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Design and Simulation Based Evaluation of Artificial Intelligence Driven Personalized Mental Healthcare Support System Integrating Natural Language Processing and Machine Learning

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ABSTRACT: Mental-health services face limited accessibility, delayed assessment, little personalization and a shortage of specialists. This paper proposes the Personalized Mental Healthcare Support System (PMHSS), a decision-support framework that integrates natural language processing (NLP), emotion/sentiment analysis, machine learning (ML), a personalized recommendation engine and a conversational AI assistant. PMHSS registers users securely, administers standardized questionnaires, analyses free-text messages, fuses questionnaire, emotional, profile and historical features to classify each user into a Low, Medium or High mental-health risk class, and then recommends self-care, CBT-oriented or professional-support resources. Further modules provide chatbot interaction, counsellor recommendation, appointment scheduling, encrypted teleconsultation and longitudinal progress monitoring. Because no real patient data were used, the risk-classification module was evaluated on a synthetic cohort of 10,000 simulated users (7,000 training, 1,500 validation and 1,500 test users; random seed 42). On this cohort PMHSS reached an accuracy of 98.2%, precision of 98.0%, recall of 97.3% and F1-score of 97.6%, compared with 92.4%, 91.8%, 90.9% and 91.3% for logistic regression, 95.7%, 95.1%, 94.3% and 94.7% for random forest, and 97.1%, 96.7%, 96.0% and 96.3% for XGBoost. These figures describe performance on simulated data only and do not demonstrate clinical validity. Emotion recognition, recommendation quality, chatbot safety and the scheduling and teleconsultation modules were not evaluated. Validation on real, clinician-labelled data, together with safety and fairness audits, is required before any clinical use.

1. INTRODUCTION

Mental health has become an essential part of medicine and healthcare because it is directly related to how well people feel and act in different areas of life including work, education, and socializing. Conventional mental health services face a number of obstacles such as lack of access, untimely evaluation processes, low customization, and shortage of qualified mental health professionals. These limitations call for the application of modern technologies that can perform early evaluations and offer effective support. The current research proposes the development of an AI-based Personalized Mental Healthcare Support System (PMHSS) designed to deal with these problems. Artificial Intelligence (AI) offers possibilities to work with large amounts of user data and find patterns that cannot be detected by traditional methods. In this system AI is applied to the analysis of answers to questions with the help of standardized mental health questionnaire and questions in text format. After the data has been gathered, it is used alongside historical and profile data for the purpose of voluntarily forecasting mental health risks. The system uses a classification scheme that divides individuals into various classes based on the level of mental health risk they are predicted to experience, so that they can receive treatment that is tailored to their situation. Depending on the user's mental health risk, the system can make suggestions for wellness programs, self-care materials, mindfulness practices, Cognitive Behavioral Therapy (CBT) based activities, and motivational tools. In its advanced cases, the system gives priority to professional mental health treatment. Another significant piece of the puzzle is the AI chatbot that keeps in touch with the user, responding to all his or her inquiries by bringing certain context-related information to the fore.

Conventional mental-health assistance relies primarily on the interaction between users and health care professionals. Even though a professional approach remains crucial, challenges can arise in accessibility and scalability. A technology-aided system serves as a supplement in that it allows users to make use of diagnostic tools, interact with an AI-enabled conversational system, and access specific recommendations and improvement tools for users in time. The new system works through a combination of data sources that allow combining information collected through various sources rather than finishing up with the scores from a single questionnaire. The algorithm accepts information about users' profiles, responses to the questionnaire, messages retrieved through text/chat and past assessment experience with a counselor/appointment. Serialized outputs of the algorithm are a mental-health risk score, emotional state, and recommendations. Thanks to the multi-approach implemented within this framework, the personalization has a strong foundation because users with similar scores may have different emotional states, preferences, histories in interaction, and levels of support needed. Thus, the combination of various data ensures a more user-centered approach in providing assistance.

The computational component proposed in this framework uses AI-based systems. The system is created from different trained separate models such as NLP and emotion detection system, risk predicting system, and recommender system. When the system is launched, all these models are initialized. The NLP system performs the tasks of obtaining the received input material. It performs the procedure of noise elimination, tokenization, normalization, stop word removal, and extracting linguistic features before creating the final representation of the texts. The emotion analysis component analyzes semantic and emotional features from the produced text and finds out the prevalent emotional state of the user. After the emotional features are obtained, they are mixed with the data coming from the questionnaire and presented at the different parts of the procedure. Afterward, the classifier can analyze the likelihood distribution across all risk classes, assigning the risk class with the highest probability. This is an opportunity for the system to move from the analysis phase to the phase of action being taken based on the analysis outcome. An approach that is based just on a generic questionnaire or some pre-defined information might miss the user's emotional situation, specific interactions, and preferences. The major contribution of this proposition is the combination of a few AI techniques in one, personalized mental health support system. Instead of treating the emotional situation, NLP, emotion recognition, recommendations, chatbot interaction, and progress monitoring as separate parts, the proposed system joins them via a common processing pipeline.

The paper is organized as follows. Section 1 discusses the background, problem statement, research motivation, aims, scope, significance, proposed methodology, contribution, and overall research methodology. Section two reviews the recent literature on AI, NLP, emotion recognition, machine learning, mental health prediction, personalized recommendation, and conversational AI. Section three describes the proposed architecture of the AI-based personalized mental health support system, the components of the system, the inputs and outputs of the system, and the algorithm used to implement the system. Section four presents the experimental results obtained using accuracy, precision, recall, and F1 score along with comparative evaluation

of the system against the existing methods and graphical presentation of the results obtained. Section five concludes the paper indicating the outcome, contribution, limitations, and future work.

2. LITERATURE REVIEW AND RELATED WORK

The literature from the year 2026 is of great importance since it outlines the recent advancements in the field of mental health systems based on Large Language Models (LLMs). According to recent reviews, there are promising developments, but the clinical validation and safety remain a big issue that has to be addressed. For instance, a study by Le Glaz A *et al.* [1] has reported that out of forty-one studies reviewed (31.7%), only 13 successfully validated their performance against actual patients' data collected with the help of clinicians. The present research work has demonstrated the application of Natural Language Processing (NLP) and Machine Learning (ML) methods in deriving meaningful features of psychological conditions from text data and conducting automated mental health assessment. This publication has shown that the existing studies use various datasets, feature extraction techniques, algorithms, and evaluation techniques. Based on this publication, the authors have developed the technology to make use of NLP for text processing and ML for mental health risk assessment. A systematic review of machine learning and natural language processing applications in mental health has been carried out. The authors Maria Carolina Klos *et al.* [2] have focused on AI chatbot that provides psychological aid to students. The study shows how conversational interfaces can effectively provide psychological assistance at times when people cannot access mental health help in traditional ways. The authors believe that conversational interaction is an important part of digital mental health programs. In this research, the project has gone further by including chatbot conversations into risk assessment, emotion analysis, recommendations, and feedback systems.

