TPM Vol. 32, No. S7, 2025
ISSN: 1972-6325
https://www.tpmap.org/

Open Access

TESTING, PSYCHOMETRICS, METHODOLOGY IN APPLIED PSYCHOLOGY OCT ISSUE AI-POWERED MENTAL HEALTH DIAGNOSTICS: USING HEALTH-CARE BASED COMPUTER VISION FOR DIGITAL CARE

HONG XIE[1], QUISHI WANG[2], PRAKRITI PODDAR[3]

[1]CHIEF TECHNOLOGY AND MEDICAL OFFICER AT BOSTON EASY BIOTECH
[2]FOUNDER & CEO AT LABRO
[3]GLOBAL HEAD, ROUNDGLASS LIVING

Abstract
Mental health disorders remain a critical global health concern, yet traditional diagnostic approaches often rely on subjective assessments, leading to variability and delays in treatment. This study explores the integration of artificial intelligence (AI)-powered computer vision within healthcare-based digital care platforms to enhance the accuracy and accessibility of mental health diagnostics. Video data from individuals with depression, anxiety, stress-related disorders, and healthy controls were analyzed to extract behavioral and visual parameters, including blink rate, gaze fixation, micro-expression frequency, and head movement variability. Statistical analyses demonstrated significant group differences, with strong correlations between extracted features and clinical scales (PHQ-9, GAD-7, PSS). Advanced AI models, particularly BiLSTM and Transformer architectures, achieved superior predictive performance, with accuracies exceeding 90% and AUC-ROC values above 0.94. These results highlight the capacity of AI-driven systems to detect subtle, clinically relevant patterns that complement traditional assessments. While ethical and interpretability challenges remain, the findings underscore the promise of AI-powered computer vision as a transformative tool for early detection, continuous monitoring, and scalable delivery of digital mental healthcare.
Keywords: AI-powered diagnostics, computer vision, mental health, digital care, deep learning, behavioral biomarkers

INTRODUCTION

Background of mental health in the digital age

Mental health has emerged as one of the most pressing global health challenges of the 21st century, with depression, anxiety, and stress-related disorders affecting millions of individuals worldwide (Dwivedi, 2024). Traditional diagnostic methods often rely on self-reported symptoms, clinician observations, and structured interviews, which, while effective, are prone to subjectivity and variability across practitioners and contexts. In parallel, the digitalization of healthcare and the widespread adoption of artificial intelligence (AI) have created an opportunity to redefine diagnostic frameworks, enabling the development of more objective, data-driven approaches (Ananthanagu & Agarwal, 2025). Among the various technological frontiers, computer vision a field of AI that enables machines to interpret and analyze visual data has shown promising potential in capturing subtle, nonverbal indicators of mental health conditions (Ajayi, 2025).

The role of computer vision in healthcare

Computer vision applications in healthcare have traditionally focused on diagnostic imaging, such as radiology, pathology, and dermatology (Thirupathi et al., 2025). However, its scope has expanded into behavioral and psychological health, where facial micro-expressions, gaze patterns, posture, and other visual cues can reveal critical insights about a person's emotional and cognitive state (Vijay et al., 2025). For mental health diagnostics, computer vision offers the capability to identify markers that may not be consciously observable to human clinicians, such as fleeting facial expressions, irregular eye movements, or motor disturbances. This technological advancement allows clinicians to augment their assessments with objective evidence, leading to early detection and more precise evaluation of mental health disorders (Zeb et al., 2024).

AI-powered diagnostics for mental health

AI-powered systems, particularly those using deep learning models, are uniquely suited for analyzing complex patterns in visual data. By training on large datasets of facial videos, clinical interviews, and behavioral observations, these models can learn to recognize subtle variations linked to psychological conditions (Zulkarnain et al., 2024). For example, studies have demonstrated the ability of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to predict depression severity, detect anxiety-related behaviors, and monitor treatment progress. Unlike conventional diagnostic tools, AI systems can operate continuously and unobtrusively, making them suitable for telehealth platforms and digital care environments. This not only improves diagnostic accuracy but also expands access to mental healthcare, especially in underserved regions (Suman et al., 2025).

