Raunak Sawa, 2026, 14:4
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

AI-Driven Mental Health Assessment Through Digital Behavioral and Physiological Signals: A Focused Review

Raunak Sawa, Sharad Menon, Rishabh Gupta, Umamaheshwari M
Department of Computer Science, Vellore Institute of Technology, Vellore, India

Abstract- With the advent of artificial intelligence (AI), it is now pos-sible to assess mental health conditions in new ways using data from dig-ital sources. Traditional diagnosis is based on patients' statements and a few tests, along with clinical observations, which can result in a delay in diagnosing and treating issues early. In recent years, research on the application of AI and machine learning in mental health assessment has increased. This review is a summary of literature published from 2015 to present date. The studies relied on the data collected from smartphones, wearable devices and social media. Sophisticated temporal and behav-ioral patterns in mental health-related information have been captured with the help of deep learning techniques. Issues with the problems are however that the data is not standardized, there is a lack of understand-ing of the models, privacy concerns and clinical validation of the models is poor. This review identifies gaps that need to be addressed in research on technologies, including real-time monitoring systems, explainable AI methods, personalized prediction models, and privacy-preserving learn-ing. Such advancements are crucial for enhancing the reliability, equity, and trustworthiness of the system and unlocking the potential of AI in mental health diagnostics and applications.

Keywords: Mental Health Detection, Artificial Intelligence, Machine Learning, Digital Phenotyping, Wearable Sensing, Smartphone Behav-ioral Data, Multimodal Health Monitoring.

I. INTRODUCTION

Mental health disorders is one of the fastest-growing areas, as it is one of the most relevant public health problems around the world affecting hundreds of mil-lions of individuals and contributing to social and economic burden of diseases in health systems [1,2]. Conventional methods of diagnosis are highly dependent on subjective clinical examination and episodic patient reporting, which can result in delayed and limited continuous monitoring and intervention [3]. The unprece-dented integration and growth of digital technologies like smartphones, wearable biosensors, and internet-based technologies has allowed for the continuous and passive monitoring of behavior and objective monitoring of psychological condi-tions [4,13].

Lately, the development of artificial intelligence (AI) and machine learning (ML) has enabled the analysis of large amounts of digital data streams and the extraction of clinically meaningful behavioral and physiological markers [5,2]. Correlating studies have collected data related to the use of the smartphone, to the use of social media and to linguistic patterns on social media. Other diseases, such as depression, anxiety, and stress, were also detected using physiological sensing systems that can be worn by the user, and through multimodal data fusion and combination [6,10,11]. While the results are promising, there are several problems with the generalizability, interpretability, privacy and clinical application of current research [7,9].

II. METHODOLOGY

A systematic literature search was conducted to identify relevant studies on the application of artificial intelligence and machine learning in the assessment of mental health. The combinations of mental health detection, artificial intelligence in mental health, machine learning for depression detection, deep learning mental health analysis and digital phenotyping were searched in IEEE Xplore, Google Scholar, Scopus and PubMed. Studies were restricted to those published between 2015 and 2025.

Inclusion criteria were English language peer-reviewed conference papers and journal articles using AI or ML on smartphone, wearable, social media or mul-timodal data and reporting experimental results or evaluation metrics. Studies were excluded if they were duplicate publications, conventional clinical assess-ment studies, or studies with insufficient methodological details. We identified approximately 150 records, screened 70 titles and abstracts, assessed 36 full text articles and included 15 studies.

III. DIGITAL MENTAL HEALTH DETECTION

Smartphone Behavioral Sensing

Smartphones have become one of the most scalable platforms of passive digital phenotyping and are able to constantly monitor behavioral patterns correlated with psychological states[4]. Contextual data from mobile devices includes GPS movements, screen interaction, communication statistics, typing behavior and physical activity. Studies show that depressive and anxiety-related symptoms are related to variability in mobility patterns, alterations in routines, and changes in device usage[8].

