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Artificial Intelligence–Based Clinical Assessment in Mood Disorders: A Narrative Review

Duygudurum Bozukluklarında Yapay Zekâ Destekli Klinik Değerlendirme: Bir Anlatı Derlemesi

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ABSTRACT

Mood disorders, particularly major depressive disorder and bipolar disorder, pose significant challenges in clinical diagnosis. With the rapid advancement of artificial intelligence (AI) technologies in recent years, new opportunities have emerged to enhance diagnostic accuracy, monitor disease progression, and develop personalized treatment approaches for these disorders. This study aims to explore how AI-supported methods contribute to the early diagnosis and monitoring of mood disorders through a comprehensive and up-to-date narrative review approach. Through machine learning and deep learning techniques (subfields of AI) various data sources such as facial expressions, speech features, body movements, and social media content can be analyzed, allowing for the objective assessment of patients' mood states. Moreover, biomarker data collected through high-accuracy smartphones and wearable devices can be used to monitor depressive and manic episodes and to develop predictive models for these periods. Briefly, the use of AI-based technologies in the field of mental health holds critical potential for improving early intervention opportunities and creating personalized treatment plans. However, issues related to ethics, privacy, and data security present significant limitations to the integration of these technologies into clinical practice. Therefore, more comprehensive and interdisciplinary research is needed to assess the applicability of these technologies.
Keywords: Artificial intelligence, clinical assessment, mood disorders, depression, bipolar disorders

ÖZ

Duygudurum bozuklukları, özellikle majör depresif bozukluk ve bipolar bozukluk, klinik tanı süreçlerinde önemli güçlükler barındırmaktadır. Son yıllarda yapay zekâ teknolojilerinin hızla gelişmesiyle birlikte, bu bozukluklarda tanı doğruluğunun arttırılması, hastalık seyrinin izlenmesi ve kişiselleştirilmiş tedavi yaklaşımlarının geliştirilmesi yönünde yeni olanaklar ortaya çıkmıştır. Bu çalışmada, yapay zekâ destekli yöntemlerin duygudurum bozukluklarının erken tanısı ve hastalık sürecinin izlenmesi bağlamında nasıl katkı sağladığı güncel ve kapsamlı bir anlatı derlemesi tekniği ile ele alınacaktır. Yapay zekânın alt disiplinlerinden olan makine öğrenmesi ve derin öğrenme teknikleri sayesinde, yüz ifadeleri, ses özellikleri, vücut hareketleri ve sosyal medya içerikleri gibi çok çeşitli veri kaynakları analiz edilebilmekte ve böylece hastaların duygudurumları objektif ölçütlerle değerlendirilebilmektedir. Buna ek olarak, yüksek doğruluk oranlarına sahip akıllı telefonlar ve giyilebilir cihazlar üzerinden toplanan biyobelirteç verileri aracılığıyla depresif ve manik dönemler izlenebilmekte, bu dönemleri tahmin eden öngörü modelleri geliştirilebilmektedir. Kısaca, yapay zekâ tabanlı teknolojilerin ruh sağlığı alanındaki kullanımı, erken müdahale olanaklarının artırılması ve kişiye özel tedavi planlarının oluşturulması açısından önemli bir potansiyele sahiptir. Bununla birlikte, etik, mahremiyet ve veri güvenliği gibi konular, bu teknolojilerin klinik uygulamalara entegrasyonunda önemli sınırlılıklar doğurmaktadır. Bu nedenle, söz konusu teknolojilerin uygulanabilirliği üzerine daha kapsamlı ve disiplinlerarası araştırmalara gereksinim bulunmaktadır.
Anahtar sözcükler: Yapay zekâ, klinik değerlendirme, duygudurum bozuklukları, depresyon, bipolar bozukluk

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Introduction

Mood disorders are psychological conditions that negatively affect individuals' quality of life, reduce their functionality, and may lead to serious consequences if left untreated (Bridley and Daffin 2018). As with all mental health disorders, clinical assessment and accurate diagnosis are indispensable for mood disorders. Moreover, these disorders are significant not only when they reach the full-syndrome level but also in subthreshold stages. This is because such conditions, which carry the risk of progression and chronicity, may lead to severe outcomes such as suicide attempts and even death if timely intervention is not provided (Uğur 2008). Early diagnosis and treatment, on the other hand, can increase disease control and reduce these risks (Kadkhoda et al. 2022).