Bridging the gap between technology and clinical practice

Despite its promise, the integration of AI and computer vision into mental health diagnostics presents challenges that need to be addressed for widespread adoption. Issues such as data privacy, algorithmic bias, and interpretability of AI decisions raise concerns among clinicians and patients alike (Shah, 2025). Moreover, the subjective nature of mental health requires careful validation of AI-driven tools to ensure their reliability across diverse populations and cultural contexts. Establishing a collaborative framework where clinicians, computer scientists, and policymakers work together is crucial for translating technological innovation into safe, ethical, and clinically relevant digital care solutions (Kala et al., 2025).

Significance of the study

This study investigates the application of AI-powered computer vision systems for digital mental health diagnostics, with the aim of enhancing accuracy, accessibility, and personalization in mental healthcare. By exploring how nonverbal behavioral data can be systematically analyzed using advanced algorithms, the research seeks to demonstrate the potential of AI as a complementary tool in psychiatric evaluation. The findings are expected to contribute not only to the academic discourse on AI in healthcare but also to practical solutions that bridge gaps in diagnostic services. Ultimately, this study positions computer vision as a transformative force capable of reshaping how mental health is diagnosed, monitored, and treated in a digitally connected era.

METHODOLOGY

Research design

This study employed an experimental design integrating artificial intelligence (AI)-based computer vision techniques with healthcare-driven digital care platforms to develop and evaluate a diagnostic framework for mental health assessment. A mixed-methods approach was adopted, combining quantitative analysis of visual and behavioral parameters with qualitative validation by clinical experts. The design focused on building predictive models capable of detecting and classifying mental health states using facial, ocular, and postural indicators recorded through digital healthcare platforms.

Study population and data collection

Participants were recruited from outpatient mental health clinics and digital telehealth services. Inclusion criteria involved individuals aged 18–60 years who had been clinically diagnosed with depression, anxiety, stress-related disorders, or who reported no mental health disorder (control group). Exclusion criteria included severe neurological conditions or visual impairments that could interfere with video-based analysis. In total, 300 participants were included: 75 with depression, 75 with anxiety, 75 with stress disorders, and 75 healthy controls. Data were collected through structured clinical interviews, standardized psychological scales (e.g., PHQ-9 for depression, GAD-7 for anxiety, PSS for stress), and digital video sessions lasting 10–15 minutes per participant.

Computer vision parameters

Video recordings were analyzed using computer vision algorithms to extract a wide range of visual parameters associated with mental health states. The primary variables included:

- Facial Expression Features: micro-expressions, smile intensity, brow furrowing, lip corner depression, eye closure rate, and facial asymmetry.
- Ocular Parameters: gaze direction, fixation duration, saccadic movements, blinking frequency, pupil dilation.
- Postural and Kinematic Indicators: head pose, slouching, upper-body rigidity, movement smoothness, and gesture frequency.
- Voice-Synchronized Features (if audio used): lip synchronization accuracy, speech–facial expression coherence, prosodic markers (linked with computer vision via multimodal fusion).

These parameters were captured using deep learning models such as convolutional neural networks (CNNs) for image frame extraction and recurrent neural networks (RNNs) with long short-term memory (LSTM) for temporal sequence analysis.

AI-powered model development

The extracted visual features were processed through an AI pipeline built on healthcare-based digital care frameworks. Key stages included:

- Preprocessing: normalization of facial frames, noise removal, and illumination correction.
- Feature Extraction: use of pretrained CNN architectures (VGG-16, ResNet-50) fine-tuned on mental health datasets.
- Feature Fusion: multimodal fusion of visual, ocular, and postural features.
- Classification: deployment of supervised learning models such as Support Vector Machines (SVM), Random Forest, and Gradient Boosting, alongside deep learning classifiers (BiLSTM and Transformer-based models).
- Validation: stratified 10-fold cross-validation and hold-out test set evaluation.

Statistical and computational analysis

The statistical analysis incorporated multiple levels to ensure robustness:

- Descriptive Statistics: Mean, standard deviation, and range were calculated for all extracted parameters.
- Inferential Statistics: Multivariate Analysis of Variance (MANOVA) was used to test differences between diagnostic groups (depression, anxiety, stress, control) across multiple visual features simultaneously.