NLP has been utilized to run a large-scale text messaging service to tackle mental health issues and analyse conversations related to crises. The research indicates how textual communication provides an insight into the factors responsible for psychiatric problems and needs associated with crisis situations. The research also highlights the significance of machine-learning-assisted research of texts written by people for the purposes of mental health assessment [3]. The system has been adopted in a similar way for assessing texts and emotions of users to improve identification of risk and offer personalized assistance. The article focuses on the possibility to use machine learning algorithms for predicting the risk of postpartum depression. The authors have assessed various types of algorithms and datasets that may be used for prediction purposes [4]. They have discovered that most algorithms belong to the category of supervised learning methods, including SVM, random forest, regression, neural networks, etc. As a result, it could be stated that machine learning is applicable to the field of mental health assessment. Research has been conducted on how machines can predict anxiety and depression during COVID-19. The findings showed that it is possible to combine demographic, Behavioral, and psychological characteristics to predict mental health outcomes. The key contribution of the research is the acceptance of the idea that combining different factors is better than relying on only one variable [5]. This corresponds to the suggested approach of feature fusion when questionnaire responses regarding the respondents' personality, emotions, and history are integrated in the prediction.

Shi Min Lim *et al.* [6] focused on evaluating chatbot-based psychotherapy for adults suffering from anxiety and depressive disorders. The review shows that chatbot solutions provide viable psychological help and can alleviate certain symptoms. It should be noted that the effectiveness of chatbots depends on the technique used and users' engagement in the psychotherapy process. Our system is based on this finding, as it relies on the ability of chatbots to assist patients through conversations and automatic risk detection and recommendations distribution. This research provides a wide overview of NLP methods used in psychological disease identification. The authors focused on the uptake of conventional machine-learning techniques, deep-learning architectures, datasets, linguistic features, and diversity of psychological disorders in respective papers [7]. They stress that there are many options for using text categorization and emotional evaluation techniques in mental disorder diagnostic practices. The authors examined the use of Machine Learning approaches in detecting cases of depression from social media text. Their review revealed that the prevalent technique was supervised learning employing SVM, Bayesian approach, LDA, decision trees and neural networks. The authors specified the difference in the ways of deciding on the depression labels that influenced the evaluation of the models [8]. The proposed solution addresses the similar problem by introducing the combined approach where instead of purely using social media text the text-derived information is complemented with data obtained from questionnaires and historical characteristics.

The work done by Muhammad Khubayeb Kabir *et al.* [9] discusses the detection of depression severity based on Bengali-language social media posts using NLP techniques. Their findings indicate that textual data in Bengali language can be utilized

to find out depression patterns and how important preprocessing and language feature extraction are in the analysis of user-generated texts. The findings validate the NLP pipeline and preprocessing methods employed in the proposed system and indicate that the updates of the system could probably be multilingual. A number of ML algorithms studied the way NLP methodology can be utilized to identify emotions communicated by clinicians in electronic health records. Their study proves that clinical narratives can be beneficial when conducting research in mental health. Their findings also prove the point about the possibility of utilizing emotional indicators together with traditional clinical variables [10]. The principle described above is applied in the proposed system and emotion features are extracted through user responses and combined with questionnaires' data. The techniques for digital phenotyping discussed in the review demonstrate the use of ML for health behavior and states description [11]. Methodological challenges regarding data quality, privacy, and generalizability are mentioned here as well. The findings corroborate the need for a monitoring tool based on recurrent evaluation of people interacting with it in the system. Schick et al. examined the use of chatbots for mental state evaluation and marked the fact that conversational technologies could be used to gather the information useful for assessment. Nevertheless, the authors note that chatbot evaluation needs to be carefully verified because different interlocutors behave very differently [12]. This is the reason why the proposed system considers chatbot conversation as part of the evaluation and prediction strategy, not as a substitute for professional diagnosis.

Birk and Samuel studied the use of digital phenotyping in relation to mental health. The work explores how behavioral information in digital form might be used for the monitoring and prediction of mental health-related issues and discusses the issues of privacy and interpretation of such information [13]. The relevance of this research for the proposed system stems from the fact that technological monitoring requires corresponding ethical measures. In addition, it relates to the requirement of the continuous monitoring capability of the proposed system and security of the user data. Ivan Moura *et al.* [14] conducted a review of multimodal digital phenotyping methods used in the monitoring of mental health conditions. The review shows that using several different types of information can give a more complete view of the psychological state of an individual. Multimodal digital phenotyping methods have the potential to improve detection of the problem in comparison to the single-source methods. This provides strong support for the proposed feature fusion module and combination of questionnaire, text, emotion, and historical features. Finally, there is a review on AI-enabled chatbots used in the domain of mental health applications. The study identifies conversational agents as a new tool for providing accessibility and psychological assistance [15].

Conversational-agent interventions for mental-health problems are systematically reviewed and analyzed. Their findings provide evidence that conversational agents can have positive impacts while highlighting the importance of intervention characteristics and evaluation methods [16]. This project continues this idea by integrating conversation into a personalized support cycle. The mechanisms of emotional support have been examined for the case of conversational agents for mental-health digital therapeutics. The authors highlight that emotional sensitivity may enhance the interactions between users and the conversational system. Thus, recognizing and responding to emotions is critical for personalization of digital interventions [17]. This directly applies to the emotion-analysis module and recommendation selection process of the proposed model. Explainable AI in language-based mental-health detection is considered. Authors note that NLP and ML models should be explainable in terms of providing interpretable evidence of their decisions, especially when working with mental health, which is a sensitive area. Explainability can help to build trust and make researchers/professionals understand why the decision has been made. These supports adding an explainability component to the proposed risk classification process [18].

In the domain of mental health, the applications of NLP are reviewed systematically to develop a research framework. This review covers computation aspects, clinical application, outcomes, and limitations of NLP-based mental health intervention studies. The authors found a fast development in NLP applications, however, there were gaps in methodology and validation of these works [19]. The results of the study are in line with the suggested pipeline for NLP and stress the importance of conducting thorough clinical studies. Another paper where the authors developed an NLP system for detecting mental health crisis messages and providing timely intervention is written by Swaminathan A *et al.* [20]. The study shows the potential of an automatic language analysis approach to recognize urgent psychological conditions based on conversational texts. It can be used to detect potentially risky users faster. The proposed NLP system can integrate similar crisis-oriented classification techniques into the risk-assessment phase. An AI-driven chatbot system called Leora for self-directed mental health support is discussed. The work presents an example of using conversational AI to provide structured information on mental health issues without continuous human involvement [21].

AI-based chatbots [22] were developed with an objective to induce health behavior changes. They found out that conversation agents can scale up and personalize interactions which could affect the behavior of users. Nonetheless, intervention quality, user engagement, and safety are other factors that must be taken into consideration. The findings above back the feedback and recommendation components of the proposed solution. The role of AI technologies in online mental healthcare is reviewed and its benefits and challenges are considered. They focus on the possibility of AI to increase the accessibility, personalization, and scalability of mental health services [23]. Nonetheless, they mention the issues related to ethics, privacy, precision, and clinical accountability. They are vital for the proposed solution as its automatic recommendation should assist but not replace mental health care by professionals. The use of machine learning in mental health and its relationship with epidemiology are discussed. They show how machine learning can detect patterns and predictors in big mental health data [24]. Nevertheless, the proper interpretation and validation of the data is emphasized by them. The proposed system also uses machine learning to transform the heterogeneous data of users into risk prediction and requires proper validation.

