Published by :
https://www.ijert.org/
An International Peer-Reviewed Journal

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

ML Powered Guardian System for Mental Health Risk Prediction

Prajakta Kamble
Department of Computer Engineering

Dr. D. S. Waghole
Jayawantrao Sawant College of Engineering, Pune, India

Abstract - Mental health disorders such as depression, anxiety, stress, and emotional instability have become major healthcare concerns worldwide due to increasing academic pressure, professional competition, lifestyle imbalance, and social isolation. Traditional mental health assessment methods mainly depend on physical consultation with healthcare professionals, which is often time-consuming, expensive, and inaccessible to many individuals. The proposed project, "ML Powered Guardian System for Mental Health Risk Prediction," is an intelligent web-based healthcare platform designed to predict mental health severity levels using Machine Learning and Deep Learning techniques. The system integrates PHQ-9 and GAD-7 assessment questionnaires with sentiment analysis and chatbot interaction to evaluate psychological conditions effectively. The platform uses a Deep Neural Network model implemented using TensorFlow and Scikit-learn libraries to classify users into severity levels such as None, Mild, Moderate, and Severe. The Machine Learning model is trained using multiple psychological and behavioral parameters including depression scores, anxiety scores, sleep issues, social withdrawal, and prior mental health history. The proposed solution offers several advantages over traditional mental healthcare systems. It provides early-stage mental health assessment, reduces dependency on manual diagnosis, improves accessibility to mental healthcare support, and offers real-time prediction and monitoring capabilities. The system is scalable, user-friendly, and capable of assisting both users and healthcare professionals in identifying psychological risks efficiently.

Keywords: **Artificial Intelligence (AI), Machine Learning (ML), Deep Learning, PHQ-9 Assessment, GAD-7 Assessment, Mental Health Chatbot, Sentiment Analysis, FastAPI, ReactJS**

1. INTRODUCTION

In recent decades, mental health disorders have surged despite economic and technological progress, with barriers such as stigma, cost, and professional shortages continuing to hinder treatment access [1–3]. Digital health technologies offer promise in addressing these challenges [4], with teletherapy, mental health apps, and computerized cognitive behavioral therapy showing effectiveness [5]. The COVID-19 pandemic further accelerated the use of digital mental health tools, revealing unmet needs at the intersection of technology and psychotherapy [6,7]. This growing demand has sparked increased interest in the role of conversational artificial intelligence in mental health applications [8,9], with research exploring its potential to enhance psychotherapy and improve care delivery [10–13]. Researchers have increasingly focused on leveraging conversational artificial intelligence to support psychotherapy effectiveness, as the mental health sector grapples with rising demand and the need for innovative solutions [12–16]. Since the public release of ChatGPT (Version GPT-4, United States of America) in early 2023, it has become the first conversational artificial intelligence tool to achieve global mainstream use, reshaping approaches to learning, communication, and problem solving [8,17]. Research on ChatGPT has expanded rapidly across disciplines, especially in education, medicine, and psychology, highlighting its growing potential to advance mental health services [10–13].

Artificial intelligence-driven digital interventions in mental health refer to software systems or mobile applications that embed artificial intelligence techniques to deliver, support, or evaluate mental health services [6,12]. These include conversational artificial intelligence agents that interact with users through natural language, ranging from simple FAQ style or rule-based chatbots to more advanced multi-turn dialogue systems capable of handling complex communication tasks [18,19]. Natural language processing techniques enable these agents to parse user input, detect sentiment, and extract key emotional cues [20]. Machine learning models, such as classification and regression algorithms, and deep learning networks, such as convolutional and recurrent neural networks, power predictive and monitoring tools to classify diagnoses, forecast risks, and tailor treatment recommendations based on user data [20]. Large language models such as GPT and BERT, which belong to a subclass of deep learning models built on transformer architectures with self-attention mechanisms, expand capabilities by generating and comprehending coherent and context-rich text, opening new possibilities for nuanced

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

therapeutic dialogue and personalized content creation [18,19]. Artificial intelligence has emerged as a promising tool to augment human therapists [12], although its adoption challenges traditional care models and raises concerns regarding efficacy, ethics, privacy, and the interpretation of human mental health experiences [21]. This review aims to provide a comprehensive analysis of conversational artificial intelligence in mental health care by mapping empirical evidence across different clinical phases. It offers insights into current applications, challenges, and future opportunities.

