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Review Article

Intelligent Internet of Medical Things for Depression: Current Advancements, Challenges, and Trends

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We investigated the fusion of the Intelligent Internet of Medical Things (IIoMT) with depression management, aiming to autonomously identify, monitor, and offer accurate advice without direct professional intervention. Addressing pivotal questions regarding IIoMT's role in depression identification, its correlation with stress and anxiety, the impact of machine learning (ML) and deep learning (DL) on depressive disorders, and the challenges and potential prospects of integrating depression management with IIoMT, this research offers significant contributions. It integrates artificial intelligence (AI) and Internet of Things (IoT) paradigms to expand depression studies, highlighting data science modeling's practical application for intelligent service delivery in real-world settings, emphasizing the benefits of data science within IoT. Furthermore, it outlines an IIoMT architecture for gathering, analyzing, and preempting depressive disorders, employing advanced analytics to enhance application intelligence. The study also identifies current challenges, future research trajectories, and potential solutions within this domain, contributing to the scientific understanding and application of IIoMT in depression management. It evaluates 168 closely related articles from various databases, including Web of Science (WoS) and Google Scholar, after the rejection of repeated articles and books. The research shows that there is 48% growth in research articles, mainly focusing on symptoms, detection, and classification. Similarly, most research is being conducted in the United States of America, and the trend is increasing in other countries around the globe. These results suggest the essence of automated detection, monitoring, and suggestions for handling depression.

Keywords: AI; AI for depression; anxiety; future intelligence; IoMT for depression; IoT; IoT for depression; medical intelligence; mental disorder; psychological disorders

1. Introduction

Pandemic situations have altered human behavior recently, causing psychological and neurological alterations that have triggered melancholy and anxiety [1]. According to the World Health Organization (WHO), depression was expected to be the second most common cause of disability in 2020 [2], impacting 50 million people worldwide, 80% residing in developing countries [3]. Human psychological illnesses such as anxiety, depression, and mood swings are linked to human behavior [4] and eating disorders [5]. The increasing neuropathologies brought on by common neurodegenerative diseases, including Alzheimer, Parkinson, and Huntington, have been connected to the detrimental effects of depression on the human brain [6, 7]. Anxiety and sadness have showed to affect health and quality of life (QoL) negatively [8]. It has been noted that stress is more effective in females than in males and causes depression and tension, which affects the physiology of neuroimmune repercussions [9].

The state of one's mental health has a significant impact on both personal and societal well-being. According to WHO, mental illness is a significant global public health problem [10, 11]. In terms of one's own and overall mental health, depression is considered a severe medical condition that can affect anyone, regardless of age, gender, or socioeconomic standing [12–14]. A person's lifestyle may be negatively impacted by depression, which could impede their social life [15]. In addition, symptoms of clinical depression include melancholy, loss of appetite, irregular sleep patterns, guilt, and difficulty making decisions, all of which can lead to attempts at self-harm [16]. Depression is linked to physical sickness, significant cognitive impairment, and poor therapeutic outcomes across various populations [15]. There are several time-consuming diagnostic procedures for diagnosing depression. In addition, the majority adhere to patient self-reporting or self-diagnosis [13], and they frequently seek the advice of psychiatrists or psychologists [12, 14]. In other words, several tried-and-true ways for diagnosis call for qualified medical personnel. Due to overlapping symptoms of many diseases, misdiagnosis is likely, which raises the risk of persistent major depression. In order to treat depressive disorders effectively and speed up recovery, diagnosis is a crucial step.

Learning, reasoning, problem-solving, creativity, emotional intelligence, perception, and memory are just a few of the cognitive skills that make up intelligence. Intelligence has been intensively studied in a number of disciplines, including psychology, neuroscience, and artificial intelligence (AI). Different types of intelligence, including linguistic, logical-mathematical, spatial, musical, bodily kinesthetic, interpersonal, and intrapersonal intelligence, are proposed by a number of theories of intelligence, including Gardner's idea of multiple intelligences [17]. Intelligence is highly valued in society and is essential for the development of intelligent machines such as AI and robots and for social interaction [18].

The Internet of Things (IoT) is a network of physical items, machines, and vehicles that are equipped with sensors, software, and other technologies and that communicate with other objects, machines, and systems over the Internet to exchange data [19, 20]. Numerous industries, including healthcare, manufacturing, transportation, agriculture, and smart cities, have numerous uses for the IoT. IoT devices have the ability to gather data that may be analyzed to learn more, improve procedures, and come to wise judgments. Technology improvements such as low-cost sensors, wireless communication, and cloud computing that make it simpler and more economical to link objects and gather data are what are causing the IoT to grow.

The term Internet of Medical Things (IoMT) describes a network of Internet-connected healthcare technologies, including wearables, sensors, and medical devices [21, 22]. IoMT devices can gather a variety of information, including vital signs, medication adherence, patient behavior, and environmental factors. This information can then be analyzed in real time to give insights into a patient's health status. By enhancing patient outcomes, cutting costs, and expanding access to care, IoMT has the potential to revolutionize the way healthcare is delivered [21]. IoMT tools, such as blood glucose monitors, smartwatches, wearable fitness trackers, and remote patient monitoring systems, can be utilized to follow chronic diseases, spot early disease symptoms, and offer remote consultations and diagnostics. Previously, Chen et al. [23] designed an intramodal and intermodal fusion framework for Corpus-based depression detection using IoMT. Sharma et al. [24] introduced an automatic detection system based on IoMT for depression detection. Kumar et al. [25] introduced a neurosymbolic classification model for depression using IoMT. Jeya Daisy et al. [26] used IoMT for early stage depression detection.

AI and ML technologies [27, 28] are incorporated into the IoMT ecosystem under the Intelligent IoMT (IIoMT) umbrella. AI algorithms [29, 30] are used by IIoMT devices to analyze enormous volumes of patient data in real time, spot trends, and forecast a patient's state of health. IIoMT can enhance medical imaging accuracy, support drug research and development, and enable more precise diagnoses and individualized treatment strategies. To fully realize the potential of IIoMT in altering healthcare delivery, issues including data privacy and security, standardization, interoperability, and potential bias in AI algorithms must be addressed. Previously, Misgar and Bhatia [31] introduced an IIoMT-based approach for depression (unipolar and bipolar) detection.

1.1. Related Work

1.1. Related Work. As far as we know, there is no study that combines AI with IoT for automatic depression diagnosis, classification, monitoring, and guidance. Some methods use a manual process rather than an autonomic system to analyze, categorize, and monitor depression. Such systems are useful in a range of scenarios as IoT devices are frequently considered for specialized applications (such as monitoring of diseases). IoT data analysis is necessary for a single type of device being considered by one business, and for various device types that multiple enterprises are investigating. The application of integrated Intelligent IoT settings such as smart healthcare will boost the ubiquity of such a diverse range of devices. This demonstrates the growing need for quick, accurate IoT medical data analysis that can handle abnormalities such as sadness, stress, and anxiety. The main reason for doing this study is to analyze the existing systems to discover which functionalities they offer and where they fall short of those required for IoT medical data analytics to create new solutions.

Previously, the authors [32] examined the possibility of predicting therapy response in depression using deep learning (DL) algorithms. It emphasizes eight trials with impressively high rates of around 80% accuracy in predicting treatment response. Small sample numbers are still a significant disadvantage for these studies, though. DL has enormous potential to transform the practice of psychiatry and depression treatment toward personalized medicine, but more research is required to expand dataset sizes and enhance the readability of outcomes. In [33], sentiment analysis methods for diagnosing depression using text, emoticons, and emojis from social media are reviewed. DL techniques for multiclass classification are proven to be the most accurate. Sentiment analysis, which can be positive, negative, or neutral, is helpful for understanding opinions and feelings in a variety of circumstances. Data are categorized using machine learning (ML) and DL algorithms according to the polarity of the sentiment [34–36]. In [37], the authors contrasted classical ML versus DL for the automated diagnosis of depression using electroencephalogram (EEG) signals [38]. The review examines EEG-based biomarkers, data-gathering methods, and multimodal data fusion while comparing a range of signal processing and classification techniques used in the literature. The paper also briefly discusses the use of EEG signals and ML approaches to predict the treatment outcome response for depression.

The application of DL algorithms for the early identification and nonclinical diagnosis of depression, self-harm, and suicide thoughts from online social network information was described by authors in [39]. A systematic literature study thoroughly covered the state-of-the-art methodologies, features, datasets, and performance indicators. The document covers research gaps, difficulties, and potential future paths in the area of mental health surveillance. The authors [40] examined the application of DL for oral and visual cue–based automatic depression identification. The DL techniques utilized for depression detection were explained together with the databases and objective markers used for depression estimation. The use of AI for the automated detection of adolescent anxiety and depressive disorders—risk factors for suicide behaviors—was covered by the author in [41]. Their review summarizes the current research showing the positive effects of AI tools in this field and suggests combining features from DL models in the future work. Although using AI technologies for suicidal thoughts exhibits certain drawbacks, the benefits outweigh them, making it a useful suicide prevention strategy [42]. The authors discussed the DL techniques for depression detection as well as databases and objective indicators utilized for depression assessment.

Moreover, wearable devices–based AI algorithms have been used to diagnose depression due to the shortcomings of conventional methods. Abd-Alrazaq et al. [43] reviewed wearable AI's efficacy in identifying and forecasting depression systemically. Although it is still in its infancy and not suitable for application in clinical practice, wearable devices–based AI algorithm is a potential tool for depression diagnosis and prediction. Wearable device–based AI algorithms should be used in conjunction with other techniques for diagnosing and forecasting depression until more research improves its performance. The effectiveness of wearable device data and neuroimaging data needs to be investigated further, as well as how to distinguish individuals with depression from those with other conditions.

The literature on AI and IoT for depression is rich. However, no review to date has widely studied all of the technologies that comprise combined IIoMT depression systems. In this review, we examined how AI and IoT can be used together to design an accurate, robust, and explainable IIoMT system for depression. Table 1 compares the current review related to depression with AI and IoT.

1.2. Research Questions of This Survey. The main goal of this review is to describe, categorize, and analyze depression and its integration with IIoMT for automatic advice and monitoring without the need for a physician or psychologist. Consequently, we aimed in this survey to answer the following questions:

- What are the primary characteristics of depression and its associations with other psychoneurological conditions, such as stress and anxiety?
- What are the significant associations between depression and oxidative stress, inflammation, and mitochondrial dysfunction?
- What is the principle role of ML and DL models in understanding and addressing depression?
- How can IIoMT help with depression identification, monitoring, and management automatically?
- What are the global research trends of depression with AI, IoT, IoMT, and IIoMT?
- What are the difficulties, drawbacks, and prospects for depression and IIoMT integration?

1.3. Key Contributions of This Survey. Integrating AI and IoT will broaden the scope of our studies on depression. In order to comprehend the notion of data science modeling and deliver intelligent services in practical settings, a thorough explanation of it, including everything from business difficulties to data products and automation, is crucial. Hence, this survey paper integrates the IoT, IoMT, and AI with depression for autonomic diagnosis, classification, monitoring, and guidance. The paper also quickly discusses the benefits of data science for the IoT. Similarly, it aims to address pivotal questions regarding IIoMT's role in depression identification, its correlation with stress and anxiety, the impact of ML and DL on depressive disorders, and the challenges and potential prospects of integrating depression management with IIoMT. The key contributions of our work in this manuscript are as follows:

- This paper covers the gaps that exist in the current literature, as presented in Table 1. The major contribution is to provide a comprehensive and structured overview of extensive research on the integration of IoMT and AI with depression for autonomic diagnosis, classification, monitoring, and guidance of depression and anxiety.

Table 1: Comparison of the current review in AI and IoT for depression.

Ref.		[32]	[33]	[37]	[39]	[40]	[41]	[42]	[43]	[44]	This work
Depression background	General	✓	✕	✓	✓	✓	✓	✓	✓	✓	✓
	Types	✕	✕	✓	✕	✕	✕	✓	✕	✓	✓
	Association with others	✕	✕	✕	✕	✕	✓	✕	✕	✓	✓
Monitoring of depression	Questionnaire	✕	✕	✕	✕	✓	✕	✕	✕	✕	✓
	Machine learning	✕	✓	✓	✕	✕	✓	✓	✓	✓	✓
	Deep learning	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Challenges and issues		✕	✕	✓	✓	✕	✓	✓	✓	✓	✓
Architecture for IIoMT in depression		✕	✕	✕	✕	✕	✕	✕	✕	✕	✓
Bibliometric analysis		✕	✕	✕	✕	✕	✕	✕	✕	✕	✓
Preventive measures		✕	✕	✕	✕	✕	✕	✕	✕	✓	✓
New perspectives		✕	✕	✓	✕	✓	✕	✓	✕	✓	✓

Note: ✓: available; ✕: not available.

- This paper outlines the IIoMT architecture for collecting, analyzing, monitoring, and preventing depressive disorders. Employing IIoMT to identify, track, and analyze depression, including applying sophisticated analytics techniques to enhance the apps' intelligence and capabilities.
- This paper discusses and assesses the applicability and value of IoT-based approaches in various real-world application fields by contrasting the traditional and intelligent approaches.
- This paper highlights and discusses the IIoMT's bibliometric analysis in the context of depressive scenarios. Along with this, it identifies and describes current problems, potential directions for future study, and potential fixes.

1.4. Organization of the Survey. The rest of the work is organized as follows: Section 2 discusses about methodology related to our paper. Section 3 discusses the understanding of depression based on biology and medical prospects. Section 4 focuses on the detection, monitoring, and analysis of depression, and Section 5 discusses the performance indicators. Section 6 explains the architecture of IIoMT. Section 7 discusses IIoMT prevention strategies. Section 8 covers the bibliometric analysis based on several parameters. Sections 9 and 10 present the discussion and main issues. Section 11 discusses future possibilities and potential solutions. Section 12 discusses conclusions.

2. Methods

This survey's primary goal is to look into the potential benefits of using IIoMT for the automatic detection, monitoring, and guidance of depression and its associated outcomes. To accomplish this goal, we examined how intelligent methods (DL and ML) combined with IIoMT improve human well-being via early detection and monitoring of depression. There are two potential dangers that could compromise the accuracy of this survey: improper data extraction and inadequate primary study selection [22]. We have filtered the document based on research topics and a variety of relevant keywords to lessen potential dangers.

2.1. Search Strategy. We gathered crucial data from multiple databases, including Elsevier, IEEE, Springer, ACM, Hindawi, Wiley, Taylor and Francis, Nature, Google Scholar, PubMed, and Web of Science (WoS), in order to respond to the aforementioned research questions. A bibliometric analysis was conducted for this analysis using a standardized search technique. The search method involved using specific keywords such as "AI" AND "Depression," "Artificial Intelligence" AND "Depression," "ML" AND "Depression," "Machine Learning" AND "Deep Learning," "Internet of Things" AND "Depression," "IoT" AND "Depression" and "IoMT" AND "Depression" in the article's title, abstract, and keywords. The study covered all pertinent original publications, reviews, and research letters that contained the given keywords, and 378 articles were selected.

2.2. Study Selection. The IIoMT for depression identification, monitoring, and analysis was the main topic of this research. Articles authored in languages other than English, duplicate articles, books, and reviews covering the same subject were eliminated. In a similar vein, articles that failed to match our pre-established inclusion criteria based on abstract and title screening were also disqualified. More than 200 articles were rejected that did not meet the conditions of this manuscript.

2.3. Data Extraction. Using a predetermined data extraction form, we took information from the chosen papers, such as sample size, study design, outcome measures, intervention specifics, and major findings. After eliminating communications, books, editorials, and chapters, 278 research papers were selected. Among them, 110 were excluded as they were repeated techniques or applications without any extension or expansion of application. Finally, 168 research papers closely addressing the aims and scope of this manuscript were considered. The quality and bias risk of the included studies were assessed using a standardized approach. A majority of the studies focused on detecting, monitoring, and tracking physiological responses of depression using IIoMT devices were included.

3. Understanding of Depression Based on a Biomedical Perspective

In this section, we delved into an analysis of depression subtypes and their correlations with various psychoneurological conditions (Figure 1) [44]. Moreover, we explored the intricate interplay of oxidative stress, inflammation, and mitochondrial dysfunction within the context of depression.

3.1. Types of Depression. Depression is a mental disorder characterized by various symptoms, such as depressed moods, loss of interest in previously enjoyed activities, changes in eating and sleep patterns, lack of energy, and self-deprecating thoughts [45]. In rare situations, people who are depressed may also have trouble concentrating and have suicidal thoughts. Depending on the length and intensity of the symptoms, as well as any underlying causes, depression can be divided into many categories:

3.1.1. Major Depressive Disorder (MDD). MDD, referred to as clinical depression, is a mental health condition that is characterized by a persistent sense of hopelessness, pessimism, and a lack of interest or pleasure in once-enjoyed activities. While the signs and symptoms of MDD can differ from person to person, they frequently involve a combination of protracted sadness, boredom with activities, changes in appetite or weight, insomnia or excessive sleeping, exhaustion or a loss of energy, feelings of worthlessness or excessive guilt, difficulty concentrating or making decisions, and thoughts of death or suicide. These signs and symptoms must last at least 2 weeks and impair daily functioning in order to qualify for an MDD diagnosis. It should be noted that these symptoms cannot be caused by a disease or drug addiction. Although the causes of MDD are complex and not entirely understood, a combination of genetic, environmental, and biochemical variables are thought to be the starting point [46]. Combining treatment and medication is widely used to treat MDD. Some typical methods used to treat MDD include psychodynamic therapy, interpersonal therapy, and cognitive-behavioral therapy (CBT) [47]. IPT focuses on enhancing interpersonal connections, CBT identifies and changes negative thought patterns and behaviors, and psychodynamic therapy explores unconscious thoughts and feelings that could contribute to depression. Antidepressants are one type of drug that is frequently used to treat MDD.

3.1.2. Persistent Depressive Disorder (PDD). Dysthymia, commonly referred to as PDD. It is a kind of depression that is chronic and lasts for at least 2 years. This disorder is characterized by a recurring sense of melancholy or depression accompanied by multiple symptoms, such as low energy, an uncontrollable need to overeat, trouble sleeping or excessive sleeping, low self-esteem, poor attention, and thoughts of hopelessness [48]. PDD frequently displays milder symptoms that last for a longer period of time than MDD, which is characterized by more severe symptoms that might interfere with daily life. However, it is crucial to remember that PDD is just as treatable as MDD, given how much of an impact it may have on a person's QoL and how much more likely they are to experience other mental health issues such as anxiety or substance addiction. PDD is thought to be brought on by a confluence of environmental, genetic, and psychological factors. However, its exact causes are unknown. Along with antidepressant medicines to treat the symptoms, CBT, IPT, and other forms of therapy are frequently used to treat PDD.

