AI based Digital Assistant for the Assessment of Mental Health

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***Abstract*— Artificial Intelligence (AI) has become a critical component in the majority of digital services today. In healthcare, AI is utilized extensively, including automated medical image analysis and real-time monitoring of patients' vital signs. However, the adoption of AI technologies in the field of mental healthcare has been relatively slow. This gap needs to be addressed as multiple studies and surveys have established that mental health is just as important as physical health. Recently, the significant disparity in the demand for mental healthcare services has led to an accelerated adoption of digital mental health tools to assist both healthcare providers and patients. Though this is a positive development, several challenges remain unresolved, such as understanding the context of conversations and empathizing with patients. This study introduces an AI-enabled digital system that facilitates psychologists in the assessment of their patients' mental health. The system is designed to make it easier for patients to communicate their problems and enables healthcare providers to understand the conditions and needs of their clients in a more accelerated and efficient manner, thereby elevating the quality of mental healthcare services.**

***Index Terms*— Health care systems, Psychology, Mental health, Psychotherapy, AI, Machine Learning, Response generation**

I. INTRODUCTION

Mental health disorders, such as depression, anxiety, substance abuse, and post-traumatic stress disorder, affect a significant number of individuals worldwide. These conditions can have severe consequences and although therapy can be effective in many cases, only a small percentage of individuals with mental illnesses seek and receive treatment [1]. The COVID-19 pandemic has further exacerbated this issue by limiting in-person appointments and access to care, prompting the deployment of virtual care solutions and digital therapies to address anxiety and symptoms of depression, as well as enhance social support. While technological advances have provided potential solutions to address the challenges of access and need for treatment in mental healthcare, they are still reliant on human involvement and subject to biases, lack of resources, and ambiguity. This is where Artificial Intelligence (AI) has the potential to play a significant role. The core concept of AI systems is the ability to learn from data in an unbiased fashion and automate repetitive tasks while maintaining efficiency.

This paper details the development of an Artificial Intelligence-based digital assistant for the provision of mental health care services such as counseling and expert appointments. The process of creating the system, as well as the challenges encountered during the development process, are described. The system has undergone testing and the results have been analyzed to determine its strengths and weaknesses. The paper is organized as follows: In Section II, a comprehensive examination of the current utilization of artificial intelligence within the field of mental healthcare is presented. Section III provides an overview of the system's design and components along with techniques and algorithms utilized within the system. Section IV describes the system workflow. In Section V, the results of the experimental evaluations are presented along with reservations. The paper concludes with final observations and a list of references.

II. AI IN HEALTHCARE

The utilization of Artificial Intelligence (AI) in healthcare primarily pertains to applications that can analyze data generated in the field of medicine, such as health records and images, and reveal patterns and insights that humans may not be able to discover on their own [7]. With the advent of rapid technological advancements in fields such as cell capture, molecular biology, phenotyping, and bioinformatics in the post-2000s, various opportunities have arisen for the implementation of AI in healthcare. Examples of such applications include the identification of biomarkers for diseases such as cancer [10], [11], protein folding [8], [9], drug repurposing for COVID-19 [12], and the detection of Diabetic Retinopathy. These examples are merely the tip of the iceberg in terms of the real-world use cases of AI in physical healthcare. AI systems are now

