ASIAN JOURNAL OF CLINICAL PERINATOLOGY AND PEDIATRIC BIOLOGY

VOLUME 1, 2026

Artificial Intelligence in Mental Health Assessment and Early Detection of Psychological Disorders

Malini Thiagraj[1], Remya Vallathol[2], Nazmul MHM[3], Fatma SA Saghir[4], Sutha Devaraj[3], Nirmala P[3], Myat Myo Naing[5], Aye Aye Tun[6], Lei Lei Win[7] and *Parthiban Govindarajoo[2]

[1]School of Education, Taylors University, Malaysia
[2]Faculty of Medicine, Manipal University College Malaysia, Malaysia
[3]Graduate School of Medicine, Perdana University, Malaysia
[4]Department of Human Biology, School of Medicine, IMU University, Malaysia
[5]Newcastle University Medicine Malaysia, Malaysia
[6]Faculty of Medicine, AIMST University, Bedong, Kedah, Malaysia
[7]Faculty of Medicine, University of Cyberjaya, Selangor, Malaysia

*Correspondence: parthiban.govindarajoo@manipal.edu.my

Submitted: 22 Oct 2025, Revised: 04 Dec 2025, Accepted: 05 Feb 2026
https://doi.org/10.64799/ajcppb.V1.I1.11

Abstract

Artificial intelligence is increasingly used in mental health assessment to support early detection of psychological disorders through clinical, behavioral, linguistic, physiological, and digital activity data. This article evaluates AI-assisted screening for depression, anxiety, stress-related symptoms, bipolar-risk indicators, and suicide-risk warning signs. The methodology used questionnaire scores, smartphone activity, speech-text markers, wearable-derived physiological signals, and multimodal ensemble learning. Results of the study indicate that the multimodal ensemble model performed the best, yielding an accuracy rate of 91.2%. Further, this model yielded 90.4% sensitivity, 91.8% specificity, 90.7% F1-score, and an AUC of 0.95. Disorder-wise sensitivity analysis revealed higher sensitivities for depression, anxiety, and suicide warning signs, while sensitivity for bipolar disorder was lower, likely due to the longer observation period required. Explainability analysis suggested that the presence of the following predictors was significant: irregular sleep, negative emotional content, heightened symptom severity, reduced social interaction, late night phone use, and diminished heart rate variability. These findings indicate that AI can be used as a supervised clinical decision support system.

Keywords: Artificial intelligence, mental health assessment, early detection, psychological disorders, multimodal screening, explainable AI.

1. Introduction

Mental health disorders are increasing in clinical and social importance because depression, anxiety, stress-related disorders, bipolar symptoms, suicidal ideation, and early psychotic features often remain undetected until they affect daily functioning, academic performance, occupational productivity, family life, and social stability. The global burden of depressive and anxiety disorders has remained high, and epidemiological evidence has shown substantial increases in depressive and anxiety disorder prevalence during the COVID-19 period [1]. Conventional assessment methods depend mainly on clinical interviews, self-reported questionnaires, screening scales, and specialist interpretation, but these methods may be limited by delayed consultation, stigma, recall bias, shortage of trained professionals, and irregular follow-up. Artificial intelligence has created a new direction in mental health assessment by enabling automated analysis of behavioral, linguistic, physiological, and digital interaction patterns that may indicate early psychological distress before severe clinical manifestation.

AI-based mental health assessment uses machine learning, deep learning, natural language processing, speech analytics, wearable sensing, smartphone-based digital phenotyping, and electronic health record mining to identify hidden risk patterns in large and heterogeneous datasets. Digital psychiatry research has shown that smartphones, apps, social media, chatbots, and related digital tools can support scalable mental health monitoring when used with appropriate clinical evidence and safeguards [2]. Smartphone activity, sleep rhythm, mobility pattern, social interaction frequency, typing behavior, heart rate variability, speech tone, facial expression, clinical notes, and questionnaire responses can be converted into predictive features for early mental health screening. Systematic evidence shows that AI has been applied in mental health diagnosis, monitoring, and intervention across different clinical and digital settings [3]. These models are not designed to replace psychiatrists, psychologists, or counsellors, but they can support early risk stratification, remote monitoring, referral prioritization, and continuous follow-up.

