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Review Article

Internal Medicine Section

Utilising Artificial Intelligence (AI) in the Diagnosis of Psychiatric Disorders: A Narrative Review

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ABSTRACT

In the era of machinery, Artificial Intelligence (AI) has become the new tool for managing patients in psychiatry. Nowadays, many psychiatric disorders are being diagnosed and treated with the help of AI. New technologies like Machine Learning (ML), robots, Deep Learning (DL), and sensor-based systems provide a different perspective on psychiatric disorders. The present narrative review article summarised the use of AI in diagnosing and treating psychiatric disorders. AI can assist a patients with a psychiatric diseases in prognosis, clinical diagnosis, management therapy, and addressing clinical and technological issues. It highlights various AI methods used in mental healthcare, with a focus on multiple ML perspectives. Additionally, AI has the potential to address several factors, including privacy, transparency, bias, and other social and ethical considerations. The aim of the present review was to redefine mental disorders more objectively, personalise treatments, facilitate early diagnosis, and provide patients with more choices in their care. Through the present article, author aimed to highlight the use of AI in the diagnosis of various psychiatric disorders such as depression, schizophrenia, bipolar disorder, Autism Spectrum Disorder (ASD), and Alzheimer's Disease (AD).

Keywords: Bipolar, Mental, Neuroimaging, Robotics, Schizophrenia

INTRODUCTION

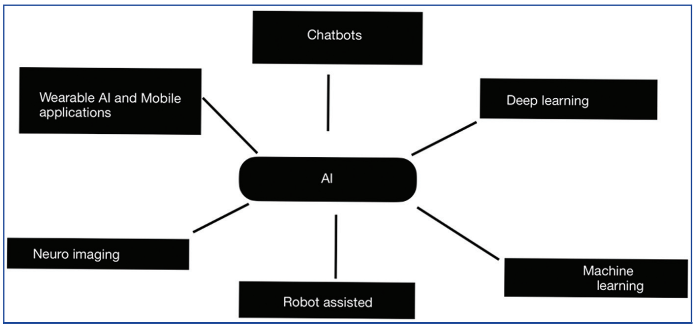
The AI refers to the emulation of human intelligence in machines, which are designed to think like people and replicate their actions [1]. AI techniques focus on actively manipulating the environment, making consensus-based decisions, utilising robotics, and employing collective intelligence techniques. AI can be categorised into several types based on the level of its system's functionality: AI with self-awareness, limited memory, theory of mind, and reactive machines [1]. The following procedures and techniques can be employed in conjunction with AI to address practical issues: (DL), robotics, expert systems, fuzzy logic, natural language processing, and (ML) [1]. Mental disorders have an impact on psychological, social, behavioural, and emotional well-being [1]. The variability in the presentation of diseases, signs, and symptoms, coupled with the limitations in the understanding of aetiological pathways, makes diagnosing mental disorders challenging. The Diagnostic and Statistical Manual of Mental Disorders (DSM-5) and the International Classification of Diseases (ICD-11) manuals serve as the foundation for current methods of diagnosing mental illnesses [1]. The process of diagnosing mental problems using diagnostic instruments, interviewing family members or caregivers, and gathering health histories can be time consuming and resource intensive [2].

For supporting and enhancing the diagnostic and interventional aspects of psychiatric treatment, digital health tools and technology present excellent practices [3]. Mental diseases have been diagnosed using AI. The AI is a significant and popular example of these digital technologies because it enables machines to identify complex, underlying patterns and provide practical insights by understanding queries and sifting through and connecting vast amounts of data [4]. AI can significantly transform how to perceive, diagnose, and treat mental illnesses. AI can be utilised with electronic records, radiological investigations, sensor-based tracking systems, and social media to predict and categorise psychiatric disorders and issues such as suicidality [5]. An increasing range of AI applications to electronic records, investigations, sensor-based tracking systems, and social media have successfully predicted and categorised mental issues like suicidality in various domains [4]. By focusing on various illustrative publications, it provides insights into AI techniques in mental health care, aiming to assist with diagnosis, prognosis, management, and addressing clinical and technological issues [2-4,6]. It sheds light on how the use of AI has transformed the landscape of diagnosing and treating psychiatric disorders. The advantages of using AI in psychiatry may not be immediately apparent. One concern is that individuals may be hesitant to share their personal issues and history with doctors [2]. Through AI, it would be easier for patients to communicate their problems to a doctor without worrying about being judged. Machines can provide more effective treatment because they lack human factors such as distraction, stress, and fatigue [3]. They are also immune to the same personal biases that can affect human therapists. AI robots can take into account a patient's race, ethnicity, or socioeconomic background when adjusting treatment. However, AI algorithms may have drawbacks such as bias, fragility, and limited applicability outside their training domain [1].

