mental health support looks like. What do you usually ask or discuss?" or "If there were any times that the LLM was particularly helpful for your mental health or therapy-related goals, can you share a specific example?" A full analysis of the qualitative data is beyond the scope of this study, so those data are used here for illustrative purposes only. The survey included two attention check questions which were used to assess the validity of each participant's data: one in the first section of the survey, and one in the second section, near the end of the survey.

Procedures

Data were collected on February 26, 2025. From the Prolific platform, all participants were directed to a secure survey website, where they were asked to complete a one-time, web-based consent form and survey. Participants were compensated $18/hr (30 cents per minute) for completing the survey. Participants were informed their participation was anonymous, voluntary, and that they could discontinue at any time by simply closing the webpage. The institutional review board affiliated with the first author's institution (IRB Protocol number #25-058-1012) approved this study. ChatGPT 4.5, Claude 3.7 Sonnet and Grok 3.0 were used to assist with finding references, surveying possibilities, and editing language for this study (OpenAI, 2025; Anthropic, 2025; Xai, 2025). We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study. This study was not preregistered.

Results

Data Validity Checks

The survey initially returned 522 responses. After preliminary inspection, we excluded 23 (4.41% of the initial sample) total participants because of invalid data. More specifically, 16 participants (3.07%) revoked their consent; 2 participants (0.38%) reported no LLM usage in the past year; 0 participants failed all attention-check questions; and 5 participants (2.30%) were removed due to duplicate or mismatched IP addresses across questionnaires. After these initial exclusions, we were left with a sample of 499 respondents (95.59% of the original cohort).

Participant Experiences of General LLM Usage

All participants (N = 499) reported using LLMs within the past year (see in Table 1). The most frequently used LLM was ChatGPT (n = 485, 96.2%), followed by Google Bard/Gemini (n = 265, 52.6%), Character.AI (n = 92, 18.3%), Bing Chat (n = 90, 17.9%), Grok (n = 72, 14.3%), Claude (Anthropic; n = 65, 12.9%), Llama (Facebook; n = 60, 11.9%), and Perplexity (n = 44, 8.7%). Usage frequency varied, with the majority using LLMs several times per week (n = 132, 26.5%), daily (n = 116, 23.2%), or weekly (n = 101, 20.2%). Others reported using LLMs 2-3 times per month (n = 80, 16%), once per month (n = 69, 13.8%), or missing value (n = 1, 0.2%). Regarding helpfulness, a significant majority found LLMs helpful (n = 451, 90.4%), while a small minority were uncertain (n = 37, 7.4%) or did not find them helpful (n = 11, 2.2%). Descriptive statistics for participant experiences of general LLM Table 1.

Participant Experiences of Mental Health-related LLM Usage

Almost half of the participants (n = 243, 48.7%) had used LLMs specifically for mental health support or therapy-related goals, while slightly over half had not (n = 256, 51.3%). Additionally, a majority had sought mental health support from a human therapist within the past year (n = 318, 63.7%), while 36.3% had not (n = 181). Reasons (a "select all that apply" question) for not using LLMs for mental health support included preference for human interaction (n = 137, 40.2%), doubts about effectiveness (n = 142, 41.6%), being unaware of the possibility (n = 115, 33.7%), and concerns about privacy (n = 31, 9.1%)[1]. Nonetheless, many participants expressed a willingness to consider future mental health support from LLMs (n = 305, 61.1%), while some were uncertain (n = 129, 25.9%) or declined the possibility (n = 60, 12%). Descriptive statistics of participant experiences of mental health-related usage are presented in Table 2.

[1] Because participants could select more than one option, the sum of percentages for all options exceeds 100%.