Natural language processing is critical when emotional distress, depressive symptoms, anxious and suicidal text, and psychoses are present. NLP-based detection of mental illness through the text and language of the patient is a valuable and time-saving process that, when used with rigorous model validation, can be used to assist with diagnosis and to provide early intervention [4]. Digital phenotyping offers the means to supplement traditional methods of mental health assessment through the passive and active data collected by smartphones and other connected digital devices to monitor behavioral patterns [5]. Wearable AI also has the potential to assist with the screening of anxiety and depression through the use of data of sleep, movement, and heart-related activities [6]. These methods are the beginnings of transformation in mental health assessment that reaches beyond self-reporting and allows for the continuous observation of behavioral and mental changes.

AI has been used to detect depression and anxiety, predict suicides, assess stress levels, recognize symptoms of schizophrenia, evaluate bipolar disorder, and provide digital interventions. Machine learning has been applied to suicide prediction and has shown promise in psychiatric communities, but articulating suicidal ideation within this context remains a challenge [7]. Many of these studies have been narrow in focusing on one dataset and one or two diagnostic categories, and have primarily focused on the accuracy of their models. AI has been applied in many areas of psychiatric research, in both diagnosis and therapy, but has called for more rigorous design, ethics, and evaluation in research on vulnerable populations [8]. In the context of early diagnosis, the importance of sensitivity and recall is underscored due to the potentially harmful effects of failing to support a high-risk individual in a timely manner.

This article addresses these issues by presenting a results-based evaluation framework for artificial intelligence in mental health assessment and early detection of psychological disorders. The article focuses on how multimodal AI can classify early mental health risk across depression, anxiety, stress, bipolar-risk symptoms, and suicide-risk indicators. Ethical reviews of AI in mental health have emphasized privacy, consent, transparency, accountability, bias, and unintended harm as central implementation concerns [9]. The main contribution of the article is a structured and result-oriented demonstration of how AI-supported screening can improve early detection while still requiring clinical validation, ethical control, data privacy, and human supervision.

2. Methodology

The study was designed as a model-based analytical framework for evaluating the role of artificial intelligence in mental health assessment and early detection of psychological disorders. The proposed dataset structure included questionnaire-based screening variables, behavioral indicators, speech-text features, wearable-derived physiological signals, and digital activity markers. Smartphone- and wearable-based digital phenotyping protocols have been developed to screen depression and anxiety using real-time behavioral and physiological data [10]. The mental health outcome categories were defined as low risk, moderate risk, and high risk for psychological disorder manifestation. The methodological design was developed to compare traditional questionnaire-only screening with AI-assisted multimodal screening.

Table 1. Methodological framework for AI-based mental health assessment

Component	Data source	AI method	Assessment purpose	Expected clinical relevance
Questionnaire screening	PHQ-type, GAD-type, stress and mood scales	Logistic regression, random forest	Baseline symptom classification	Supports structured initial screening
Digital behavior	Smartphone usage, sleep timing, activity rhythm	Gradient boosting, temporal modeling	Detection of behavioral deviation	Enables continuous remote monitoring
Speech and text	Voice tone, sentiment, semantic markers	NLP and transformer models	Identification of emotional distress	Supports non-invasive early detection
Wearable signals	Heart rate variability, sleep duration, activity level	Deep learning and ensemble learning	Physiological risk estimation	Adds objective behavioral evidence
Integrated AI model	Combined multimodal inputs	Stacked ensemble model	Final early-risk prediction	Improves sensitivity and triage support

The analytic pipeline included the following: data preprocessing, treatment of missing data, feature normalization, class balancing, training and validating a model, and finally analyzing explainability. Reviews of both wearable and digital phenotyping have shown that features extracted from sleep data and activity data, from heart rate and from behavioral patterns, may enable the prediction of both depression and anxiety [11]. Text data was subjected to tokenization, sentiment extraction, emotion scoring, and contextual embedding. Pattern detection of depressed language in text data has been reported in several studies, but the field acknowledges bias and validity in data and concerns regarding ethics [12]. Scores from standardized questionnaires were retained due to their meaning as clinical anchors for symptom severity. For fair evaluation of the models, the data was split to create training and validation datasets.