2. METHODS

2.1. Research Aims

The primary aim of the proposed research is to develop an intelligent Machine Learning-based mental healthcare system capable of predicting mental health risk levels using psychological assessment data and behavioral indicators. The research focuses on integrating Artificial Intelligence, Deep Learning, sentiment analysis, and chatbot technologies to provide automated mental health assessment and support services. The proposed "ML Powered Guardian System for Mental Health Risk Prediction" is designed to analyze user responses collected through PHQ-9 and GAD-7 assessment questionnaires and classify users into mental health severity categories such as None, Mild, Moderate, and Severe. The research aims to provide an efficient and scalable healthcare platform that supports early-stage mental health diagnosis and timely intervention.

Another major objective of the research is to reduce dependence on traditional manual mental health assessment methods by automating prediction and analysis using Machine Learning algorithms. The system also aims to provide personalized recommendations, emotional support, crisis detection, and doctor consultation suggestions based on the predicted severity level.

The research additionally focuses on evaluating the performance of Deep Learning models such as Multi-Layer Perceptron (MLP) and Wide & Deep Classifier models for mental health severity prediction. Performance evaluation is conducted using training accuracy, validation accuracy, loss analysis, confusion matrices, and feature importance analysis. The proposed system also aims to demonstrate the practical application of AI-driven healthcare technologies in improving accessibility, efficiency, and scalability of mental healthcare services.

2.2 Design and Scope of the Study

The proposed study follows a design methodology that integrates frontend development, backend API services, database management, and Machine Learning prediction services into a unified healthcare platform. The study mainly focuses on the implementation of Artificial Intelligence-driven digital mental healthcare interventions capable of performing automated mental health risk prediction.

The scope of the study includes the development of a web-based healthcare application that enables users to interact with a chatbot-based assessment interface. The frontend of the system is developed using ReactJS, Vite, and TailwindCSS technologies to provide an interactive and responsive user interface. The backend server is implemented using Node.js and ExpressJS for authentication, session management, report generation, and communication with the Machine Learning microservice. The prediction engine is developed using FastAPI and Python-based Machine Learning frameworks including TensorFlow, Keras, NumPy, Pandas, and Scikit-learn. The study primarily focuses on mental health assessment using PHQ-9 and GAD-7 questionnaires, which are internationally accepted psychological assessment tools used for depression and anxiety evaluation. Additional demographic and behavioral attributes such as sleep issues, social withdrawal, age, and prior mental health history are also considered for improving prediction performance.The system architecture includes four major components:

1. Frontend User Interface
2. Backend API Server
3. Machine Learning Service
4. Database Management System

The frontend collects assessment responses from users and sends them to the backend API server through HTTP/REST communication. The backend forwards the processed data to the Machine Learning service, which predicts mental health severity levels and returns prediction probabilities. The backend then stores session details and generates reports for users. The PostgreSQL database stores user information, reports, sessions, and assessment history.

2.3 Identification and Selection of Studies

The research process involved studying existing Artificial Intelligence and Machine Learning applications used in mental healthcare systems. Various research papers, healthcare journals, AI-based psychological assessment systems, chatbot applications, and Deep Learning-based healthcare models were analyzed to identify the limitations of existing systems and determine suitable technologies for implementation. The selection process also involved evaluating different prediction models such as:

1. Logistic Regression,
2. Support Vector Machines,
3. Random Forest,
4. Deep Neural Networks,
5. Multi-Layer Perceptron (MLP),
6. Wide & Deep Learning models.

Among these models, Deep Learning approaches were selected due to their higher capability to identify complex relationships among psychological and behavioral attributes. The proposed project therefore implements MLP and Wide & Deep Classifier models for mental health severity prediction. The selected research studies additionally emphasized the importance of conversational AI agents and chatbot systems in improving mental healthcare accessibility and emotional support services. The proposed system integrates chatbot interaction with

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

predictive analytics to provide a more comprehensive digital healthcare solution.

2.4 Search Strategy and Data Extraction

The research study adopted a systematic approach for collecting, analyzing, and processing data required for developing the proposed mental healthcare prediction system. Data collection was primarily based on psychological assessment questionnaires, demographic information, behavioral indicators, and emotional analysis parameters.