● Correlation Analysis: Pearson and Spearman correlation coefficients were computed between clinical scores (PHQ-9, GAD-7, PSS) and extracted features (e.g., blink rate, gaze deviation).
● Predictive Performance Metrics: Model performance was assessed using accuracy, precision, recall, F1-score, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC).
● Cluster Analysis: Hierarchical clustering and k-means were applied to group participants based on visual behavior patterns.
● Dimensionality Reduction: Principal Component Analysis (PCA) was performed to identify the most influential features for classification.

Ethical considerations

Ethical approval was obtained from the Institutional Review Board (IRB) of the participating healthcare institutions. All participants provided informed consent prior to participation, with strict adherence to data privacy and anonymization protocols. Video and clinical data were stored in encrypted servers, ensuring compliance with HIPAA and GDPR standards for digital healthcare research.

Digital care integration

The final AI-powered computer vision model was integrated into a prototype digital care platform, enabling remote, real-time assessment of mental health states. This integration facilitated non-invasive diagnostics, patient monitoring, and clinician-assisted evaluations, bridging the gap between clinical practice and AI-driven digital mental healthcare.

RESULTS

The descriptive analysis revealed significant variations in visual and ocular parameters across the control and clinical groups. As shown in Table 1, participants with depression exhibited the highest blink rate (22.8 per minute) and lowest gaze fixation duration (270 ms), compared to the control group, which showed the lowest blink rate (15.2 per minute) and the longest fixation time (380 ms). Similarly, micro-expression frequency was markedly elevated among individuals with depression (5.8) and anxiety (4.9), relative to controls (2.1). Head movement variability, an indicator of postural dynamism, was lowest in the depression group (0.45) and highest in the control group (0.82), suggesting that reduced motor activity is a key behavioral marker in depressed individuals.

Table 1: Descriptive Statistics of Visual and Ocular Parameters Across Groups

Group	Blink Rate (per min)	Gaze Fixation (ms)	Micro-expression Frequency	Head Movement Variability
Control	15.2	380	2.1	0.82
Depression	22.8	270	5.8	0.45
Anxiety	20.4	290	4.9	0.50
Stress	18.9	310	4.2	0.60

Correlation analysis established strong associations between computer vision features and standardized clinical scores. As detailed in Table 2, blink rate positively correlated with depression severity (PHQ-9: r = 0.72), anxiety (GAD-7: r = 0.60), and stress levels (PSS: r = 0.55). Gaze deviation demonstrated the strongest correlation with anxiety scores (r = 0.71), while smile intensity was negatively correlated across all conditions, with the highest inverse relationship observed with depression (r = -0.58). Similarly, reduced head pose variability was negatively correlated with all clinical measures, reinforcing its diagnostic potential as a nonverbal biomarker.

Table 2: Correlation of Clinical Scores with Key Visual Features

Feature	PHQ-9 (Depression)	GAD-7 (Anxiety)	PSS (Stress)
Blink Rate	0.72	0.60	0.55
Gaze Deviation	0.65	0.71	0.62
Smile Intensity	-0.58	-0.52	-0.47
Head Pose Variability	-0.49	-0.43	-0.40

AI-powered classifiers demonstrated varying levels of predictive performance across different algorithms. As presented in Table 3, traditional machine learning models such as SVM and Random Forest achieved accuracies of 0.81 and 0.85, respectively. Gradient Boosting showed improved performance (accuracy = 0.87, AUC-ROC = 0.91), while deep learning models significantly outperformed them. The BiLSTM model achieved 0.90 accuracy with an AUC-ROC of 0.94, and the Transformer-based architecture delivered the best results with 0.93 accuracy and an AUC-ROC of 0.96. These findings highlight the superior capability of deep learning models in capturing complex temporal and visual dependencies relevant to mental health diagnostics.