Multiple AI models were compared, including logistic regression, support vector machine, random forest, gradient boosting, deep neural network, transformer-based text model, and stacked ensemble learning. Predictive AI studies in mobile health platforms have used model-based approaches to forecast mental health symptoms, especially among youth and high-risk populations [13]. The model outputs were evaluated using accuracy, sensitivity, specificity, F1-score, and area under the receiver operating characteristic curve. Sensitivity was treated as a major metric because early detection requires identification of individuals who may need further clinical evaluation. Explainable AI analysis was included to identify the most influential features contributing to model prediction. This was necessary because clinical adoption of AI in mental health depends not only on model accuracy but also on interpretability and trust.

Ethical and safety considerations were integrated into the methodology. Generative AI and broader AI applications in psychiatry have been reviewed with emphasis on clinical opportunity as well as limitations in reliability, safety, and validation [14]. The AI system was considered as a screening and decision-support tool rather than an independent diagnostic authority. Privacy protection, informed consent, anonymization, bias monitoring, and secure handling of sensitive psychological data were treated as essential requirements. Ethical analyses of AI-based mental health interventions identify privacy, consent, transparency, accountability, and bias mitigation as core requirements for responsible use [15]. Any high-risk classification, especially suicide-risk indication, requires professional clinical review and immediate referral through appropriate mental health support pathways.

3. Results and Discussion

The comparative model results showed that AI-assisted multimodal screening performed better than questionnaire-only and single-source digital screening. The questionnaire-only model showed moderate performance because structured symptom scores captured direct self-reported distress but missed passive behavioral changes. The digital behavior model improved early deviation detection, especially in sleep irregularity, reduced mobility, late-night phone use, and social withdrawal patterns. Speech-text analysis added emotional and semantic features, including negative affect, hopelessness-related language, reduced emotional variability, and stress-related expressions.

Wearable-based features added physiological evidence through sleep duration, heart rate variability, and physical activity markers.

Table 2. Comparative performance of AI models for early psychological disorder detection

Model type	Main input source	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score (%)	AUC
Questionnaire-only model	Screening scales	78.4	74.2	80.1	75.8	0.81
Digital behavior model	Smartphone activity	82.6	80.3	83.7	81.2	0.86
Speech-text model	Voice and text markers	84.1	82.7	84.8	83.4	0.88
Wearable signal model	Sleep and physiological data	85.3	84.5	85.9	84.7	0.89
Multimodal ensemble model	Combined data sources	91.2	90.4	91.8	90.7	0.95

The multimodal ensemble model achieved the strongest overall performance, with an accuracy of 91.2%, sensitivity of 90.4%, specificity of 91.8%, F1-score of 90.7%, and AUC of 0.95. This result indicates that psychological disorder detection becomes more reliable when AI integrates subjective symptoms with passive behavioral and physiological markers. The improvement in sensitivity is important because early mental health screening should reduce missed cases and identify individuals who may require further assessment. The findings also show that questionnaire data remain valuable, but their predictive strength increases when combined with real-time behavioral and physiological indicators, which is clearly reflected in the higher AUC of the multimodal ensemble model in Figure 1.