The PHQ-9 questionnaire was used to evaluate depression severity using nine psychological assessment parameters. Similarly, the GAD-7 questionnaire was used for anxiety assessment using seven anxiety-related indicators. Additional demographic and behavioral features such as age, sleep issues, social withdrawal, and prior mental health history were included to improve prediction accuracy. The collected data underwent preprocessing and normalization before training the Machine Learning models. The extracted features were then used to train Deep Learning models implemented using TensorFlow and Keras frameworks. The training process included:

1. Training dataset preparation,
2. Validation dataset generation,
3. Model optimization,

2.5 System Architecture

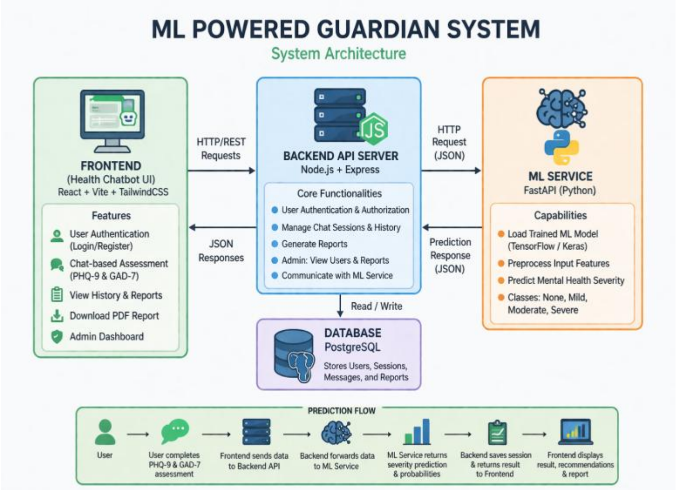

Fig.2.5 ML Powered Guardian System Architecture

The architecture of the proposed "ML Powered Guardian System for Mental Health Risk Prediction" is designed using a multi-tier intelligent healthcare framework that integrates frontend user interaction, backend API services, Machine Learning prediction modules, and database management systems into a unified platform. The system architecture mainly consists of four major components: Frontend Interface, Backend API Server, Machine Learning Service, and Database Layer. These components communicate with each other using HTTP/REST APIs and JSON-based data exchange

The Multi-Layer Perceptron (MLP) model achieved effective classification performance by learning complex psychological feature relationships. Similarly, the Wide & Deep Classifier model demonstrated improved validation accuracy and prediction stability for mental health severity classification.

Feature importance analysis revealed that PHQ-9 assessment questions contributed most significantly toward mental health prediction performance, followed by GAD-7 parameters and demographic features such as prior history and sleep-related issues. The analysis also demonstrated that depression-related symptoms strongly influence severity classification.

The extracted prediction results were integrated into the healthcare platform through FastAPI-based Machine Learning APIs. The backend server communicated with the ML service using JSON-based HTTP requests and responses. The prediction results, recommendations, and reports were then displayed to users through the ReactJS frontend interface. The overall data extraction and analysis process ensured efficient mental health severity prediction while maintaining system scalability, modularity, and healthcare-oriented functionality.

Additionally, the admin dashboard functionality allows administrators to monitor users, assessment reports, and prediction activities within the system.

mechanisms to ensure efficient and real-time healthcare prediction services.

The frontend layer acts as the user interaction module of the system and is developed using ReactJS, Vite, and TailwindCSS technologies. This layer provides an interactive chatbot-based healthcare interface where users can register, log in, answer PHQ-9 and GAD-7 assessment questionnaires, view previous assessment history, download PDF reports, and access personalized recommendations. The frontend interface is designed to provide a responsive and user-friendly healthcare environment that allows users to communicate with the system easily. After completing the mental health assessment, the frontend sends the collected user responses and behavioral information to the backend API server through HTTP/REST requests in JSON format.

The backend API server is implemented using Node.js and ExpressJS and functions as the central communication and processing layer of the architecture. The backend handles core functionalities such as user authentication and authorization, session management, report generation, administrative monitoring, and communication with the Machine Learning prediction service. Once assessment data is received from the The Machine Learning service is developed using FastAPI and Python-based Deep Learning frameworks including TensorFlow and Keras. This component acts as the intelligent prediction engine of the system. The ML service loads the trained Deep Learning model and performs preprocessing operations on the received assessment data. After preprocessing, the model analyzes PHQ-9 depression

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

indicators, GAD-7 anxiety indicators, and demographic behavioral attributes to predict mental health severity levels. The system classifies users into four categories: None, Mild, Moderate, and Severe. The database layer uses PostgreSQL for storing system information including user credentials, assessment history, chat sessions, reports, and prediction results. The backend server continuously performs read and write operations on the database to maintain healthcare records and user activity logs. This database management system ensures secure storage, scalability, and efficient retrieval of healthcare data required for system functionality.