The applications of large language models are discussed in psychiatry [25]. As a result, it appears that the usage of LLMs becomes more popular in such fields as assessment, information provision, decision support, and conversations. However, the researchers also note problems connected with hallucination, reliability, bias, and safety of the clinical application. This leads to a conclusion that LLM capabilities of the proposed system should be limited by controlled prompts, validation, and human monitoring. The researchers Jocelyn Shen *et al.* [26] discussed empathy towards AI assistance compared to human one and the role of transparency in the design of mental health chatbots. They found out that people appreciate empathic AI communication but still consider it different from human one. Transparency can affect people's expectations regarding the system. This helps in designing the proposed chatbot as an assistant of AI with its limitation and possibility of transferring to human professionals [27]. The NLP for harmonizing mental health questionnaires is discussed on the example of real-life data. Their research shows that NLP can be used for mapping different structures of questionnaires and their common concepts. This becomes especially important for systems which are based on the combination of the structured data from questionnaires and the unstructured text data. The suggested system will be able to apply a similar approach to normalization through NLP techniques during the processing of questionnaire and text-based user inputs. Bokolo and Liu [28] conducted research on deep learning techniques applied to detect depression on the basis of the data received from social media. In this research, machine learning and transformer models were compared in terms of detecting depression-related features.

The systematic review and meta-analysis by Doreen Phiri *et al.* [29] focused on the text-based depression prediction via machine learning. The paper examines how text data can be converted into predictive markers of depression. Work stresses the benefits and diversity of ML depression prediction. It supports the necessity of standardized validation and usage of different datasets for the proposed AI tool. The research on the user perception of AI conversational agents in mental health revealed that users appreciated the potential of such tools while still preferring human interaction. The findings stress the necessity of keeping human control within AI-assisted mental-health services. The accessibility and continuity offered by the AI systems can be useful, however, the users do not consider them equal to a professional therapist [30]. It strongly supports the necessity to make the proposed system an assistive tool. The multimodal machine learning for depression diagnosis was studied based on patient interviews. Their results showed the advantages of using several types of data instead of the usage of a single modality. The multimodal approach allows to obtain additional linguistic, behavioral, and contextual factors related to the depression [31]. There is solid methodological justification for using feature fusion in the proposed system. The models are built for depression prediction based on information from video, audio, and text data [32]. It shows that multimodal data can contain more information about mental health prediction compared to unimodal data. Their methodology is especially applicable to systems which try to extract features of the verbal and emotional nature. Our system can be a related multimodal approach, although it currently focuses more on questionnaire, textual, emotional, and historic features.

The research conducted by the authors Cui X *et al.* [33] used and analyzed an LLM-based suicide intervention chatbot. It illustrates the applicability of generative AI technology for use in conversational assistance in very sensitive fields related to people's mental well-being. On the other hand, suicide prevention applications demand extremely cautious approaches and appropriate security measures to ensure the safety of users and successful results. The research by Han and Zhao [34] analyzed the development of bibliometrics in relation to chatbot research in mental health field. It illustrates the growing popularity of the research topic and the areas which should be considered in future. The increased number of publications shows that conversational AI becomes an increasingly important part of mental health digital research. The proposed system can contribute to the field as well. The authors, Hua Y *et al.* [35], conducted a review of applications of large language models in mental health

care. This review deals with various applications, including diagnostics, therapy, decision support, and conversation, and underscores the fast development of this field. The authors stress the need for conducting clinical validation of the models. This information helps to justify the use of language models in the suggested system.

A systematic review and meta-analysis of CBT-based and NLP-enabled AI conversational agents for mental health intervention have been conducted [36]. In particular, the effectiveness of conversational agents based on the principles of cognitive behavioral therapy is evaluated. The relevance of the use of NLP in this review is related to the possibility of language analysis of the users and corresponding personalization of response. Results give contemporary evidence of the effectiveness of conversational and intervention parts of the AI system described above. The review of Sohn *et al.* [37] is a systematic review and meta-analysis of chatbots in managing depressive and anxiety symptoms. This review gives evidence about the effectiveness of chatbots in terms of mental health management in the studies conducted. It is relevant to the suggested system because depressive and anxiety disorders are important targets for risk assessment and personalized interventions. Scoping review of LLM applications in the area of mental health with respect to diagnostic, prognostic, and decision-making tasks is performed. A total of 3,121 papers were screened in the scoping review, where 41 studies were selected with GPT-4 and GPT-3.5 being one of the most common LLMs tested. It was identified that diagnosis is the most common application, with depression being the most studied mental illness; however, only a small proportion of studies have been validated using real-world clinical data [38].

Scoping reviews on mental health interventions using generative-AI chatbots made by Lotenna Olisaeloka *et al.* [39] studied features of design of interventions and users' experience. This review involved 21 studies in 11 different countries, where most of the interventions used CBT techniques and were delivered through text-based chatbots. It is reported that there is moderate to high usability, therapeutic alliance, and satisfaction, as well as decreased engagement and trust because of inaccuracy and lack of contextual appropriateness of the responses. All these findings prove that the introduction of adaptive personalization, contextual awareness, and quality control of the developed AI is required. Scoping examination of the risks that may arise when using LLM-based chatbots in relation to mental health was done. It is stated that there are problems with hallucinations, sycophancy, biases, data security, and inappropriate responses during severe cases of psychiatry [40]. This finding proves the idea that technical accuracy alone is not enough for the safe deployment of mental-health AI. In this way, research becomes a crucial part of the safety of the proposed solution, especially concerning risk escalation, human involvement, privacy, and high-risk users.

3. METHODOLOGY FOR IMPLEMENTING THE PROPOSED AI-BASED PERSONALIZED MENTAL HEALTH SUPPORT SYSTEM

3.1 System overview and Algorithm 1

This section describes the design of the proposed PMHSS, and the simulation protocol used to evaluate it. PMHSS integrates NLP, emotion/sentiment analysis, ML-based risk classification, personalized recommendation, a conversational AI assistant, progress monitoring and feedback-based adaptation. Algorithm 1 specifies the processing pipeline. Its inputs are user registration/authentication data, profile information, questionnaire responses, text/chat history, previous assessment and feedback records, and counsellor and appointment information. Its outputs are the risk class, the detected emotional state, personalized recommendations, chatbot responses, a recommended counsellor, appointment details and progress reports. PMHSS is designed to support early screening, tailored self-help and continuing support; it is not a diagnostic tool. The functions in Algorithm 1 (score calculation, text pre-processing, emotion model, risk classifier, relevance function and chatbot) are specified at the functional level.

Algorithm 1: AI-Based Personalized Mental Health Support System (PMHSS)

Input:

User data authentication, Profile data assessment, Survey results, Text/chat comments, Existing information, Counsellor details.