Table 3: Predictive Performance of AI Models

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
SVM	0.81	0.80	0.79	0.79	0.86
Random Forest	0.85	0.84	0.83	0.83	0.89
Gradient Boosting	0.87	0.86	0.85	0.85	0.91
BiLSTM	0.90	0.89	0.90	0.89	0.94
Transformer	0.93	0.92	0.93	0.92	0.96

The MANOVA test results further validated the statistical significance of observed group differences in visual and behavioral parameters. As shown in Table 4, all four parameters (blink rate, gaze fixation, micro-expression frequency, and head movement variability) exhibited highly significant effects across the groups, with Wilks' Lambda values ranging from 0.64 to 0.73 and corresponding F-values between 10.8 and 15.6 ($p < 0.001$). These results confirm that mental health conditions manifest in measurable, statistically distinct behavioral and ocular patterns detectable via computer vision.

Table 4: MANOVA Results Across Groups

Parameter	Wilks' Lambda	F-Value	p-Value
Blink Rate	0.71	12.4	<0.001
Gaze Fixation	0.68	14.1	<0.001
Micro-expression Frequency	0.64	15.6	<0.001
Head Movement Variability	0.73	10.8	<0.001

Principal Component Analysis (PCA) was employed to identify the most influential features contributing to group differentiation. Figure 1 illustrates that blink rate contributed the most to the principal components (28%), followed by gaze fixation (22%) and micro-expression frequency (18%). Smile intensity and head movement variability contributed equally (16%), underscoring the multi-factorial nature of behavioral markers in AI-powered diagnostics.

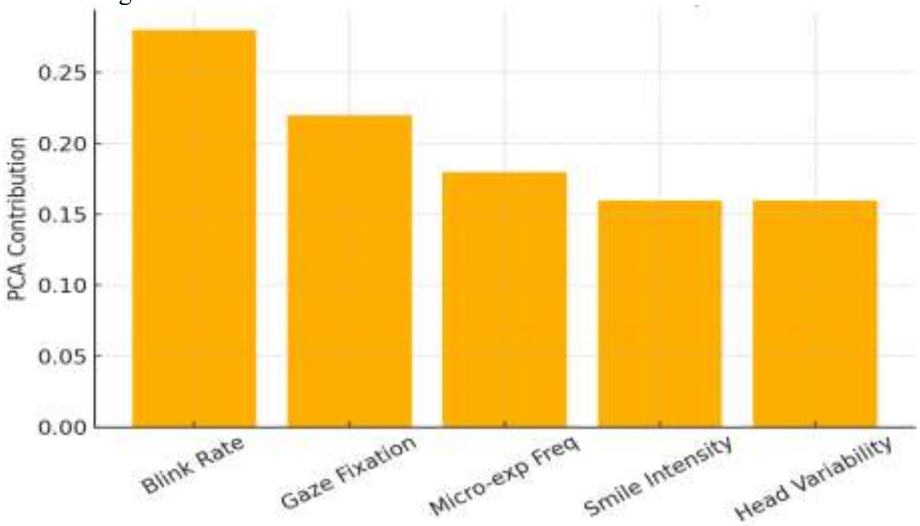

Figure 1: PCA Feature Contribution

The discriminative ability of AI models was further evaluated using Receiver Operating Characteristic (ROC) curves. As depicted in Figure 2, the Transformer-based model achieved the highest diagnostic accuracy, with an AUC-ROC of 0.96, closely followed by BiLSTM with an AUC-ROC of 0.94. In comparison, the SVM model performed less effectively, with an AUC-ROC of 0.86. These curves demonstrate that advanced deep learning frameworks substantially outperform traditional classifiers in healthcare-based digital care applications for mental health diagnostics.