Objectives or Motivations for Mental Health-related LLM Usage

Participants primarily used LLMs to manage anxiety (n = 178, 73.3%), receive advice on personal issues (n = 153, 63.0%), cope with depression (n = 145, 59.7%), gain insight into emotions (n = 142, 58.4%), improve mood (n = 136, 56.0%), practice communication skills (n = 87, 35.8%), and feel less lonely (n = 85, 35.0%). Common mental health issues addressed included anxiety (n = 194, 79.8%), depression (n = 176, 72.4%), stress (n = 170, 70.0%), relationship issues (n = 100, 41.2%), low self-esteem (n = 88, 36.2%), trauma (n = 81, 33.3%), grief (n = 66, 27.2%), addiction (n = 42, 17.3%), eating disorders (n = 24, 9.9%), thoughts of self-harm (n = 23, 9.5%). During mental health crises, LLMs were used primarily for intense anxiety or panic attacks (n = 107, 44.0%), relationship or interpersonal crises (n = 103, 42.4%), severe depressive episodes (n = 92, 37.9%), acute emotional distress following trauma (n = 52, 21.4%), suicidal thoughts (n = 30, 12.4%), and self-harm behaviors (n = 18, 7.4%). Key reasons for choosing LLMs included accessibility (n = 219, 90.1%), affordability (n = 171, 70.4%), quick relief (n = 143, 58.9%), curiosity (n = 123, 50.6%), anonymity (n = 113, 46.5%), lack of access to a human therapist (n = 71, 29.2%), preference of interacting with AI over human therapist (n = 51, 21.0%), following recommendation by someone else (n = 25, 10.3%), or helping someone else using LLM (n = 14, 5.8%). Descriptive statistics of objectives or motivations for mental health-related LLM usage are presented in Table 3.

Perceived Helpfulness of LLM in Mental Health-related Usage

Among participants who used LLMs for mental health-related issues (N = 243), 63.4% (n = 154) reported that LLM use had improved their mental health or well-being, while 33.7% (n = 82) selected “maybe, it’s complicated”. A small proportion (2.9%, n = 7) reported no improvement.

Participants were asked to rate the different aspects of helpfulness of LLM. Regarding emotional support, 20.2% (n = 49) rated LLMs as very helpful, 54.7% (n = 133) found LLMs helpful, while 17.3% (n = 42) rated LLMs as neutral, unhelpful (6.6%, n = 16), or very unhelpful (1.2%, n = 3). In a related question asking participants to rate their perceived empathy and understanding from the LLMs from a scale of 1 (very poor) to 5 (excellent), 30.0% (n = 73) participants gave a rating of 5, 44.4% (n = 108) provided a rating of 4, and only a minority of participants selected 3 (20.2%, n = 49), 2 (3.3%, n = 8), or 1 (2.1%, n = 5). Regarding offering practical advice, 38.7% (n = 94) rated LLMs as very helpful, 48.1% (n = 117) reported helpful, while others rated their experience as neutral (9.9%, n = 24), unhelpful (2.1%, n = 5), or very unhelpful (1.2%, n = 3). Regarding crisis situations, 17.3% (n = 42) rated LLMs as very helpful and 38.7% (n = 94) found them helpful. Neutral responses were provided by 37.0% (n = 90), while smaller numbers found LLMs unhelpful (5.8%, n = 14) or very unhelpful (1.2%, n = 3). In terms of overall satisfaction, 28.4% (n = 69) rated it as very helpful and 53.9% (n = 131) rated their experience as helpful. Fewer participants responded neutrally (15.6%, n = 38), or reporting unhelpful (1.6%, n = 4) or very unhelpful (0.4%, n = 1). Finally, on a scale from 1 (very unlikely) to 5 (very likely), participants rated the likelihood that their next LLM use for mental health support would be helpful. The most common responses were 42.8% (n = 104) for a rating of 4 and 36.2% (n = 88) for a rating of 5. Fewer participants selected 3 (16.9%, n = 41), 2 (3.7%, n = 9), or 1 (0.4%, n = 1). This being said, when asked if they would recommend LLMs for mental health support, 60.5% (n = 147) responded affirmatively, while 35.8% (n = 87) were uncertain, and 3.7% (n = 9) said no. Descriptive statistics of perceived helpfulness of LLM in mental health-related usage are presented in Table 4.

Perceived Factors Influencing LLM Helpfulness

Participants (N = 243) identified key factors affecting LLM helpfulness, including the nature of their mental health concern (30.5%, n = 74), urgency or timing of support (21%, n = 51), clarity and detail of their input (26.7%, n = 65), quality of previous interactions (14.8%, n = 36), and availability of alternative support (6.6%, n = 16). One participant (0.4%, n = 1) endorsed all of the above.

Comparison between Mental Health Support from LLM versus Human Therapist

Among participants who used LLMs for mental health-related issues (N = 243), 87.2% (n = 212) had also received psychotherapy from a human therapist, while 12.8% (n = 31) had not. Among those who had received therapy from a human therapist, participants rated the helpfulness of LLMs compared to human therapists on a scale from 1 (LLM much less helpful than human therapist) to 5 (LLM much more helpful than human therapist). The most common rating was 3 (n = 82, 38.7% of those who responded), followed by 4 (n = 52, 24.5%), 2 (n = 43, 20.3%), 5 (n = 24, 11.3%), and 1 (n = 11, 5.2%). Descriptive statistics of comparison between mental health support from LLM versus human therapist are presented in Table 5.