3.1.3. Bipolar Disorder (BPD). BPD involves intense mood swings. It features highs called manic or hypomanic episodes and lows known as depressive episodes. These fluctuations occur alongside periods of stable mood. Bipolar illness sufferers may have heightened or irritated moods, increased energy, a decreased need for sleep, fast thinking, lofty thoughts about themselves or their skills, and impulsive or reckless behavior during manic or hypomanic episodes. Symptoms of depressive episodes include feelings of worthlessness or excessive guilt, difficulty concentrating or making decisions, thoughts of death or suicide, changes in appetite or weight, sleep disturbances, fatigue or decreased energy levels, and protracted feelings of sadness, hopelessness, or emptiness. Though the underlying causes of bipolar illness are complex and not entirely understood, it is believed to be the result of a confluence of biological, environmental, and hereditary variables. The symptoms of a person, medical history, and family history of BPD or associated disorders are frequently used to make the diagnosis of BPD. Medication and counseling are typically used in the treatment of BPD. Lithium or other mood stabilizers are routinely used to treat manic or hypomanic episodes, whereas antidepressants or other drugs may be used to treat depressed episodes. CBT and IPT are two forms of psychotherapy that can be effective in treating BPD.

3.1.4. Seasonal Affective Disorder (SAD). Due to the shorter days and less sunlight in the winter, a type of depression known as SAD is more common. SAD is a type of MDD and is characterized by a protracted feeling of hopelessness, emptiness, or despair, as well as other symptoms such as exhaustion, low energy, changes in appetite or weight, insomnia, decreased zeal for activities, and problems concentrating or making decisions. Though the precise origin of SAD is not yet entirely understood, it is believed to be related to the body's natural reaction to variations in sunshine length. Wintertime reductions in solar exposure have the potential to throw off the body's internal clock and affect mood, energy levels, and sleep cycles. The conventional SAD treatment regimen combines light therapy, medicine, and psychotherapy. The body's internal clock can be regulated, and mood can be elevated through phototherapy, which entails spending 20–30 min each morning in a light box that

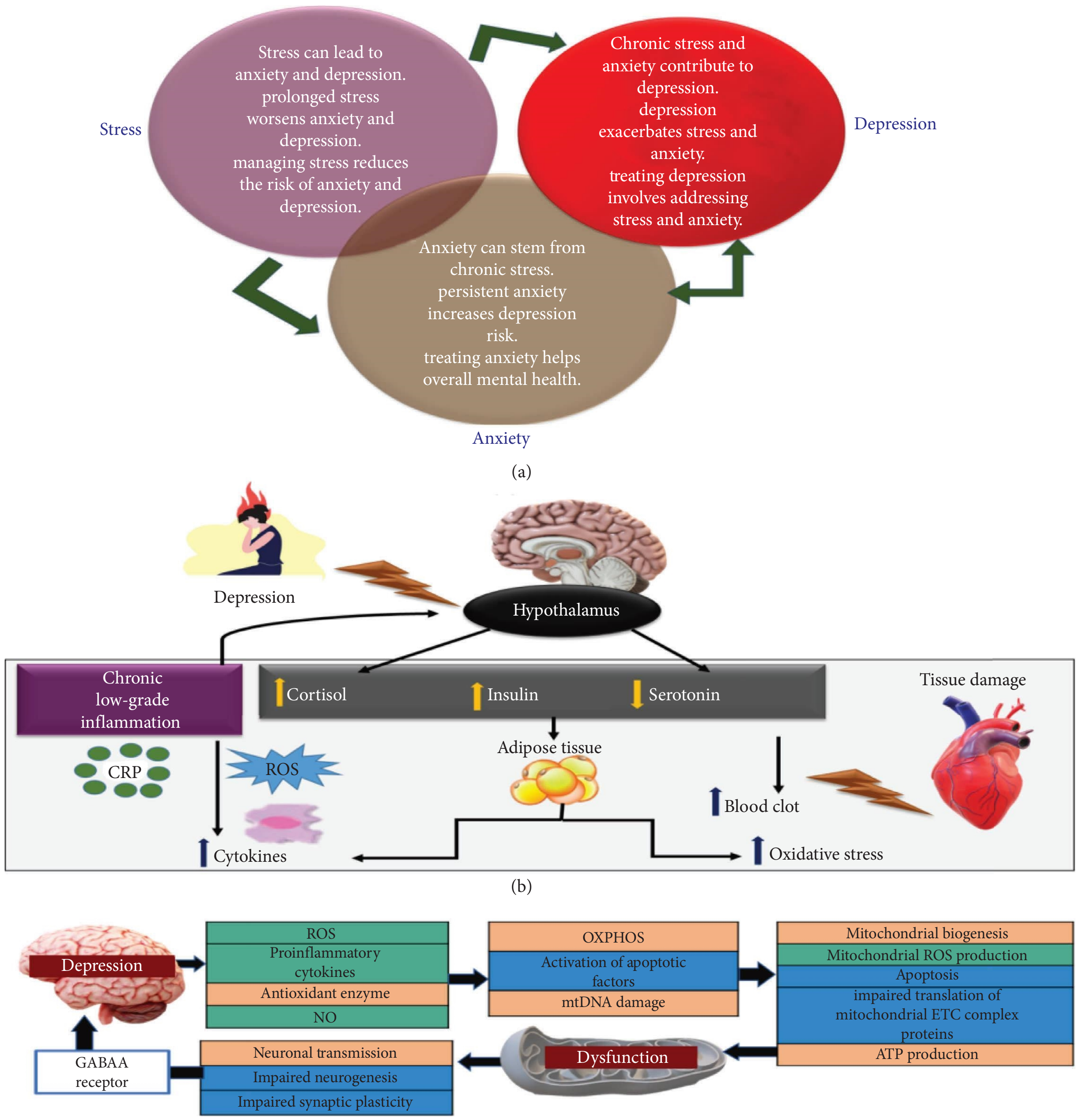

Figure 1: Understanding of depression based on biomedical perspectives, including (a) the association between stress and anxiety with depression, (b) the impact of depression on the cardiac system, and (c) the role of oxidative stress, mitochondrial dysfunction, and inflammation in depression.

simulates natural sunlight. Selective serotonin reuptake inhibitors (SSRIs), an antidepressant drug, may also be given to help treat SAD symptoms by balancing mood and energy levels [49]. The treatment of SAD may also benefit from psychotherapy, such as CBT and IPT.

3.1.5. Postpartum Depression (PPD). A form of depression known as PPD strikes women soon after giving birth. It usually manifests within the first few weeks or months following delivery; however, it can sometimes happen up to a year later [50]. PPD is characterized by feelings of sadness, hopelessness, or emptiness that last for a long time, as well as other symptoms such as exhaustion, changes in appetite or weight, trouble sleeping, a loss of interest in previously enjoyed activities, and thoughts of harming oneself or the baby [51]. Although the precise causes of PPD are not entirely understood, it is thought that a mix of hormonal, psychological, and environmental variables may be responsible. Significant hormonal changes that occur during pregnancy and childbirth can have an impact on a woman's mood and emotions [52]. PPD can also develop due to the difficulties in adjusting to parenthood and the physical and mental responsibilities of caring for a newborn. Psychotherapy and medicine are frequently used to treat PPD. While psychotherapy, such as CBT or IPT, can assist women in developing coping mechanisms and enhancing their social and interpersonal skills, antidepressant medication may be prescribed to help manage the symptoms of depression.

3.1.6. Premenstrual Dysphoric Disorder (PMDD). In the days before a woman's period, PMDD, a severe form of premenstrual syndrome, might affect her [53]. Various mental and physical symptoms make up the illness, which can significantly impact a woman's QoL. Anxiety, depression, mood swings, weariness, changes in appetite or sleep patterns, and physical symptoms such as bloating or breast tenderness are among the most typical symptoms. Hormonal changes that occur during the menstrual cycle are thought to be connected despite the fact that the precise causes of PMDD are not well understood. During this time, changes in estrogen and progesterone levels may have a greater impact on PMDD-afflicted women [54]. PMDD is often treated with a mix of medication and dietary modifications. Nonsteroidal anti-inflammatory medicines (NSAIDs) or hormonal contraceptives may be used to treat physical symptoms, while antidepressant medication may be recommended to treat mental issues. PMDD symptoms can also be managed with the aid of psychotherapy, such as CBT. Other advised lifestyle modifications that may lessen the symptoms of PMDD include regular exercise, healthy nutrition, stress management, and sound sleeping practices. Women with PMDD should collaborate with their doctor to create a personalized treatment plan and keep track of their symptoms. Even while PMDD can negatively impact a woman's functionality and QoL, with the right support and therapy, the majority of women can control their symptoms and enhance their general well-being.

3.2. Association Between Stress and Anxiety With Depression. Stress, anxiety, and depression are three major concepts that can be used to define psychological suffering [55, 56]. On the other hand, anxiety is characterized by a passing fear and uncertainty about the future, with the severity varying according to the frequency and degree of the anxiety experienced. Stress can show up as mental or physical symptoms, such as irritability or digestive problems [57]. Stress can be brought on by various outside circumstances, including routinely stressful situations, academic expectations for adolescents, and financial difficulties for adults. Stress can make people irritable. Chronic stress and an inability to resolve issues can result from persistent irritation and help lead to depressive illnesses [58]. General and prenatal anxiety, phobias, panic attacks, social anxiety disorder, obsessive-compulsive disorder, posttraumatic stress disorder (PTSD), and body dysmorphic disorder are just a few of the ailments that fall under the category of anxiety disorders [59]. Evidence suggests that daily stressors can compound and negatively affect heart health, such as through bad eating habits and a sedentary lifestyle [60], and that chronic stress and anxiety can cause depression [61]. Daily stresses can have an impact on a person's health, causing worry, and eventually a melancholy condition. This progression from stress to melancholy is significant in understanding the broader implications of mental health on individuals' overall well-being.

Numerous studies have delved into the connection between depression and QoL, revealing that major depressive disorder can substantially diminish QoL [62]. This indicates that the psychological burden stemming from daily stresses can escalate into clinical depression, further deteriorating one's QoL. Understanding this relationship underscores the importance of early intervention and holistic approaches to manage mental health challenges, ultimately striving to improve individuals' overall well-being. Major depressive illnesses are frequently accompanied by psychological stress [63], which can activate inflammatory pathways and cause inflammation [64]. Inflammation that results might lead to brain problems and coronary heart disorders. Stressors can have an impact on how the brain functions cognitively and autonomically, causing an increase in catecholamine synthesis, a decrease in cholinergic activity, a decrease in glucocorticoid activity, and an increase in cortisol levels. These elements may result in chronic inflammation and interfere with the brain's natural function, resulting in depression, anxiety, and cardiovascular conditions [65].

Neurotransmitters, including catecholamines, norepinephrine, and dopamine, are crucial in the treatment of serious depressive disorders [66]. It is yet unclear how catecholamine actions play a factor in the pathophysiology of serious depression. Norepinephrine possesses the capability to bind to both α- and β-adrenergic receptors, thereby initiating cell signaling pathways, notably elevating intracellular levels of phospholipase C and cAMP [67, 68]. However, activation of the 2-adrenergic receptor suppresses intracellular cAMP and inhibits signaling [69]. Norepinephrine can increase anxiety and hyperarousal in melancholic melancholy, encourage corticotropin-releasing hormone-mediated hypercortisolism, encourage insulin resistance, and result in bone loss [70]. An experimental study compared the urine catecholamine levels of sad and nondepressed people and found that the latter had much higher amounts [71]. Both coding and noncoding sections of DNA may be impacted by the production of reactive oxygen species (ROS) as a result of elevated plasma catecholamine levels in depression and anxiety. Transcriptional stress is brought on by ROS, which accumulates in polysomes and generates transitory dynamics of si-IncRNA in the nucleus [72]. An experimental investigation that demonstrated downregulation of the Dusp6 gene in female mice under stress, impacting the transcriptional pathway, whereas extracellular-signa–regulated kinase signaling and neuron excitability increased in male mice suggests that the effects of stress on the molecular level may vary between genders [73]. These transcriptional changes contribute to MDD and may provide information for the creation of antidepressant drugs. According to a study conducted on university students in China, depression was linked to high sugar intake, gender, grades, stress, and anxiety complaints [74]. Another study also revealed a link between depression, injury, and a high-fat diet with anxiety and stress, underscoring the role of stress, sadness, and anxiety in producing psychological distress [75]. The association of the stress and anxiety with depression is mentioned in Figure 1(a).

3.3. Impact of Depression in the Brain and Heart. Clinical depression, a severe manifestation of chronic stress, detrimentally affects mental health by impairing hippocampal function due to elevated glucocorticoid levels [76]. Persistent stress leads to hippocampal volume reduction and dendritic atrophy in the CA3 region, exacerbating memory and cognitive deficits [77, 78]. Depression also disrupts synaptic function, reducing NMDA receptors and activating the TPA/plasmin system [79]. Histopathological studies reveal cortical and subcortical alterations postpartum, contributing to functional impairment [80]. Neuroimaging identifies reduced cortical thickness and diminished neuron/glial cell density in the orbitofrontal region, aiding in major depression diagnosis [81]. Depression elevates oxidative stress, leading to neurodegenerative disorders and cardiac hypertrophy, exacerbating heart failure risk [82–86]. ROS are implicated in myocardial infarction pathogenesis, exacerbating atherosclerosis and acute coronary artery disease [87, 88]. Studies show increased cardiac mortality in depressed individuals, regardless of cardiac disease presence, with minor depression particularly affecting the elderly [78, 89]. Stress-induced cardiomyopathy, mimicking coronary heart disease, is characterized by elevated troponin levels and can lead to heart attack [90, 91]. Stress impacts the nervous and cardiac systems via hypothalamic-pituitary axis activation, leading to neurohormone secretion and sympathovagal imbalance [92]. Immune suppression and proinflammatory cytokine release contribute to coronary artery disease progression and acute episodes (Figure 1(b)).

3.4. Confluence of Oxidative Stress, Inflammation, and Mitochondrial Dysfunction in Depression. The confluence of oxidative stress, inflammation, and mitochondrial dysfunction represents a pivotal nexus in understanding the pathophysiology of depression. Emerging research suggests intricate interactions between these biological processes, shedding light on their collective role in the etiology and progression of depressive disorders. By exploring the interplay of these mechanisms, we aimed to elucidate novel therapeutic targets and interventions for mitigating the burden of depression.

Morava et al. [93] highlighted the association between chronic mild stress and mitochondrial dysfunction in depression, demonstrating dissipation of mitochondrial membrane potential, inhibition of oxidative phosphorylation, and structural damage in brain areas such as the hippocampus, cortex, and hypothalamus.

This dysfunction contributes to compromised brain energy and potentially triggers depression. Reduced glucose utilization in specific brain regions such as the prefrontal cortex, caudate nucleus, and anterior cingulate gyrus has been observed in depressed patients [94]. Studies further indicated that major depression involves activation of inflammatory, immune, oxidative, hypothalamic-pituitary-adrenal axis, and nitrosamine stress pathways. These processes induce mitochondrial damage, particularly through suppression of mitochondrial Complexes I and IV, resulting from cytokine-induced effects. ROS production is heightened in the brain due to inflammatory stimulation, leading to oxidative damage to mitochondrial components. In addition, depression is linked to an imbalance between ROS production and antioxidant defense mechanisms, which escalates oxidative stress, reduces brain antioxidant levels, and impairs mitochondrial structures and functions. Mitochondrial dysfunctions exacerbate oxidative stress, impacting mitochondrial DNA, intracellular calcium levels, cellular morphology, and ultimately leading to neuronal death. The increased energy demand for cellular repair worsens mitochondrial damage, forming a cycle of further impairment [95] (Figure 1(c)).

4. Monitoring of Depression

IIoMT and conventional questionnaire methods are used to identify depressive disorders. Both approaches are examined, along with advantages and disadvantages, as shown below.

4.1. Questionnaires' Techniques for Depression. Depression can be identified using a variety of procedures and questionnaires. Some of the techniques defined are as follows.

4.1.1. Beck Depression Inventory (BDI). The 21-question BDI questionnaire is a self-reported evaluation used to determine the severity of depressive symptoms. There is a wide range of symptoms covered by it, such as depression, guilt, hopelessness, impatience, and lack of interest or pleasure [96]. Each question has four options for responses, ranging from 0 (*absent*) to 3 (*severe*), and respondents must select one. Higher total scores, which range from 0 to 63, indicate more severe depression. The BDI questionnaire is regarded as a trustworthy tool for measuring depression symptoms due to its extensive study and broad use in both clinical and research settings.

4.1.2. Patient Health Questionnaire (PHQ-9). A self-administered questionnaire called the PHQ-9 was developed to detect and monitor depression symptoms in primary care settings [97]. It consists of nine questions and covers a range of symptoms, such as depression, pleasure loss, and sleep problems. A four-point scale, ranging from 0 (*not at all*) to 3, is used by respondents to respond to each question. A higher total score indicates more severe depression; the range is 0–27. The PHQ-9 is a widely used tool in primary care settings and has undergone extensive investigation.

4.1.3. Hamilton Rating Scale for Depression (HAM-D). A questionnaire called the HAM-D is used by therapists to gauge the severity of depression symptoms [98]. There are 21 questions in total that examine a range of symptoms, such as low mood, guilt or worthlessness, and lack of energy or interest [99]. Higher scores indicate more severe depression, with the questions being graded on a scale from 0 to 4. Scores exceeding 24 are considered to indicate serious depression. The total score runs from 0 to 63. The HAM-D has undergone substantial investigation and is frequently used in research and clinical trial settings.

4.1.4. Geriatric Depression Scale (GDS). A self-administered questionnaire called the GDS is used to assess depression in elderly people [100]. It consists of 30 items that evaluate a range of depressive symptoms, such as low mood, interest loss, and social isolation. The overall score goes from 0 to 30, with higher values indicating greater depression severity. Respondents express their answers in a yes/no style. The GDS is a well-researched tool that is frequently used in settings including geriatric care.

4.1.5. Montgomery–Asberg Depression Rating Scale (MADRS). A clinician-administered questionnaire called the MADRS consists of 10 questions with the goal of gauging the severity of depressive symptom severity [101]. The questionnaire asks about a wide range of symptoms, such as depression, tension, and disturbed sleep. The ratings for each question range from 0 to 6, with higher scores indicating more severe depressed symptoms. Scores exceeding 30 indicate a high level of depression severity on the scale of 0–60. The MADRS has undergone extensive research and is frequently used in clinical trials and research settings as a useful instrument for evaluating depression symptoms.