However, the lack of data, irregular device access, hardware and operating system diversity, and different pipelines for feature extraction make it difficult to make cross-study comparisons[9]. Another issue around continuous behavioral tracking is the ethical ones that need to be sorted out and addressed before its extensive use in the clinical setting[7]. Despite this, smartphone sensing has its significance due to its low implementation cost, scalability and continuous real-time data capturing ability.

Social Media and Language-Based Detection

Social media gives behavioral and linguistic information which can represent the mental condition of the users[10]. Lexical patterns, semantic patterns, and emo-tional tone are used to detect risk indicators with natural language processing methods. The language model using a transformer has enhanced prediction by capturing relationships and subtle linguistic information[15]. But cultural, demographic and platform biases make linguistic models sensi-tive. Interpretation can be challenging due to sarcasm, abbreviations, multilin-gualism and changing online language. Some privacy concerns are raised due to the fact that text could include personal and identifiable information, as well as the fact that it is unethical to diagnose mental health issues without the consent of the user[7].

Wearable Physiological Sensing

The use of wearables isn't just for observing behavior, it can capture physiolog-ical signals associated with the activity of the autonomic nervous system[12,13]. Heart rate variability, electrodermal activity, sleep, movement, and respiration are measured using smartwatches, fitness bands, and biosignal sensors. Base-lines are also personalized with constant sensing, which allows for the detection of deviations unique to an individual.
Nevertheless, the wearable sensing is experiencing a number of motion arti-facts, environmental noise, device placement variation, battery constrains, hard-ware heterogeneity, and inconsistent user compliance[12]. There is also limited clinical validation since many systems are evaluated in a controlled population rather than diverse real-life populations.

Multimodal Mental Health Detection

Multimodal mental health detection is the integration of behavioral, linguistic, physiological, and contextual signs[11]. The fusion of heterogeneous outputs is called feature-level fusion and the fusion of separate model predictions is called decision-level fusion. The attention and transformer networks can dynamically balance information from each modality[14]. They are also very difficult to im-plement and compute. Time alignment and pre-processing is necessary for het-erogeneous streams, while more dimensions cause overfitting and interpretability issues. The more personal data sources that are linked into connected profiles, the more risky it is for privacy. The utility of their use is thus dependent on whether they can be improved that outweighs the increased complexity and privacy infringement.

IV. CHALLENGES AND FUTURE DIRECTIONS

The use of AI in digital mental health monitoring has advanced, but there are numerous systems that are effective in certain settings, populations, and devices that do not work in others. No standard approach is used in the collection and comparison of data and studies are often conducted using participants from a single institution. Various processing and evaluation techniques also limit direct comparisons[4,9].

Table 1. Analysis of AI-based digital mental health detection modalities

Modality	Data Source	Typical ML Approaches	Strengths and Limitations
Smartphone Behavioral Sensing	GPS mobility, Screen usage, communication logs, typing behavior, activity patterns [8]	Classical ML, temporal deep learning, behavioral feature modeling	Low cost and continuous monitoring; device heterogeneity, privacy concerns, and limited standardization [9]
Social Media Language Analysis	Text posts, sentiment patterns, interaction dynamics, longitudinal language behavior [10]	NLP models, transformers, deep Language embeddings [15]	Captures self-expressed emotions; cultural bias, ambiguity, consent issues, and platform dependency
Wearable Physiological Sensing	Heart-rate variability, electrodermal activity, sleep, respiration, and motion [12]	Physiological feature modeling, signal fusion, multimodal ML	Objective and continuous signals; noise, hardware variability, user compliance, and weak real-world validation [13]
Multimodal Fusion Systems	Integrated smartphone, linguistic, physiological, and contextual data [11]	Attention-based fusion, transformers, cross-modal learning [14]	Complementary evidence and robustness; synchronization, computational complexity, and amplified privacy risk

A lot of AI models are not transparent. They can make predictions, but not sure how they make those predictions, and clinicians and patients might not trust them[3]. Privacy is also very important as smart phones and wearables can gather location, communication, activity, and physiological data. The issue of consent, data ownership, data retention, bias, and appropriate use of the system must therefore be taken into account during the design of the system[7,13].