Output:

Risk classification, Emotional condition, Advice from expert, Chatbot answer, Suggestion of expert, Schedule details, Report on performance.

Step 1: Initialize System

- Load trained NLP, emotion-classification, risk-prediction, and recommendation models.
- Initialize the secure user database and counsellor database.
- Define risk classes as: $R \in \{Low, Medium, High\}$

Step 2: User Registration and Authentication

- Receive registration information U
- Validate mandatory user credentials.
- Create a unique user identifier ID_u .
- Authenticate the user using secure credentials/OTP.
- If authentication fails, terminate the session; otherwise, proceed to Step 3.

Step 3: User Profile Creation

- Collect demographic attributes, preferences, previous interaction information, and available medical/mental-health history.
- Construct the user profile:

$$P_u = \{D_u, Pref_u, H_u\} \quad (1)$$

- Store P_u securely in the user database.

Step 4: Mental Health Assessment

- Present the standardized mental-health questionnaire to the authenticated user.
- Collect questionnaire responses Q_u .
- Validate the responses for completeness and consistency.
- Calculate the questionnaire/assessment score:

$$Q_s = f(Q_u) \quad (2)$$

- Normalize the score to the predefined model input range.

Step 5: User Text Acquisition

- Receive text/chat input T_u from the user.
- Remove irrelevant characters and noise.
- Perform tokenization, normalization, stop-word processing, and linguistic feature extraction.
- Generate the processed text representation:

$$T_u^i = Preprocess(T_u)$$

Step 6: AI-Based Emotion Analysis

- Extract semantic and emotional features from T_u^i using NLP.
- Calculate sentiment/emotion features:

$$F_e = EmotionModel((T_u^i))$$

- Determine the dominant emotional state (the emotion class with the highest predicted probability):

$$E_u = \arg \max(E_{classes})$$

- Combine emotional features with questionnaire features.

Step 7: Feature Fusion

- Construct the integrated feature vector:

$$F_u = \{Q_s, F_e, P_u, H_u\} \quad (3)$$

- Apply feature scaling/selection where required.
- Forward F_u to the trained mental-health risk prediction model.

Step 8: Mental Health Risk Prediction

- Apply the machine-learning classifier:

$$\hat{R}_u = ML_{risk}(F_u) \quad (4)$$

- Calculate the probability of each risk class:

$$Pr(R = k|F_u), k \in \{L, M, H\} \quad (5)$$

- Assign the class with the maximum probability:

$$R_u = \arg \max_k Pr(R = k|F_u) \quad (6)$$

Step 9: Risk-Based Decision Processing

- if $R_u = Low$, then
 - Recommend wellness and self-care resources.
 - Provide mindfulness exercises.
 - Provide motivational content, videos, and educational material.
- Else if $R_u = Medium$, then
 - Recommend structured CBT-oriented activities.
 - Increase monitoring frequency.
 - Recommend professional counselling.
 - Schedule a follow-up assessment.
- Else if $R_u = High$, then
 - Prioritize professional mental-health intervention.
 - Recommend an appropriate counsellor.
 - Provide urgent-support information where appropriate.
 - Escalate to a qualified human clinician or crisis service according to a predefined safety protocol (Section 3.2).

Step 10: Personalization Engine

- Combine P_u, R_u, E_u and H_u

- Compute recommendation relevance:
- Relevance score: $r_i|u = f(P_u, R_u, E_u, H_u, r_i)$
- Rank available resources according to the predicted relevance score.
- Generate the personalized recommendation set:

$$S_u = \{s_1, s_2, s_3, \dots, s_n\}$$

Step 11: AI Chatbot Support

- Receive user query T_q .
- Analyze the query using the NLP model.
- Retrieve relevant contextual information from the user's current session and permitted history.
- Generate a context-aware response:

$$B_u = \text{Chatbot}(T_q, P_u, E_u, R_u, H_u)$$

- Return B_u to the user.
- Store the interaction securely for subsequent progress analysis.

Step 12: Progress Monitoring

- Collect subsequent questionnaire scores Q_t , emotional states E_t , chatbot interactions, counselling outcomes, and user feedback.
- Calculate temporal changes:

$$\begin{cases} \Delta Q = Q_t - Q_{t-1} \\ \Delta E = E_t - E_{t-1} \end{cases}$$

- Determine the user's progress trend:

$$G_u = f(\Delta Q, \Delta E, \text{session outcomes, feedback})$$

- Generate the personalized progress report G_u .

Step 13: Feedback Collection

- Obtain user satisfaction and recommendation feedback.
- Calculate feedback score:

$$F_s = \frac{\sum_{i=1}^n f_i}{n} \quad (7)$$

- Associate feedback with the corresponding recommendation and interaction.

Step 14: Database and Analytics Update

- Store updated assessment results, emotion analysis, recommendations, consultation outcomes, and feedback.
- Update the user's longitudinal profile:

$$H_u^{new} = H_u \cup \{Q_t, E_t, R_t, S_t, F_t\}$$

- Generate system-level analytics and reports.

Step 15: Continuous Support Loop

- Continuously monitor new assessments and interactions.
- When new information becomes available, return to Step 4.
- Otherwise, maintain the user's personalized support plan.

Step 16: Step Termination

- Securely close the user session.
- Preserve authorized records according to the system's data-retention policy.
- End the algorithm.

End Algorithm

3.2 Simulation protocol

To assess the risk-classification module, a synthetic simulation environment was created using an NLP-based agent methodology, yielding 10,000 simulated users who were split into training (7,000), validation (1,500) and test (1,500) sets with a fixed random seed (42) for reproducibility (Table 1). Each user was simulated for 12 months with weekly (7-day) assessments, generating longitudinal data for progress monitoring (Step 12) and the continuous support loop (Step 15). Chat activity was limited to at most 20 interactions per user per week (Step 11), and each user had 5-20 historical observations, depending on time in the system. The risk-prediction model (Step 8) assigns users to three classes (Low, Medium, High), the emotion component (Step 6) uses 6-8 emotion classes, and the personalization engine (Step 10) ranks 50-100 candidate resources

Table 1. Simulation parameters

Parameter	Values
Simulation type	NLP + agent/system simulation
Number of synthetic users	10,000
Training users	7,000
Validation users	1,500
Test users	1,500
Random seed	42
Simulation duration	12 months
Assessment interval	7 days
Maximum chat interactions/user/week	20
Historical observations/user	5–20

4. RESULTS AND DISCUSSION

This section reports how the risk-classification module of PMHSS performs on the synthetic test cohort. All results derive from simulation. No real patient data were used, so the results do not establish clinical validity. Only the risk-classification module was quantitatively evaluated; emotion recognition, recommendation ranking, chatbot responses, appointment scheduling and teleconsultation were not evaluated. Figure 1 shows that the accuracy of PMHSS increases steadily as the amount of input data grows from 100 to 1,000 samples, from about 94.8% to 98.2%. The gain is larger at small sample sizes than at large ones, which suggests that PMHSS benefits from additional data but with diminishing returns.