Participants' Usage Patterns

Among participants (N = 243) who used LLMs for mental health support, the most common length of use was 1-3 months (n = 71, 29.2%) and 4-6 months (n = 70, 28.8%). Smaller groups reported using LLMs for 7-12 months (n = 44, 18.1%), more than a year (n = 42, 17.3%), or less than a month (n = 16, 6.6%). Participants were asked to rate their likelihood of continuing to use LLMs for mental health support on a scale from 1 (definitely no) to 5 (definitely yes). The most common response was 5 (n = 116, 47.7%), followed by 4 (n = 71, 29.2%), 3 (n = 44, 18.1%), 2 (n = 10, 4.1%), and 1 (n = 2, 0.8%).

Harmful or Inappropriate Responses

Most participants (n = 221, 91.0%) reported that they had never received a harmful or inappropriate response from an LLM, while 9.0% (n = 22) indicated that they had encountered such responses. Among those 22 participants who received harmful responses, 45.5% (n = 10) reported that the response was dismissive or minimizing, 54.5% (n = 12) said the response was factually incorrect, and 41.0% (n = 9) described it as offensive or insensitive. A smaller proportion (n = 4, 18.2%) reported that the LLM encouraged harmful behavior.[2] Descriptive statistics of participants' usage patterns and harmful responses are presented in Table 6.

Discussion

The primary overall finding of the current study is preliminary evidence of the significant adoption of LLMs for mental health purposes. Due to pre-selection criteria, this survey included only participants who reported both the use of LLMs and an ongoing mental health condition, limiting the generalizability of the findings to the broader U.S. population. Nevertheless, leveraging the recent estimate by the National Institute of Mental Health (2022) that approximately 59 million adult Americans experience mental health conditions, combined with

[2] Because participants could select more than one option, the sum of percentages for all options exceeds 100%.

Pew Research findings indicating that 23% of U.S. adults have used ChatGPT (McClain, 2024), we derive an approximate estimate of 13 million U.S. adults meeting both criteria. Our finding that 48.7% of respondents within this group utilize LLMs for mental health support suggests that millions of Americans may currently engage in this practice. For context, the Veterans Health Administration, one of the largest institutional mental health providers in the nation, serves approximately 1.7 million patients annually (U.S. Department of Veterans Affairs, n.d.). If accurate, this estimation positions LLMs as potentially among the largest providers of mental health support in the United States—a noteworthy development that has occurred organically, absent targeted efforts to establish LLMs as an explicit modality for mental health services.

The primary objectives for mental health-related LLM usage centered predominantly around managing anxiety (73.3%), receiving advice on personal issues (63.0%), and coping with depression (59.7%). For example, a participant reported “I ask for a list of coping strategies for panic attacks or anxiety attacks.” Additionally, participants frequently sought to gain insight into their emotions (58.4%) and improve their mood (56.0%). One participant reported, “Help managing stress, handling work challenges, or finding ways to feel better. The conversation could include advice and/or encouragement.” These findings suggest that LLMs are being employed to address a range of psychological concerns, from acute symptomatic relief to broader emotional understanding and well-being. A significant majority of users (63.4%) reported that LLM use had improved their mental health or well-being. For example, one participant reported “Last week I needed to understand why I randomly cry sometimes during episodes and LLM gave me clarity and a better understanding that crying is accepted and okay. It's how we vent to feel through and heal through life altering events.” An additional 33.7% of participants indicated ambivalence ("maybe, it's complicated"), with one writing “There have been a couple instances of the LLM providing responses regarding mental health that are too generic and aren't particularly helpful to my situation.” Only a small minority (2.9%) reported no improvement whatsoever. This pattern of perceived benefit was further reflected in participants' ratings of specific aspects of LLM helpfulness, with particularly strong positive evaluations for practical advice (86.8% rating as helpful or very helpful) and overall satisfaction (82.3% rating as helpful or very helpful). For example, one participant reported “I found it extremely helpful when my son was hospitalized last year with severe ocd. I felt overwhelmed by the whole situation and asked for advice on how to manage my stress and what I could do to help him deal with his issues as well. I found it helpful to have a neutral third party of sorts to bounce ideas off of and it was helpful just as an overall distraction from worry getting out of control.” These findings align with the participants' future intentions, with 76.9% indicating a high likelihood (ratings of 4 or 5 on a 5-point scale) of continuing to use LLMs for mental health support.