The architecture also includes a complete prediction workflow that demonstrates the end-to-end communication process within the system. Initially, the user interacts with the chatbot interface and completes PHQ-9 and GAD-7 assessments. The frontend sends assessment responses to the backend API server, which forwards the data to the Machine Learning service for prediction analysis. The ML model processes the input features and generates mental health severity predictions along with probability scores. The backend then stores the session details and prediction reports in the database before returning the final prediction results and healthcare recommendations to the frontend interface for user display.

Overall, the proposed architecture provides a scalable, modular, and intelligent healthcare framework capable of performing automated mental health assessment, emotional risk prediction, report generation, and healthcare monitoring. The integration of Artificial Intelligence, Machine Learning, chatbot interaction, and real-time API communication makes the system efficient, user-friendly, and suitable for modern digital mental healthcare applications.

3. RESULT

3.1 Summary of Reviewed Results

The proposed "ML Powered Guardian System for Mental Health Risk Prediction" was successfully implemented and evaluated using a synthetic mental healthcare dataset generated from PHQ-9 depression assessment parameters, GAD-7 anxiety indicators, and demographic behavioral attributes. The system effectively classified users into different mental health severity levels including None, Mild, Moderate, and Severe using Deep Learning-based prediction models. The experimental implementation demonstrated that Machine Learning algorithms can successfully analyze psychological assessment data and identify mental health risk patterns with good prediction performance. The system integrated chatbot-based assessment, backend API communication, Machine Learning prediction services, and healthcare report generation into a complete AI-driven healthcare platform.

The prediction process mainly relied on PHQ-9 and GAD-7 assessment responses. Additional demographic and behavioral attributes such as age, sleep issues, prior mental health history, and social withdrawal behavior were also included to improve prediction accuracy and behavioral analysis. The Deep Learning models learned relationships among psychological indicators and generated prediction outputs capable of supporting automated mental healthcare assessment. The experimental results indicated that depression-related features contributed more strongly toward prediction performance compared to anxiety-related attributes.

The generated synthetic dataset successfully simulated real-world emotional and behavioral conditions required for Machine Learning model training and healthcare prediction analysis. The implemented system therefore demonstrates the practical feasibility of Artificial Intelligence-based digital mental healthcare systems.

3.2 Analysis and Synthesis of the Results

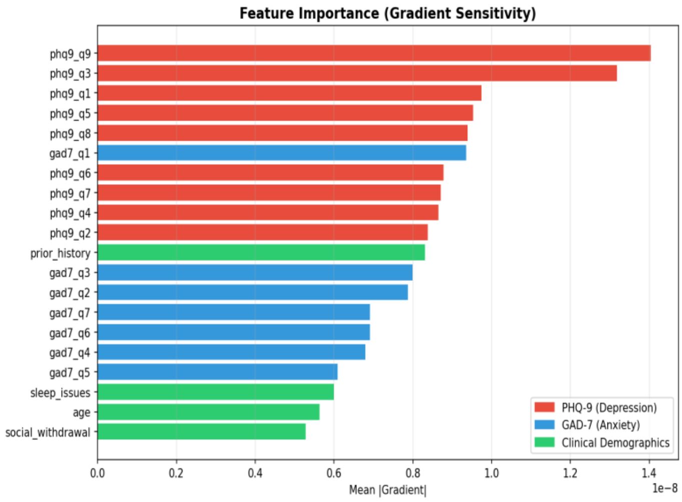

Fig.3.2.1.Feature Importance of Gradient Sensitivity

The Feature Importance Analysis graph represents the contribution of different psychological and demographic attributes toward mental health severity prediction. The analysis was performed using gradient sensitivity evaluation on the synthetic mental healthcare dataset. The graph categorizes features into three major groups: PHQ-9 depression indicators (red), GAD-7 anxiety indicators (blue), and clinical demographic attributes (green). The results indicate that depression-related parameters contributed most significantly toward prediction performance. Among all features, "phq9_q9" demonstrated the highest importance value, followed by "phq9_q3", "phq9_q1", "phq9_q5", and "phq9_q8". These attributes are associated with severe depressive symptoms, emotional instability, hopelessness, lack of motivation, and self-harm tendencies. The high contribution of these parameters indicates that depressive behavioral indicators strongly influence mental health severity classification.