4.1.6. Depression, Anxiety, and Stress Scale (DASS). The DASS is a questionnaire that people can fill out on their own to gauge how severe their symptoms of stress, anxiety, and depression are [102]. It consists of 21 questions covering a variety of symptoms such as anxiety, helplessness, and impatience. For each question, the respondent has a choice of four answers, ranging from 0 (*not applicable to me*) to 3 (*applied to me most of the time*). With a range of 0–63, a higher score on each subscale denotes more severe signs of stress, anxiety, or depression. The DASS has undergone extensive investigation and is frequently used in both clinical and research settings.

4.1.7. SAD Questionnaire (SAD-Q). The SAD-Q is a self-administered questionnaire with six questions intended to assess the presence and severity of SAD [103]. Its tendency to arise in the autumn and winter months is what distinguishes this type of depression. The questionnaire's questions evaluate a range of symptoms, including mood, sleep, and appetite abnormalities. A scale from 0 to four is used to grade the questions, with 0 denoting "*never*" and 4 denoting "*always.*" A total score between 0 and 24 can be obtained; higher scores signify more severe SAD symptoms. The research indicates that the SAD-Q is an accurate and valid measure for assessing SAD symptoms.

4.1.8. Self-Rating Depression Scale (SDS). People fill out the SDS questionnaire to rate the severity of their depression symptoms [104]. It has 20 questions that cover a range of depressive symptoms, including altered sleep and food patterns as well as emotions of worthlessness, remorse, and melancholy. Each question has four possible answers that range from 0 (*not present*) to 3 (*severe*), and the overall score can be anywhere from 0 to 60. Higher scores indicate more severe depression. In both clinical and research situations, the SDS has showed strong reliability and validity [105].

These surveys are frequently used in clinical and academic contexts to identify and track depression. The features of the patient population, the context of the assessment, and the particular depression symptoms being assessed may all influence the use of a particular questionnaire.

4.2. Analysis of Depression Using Intelligent Approaches. The AI area of ML enables computer systems to automatically enhance their performance on a particular job by learning from data without being explicitly programmed [7, 106]. In order to make predictions or choices, it entails creating algorithms that can learn from data. There are numerous algorithms available in ML that can be applied to classification and prediction problems. Computer vision, natural language processing (NLP), speech recognition, gene expression, image recognition, and signal processing are just a few of the scientific disciplines where ML is becoming a more active research topic [107–109]. DL, on the other hand, is a subset of ML that studies how to learn. It is possible to extract information from signals using a deep neural network (DNN), a subset of DL. The detail description of the ML and DL models with dataset are mentioned in Tables 2 and 3. In addition**,** the detail literature of the models is also given below.

4.2.1. Random Forest (RF). An ensemble learning technique called RF makes predictions by using numerous decision trees (DTs). RF is frequently employed in medical procedures, including disease diagnostics and medicine development. For instance, RF can be used to forecast a drug's effectiveness, given on its chemical characteristics and the patient's medical background. Previously, Zhang et al. [117] used the RF model for the prediction of depression in pregnant women. de Souza Filho et al. [118] used the RF classifier as a screening tool for the evaluation of depression. Pearson et al. [149] used the RF algorithm for the prediction of treatment outcomes of depression. Solomonov et al. [137]

Table 2: Previously used ML and DL models in depression research.

Ref.	ML/DL model	Perf. (%)
2024 [110]	BF tree, KNN, and AB	Acc: 96.36
2024 [111]	DT, LR, NB, RF, and SVM	AUC: 81.00; Acc: 83.00; Sens: 76.00
2024 [112]	AB, LDA, RF, KNN, NB, and SVM	Acc: 71.80; AUC: 78.03
2024 [113]	LR and SVM	—
2024 [114]	LR and XGB	—
2023 [115]	SVM	AUC: 73.00
2021 [116]	Bootstrap	Acc: 97.00
2021 [117]	RF, DT, XGB, LR, and MLP	AUC: 93.70
2021 [118]	LR, KNN, CART, AB, GB, XGB, RF, and SVM	Sens: 90.00; AUC: 87.00
2021 [61]	DT	AUC: 71.20; Sens: 34.90; Spec: 90.50
2020 [70]	SVM	Acc: 95.00
2020 [119]	Bagged DT	Acc: 74.18
2020 [72]	RF	Acc: 79.10
2020 [60]	RF	Acc: 99.00
2020 [73]	GBM	AUC: 97.00
2020 [59]	RF	Acc: 80.00
2020 [120]	LR, NN, RF	AUC: 91.00
2020 [65]	SVM	Sens: 82.00
2020 [75]	RF	Acc: 76.80
2020 [121]	FFS-RF, SVM	Sens: 69.00; AUC: 78.00
2020 [77]	LDA	Acc: 91.00
2020 [78]	SVM	Acc: 82.40; Sens: 79.20; Spec: 85.50
2020 [79]	DT	AUC: 73.40; Sens: 94.10; Spec: 43.30
2020 [80]	RF	Acc: 73.40
2020 [122]	SVM-Kernel	AUC: 69.00; Sens: 62.00; Spec: 66.00
2020 [123]	LR, SVM-Kernel, and RF	Acc: 80.00; Sens: 54.00; Spec: 93.00
2019 [82]	LR	Acc: 91.00; Spec: 94.00; AUC: 96.00
2019 [83]	SVM	Acc: 84.86
2019 [124]	LR, SVM, and MLPs	Acc: 91.70
2019 [85]	RF	AUC: 94.40; Sens: 83.91; Spec: 92.18
2019 [86]	SVM	Acc: 78.60
2018 [87]	LR	Acc: 66.00
2018 [88]	SML	Acc: 64.00
2018 [89]	RF	Acc: 72.50
2017 [90]	SVM	Acc: 90.10
2021 [15]	DL	—
2020 [16]	Combination of CNN and LSTM	Acc: 98.84
2020 [92]	NLP	AUC: 90.00
2020 [13]	BERT and RoBERTa	F1 score: 85.60
2020 [11]	CNN	Acc: 98.85
2020 [91]	NN	AUC: 80.00
2020 [14]	2D CNN	Acc: 80.74
2019 [125]	CNN and LSTM	Acc: 98.32, Sens: 98.34
2019 [94]	DL	AUC: 77.00
2019 [95]	FCN	Acc: 81.40
2019 [126]	SVM, LR, KNN, DNN, and deep-CNN	Acc: 94.00
2018 [127]	MFNNs	Acc: 82.28

Abbreviations: Acc, accuracy; BF tree, best-first tree; CDRN, clinical data research network; DNN, deep neural network; DT, decision tree; EEG, electroencephalogram; EHR, electronic health record; FCN, fully convolutional neural network; fMRI, functional magnetic resonance imaging; LR, logistic regression; NLP, natural language processing; RF, random forest; Sens, sensitivity; Spec, specificity; SVM, support vector machine; WCM, Weill Cornell medicine.

used RF for the prediction of late-life depression. In addition, some other researchers used RF classifiers to detect or predict depression based on different types of data processing [134].

4.2.2. DT. A straightforward and understandable method called a DT employs a tree-like model to anticipate outcomes. DT is frequently employed in medical settings, including the diagnosis and prescription of cancer treatments.

Table 3: Previously used datasets in depression research.

Reference	Objective	Part	Dataset
[116]	Discrimination	240	MDD, BD, and HC
[117]	Prediction	69,169	HER, WCM, and CDRN
[118]	Evaluation	971	Brazilian National Network for Research on Cardiovascular Diseases
[128]	Development and validation	214,359	CHS-EHR
[129]	Prediction	167	CHR syndromes and ROD
[130]	Development	335	60 years or older with Parkinson's disease
[119]	Differentiation	126	Hebrew speakers with normal or corrected-to-normal eyesight
[131]	Cross-trial prediction	351	STEPd
[132]	Prediction	28,755	Pregnancy risk assessment monitoring system 2012 to 2013
[133]	Classification	79,889	English-speaking health forums.
[134]	Classification and prediction	150	Mohammed VI University Hospital Center of Marrakech
[135]	Analysis	168	MDD case-control
[136]	Detection	—	Twitter
[137]	Prediction	221	12 weeks of problem-solving or supportive therapy
[120]	Prediction	—	IMID
[138]	Prediction	518	iSPOT-D
[139]	Identification	365	Reddit posts from fathers straddling 6 months during the birth of kid
[140]	Recognition	9435	Population-representative sample
[141]	Diagnosis	412	Amazon Mechanical Turk
[121]	Prediction	508	Women's pregnancy period from a cohort
[142]	Prediction	6558	A nationwide survey from the KoWePS
[143]	Classification	8063	Chinese middle and high school students
[144]	Identification	31	fMRI
[145]	Prediction	122	EEG
[146]	Evaluation	1000	BDI-II, China
[47]	Identification	1435	CBT and CID
[147]	Identification	1500	NSSD
[122]	Differentiation	162	PROTAHBI and PROTHUM
[123]	Identification	—	TSST-C
[148]	Prediction	47	Actiwatch, EMA
[149]	Predict the treatment	283	Depression-focused Internet intervention
[150]	Discovery	610	PHQ
[151]	Age estimation	78	IXI and OASIS
[152]	Recognition	—	Lanzhou University Second Hospital
[124]	Prediction	2388	Posts in daily life group
[153]	Identification	84,317	INPC
[154]	Prediction	—	Eight-channel EEG pre- and post-TMS in resting stage
[155]	Drug discovery	—	CMap, ATC, and MEDI-HPS
[156]	Prediction	356	NESDA
[157]	Prediction	90	MI-ANXDEP, Sweden
[158]	Prediction	81	PET
[15]	Detection	29	Community-dwelling, North East, England
[16]	Detection	—	University of New Mexico
[159]	Classification	81	Trauma survivors, New York
[13]	Prediction	13,993	Weibo, China
[12]	Prescreening	34	EEG dataset
[160]	Treatment selection	2757	Data from CO-MED
[14]	Recognition	51	Lanzhou University
[125]	Diagnosis	30	EEG dataset
[161]	Identification	19,725	NHANES and K-NHANES
[162]	Examine	1190	ADE20K, China
[126]	Impact	19	fMRI dataset
[127]	Prediction	8	The National Health Research Institute, Taipei Veterans General Hospital
[114]	Prediction	—	LONGSCAN, FUUS, NHANES, UK Biobank
[110]	Screening	55	EEG dataset

Table 3: Continued.

Reference	Objective	Part	Dataset
[111]	Inventory	20,990	Questionnaire
[115]	Validation	189	Clinical, sMRI, and resting-state fMRI
[112]	Prediction	—	Questionnaire

Abbreviations: AB, AdaBoost; ATC, anatomical therapeutic chemical; BD, bipolar disorder; BDI-II, Beck Depression Inventory-II; BERT, bidirectional encoder representations from transformers; CART, classification and regression tree; CBT, cognitive-behavioral therapy; CHR, Clinical High Risk; CHS, Clalit Health Services; CMap, connectivity map; CNN, convolutional neural network; FFS-RF, random forest–based filter feature selection; fMRI, functional magnetic resonance imaging; KoWePS: Korean Welfare Panel Study; GB, gradient boost; GLM, generalized linear model; HC, health control; iCBT, Internet–delivered cognitive behavior therapy; IMID, immunomodulatory imide drug; INPC, indiana network for patient care; iSPOT-D, international study to predict optimized treatment in depression; KNN, K-nearest neighbor; LSTM, long short-term memory; MDD, major depressive disorder; MEDI-HPS, medication indication resource high-precision subset; MFNNs, multilayer feedforward neural networks; MLPs, multilayer perceptrons; NESDA, National E-Governance Service Delivery Assessment; NSSD, National Survey on Symptomatology of Depression; OASIS, open access series of imaging studies; PCC, person-centered counseling; PHQ, patient health questionnaire; PPD, postpartum depression; PROTAHBI, programa de transforms bipolarize; PROTHUM, programa de transtornos de humor; RoBERTa, robustly optimized bidirectional encoder representations from transformers pertaining approach; ROD, recent-onset depression; SML, supervised machine learning; sMRI: structural magnetic resonance imaging; STEPd, stellariaherllida; STFT, short-time Fourier transform; tDCS: transcranial direct current stimulation; TMS, transcranial magnetic stimulation; TSST-C, trier social stress task for children; XGB, extreme gradient boost.

For instance, using the patient's age, tumor size, and other clinical factors, DT can be used to forecast the chance of cancer recurrence. Previously, the DT classifier was used for the prediction of PPD [128].

4.2.3. Classification and Regression Tree (CART). CART is a DT algorithm that can be used for classification and regression problems. CART is commonly used in medical applications, such as disease diagnosis and risk prediction [118]. For example, CART can be used to predict the risk of developing heart disease based on a patient's lifestyle habits and medical history.

4.2.4. Logistic Regression (LR). Binary classification problems are handled by the statistical procedure known as LR. Medical applications, including the diagnosis of diseases and risk assessment, frequently employ LR. Using the patient's age, weight, and other clinical factors, for instance, LR can be used to determine their risk of getting diabetes. Previously, LR was used to identify large-scale modulated activity of dopaminergic enhancement in depression [144]. McGinnis et al. [123] identified depression using LR based on speech data. Some other authors used LR for the prediction/identification of the different types of depression with other diseases [118].

4.2.5. K-Nearest Neighbor (KNN). A nonparametric approach called KNN is employed for classification and regression issues. The KNN is frequently utilized in healthcare applications such as disease diagnostics and therapeutic development. Using the patient's genetic profile and medical history, for instance, KNN can be used to forecast a drug's success [126].

4.2.6. Support Vector Machine (SVM). A powerful approach used for classification and regression issues is a SVM. The SVM is frequently utilized in medical contexts, including cancer detection and drug development. For instance, using the patient's gene expression profile and clinical factors, the SVM can be used to forecast the chance of cancer recurrence. McGinnis et al. [123] used speech data to identify anxiety and depression in early childhood. In addition, authors used the SVM for the recognition/detection of depression based on different types of data processing [139].

4.2.7. AdaBoost (AB). An ensemble learning technique called AB combines several weak learners to produce predictions. Medical applications such as disease diagnosis and drug discovery frequently use AB. For instance, AB can be used to forecast a medication's efficacy based on the patient's medical background and other clinical factors [118].

4.2.8. Naive Bayes (NB). NB is an easy probabilistic approach for categorization issues. Medical applications such as illness diagnosis and risk assessment frequently use NB. For instance, using the patient's lifestyle choices and medical history, NB can be used to estimate the likelihood that the patient will acquire heart disease [136].

4.2.9. Self-Organizing Map (SOM). Data grouping and visualization are done using a sort of neural network called a SOM. The SOM has uses in medicine, including the study of patient data for personalized care. For instance, the SOM can be used to find patient subgroups with comparable medical histories and genetic profiles for individualized therapies [163].

4.2.10. Artificial Neural Network (ANN). ANNs are used for classification and regression issues. Medical uses for the ANN include disease detection and picture analysis. For instance, medical imaging of epilepsy patients can be used to identify abnormal brain activity using the ANN [164].

4.2.11. Statistical ML (SML). A subset of ML called SML is concerned with creating statistical models for data analysis and prediction. SML has uses in medicine, including the diagnosis and prognosis of illnesses. For instance, it can be used to forecast a patient's risk of getting diabetes based on their health history and lifestyle choices.

4.2.12. Linear Discriminant Analysis (LDA). An analytical technique called LDA is applied to classification issues. Medical applications for LDA include risk assessment and disease diagnosis. For instance, LDA can be utilized to forecast a patient's risk of getting heart disease depending on their medical background and lifestyle choices.

4.2.13. Generalized Linear Model (GLM). The GLM is a statistical framework for modeling data with different distributions. It can be used in medical applications, such as disease diagnosis and prognosis. For example, it can predict the likelihood of a patient developing a certain disease based on their medical history and lifestyle habits.

4.2.14. Convolutional Neural Network (CNN). A particular kind of a neural network called a CNN is employed for image analysis and recognition tasks. Applications of the CNN in medicine include illness detection and analysis of medical images. The CNN, for instance, can be used to spot malignant tumors in photographs of patients.

4.2.15. Long Short-Term Memory (LSTM). The LSTM is an example of a recurrent neural network (RNN) used for sequential data analysis. It is also used for time series analysis and NLP. Medical applications for LSTM include analyzing patient data collected over time for disease diagnosis and treatment advice.

4.2.16. RNN. Similar to LSTM, RNNs are employed for sequential data analysis. The RNN can be utilized in medical applications, such as the study of patient data over time for disease diagnosis and prognosis. For instance, using a patient's medical history and vital signs, the RNN can be used to forecast the risk that they would experience difficulties after surgery.

4.2.17. DNN. Multiple-layer neural networks, such as the DNN, can be utilized for various ML applications, such as classification and regression. The DNN can be applied to medical tasks such as disease diagnosis and treatment suggestions. The DNN, for instance, can be used to forecast a patient's likelihood of responding to a specific medication based on their genetic makeup and medical background.

4.2.18. Multilayer Perceptron (MLP). The MLP is a class of neural networks that can be applied to classification and regression issues. It has numerous layers of nodes. Medical applications such as image analysis and disease diagnosis frequently use the MLP. The MLP, for instance, can be utilized to recognize malignant cells in medical imaging.

4.2.19. Gradient Boosting Machine (GBM). Several weak learners are combined to create predictions using the ensemble learning technique known as the GBM. The GBM is frequently utilized in medical applications, including the diagnosis of diseases and the prescription of therapies. For instance, using a patient's medical history and genetic profile, the GBM can be utilized to forecast a drug's effectiveness.

4.2.20. Extreme Gradient Boosting (XGB). XGB, a technique for ensemble learning, mixes many DTs to produce predictions. Medical applications, such as the diagnosis and prognosis of diseases, frequently use XGB. For instance, a patient's medical history can be used to predict the risk of contracting a specific disease using XGB. Kambeitz et al. [165] used XGB to find the transcranial direct current stimulation (tDCS) response in depression.

4.2.21. Gradient Boosting (GB). GB is an ensemble learning technique that pools the predictions of several weak learners. GB is frequently utilized in medical applications, including the diagnosis and prognosis of diseases. Patient's genetic profile, for instance, can be used to predict the likelihood that they will get cancer using GB.

4.2.22. Generalized Boosted Regression (GBR). The GBR model, a technique for ensemble learning, combines many regression models to produce predictions. GBR is frequently utilized in medical applications, including the prognosis of diseases and the recommendation of treatments. For instance, using a patient's genetic profile and medical history, GBR can be used to predict how well a treatment will work.