In the field of psychiatry, the potential of artificial intelligence (AI) stands out particularly in enhancing diagnostic accuracy and improving treatment efficacy (Rony et al. 2025). Evaluating mood changes solely through self-report scales may compromise objectivity due to social desirability bias (Kwak et al. 2021). AI-integrated assessment tools, however, can provide data-driven support to mental health professionals (Cruz-Gonzalez et al. 2025) and play a crucial role in improving treatment outcomes (Milic et al. 2025).

This study aims to explore the potential of AI-assisted diagnostic support systems in the evaluation of mood disorders and to examine the applicability of analytical methods that integrate various data sources (e.g., wearable devices, written expressions, chatbots, EEG data, etc.). The literature on AI-based multimodal systems for the early detection of mood disorders and the dynamic monitoring of treatment response remains limited. By addressing this gap, the present study aims to introduce a data-driven approach to clinical diagnostic processes and to contribute to the enhancement of diagnostic practices and the development of more effective intervention strategies for mood disorders.

Mood Disorders and Their Assessment

Definition and Clinical Features

Mood refers to a sustained or temporary affective state that influences an individual's emotional experience and occurs independently of any specific object (Karakaş 2017). A mood disorder, on the other hand, signifies much more severe and prolonged changes; the symptoms are maladaptive, distressing, intense, and persistent, and they significantly impair functioning in relationships and occupational performance (Butcher et al. 2013).

According to the DSM-5-TR (American Psychiatric Association 2022), which constitutes the basis of this study, mood disorders can be primarily classified into two main categories: Depressive Disorders and Bipolar and Related Disorders. While depressive disorders represent a unipolar condition characterized solely by depressive symptoms, bipolar and related disorders exhibit a bipolar structure, involving alternating depressive and manic or hypomanic episodes (Uğur 2008). Consistent with the most frequently encountered classifications in the literature review, this study focuses exclusively on two major mood disorders: Major Depressive Disorder and Bipolar Disorder. Major Depressive Disorder is a mood disorder characterized by symptoms such as depressed mood, loss of interest and pleasure, changes in weight and appetite, sleep disturbances, decreased energy, feelings of worthlessness, and concentration difficulties (APA 2022). Bipolar and related disorders, by contrast, are characterized not only by depressive episodes but also by mood fluctuations involving manic, hypomanic, or mixed episodes (APA 2022). Manic episodes are defined by elevated energy levels, decreased need for sleep, racing thoughts, pressured speech, and difficulties in attention and concentration. Hypomanic episodes share similar symptoms with manic episodes but differ in that they last for a minimum of four days and may not necessarily lead to marked functional impairment.

Standard Assessment

Clinical interviews, expert observations, and self-reports continue to serve as standard methods in the evaluation of psychiatric patients (Lader 1981). Clinical interviews are conducted with reference to diagnostic systems such as the DSM-5-TR or the International Classification of Diseases (ICD-11) and can be administered in unstructured, semi-structured, or structured formats (Bilican 2020). During this process, clinicians may utilize standardized tools such as the SCID-5 (Structured Clinical Interview for DSM-5) (First et al. 2016). Among the most commonly used standardized psychometric tests for assessing depression are the Beck Depression Inventory (Beck et al. 1996), the Minnesota Multiphasic Personality Inventory (Hathaway 1964), and the Hamilton Depression Rating Scale (Hamilton and Guy 1976). The identification of hypomanic symptoms and longitudinal clinical evaluation are of critical importance in distinguishing bipolar disorder from other conditions (Vieta et al. 2018). Various psychometric instruments, such as the Bipolar Spectrum Diagnostic Scale (Ghaemi et al. 2005; BSDS), are employed to support the diagnostic process.