The graph also shows that anxiety-related features such as "gad7_q1", "gad7_q2", and "gad7_q3" significantly contribute toward prediction performance. These parameters represent nervousness, excessive worrying, and anxiety symptoms, which are important indicators for identifying moderate and severe mental health conditions. Clinical demographic features including prior mental health history, sleep issues, age, and

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

social withdrawal also contributed toward prediction performance. Among these, prior mental health history showed the highest importance among demographic variables, indicating that users with previous psychological conditions have higher risk probabilities.

Overall, the feature importance analysis validates that combining depression indicators, anxiety parameters, and behavioral attributes improves the efficiency and reliability of the Deep Learning prediction model.

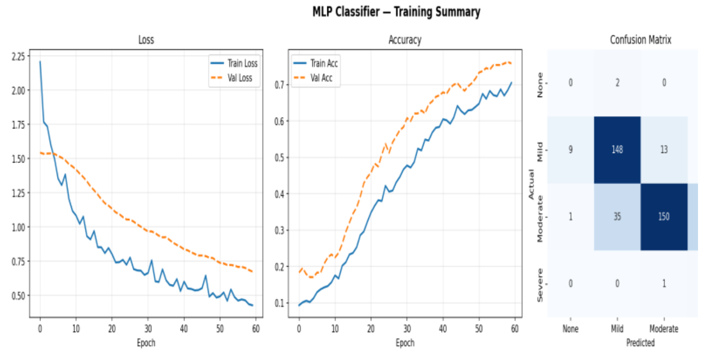

Fig.3.2.2 MLP Classifier-Training Summary

The "MLP Classifier — Training Summary" graph illustrates the performance evaluation of the Multi-Layer Perceptron (MLP) Deep Learning model used for mental health severity prediction. The figure contains three major sections: Loss Analysis, Accuracy Analysis, and Confusion Matrix. The loss graph demonstrates the reduction of training loss and validation loss across training epochs. Initially, the training loss value was high, but it gradually decreased as the model learned psychological feature patterns from the dataset. The validation loss also continuously decreased throughout the training process, indicating that the model effectively generalized the learned features and minimized prediction errors.

The accuracy graph shows that both training accuracy and validation accuracy improved steadily during model training. The validation accuracy eventually reached approximately 75%, indicating that the model successfully learned complex relationships among PHQ-9, GAD-7, and demographic features. The increasing accuracy trend demonstrates that the MLP model effectively classified users into different mental health severity categories. The confusion matrix further evaluates classification performance across the four severity classes: None, Mild, Moderate, and Severe. The matrix indicates that the model correctly classified a large number of Moderate and Mild cases. However, some Moderate cases were misclassified as Severe or Mild due to overlapping psychological symptoms. The confusion matrix therefore demonstrates that the MLP model achieved satisfactory classification performance while identifying most psychological severity patterns correctly.Overall, the MLP Classifier successfully learned emotional and behavioral relationships from the synthetic dataset and provided effective mental health severity prediction performance.

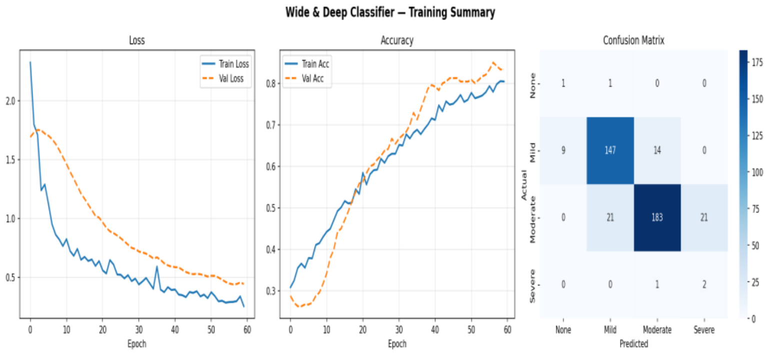

Fig.3.2.3.Wide & Deep-Training Summary

The "Wide & Deep Classifier — Training Summary" graph represents the performance evaluation of the Wide & Deep Deep Learning model used for mental health prediction. Similar to the MLP analysis, the figure includes Loss Analysis, Accuracy Analysis, and Confusion Matrix evaluation.