4.2.23. Bootstrap. The statistical resampling method known as bootstrap is used to determine how a statistic's sampling distribution will look. To calculate the degree of uncertainty surrounding a statistical finding, such as the variation in mean blood pressure between two patient groups, bootstrap can be utilized in the medical research. Previously, Poletti et al. [116] used bootstrap algorithm for the discrimination between unipolar and bipolar depression.

4.2.24. NLP. The subject of study known as NLP is concerned with how computers and human language interact. Medical uses for NLP include reviewing patient comments and medical records. NLP, for instance, can be used to find patient complaints and enhance medical services [92].

4.3. Performance Indicators. The effectiveness of ML models in medical applications is assessed using performance indicators, which are crucial metrics. The detail mathematical expression are mentioned in equations (1)–(7) [166–168]:

4.3.1. Accuracy. A dataset's accuracy is determined by the proportion of correctly categorized instances. A ML model's ability to predict patient outcomes or diagnose diseases can be measured using accuracy in medical applications.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{FP} + \text{FN} + \text{TN} + \text{TP}}. \quad (1)$$

4.3.2. Sensitivity. Sensitivity indicates the proportion of genuine positive cases that the ML model accurately detected. Sensitivity is crucial for detecting the existence of a disease or other medical condition in medical applications.

$$\text{Recall/Sensitivity/True Positive Ratio} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \quad (2)$$

4.3.3. Specificity. The percentage of instances of true negatives that the ML model properly detected is known as specificity. Specificity is crucial in medical applications to rule out the existence of a disease or other medical condition.

$$\text{Specificity/True Negative Ratio} = \frac{\text{TN}}{\text{TN} + \text{FP}}. \quad (3)$$

4.3.4. Precision. Precision is the proportion of positive cases among all instances the ML model predicted to be positive. Precision is crucial for reducing false positives in medical applications because they can result in pointless treatments or testing.

$$\text{Precision/Positive Predictive Value} = \frac{\text{TP}}{\text{TP} + \text{FP}}. \quad (4)$$

4.3.5. Negative Predictive Value. The percentage of cases that are truly negative, out of all those that the ML model predicted as being negative, is measured by a negative predictive value. A negative predictive value is crucial for excluding the presence of a disease or other medical condition in medical applications.

$$\text{Negative Predictive Value} = \frac{\text{TN}}{\text{TN} + \text{FN}}. \quad (5)$$

4.3.6. F1-Score. The model's performance is assessed using the $F1$-score, which is the harmonic mean of precision and sensitivity. The $F1$-score can be used in medical applications to assess a ML model's general efficacy in identifying diseases or predicting patient outcomes.

$$F - \text{score}/F1 - \text{score/Dice Coefficient} = \frac{2 \times (\text{Recall} \times \text{Precision})}{(\text{Recall} + \text{Precision})} = \frac{2(\text{TP})}{\text{FN} + 2(\text{TP}) + \text{FP}}. \quad (6)$$

4.3.7. Matthews Correlation Coefficient (MCC). The MCC, which accounts for both true and false positives and negatives, calculates the correlation between the actual and anticipated values. The MCC is a helpful performance measure for assessing a ML model's overall effectiveness in medical applications, particularly when the dataset is unbalanced, and the model is used to predict patient outcomes or diagnose diseases [169].

$$\text{Matthews Correlation Coefficient} = \frac{\text{TP} \times \text{TN} - \text{FP} \times \text{FN}}{\sqrt{(\text{TP} + \text{FP}) \times (\text{TP} + \text{FN}) \times (\text{TN} + \text{FN})}}, \quad (7)$$

where TP is true positive, FP is false positive, TN is true negative, and FN is false negative.

5. Prevention Measures for Depression

A person's life can be significantly affected by a mental health disorder known as depression. Although there is no surefire way to stop depression, people can take a number of precautions to safeguard their mental health and reduce the likelihood that they will go through despair. We described some measures to prevent depression:

5.1. Build a Support System. In order to prevent emotions of loneliness and isolation, which are risk factors for depression, social support is crucial for mental health. A sense of security, belonging, and purpose can also come from having healthy relationships with friends and family. Consider getting involved in your community through volunteering, joining a club or group that shares your interests, or contacting friends and family to create a support network.

5.2. Practice Good Self-Care. Maintaining good physical health has a positive impact on your mental wellbeing. This entails following a balanced diet full of fruits, vegetables, and whole grains, exercising frequently, and getting adequate sleep. Because exercise releases endorphins, which are natural mood enhancers, it can be especially helpful for easing the symptoms of depression.

5.3. Learn Healthy Coping Skills. The techniques people employ to deal with stress and challenging emotions are known as coping skills. Healthy coping techniques can include deep breathing, mindfulness meditation, writing, and time spent in nature. These abilities can assist people in controlling their emotions and lowering their risk of depression.

5.4. Seek Professional Help. It is critical to get professional assistance from a mental health expert if you are showing signs of depression. You can create a treatment plan that is specific to your requirements and the causes of your depression with the aid of a therapist or counselor. Depression can be treated with therapy, medicine, or a combination of the two.

5.5. Avoid Substance Abuse. Abuse of drugs or alcohol can make depression worse and raise the likelihood of getting it. Utilizing alcohol and drugs to deal with challenging emotions can result in addiction, health issues, and societal issues. Consider contacting a mental health professional for assistance or using healthy coping mechanisms rather than abusing substances.

5.6. Stay Active and Engaged. Depression risk can be lowered by maintaining an active lifestyle and participating in enjoyable and meaningful pursuits. This can involve pastimes, community service, or social engagements. Activities that give one a feeling of achievement or purpose might also be advantageous.

5.7. Manage Stress. Learning appropriate stress management techniques is critical because stress can lead to depression. Exercise, meditation, deep breathing, and friendly conversation are a few examples of this. It can also be beneficial to lessen pressures in your life; such as issues at work or in your relationships.

5.8. Get Treatment for Chronic Illnesses. Depression risk can be increased by long-term conditions, such as diabetes, cancer, and heart disease. Taking care of these diseases and receiving the proper care can help lower the risk. This can entail taking medicine, altering one's lifestyle, or consulting a healthcare professional.

However, keeping strong social ties, obtaining professional assistance when necessary, and caring for your physical and mental health can all help lower the risk of depression. Getting professional help as soon as possible is crucial if you are showing signs of depression. Depression is a treatable disorder, and with the right care and assistance, people can get better and lead happy lives.

6. Architecture of Proposed IIoMT in Depression

The perception layer, network layer, cloud layer, application layer, and privacy and security are the foundations of the IIoMT's detailed architecture in depression (Figure 2). The specifics are provided below.

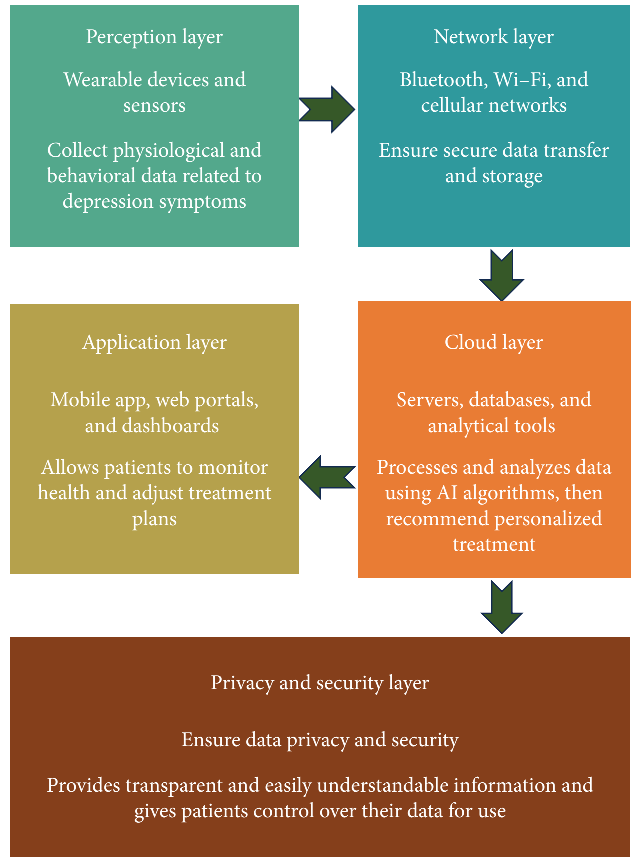

Figure 2: Proposed architectural block diagram of IIoMT for depression.

6.1. Perception Layer. The IIoMT system for depression incorporates a variety of wearable gadgets and sensors in the perception layer that may monitor numerous physiological and behavioral depression indicators. Smartwatches, activity trackers, mood sensors, sleep monitors, and other gadgets that can gather information on heart rate, blood pressure, sleep quality, physical activity, social contact, and other variables that may have an impact on mental health may be included in this layer. Mobile applications that enable patients to enter subjective information, such as mood, behavior, and other symptoms, may also be a part of the perception layer.

6.2. Network Layer. The network layer, which links the perception layer to the cloud layer, makes secure data transit and storage possible. This layer transmits information from the perception layer to the cloud layer via wireless communication technologies such as Bluetooth, Wi-Fi, and cellular networks. The network layer also offers secure data storage and transfer protocols to safeguard patient data from unauthorized access and ensure encryption.

6.3. Cloud Layer. The IIoMT system for depression's cloud layer is in charge of processing and analyzing the information gathered from the perception layer. This layer consists of servers, databases, and analytical tools that look for patterns and anomalies associated with depressive symptoms using ML algorithms and other AI techniques. On the basis of the patient's data, the cloud layer may also contain decision-support systems that might offer mental health practitioners' personalized therapy recommendations.

6.4. Application Layer. The IIoMT system for depression's interface with users, such as patients, and mental health professionals, is the application layer. This layer consists of dashboards, web portals, and mobile apps that let users monitor their mental health and communicate with the system. Mental health specialists may also use this layer to keep tabs on patient progress, offer criticism, and modify treatment methods as necessary. Patients may also receive instructional materials on depression, self-care techniques, and coping skills through the application layer.

6.5. Privacy and Security Layer. Patient data must be gathered, kept, and sent securely and in accordance with any applicable privacy laws for the IIoMT system for depression. To safeguard patient information from unauthorized access or disclosure, the system should employ encryption and other security measures. The system should also give patients control over their data, the capacity to consent to its use, and clear and understandable information about how their data will be used.

However, the way mental health is tracked and treated might be completely changed by an IIoMT system for depression. This kind of system may be able to offer patients and mental health practitioners' insightful information about the patient's mental health condition and assist in guiding treatment choices by gathering and analyzing data on a variety of physiological and behavioral markers of depression. By encouraging self-care and empowering individuals to manage their mental health actively, the system may also help lessen the stigma associated with mental illness.

7. Automatic Detection of Depression

Automatic detection of depression has advanced significantly with the integration of AI, IoT, IoMT, wearable devices, and sensors [170]. AI's ability to detect depression hinges on the comprehensive analysis of diverse data sources, including text, speech, and behavioral data. Text analysis utilizes NLP to scrutinize written content from sources such as social media posts, emails, and online forums [92]. By identifying linguistic patterns and emotional cues, NLP can uncover signs of depression that may be subtle or overlooked by traditional methods. Similarly, speech analysis employs AI to assess vocal characteristics—such as tone, pitch, and speech rate—which can reveal emotional distress and potential depressive states. This dual approach of analyzing both text and speech enables a more nuanced understanding of an individual's mental health.

In addition, AI systems are adept at processing data from wearable devices and mobile applications. These technologies monitor various behavioral indicators such as sleep patterns, physical activity, and social interactions. For example, wearable devices such as smartwatches and fitness trackers continuously record physiological metrics including heart rate variability and physical activity levels. By analyzing these data, AI can detect deviations from an individual's baseline behaviors, which may indicate the onset of depressive episodes. The integration of such diverse data sources helps create a holistic view of an individual's mental health, enhancing the accuracy of depression detection.

The process of utilizing AI for depression detection involves several crucial steps. Initially, data are collected from multiple sources to ensure a comprehensive assessment of mental health. These data undergo preprocessing to remove noise and standardize it for analysis. Preprocessing includes tasks such as cleaning text data, normalizing speech recordings, and filtering out irrelevant information. Then, feature extraction identifies relevant characteristics—such as keyword frequency in text, pitch variations in speech, or physiological changes in wearable data. AI models are then trained on labeled datasets, where instances of depression are known, using techniques such as classification algorithms and sentiment analysis. Cross-validation is employed to test the models' accuracy and reliability, ensuring that they perform well before being deployed in real-world applications. Once trained, these models are integrated into platforms that can provide real-time or periodic assessments of mental health, allowing for timely intervention.

The recent research highlights significant advancements in automatic depression detection. Zhang et al. [171] developed a DL-based system for detecting depression in social media users, demonstrating the potential of AI in analyzing textual data from online platforms. Choudhary et al. [172] proposed a model that utilizes spatiotemporal features with DL techniques to enhance detection accuracy. Yeul Kim et al. [173] introduced a system based on the Wartegg Zeichen test's image, employing CNNs for analysis. Liu et al. [174] focused on optimizing depression interventions through DL techniques, while Khan et al. [110] applied ML techniques based on temporal features for automatic detection. Nasim et al. [175] explored meta-learning techniques using questionnaire data. In addition, the research has expanded to include the use of AI models for analyzing social media text, blood DNA methylation, and speech data [176–178]. Chen et al. [23] demonstrated the effectiveness of IoMT-based multimodal approaches for depression detection. Pal et al. [56] introduces a novel system for detecting and reducing anxiety among university students using a smart belt combined with IIoMT and Mano Shakti Yoga (MSY). Over six weeks, 66 students with anxiety, identified via a SAS and smart belt data, were split into an experimental group undergoing MSY twice a week and a control group. ML algorithms achieved an 80% accuracy in classification. Results showed that MSY significantly reduced anxiety ($p < 0.05$) compared to the control group, demonstrating the effectiveness of integrating wearable technology with mindfulness practices for improving mental health in students. The procedure of this approach is presented in Figure 3.

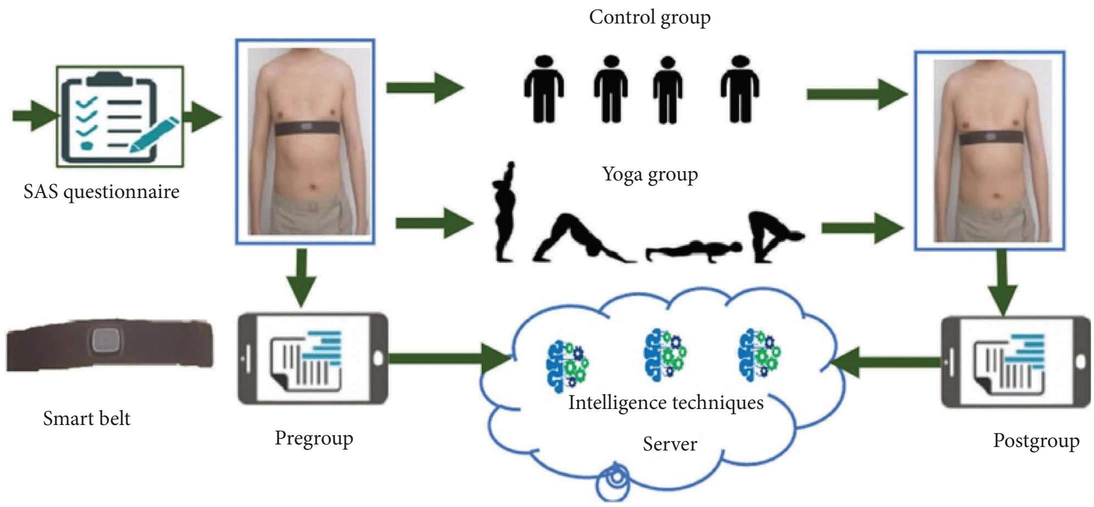

Figure 3: Automatic detection of anxiety based on smart belt in yoga practitioners [56].

Bin Heyat et al. [55] presents a study on an automatic mental stress detection system utilizing wearable smart T-shirts equipped with flexible cardiac electrodes and ML models (Figure 4). By analyzing ECG signals from 20 subjects (10 under mental stress after extensive laboratory work and 10 in a normal state post-rest) and employing scoring techniques such as the Chalder Fatigue Scale and DASS, the study aimed to identify stress levels. The research, which recorded 1800 min of ECG data, found that the DT classifier outperformed others in detecting intra-subject stress, with high recall (93.30%), specificity (96.70%), precision (94.40%), accuracy (93.30%), and $F1$-score (93.50%). For intersubject classification, the DT classifier achieved 94.10% accuracy. Key contributions include the introduction of flexible dry electrodes in smart T-shirts, the development of an automated stress detection system using demographic and ECG features, the exploration of feature relationships through clustering, and the comparative evaluation of ML classifiers to optimize stress detection accuracy.

AI offers several advantages over traditional methods of depression detection. It provides a more objective and consistent approach, minimizing the variability introduced by human judgment and personal biases. AI systems can analyze large volumes of data quickly, enabling the early detection of depression before it becomes severe, which facilitates timely intervention. In addition, AI's scalability allows it to reach a broader audience, including those in underserved or remote areas where mental health resources are limited. Continuous monitoring by AI systems ensures that assessments are not restricted to periodic check-ups but are conducted in real time, allowing for dynamic adjustments to treatment and support. Furthermore, AI can be seamlessly integrated with other health systems, such as mobile health apps and electronic health records, to enhance the overall management of mental health.

8. Bibliometric Analysis of the IIoMT on Depression

Between 2011 and 2024, the WoS database yielded 239 scientific materials on depression, with 216 being original research papers. These papers were notably frequent in publication. One set of papers averaged 2.54 citations, while the other set averaged 15.89 citations. The documents had 9032 references and a cumulative age of 48.6 years since publication. Five hundred and seventy-eight author keywords and more than 626 citation IDs were found in the document's contents. According to the survey, there were 1282 authors; of these, two published their articles as single authors, while 43 published with multiple authors. The 39 articles were published each year starting in 2020; the maximum number of articles published each year was 78 in 2022. The rise of papers published in 2022 suggested that there was a rising demand for studies on depression. In addition, the average number of citations each year was calculated by examining the number of citations these documents received. Table 4 illustrates the overall information on depression studies published in the WoS database from 2011 to 2024.

8.1. Greatest Influence and Relevance Within a Particular Geographic Area. The results of the top 10 sources that concentrated on depression articles and had the biggest local impact are shown in Table 5. It also includes the top 10 sources, as determined by the h factor, with the most notable local citations. According to the report, with 318 and 142 articles, respectively, the Journal of Affective Disorders and Public Library of Science (PloS) One had the most local citations.