While psychometric scales serve as powerful tools that assist clinicians in making diagnoses, their reliance on self-report data introduces certain limitations, as they remain susceptible to response biases. The identification of objective biomarkers that can enhance current diagnostic methods—not only for mood disorders but also for mental health assessment in general—has therefore become an increasingly important and rapidly evolving research area. In this context, the integration of artificial intelligence-based technologies represents a promising direction for advancing mental health research (Cummins et al. 2020).

Method

This study is a comprehensive narrative review examining the current state of artificial intelligence applications in the clinical assessment of mood disorders (Ferrari 2015). The narrative review method was selected rather than systematic review protocols (e.g., PRISMA) to present a broader conceptual framework and to capture emerging trends in the literature from a holistic perspective. The literature search focused on studies published between 2015 and 2025 that investigated the role of artificial intelligence-based methods in the clinical assessment of mood disorders (e.g., major depressive disorder, bipolar disorder). Major databases consulted included PubMed, Google Scholar, APA PsycNet, ScienceDirect, and ULAKBİM TR Dizin. The keywords "artificial intelligence," "machine learning," "deep learning," "mood disorders," "major depression," "bipolar disorder," and "clinical assessment" were used in both Turkish and English. In the selection of studies, currency, specificity to mental disorders, and potential for clinical application were taken as the main criteria, and the publications obtained were evaluated by classifying them under thematic headings according to their content.

Results

Artificial Intelligence

Artificial intelligence (AI) is a non-natural form of intelligence created by humans through various scientific and engineering techniques (Kumar 2013). It is achieved by endowing a computer or machine with abilities such as thinking, reasoning, problem-solving, and learning from past experiences (Yılmaz 2021), and it is increasingly preferred as an optimal solution across numerous domains today (Köroğlu 2017). Machine learning, one of the subcategories of AI-based computational systems, has within it a further subcategory known as deep learning (Bhattacharyya et al. 2020).

Machine Learning and Deep Learning

Machine learning enables systems to learn autonomously and improve through experience by using specific algorithms, and its strength lies in accomplishing this without being explicitly programmed (El Naqa and Murphy 2015). As a data-driven approach, machine learning allows the extraction of specific features from datasets (Zhou et al. 2022) and the identification of patterns within unstructured data (Sharma et al. 2021). Consequently, the greater the amount of data available, the higher the performance of machine learning algorithms (El Naqa and Murphy 2015).

Deep learning, as a subset of machine learning, focuses on methods that learn representations from data. It is based on artificial neural networks, and the term "deep" refers to its multilayered structures that enhance performance (LeCun et al. 2015). Deep learning can generate highly accurate predictions by leveraging large volumes of data and integrating various components such as linear algebra, calculus, probability, optimization, signal processing, programming, algorithms, and high-performance computing (Fleuret 2024). It constitutes the fundamental technology that enables self-driving cars to recognize stop signs or distinguish between a pedestrian and a streetlight (Zohuri and Zadeh 2020).

With the rise of digitalization, access to large volumes of data has become increasingly easy; however, interpreting these data without the use of AI-based methods has become progressively more challenging (Orabi et al. 2018). Machine learning algorithms capable of analyzing data from diverse sources—such as the internet, social media, smartphone usage, and genetic information—can make highly accurate predictions of psychological states, thereby offering substantial contributions to early diagnosis and risk assessment in the field of mental health.

The Role of Artificial Intelligence in the Assessment of Mood Disorders

Artificial intelligence-based machine learning and deep learning enable the use of smartphone-based systems and the analysis of data from wearable technologies. In addition, specific algorithms can process facial expressions, social media content, and postural indicators, and can analyze text-based data and biomarkers.

Smartphone Applications and Analysis of Wearable Technology Data

Smartphones and wearable devices are important instruments for distinguishing bipolar disorder because they provide continuous data collection (Faurholt-Jepsen et al. 2020). In a review by Antosik-Wójcińska and colleagues (2020), smartphone-based systems were reported to predict bipolar disorder from voice data with 67% accuracy and from usage patterns with 97% accuracy. Similarly, Faurholt-Jepsen et al. (2020) reported that smartphone-based voice features achieved 72% accuracy in predicting bipolar disorder. The sensor-embedded shirt PSYCHE, developed by Valenza et al. (2013) from wearable technology products, aimed to evaluate mood in patients with bipolar disorder by monitoring autonomic nervous system signals. This garment consists of a sensor system capable of obtaining long-term daytime and nighttime recordings of interbeat intervals, heart rate, and respiratory dynamics. Preliminary evaluation results indicate that this system was able to identify mood states with 95.5% accuracy. However, the generalizability of such studies and their cross-cultural validity have not yet been fully established.