These limitations are particularly pronounced in cases of mental health problems because these conditions require softer skills such as building rapport with patients, establishing relationships, and observing emotions and behaviour [4]. Another drawback is the lack of human empathy and compassion, which are essential elements in treating patients who have experienced mental trauma or are dealing with a mental condition. AI devices must undergo the same rigorous regulatory review and risk assessment procedures as conventional medical devices before they can be approved for clinical use [5]. When using AI applications, Diagnostic and Statistical Manual of Mental Disorders (DSMs) criteria guidelines must be followed for research or clinical evidence purposes. There is a remote possibility that human-machine interactions may not translate to human-human interactions or may even further restrict human-to-human interactions [3,4]. The goal of AI is to assist people by acting as their assistants in improving the world. Their makeup should include prosocial traits such as empathy, generosity, self-awareness, and effective control, as well as the ability to accept and decisively act on differing points of view [1,3].

Artificial Intelligence (AI) in Depression

Major Depressive Disorder (MDD) is a highly prevalent psychiatric disorder that has a significant impact on socioeconomic burden and Quality of Life (QoL). The criteria outlined in the DSM and a patient's response to treatment are commonly used for diagnosing MDD [5]. In the case of depression, (ML) techniques can generate reliable predictions of treatment outcomes [6]. ML encompasses a range of models that utilise empirical data to create training models and accurately classify new input [7]. Its benefits for MDD extend beyond diagnosis and include the ability to predict the future progression of the disease. Its capacity for individual-level analysis is particularly noteworthy in recent years. Research focused on depression biomarkers has seen substantial growth, particularly in using MRI in conjunction with pattern recognition methods [8,9]. These techniques can predict treatment outcomes and differentiate between individuals with depression and healthy controls with high accuracy [10,11]. Exploratory research is still predominantly focused on strategies for integrating MRI data with ML techniques. The merging of ML algorithms and MRI data in depression is gaining increasing attention due to its high potential and ability to reveal additional information about underlying brain regions. Studies have utilised genetic, Electronic Medical Record (EMR), neuroimaging, and speech data to model the progression of depression [12]. Patients at risk of self-harm behaviour can be identified using demographic, social, mental, and physical health data, as well as administrative data from healthcare encounters. A history of high-risk events can predict short-term future high-lethality suicide attempts. Multimodal sensing, which includes wearables, smartphones, physiological sensors such as heart rate and electrodermal activity, as well as ambient sensors like motion, temperature, and light, enables the continuous collection of real-world data on symptoms, treatment response, behaviours, thoughts, and emotions [13,14]. If it becomes possible to continuously identify behaviours related to mental health, a new generation of highly personalised, contextualised, dynamic mobile health (mHealth) tools that can listen rather than ask and seamlessly interact, learn, and grow with users could emerge [14]. Platforms such as mindLAMP [15], AWARE [16], and crosscheck [17] facilitate multimodal data collection, making continuous remote monitoring and the detection of subjective and objective signs of psychotic relapse more accessible. The urgency of reversing the trend of increasing suicide rates has led to the development of technology-based tools, such as text messaging, smartphone apps, smartphone sensors, electronic health records, and ML algorithms, which can provide crucial data to improve suicide prognosis or offer immediate support to those at risk [16]. Innovative data processing, modelling, and signal detection techniques are being developed and evaluated to detect changes within individuals over time, with the aim of enhancing treatment and prevention [17,18]. This would expedite the identification of individuals at risk or in need of treatment. Additionally, a number of chatbots and applications [Table/Fig-1] [1,2]. It plays a significant role in the treatment of depression, not only providing emotional support but also addressing underlying conditions [19,20].