The American Journal of Psychiatry and Psychological Medicine came in second and third, respectively, with 115 and 113 papers. According to the report, Journal of Affective

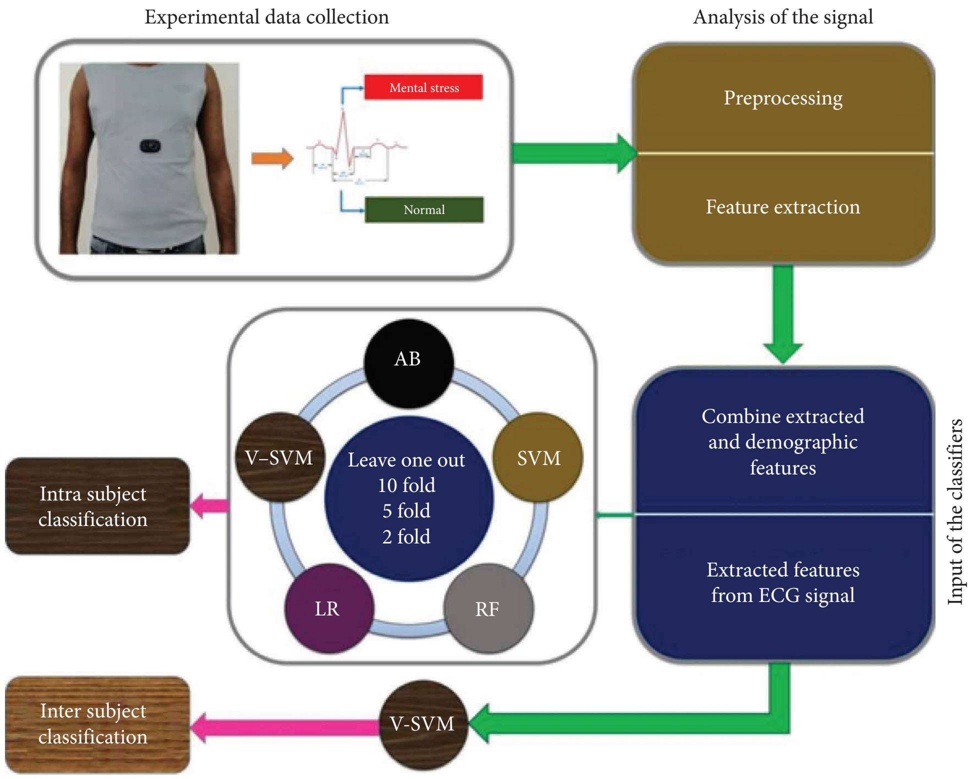

Figure 4: Smart t-shirt–based automatic mental stress detection system [55].

Table 4: Overall information on depression studies published in the Web of Science database from 2011 to 2024.

Description	Results
Main information about data	
Timespan	2011: 2024
Sources (journals and books)	125
Documents	216
Annual growth rate %	48.6
Document average age	2.54
Average citations per doc	15.89
References	9032
Document contents	
Keywords plus (ID)	626
Author's keywords (DE)	578
Authors	
Authors	1282
Single-author's docs	2
Authors' collaboration	
Single-author' docs	2
Co-authors per doc	6.86
International co-authorships %	43.06
Document type	
Article	216

Disorders, PloS One, Frontiers in Psychiatry, and Psychological Medicine were among the journals with a high citation rate. The Informatics journal additionally placed seventh with seven local citations (h-index: 3, m-index: 0, and total citation (TC): 70, respectively), while JMIR Formative Research, JMIR mHEALTH, and JMIR uHEALTH placed seventh and eighth for the local source effect, with TCs of 23 and 64 and corresponding h indices of three and three, respectively.

The American Journal of Psychiatry and Psychological Medicine followed closely behind with 115 and 113 papers, respectively. The report also reveals that the Journal of Affective Disorders, PloS One, Frontiers in Psychiatry, and Psychological Medicine were among the publications with a high citation rate. In addition, the Informatics journal ranked seventh with seven local citations (h-index: 3, m-index: 0.4, and TC: 70, respectively), while JMIR Formative Research and JMIR mHEALTH and uHEALTH placed seventh and eighth for the local source effect, with TCs of 23 and 64 and corresponding h-indices of three and three. One noteworthy local resource was "PloS One," a peer-reviewed scientific journal that has been released by the PloS since 2006 and covers a wide range of academic areas.

8.2. Highest Number of Citations Based on Locally and Globally. Tables 6 and 7 in this section list the papers that have garnered the most local and international citations from 2011 to 2022. The number of sources used to support a report's data analysis from other papers that were focused on the same subject is indicated by the local citation count. The impact of the writing is measured by a global citation count, which is the total number of citations within the database. Frequently, works on unrelated topics make up the majority of the critical citations for an article. An article's citation count does not necessarily indicate how good it is, but it does indicate how influential and well-known it is in

Table 5: Most relevant sources on depression articles.

Journal	Most significant local source imapct				Maximum local citation	Documents
	h-index	g-index	m-index	TC		
Journal of Affective Disorders	7	11	1.400	142	Journal of Affective Disorders	318
PloS One	5	7	0.455	91	PloS One	142
Frontiers in Psychiatry	4	8	0.667	106	American Journal of Psychiatry	115
Psychological medicine	4	4	0.800	49	Psychological medicine	113
IEEE Journal of Biomedical and Health Informatics	3	4	0.600	70	Journal of Medical Internet Research	103
JMIR Formative Research	3	4	0.750	23	Biological Psychiatry	99
JMIR mHEALTH and uHEALTH	3	3	0.600	64	NeuroImage	95
Journal of Alternative and Complementary Medicine	3	3	0.250	40	Archives of General Psychiatry	88
Journal of Medical Internet Research	3	4	0.500	40	British Journal of Psychiatry	78
Scientific Reports	3	3	0.750	77	Psychiatry Research	77

the field of study. Intriguingly, the number of local citations seems to boost a study's influence on continuing research efforts, such as those looking into depression. The paper with the most worldwide citations was written by Chekroud et al. [179] and was titled "Cross-Trial Prediction of Treatment Outcome in Depression: A ML Approach," with 328 total citations and an average of 41 citations per year. With a total of 241 citations and an average of 22 per year, the second-most cited article worldwide was written by Hosseinifard et al. [180] in 2013. An article written by Helbich et al. [162] that was published in 2019 and has 195 citations in the journal Environment International, is the third-most cited article.

Among the top 10 most cited publications, the work titled "Cross-Trial Prediction of Treatment Outcome in Depression: A ML Approach" was the most popular, proving its superiority. According to the citation data, the study by Chekroud et al. was one of the most widely and locally cited studies. The study by Chekroud received 328 worldwide and 19 local citations in total, placing it #1 in terms of local citations. The second-most mentioned local piece was Hosseinifard's study, with Islam's paper coming in third. Notably, Chekroud's work received more regional citations than international citations.

8.3. Comparison Between Keywords and Occurrences. Figure 5 shows these keywords provide information about the research's thematic focus and emphasis. The prevalence of terms such as "symptoms," "disorder," and "anxiety" indicates a noteworthy focus on characterizing and comprehending the psychological aspects and clinical presentations of depression in the context of IIoMT applications. Furthermore, using words such as "classification" and "prevalence" suggests that IoMT will be discussing the epidemiological and classification aspects of depression. The word "risk" frequently appears in the research, which emphasizes its investigation of variables that lead to the onset or worsening of depression. This may involve looking at risk assessment techniques or predictive models made possible by IoMT technologies.

In addition, the prominence of terms such as "health" and "mental health" points to a broader understanding of the comprehensive well-being of depressed people and the potential contribution of IoMT to the promotion and monitoring of mental health.

8.4. Spread or Dissemination of the Author Keywords. A bibliometric examination of author keywords over the current study period uncovered 578 keywords. The top 20 author keywords for articles on depression were analyzed and grouped. The node weight is represented by the size of the node and word, while the distance between them shows the strength of the relationship. The terms are connected by thin lines, with stronger lines denoting more co-occurrence. Color-matched nodes are clustered together. According to the research trend, the top four commonly used terms were "machine learning," "depression," "deep learning," and "artificial intelligence." Furthermore, the biblioshiny interface was used to examine the term spread of the top 20 most common keywords and coword networks. According to the results of the poll combined with the keywords, the top four commonly used terms were "machine learning," "anxiety," "mental health," and "classification." The author's keywords and these findings shared some similarities. Terms including "depression detection," "prediction," "EEG," "sentiment analysis," "major depressive disease," "diagnosis," "support vector machine," and "supervised machine learning" were among the top 20 most common searches, and these terms were similar to the author's keyword findings.

8.5. Highest Number of Citations and International Collaboration on a Global Scale. The top 10 nations with the most article citations, together with their overall and average citation counts, are shown in Table 8 and Figure 6. Notably, with a total of 1002, 474, 339, and 241, respectively, the United States, China, Germany, and Iran had the most citations. The four colors of the map show that there are more varied research trends today. Assessing interinstitutional partnerships can be a helpful strategy to gauge the degree of cooperation between nations and their exchange of involvement with top-tier countries in this area. The important nations are shown as vital nodes, and the links between them are symbolic of institutional ties. The degree of cooperation among the countries is shown by the distance between the nodes and the strength of the linkages. In addition, the thickness of the link between two countries is positively connected with the strength of their collaborative relationship, but the reverse is true. The United States of America, Israel, Japan, Sweden, and Korea had the strongest connections with the other nations in this cooperative network. The most important group, which included Canada and neighboring nations such as Brazil in addition to its local geographic area, was led by the United States. In terms of cross-border collaboration, the second group, which was led by the United Kingdom and included Singapore and Canada, might be regarded as one of the network's main centers.

The third group, which included the United States and France at the top, had a lot in common. Germany built beneficial friendships with other European nations such as Australia and India while maintaining close ties to Israel. Lastly, Pakistan and Saudi Arabia joined forces with the fourth group, which was led by Spain. In a similar vein, we discovered that Dartmouth College has the largest network of collaborators in the study of stress, anxiety, and depression.

8.6. Network Visualization Based on Previously Published Studies. Using *VOSviewer*, we created the network visualization based on previously published research (Figure 7). This network visualization contains 95 objects, 5 clusters, 3379 links, and 11,683 link strengths. The terms most closely related to our study were presented in this network visualization. To determine the precise task associated with

Table 6: Most relevant global citation documents.

DOI	1st author	Journal	TC	TC/year	Normalized TC
[179]	Chekroud	Lancet Psychiat	328	41.00	3.42
[180]	Hosseinifard	Comput Meth Prog Bio	241	21.91	1.81
[162]	Helbich et al.	Environ Int	195	39.00	5.74
[181]	Koutsouleris	Jama Psychiat	175	29.17	2.69
[182]	Fulmer	Jmir Ment Health	116	19.33	1.78
[183]	Nouretdinov	Neuroimage	105	8.08	1.00
[184]	Patel	Int J Geriatr Psych	90	10.00	1.69
[185]	Islam	Health Inf Sci Syst	89	14.83	1.37
[127]	Lin	Front Psychiatry	78	13.00	1.20
[186]	Ay	J Med Syst	77	15.40	2.27

Table 7: Most relevant local citation documents.

Reference	Year	LC	GC	LC/GC ratio (%)
[179]	2016	19	328	5.79
[180]	2013	9	241	3.73
[185]	2018	8	89	8.99
[121]	2020	7	24	29.17
[156]	2018	6	61	9.84
[187]	2015	5	35	14.29
[184]	2015	5	90	5.56
[188]	2016	5	38	13.16
[158]	2018	5	44	11.36
[186]	2019	5	77	6.49

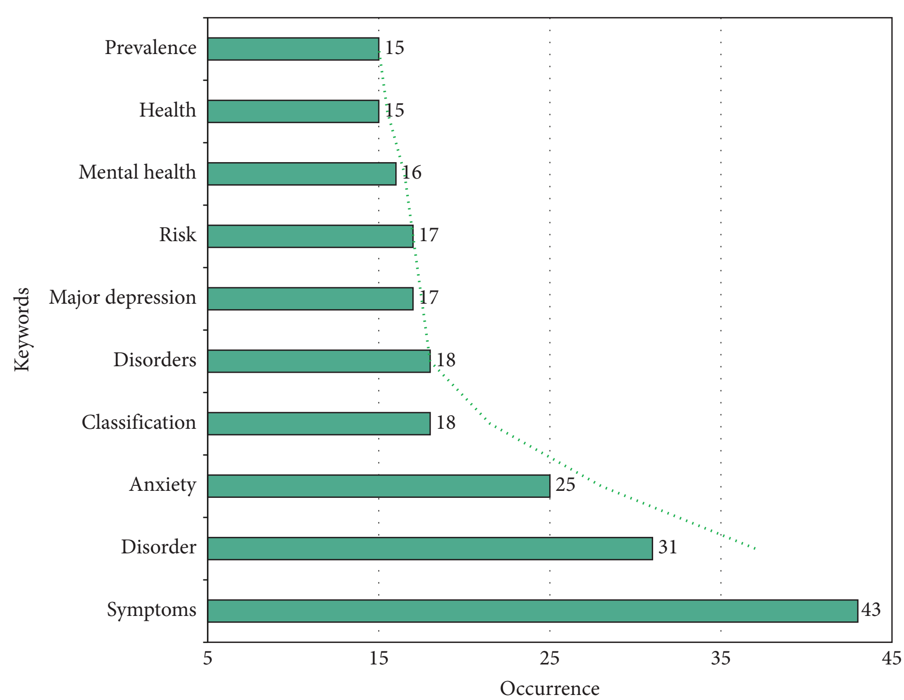

Figure 5: Comparison between most frequent keywords and occurrences.

IIoMT and depression, researchers, academicians, academics, scientists, and doctors would benefit from knowing the closest phrases. This research will create a new avenue for finding important and pertinent work on depression. Previously, we also implemented this technique in the field of premenstrual syndrome with oxidative stress [189], insomnia sleep disorder [190], bruxism sleep disorder [191], stress with ML [108], blockchain technology with cryptocurrency [192], anxiety with medical intelligence [193], lumpy skin disease [194], and smartphone addiction with

Table 8: Most relevant total citation countries.

Country	TC	Average article citations
United States of America	1002	20.45
China	474	11.85
Germany	339	56.50
Iran	241	24.10
Australia	143	14.30
Korea	133	7.00
United Kingdom	109	13.63
Denmark	106	53.00
Netherlands	98	19.60
Bangladesh	91	45.50

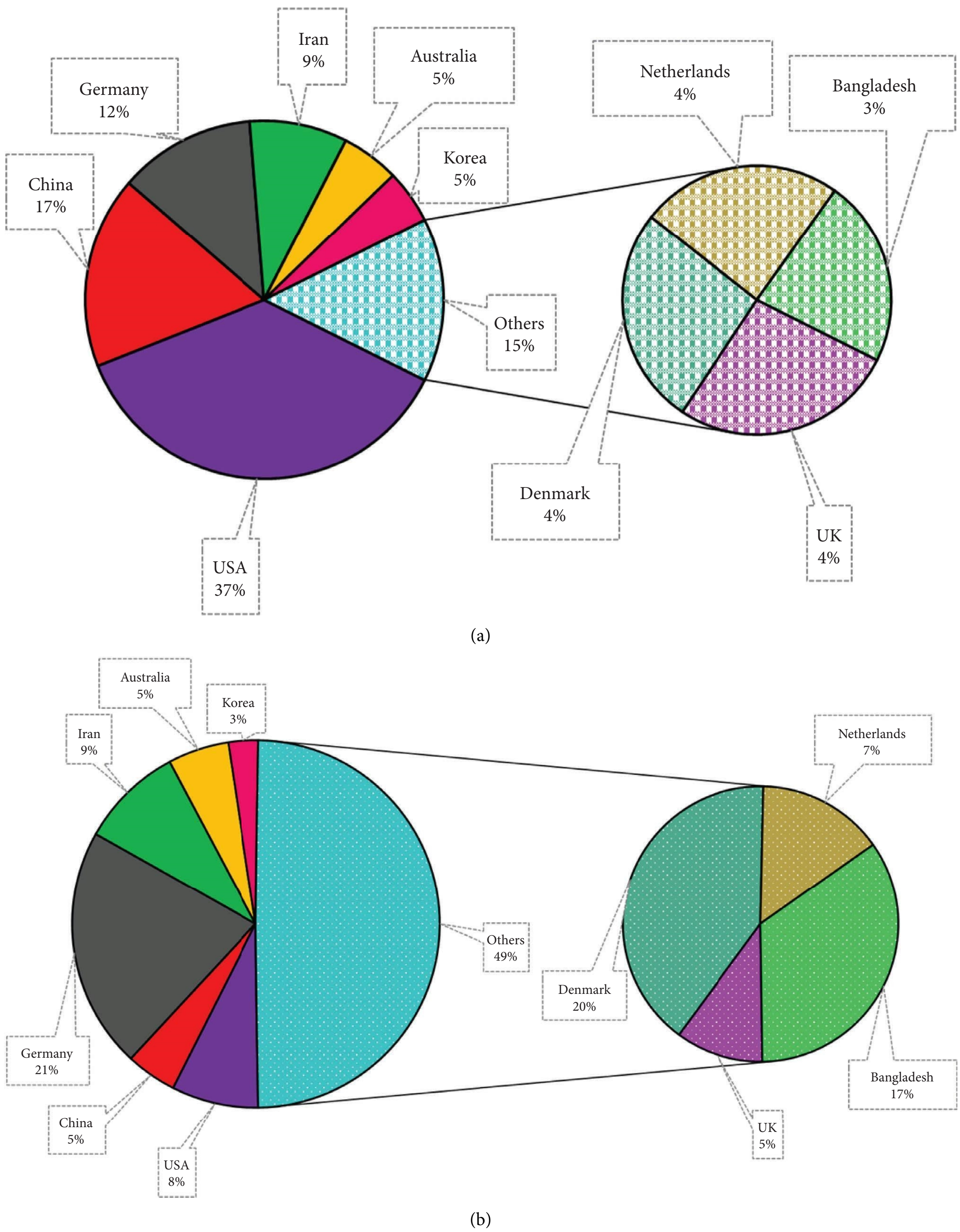

Figure 6: Top 10 nations based on (a) total and (b) average per article, citations.

oxidative stress [195]. In this study, we analyzed depression research using established and cutting-edge intelligent IoT methodologies.