In a study conducted by Tazawa et al. (2020), a machine learning algorithm was developed using data obtained from wearable technologies to screen for depression and assess its severity. The wearable device used in that study measured multiple physiological and environmental variables, including step count, energy expenditure, body movement, sleep duration, heart rate, skin temperature, and ultraviolet light exposure. Another study by Jo et al. (2024) demonstrated that biomedical signals obtained via simple methods such as common smartwatches are associated with psychiatric symptoms such as depression. Moreover, mood disorders can be analyzed through the monitoring of digital trace data (Cummins et al. 2020). Digital traces may include search and messaging logs, social media usage, or socially inferred activities tracked via Bluetooth; they may also contain activity levels estimated from embedded sensors or global positioning system (GPS) data.

Ecological Momentary Assessment (EMA) emerges as an innovative method in the clinical assessment of mood disorders by enabling the real-time measurement of individuals' symptoms and mood in their natural environments (Ebner-Priemer and Trull 2009). EMA overcomes the limitations of traditional retrospective self-reports by minimizing recall bias and temporal distortions. Through repeated measurements, EMA facilitates the detection of dynamic processes and allows for the integration of psychological, physiological, and behavioral data. EMA can identify context-specific relations of symptoms or behaviors, provide real-time feedback, and increase the ecological validity of findings by measuring phenomena in real-world conditions. These advantages make EMA more distinctive and effective than laboratory-based or survey-based approaches in studies of mood disorders and emotion-regulation problems. Nonetheless, to harness EMA's full potential in clinical practice, the development of reliable, valid, and change-sensitive standard e-diary instruments and temporal protocols is required (Shiffman et al. 2008). When integrated with smartphone applications and wearable technologies, EMA enables continuous and time-sensitive measurement of clinical symptoms, thereby offering significant clinical utility for diagnosis, monitoring, and treatment processes. In this way, EMA contributes to the development of personalized interventions and the optimization of clinical decision-support systems.

These studies indicate that AI-supported systems are effective and feasible for identifying mood disorders through passive monitoring of individuals' daily-life data. Among the greatest advantages of data collected through smartphones and wearable devices is their capacity to provide continuous and extensive data.

However, the inability to measure certain activities and emotional states, the risk of context-independent interpretations leading to inaccurate clinical inferences, and the influence of users' device usage habits and motivations on reliability are considered disadvantages that require careful consideration.

Analysis of Facial Expressions

Visual analysis encompassing facial muscle movements, eye movements, body gestures, and gait contains important cues and is therefore widely used in affective computing systems that recognize and respond to emotions (Cummins 2017). Through object-recognition and content-recognition capabilities developed within machine learning and deep learning frameworks, AI can be integrated into systems for facial expression recognition and emotion detection (Zohuri and Zadeh 2020). Because the facial expressions of healthy individuals differ markedly from those of persons diagnosed with unipolar or bipolar disorders, such integration aims to detect emotions based on facial features such as eye contact, gaze direction, and mouth dimensions (Salem 2022).

Guo et al. (2019) constructed a database of participants' facial expressions to identify depression symptoms using deep learning methods and extracted features from these expressions with an artificial neural network model to classify depressive affect. He et al. (2018) developed a novel feature descriptor called Median Robust Local Binary Patterns (MRLBP) for analyzing facial expressions from video recordings and proposed an automatic depression detection system by classifying these features using the Fisher Vector method. Hong et al. (2019) adopted a decision-level data-fusion approach for diagnosing mood disorders by combining macroscopic and microscopic facial expressions extracted from video recordings to perform classification. The method developed by Abaei and Al Osman (2020) for classifying bipolar disorders is based on emotion recognition from video footage; this approach employed a Convolutional Neural Network model for feature extraction and a Long Short-Term Memory (LSTM) model for classification. Sharma et al. (2024) developed a multimodal depression detection system that analyzes users' facial expressions via Convolutional Neural Networks and textual inputs via Natural Language Processing algorithms, reporting successful capture of emotional cues indicative of depression.