[Table/Fig-1]: Different form of Artificial Intelligence (AI) use in psychiatric disorders [1,2].

Artificial Intelligence (AI) in Schizophrenia

Schizophrenia is a highly diverse psychiatric disorder characterised by abnormal perceptions of reality. AI has the potential to be applied in various ways to address this heterogeneity and improve predictions and understanding of the disorder's neurological basis. New developments in functional mapping and electric field modeling can enhance the effectiveness of brain stimulation on social cognitive networks [21]. Targeting specific networks using techniques like repetitive Transcranial Magnetic Stimulation (rTMS) can be utilised. New strategies are being developed to consider neuroanatomical diversity and optimise coil placement to maximise target engagement for each individual [21]. By combining L1-norm authorised sparse canonical correlation analysis and Sparse Logistic Regression (SLR), reliable classification of Schizophrenia Spectrum Disorder (SSD) has been achieved in rs-fMRI studies [21]. The spectrum of schizophrenic disorders includes schizophrenia, schizotypal personality disorder, schizophreniform disorder, brief psychotic disorder, schizoaffective disorder, delusional disorder, and psychosis induced by substance use or medical conditions [22]. The European First Episode Schizophrenia Trial (EUFEST) trial, a large multisite treatment database in Europe for first-episode schizophrenia, has provided prospective phenotypic data on mental disorders, enabling accurate prediction of treatment outcomes using effective ML techniques [23]. Recent AI techniques have demonstrated that Functional Striatal Abnormalities (FSA) are strongly associated with a range of severity in the spectrum of mental disorders, with the most pronounced dysfunction observed in schizophrenia [24].

Artificial Intelligence (AI) in Bipolar Disorder

The ML approaches can provide physicians and researchers with crucial information for the diagnosis, personalised therapy, and prognostic guidance for patients with bipolar disorder due to the clinical heterogeneity of samples. By utilising multivariate techniques and ML, available data can be considered simultaneously. Furthermore, ML-generated outcome biomarkers can help determine the type and level of care required by the patient immediately. Supervised ML, based on neuroimaging data from previous responders and non responders, may be able to predict the success of a therapy and aid in selecting the best course of action [25]. In high-risk cases, ML could assist in predicting the transition to full-blown bipolar disorder [26]. Identifying those at greatest risk of bipolar disorder would enable the application of targeted preventive interventions. AI focuses on genetic data, cognitive or clinical measures, peripheral biomarkers, electrophysiological techniques, and multimodal strategies for diagnosing bipolar disorder. Various markers and ML algorithms achieve accurate categorisation of bipolar disorder. With the help of ML, bipolar disorder can be accurately distinguished from other mental illnesses. However, further research is needed to establish the best practices in this approach [25-27].

Artificial Intelligence (AI) in Autism Spectrum Disease

The results of rs-fMRI studies have demonstrated a valid neuroimaging-based classifier for Autism Spectrum Disorder (ASD) that shows the spatial distribution of the 16 Fragment Crystallisable (FCs) found in the data at various locations, as agreed upon by machine learning algorithms. Additionally, genome-level investigations have revealed a significant level of polygenic risk for ASD in relation to schizophrenia, but not in relation to Attention Deficit Hyperactivity Disorder (ADHD) or Major Depressive Disorder (MDD) [26-28]. Clinical and behavioural investigations provide growing evidence of a connection between ASD and schizophrenia [28]. AI has been extensively utilised to explore ASD, with the ultimate goal of streamlining and expediting the diagnostic process and enabling early access to therapy [28]. ML shows potential in various ASD investigations, including behaviour, locomotion, speech, facial emotion expression, neuroimaging, genetics, and metabolomics [29,30]. Consequently, AI techniques are increasingly being utilised and accepted, demonstrating the effectiveness of ML methods in extracting information from large datasets. This makes ML an attractive tool for ongoing ASD clinical and research projects, offering potential avenues for enhancing ASD screening, diagnosis, and treatment tools. Cutting-edge technologies like ML have been studied and applied to increase diagnostic efficiency, speed, and quality in ASD research. These ML methods include artificial neural networks, support vector machines, a priori algorithms, and decision trees [31]. Many of these methods have been used to construct prediction models for autism-related datasets. In the rehabilitation of autistic patients, robots are being employed as social interaction facilitators. Robot-assisted Autism Therapy (RAAT) is used to encourage children to speak or engage in activities [27,30]. The robot can interact with autistic children in ways that promote the development of shared attention. Video games are also utilised to enhance motor skills and body schema orientation [26,30].