Along with network visualization, we also provided detailed information about depression and its associations. We also provided the IIoMT architecture with problems and their fixes. For the identification, advice, categorization, and prediction of depression, we discovered that intelligent strategies are more precise and effective. Multidisciplinary specialists would benefit from our study because it combines intelligent approaches with biological and medicinal approaches.

9. Discussion

Integrating AI, IoT, and IoMT in managing depression offers numerous opportunities for enhancing mental health care, but it also brings several challenges that must be carefully navigated. This comprehensive approach leverages the strengths of both AI and IoMT to provide personalized, efficient, and accessible treatment for depression while also addressing concerns related to privacy, accuracy, technical implementation, and ethical considerations.

One of the most significant strengths of integrating AI with IoMT in treating depression is the ability to provide personalized treatment. AI algorithms can analyze data from various IoMT devices, such as wearable sensors, smart home devices, and mobile health applications, to create tailored treatment plans that address the unique needs of each individual. This data-driven approach enables dynamic adjustments to treatment plans based on real-time data, leading to more effective and responsive care. Similarly, there is the potential for early detection and prevention of depressive episodes and mental health care. Continuous monitoring through IoMT devices allows for the tracking of physiological and behavioral indicators, such as sleep patterns, activity levels, heart rate variability, and even speech patterns. AI can analyze these indicators to detect early signs of depression, enabling timely interventions that can prevent the progression of the disorder. Predictive analytics powered by AI can identify patterns and risk factors, potentially predicting depressive episodes before they occur, allowing for proactive measures to be taken. Remote monitoring capabilities allow patients to be observed in real-time without the need for frequent in-person visits, making mental health care more accessible to those who may have difficulties attending regular appointments due to geographical, physical, or logistical barriers. Telemedicine platforms enhanced with AI can offer immediate support and resources, including AI-powered chatbots and virtual therapists that provide round-the-clock assistance, thereby bridging gaps in care availability. Enhanced data collection and analysis are further strengths of this integration. AI can synthesize data from multiple IoMT devices to comprehensively view a patient's mental health. By processing vast amounts of data, AI can uncover insights that might be missed by traditional methods, leading to a more nuanced understanding of the factors contributing to depression. This comprehensive data integration enables healthcare providers to make more informed decisions, improving the overall quality of care.

Despite these significant strengths, notable weaknesses and challenges are associated with integrating AI with IoMT in managing depression. One of the primary concerns is data privacy and security. Mental health data are highly sensitive, and any breach of this information can have serious consequences for patients. Ensuring the privacy and security of data collected through IoMT devices and processed by AI systems is paramount. The accuracy and reliability of AI algorithms and IoMT devices also pose significant challenges. AI algorithms may be biased if they are trained on nonrepresentative datasets, leading to incorrect assessments or recommendations. Ensuring the reliability and accuracy of IoMT devices is equally important, as any malfunction or error can result in incorrect data being fed into AI systems, potentially leading to flawed conclusions and inappropriate interventions. Continuous validation and improvement of these technologies are necessary to maintain high standards of accuracy and reliability. Human oversight remains crucial in the integration of AI with IoMT to manage depression. While AI can provide valuable insights, clinical supervision is essential to interpret these data accurately and make informed decisions. There is a risk of over-reliance on AI, which could lead to the negligence of traditional clinical judgment and the important human element of patient-provider interactions. Striking the right balance between leveraging AI's capabilities and maintaining human oversight is critical for effective and compassionate mental health care.

For the diagnosis of depression and its treatment, several methodologies have been put forth. Most of the investigations used various diagnosis methods, such as questionnaires used for self-reporting. Extensions to this include numerous multimodal techniques, but the results are subpar. To benefit patients, clinicians, and society, we should explore more efficient procedures and multimodal approaches instead of fixating on time limitations and diagnostic accuracy alone. There is a chance that patients are giving inaccurate information in the authors' discussion [118] of the lack of information regarding patients' histories and socioeconomic circumstances from various geographic places. Geographical and satirical region diversifications are essential inputs. Studies using many modalities that combine patient biomarkers with electronic health record data and various other criteria can provide reliable and accurate predictions of the stages of depression, the impact of treatment, and predicted results. The majority of the studies included methods of diagnosis, such as self-reporting questionnaires. Extensions of this include numerous multimodal strategies currently in use, although the results are subpar. Contrary to time restrictions and the accuracy of diagnosis, we need to think about more effective methods and multimodal strategies that will benefit patients, medical professionals, and society as a whole.

This review uses bibliometric analysis to examine the development of knowledge tracking and assess research trends in depression as one of its key goals. Our study

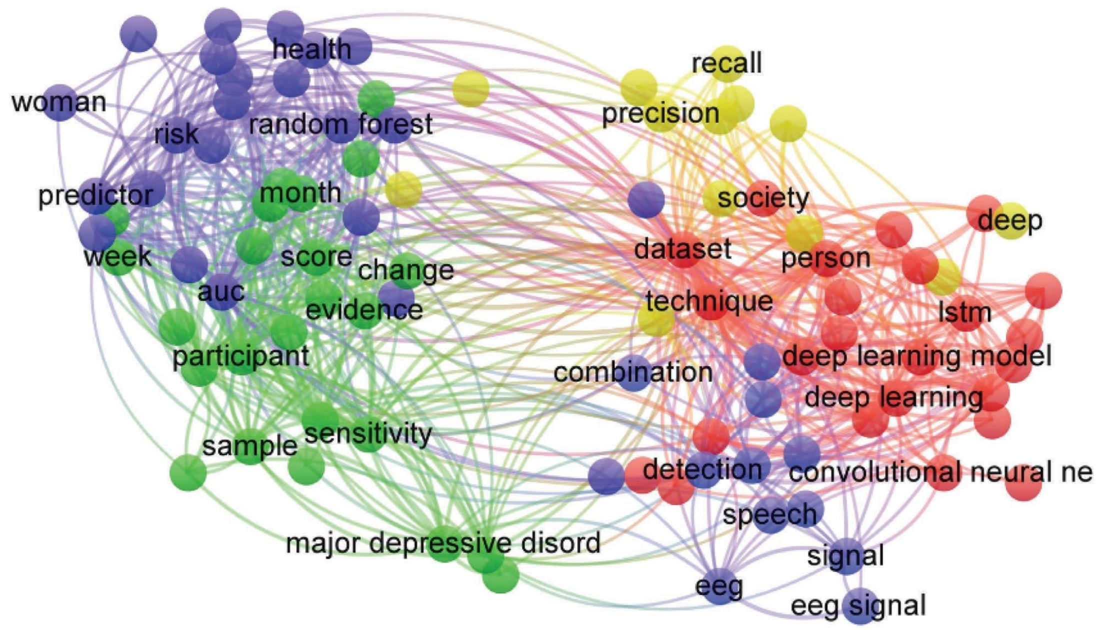

Figure 7: Network visualization based on existing studies using *VOSviewer*.

showed that the research production has significantly increased in recent years, highlighting the necessity for a thorough evaluation of the state of depression research to direct future research goals. In order to conduct a global bibliometric analysis of depression research, we looked at publishing patterns, prolific authors, journals, and nations. Our findings imply that a good indicator of output and progress in the discipline is the number of publications in that field. Notably, the most significant national and international citations for research on depression were given to the Journal of Affective Disorders and Frontiers in Psychiatry. Throughout the study period, we noticed fluctuations in the volume of publications on depression, with a general uptick in 2022.

A national-level summary of the development of depression research in nations on several continents was also offered by the analysis. Germany and the United States were notably active in the field of depression study, with American contributions predominating in all other scholarly journals. According to our analysis, the United States of America collaborated with other countries more frequently than any other country, with the closest relationships being experts from the United States, Germany, and China. Furthermore, our findings suggest that most countries were interconnected through a network of cooperation, as indicated by the lines on the network map. In terms of citations and h-index, China, the United States, and Germany were the top three countries. According to the statistics, Turecki and Benrimoh were the writers who had the biggest influence on depression research, and Dartmouth College was one of the key institutions and organizations in the field.

Last but not least, the keyword co-occurrence analysis revealed several study topics of interest to scientists, with "ML" and "depression" appearing most frequently. As a result, our study offers insightful information on the development of the depression research that might guide future research goals and promote collaborations between researchers in other domains.

Incorporating bibliometric analysis into research has become increasingly common due to its diverse applications and benefits [196]. Firstly, the bibliometric analysis allows researchers to gain insights into previously published works, facilitating a comprehensive understanding of the existing literature relevant to their field of study. By analyzing publication details such as authorship, citation counts, and journal impact factors, researchers can identify seminal papers, influential authors, and key research trends, aiding in the formulation of research questions and hypotheses. Moreover, the bibliometric analysis enables the assessment of research productivity and impact on a global scale, providing valuable metrics such as country-wise publication distributions and citation indices such as the h-index. These metrics not only assist researchers in benchmarking their own performance but also aid funding agencies, academic institutions, and policymakers in evaluating the impact of research outputs and allocating resources effectively. In addition, the bibliometric analysis facilitates interdisciplinary collaboration by mapping collaboration networks and identifying potential research partners across different institutions and geographic regions. Furthermore, authors conducted the bibliometric analysis to track the dissemination and impact of their own work, monitor citation trends, and identify potential avenues for future research. Overall, the bibliometric analysis serves as a powerful tool for researchers to navigate the vast landscape of scholarly literature, assess research impact, and make informed decisions in their academic pursuits [197–199].

10. Current Challenges and Issues

It is crucial to acknowledge that the literature data sources for this study were limited to the WoS database, which may not provide a comprehensive understanding of depression. Nevertheless, the study drew from high-quality international journals, which serve as the foremost source of scientific communication in the field. Furthermore, because the terminology used in abstracts was not considered, the study might have missed some articles that do not employ instructional keywords in the title. The gray literature and articles written in languages other than English were also excluded, and any reference lists of eligible articles that would have pointed to any potentially missing studies. This may have led to the omission of pertinent documents that were published in conference proceedings and gazettes. The study also identified trends in scientific discoveries that are likely to have an impact on future research initiatives by focusing purely on the scientific research literature.

Depression, a prevalent mental health condition, affects millions worldwide. With advancements in technology and the Internet, IoT has a growing interest in utilizing intelligent IoT systems for the detection, prediction, and analysis of depression. These systems leverage connected devices and sensors to gather continuous data about individuals' behaviors, activities, and physiological parameters. While promising, implementing IoT-based solutions for depression detection presents several complex challenges that need to be addressed to ensure efficacy, accuracy, and ethical standards. This section highlights various research challenges in detecting, analyzing, predicting, and monitoring depression using Intelligent IoT. The detailed challenges and issues are given below.

10.1. Data Quality and Reliability. IoT devices are used for monitoring depression symptoms that rely heavily on data collected from various sensor devices, such as heart rate monitors, sleep trackers, and accelerometers. The major challenges lie in the reliability and quality of the collected data as various factors, including noise, environmental interference, and sensor accuracy, impact the data. Intelligent approaches, such as ML and DL, are used to analyze depression, which depends on input data's reliability and quality. Thus, ensuring data quality and implementing robust data validation techniques are critical for reliable depression detection and prediction.

10.2. Interpretation of Behavioral Cues. Analyzing IoT-generated data to detect subtle behavioral cues indicative of depression poses a significant challenge. Depression manifests differently in individuals, making it challenging to develop standardized behavioral models. ML and AI algorithms need to interpret complex behavioral patterns accurately. Contextual understanding of behavior, such as changes in social interactions, sleep patterns, and physical activity, is crucial for reliable depression analysis. There is a dearth of IoT-generated data on the long-term effects of depression treatments despite many of them being helpful in the short term. It is necessary to conduct further research to comprehend the long-term effects of depression and its treatment on people's physical and mental health as well as on society at large.

10.3. Privacy and Data Security. IoT devices collect sensitive data related to individuals' mental health, which raises significant privacy and security concerns. Ensuring data encryption, secure transmission, and storage protocols are essential to protect users' confidentiality and prevent unauthorized access. Privacy-preserving techniques such as data anonymization and decentralized data processing must be implemented to maintain individuals' privacy rights and comply with data protection regulations.

10.4. Long-Term Monitoring and User Engagement. The co-occurrence of depression with other mental and physical health issues is common, which can make diagnosis and treatment more challenging. In order to create effective interventions for people with comorbid disorders, the research is required better to understand the connections between depression and other health issues. The availability of mental health services, particularly treatment for depression, is frequently restricted by issues including cost, location, and stigma. These care-related obstacles must be identified and addressed to create efficient solutions available to everyone. Continuous monitoring of depression symptoms over extended periods using IoT devices requires addressing user engagement and device usability challenges. Maintaining user motivation and compliance with IoT-based monitoring protocols can be difficult. Factors such as device comfort, battery life, and user experience play a crucial role in ensuring long-term user engagement and adherence to monitor programs.

10.5. Ethical Considerations and Stigma. The use of IoT for mental health monitoring raises important ethical considerations, particularly regarding consent, autonomy, and stigma. Individuals must have control over their data and be informed about how these will be used. Ensuring transparency in data collection and analysis processes is essential to build trust and minimize stigma associated with mental health monitoring technologies. When conducting the research on depression, ethical issues must be considered, just like in other fields of study. For instance, researchers must weigh the potential advantages of novel therapies against the risks of harm to study participants. They also must make sure that the research is carried out with cultural sensitivity and respect.

10.6. Integration and Interoperability. Integrating diverse IoT devices and sensors into a unified platform for depression monitoring requires addressing interoperability challenges. Different devices may use varying data formats, communication protocols, and data transmission rates. Ensuring seamless integration and interoperability among IoT components is essential for creating a comprehensive and effective depression monitoring system. The creation of new technology and tools for researching depression presents a challenge for engineering researchers. For instance, while neuroimaging methods such as fMRI and EEG have contributed to our understanding of the neurological mechanisms underlying depression, their capacity to portray the disorder's complex and dynamic character is constrained [200, 201].

10.7. Personalization and Adaptability. Depression is a highly personalized condition, and its symptoms can vary widely among individuals. Developing personalized IoT-based depression monitoring systems that can adapt to individual differences is crucial for accurate assessment and intervention. Accurate diagnosis of depression is one of the problems with the depression research. There are no particular biomarkers or tests that can accurately diagnose depression because it is a complicated condition that can manifest in a variety of ways. Furthermore, depression frequently co-occurs with other mental health conditions, such as anxiety or substance use disorders, making diagnosis and treatment more difficult. ML models must be trained on diverse datasets to account for individual variability and ensure generalizability across different population groups.

10.8. Validation and Clinical Adoption. Validating the effectiveness and clinical utility of IoT-based depression monitoring systems is a critical challenge. Robust clinical trials and studies are needed to evaluate these systems' accuracy, sensitivity, and specificity compared to traditional assessment methods. Collaborating with mental health professionals and regulatory bodies to validate IoT-based depression monitoring solutions is essential for their widespread adoption and integration into clinical practice. Although many people with depression find that drugs work well for them, nonpharmacological treatments such as psychotherapy, physical activity, and mindfulness-based approaches are gaining popularity. Research is required to determine the people who may benefit from these treatments and better understand the underlying mechanisms. Despite the fact that depression is frequently categorized as a mental health disease, the psychological processes that cause depression are still not entirely understood. It is necessary to conduct more research using more wearable devices to comprehend how psychological elements such as stress, trauma, and personality features may contribute to the onset, monitoring, and maintenance of depression.

11. New Prospective

Our study covered a range of investigations into the effects of depression on patients' general QoL. Future research can address various issues and shortcomings, starting with proposing a multimodal diagnostic strategy to handle depression diagnosis. At the same time, we can consider creating new models for early diagnosis that support boosting treatment effectiveness. Diagnostic methods used in telemedicine would aid the treatment. We can envision microbiota analysis and stimulation as ways to improve patient care. Last but not least, we can use several techniques, including fMRI, MRI, EEG, ECG, and facial expression recognition. In general, understanding depression diagnosis and treatment outcomes can be aided by yoga and integrative medicine interventions. Future research on depression may also examine a number of additional areas of the studies given below:

11.1. IoT Devices for Detection and Monitoring. IoT devices are playing a transformative role in the early detection and continuous monitoring of depressive symptoms. These devices, equipped with sensors and connectivity, gather real-time data on various physiological and behavioral parameters, providing valuable insights into an individual's mental state. For instance, wearable biosensors can track changes in heart rate variability, sleep patterns, activity levels, and skin conductance—biomarkers that correlate with depressive symptoms. By continuously collecting and analyzing these data points in real-time, IoT systems can detect subtle changes indicative of depressive episodes. ML algorithms can process this information, learning individual patterns and detecting deviations that may signal the onset of depressive episodes. Real-time monitoring and analysis of brain activity using brain-computer interfaces (BCIs) could lead to new understandings of the neurological mechanisms causing depression. BCIs could also be utilized to create fresh approaches to brain stimulation therapy for depression. This proactive monitoring enables timely interventions, such as alerts to caregivers or healthcare providers, enhancing early intervention strategies. Similarly, blockchain technology may be utilized to provide safe and confidential platforms for exchanging health information, opening the door to increased collaboration and inventiveness in the field of treating and researching depression.

11.2. Predictive Analytics and Risk Assessment. IoT-driven predictive analytics hold promise in identifying individuals at higher risk of developing depression. By integrating diverse data sources—ranging from social media activity and smartphone usage patterns to environmental factors—IoT platforms can create comprehensive risk profiles. For example, NLP algorithms can analyze text data from social media posts to identify linguistic markers associated with depressive tendencies.

Combining these insights with demographic, genetic, and lifestyle data enables the development of personalized risk models. These models can predict the likelihood of depressive episodes with increasing accuracy, facilitating targeted preventive interventions. Early identification of high-risk individuals empowers healthcare providers to implement tailored interventions, potentially reducing the severity and frequency of depressive episodes. There is still a lack of research in the prevention and treatment of efficient therapies for depression. Researchers may, for instance, look into the effectiveness of complementary therapies such as exercise, mindfulness-based interventions, and dietary changes in preventing or treating depression.

11.3. Ambient Assistive Technologies. IoT-enabled ambient assistive technologies are reshaping the therapeutic landscape for individuals with depression. Smart home devices equipped with voice assistants and adaptive lighting systems can create supportive environments responsive to emotional states. For instance, these systems can adjust room lighting based on mood cues or play soothing music in response to stress indicators.

Moreover, IoT-driven virtual reality (VR) and augmented reality (AR) applications offer immersive therapeutic experiences. Anxiety and PTSD are two mental health issues that VR and AR can have promising future in treatment. VR simulations can provide exposure therapy for anxiety or depression in controlled environments, offering a safe space for cognitive-behavioral interventions. AR applications overlay contextual information in real time, aiding individuals in navigating challenging social situations or managing daily activities.