In summary, analysis of facial expressions with AI algorithms offers a promising approach with high accuracy for the classification of mood disorders such as depression and bipolar disorder. Nevertheless, due to cultural, individual, and contextual variability in facial expressions, the possibility of emotion concealment, and technical limitations affecting data quality (e.g., lighting, camera angle), results derived from facial-expression-based analyses must be interpreted cautiously and corroborated with other data sources.

Analysis of Social Media Content

With the rapid increase in social media use, numerous studies have reached a consensus that social media messages can serve as valuable data sources for monitoring various mental health problems, including depression (Chiong et al. 2021). For instance, one study collected posts from mental health-related subforums on Reddit and developed a deep learning model integrated with natural language processing techniques to identify potential mental health disorders—such as depression and bipolar disorder—based on users' written content (Kim et al. 2020).

In another study based on X data, linguistic, behavioral, cognitive, and emotional features consistent with bipolar disorder symptoms were extracted and categorized as either dynamic or static. When comparing different models, the user model integrating all feature types demonstrated the highest accuracy (Kadkhoda et al. 2022). In machine learning research aimed at detecting bipolar disorder via social media, researchers first applied the Latent Dirichlet Allocation method to classify post topics, then used attention mechanisms to determine which text clusters were most influential in classification. These weights were visualized to explain classification results, and case studies were presented to illustrate these explanations. The proposed model achieved the best performance compared to other models (Thamrin et al. 2025).

A separate study sought to determine whether a person was depressed based on tweet content and X profile activity, employing comprehensive preprocessing steps such as data preparation, labeling, feature extraction, and feature selection. Multiple machine learning algorithms and feature sets were tested, with Support Vector Machines (SVM) yielding the highest accuracy (AlSagri and Yhklef 2020). Similarly, a study employing the Bidirectional Long Short-Term Memory (Bi-LSTM) model to detect depressive tweets found that deep learning techniques effectively identified emotional patterns in X users' posts (Nooruldeen and Savaş 2024).

In sum, linguistic and behavioral analyses of social media posts can reveal clues about an individual's psychological state, allowing for remote screening of mood disorders. However, caution is necessary when interpreting such findings, as online posts may not always reflect genuine emotions. Misinterpretation of language, humor, or sarcasm, as well as variability in users' posting frequency, may affect the reliability and validity of these assessments.

Analysis of Postural Indicators

Individuals experiencing negative emotions often exhibit slumped posture, lowered head position, and downward gaze—reflecting the embodiment of emotional distress (Veenstra et al. 2017). Santhoshkumar et al. (2019) proposed detecting emotional states through body movements using a Convolutional Neural Network (CNN). Ahmed et al. (2020) introduced a two-layer approach to emotion recognition based on features extracted from body motion. In the first layer, statistical techniques were used to eliminate irrelevant features, while the second layer employed a binary chromosome-based genetic algorithm to generate a subset of relevant features. Another study used a pre-trained ResNet-50 network to evaluate depression severity by extracting facial expressions and body posture data from video recordings, finding that combined analysis of facial and postural cues provided an effective screening approach (Liu et al. 2025).

Halabi et al. (2023) proposed an innovative method for analyzing 24-hour postural dynamics in participants diagnosed with bipolar disorder or other severe mental illnesses using a shirt-based wearable device. Their findings indicated that posture was associated with clinical variables reflecting disease burden and highlighted the importance of evaluating daily posture transitions. Analyses based on postural data demonstrate that physical indicators reflecting mood can be quantified through AI models and integrated into clinical assessment. Nonetheless, when analyzing postural indicators, factors such as environmental conditions, fatigue, musculoskeletal problems, and sensor errors must be considered, as they may lead to misleading results.