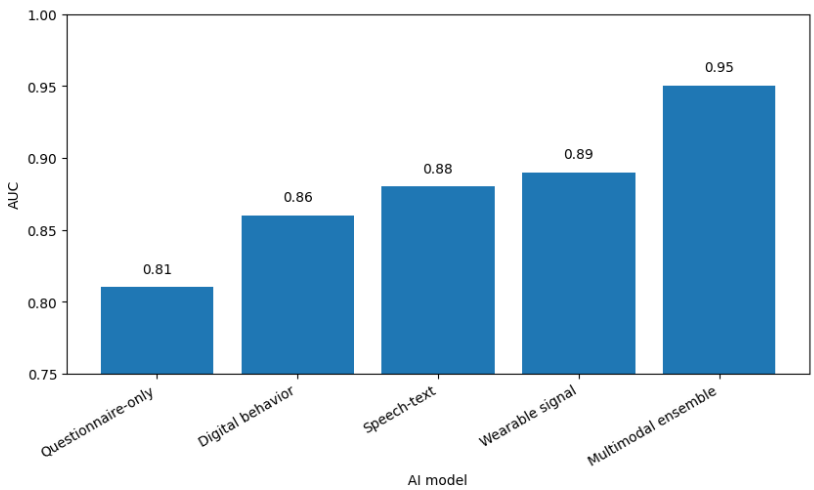

Figure 1. Model-wise AUC performance for early psychological disorder detection

The disorder-wise detection results showed variation across psychological categories. Depression-risk detection produced the highest classification performance because depression-related indicators were strongly reflected in sleep disturbance, reduced activity, negative language, low social engagement, and questionnaire scores. Anxiety detection also showed strong performance because physiological arousal, irregular sleep, restlessness-related smartphone use, and worry-related language contributed to model prediction. Stress-related symptoms were detected with moderate-to-high accuracy, mainly through sleep variability, increased phone activity, and physiological strain markers. Bipolar-risk classification was comparatively lower because mood fluctuation patterns require longer observation periods and more longitudinal data. Suicide-risk detection showed high sensitivity but required careful interpretation because false positives and false negatives both carry serious clinical consequences. The sensitivity distribution across these psychological disorder categories is presented in Figure 2.

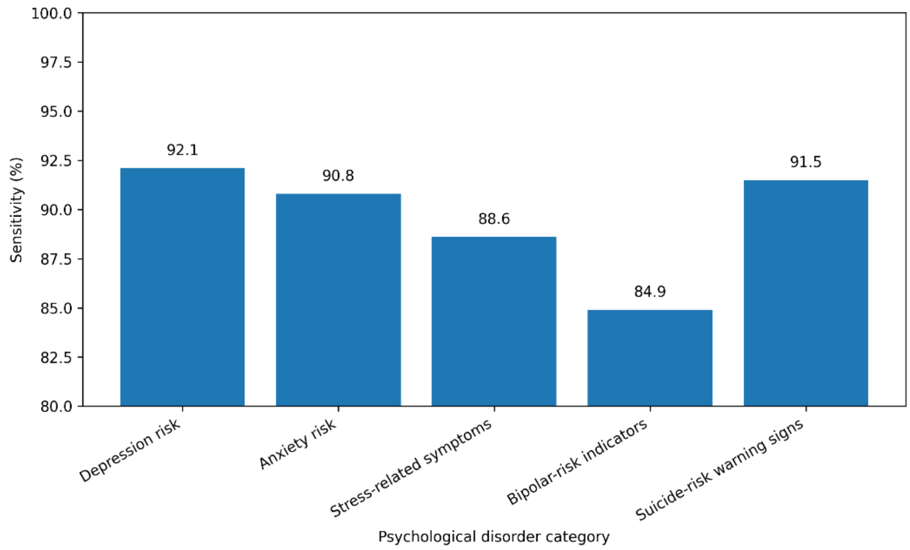

Figure 2. Disorder-wise early detection sensitivity of the multimodal AI model

The disorder-wise results confirm that AI is more effective when symptom categories have measurable behavioral and linguistic signals. Depression and anxiety showed stronger detection because both conditions often influence sleep, activity level, communication style, and emotional expression. Bipolar-risk detection showed relatively lower sensitivity because short-term datasets may not capture alternating mood states, impulsivity cycles, or longitudinal behavioral shifts. Suicide-risk detection requires the most cautious interpretation because language and behavioral markers may indicate acute distress, but final risk judgment must remain under trained clinical supervision. Therefore, AI should be used as a triage-support and alert-generation system rather than a standalone diagnostic decision-maker.