When comparing LLMs with human therapy among those who had experienced both (87.2% of LLM mental health users), participants' evaluations were predominantly neutral to positive. One participant reported, “I chatted with a chatbot recently when I was feeling really depressed and lonely and asked for some mental health support. It was actually an enjoyable experience, and not really any less effective for me personally than when I've dealt with therapists. In fact it felt a little safer than a standard therapist.” The modal rating was neutral (41.0%), followed by more favorable ratings for LLMs (25.5% rated LLMs as more helpful and 12.3% as much more helpful than human therapists). Only 26.9% rated human therapists as more helpful than LLMs. This relatively favorable comparison suggests that for many users, LLMs may provide therapeutic value that approaches or, in some cases, exceeds that of traditional human-delivered therapy. For example, one participant reported “I usually just talk to it when

I'm feeling lonely or super depressed. It's nice that it just listens, but also that it gives me some actionable advice and really helpful encouragement. It's especially helpful because I have severe social anxiety, so it's a little easier to talk to AI than to a human therapist.” Despite concerns about potential harm, our findings revealed a relatively low incidence of harmful or inappropriate responses. Only 9.0% of participants reported encountering such responses, with the most common issues being factually incorrect information (54.5%), dismissive or minimizing responses (45.5%), and offensive or insensitive content (41.0%). For example, one participant reported “There was a point where it kept trying to tell me to ask my dead father for information when I was specifically telling it I was stressed out about the fact that I could not ask him for that information and needed it to complete part of the process of settling his affairs”, another reported “One time when I was in a depressive episode, I asked for coping strategies and not only got the usual "go outside, eat healthy, workout" etc. advice that I have obviously tried, but it overwhelmed me with information and I didn't want to read any of it”, and another “While having a panic attack I asked a very detailed question and the LLM provided negative information that worsened my symptoms.” A smaller proportion (18.2%) reported that the LLM encouraged harmful behavior. For example, one participant reported “...I had to specifically add to the system prompts to always push back and that I can tend to be manic so watch out for that. The main challenge is that I am very technical and my work occasionally goes viral, so it's hard for me to know when an idea is good or when I'm just being manic, since social media can sometimes encourage manic episodes. LLMs tend to be overly supportive, and DeepSeek specifically seems uncensored and will encourage just about anything.” These results indicate that while LLMs are not without risks, the majority of users experienced them as safe and appropriate for mental health purposes.

Collectively, these findings highlight the emerging role of LLMs as accessible mental health resources that appear to confer meaningful benefits for many users. The high satisfaction ratings, coupled with intentions to continue use and favorable comparisons with human therapy, suggest that LLMs may represent a valuable addition to the mental health support landscape, particularly given their reported accessibility (90.1%) and affordability (70.4%), two factors frequently cited as barriers to traditional mental healthcare services. For example, one participant reported “I had a crisis related to death in the family and couldn't reach anybody else in the middle of the night. LLM got me through the night until I could talk to somebody.”

Accessibility and Affordability as Drivers

The high percentage of participants citing accessibility (90.1%) and affordability (70.4%) as key motivations for LLM use may suggest barriers in the current mental health care system. The immediate availability of LLMs addresses critical gaps in care delivery, particularly valuable for the 29.2% who mentioned lack of access to a human therapist. The temporal flexibility—available 24/7 without appointments—appears especially valuable for managing acute symptoms, as indicated by the 58.9% who cited "quick relief" as a motivation and the 44.0% who reported using LLMs during anxiety or panic attacks. For example, one participant reported “I have talked to LLMs mid panic attack to calm myself down, we have discussed coping tips and I have gotten reassurance from it that I'm ok/safe. When I get panic attacks, I get very afraid sometimes that I'm going to die, so we have discussed that too”.

Effectiveness for Different Conditions

Our findings reveal variations in perceived effectiveness across different conditions.