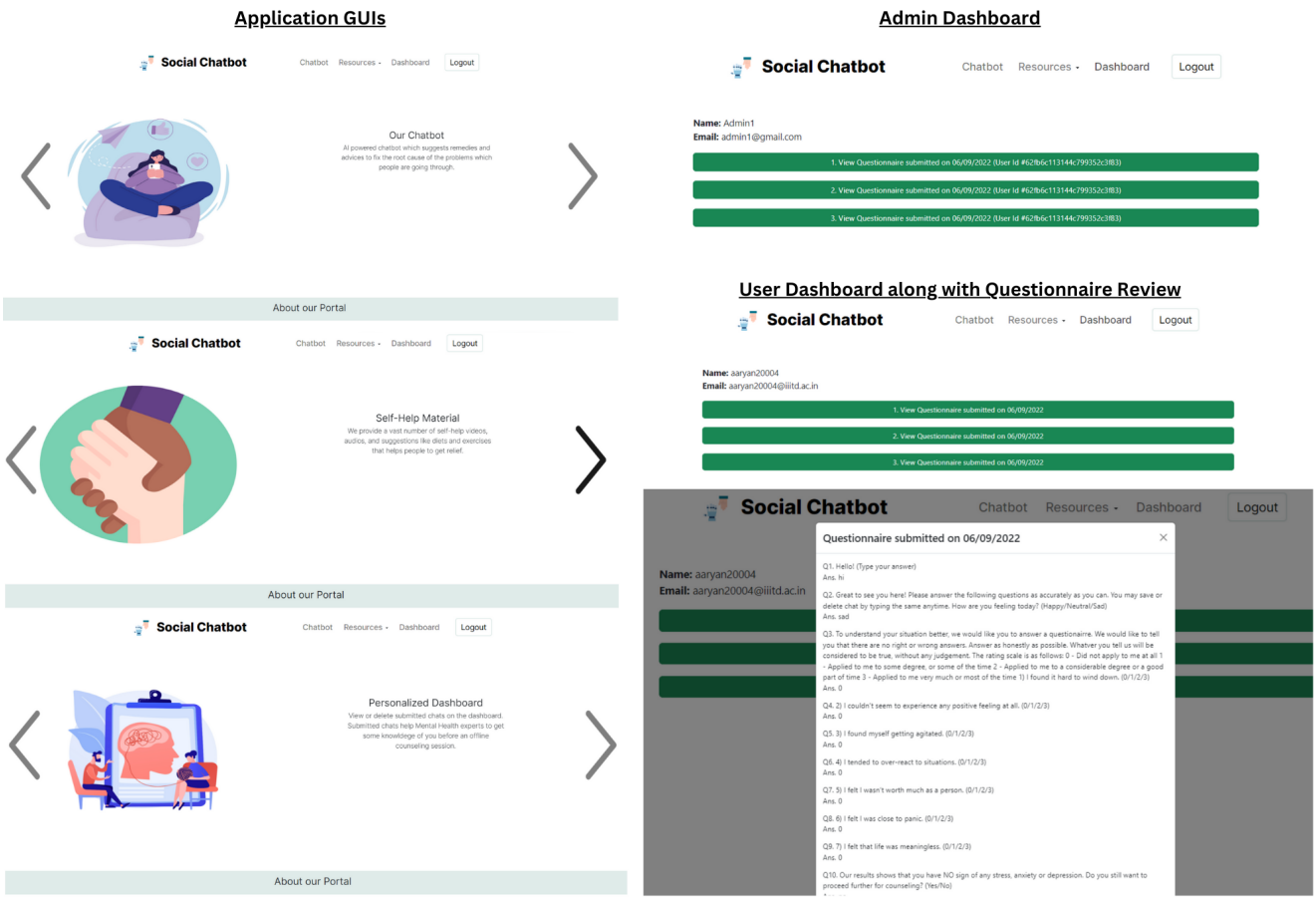

Fig. 1. Our Digital Mental Healthcare System

able to provide a personalized, user-centered experience, increasing efficiency and enhancing the performance of clinical and operational workflows. Additionally, AI can also connect disparate healthcare data, thus providing a comprehensive approach to healthcare.

A. AI in Mental Healthcare

In recent years, there has been a significant push towards the adoption of digital technologies for delivering mental health services. Along with this, the utilization of Artificial Intelligence (AI) to improve their delivery has also gained momentum. One notable initiative in this regard is the Trevor Project, which is the world's largest suicide prevention and crisis intervention organization for LGBTQ youth. Additionally, AI-powered chatbots such as Woebot [3], Wysa [4], and Tess [5] have been designed to provide support for mental health disorders such as substance abuse and to perform cognitive-behavioral therapy (CBT). Despite these remarkable achievements, the use of AI in providing mental healthcare and in improving current technologies that support the mental healthcare industry is still lacking.

When dealing with mental ailments, the demarcation between "healthy" and "unhealthy" is not as clear-cut as it is with physical ailments. Mental health problems do not have specific biomarkers or visual diagnoses that indicate the mental health pathology or the severity of it. Quantitative biomarker analysis proves to be difficult as it is almost impossible to extract relevant biomarkers from the patient at the exact time when the patient is experiencing the ailment. Not only are mental states much more volatile than physical states, but unlike physical ailments, there are mysterious "missing links" between illnesses and symptoms such as anxiety and restlessness or depression and fatigue. Therefore, estimating the cause, severity, and effects of mental health is challenging due to these difficult-to-quantify factors.