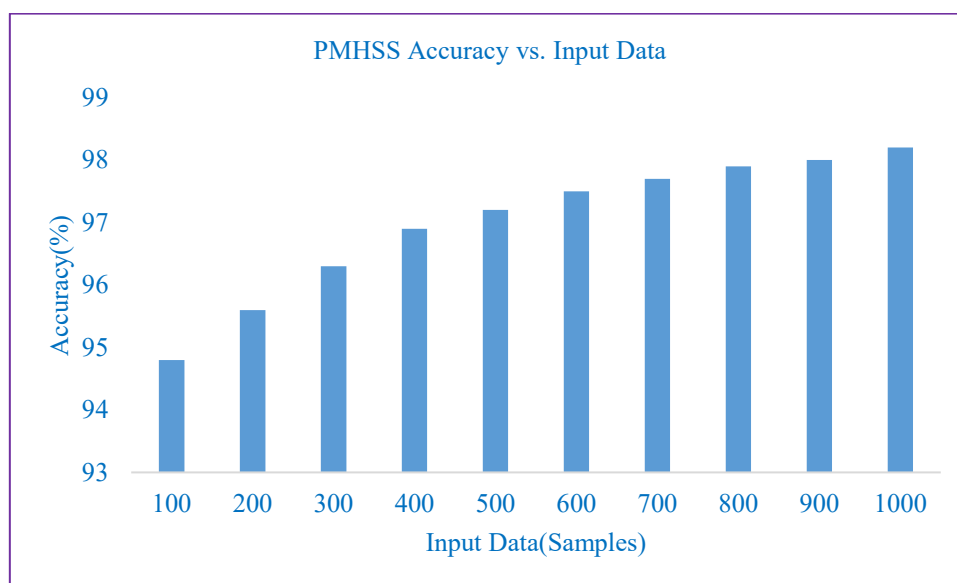


Figure 1. Accuracy of the PMHSS algorithm as a function of the amount of input data (training samples).

According to Figure 2, we can see that precision of PMHSS is improving when the input data increases. For only 100 data points, the precision is nearly 93.9% but goes up steadily with time. With 500 data points, the precision is approximately 96.6%, while at 1000 data points the precision reaches about 98%. The increase of precision happens rather quickly at the beginning (100 to 400 samples) and then starts to slow down, indicating the approach of diminishing returns. This phenomenon is typical for statistical or ML models, taking place where the model learns from the training data, which helps to handle the task better and decrease the prediction errors.

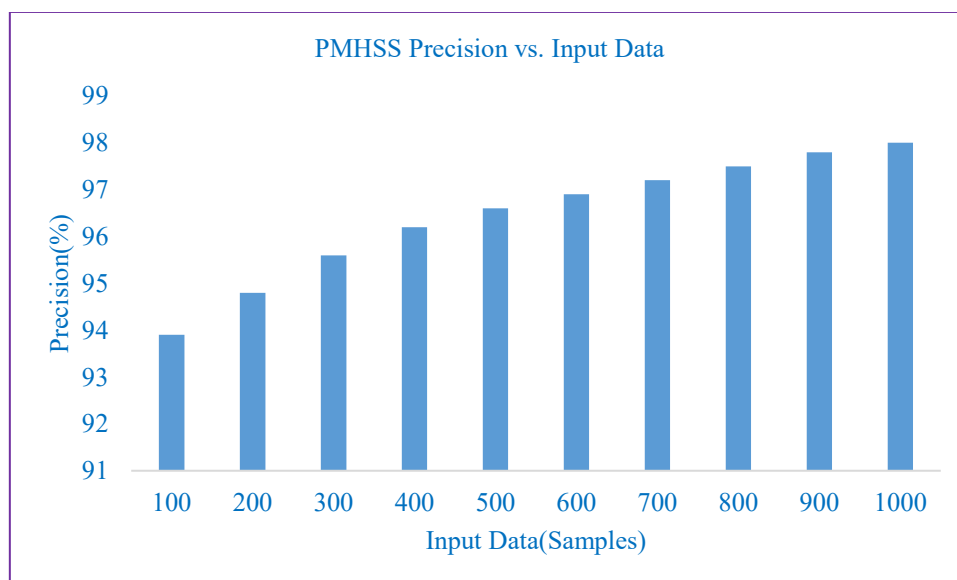


Figure 2. Result of Precision of the PMHSS algorithm as a function of input data.

The figure 3 illustrates the change in PHMSS recall compared to the amount of input data. Starting from an initial recall value of approximately 92.7% at a sample size of 100, the recall increases steadily as more data samples are fed into the model. After the inclusion of 500 samples, the recall reaches approximately 95.8% and reaches around 97.3% once the size of samples reaches 1000. Just like the trend shown in the precision graph, it can be observed that the increase is very sharp in the initial stages of data input.

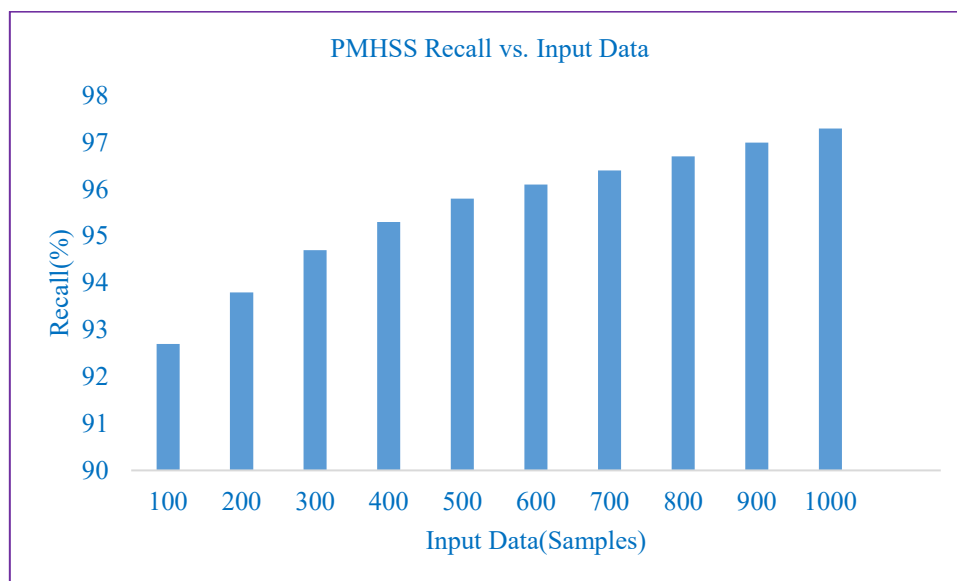


Figure 3. Result of Recall of the PMHSS algorithm as a function of input data.

According to Figure 4, the PMHSS F-1 score increases in constant proportion to the amount of input data available. The F-1 score starts at around 93.2%, and as the amount of data increases to 500 samples, this result keeps increasing until it reaches about 96.2%. The F-1 score will then continue to reach around 97.6% when the number of samples increases to 1000 and this increasing trend is clear, showing improvement throughout the period. There is the same situation as in precision and recall. Therefore, since F-1 score combines precision and recall, we can conclude that both measures improve together and not at the expense of one another.