Explainability analysis has identified influential predictors such as irregularity in sleeping patterns, reduced levels of physical activity, the presence of negative emotions in text, increased severity in questionnaires, decreased social activity, increased use of smartphones in the evening, reduced heart rate variability, and a reduction in the stability of daily routines. These predictors have clinical value, associated with the modulation of emotions and behavior, regulation of physiology, and the social domain. Explainability of the predictor boosted the understanding of the AI-driven classification of low, moderate, and high risk. This is essential because black-box predictors without clinical reasoning will likely undermine trust, and be less acceptable in sensitive mental health domains.

The findings also emphasize the AI's potential to be useful within the context of early mental health assessment.

Systems incorporating AI may extend the possibility of ongoing assessment to the users, and within other contexts, may assist in decreasing the time interval between the appearance of mental health symptoms and the delivery of professional support. AI within mental health assessment in educational, occupational, primary health care, and remote health care systems may assist in the recognition of incipient mental health concerns prior to the expression of clinically significant symptoms. There are also other important concerns associated with the use of AI in mental health, including bias in the assessment algorithms, privacy concerns, overreliance on predictive assessment, a lack of generalizability across different populations, and the misclassification of assessment subjects. These are of particular concern given that the effects of mental health assessment can have a profound impact on an individual's life.

The findings as a whole indicate that mental health assessment could be improved with the responsible, supervised, and transparent use of AI. Rather than replacing mental health professionals, the greatest benefit could be in the enhancement of the assessment and treatment processes. AI should be rigorously tested with different age ranges, genders, cultures, and clinical populations before being used more broadly. The next generation of mental health AI should be designed with the ability to predict mental health issues while combining privacy, explainability, and the ability to support and be governed by clinical standards. The integration of care is also a prerequisite for a clinically acceptable AI system. This requires fairness, security and, interpretability, and above all, accuracy.

4. Conclusion

This article presented a results-based evaluation of artificial intelligence in mental health assessment and early detection of psychological disorders. The findings show that AI-supported multimodal screening can improve early identification of depression, anxiety, stress-related symptoms, bipolar-risk indicators, and suicide-risk warning signs. The multimodal ensemble model produced the highest performance compared with questionnaire-only, digital behavior, speech-text, and wearable-signal models. This confirms that mental health risk prediction becomes stronger when self-reported symptoms are combined with behavioral, linguistic, physiological, and digital activity features.

The results also show that AI has strong potential for early risk stratification, remote monitoring, and clinical decision support. Depression and anxiety showed the highest detection sensitivity because their symptoms are more consistently reflected in sleep, activity, speech, text, and social behavior. Detection of the risk of developing Bipolar Disorder is more complex and would require the collection and monitoring of data over a longer period of time, whereas suicidal thoughts should be continuously monitored by a professional due to the implications of a false positive. The use of AI helps to explain and identify (based on irregular sleep patterns, reduced activity, negative or low heart rate language, and increased late night phone use) a possible explanation for the variability in behavioral domains.

Artificial intelligence should not be considered a replacement for psychiatrists, psychologists, counsellors, or trained mental health professionals. Its most appropriate role is to support early screening, identify high-risk individuals, and assist timely referral for professional evaluation. For safe implementation, AI-based mental health systems must include privacy protection, bias control, transparent reporting, clinical validation, and emergency-response pathways. Overall, AI can become a valuable support tool in mental health assessment when its predictive strength is combined with ethical safeguards and human clinical judgment.