Analysis of Text-Based Data

The fact that users find it easier to express themselves in writing rather than verbally when they are confident about the privacy of their data (Oak 2017) constitutes a major strength of text-based data. A machine learning model developed in Python and trained on text-based data from neuropsychiatric hospitals in Lagos was designed to classify depression patterns, achieving an accuracy rate of 83.6% (Mary and Nwoye 2023). The study demonstrated that AI and machine learning approaches could provide significant clinical and patient-level benefits in the early diagnosis of depression. Another study analyzed individuals' text records using deep learning and machine learning models, aiming to develop a hybrid model with improved accuracy for depression detection (Firoz et al. 2023).

In essence, the analysis of written expressions constitutes a meaningful data source in AI-assisted mood diagnosis, as textual data reflect individuals' cognitive patterns related to emotional states. This approach enables the rapid evaluation of affective, cognitive, and behavioral patterns and facilitates the automatic extraction of meaning from written data. However, since factors such as language use, spelling errors, cultural context, figurative expressions, and incomplete data can lead to misinterpretations and inaccurate psychological evaluations, these risks must be carefully considered when analyzing text-based data.

Chatbots

Chatbots are AI-based systems designed to interact with human users through natural language in spoken, written, or visual form (Vaidyam et al. 2019). These systems hold significant potential for increasing access to mental health interventions (Abd-alrazaq et al. 2019). In the AI-supported chatbot developed by Thosar et al. (2018), users' mood responses were analyzed through text processing techniques, webcam-captured facial images, and interactive dialogues. Similarly, the chatbot developed by Podrazhansky et al. (2020) processed multimodal data—including text, audio, and video—using a neural network to evaluate users' overall mood and changes over time and to construct user profiles.

The chatbot DEPRA, developed for depression assessment using the Dialogflow platform (Kaywan et al. 2023), does not aim to replace mental health professionals but supports automated assessment processes by analyzing text via validated scoring systems and offering confidential communication. Another AI-based chatbot, Woebot, was designed to provide psychological support and can be used as a valuable adjunct tool in pre-session assessments and early detection of mood disorders (Yeh et al. 2025).

Chatbots represent innovative tools that enhance accessibility to mental health services and play a supportive role in assessment processes. By interacting with users and collecting linguistic and behavioral data, these bots can offer initial insights into mental states and provide easily accessible psychological support. Nevertheless, several risks must be acknowledged: such systems may fail to fully comprehend human emotions, overlook contextual subtleties, or produce inaccurate or incomplete interpretations, potentially fostering false reassurance or unnecessary anxiety in users.

Analysis of Electroencephalography (EEG) and Biomarkers

EEG biomarkers are highly significant in examining the complex neural mechanisms underlying depression and are frequently evaluated in psychological research using artificial intelligence approaches (Baskaran et al. 2012). In a study conducted by Noda et al. (2024), machine learning methods based on artificial intelligence were applied to resting-state and transcranial magnetic stimulation-derived EEG data to assist in the diagnosis of depression. Models were developed using four different EEG features, and the highest predictive performance was achieved according to receiver operating characteristic (ROC) curve analysis using linear discriminant analysis (LDA).

Anik et al. (2024) proposed a deep learning-based method utilizing brain waves in EEG signals for the diagnosis of major depressive disorder. The proposed 11-layer expanded dimensional Convolutional Neural Network (Ex-1DCNN) model learns directly from EEG data and demonstrates high accuracy in classifying individuals as depressive or healthy. It was particularly noted that when gamma waves were used, the model strongly exhibited its potential for precise diagnosis.

In the study by Hu et al. (2023), numerous biomarkers, including cortisol, melatonin, C-reactive protein, and interleukins, which are used in the diagnosis of bipolar disorder, were examined in detail, emphasizing that multi-level tests incorporating multiple biomarkers enhance diagnostic accuracy for bipolar disorder. Campos-Ugaz et al. (2023) reviewed ten EEG studies that employed existing machine learning-based methods for the diagnosis of bipolar disorder, reporting accuracy rates of approximately 90%. Another study employed a deep learning approach, demonstrating that the analysis of resting-state EEG data could accurately distinguish healthy individuals from those diagnosed with major depressive disorder, atypical depression, psychotic depression, depressive episode bipolar disorder, and manic episode bipolar disorder (Ravan et al. 2024).