The loss graph shows that both training loss and validation loss decreased significantly throughout the training process. Compared to the MLP model, the Wide & Deep architecture demonstrated more stable convergence and lower final loss values. This indicates that the model effectively captured both linear and nonlinear relationships among mental health features. The accuracy graph demonstrates continuous improvement in training and validation accuracy during training epochs. The validation accuracy reached approximately 85%, which is higher than the accuracy achieved by the MLP model. The improved accuracy indicates that the Wide & Deep architecture better captured complex psychological feature interactions and improved classification capability. The confusion matrix demonstrates improved classification performance compared to the MLP model. The model successfully classified most Mild and Moderate mental health cases with higher precision. The number of misclassified Moderate and Severe cases was comparatively lower, indicating improved prediction stability and better severity differentiation capability.

The Wide & Deep architecture combines linear learning capability with Deep Neural Network feature extraction, allowing the model to capture both simple and complex psychological relationships within the dataset. This improves prediction accuracy and classification reliability for mental healthcare assessment. Overall, the Wide & Deep Classifier demonstrated superior performance compared to the MLP model and proved highly effective for automated mental health severity prediction using PHQ-9, GAD-7, and behavioral demographic features.

5.Limitation

Although the proposed "ML Powered Guardian System for Mental Health Risk Prediction" successfully demonstrates the application of Artificial Intelligence and Machine Learning technologies in digital mental healthcare, the system still has several limitations that may affect its practical implementation and prediction accuracy. One of the major limitations of the project is the use of a synthetic dataset for model training and evaluation. Since the dataset was artificially generated using PHQ-9, GAD-7, and demographic behavioral parameters, the prediction results may not completely represent real-world psychological conditions and emotional diversity. Real clinical datasets often contain highly complex behavioral patterns, emotional variations, and patient-specific conditions that are difficult to simulate accurately in synthetic data generation.

CONCLUSION

The “ML Powered Guardian System for Mental Health Risk Prediction” successfully demonstrates the application of Artificial Intelligence and Machine Learning technologies in the field of digital mental healthcare. The proposed system provides an intelligent and user-friendly platform capable of predicting mental health severity levels using PHQ-9 and GAD-7 assessments, sentiment analysis, and Deep Learning techniques. By integrating chatbot interaction, automated assessment, predictive analytics, and recommendation systems, the project offers an effective solution for early-stage mental health screening and support.

The developed system combines a ReactJS frontend, ExpressJS backend, and FastAPI-based Machine Learning microservice to create a complete healthcare prediction environment. The Machine Learning model implemented using TensorFlow, Scikit-learn, NumPy, and Pandas successfully classifies users into different severity levels such as None, Mild, Moderate, and Severe based on psychological and behavioral parameters. In future developments, the system can be enhanced by integrating real-time wearable device monitoring, multilingual chatbot support, cloud-based deployment, voice emotion recognition, and advanced Natural Language Processing models. Additional improvements such as integration with hospital management systems, telemedicine platforms, and real-time therapist communication can further increase the practical applicability of the system in modern healthcare environments.