B. Problems associated with existing AI Mental Health Assistants

Artificial Intelligence (AI) health assistants have gained significant popularity in the healthcare industry by providing patients with accessible and convenient medical advice. However, the integration of AI technology in healthcare also poses several challenges and problems. One of the major issues is the lack of regulation for AI health assistants, which leads to inconsistencies in the quality and accuracy of the information provided. This

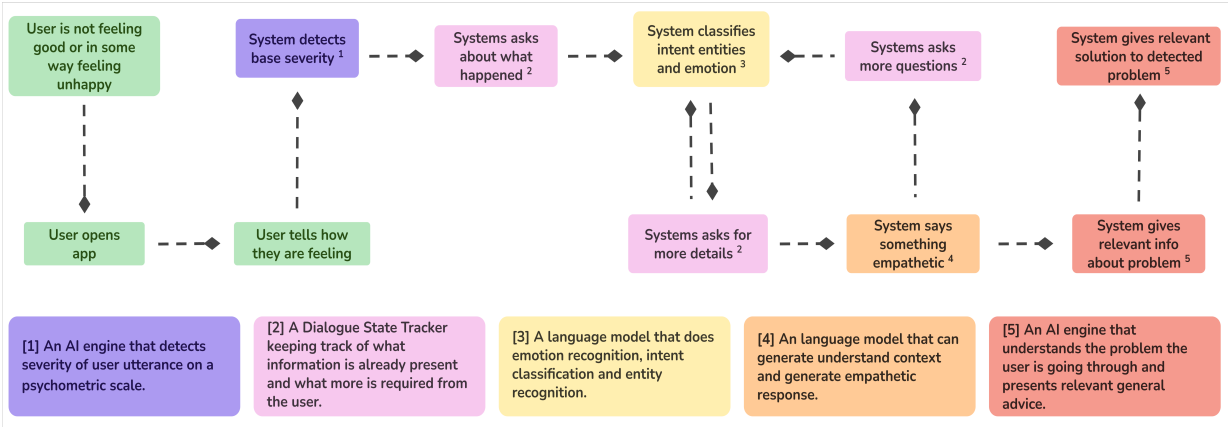

Fig. 2. Framework of our Digital Mental Healthcare System

can result in inaccurate or unfair diagnoses and treatment recommendations. Another issue is that AI health assistants may perpetuate biases and discrimination based on the data they are trained on. Additionally, the use of AI health assistants raises concerns about patient privacy and security, as personal health information is vulnerable to breaches and unauthorized access. Furthermore, AI health assistants are currently limited in their diagnostic capabilities and may not be able to fully replace human doctors or healthcare professionals. Over-reliance on AI health assistants may also lead to decreased critical thinking and decision-making skills among patients and healthcare professionals. In order to fully realize the potential benefits of AI health assistants in providing accessible and efficient healthcare for patients, it is important for the healthcare industry to address these challenges and problems through continued research and development as well as the implementation of comprehensive regulatory frameworks.

III. SYSTEM OVERVIEW AND COMPONENTS

The fundamental principle of our proposed system is to serve as a digital assistant to trained mental healthcare providers. The system has dual functionality, with the first being to interact in an empathetic and supportive manner, providing a safe and confidential space for those seeking help. The system's goal is to understand the specific needs of the user by utilizing natural language processing techniques to analyze their responses. The second functionality of the system is to assist mental healthcare professionals in improving the efficiency of their care-giving. By providing data and preliminary analysis, the system enables the healthcare professional to gain a deeper understanding of the user's requirements and the problems they may be facing, thus facilitating the development of a treatment plan prior to the session. This approach saves valuable time and effort for the preliminary diagnosis and enables the healthcare professional to provide more efficient and effective care.

A. Overview

We have designed a system that addresses some critical gaps present in current digital mental healthcare assistants. We adopted a multidisciplinary approach involving psychologists, computer scientists, UI designers, and AI experts to design a context-aware, empathetic system that provides practical, effective, and simple solutions to the user. Our system is trained on empathetic conversations [2] that can provide a mental healthcare provider with a preliminary insight into the client's requirements. This streamlines the workflow and potentially reduces the time spent per patient, thus helping to reduce clinician burnout. Additionally, the automated extraction of patient information also helps to reduce the administrative burden.