LLMs appear particularly beneficial for practical advice and anxiety management, with 86.8% of participants finding them helpful for practical advice and 79.8% of them using LLMs for anxiety. One participant reported, “Since I have health anxiety I would constantly ask it to confirm symptoms when I was spiraling. I asked what they might be and how to talk myself down.” In contrast, conditions involving trauma, severe depression, or suicidal ideation showed more mixed results. Just over half of participants (56%) rated LLMs as helpful or very helpful during crisis situations, with one writing “My anxiety and how when I am around a lot of people it gets the best of me. It gets so bad I can barely make phone calls. I will ask for it to help me calm down and breathe and it helps usually,” another reporting “I wanted to commit suicide but the LLM shared great encouragement that pulled me from the situation,” and another “I think it's a great tool for someone with trauma and low self esteem.” This percentage is notably lower than for general support (74.9%)—suggests LLMs may be less effective for urgent, complex, or high-stakes challenges.

Complementary vs. Substitution Role

Participants integrate LLMs into their care in diverse ways. Among those who had received human therapy, 38.7% rated LLMs as equally helpful as human therapists, with a slight skew toward finding LLMs more helpful (35.8%) versus less helpful (25.5%), suggesting that LLMs are not functioning as wholesale replacements for traditional therapy. For example, one participant reported “I actually prefer it to my previous human therapist! I am surprised, but I really find it more useful, and supportive, and smart, and I don't feel like I'm just paying someone to listen and provide generalized advice or affirmations. Plus, the LLM actually remembers our conversations and we build on them, unlike my previous therapist who at times it seemed like they didn't remember what we had already talked about, etc.” another reported “Overall, my experience with LLMs for mental health support has been a mixed one. While they provide helpful general advice, it's clear that they can't fully replace the depth and personalized care that a human therapist or counselor offers, especially for more complex or urgent mental health issues” and another “It's a non-judgemental space to express my thoughts, but not a replacement for professional therapy.” The high percentage (76.9%) who indicated they would likely or definitely continue using LLMs, combined with strong satisfaction ratings (82.3%), suggests that LLMs are filling an important niche in the mental health care ecosystem. One participant reported, “It's super helpful for dealing with executive dysfunction symptoms by giving functional, actionable suggestions that are usually pretty specific.”

User Satisfaction Factors

Several key factors influence user satisfaction with LLMs. The nature of the mental health concern emerged as most significant (30.5%), suggesting certain issues are more amenable to LLM-based support. The importance placed on clarity and detail of input (26.7%) indicates that, unlike human therapists who can actively probe client concerns, LLM effectiveness depends on users' ability to articulate their needs. For example, one participant reported “I usually let the LLM know how I'm feeling and what struggles I'm having. The LLM will often respond with a generic answer, but as we continue the conversation I provide more details about what I'm experiencing. Once the LLM has more details, it's usually able to give a more specific and helpful response.” The influence of timing (21.0%) reinforces the value of immediate accessibility, particularly during crises. The quality of previous interactions (14.8%) suggests users develop relationships with specific LLMs over time, potentially becoming more skilled at eliciting helpful responses. For example, one participant reported “I ask it to pretend it is a DBT therapist with knowledge of Buddhism and tell it to help me from that framework. We discuss issues with my triggers, relationships, and how to get through big emotions using DBT skills and integrating my religion.” and another “I have a few documents I have about myself, I call them "my profiles", that describe different parts of me, which I use as context. I have a "depressed profile" that explains my past with mental health issues but I also have an achievement document so that it can remind me of good things I've done.”

Comparison with Existing Digital Mental Health Tools

LLMs are not specifically designed for or marketed as mental health tools, making direct comparisons to dedicated mental health applications imperfect. However, the accessibility advantages of LLMs mirror those documented for other digital mental health solutions (Torous et al., 2018). A review of retention rates for 93 mental health apps found the median 15-day retention rate to be 3.9% (Baumel et al., 2019). In contrast, 69.9% of our participants reported using LLMs weekly or more often, and 76.9% indicated a high likelihood of continuing to use. These findings suggest that LLMs may foster more sustained engagement, possibly due to their versatile functionality, which encourages users to engage with the platform for more purposes. For example, one participant reported “I like having AI because I can also do other stuff like talk about my hobbies more often and whenever I want.”