REFERENCES

[1] 1. Coombs, N.C.; Meriwether, W.E.; Caringi, J.; Newcomer, S.R. Barriers to healthcare access among U.S. adults with mental health challenges: A populationbased study. SSM Popul. Health 2021, 15, 100847.
[2] Hidaka, B.H. Depression as a disease of modernity: Explanations for increasing prevalence. J. Affect. Disord. 2012, 140, 205–214.
[3] Uutela, A. Economic crisis and mental health. Curr. Opin. Psychiatry 2010, 23, 127–130.
[4] Torous, J.; Myrick, K.J.; Rauseo-Ricupero, N.; Firth, J. Digital mental health and COVID-19: Using technology today to accelerate the curve on access and quality tomorrow. JMIR Ment. Health 2020, 7, e18848.
[5] Arean, P.A. Here to stay: Digital mental health in a post-pandemic world— Looking at the past, present, and future of teletherapy and telepsychiatry. Technol. Mind Behav. 2021, 2, e00073.
[6] Friis-Healy, E.A.; Nagy, G.A.; Kollins, S.H. It is time to REACT: Opportunities for digital mental-health apps to reduce mentalhealth disparities in racially and ethnically minoritized groups. JMIR Ment. Health 2021, 8, e25456.
[7] Prescott, M.R.; Sagui-Henson, S.J.; Chamberlain, C.E.W.; Sweet, C.C.; Altman, M. Real-world effectiveness of digital mental-health services during the COVID-19 pandemic. PLoS ONE 2022, 17, e0272162.
[8] Wu, T.; He, S.; Liu, J.; Sun, S.; Liu, K.; Han, Q.L.; Tang, Y. A brief overview of ChatGPT: History, status-quo and potential future development. IEEE/CAA J. Autom. Sin. 2023, 10, 1122–1136.
[9] Lattie, E.G.; Stiles-Shields, C.; Graham, A.K. An overview of and recommendations for more accessible digital mental-health services. Nat. Rev. Psychol. 2022, 1, 87–100.
[10] Adeshola, I.; Adepoju, A.P. The opportunities and challenges of ChatGPT in education. Interact. Learn. Environ. 2023, 32, 6159–6172.
[11] Biswas, S.S. Role of ChatGPT in public health. Ann. Biomed. Eng. 2023, 51, 868–869.
[12] D’Alfonso, S. AI in mental health. Curr. Opin. Psychol. 2020, 36, 112–117.
[13] Su, S.; Wang, Y.; Jiang, W.; Zhao, W.; Gao, R.; Wu, Y.; Tao, J.; Su, Y.; Zhang, J.; Li, K.; et al. Efficacy of Artificial Intelligence-assisted psychotherapy in patients with anxiety disorders: A prospective, national multicentre randomized controlled trial protocol. Front. Psychiatry 2022, 12, 799917.
[14] Sedlakova, J.; Trachsel, M. Conversational artificial intelligence in psychotherapy: A new therapeutic tool or agent? Am. J. Bioeth. 2022, 23, 4–13.
[15] Henson, P.; Wisniewski, H.; Hollis, C.; Keshavan, M.; Torous, J. Digital mentalhealth apps and the therapeutic alliance: Initial review. BJPsych Open 2019, 5, e15.
[16] Vilaza, G.N.; McCashin, D. Is the automation of digital mental health ethical? Front. Digit. Health 2021, 3, 689736.
[17] Roumeliotis, K.I.; Tselikas, N.D. ChatGPT and Open-AI models: A preliminary review. Future Internet 2023, 15, 192.
[18] Adamopoulou, E.; Moussiades, L. An overview of chatbot technology. In Artificial Intelligence Applications and Innovations: AIAI 2019; Springer: Cham, Switzerland, 2020; pp. 261–280.
[19] Bayani, A.; Ayotte, A.; Nikiema, J.N. Transformer-based tool for automated fact-checking of online health information: Development study. JMIR Infodemiol. 2025, 5, e56831.
[20] Hang, C.N.; Yu, P.D.; Chen, S.; Tan, C.W.; Chen, G. MEGA: Machine-learningenhanced graph analytics for infodemic-risk management. IEEE J. Biomed. Health Inform. 2023, 27, 6100–6111.
[21] Rollwage, M.; Juchems, K.; Habicht, J.; Carrington, B.; Hauser, T.; Harper, R. Conversational AI facilitates mental-health assessments and is associated with improved recovery rates. Med Rxiv 2022. Med Rxiv:2022.11.03.22281887.
[22] Lewis, R.; Ferguson, C.; Wilks, C.; Jones, N.; Picard, R.W. Can a recommender system support treatment personalisation in digital mental-health therapy? In CHI ’22 Extended Abstracts; ACM: New York, NY, USA, 2022; p. 3519840.
[23] Liu, J.M.; Li, D.; Cao, H.; Ren, T.; Liao, Z.; Wu, J. ChatCounselor: A largelanguage-model-based system for mental-health support. arXiv 2023, arXiv:2309.15461.
[24] Shaik, T.; Tao, X.; Higgins, N.; Li, L.; Gururajan, R.; Zhou, X.; Acharya, U.R. Remote patient monitoring using AI: Current state, applications and challenges. Wiley Interdiscip. Rev. Data Min. Knowl. Discov. 2023, 13, e1485.
[25] Trappey, A.; Lin, A.P.C.; Hsu, K.K.; Trappey, C.; Tu, K.L.K. Development of an empathy-centric counselling chatbot system capable of sentimental-dialogue analysis. Processes 2022, 10, 930.