The system is deployed as a chatbot, making it easier for the user to interact with it. Using inputs from psychologists, we trained the model to find the appropriate questions to ask to investigate the user's problems in detail. Once the conversation is over, the conversation and analysis are compiled and sent to the trained mental healthcare provider, who can better understand the user's requirements. Thus, the system also assists the practitioner in the initial prognosis of the patient. Professionals can use the chatbot to streamline the process, better utilize their time, and provide support to the client faster.

Building such a system is a non-trivial task as it incorporates many moving parts that must work together to realize our complete vision. Here we highlight the components, the associated challenges, and how we approached them.

1) Enhancing User Comfort: To ensure that users are able to discuss their issues candidly with the chatbot, without fear of judgement or stigma, we have emphasized the generation of empathetic responses. We have fine-tuned the Facebook's ParlAI [6] engine and trained it on an empathetic dialogue dataset [2] to achieve this objective.

2) Identifying Scenarios: As every user and their situations are unique, digital assistants often fall into the trap of providing generalized and non-unique solutions. To

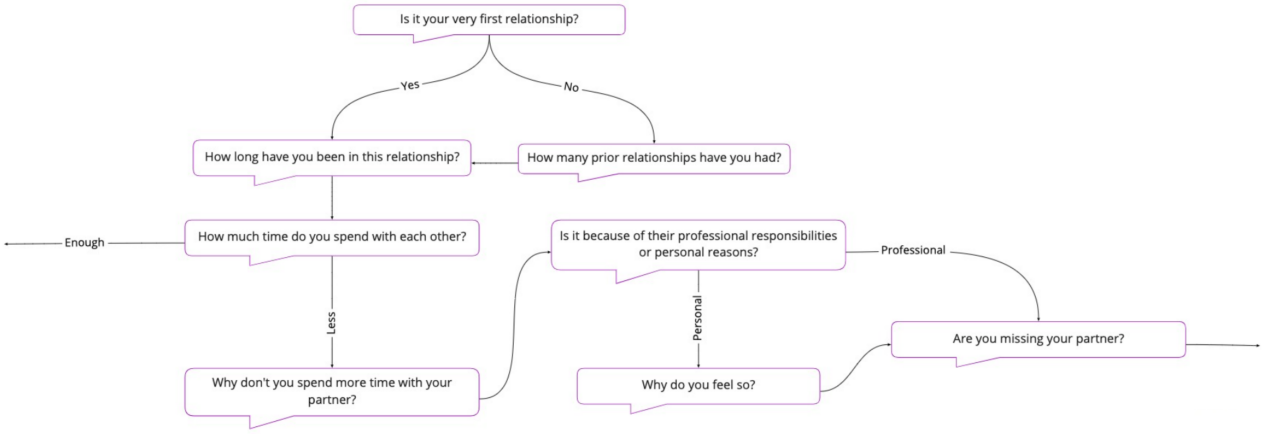

Fig. 3. Sample Decision Tree used in the system

overcome this issue, we have utilized the domain expertise of psychologists to identify 33 primary scenarios that cause problems such as depression, anxiety and stress. Examples of such primary scenarios are - relationship issues, drug abuse, procrastination, etc. We analyze the user's responses to extract linguistic features that identify the primary scenario(s) for the user's problems. Once a primary situation is identified, the system asks questions using the dialogue state tracker to zero in on the specific issue faced by the user.

3) Dialogue State Tracking: The system includes a dialogue-state tracker that determines the response that needs to be given to the user. It analyzes the user's previous responses and determines the next question that needs to be asked. In cases where more information might be required, the dialogue state tracker can request clarity and determine if specific questions need to be repeated.

4) Paraphrasing Engine: In cases where a user might not provide the requested information at the time a question is asked, the system saves such questions to be asked later. After a few more utterances, the system prompts the user for the missing information. However, instead of repeating the same question, the system passes the question text through a state-of-the-art paraphrasing engine to generate a semantically similar question. This module uses a retrained Google's T5 [14] model for question generation.

5) Providing Support using Predictive Analytics: Finally, we have implemented a module that provides counsel to the user based on the results of the inference engine. Such counsel can be in the form of blogs, websites and relevant YouTube videos. This explains the probable cause of the problem to the user and provides immediate help before they get the chance to seek help from the practitioner.