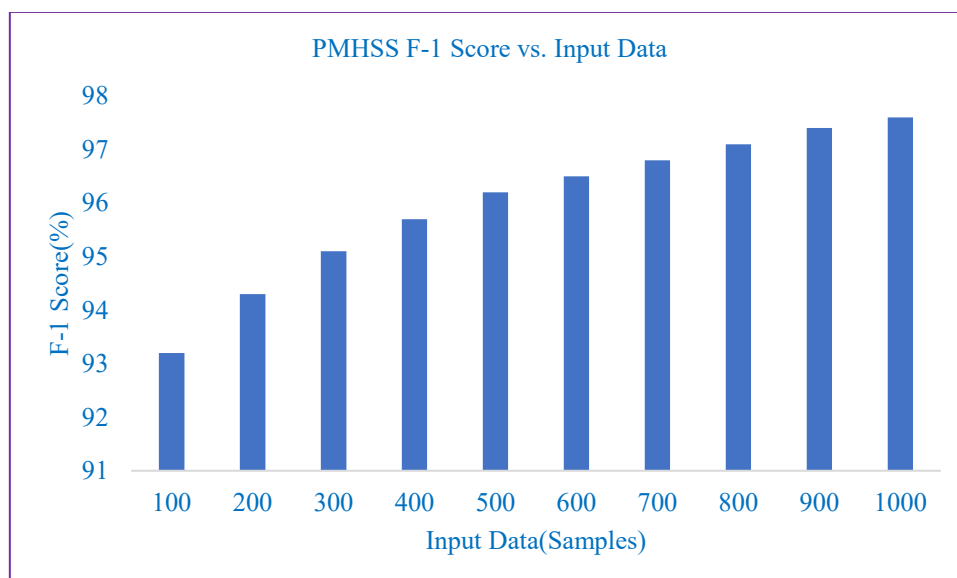


Figure 4. Result of F-1 of the PMHSS algorithm as a function of input data.

The comparison results in figure 5 represents how existing, such as Logistic Regression, Random Forest, XGBoost, and proposed PHMSS perform with respect to four parameters which are Accuracy, Precision, Recall and F1-score. The Logistic Regression model performs poorly compared to the other three models as its scores range from 93%-94%. The Random Forest significantly performs better in terms of scoring in the range of 94.5%-95.7%. The XGBoost model performs still better with scores like 96%-97.1%. Lastly, PMHSS model tops all other models in terms of the score regarding different metrics (scoring

about 97.2%-98%). Thus, in summary, it can be concluded that PMHSS is the best model among all the tested models when it comes to this classification task.

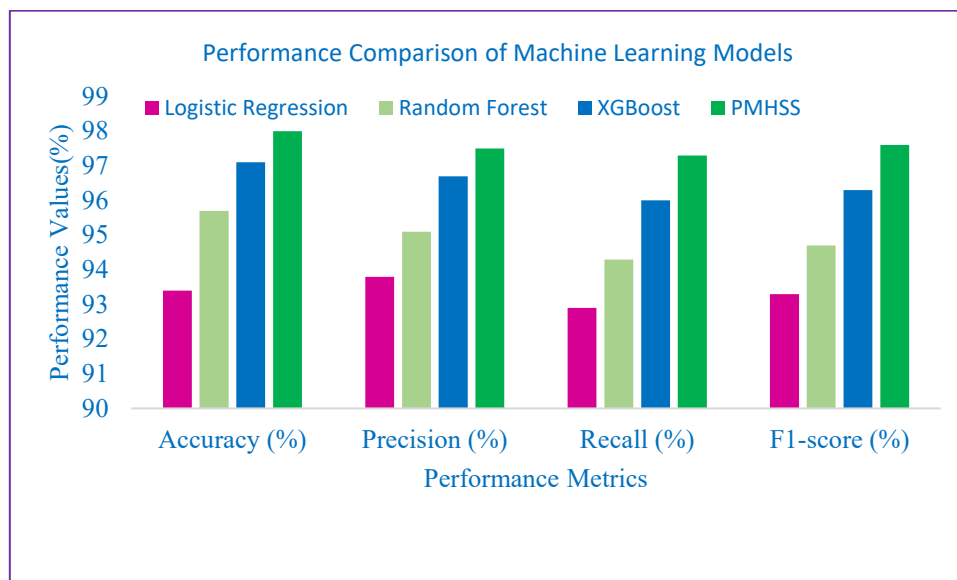


Figure 5. The overall result comparison of PMHSS with existing algorithms.

Table 2 shows a comparison of the full performance of the PMHSS algorithm with 3 of the comparable algorithms already present, which are the Logistic Regression, Random Forest, and XGBoost based on the accuracy of the model, precision, recall, and F1-score respectively. The Logistic Regression model is much simpler as compared to other algorithms and shows the worst performance among the competitors with only 92.4% of accuracy which belongs to LP due to its nature of being linear. Random Forest and XGBoost algorithms are expected to perform much better than Logistic Regression as they are ensemble algorithms.

Table 2. Comparison of the overall performance of the PMHSS with existing algorithms.

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Logistic Regression	92.4	91.8	90.9	91.3
Random Forest	95.7	95.1	94.3	94.7
XGBoost	97.1	96.7	96.0	96.3
PMHSS	98.2	98.0	97.3	97.6

However, Random forests perform at the accuracy of 95.7% while XGBoost shows the best accuracy of 97.1%. The PMHSS algorithm, in this case, shows the best results of PMHSS performance according to all the indicators provided by the table. Based on these results, PMHSS achieved 98.2% accuracy, 98% precision, 97.3% recall, and 97.6% F1 score, which means that PMHSS performance is very high. This can be justified by implementation of the new PMHSS method that integrates several features from various sources, such as questionnaires and derives emotional features through using NLP.

5. CONCLUSION

The proposed AI-powered PMHSS offers an innovative and reliable platform that is meant to enhance accessibility, effectiveness and customization of mental health services. The system makes use of AI such as NLP, sentiment analysis, and machine learning techniques to understand people's emotions, evaluate their mental health, and offer personalized suggestions accordingly. By combining an AI chatbot with the support of professional counsellors, scheduling, and secure communication, we help users obtain continuous support in mental health care and eliminate existing obstacles faced in traditional mental health

care systems. The system design allows the timely recognition of mental health threats, performance of necessary interventions, and formulation of effective individual wellness plans based on users' emotional characteristics. Moreover, due to the implementation of the data analytics-based recommendation engine, the system gains the ability to improve its precision over time. Overall, the system offers the opportunity to increase engagement, support proper mental health practices, and assist health professionals in providing medical services.

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AUTHOR CONTRIBUTIONS

Shivashankar: Involved in concept formation, formal analysis, problem formulation, methodology, implementation, result discussion, rough manuscript preparation.

Dr. Prof. Md Shohel Sayeed: Research supervision and revision of manuscript for scientific and intellectual contented.

Dr. Andrews Samraj: Research supervision, editing, and correction of manuscript.