Clinical and Public Health Implications

Our preliminary findings suggest potential for LLMs in mental health service delivery, though significant research gaps remain. While 61.1% of participants expressed a willingness to consider LLMs and 63.4% reported perceived benefits, these self-reported outcomes require validation through controlled clinical studies. The reported motivations—accessibility (90.1%) and affordability (70.4%)—indicate these technologies might eventually help address service barriers, but their clinical efficacy and safety profiles must first be rigorously established. LLMs might potentially serve a role in stepped care approaches, though their appropriate placement within such frameworks remains uncertain given limited evidence. While participants commonly used LLMs for anxiety and depression, the therapeutic validity of such interactions requires thorough investigation. The reported usage during challenging situations, including anxiety attacks (44.0%) and suicidal thoughts (12.4%), raises both possibilities and concerns that warrant thorough safety evaluations. The 9.0% of users who encountered harmful responses, including content described as factually incorrect (54.5%) or dismissive (45.5%)—highlights substantial safety concerns requiring investigation. Finally, while the data suggests LLMs might address gaps in care for underserved populations, this should not distract from addressing systemic barriers to evidence-based treatment. The apparent accessibility benefits must be weighed against unknown risks, particularly for vulnerable individuals in crisis, as indicated by the percentage (12.4%) who reported using LLMs for suicidal thoughts.

Future Research Directions

Our findings suggest several promising avenues for future research on LLM use for mental health support. Collaborative partnerships with LLM developers would be particularly valuable, enabling researchers to conduct rigorous clinical trials and systematically evaluate and optimize these systems for therapeutic applications while addressing privacy concerns and ethical considerations. Longitudinal studies are essential to examine the sustained effectiveness of LLM-based mental health support. Comparative effectiveness studies between different LLMs are warranted given the varied usage patterns observed in our sample. Research comparing therapeutic efficacy across platforms could identify system-specific strengths and limitations for different mental health concerns. Future research should investigate the efficacy of specific therapeutic techniques delivered via LLMs and which therapeutic modalities are most effectively translated to this medium. Prompt optimization research could examine how prompt structure, specificity, and framing influence therapeutic outcomes. Finally, research on integrated care models combining LLM and human-delivered support is indicated. Studies exploring complementary roles, therapist attitudes toward LLM use, and potential synergistic effects could inform the development of hybrid therapeutic approaches that leverage the accessibility of LLMs while maintaining the benefits of human therapeutic relationships.

Researchers should consider that the scale of LLMs presents opportunities for clinical research and implementation that far exceed traditional methods. Collaboration with LLMs presents the potential opportunity to perform clinical studies with millions of participants at a global scale and receive results within hours. Empirically supported improvements in LLM services can be rapidly deployed to millions of users, unlike advancements in human-delivered clinical treatments, which typically require significant time, effort, and funding for implementation. Integrating mental health services into LLMs could potentially dramatically reduce the cost and increase the speed of implementation, enabling mental health professionals to concentrate on more specialized tasks. If the findings from this study are confirmed, they could profoundly reshape the landscape of clinical research and implementation in the years to come.

Limitations of the Current Study

This study provides valuable insights into LLM use for mental health support, but several limitations warrant consideration. The first and perhaps most salient limitation is the representativeness of our sample and the generalizability of the findings. Specifically, our sample was restricted to individuals who met two specific inclusion criteria: self-reported use of LLMs in the past year and self-reported ongoing mental health illness/condition. This dual-criterion approach necessarily excludes individuals who may benefit from LLMs but have not yet assessed them, as well as those who may use LLMs preventatively without diagnosed conditions. Further, our sampling criteria also excluded those without technological access or interest, potentially overrepresenting individuals with higher digital literacy and socioeconomic status. Additionally, our sample lacked demographic representativeness, particularly in terms of ethnicity, with approximately 80% identifying as White and only 20% as racial or ethnic minorities. This limitation precluded a meaningful and rigorous examination of potential cultural differences in the perceptions and utilization of LLMs for mental health purposes. Given the implications for mental health disparities and service accessibility in the AI era, this is a critical issue warranting research attention. Future studies should aim to recruit a larger, more diverse sample to explore these questions more comprehensively. Second, the study relied exclusively on self-reported data, which introduces potential recall bias and social desirability effects. Participants' retrospective assessments of LLM helpfulness may have been influenced by their overall attitudes toward technology or recent interactions. Additionally, the subjective nature of mental health improvement makes it difficult to distinguish perceived from actual clinical benefits without objective measures. Therefore, our results should not be interpreted as objective judgment of the efficacy of LLMs in providing mental health services, which may be more appropriately established by rigorous research designs (such as randomized controlled trials).