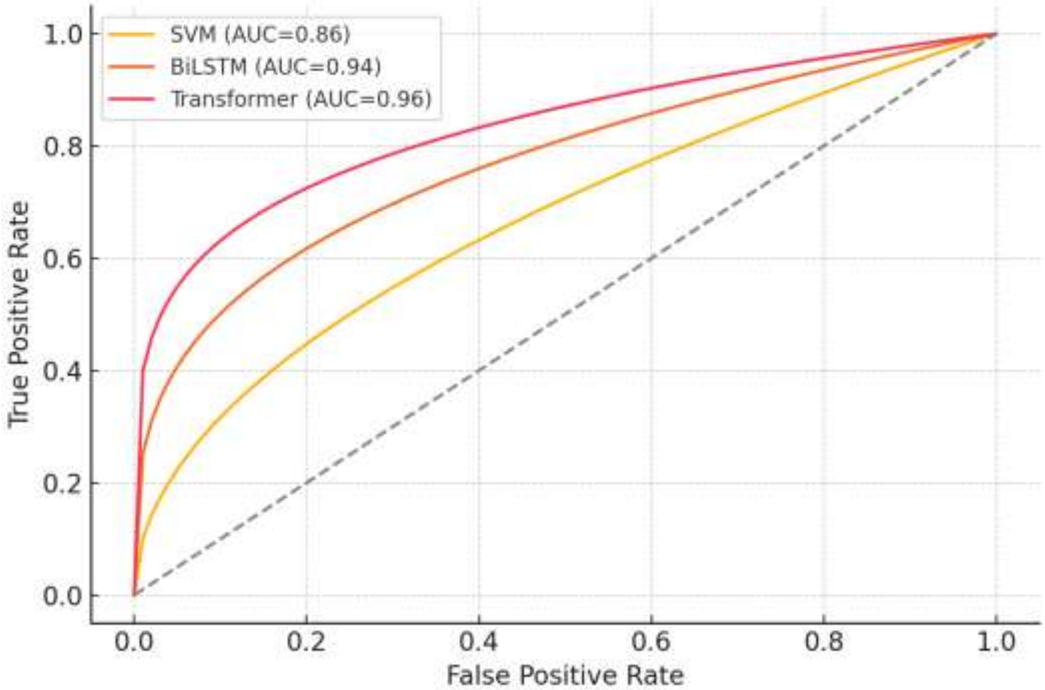

Figure 2: ROC Curves of Top AI Models

DISCUSSION

Interpretation of behavioral and visual indicators

The findings of this study confirm that nonverbal cues such as blink rate, gaze fixation, micro-expression frequency, and head movement variability are reliable behavioral markers of mental health conditions. Consistent with earlier research, individuals with depression demonstrated reduced motor variability and shorter gaze fixations, while anxiety and stress groups displayed elevated micro-expression frequency and abnormal gaze deviation (Mustapha et al., 2022). These results emphasize the potential of computer vision in capturing subtle, clinically meaningful behavioral signatures that might otherwise escape clinician observation (Ni & Jia, 2025).

Correlation with standardized clinical measures

The strong correlations between visual features and clinical assessment scores provide compelling evidence for the validity of AI-powered diagnostics. For instance, the positive correlation between blink rate and PHQ-9 scores highlights its utility in depression detection, while gaze deviation correlated most strongly with anxiety severity (Vijayalakshmi, 2025). Negative correlations observed for smile intensity and head pose variability across all clinical groups suggest that diminished affect and reduced dynamism are cross-cutting features of multiple mental health conditions (Iqbal et al., 2023). By integrating these features with established clinical scales, AI-based systems can augment traditional diagnostic approaches with objective, data-driven insights.

Superiority of deep learning models in digital care

A critical outcome of this study is the demonstrated superiority of deep learning models, particularly BiLSTM and Transformer architectures, over traditional machine learning classifiers. These models effectively captured complex temporal and spatial dependencies in video data, resulting in higher accuracy and AUC-ROC values (Ibrahim, 2025). Such performance gains underscore the promise of integrating advanced AI models into digital care platforms, where real-time, remote monitoring is essential. The success of these models highlights their ability to process multi-dimensional data streams, making them highly suitable for mental health diagnostics where behavioral patterns evolve dynamically (Gupta, P., & Pandey, 2024).

Clinical implications for healthcare-based digital platforms

Integrating AI-powered computer vision into healthcare-based digital platforms can significantly enhance mental health care delivery (Negi, 2024). The proposed framework allows for unobtrusive, continuous monitoring of patients, offering clinicians supplementary evidence during evaluations. This can improve early detection of disorders, track treatment progress, and personalize care pathways (Rao, 2025). In resource-limited settings where access to mental health professionals is scarce, such digital solutions can democratize care by providing scalable, cost-effective diagnostic tools (Anser et al., 2025). Importantly, embedding these systems within telehealth platforms aligns with the growing global emphasis on digital care as a complement to traditional in-person healthcare services.