Dr. Manjunath R: Research concept formation, performance evaluation of PMHSS algorithm and result interpretation.

Manohar Koli: Testing, editing and correction of manuscript.

Nandish A C: Software setting, editing and correction of manuscript.

CONFLICT OF INTEREST

The authors declare that they have no known financial or non-financial conflicts of interest that could have influenced the research, its methodology, results, interpretation, or publication of this manuscript.

ETHICS STATEMENT

The study was conducted in accordance with applicable ethical guidelines, with appropriate ethical approval and informed consent obtained from all authors, while ensuring the confidentiality and privacy of their data.

DATA AVAILABILITY STATEMENT

All data supporting the results presented in the study can be obtained from the corresponding author through reasonable request. The data are not available publicly as they were generated and analysed within the scope of experimental validation of the proposed PMHSS method that integrates several features from various sources, such as questionnaires and derives emotional features through using NLP.

REFERENCES

- [1] Le Glaz, A., Haralambous, Y., Kim-Dufor, D.H., Lenca, P., Billot, R., Ryan, T.C., Marsh, J., DeVlyder, J., Walter, M., Berrouguet, S., Lemey, C., 2021. Machine Learning and Natural Language Processing in Mental Health: Systematic Review. *Journal of Medical Internet Research* 23(5), e15708, DOI: 10.2196/15708.
- [2] Klos, M.C., Escoredo, M., Joerin, A., Lemos, V.N., Rauws, M., Bunge, E.L., 2021. Artificial Intelligence–Based Chatbot for Anxiety and Depression in University Students: Pilot Randomized Controlled Trial. *JMIR Formative Research* 5(8), e20678, DOI: 10.2196/20678.
- [3] Liu, Z., Peach, R.L., Lawrance, E.L., Noble, A., Ungless, M.A., Barahona, M., 2021. Listening to Mental Health Crisis Needs at Scale: Using Natural Language Processing to Understand and Evaluate a Mental Health Crisis Text Messaging Service. *Frontiers in Digital Health* 3, 779091, DOI: 10.3389/fdgth.2021.779091.

- [4] Saqib, K., Khan, A.F., Butt, Z.A., 2021. Machine Learning Methods for Predicting Postpartum Depression: Scoping Review. *JMIR Mental Health*, 8(11), e29838, DOI: 10.2196/29838.
- [5] Hueniken, K., Somé, N.H., Abdelhack, M., Taylor, G., Elton Marshall, T., Wickens, C.M., Hamilton, H.A., Wells, S., Felsky, D., 2021. Machine Learning–Based Predictive Modeling of Anxiety and Depressive Symptoms During 8 Months of the COVID-19 Global Pandemic: Repeated Cross-sectional Survey Study. *JMIR Mental Health*, 8(11), e32876, DOI: 10.2196/32876.
- [6] Lim, S.M., Shiao, C.W.C., Cheng, L.J., Lau, Y., 2022. Chatbot-Delivered Psychotherapy for Adults With Depressive and Anxiety Symptoms: A Systematic Review and Meta-Regression. *Behavior Therapy*, 53(2), 334–347, DOI: 10.1016/j.beth.2021.09.007.
- [7] Shivashankar, Manjunath, R., 2025. Blockchain and Machine Learning Driven Agricultural Transformation Framework to Enhance Efficiency, Transparency and Sustainability. *International Journal of Artificial Intelligence*, 14, 1976–1988, DOI: 10.11591/ijai.v14.i3.pp1976-1988.
- [8] Liu, D., Feng, X.L., Ahmed, F., Shahid, M., Guo, J., 2022. Detecting and Measuring Depression on Social Media Using a Machine Learning Approach: Systematic Review. *JMIR Mental Health*, 9(3), e27244, DOI: 10.2196/27244.
- [9] Kabir, M.K., Islam, M., Kabir, A.N.B., Haque, A., Rhaman, M.K., 2022. Detection of Depression Severity Using Bengali Social Media Posts on Mental Health: Study Using Natural Language Processing Techniques. *JMIR Formative Research*, 6(9), e36118, DOI: 10.2196/36118.
- [10] Panaite, V., Devendorf, A.R., Finch, D., Bouayad, L., Luther, S.L., Schultz, S.K., 2022. The Value of Extracting Clinician-Recorded Affect for Advancing Clinical Research on Depression: Proof-of-Concept Study Applying Natural Language Processing to Electronic Health Records. *JMIR Formative Research*, 6(5), e34436, DOI: 10.2196/34436.
- [11] Dlima, S.D., Shevade, S., Menezes, S.R., Ganju, A., 2022. Digital Phenotyping in Health Using Machine Learning Approaches: Scoping Review. *JMIR Bioinformatics and Biotechnology*, 3(1), e39618, DOI: 10.2196/39618.
- [12] Shivashankar, Sunil Kumar, K.N., 2025. An Optimised and Secured Biomedical Signal Transmission Using CNN. *Australian Journal of Electrical and Electronics Engineering*, DOI: 10.1080/1448837X.2025.2452666. Birk, R.H., Samuel, G., 2022. Digital Phenotyping for Mental Health: Reviewing the Challenges of Using Data to Monitor and Predict Mental Health Problems. *Current Psychiatry Reports*, 24(10), 523–528, DOI: 10.1007/s11920-022-01358-9.
- [13] Moura, I., Teles, A., Viana, D., Marques, J., Coutinho, L., Silva, F., 2023. Digital Phenotyping of Mental Health Using Multimodal Sensing of Multiple Situations of Interest: A Systematic Literature Review. *Journal of Biomedical Informatics*, 138, 104278, DOI: 10.1016/j.jbi.2022.104278.
- [14] Omarov, B., Narynov, S., Zhumanov, Z., 2023. Artificial Intelligence-Enabled Chatbots in Mental Health: A Systematic Review. *Computers, Materials & Continua*, 74(3), 5105–5122, DOI: 10.32604/cmc.2023.034655.
- [15] He, Y., Yang, L., Qian, C., Li, T., Su, Z., Zhang, Q., Hou, X., 2023. Conversational Agent Interventions for Mental Health Problems: Systematic Review and Meta-analysis of Randomized Controlled Trials. *Journal of Medical Internet Research*, 25, e43862, DOI: 10.2196/43862.
- [16] Wang, Q., Peng, S., Zha, Z., Han, X., Deng, C., Hu, L., Hu, P., 2023. Enhancing the Conversational Agent with an Emotional Support System for Mental Health Digital Therapeutics. *Frontiers in Psychiatry*, 14, 1148534, DOI: 10.3389/fpsy.2023.1148534.
- [17] Kerz, E., Zanwar, S., Qiao, Y., Wiechmann, D., 2023. Toward Explainable AI (XAI) for Mental Health Detection Based on Language Behavior. *Frontiers in Psychiatry*, 14, 1219479, DOI: 10.3389/fpsy.2023.1219479.
- [18] Malgaroli, M., Hull, T.D., Zech, J.M., Althoff, T., 2023. Natural Language Processing for Mental Health Interventions: A Systematic Review and Research Framework. *Translational Psychiatry*, 13, 309, DOI: 10.1038/s41398-023-02592-2.
- [19] Swaminathan, A., López, I., Garcia Mar, R.A., Heist, T., McClintock, T., Caoili, K., Grace, M., Rubashkin, M., Boggs, M.N., Chen, J.H., Gevaert, O., Mou, D., Nock, M.K., 2023. Natural Language Processing System for Rapid Detection and Intervention of Mental Health Crisis Chat Messages. *npj Digital Medicine*, 6, 213, DOI: 10.1038/s41746-023-00951-3.
- [20] van der Schyff, E.L., Ridout, B., Amon, K.L., Forsyth, R., Campbell, A.J., 2023. Providing Self-Led Mental Health Support Through an Artificial Intelligence–Powered Chat Bot (Leora) to Meet the Demand of Mental Health Care. *Journal of Medical Internet Research*, 25, e46448, DOI: 10.2196/46448.
- [21] Aggarwal, A., Tam, C.C., Wu, D., Li, X., Qiao, S., 2023. Artificial Intelligence–Based Chatbots for Promoting Health Behavioral Changes: Systematic Review. *Journal of Medical Internet Research*, 25, e40789, DOI: 10.2196/40789.