11.4. Data-Driven Insights and Treatment Optimization. The integration of IoT data with advanced analytics presents opportunities for refining treatment strategies and optimizing outcomes for individuals with depression. By aggregating real-world data from diverse IoT sources—clinical records, wearable devices, and patient-reported outcomes—healthcare providers gain comprehensive insights into treatment efficacy and patient response.

Analyzing these data using AI algorithms unveils patterns and correlations unobservable through traditional methods. These insights inform personalized treatment plans, guiding medication adjustments or therapy modifications tailored to individual needs. Furthermore, real-time feedback loops enabled by IoT technologies facilitate continuous monitoring of treatment adherence and progress, fostering collaborative patient-provider relationships.

While a substantial corpus of studies has been done on the molecular causes of depression, additional research is still required to fully comprehend the neurobiology of this condition. Researchers could, for instance, look at the role that neurotransmitters, hormones, and genetics play in the onset of depression. With other mental health diseases and physical illnesses, depression frequently coexists. The relationships between depression and other illnesses such as anxiety, BPD, and cardiovascular disease could be studied in the future using various wearable devices.

11.5. Ethical Considerations and Challenges. While IoT-driven innovations offer transformative benefits, they also raise ethical considerations and challenges. Data privacy and security remain paramount, necessitating robust encryption protocols and transparent consent mechanisms. Furthermore, biases inherent in AI algorithms must be mitigated to ensure equitable and accurate outcomes across diverse populations.

Integration into existing healthcare systems requires interdisciplinary collaboration and regulatory frameworks to ensure safety and efficacy. In addition, addressing the digital divide—ensuring equitable access to IoT technologies—is essential to prevent exacerbating healthcare disparities.

12. Conclusions

The IIoMT is catalyzing a paradigm shift in the detection, prediction, and analysis of depression. By harnessing IoT devices and advanced analytics, healthcare systems are moving towards personalized, proactive, and data-driven approaches to mental health care. Embracing this technological revolution requires navigating ethical challenges and fostering inclusive innovation, ultimately enhancing outcomes and QoL for individuals affected by depression. This review offers a thorough analysis of the interaction between AI, IoMT, and depression that examines various characteristics and pertinent major difficulties. The paper covers a variety of depression prevention strategies, and detailed discussion of depression and bibliometric analyzes of depression in various contexts. In identifying, analyzing, and monitoring depression, the paper also contrasts conventional and intelligent approaches. In addition, it describes the IIoMT architecture used for identifying and monitoring depression. Finally, a thorough discussion of the difficulties, problems, and potential future prospects for research into the integration of depression and IIoMT applications was conducted.

Data Availability Statement

All data used in this study are available within this paper.

Conflicts of Interest

The authors declare no conflicts of interest.

Author Contributions

Md Belal Bin Heyat: conceptualization, data curation, methodology, formal analysis, software, validation, and writing–original draft; Deepak Adhikari: data curation, methodology, investigation, validation, visualization, and writing–review and editing; Faijan Akhtar: conceptualization, methodology, formal analysis, software, validation, and writing–original draft; Saba Parveen and Hafiz Muhammad Zeeshan: data curation, methodology, investigation, visualization, and writing–review and editing; Hadaate Ullah: conceptualization, formal analysis, funding acquisition, resources, supervision, project administration, and writing–review and editing; Yun-Hsuan Chen: data curation, formal analysis, investigation, validation, resources, and writing–review and editing; Lu Wang and Mohamad Sawan: conceptualization, formal analysis, funding acquisition, resources, supervision, project administration, and writing–review and editing. All authors read and agreed for the publication.

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References

[1] J. Xiong, O. Lipsitz, F. Nasri, et al., "Impact of COVID-19 Pandemic on Mental Health in the General Population: A Systematic Review," *Journal of Affective Disorders* 277 (2020): 55–64, https://doi.org/10.1016/j.jad.2020.08.001.

[2] M. S. Reddy, "Depression: The Disorder and the Burden," *Indian Journal of Psychological Medicine* 32 (2010): 1–2, https://doi.org/10.4103/0253-7176.70510.

[3] Y. Zenebe, B. Akele, M. W/Selassie, and M. Necho, "Prevalence and Determinants of Depression Among Old Age: A Systematic Review and Meta-Analysis," *Annals of General Psychiatry* 20 (2021): https://doi.org/10.1186/s12991-021-00375-x.

[4] K. J. MacLeod, S. English, S. K. Ruuskanen, and B. Taborsky, "Stress in the Social Context: A Behavioural and Eco-Evolutionary Perspective," *Journal of Experimental Biology* 226 (2023): https://doi.org/10.1242/jeb.245829.

[5] B. Feng, J. Harms, E. Chen, P. Gao, P. Xu, and Y. He, "Current Discoveries and Future Implications of Eating Disorders," *International Journal of Environmental Research and Public Health* 20 (2023): 6325, https://doi.org/10.3390/ijerph20146325.

[6] C. P. C. Galts, L. E. B. Bettio, D. C. Jewett, et al., "Depression in Neurodegenerative Diseases: Common Mechanisms and Current Treatment Options," *Neuroscience & Biobehavioral Reviews* 102 (2019): 56–84, https://doi.org/10.1016/j.neubiorev.2019.04.002.

[7] M. S. Iqbal, M. Belal Bin Heyat, S. Parveen, et al., "Progress and Trends in Neurological Disorders Research Based on Deep Learning," *Computerized Medical Imaging and Graphics* 116 (2024): 102400, https://doi.org/10.1016/j.compmedimag.2024.102400.

[8] J. C. Prisnie, T. T. Sajobi, M. Wang, et al., "Effects of Depression and Anxiety on Quality of Life in Five Common Neurological Disorders, Gen. Hosp," *Psychiatry* 52 (2018): 58–63, https://doi.org/10.1016/j.genhosppsych.2018.03.009.

[9] M. Bekhbat and G. N. Neigh, "Sex Differences in the Neuro-Immune Consequences of Stress: Focus on Depression and Anxiety," *Brain, Behavior, and Immunity* 67 (2018): 1–12, https://doi.org/10.1016/j.bbi.2017.02.006.

[10] S. Evans-Lacko, S. Aguilar-Gaxiola, A. Al-Hamzawi, et al., "Socio-economic Variations in the Mental Health Treatment Gap for People With Anxiety, Mood, and Substance Use Disorders: Results From the WHO World Mental Health (WMH) Surveys," *Psychological Medicine* 48 (2018): 1560–1571, https://doi.org/10.1017/S0033291717003336.

[11] Universidad de Washington, Global Health Data Exchange, *Institute for Health Metrics and Evaluation* (2023).

[12] M. Kang, H. Kwon, J. H. Park, S. Kang, and Y. Lee, "Deep-Asymmetry: Asymmetry Matrix Image for Deep Learning Method in Pre-Screening Depression," *Sensors* 20 (2020): 1–12, https://doi.org/10.3390/s20226526.

[13] X. Wang, S. Chen, T. Li, et al., "Depression Risk Prediction for Chinese Microblogs via Deep-Learning Methods: Content Analysis," *JMIR Medical Informatics* 8 (2020): e17958, https://doi.org/10.2196/17958.

[14] X. Li, R. La, Y. Wang, B. Hu, and X. Zhang, "A Deep Learning Approach for Mild Depression Recognition Based on Functional Connectivity Using Electroencephalography," *Frontiers in Neuroscience* 14 (2020): https://doi.org/10.3389/fnins.2020.00192.

[15] B. Little, O. Alshabrawy, D. Stow, et al., "Deep Learning-Based Automated Speech Detection as a Marker of Social Functioning in Late-Life Depression," *Psychological Medicine* 51 (2021): 1441–1450, https://doi.org/10.1017/S0033291719003994.

[16] P. P. Thoduparambil, A. Dominic, and S. M. Varghese, "EEG-Based Deep Learning Model for the Automatic Detection of Clinical Depression," *Physical and Engineering Sciences in Medicine* 43 (2020): 1349–1360, https://doi.org/10.1007/s13246-020-00938-4.

[17] M. Mujib, S. Sukestiyarno, H. Suyitno, and I. Junaedi, "Mathematical Critical Thinking Profile-Based Ennis and Gardner's Theory of Multiple Intelligences," *AlphaMath: Journal Mathematics Education* 8 (2022): 60, https://doi.org/10.30595/alphamath.v8i1.13374.

[18] F. Kousar, A. Sultana, M. Al Albahar, et al., "A Cross-Sectional Study of Parental Perspectives on Children about COVID-19 and Classification Using Machine Learning Models," *Frontiers in Public Health* 12 (2024): https://doi.org/10.3389/fpubh.2024.1373883.

[19] C. Chola, M. B. Bin Heyat, F. Akhtar, et al., "IoT Based Intelligent Computer-Aided Diagnosis and Decision Making System for Health Care," in *2021 International Conference on Information Technology ICIT 2021* (Amman, Jordan, July 2021), 184–189, https://doi.org/10.1109/ICIT52682.2021.9491707.

[20] R. Abbasi, A. K. Bashir, A. O. Almagrabi, M. B. Bin Heyat, and G. Yuan, "Efficient Lossless Based Secure Communication in 6G Internet-Of-Things Environments," *Sustainable Energy Technologies and Assessments* 57 (2023): 103218, https://doi.org/10.1016/j.seta.2023.103218.

[21] H. M. Zeeshan, M. B. Bin Heyat, M. A. Bin Hayat, et al., "Worldwide Research Trends and Hotspot on IOMT Based on Bibliometric Analysis," in *2023 20th International Computer. Conference on Wavelet Active. Media Technology and. Information Processing. (ICCWAMTIP 2023)* (Chengdu, China: IEEE, December 2023), 1–14, https://doi.org/10.1109/ICCWAMTIP60502.2023.10387075.

[22] R. Pal, D. Adhikari, M. B. Bin Heyat, I. Ullah, and Z. You, "Yoga Meets Intelligent Internet of Things: Recent Challenges and Future Directions," *Bioengineering* 10 (2023): 459, https://doi.org/10.3390/bioengineering10040459.

[23] J. Chen, Y. Hu, Q. Lai, et al., "IIFDD: Intra and Inter-Modal Fusion for Depression Detection With Multi-Modal Information From Internet of Medical Things," *Information Fusion* 102 (2024): https://doi.org/10.1016/j.inffus.2023.102017.

[24] G. Sharma, A. M. Joshi, and E. S. Pilli, "DepML: An Efficient Machine Learning-Based MDD Detection System in IoMT Framework," *SN Computer Science* 3 (2022): https://doi.org/10.1007/s42979-022-01250-6.

[25] A. Kumar, S. R. Sangwan, A. Arora, and V. G. Menon, "Depress-DCNF: A Deep Convolutional Neuro-Fuzzy Model for Detection of Depression Episodes Using IoMT," *Applied Soft Computing* 122 (2022): 108863, https://doi.org/10.1016/j.asoc.2022.108863.

[26] I. Jeya Daisy, B. V. Kumar, and M. Krishnamoorthy, "Early-Stage Depression Detector Using IoMT," in *2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA 2021)* (Virtual Conference, October 2021), https://doi.org/10.1109/ICAECA52838.2021.9675629.

[27] S. Parveen, M. B. Bin Heyat, F. Akhtar, et al., "Interweaving Artificial Intelligence and Bio-Signals in Mental Fatigue: Unveiling Dynamics and Future Pathways," in *2023 20th International Computer. Conference on Wavelet Active. Media Technology and. Information Processing. (ICCWAMTIP 2023)* (Chengdu, China: IEEE, December 2023), 1–9, https://doi.org/10.1109/ICCWAMTIP60502.2023.10387132.

[28] A. Sultana, F. Akhtar, M. B. Bin Heyat, et al., "Unveiling the Efficacy of Unani Medicine in Female Disorders Through Machine Learning: Current Challenges and Opportunities," in *2023 20th International Computer. Conference on Wavelet Active. Media Technology and. Information Processing. (ICCWAMTIP 2023)* (Chengdu, China: IEEE, December 2023), 1–6, https://doi.org/10.1109/ICCWAMTIP60502.2023.10385245.

[29] C. Zhu, "Computational Intelligence-Based Classification System for the Diagnosis of Memory Impairment in Psychoactive Substance Users," *Journal of Cloud Computing* 13 (2024): 119, https://doi.org/10.1186/s13677-024-00675-z.

[30] C. Zhu, "Research on Emotion Recognition-Based Smart Assistant System: Emotional Intelligence and Personalized Services," *Journal of System and Management Sciences* 13 (2023): https://doi.org/10.33168/JSMS.2023.0515.

[31] M. M. Misgar and M. P. S. Bhatia, "Detection of Depression from IoMT Time Series Data Using UMAP Features," in *3rd IEEE International Conference on Computing, Communication, and Intelligent Systems (ICCCIS-2022)* (Greater Noida, India: IEEE, November 2022), 623–628, https://doi.org/10.1109/ICCCIS56430.2022.10037751.

[32] L. Squarcina, F. M. Villa, M. Nobile, E. Grisan, and P. Brambilla, "Deep Learning for the Prediction of Treatment Response in Depression," *Journal of Affective Disorders* 281 (2021): 618–622, https://doi.org/10.1016/j.jad.2020.11.104.

[33] N. V. Babu and E. G. M. Kanaga, "Sentiment Analysis in Social Media Data for Depression Detection Using Artificial Intelligence: A Review," *SN Computer Science* 3 (2022): 74, https://doi.org/10.1007/s42979-021-00958-1.

[34] G. Obaido, B. Ogbuokiri, T. G. Swart, et al., "An Interpretable Machine Learning Approach for Hepatitis B Diagnosis," *Applied Sciences* 12 (2022): 11127, https://doi.org/10.3390/app122111127.

[35] S. A. Ebiaredoh-Mienye, E. Esenogho, and T. G. Swart, "Integrating Enhanced Sparse Autoencoder-Based Artificial Neural Network Technique and Softmax Regression for Medical Diagnosis," *Electron* 9 (2020): 1–13, https://doi.org/10.3390/electronics9111963.

[36] S. A. Ebiaredoh-Mienye, T. G. Swart, E. Esenogho, and I. D. Mienye, "A Machine Learning Method With Filter-Based Feature Selection for Improved Prediction of Chronic Kidney Disease," *Bioengineering* 9 (2022): 350, https://doi.org/10.3390/bioengineering9080350.

[37] A. Khosla, P. Khandnor, and T. Chand, "Automated Diagnosis of Depression from EEG Signals Using Traditional and Deep Learning Approaches: A Comparative Analysis," *Biocybernetics and Biomedical Engineering* 42 (2022): 108–142, https://doi.org/10.1016/j.bbe.2021.12.005.

[38] H. Pan, Z. Li, Y. Fu, X. Qin, and J. Hu, "Reconstructing Visual Stimulus Representation from EEG Signals Based on Deep Visual Representation Model," *IEEE Transactions on Human-Machine Systems* 54 (2024): 711–722, https://doi.org/10.1109/THMS.2024.3407875.

[39] A. Malhotra and R. Jindal, "Deep Learning Techniques for Suicide and Depression Detection From Online Social Media: A Scoping Review," *Applied Soft Computing* 130 (2022): https://doi.org/10.1016/j.asoc.2022.109713.

[40] L. He, M. Niu, P. Tiwari, et al., "Deep Learning for Depression Recognition With Audiovisual Cues: A Review," *Information Fusion* 80 (2022): 56–86, https://doi.org/10.1016/j.inffus.2021.10.012.

[41] P. D. Barua, J. Vicnesh, O. S. Lih, et al., "Artificial Intelligence Assisted Tools for the Detection of Anxiety and Depression Leading to Suicidal Ideation in Adolescents: A Review," *Cognitive Neurodynamics* 18 (2024): 1–22, https://doi.org/10.1007/s11571-022-09904-0.

[42] U. Yadav, A. K. Sharma, and D. Patil, "Review of Automated Depression Detection: Social Posts, Audio and Video, Open Challenges and Future Direction," *Concurrency and Computation: Practice and Experience* 35 (2023): https://doi.org/10.1002/cpe.7407.

[43] A. Abd-Alrazaq, R. AlSaad, F. Shuweihdi, A. Ahmed, S. Aziz, and J. Sheikh, "Systematic Review and Meta-Analysis of Performance of Wearable Artificial Intelligence in Detecting and Predicting Depression," *npj Digital Medicine* 6 (2023): https://doi.org/10.1038/s41746-023-00828-5.

[44] M. B. Bin Heyat, F. Akhtar, F. Munir, et al., "Unravelling the Complexities of Depression with Medical Intelligence: Exploring the Interplay of Genetics, Hormones, and Brain Function," *Complex and Intelligent Systems* 10 (2024): 5883–5915, https://doi.org/10.1007/s40747-024-01346-x.

[45] L. Wang, X. Wang, L. Deng, et al., "Pexidartinib (PLX3397) Through Restoring Hippocampal Synaptic Plasticity Ameliorates Social Isolation-Induced Mood Disorders," *International Immunopharmacology* 113 (2022): 109436, https://doi.org/10.1016/j.intimp.2022.109436.

[46] Y. Gan, H. Huang, X. Wu, and M. Meng, "What Doesn't Kill Us Makes Us Stronger: Insights from Neuroscience Studies and Molecular Genetics," *Curr. Opin. Behav. Sci.* 59 (2024): 101431, https://doi.org/10.1016/j.cobeha.2024.101431.

[47] J. Delgadillo and P. G. Salas Duhne, "Targeted Prescription of Cognitive-Behavioral Therapy versus Person-Centered Counseling for Depression Using a Machine Learning Approach," *Journal of Consulting and Clinical Psychology* 88 (2020): 14–24, https://doi.org/10.1037/ccp0000476.

[48] P. Saneei, A. Esmaillzadeh, A. H. Keshteli, et al., "Combined Healthy Lifestyle is Inversely Associated With Upper Gastrointestinal Disorders Among Iranian Adults," *Digestive Diseases* 39 (2021): 77–88, https://doi.org/10.1159/000509208.

[49] P. W. Dimmock, K. M. Wyatt, P. W. Jones, and P. M. S. O'Brien, "Efficacy of Selective Serotonin-Reuptake

Inhibitors in Premenstrual Syndrome: A Systematic Review," *Lancet* 356 (2000): 1131–1136, https://doi.org/10.1016/S0140-6736(00)02754-9.

[50] J. Slomian, G. Honvo, P. Emonts, J. Y. Reginster, and O. Bruyère, "Consequences of Maternal Postpartum Depression: A Systematic Review of Maternal and Infant Outcomes," *Women's Health* 15 (2019): https://doi.org/10.1177/1745506519844044.