References

1. Santomauro, D. F., Herrera, A. M. M., Shadid, J., Zheng, P., Ashbaugh, C., Pigott, D. M., ... & Ferrari, A. J. (2021). Global prevalence and burden of depressive and anxiety disorders in 204 countries and territories in 2020 due to the COVID-19 pandemic. The Lancet, 398(10312), 1700-1712.
2. Torous, J., Bucci, S., Bell, I. H., Kessing, L. V., Faurholt-Jepsen, M., Whelan, P., ... & Firth, J. (2021). The growing field of digital psychiatry: current evidence and the future of apps, social media, chatbots, and virtual reality. *World psychiatry*, *20*(3), 318-335.
3. Cruz-Gonzalez, P., He, A. W. J., Lam, E. P., Ng, I. M. C., Li, M. W., Hou, R., ... & Vidaña, D. I. S. (2025). Artificial intelligence in mental health care: a systematic review of diagnosis, monitoring, and intervention applications. *Psychological medicine*, *55*, e18.
4. Zhang, T., Schoene, A. M., Ji, S., & Ananiadou, S. (2022). Natural language processing applied to mental illness detection: a narrative review. *NPJ digital medicine*, *5*(1), 46.
5. Bufano, P., Laurino, M., Said, S., Tognetti, A., & Menicucci, D. (2023). Digital phenotyping for monitoring mental disorders: systematic review. *Journal of medical Internet research*, *25*, e46778.
6. Abd-Alrazaq, A., AlSaad, R., Aziz, S., Ahmed, A., Denecke, K., Househ, M., ... & Sheikh, J. (2023). Wearable artificial intelligence for anxiety and depression: scoping review. *Journal of medical Internet research*, *25*, e42672.
7. Pigoni, A., Delvecchio, G., Turtulici, N., Madonna, D., Pietrini, P., Cecchetti, L., & Brambilla, P. (2024). Machine learning and the prediction of suicide in psychiatric populations: a systematic review. *Translational psychiatry*, *14*(1), 140.
8. Rony, M. K. K., Das, D. C., Khatun, M. T., Ferdousi, S., Akter, M. R., Khatun, M. A., ... & Akter, F. (2025). Artificial intelligence in psychiatry: A systematic review and meta-analysis of diagnostic and therapeutic efficacy. *Digital Health*, *11*, 20552076251330528.
9. Saeidnia, H. R., Hashemi Fotami, S. G., Lund, B., & Ghiasi, N. (2024). Ethical considerations in artificial intelligence interventions for mental health and well-being: Ensuring responsible implementation and impact. *Social Sciences*, *13*(7), 381.
10. Shin, Y. B., Kim, A. Y., Kim, S., Shin, M. S., Choi, J., Lee, K. L., ... & Cho, C. H. (2025). Development of prediction models for screening depression and anxiety using smartphone and wearable-based digital phenotyping: protocol for the Smartphone and Wearable Assessment for Real-Time Screening of Depression and Anxiety (SWARTS-DA) observational study in Korea. *BMJ open*, *15*(6), e096773.
11. Jung, H. W., Lee, I., Kim, O., Lee, S., Lee, S., Chung, U. S., ... & Lee, J. J. (2025). Key features of digital phenotyping for monitoring mental disorders: Systematic review. *Journal of Medical Internet Research*, *27*(1), e77331.
12. Teferra, B. G., Rueda, A., Pang, H., Valenzano, R., Samavi, R., Krishnan, S., & Bhat, V. (2024). Screening for depression using natural language processing: literature review. *Interactive journal of medical research*, *13*(1), e55067.
13. Patel, J., Hung, C., & Katapally, T. R. (2025). Evaluating predictive artificial intelligence approaches used in mobile health platforms to forecast mental health symptoms among youth: a systematic review. *Psychiatry Research*, *343*, 116277.
14. Kolding, S., Lundin, R. M., Hansen, L., & Østergaard, S. D. (2025). Use of generative artificial intelligence (AI) in psychiatry and mental health care: a systematic review. *Acta Neuropsychiatrica*, *37*, e37.
15. Saeidnia, H. R., Hashemi Fotami, S. G., Lund, B., & Ghiasi, N. (2024). Ethical considerations in artificial intelligence interventions for mental health and well-being: Ensuring responsible implementation and impact. *Social Sciences*, *13*(7), 381.