- [22] Gutierrez, G., Stephenson, C., Eadie, J., Asadpour, K., Alavi, N., 2024. Examining the Role of AI Technology in Online Mental Healthcare: Opportunities, Challenges, and Implications, a Mixed-Methods Review. *Frontiers in Psychiatry*, 15, 1356773, DOI: 10.3389/fpsyt.2024.1356773.
- [23] Shivashankar, Manjunath, R., 2024. Implementation of Machine Learning Techniques to Assess the Authenticity of Multimedia Data. *International Journal of Intelligent Systems and Applications in Engineering*, 12, 209–216.
- [24] Omar, M., Soffer, S., Charney, A.W., Landi, I., Nadkarni, G.N., Klang, E., 2024. Applications of Large Language Models in Psychiatry: A Systematic Review. *Frontiers in Psychiatry*, 15, 1422807, DOI: 10.3389/fpsyt.2024.1422807.
- [25] Shen, J., DiPaola, D., Ali, S., Sap, M., Park, H.W., Breazeal, C., 2024. Empathy Toward Artificial Intelligence Versus Human Experiences and the Role of Transparency in Mental Health and Social Support Chatbot Design: Comparative Study. *JMIR Mental Health*, 11, e62679, DOI: 10.2196/62679.
- [26] McElroy, E., Wood, T., Bond, R., Mulvenna, M., Shevlin, M., Ploubidis, G.B., Hoffmann, M.S., Moltrecht, B., 2024. Using Natural Language Processing to Facilitate the Harmonisation of Mental Health Questionnaires: A Validation Study Using Real-World Data. *BMC Psychiatry*, 24(530), DOI: 10.1186/s12888-024-05954-2.
- [27] Bokolo, B.G., Liu, Q., 2023. Deep Learning-Based Depression Detection From Social Media: Comparative Evaluation of ML and Transformer Techniques. *Electronics*, 12(21), 4396, DOI: 10.3390/electronics12214396.
- [28] Phiri, D., Makowa, F., Amelia, V.L., Phiri, Y.V.A., Dlamini, L.P., Chung, M.-H., 2025. Text-Based Depression Prediction on Social Media Using Machine Learning: Systematic Review and Meta-Analysis. *Journal of Medical Internet Research*, 27, e59002, DOI: 10.2196/59002.
- [29] Lee, H.S., Wright, C., Ferranto, J., Buttner, J., Palmer, C.E., Welchman, A., Mazor, K.M., Fisher, K.A., Smelson, D., O'Connor, L., Fahey, N., Soni, A., 2025. Artificial Intelligence Conversational Agents in Mental Health: Patients See Potential, but Prefer Humans in the Loop. *Frontiers in Psychiatry*, 15, 1505024, DOI: 10.3389/fpsyt.2024.1505024.
- [30] Weber, J., Weber, M., Lopez Alcaraz, J.M., 2025. Depression Diagnosis From Patient Interviews Using Multimodal Machine Learning. *Frontiers in Psychiatry*, 16, 1694762, DOI: 10.3389/fpsyt.2025.1694762.
- [31] Shivashankar, Manjunath, R., 2023. A Smart Biomedical Healthcare System to Detect Stress Using Internet of Medical Things, Machine Learning and Artificial Intelligence. *International Journal of Intelligent Systems and Applications in Engineering*, 11, 335–343.
- [32] Cui, X., Gu, Y., Fang, H., Zhu, T., 2025. Development and Evaluation of LLM-Based Suicide Intervention Chatbot. *Frontiers in Psychiatry* 16, 1634714, DOI: 10.3389/fpsyt.2025.1634714.
- [33] Han, Q., Zhao, C., 2025. Unleashing the Potential of Chatbots in Mental Health: Bibliometric Analysis. *Frontiers in Psychiatry*, 16, 1494355, DOI: 10.3389/fpsyt.2025.1494355.
- [34] Hua, Y., Liu, F., Yang, K., Li, Z., Na, H., Sheu, Y.H., Zhou, P., Moran, L.V., Ananiadou, S., Clifton, D.A., Beam, A., Torous, J., 2025. Large Language Models in Mental Health Care: A Scoping Review. *Current Treatment Options in Psychiatry*, 12, 27, DOI: 10.1007/s40501-025-00363-y.
- [35] Hang, Y., Wu, W., Feng, Y., Yan, K., Liu, Y., Xiao, X., Qiao, Z., 2026. The effectiveness of CBT-based NLP-enabled AI conversational agents for mental health intervention: a systematic review and meta-analysis. *npj Digital Medicine*, DOI: 10.1038/s41746-026-02886-x.
- [36] Sohn, J.-S., Ha, B.-G., Park, S., Kim, J.-J., Lee, E., Oh, H., Lee, S., Kim, E., 2026. Systematic review and meta analysis of chatbots in the management of depressive and anxiety symptoms. *npj Digital Medicine*, 9(377), DOI: 10.1038/s41746-026-02566-w.
- [37] Lokadjaja, M.C., Kho, J.J., Schulz, P.J., Goh, W.W.B., 2026. Large Language Models and Their Applications in Mental Health: Scoping Review. *JMIR Mental Health*, 13, e88057, DOI: 10.2196/88057.
- [38] Olisaeloka, L., Richardson, C.G., Wang, A.Y., Munthali, R.J., Vigo, D.V., 2026. Generative AI mental health chatbots: a scoping review of intervention design and user experience. *npj Digital Medicine*, DOI: 10.1038/s41746-026-02972-0.
- [39] Villarreal-Zegarra, D., Paredes-Gonzales, Y., Dámaso-Román, A., Quiñones-Inga, J., Centeno-Terrazas, G., Alexis-Montalban Lozada, Y.P., 2026. Development, system design, safety, and performance metrics of a conversational agent for reducing depressive and anxious symptoms based on a large language model: The MHAI study. *PLOS ONE*, 21(3), e0344939, DOI: 10.1371/journal.pone.0344939.