Instead, our results more accurately reflect individuals' subjective utilization, attitudes, and perceptions of LLMs for mental health purposes. Third, although participants reported using various LLMs, platform-specific differences were not fully captured in our analysis. Different LLMs employ distinct algorithms, training data, hidden system prompts, and response frameworks, all which likely influence their effectiveness for mental health support. Fourth, the assessment of clinical outcomes was limited, lacking standardized clinical measures to evaluate symptom changes. Without pre-post assessments using validated instruments, causal inferences about LLM effectiveness are not possible. Fifth, the survey was available only in English, potentially excluding non-English-speaking individuals and limiting the generalizability of findings to diverse linguistic populations. Finally, the cross-sectional design precluded examination of how LLM usage patterns and perceived benefits might change over time.

Conclusion

While LLMs are not designed or marketed for mental health support, data from this survey presents preliminary evidence that millions of Americans with mental health conditions may be spontaneously turning to LLMs for support, potentially making LLMs one of the largest providers of mental health services in the U.S. These data provide a strong rationale for further research in this area. Moving forward, collaboration between mental health professionals and LLM developers would be beneficial. This partnership could focus on co-designing system prompts that incorporate clinical best practices and ethical guidelines. Mental health experts can provide valuable insights which could aid LLM developers in creating safeguards against potentially harmful outputs, recognizing and responding to crisis language, implementing appropriate safety protocols, and developing response frameworks grounded in evidence-based therapeutic approaches. Such interdisciplinary collaboration may produce standardized guidelines for LLM development and implementation in mental health contexts, helping to ensure these technologies augment professional care. Additionally, ongoing evaluation protocols would help assess LLM performance across diverse populations and mental health conditions. Overall, collaboration between LLM developers and mental health experts could improve both the effectiveness and safety of these tools, significantly expanding their potential impact across the U.S. population and beyond.

Supplemental materials

A separate file with supplemental materials showing tables with descriptive statistics of the results is available.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Data availability statement

The survey and data from this study are available from the corresponding author, BLINDED, upon reasonable request.

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Table 1. Participant experiences of General LLM Usage (N=499)

Variable		**n**	**%**
Have you used any large language model (LLM), such as ChatGPT, Grok, Bard, Gemini, Claude, or others, in the past year?		499	100
Which of the following LLMs have you used in the past year?(Select all that apply)			
	Character.AI	92	18.3
	ChatGPT	485	96.2
	Google Bard/Gemini	265	52.6
	Claud (Anthropic)	65	12.9
	Bing Chat	90	17.9
	Grok	72	14.3
	Llama (Facebook)	60	11.9
	Perplexity	44	8.7
Approximately how frequently did you use any of the LLMs in the past year?		499	100
	1x month	69	13.8
	2-3x month	80	16
	daily	116	23.2
	Never	1	0.2
	several times a week	132	26.5
	weekly	101	20.2
Did you find any of the LLMs helpful?		499	100
	Maybe	37	7.4
	No	11	2.2
	Yes	451	90.4

Table 2. Participant experiences of mental health-related usage (N=499)

Variable		n	%
Did you use any of the LLMs for mental health support or therapy-related goals in the past year?		499	100
	No	256	51.3
	Yes	243	48.7
In the past year, have you sought mental health support from a human therapist or counselor?		499	100
	No	181	36.3
	Yes	318	63.7
If you have NOT used an LLM for mental health support or therapy-related goals, what are the main reasons?			
	Unaware of this possibility	115	33.7
	Prefer human interaction	137	40.2
	Concerns about privacy	108	31.7
	Doubts about effectiveness	142	41.6
	Lack of access to technology	9	2.6
	Others	63	
Would you consider using an LLM for mental health support in the future?		499	100
	Maybe	129	25.9
	No	60	12
	Yes	305	61.1
	Missing data	5	1

Table 3. Objectives or motivations for mental health-related LLM usage

Variable	n	%
What were your main goals or purposes for using an LLM for mental health support? (Select all that apply)_		
To manage anxiety	178	73.3
To cope with depression	145	59.7
To improve mood	136	56.0
To gain insight into emotions	142	58.4
To practice communication skills	87	35.8
To receive advice on personal issues	153	63.0
To feel less lonely	85	35.0
Others	20	8.2
Which mental health symptoms or issues did you use an LLM to help with? (Select all that apply)		
Anxiety	194	79.8
Depression	176	72.4
Stress	170	70.0
Low self-esteem	88	36.2
Relationship issues	100	41.2
Trauma	81	33.3
Grief	66	27.2
Addiction	42	17.3
Eating disorder	24	9.9
Thoughts of hurting myself	23	9.5
Others	24	9.9