Additionally, we designed simpler modules for tasks such as maintaining logs of the chat and responses and encrypting the logs before they are saved. The logs are only accessible to the practitioner and the users. We also optimized the system's interface to minimize the effort required by the user to interact with the chatbot.

B. Components

1) Q & A System: The majority of available question-answering systems are domain-specific and have exact answers to the questions [13]. These can be linked by dataset features like topics or domains, types of answers and questions. In our case, this kind of Q&A system is not usable. The reasons being:

- the questions can be so varied that mapping them down to any single domain is infeasible.
- there is no structured factual information from which questions can be generated.
- the answers to the questions depend entirely on the user's personality, vocation, present mental state, and innumerable other factors that have led to the user's current circumstances.

This motivated us to develop the system from the ground up. The work is a collaboration between computer scientists from various domains and trained mental health caregivers.

2) DASS 21: The Depression, Anxiety and Stress Scale or DASS is a self-report designed to measure the negative emotional states of depression, anxiety and stress. It measures the conventionally defined emotional states to define further, understand, and measure the ubiquitous and clinically significant emotional states usually described as depression, anxiety and stress. It meets the requirements of both researchers and scientist-professional clinicians. We have incorporated the complete DASS 42-item questionnaire for assessing dysphoria, hopelessness, devaluation of life, self-deprecation, lack of interest/involvement, anhedonia, and inertia for depression, autonomic arousal, skeletal muscle effects, situational anxiety, and subjective experiences for anxiety and levels of chronic non-specific arousal for stress. For each question, there are multiple responses with respective scores.

3) Situations: The thirty three primary situations for which we provide preliminary support are relationship issues, infidelity, alcohol or drug abuse, poor academic performance, insecurities, aimlessness, physical abuse,

domestic violence, victim of bullying, lack of motivation, homesickness, grief, emotional instability, anger & hostility, loneliness, adjustment problems, insomnia, imbalance between professional & personal life, lack of self love or care, poor social life or lack of friends, overthinking, professional growth, physical health problems, body shaming, possessive partners, rejections & failures, phobias, comparisons with others, inferiority or superiority complex, procrastination, communication skills, not being able to express themselves and marital disputes. Each of these scenarios have their own sub categories, like relationship issues with friends, family members or colleagues. A sample of how the system narrows down a situation is shown in Fig. 2.

IV. SYSTEM WORKFLOW

The workflow of our system is outlined in **Algorithm 1**, which is located on the right-hand side section of this page. The algorithm provides a detailed and comprehensive description of the various steps and processes involved in the functioning of our system.

V. RESULTS ANALYSIS AND RESERVATIONS

A. Present Scenario

Our system, being available online 24 hours a day, seven days a week, makes it more accessible than traditional in-person counseling clinics. The ability to access the service at any time without delay allows an unlimited number of individuals to seek assistance as needed. The data present within the application is kept confidential and is not shared. With regular usage, the service adapts to cater to the specific needs of users, providing a more personalized approach to treatment, as opposed to generic, one-size-fits-all advice offered by other services in this field. Although the system may not be able to provide support for all mental disorders, recent advancements in language modeling technology allow for the provision of a space for individuals to express their concerns, and engage in a continuous dialogue. This can not only aid in the feeling of not being alone, but also provide someone to talk to in times of need.

B. Result Analysis

Currently, we have conducted a pilot test of the system with a small group of individuals, during which issues were reported. Despite this, we have received positive feedback from both our institute's students and the Well-being cell (mental health counseling body). We conducted a comprehensive study to evaluate the effectiveness of our AI-based chatbot system in comparison to existing chatbot systems. The study involved a group of students who were asked to engage in a conversation with an existing chatbot and then with our system, and provide feedback on their experience. The results of this experiment were overwhelmingly positive, with participants reporting a higher level of satisfaction and engagement when using our system. Our system was designed to allow