In conclusion, the analysis of EEG data and biomarkers using artificial intelligence enables the development of objective measures that can support diagnosis and monitor treatment response in mood disorders. However, it should be noted that this approach may be influenced by factors such as individual differences, data quality, variability in measurement conditions, and limitations of the algorithms.

Privacy and Data Security

Patient confidentiality and the security of medical information are among the critical elements in today's electronic healthcare environment (Andriole 2014). Therefore, although artificial intelligence (AI) holds significant potential for enhancing diagnostic accuracy and facilitating access to mental health services, biases in algorithms, concerns regarding data privacy, and ethical debates pose obstacles to its full-scale implementation in the field (Ballı et al. 2024). Moreover, the transition of AI into clinical practice remains limited due to factors such as non-standardized medical records, restricted datasets, and stringent privacy regulations; this necessitates the development of new methods that enable data sharing while safeguarding patient confidentiality (Khalid et al. 2023).

In this context, AI-assisted clinical assessment methods have the potential to streamline processes and increase accuracy, yet the risk of sensitive information leakage should not be overlooked. Consequently, techniques such as data anonymization, synthetic data generation, and privacy-preserving model training are gaining prominence (Mandal et al. 2025). Similarly, Sarwar (2025) emphasizes the importance of developing scalable and privacy-sensitive solutions in mental health applications. Additionally, interdisciplinary collaboration is deemed critical for the development of AI tools that are culturally and linguistically adaptable (Ballı et al. 2024).

Since the medical decision-making process inherently involves uncertainties, integrating machine learning algorithms into this process can enhance diagnostic accuracy and treatment efficacy; however, it is stressed that this is only feasible when ethical principles and patient safety are strictly observed (Grote and Berens 2020; Sönmez and Hocaoğlu 2024).

Finally, since artificial intelligence's access to personal health data may pose unforeseeable risks (Minerva and Giubilini, 2023), its safe and ethical use in healthcare depends on developing innovative solutions to protect data privacy and confidentiality (Savulescu et al. 2024; Sönmez and Hocaoğlu 2024).

Therefore, the effective and safe use of artificial intelligence in the field of mental health depends on addressing the opportunities offered by technology in parallel with ethical, legal, and data security considerations.

Ethical and Legal Framework

In AI-assisted clinical assessment practices, adherence to ethical and legal frameworks is of utmost importance. In Turkey, the Personal Data Protection Law (KVKK), and in the European Union, the General Data Protection Regulation (GDPR), among other national and international regulations, mandate that data be collected solely for specified purposes, processed at a minimum level, and used only with explicit consent. In addition, anonymization and data security procedures are critically important for safeguarding patient privacy. In this context, when implementing AI-based systems in clinical settings, the principles of informed consent, purpose limitation, and data minimization must be applied with utmost diligence.

From an ethical perspective, it must be clearly stated that AI should only play a supportive role in clinical decision-making processes, with ultimate responsibility remaining with the expert clinician. Otherwise, automation bias may lead clinicians to over-rely on AI outputs, potentially resulting in false positive or false negative outcomes. Therefore, maintaining human oversight and the principle of transparency, minimizing algorithmic biases, and respecting patient autonomy are essential. The ethical guidelines published by the European Commission for trustworthy AI, along with the ethical framework proposed by Floridi et al. (2018), can be adapted to clinical practice to facilitate the practical implementation of fairness, transparency, and accountability principles.

Limitations

A review of the literature on mood disorders indicates that research on mood disorders other than major depressive disorder and bipolar disorder is limited. Therefore, the focus of this review solely on major depressive disorder and bipolar disorder constrains the examination of the topic from a broader perspective. Future studies that also evaluate other mood disorders would contribute to a more comprehensive understanding of the literature.

In addition, this study was conducted using a narrative review approach rather than a systematic review. While narrative reviews allow for the rapid synthesis of current topics, they may provide relatively less objective results due to the lack of established methodological criteria and systematic search processes (Green et al. 2006). This constitutes a significant limitation of the study. Furthermore, examining only studies published within the last ten years excludes research spanning longer time periods or covering different subfields. Finally, given the rapid development of the field, newly published studies may affect the validity of current findings over time. Moreover, the ethical responsibility arising when a patient reports a risk of self-harm or harm to others via AI, and how this should be managed without expert supervision, remains an open question (Fiske et al. 2019).