Artificial Intelligence (AI) in Alzheimer's Disease

Breakthroughs in high-quality omics platforms and imaging technologies present unprecedented opportunities to explore the origin and evolution of diseases. ML approaches offer new ways to handle multiscale data, integrate data from various sources, explain etiological and clinical heterogeneity, and discover new biomarkers. In Alzheimer's research, AI is applied in molecular neuroimaging, particularly in Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT) [32]. Optical Coherence Tomography (OCT) is a scalable imaging technique used for extensive data in neurology, particularly in neurodegenerative diseases [32]. A transcriptomic-based approach to drug repurposing involves contrasting medication-induced gene expression with AD gene expression. AI has also shown benefits in social and companionship roles, as simple animal-like robots have been found to reduce loneliness ratings in older individuals [32,33]. Socially Assistive Robots (SAR) have been shown to increase social contact with peers of the subject [34]. Robot-assisted therapy is also utilised in the treatment of Alzheimer's. Combining computer capacity with quantifiable chemical patterns, such as using ML and AI technologies, can help address these challenges. Wearable AI devices and gadgets are also used in the rehabilitation of Alzheimer's patients. Several applications and chatbots provide emotional, social, and mental support for individuals with cognitive impairment [33,34]. In addition to biofluid biomarkers, other modalities such as electrical signal measurements of brain waves, AI-mediated memory tests, and online language analysis are being investigated for AD diagnosis using AI-mediated data analysis techniques [35]. ML and AI have the potential to open new avenues for precise, non invasive, and accessible early diagnosis of AD, as well as personalised techniques for disease management based on specific prognoses and therapy responses. AI classifiers can assist in identifying individuals at high risk of developing psychotic illnesses using neuroimaging data or cognitive testing [36]. AI can significantly accelerate, improve accuracy, and enhance the objectivity of neurodegenerative disease diagnosis [36].

Artificial Intelligence (AI) in Attention Deficit Hyperactivity Disorder (ADHD)

The heterogeneous disorder known as ADHD affects the neurodevelopment of the brain. Diagnostic tools for ADHD include motion analysis, physiological signals, questionnaires, gaming simulators, performance tests, and brain MRI [37]. However, there has been a neglect of other evaluation techniques for ADHD apart from MRI and a lack of focus on utilizing data from wearable devices such as Photoplethysmography (PPG), Electrocardiography (ECG), and motion data for diagnosing ADHD [38]. Personalised educational aids have the potential to improve learning outcomes, facilitate better social integration, and reduce stigma, social exclusion, and stressful situations like bullying, which are common factors contributing to suicide attempts [39]. A significant advantage of ML approaches is their ability to consider inter-regional correlations in the brain, enabling the identification of subtle and geographically dispersed effects [40]. ML models enable individual level statistical inference, which can aid in making individual diagnostic or prognostic judgments. In addressing the limitations of various mental disorders, ML and DL methods have been applied to diagnose ADHD. They have been utilised in cognitive behaviour therapy, training, rehabilitation, behavioural change, psychosocial motivation, attention improvement, and feedback [41].