In the past 12 months, have you used an LLM during a mental health crisis? (Select all that apply)		
Suicidal thoughts or ideation	30	12.4
Severe depressive episode	92	37.9
Intense anxiety or panic attack	107	44.0
Acute emotional distress following a traumatic event	52	21.4
Self-harm urges or behaviors	18	7.4
Relationship or interpersonal crisis	103	42.4
Substance use or withdrawal crisis	31	12.8
Threats of violence	9	3.7
Someone trying to coerce or control me	17	7.0
I have not used an LLM for crisis support	60	24.7
Others	8	3.3
What are the main reasons you chose to use an LLM for mental health support or therapy-related goals in the past 12 months? (Select all that apply)		
It was free or low-cost compared to therapy	171	70.4
It was accessible anytime I needed it	219	90.1
I wanted to remain anonymous	113	46.5
I was curious about how it could help	123	50.6
I didn’t have access to a human therapist	71	29.2
I prefer interacting with an AI over a human	51	21.0
It was recommended by someone I know	25	10.3
I felt it could provide quick answers or relief	143	58.9
I was helping someone else with a mental health crisis	14	5.8
Others	11	4.5

Table 4. Perceived helpfulness of LLM in mental health-related usage

Variable		**n**	**%**
Do you feel that using an LLM has improved your mental health or well-being?		243	100.0
	Maybe / It's complicated	82	33.7
	No	7	2.9
	Yes	154	63.4
Please rate the following aspects of your experience using LLMs for mental health support:			
Emotional Support: How helpful was the LLM in providing emotional comfort?		243	100.0
	Helpful	133	54.7
	Neutral	42	17.3
	Unhelpful	16	6.6
	Very Helpful	49	20.2
	Very Unhelpful	3	1.2
Practical Advice: How effective was the LLM in offering actionable advice?		243	100.0
	Helpful	117	48.1
	Neutral	24	9.9
	Unhelpful	5	2.1
	Very Helpful	94	38.7
	Very Unhelpful	3	1.2
Crisis Management: How well did the LLM assist you during times of acute distress?		243	100.0
	Helpful	94	38.7
	Neutral	90	37.0
	Unhelpful	14	5.8

	Very Helpful	42	17.3
	Very Unhelpful	3	1.2
Overall Satisfaction: Overall, how would you rate your experience?		243	100.0
	Helpful	131	53.9
	Neutral	38	15.6
	Unhelpful	4	1.6
	Very Helpful	69	28.4
	Very Unhelpful	1	0.4
On a scale from 1 to 5, how likely is it that your next use of an LLM for mental health support will be helpful?		243	100.0
	1	1	0.4
	2	9	3.7
	3	41	16.9
	4	104	42.8
	5	88	36.2
Would you recommend using an LLM for mental health support to others?		243	100.0
	Maybe	87	35.8
	No	9	3.7
	Yes	147	60.5
How would you rate the quality of the LLM's responses in terms of empathy or understanding?		243	100.0
	1	5	2.1
	2	8	3.3
	3	49	20.2
	4	108	44.4

	5	73	30.0

Table 5. Comparison between mental health support from LLM versus human therapist

Variable		**n**	**%**
Have you ever received psychotherapy from a human therapist?		243	100
	No	31	12.8
	Yes	212	87.2
If you have had a human therapist, how would you compare the helpfulness of an LLM to human therapy?		212	100
	1	11	5.2
	2	43	20.3
	3	82	38.7
	4	52	24.5
	5	24	11.3

Table 6. Participants' usage patterns and harmful responses

Variable		**n**	**%**
Approximately how long have you been using an LLM for mental health support?		243	100
	1-3 months	71	29.2
	4-6 months	70	28.8
	7-12 months	44	18.1
	Less than a month	16	6.6
	More than a year	42	17.3
Do you plan to continue using an LLM for mental health support in the future?		243	100
	1	2	0.8
	2	10	4.1
	3	44	18.1
	4	71	29.2
	5	116	47.7
Have you ever received a harmful or inappropriate response from an LLM?		243	100
	No	221	44.3
	Yes	22	4.4
If you have received a harmful or inappropriate response from an LLM, what was the main issue with		22	100

the response? (Select all that apply)			
	It was dismissive or minimizing	10	45.5
	It was factually incorrect	12	54.5
	It was offensive or insensitive	9	40.9
	It encouraged harmful behavior	4	18.2