Conclusion

Considering the risk of progression and chronicity associated with psychological disorders, as well as severe outcomes such as alcohol-substance dependence and suicide, it is imperative to evaluate these disorders early in a precise and holistic manner. In this context, AI-assisted methods offer significant potential compared to classical assessment approaches, providing speed, accuracy, and multi-data processing capabilities. The development of machine learning and deep learning techniques, coupled with data obtained from everyday tools such as smartphones and wearable technologies, can be integrated into clinical processes. Additionally, inferences regarding mood can be drawn from facial expressions, postural indicators, social media content, and biomarkers.

Smartphones and wearable devices continuously collect individuals' physiological and behavioral data, offering clinicians real-time reporting opportunities; when integrated with methods such as EMA, they contribute to the development of personalized treatment plans and the early detection of warning signals. Digital monitoring data provides objective support in diagnostic processes and allows dynamic tracking of treatment responses. Moreover, visual data, including facial muscle movements, eye and body movements, and gait, can monitor and analyze individuals' moods to provide information about emotional states. Multimodal approaches, by combining facial expressions and text data, further aid in monitoring treatment responses and developing personalized interventions.

Social media posts can contribute to the remote screening of mood disorders such as depression and bipolar disorder by tracking individuals' linguistic and behavioral characteristics.These systems support diagnostic processes by extracting clues from users' posts, content, and patterns, enabling the early detection of potential risk periods. Body posture and movements also serve as important physical indicators of mood. By monitoring postural changes such as slouching, forward head tilt, and gaze direction, these systems can support preliminary screening for mood disorders like depression or bipolar disorder.

By employing hybrid models and hyperparameter optimizations, linguistic, cognitive, and emotional patterns in texts can be extracted, thereby facilitating the early detection of mood disorders through the analysis of written expressions. Chatbots also play a significant role in this area. For instance, DEPRA analyzes texts using automated assessment and validated scoring systems, while some bots process not only texts but also voice and visual data to generate mood profiles. Although originally designed for psychological support, Woebot can perform evaluations based on written texts. Another data source, EEG biomarkers and other neurophysiological data, when analyzed through AI-based methods, contributes to the early diagnosis of major depressive and bipolar disorders and the objective monitoring of symptoms.

These systems support diagnostic processes by learning from individuals' brain activities, enable dynamic tracking of treatment responses, and strengthen clinical decision-making.

While all these methods offer rich opportunities for data collection and analysis in mental health assessment, they also carry certain limitations and risks. Some activities and emotional states may not be measurable, context-free interpretations may lead to incorrect clinical conclusions, and users' device usage habits or motivation can affect data reliability. Facial expressions may be influenced by cultural, individual, and contextual differences, while social media and written expressions can be affected by language, figurative meanings, missing data, and variations in content production. Postural data may be impacted by environmental conditions, fatigue, musculoskeletal issues, and sensor errors, whereas chatbots may not fully comprehend human emotions and might overlook contextual subtleties. EEG and other biomarkers can also be affected by individual differences, data quality, and variability in measurement conditions. Therefore, the use of all these methods should consider accuracy and contextual limitations; findings must be interpreted carefully and supported with other data sources.

If privacy and data security are not ensured, the use of AI-based systems in clinical settings not only poses ethical and legal risks but may also result in irreversible consequences for individuals' mental health. Accordingly, the integration of AI into clinical assessment processes must be developed and implemented simultaneously with principles of data security and privacy.

From the perspective of mental health professionals, AI-assisted assessment tools can be used in a complementary manner, particularly in preliminary evaluation, screening, and risk analysis processes. These technologies can help capture symptom patterns that might be overlooked in traditional clinical interviews, contributing to the development of a more comprehensive case formulation. However, it is crucial that AI systems are structured to support, rather than replace, clinical decision-making. Finally, AI tools—which carry both advantages and risks—require further multidisciplinary research to be effectively utilized in the field of clinical assessment.

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