Artificial Intelligence (AI) in Post-traumatic Stress Disorder (PTSD)

The PTSD reactions are characterised by variability in their clinical manifestations and aetiologies. ML technologies are being employed in medical disciplines that face similar challenges of heterogeneity in aetiology and outcome to address this fundamental variability [42]. The identification of PTSD in patients can be done using imaging data, biometric data {such as sleep, Heart Rate Variability (HRV), and skin conductance}, and computer or smartphone questionnaires collected through linked devices [43]. Combining MRI and ML techniques makes it feasible to identify a patient with PTSD. Monitoring techniques have been utilised to assess the diagnostic criteria for PTSD, with Ecological Momentary Assessment (EMA) emerging as the most promising method [43,44]. Analysing various neurological substrates of PTSD using functional network models consistently revealed findings in line with previous research on desegregation in PTSD, showing increased connectivity among several networks during rest [44]. The application of Resting state- Functional MRI (rs-fMRI) network models specific to PTSD demonstrates the potential for advancement in the field [44]. The creation of vector-autoregressive networks would enable exploration of time-dependent connections between brain areas in PTSD patients and could be facilitated by temporally accurate techniques such as electroencephalography or magnetoencephalography. DL's ability to combine multimodal data from digital devices like smartphones or smartwatches offers new opportunities for identifying transdiagnostic indicators to remotely detect and monitor individuals at risk. By leveraging advances in computational psychiatry, digital phenotyping can maximise the diagnostic and prognostic value of digitally collected biomarkers. Digital communication also enables the delivery of clinical interventions through telehealth applications. AI and natural language processing are utilised in the evaluation and clinical treatment process [45]. ML techniques have significant potential in developing precise diagnostic and prediction models for PTSD and risk of stress pathology based on a various existing data sources [44].

Artificial Intelligence (AI) in Obsessive Compulsive Disorder (OCD)

Significant advancements have been made in the neurobiology of OCD in recent years [46]. Research in this area has helped in developing neurobiological models of OCD, showcasing international scientific collaboration, and leading to various therapeutic implications. Neuroimaging has been extensively utilised by researchers worldwide to study OCD [46,47]. Early studies indicated the involvement of specific brain circuits and systems in OCD, which is characterised by recurrent intrusive thoughts (obsessions) and compulsive actions [49]. CT, PET, and SPECT have been employed in OCD studies to examine brain morphometry and glucose metabolism [46-49]. Functional Magnetic Resonance Imaging (fMRI) has been used to observe brain activation patterns during specific states related to the condition, incorporating various emotional and cognitive paradigms that may be relevant [47]. For many individuals with OCD, medications and psychological therapies may not be effective [49]. As an alternative therapy, Repetitive Transcranial Magnetic Stimulation (rTMS) has shown promise [46,49]. rTMS and Deep Transcranial Magnetic Stimulation (dTMS) activation affect different brain targets in OCD, including the supplementary motor area, orbitofrontal cortex/medial prefrontal cortex, dorsolateral prefrontal cortex, and Anterior Cingulate Cortex (ACC) [49]. The introduction of dTMS Hesed (H) coils and functional neuroimaging has advanced focused brain stimulation, bringing us closer to understanding and treating OCD [47]. A study using deep TMS found that increased electroencephalogram activity during attention tasks was associated with an improvement in OCD symptoms, consistent with attention network activation [49].

CONCLUSION(S)

Robotic care and AI-based DL, ML, and DL apps can facilitate the delivery of treatment for mental illnesses, making it more accessible for patients. However, further research is needed to address the significant ethical and societal implications associated with these technologies, and the fields of AI and psychological therapies require continued study. The effectiveness of AI-based therapies in identifying, predicting, and treating mental health issues is remarkably high. AI can provide convenient options for the treatment of mental illnesses, allowing individuals to access care at their own convenience. The integration of AI frameworks can enhance the efficacy and accessibility of existing healthcare systems. To fully realise the potential of AI, collaboration among various stakeholders is essential, including experts in mental healthcare, ethics, technology, engineering, healthcare system management, entrepreneurs, and others. AI plays a crucial role in the early detection, prevention, and intervention of mental health issues. It also contributes to establishing benchmarks for improving individual mental health and providing more accurate and beneficial predictions for personal mental health.

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