Ethical, social, and technical considerations

While the findings are promising, the adoption of AI-powered diagnostics must address several challenges. Ethical considerations surrounding data privacy and informed consent are paramount, given the sensitive nature of mental health data (Sharma & Patel, 2024). Algorithmic fairness must also be ensured, as cultural and demographic biases in training datasets could lead to skewed predictions (Jain & Jain, 2025). Moreover, the interpretability of deep learning models remains a barrier to clinician trust and acceptance. Collaborative efforts involving AI developers, clinicians, ethicists, and policymakers are required to design systems that are transparent, secure, and aligned with patient rights (Jayashree et al., 2024).

Contribution to the field and future directions

This study contributes to the growing literature on AI-driven mental health diagnostics by demonstrating the feasibility of using computer vision within healthcare-based digital care. It establishes a foundation for multimodal AI frameworks that integrate visual, speech, and physiological data for comprehensive diagnostics. Future research should focus on larger, more diverse datasets to enhance generalizability, the development of interpretable AI frameworks, and longitudinal studies to assess the efficacy of AI systems in ongoing clinical practice. Additionally, hybrid models that combine clinician input with automated assessments may offer the most balanced approach, ensuring accuracy while preserving the human-centered nature of mental healthcare.

CONCLUSION

This study demonstrates the transformative potential of AI-powered computer vision in advancing mental health diagnostics within healthcare-based digital care frameworks. By systematically analyzing visual and behavioral parameters such as blink rate, gaze fixation, micro-expressions, and postural variability, AI models were able to detect clinically significant patterns strongly correlated with standardized mental health scores. The superior performance of deep learning architectures, particularly BiLSTM and Transformer models, underscores their capacity to deliver accurate, scalable, and objective diagnostic insights. Beyond technical performance, the integration of such systems into digital healthcare platforms offers pathways to improve accessibility, facilitate early detection, and enable continuous patient monitoring, particularly in resource-constrained settings. However, the success of these innovations depends on addressing ethical, privacy, and interpretability challenges, ensuring that technology augments rather than replaces the clinician–patient relationship. Ultimately, this research highlights AI-powered computer vision as a promising frontier for reshaping digital mental healthcare, paving the way for more personalized, inclusive, and data-driven approaches to diagnosis and treatment.