Moreover, proposed systems are often tested by the accuracy or F1-score of the test set instead of long term clinical trials and actual patient results. Efficient real-time monitoring, explicable AI, personalized longitudinal models, standard-izing datasets, privacy preservation methods like federated learning and differ-ential privacy, and integration with clinical workflows are suggested for future research.

V. CONCLUSION

The field of digital mental health monitoring has evolved from single-sensing solutions to multimodal analytics systems. The review covered smartphone be-havioural sensing, social media text analysis, wearable physiological sensing, and multimodal fusion models. Deep learning and multimodal methods are capable of capturing complex temporal and contextual patterns, whereas classical ML models are still relevant due to their lower computational requirements and com-paratively better interpretability.

But low reproducibility, limited interpretabil-ity, privacy issues and poor clinical validation remain critical. Mental health analytics should not only focus on accuracy metrics but also provide patient centered and clinically meaningful outcomes. Future systems should focus on explainable AI, privacy-aware learning, personalized adaptive models and align-ment with clinical workflows and regulations. AI-enabled digital phenotyping could allow for better early detection and ongoing monitoring, but innovation must be matched by ethical responsibility and human-centered design.

REFERENCES

1. Abd-Alrazaq, A., Alajlani, M., Alalwan, A., Bewick, B.M., Gardner, P., Househ, M.: Wearable artificial intelligence for detecting and predicting depression: A systematic review and meta-analysis. npj Digital Medicine 6, 84 (2023)
2. Ali, O., Abdelbaki, W., Shrestha, A., Elbasi, E., Alryalat, M.A.A., Dwivedi, Y.K.: Artificial intelligence in healthcare: A systematic literature review. Journal of Innovation & Knowledge 8(1), 100333 (2023)
3. Ray, A., Bhardwaj, A., Malik, Y.K., Singh, S., Gupta, R.: Artificial intelligence and psychiatry: An overview. Asian Journal of Psychiatry 70, 103021 (2022)
4. Mendes, J.P.M., Moura, I.R., Van de Ven, P., et al.: Sensing apps and public datasets for digital phenotyping of mental health. Journal of Medical Internet Research 24(2), e28735 (2022)
5. Su, C., Xu, Z., Pathak, J., Wang, F.: Deep learning in mental health outcome research: A scoping review. Translational Psychiatry 10, 116 (2020)
6. Moshe, I., Terhorst, Y., Asare, K.O., et al.: Predicting depression and anxiety using smartphone and wearable data. Frontiers in Psychiatry 12, 625247 (2021)
7. Maher, N.A., Senders, J.T., Hulsbergen, A.F.C., et al.: Passive data collection and ethical issues in healthcare. International Journal of Medical Informatics 129, 242–247 (2019)
8. Saeb, S., Zhang, M., Karr, C.J., et al.: Mobile phone sensor correlates of depressive symptom severity. Journal of Medical Internet Research 17(7), e175 (2015)
9. Alam, N.B., Surani, M., Das, C.K., et al.: Challenges and standardization in sensor-based mental health data. Communications Medicine 5, 360 (2025)
10. Phiri, D., Makowa, F., Amelia, V.L., et al.: Text-based depression prediction on social media. Journal of Medical Internet Research 27, e59002 (2025)
11. Khoo, L.S., Lim, M.K., Chong, C.Y., McNaney, R.: Machine learning for multimodal mental health detection. Sensors 24, 348 (2024)
12. Kang, M., Chai, K.: Wearable sensing systems for mental health monitoring.
13. Sensors 22, 994 (2022)
14. Gomes, N., Pato, M., Lourenc¸o, A.R., et al.: Survey on wearable sensors for mental health monitoring. Sensors 23, 1330 (2023)
15. Haque, M.R., Islam, M.M., Raju, S.M.T.U., et al.: MMFformer: Multimodal fusion transformer for depression detection. In: IEEE SMC (2025)
16. Qasim, A., Mehak, G., Hussain, N., et al.: Transformer-based depression severity detection. Information 16, 114 (2025)