Algorithm 1: Overview of System's Algorithm

1: **Function** *dass21()* **is**
2: The chatbot presents the **DASS 21** questionnaire consisting of 6-7 questions to the user for the assessment of symptoms of stress, anxiety, and depression.
3: After the user completes the questionnaire, the system **predicts the severity** of these symptoms, categorizing the user as having no/mild/severe symptoms of stress/anxiety/depression.
4: **Function** *ask_question(s)* **is**
5: The system then proceeds to ask the user a series of **auto generated by model, related questions**, approximately 10-12, to gain a better understanding of the cause and reasons for the mental health problem selected, as shown in Fig. 2.
6: The system continues to analyze the user's **emotional state** and narrows down the cause of the problem.
7: The discussion concludes when a conclusive reason has been determined by the model.
8: **Function** *give_suggestions(s)* **is**
9: Based on the scenarios identified and user's state, the system provides expert **suggestions and counseling videos** already stored in database to the user for assistance.
10: **Function** *main()* **is**
11: The user initiates the process by logging into the chatbot and initiating a **new chat**.
12: Call *dass21()* function and store the user's state. The system stores this information for future reference to provide relevant suggestions and counseling materials.
13: The system prompts the user to **select the probable cause** of their stress, anxiety, or depression from a list of thirty three scenarios outlined in Section III B (3).
14: Call the user's selected scenario as *s*. Call *ask_question(s)* function and **update** the user's state.
15: Once the questionnaire is over call *give_suggestion(s)* function and **store** this questionnaire in the database.
16: The user has the option to delete, view, or submit the questionnaire to the well-being cell and **request an appointment** with a mental health expert.

for more natural and free-form communication, resulting in a more personalized and effective experience for the user. The integration of expert psychological advice also contributed to the improved performance of our system. The feedback received from the participants of the study provided valuable insights into the strengths of our system and areas for further improvement. We believe that the results of this study demonstrate the superiority of our AI-based chatbot system in terms of user experience, and we are confident that our system will continue to provide exceptional results for users.

Our AI-based chatbot system has been designed with the integration of expert psychological advice, resulting in a higher level of efficiency in comparison to other chatbot systems. Unlike other chatbots such as Wysa or Woebot, our system allows for a more open and free-form communication experience for the user, where their input directly influences the system's response. Additionally, our system addresses concerns related to privacy by implementing robust protocols for the secure storage and handling of conversations conducted through the chatbot, which are further detailed in the subsequent section of this paper.

C. Privacy of Users

It is important to note that all conversations conducted through our chatbot platform are strictly confidential and accessible exclusively to the individual user. Our system utilizes robust security protocols to ensure that all data is stored securely in our database. This includes the option for the user to easily share their conversations with a designated expert, but only with their explicit consent. It is our policy to never share any user's information without their express authorization. Additionally, all login credentials are diligently protected and secured within our database to prevent unauthorized access and data breaches.

D. Reservations

The implementation of our system raises various socio-technical and ethical concerns. One of the most crucial ethical concerns is the secure storage and handling of sensitive patient information, particularly when treatment is provided over an extended period. In the digital realm, these responsibilities become even more complex and crucial. While the potential benefits of this digital revolution in mental health are widely acknowledged, the issue of accountability and oversight remains unresolved. The risk of misuse of such services is substantial, and the responsibility for addressing these concerns falls on a wide range of stakeholders, including developers, researchers, clinicians, regulators, governments, and individuals who should be aware of the benefits as well as the privacy risks associated with the system.

We are continuously working to improve the system on a daily basis. The primary feedback received from users was that the chatbot helped them to organize their thoughts and express themselves more effectively. We are actively incorporating additional scenarios and their corresponding solutions. Further experimentation and testing will be conducted in the future. Additionally, we are developing an information extraction system to generate a summary of the clients' issues for the mental healthcare professional's reference.

VI. CONCLUSIONS

In this paper, we have presented our system, which is being employed as a digital assistant at our institute. We have also discussed the research challenges facing Artificial Intelligence, specifically within the domain of Natural Language Processing. We have highlighted some of the most critical objectives that, if resolved, can improve the utility of digital assistants in mental healthcare and advance the field of Natural Language Processing as a whole. We aimed to inspire researchers to address these challenges and make contributions to this continually evolving field.

Despite the significant advancements in the integration of Artificial Intelligence technologies for affective computing and psychological research, there is still much to be done. Challenges such as analyzing user responses over short, medium and long-term intervals to evaluate the progression of mental health status, or modeling databases for counseling session transcripts with technologies for obscuring Personally Identifiable Information (PII) to enable the availability of these transcripts in the public domain for research, remain unresolved. The incorporation of audio-visual interactions with the user presents an additional set of challenges that require attention. We encourage researchers to develop solutions for these unaddressed problems in order to create an effective digital mental healthcare assistant.

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