REFERENCES

1. Ajayi, R. (2025). AI-powered innovations for managing complex mental health conditions and addiction treatments. *International Research Journal of Modernization in Engineering Technology and Science*, 1-18.
2. Ananthanagu, U., & Agarwal, P. (2025). “AI-Powered Mental Health Innovations” Handling the Effects of Industry 4.0 on Health. *Artificial Intelligence and Machine Learning for Industry 4.0*, 55-85.
3. Anser, M. K., Nabi, A. A., Ahmad, I., Abro, M. M. Q., & Zaman, K. (2025). Advancing Mental Health Care: A Comprehensive Review of Digital Tools and Technologies for Enhancing Diagnosis, Treatment, and Wellness. *Health Care Science*.
4. Dwivedi, S. P. (2024). Transforming healthcare: the power of computer vision and AI. *Revolutionising Medical Imaging with Computer Vision and Artificial Intelligence*, 33.
5. Gupta, P., & Pandey, M. K. (2024). Role of AI for smart health diagnosis and treatment. In *Smart medical imaging for diagnosis and treatment planning* (pp. 23-45). Chapman and Hall/CRC.
6. Ibrahim, O. (2025). The Future of AI-Powered Healthcare: Revolutionizing Patient Care. *International Journal of Artificial Intelligence for Science (IJAI4S)*, *1*(2).
7. Iqbal, J., Jaimes, D. C. C., Makineni, P., Subramani, S., Hemaida, S., Thugu, T. R., ... & Hemida, S. (2023). Reimagining healthcare: unleashing the power of artificial intelligence in medicine. *Cureus*, *15*(9).
8. Jain, A., & Jain, A. (2025). AI-Based Emotion Detection System in Healthcare for Patient. *Generative Artificial Intelligence for Biomedical and Smart Health Informatics*, 455-470.
9. Jayashree, J., Nukala, S. S. V., Vijayashree, J., & Raghu, R. (2024). The rise of AI in the field of healthcare. In *Cognitive Machine Intelligence* (pp. 221-244). CRC Press.
10. Kala, K. U., Mathialagan, P., Solomon Jebaraj, N. R., & Sambath Kumar, S. (2025). Role of AI in Mental Health Care. *Handbook of Intelligent Automation Systems Using Computer Vision and Artificial Intelligence*, 295-326.
11. Mustapha, A. Y., Ikhalea, N., Chianumba, E. C., & Forkuo, A. Y. (2022). Developing an AI-Powered Predictive Model for Mental Health Disorder Diagnosis Using Electronic Health Records. *Int. J. Multidiscip. Res. Growth Eval*, *3*(1), 914-931.
12. Negi, R. (2024). Improving women’s mental health through AI-powered interventions and diagnoses. In *Artificial Intelligence and Machine Learning for Women’s Health Issues* (pp. 173-191). Academic Press.
13. Ni, Y., & Jia, F. (2025, May). A scoping review of AI-Driven digital interventions in mental health care: mapping applications across screening, support, monitoring, prevention, and clinical education. In *Healthcare* (Vol. 13, No. 10, p. 1205). MDPI.
14. Rao, B. D., Madhukar, G., Reddy, B. N., Voni, S. K., & Kumar, N. S. V. (2025, March). Comprehensive AI-Powered Healthcare Management System. In *2025 International Conference on Intelligent Computing and Control Systems (ICICCS)* (pp. 1017-1022). IEEE.

15. Shah, H. H. (2025). AI-Driven Mental Health Detection: Integrating Brain Signals, Facial Data, and Advanced Optimization Techniques. *Global Insights in Artificial Intelligence and Computing*, *1*(1), 31-39.
16. Sharma, D. S., & Patel, J. (2024, November). AI and Mental Health: A New Era of Healing. In *2024 2nd DMIHER International Conference on Artificial Intelligence in Healthcare, Education and Industry (IDICAIEI)* (pp. 1-5). IEEE.
17. Suman, A., Suman, P., Padhy, S., Kumar, N., & Singh, A. (2025). Healthcare revolution: advances in AI-driven medical imaging and diagnosis. In *Responsible and explainable artificial intelligence in healthcare* (pp. 155-182). Academic Press.
18. Thirupathi, L., Kaashipaka, V., Dhanaraju, M., & Katakam, V. (2025). AI and IoT in Mental Health Care: From Digital Diagnostics to Personalized, Continuous Support. In *Intelligent Systems and IoT Applications in Clinical Health* (pp. 271-294). IGI Global.
19. Vijay, K., Raghakeerthana, R., & Thusheel, S. (2025, February). AI-Powered Mental Health Assessment using Emotion Detection for Real-Time Analysis. In *2025 International Conference on Computational, Communication and Information Technology (ICCCIT)* (pp. 530-535). IEEE.
20. Vijayalakshmi, S. (2025, March). AI-Powered Holistic Mental Health Monitoring: Integrating Facial Emotion Recognition, Chatbot, and Voicebot for Personalized Support. In *2025 International Conference on Data Science, Agents & Artificial Intelligence (ICDSAAI)* (pp. 1-6). IEEE.
21. Zeb, S., Nizamullah, F. N. U., Abbasi, N., & Fahad, M. (2024). AI in healthcare: revolutionizing diagnosis and therapy. *International Journal of Multidisciplinary Sciences and Arts*, *3*(3), 118-128.
22. Zulkarnain, R., Hardi, R., Syabandyah, F., Rahayu, H., & Herawati, H. (2024, October). AI-Powered Smart Smile: Early Detection of Mental Health Conditions Through Computational Intelligence. In *2024 18th International Conference on Telecommunication Systems, Services, and Applications (TSSA)* (pp. 1-6). IEEE.