[51] A. Syamantha Putri, T. Wurisastuti, I. Yunita Suryaputri, and R. Mubasyiroh, "Postpartum Depression in Young Mothers in Urban and Rural Indonesia," *Journal of Preventive Medicine and Public Health* 56 (2023): 272–281, https://doi.org/10.3961/jpmph.22.534.

[52] J. Li, Y. Chen, Q. Xiang, J. Xiang, Y. Tang, and L. Tang, "5HTTLPR Polymorphism and Postpartum Depression Risk: A Meta-Analysis," *Médica Sur* 99 (2020): e22319, https://doi.org/10.1097/MD.0000000000022319.

[53] N. Ciccone, M. B. Kovacheff, and B. N. Frey, "The Pharmacotherapeutic Management of Premenstrual Dysphoric Disorder," *Expert Opinion on Pharmacotherapy* 24 (2023): 145–151, https://doi.org/10.1080/14656566.2022.2114345.

[54] S. M. Appleton, "Premenstrual Syndrome: Evidence-Based Evaluation and Treatment," *Clinical Obstetrics and Gynecology* 61 (2018): 52–61, https://doi.org/10.1097/GRF.0000000000000339.

[55] M. B. Bin Heyat, F. Akhtar, S. J. Abbas, et al., "Wearable Flexible Electronics Based Cardiac Electrode for Researcher Mental Stress Detection System Using Machine Learning Models on Single Lead Electrocardiogram Signal," *Biosensors* 12 (2022): 427, https://doi.org/10.3390/bios12060427.

[56] R. Pal, D. Adhikari, M. B. Bin Heyat, et al., "A Novel Smart Belt for Anxiety Detection, Classification, and Reduction Using IIoMT on Students' Cardiac Signal and MSY," *Bioengineering* 9 (2022): 793, https://doi.org/10.3390/bioengineering9120793.

[57] C. N. Black, M. Bot, P. G. Scheffer, P. Cuijpers, and B. W. J. H. Penninx, "Is Depression Associated With Increased Oxidative Stress? A Systematic Review and Meta-Analysis," *Psychoneuroendocrinology* 51 (2015): 164–175, https://doi.org/10.1016/j.psyneuen.2014.09.025.

[58] A. A. Uliaszek, R. E. Zinbarg, S. Mineka, et al., "The Role of Neuroticism and Extraversion in the Stress-Anxiety and Stress-Depression Relationships," *Anxiety, Stress & Coping* 23 (2010): 363–381, https://doi.org/10.1080/10615800903377264.

[59] B. Basavanthappa, "Essentials of Mental Health Nursing" (2011), https://doi.org/10.5005/jp/books/11321.

[60] C. Salustri, R. Squitti, F. Zappasodi, et al., "Oxidative Stress and Brain Glutamate-Mediated Excitability in Depressed Patients," *Journal of Affective Disorders* 127 (2010): 321–325, https://doi.org/10.1016/j.jad.2010.05.012.

[61] N. S. Jacobson, K. S. Dobson, P. A. Truax, et al., "A Component Analysis of Cognitive-Behavioral Treatment for Depression," *Journal of Consulting and Clinical Psychology* 64 (1996): 295–304, https://doi.org/10.1037/0022-006X.64.2.295.

[62] Y. Cho, J. K. Lee, D. H. Kim, et al., "Factors Associated With Quality of Life in Patients With Depression: A Nationwide Population-Based Study," *PLoS One* 14 (2019): e0219455, https://doi.org/10.1371/journal.pone.0219455.

[63] H. Zhang, Z. Wang, G. Wang, et al., "Understanding the Connection Between Gut Homeostasis and Psychological Stress," *Journal of Nutrition* 153 (2023): 924–939, https://doi.org/10.1016/j.tjnut.2023.01.026.

[64] L. Yang, Y. Zhao, Y. Wang, et al., "The Effects of Psychological Stress on Depression," *Current Neuropharmacology* 13 (2015): 494–504, https://doi.org/10.2174/1570159x1304150831150507.

[65] P. H. Wirtz and R. von Känel, "Psychological Stress, Inflammation, and Coronary Heart Disease," *Current Cardiology Reports* 19 (2017): 111, https://doi.org/10.1007/s11886-017-0919-x.

[66] M. Hamon and P. Blier, "Monoamine Neurocircuitry in Depression and Strategies for New Treatments," *Progress In Neuro-Psychopharmacology & Biological Psychiatry* 45 (2013): 54–63, https://doi.org/10.1016/j.pnpbp.2013.04.009.

[67] K. C. Benton, D. S. Wheeler, B. Kurtoglu, et al., "Norepinephrine Activates β1-adrenergic Receptors at the Inner Nuclear Membrane in Astrocytes," *Glia* 70 (2022): 1777–1794, https://doi.org/10.1002/glia.24219.

[68] D. Lorton and D. L. Bellinger, "Molecular Mechanisms Underlying β-adrenergic Receptor-Mediated Cross-Talk Between Sympathetic Neurons and Immune Cells," *International Journal of Molecular Sciences* 16 (2015): 5635–5665, https://doi.org/10.3390/ijms16035635.

[69] V. Maletic, A. Eramo, K. Gwin, S. J. Offord, and R. A. Duffy, "The Role of Norepinephrine and its α-adrenergic Receptors in the Pathophysiology and Treatment of Major Depressive Disorder and Schizophrenia: A Systematic Review," *Frontiers in Psychiatry* 8 (2017): https://doi.org/10.3389/fpsyt.2017.00042.

[70] P. W. Gold and M. L. Wong, "Re-assessing the Catecholamine Hypothesis of Depression: The Case of Melancholic Depression," *Molecular Psychiatry* 26 (2021): 6121–6124, https://doi.org/10.1038/s41380-021-01133-x.

[71] B. N. Peacock, D. J. Scheiderer, and G. H. Kellermann, "Biomolecular Aspects of Depression: A Retrospective Analysis," *Comprehensive Psychiatry* 73 (2017): 168–180, https://doi.org/10.1016/j.comppsych.2016.11.002.

[72] O. T. Hernández-Hernández, L. Martínez-Mota, J. J. Herrera-Pérez, and G. Jiménez-Rubio, "Role of Estradiol in the Expression of Genes Involved in Serotonin Neurotransmission: Implications for Female Depression," *Current Neuropharmacology* 17 (2018): 459–471, https://doi.org/10.2174/1570159x16666180628165107.

[73] B. Labonté, O. Engmann, I. Purushothaman, et al., "Sex-Specific Transcriptional Signatures in Human Depression," *Nature Medicine* 23 (2017): 1102–1111, https://doi.org/10.1038/nm.4386.

[74] T. T. Weng, J. H. Hao, Q. W. Qian, et al., "Is There Any Relationship Between Dietary Patterns and Depression and Anxiety in Chinese Adolescents?" *Public Health Nutrition* 15 (2012): 673–682, https://doi.org/10.1017/S1368980011003077.

[75] B. C. Finger, T. G. Dinan, and J. F. Cryan, "High-Fat Diet Selectively Protects Against the Effects of Chronic Social Stress in the Mouse," *Neuroscience* 192 (2011): 351–360, https://doi.org/10.1016/j.neuroscience.2011.06.072.

[76] A. Werner, "Psychodynamic Treatment of Depression," *American Journal of Psychiatry* 161 (2004): 2146, https://doi.org/10.1176/appi.ajp.161.11.2146.

[77] K. H. Kim, "Level of Troponin Release Can Aid in Early Exclusion of Stress-Induced (Takotsubo) Cardiomyopathy," *Journal of Cardiovascular Imaging* 29 (2021): 234–235, https://doi.org/10.4250/jcvi.2021.0076.

[78] D. C. Mohr, K. N. Tomasino, E. G. Lattie, et al., "Intellicare: An Eclectic, Skills-Based App Suite for the Treatment of Depression and Anxiety," *Journal of Medical Internet Research* 19 (2017): https://doi.org/10.2196/jmir.6645.

[79] S. D. Robinson, T. W. Lee, D. L. Christie, and N. P. Birch, "Tissue Plasminogen Activator Inhibits NMDA-Receptor-Mediated Increases in Calcium Levels in Cultured Hippocampal Neurons," *Frontiers in Cellular Neuroscience* 9 (2015): https://doi.org/10.3389/fncel.2015.00404.
[80] P. J. Cowen, "Not Fade Away: The HPA axis and Depression," *Psychological Medicine* 40 (2010): 1–4, https://doi.org/10.1017/S0033291709005558.
[81] C. J. K. Wallace, J. A. Foster, C. N. Soares, and R. V. Milev, "The Effects of Probiotics on Symptoms of Depression: Protocol for a Double-Blind Randomized Placebo-Controlled Trial," *Neuropsychobiology* 79 (2020): 108–116, https://doi.org/10.1159/000496406.
[82] B. S. McEwen, "Stress and Hippocampal Plasticity," *Annual Review of Neuroscience* 22 (1999): 105–122, https://doi.org/10.1146/annurev.neuro.22.1.105.
[83] J. D. Bremner, M. Narayan, E. R. Anderson, L. H. Staib, H. L. Miller, and D. S. Charney, "Hippocampal Volume Reduction in Major Depression," *American Journal of Psychiatry* 157 (2000): 115–117, https://doi.org/10.1176/ajp.157.1.115.
[84] R. H. Bitsko, J. R. Holbrook, R. M. Ghandour, et al., "Epidemiology and Impact of Health Care Provider-Diagnosed Anxiety and Depression Among US Children," *Journal of Developmental and Behavioral Pediatrics* 39 (2018): 395–403, https://doi.org/10.1097/DBP.0000000000000571.
[85] P. J. Schmidt, "Depression, the Perimenopause, and Estrogen Therapy," *Annals of the New York Academy of Sciences* (2005): 27–40, https://doi.org/10.1196/annals.1347.003.
[86] J. J. Sramek and N. R. Cutler, "The Impact of Gender on Antidepressants," *Current Topics in Behavioral Neurosciences* 8 (2011): 231–249, https://doi.org/10.1007/7854_2010_118.
[87] R. T. Emeny, M. Bidlingmaier, M. E. Lacruz, et al., "Mind Over Hormones: Sex Differences in Associations of Well-Being with IGF-I, IGFBP-3 and Physical Activity in the KORA-Age Study," *Experimental Gerontology* 59 (2014): 58–64, https://doi.org/10.1016/j.exger.2014.08.001.
[88] M. E. Thase, M. H. Trivedi, and A. J. Rush, "MAOIs in the Contemporary Treatment of Depression," *Neuropsychopharmacology* 12 (1995): 185–219, https://doi.org/10.1016/0893-133X(94)00058-8.
[89] B. W. J. H. Penninx, S. W. Geerlings, D. J. H. Deeg, J. T. M. Van Eijk, W. Van Tilburg, and A. T. F. Beekman, "Minor and Major Depression and the Risk of Death in Older Persons," *Archives of General Psychiatry* 56 (1999): 889–895, https://doi.org/10.1001/archpsyc.56.10.889.
[90] R. C. Ramaker, K. M. Bowling, B. N. Lasseigne, et al., "Post-Mortem Molecular Profiling of Three Psychiatric Disorders," *Genome Medicine* 9 (2017): 72, https://doi.org/10.1186/s13073-017-0458-5.
[91] J. Abraham, J. O. Mudd, N. Kapur, K. Klein, H. C. Champion, and I. S. Wittstein, "Stress Cardiomyopathy After Intravenous Administration of Catecholamines and Beta-Receptor Agonists," *Journal of the American College of Cardiology* 53 (2009): 1320–1325, https://doi.org/10.1016/j.jacc.2009.02.020.
[92] A. Stefanatou, N. Kouris, and J. Lekakis, "Treatment of Depression in Elderly Patients With Cardiovascular Disease: Research Data and Future Prospects," *Hellenic Journal of Cardiology* 51 (2010): 142–152.
[93] E. Morava, T. Gardeitchik, T. Kozicz, et al., "Depressive Behaviour in Children Diagnosed With a Mitochondrial Disorder," *Mitochondrion* 10 (2010): 528–533, https://doi.org/10.1016/j.mito.2010.05.011.
[94] A. Gardner, A. Johansson, R. Wibom, et al., "Alterations of Mitochondrial Function and Correlations With Personality Traits in Selected Major Depressive Disorder Patients," *Journal of Affective Disorders* 76 (2003): 55–68, https://doi.org/10.1016/S0165-0327(02)00067-8.
[95] Y. Bansal and A. Kuhad, "Mitochondrial Dysfunction in Depression," *Current Neuropharmacology* 14 (2016): 610–618, https://doi.org/10.2174/1570159x14666160229114755.
[96] J. Everaert, H. Benisty, R. Gadassi Polack, J. Joormann, and G. Mishne, "Which Features of Repetitive Negative Thinking and Positive Reappraisal Predict Depression? an In-Depth Investigation Using Artificial Neural Networks With Feature Selection," *Journal of Psychopathology and Clinical Science* 131 (2022): 754–768, https://doi.org/10.1037/abn0000775.
[97] M. M. Kaggwa, S. M. Najjuka, S. Ashaba, and M. A. Mamun, "Psychometrics of the Patient Health Questionnaire (PHQ-9) in Uganda: A Systematic Review," *Frontiers in Psychiatry* 13 (2022): https://doi.org/10.3389/fpsyt.2022.781095.
[98] D. Carrozzino, C. Patierno, G. A. Fava, and J. Guidi, "The Hamilton Rating Scales for Depression: A Critical Review of Clinimetric Properties of Different Versions," *Psychotherapy and Psychosomatics* 89 (2020): 133–150, https://doi.org/10.1159/000506879.
[99] A. Seal, R. Bajpai, M. Karnati, et al., "Benchmarks for Machine Learning in Depression Discrimination Using Electroencephalography Signals," *Applied Intelligence* 53 (2023): 12666–12683, https://doi.org/10.1007/s10489-022-04159-y.
[100] C. O. Acosta Quiroz, R. García-Flores, and S. B. Echeverría-Castro, "The Geriatric Depression Scale (GDS-15): Validation in Mexico and Disorder in the State of Knowledge," *The International Journal of Aging and Human Development* 93 (2021): 854–863, https://doi.org/10.1177/0091415020957387.
[101] F. Benazzi, "The Montgomery Asberg Depression Rating Scale in Bipolar II and Unipolar Out-Patients: A 405-Patient Case Study," *Psychiatry and Clinical Neurosciences* 53 (1999): 429–431, https://doi.org/10.1046/j.1440-1819.1999.00570.x.
[102] W. S. Ahmed, N. Chowdhury, S. Mathur, S. E. Abbey, and L. G. Singer, "Influence of Depression and Anxiety on Health-Related Quality of Life While Awaiting Lung Transplant," *The Journal of Heart and Lung Transplantation* 39 (2020): S392, https://doi.org/10.1016/j.healun.2020.01.517.
[103] D. Malbos, "Seasonal Affective Disorder, Actual," *Pharmacy Times* 59 (2020): 19–22, https://doi.org/10.1016/j.actpha.2020.09.012.
[104] Y. Kim and E. Jang, "Low Self-Rated Health as a Risk Factor for Depression in south korea: A Survey of Young Males and Females," *Healthc* 9 (2021): https://doi.org/10.3390/healthcare9040452.
[105] R. Wang, Y. Liu, D. Xue, and M. Helbich, "Depressive Symptoms Among Chinese Residents: How Are the Natural, Built, and Social Environments Correlated?" *BMC Public Health* 19 (2019): https://doi.org/10.1186/s12889-019-7171-9.
[106] A. Y. Muaad, S. Raza, M. B. Bin Heyat, A. Alabrah, and J. Hanumanthappa, "An Intelligent COVID-19-Related Arabic Text Detection Framework Based on Transfer Learning Using Context Representation," *International Journal of Intelligent Systems* 2024 (2024): 1–15, https://doi.org/10.1155/2024/8014111.

[107] B. N. Teelhawod, F. Akhtar, M. B. Bin Heyat, et al., "Machine Learning in E-Health: A Comprehensive Survey of Anxiety," in *2021 International Conference on Data Analytics for Business and Industry ICDABI 2021* (Virtual Conference: IEEE, October 2021), 167–172, https://doi.org/10.1109/ICDABI53623.2021.9655966.

[108] F. Akhtar, M. B. Bin Heyat, J. P. Li, P. K. Patel, and B. Guragai, "Role of Machine Learning in Human Stress: A Review," in *2020 17th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP 2020)* (Chengdu, China: IEEE, December 2020), 170–174, https://doi.org/10.1109/ICCWAMTIP51612.2020.9317396.

[109] B. Guragai, O. Alshorman, M. Masadeh, and M. B. Bin Heyat, "A Survey on Deep Learning Classification Algorithms for Motor Imagery," in *Proceedings of International Conference on Microelectronic Systems Education ICM, IEEE* (Aqaba, Jordan, December 2020), 1–4, https://doi.org/10.1109/ICM50269.2020.9331503.

[110] S. Khan, S. M. U. Saeed, J. Frnda, et al., "A Machine Learning Based Depression Screening Framework Using Temporal Domain Features of the Electroencephalography Signals," *PLoS One* 19 (2024): https://doi.org/10.1371/journal.pone.0299127.

[111] S. Lin, C. Wang, X. Jiang, et al., "Using Machine Learning to Develop a Five-Item Short Form of the Children's Depression Inventory," *BMC Public Health* 24 (2024): 1118, https://doi.org/10.1186/s12889-024-18657-w.

[112] Y. Zhou, Z. Zhang, Q. Li, G. Mao, and Z. Zhou, "Construction and Validation of Machine Learning Algorithm for Predicting Depression Among Home-Quarantined Individuals During the Large-Scale COVID-19 Outbreak: Based on Adaboost Model," *BMC Psychology* 12 (2024): 230, https://doi.org/10.1186/s40359-024-01696-8.

[113] L. C. López Steinmetz, M. Sison, R. Zhumagambetov, J. C. Godoy, and S. Haufe, "Machine Learning Models Predict the Emergence of Depression in Argentinean College Students During Periods of COVID-19 Quarantine," *Frontiers in Psychiatry* 15 (2024): https://doi.org/10.3389/fpsyt.2024.1376784.

[114] V. N. Dang, A. Cascarano, R. H. Mulder, et al., "Fairness and Bias Correction in Machine Learning for Depression Prediction Across Four Study Populations," *Scientific Reports* 14 (2024): 7848, https://doi.org/10.1038/s41598-024-58427-7.

[115] W. B. Bruin, L. Oltedal, H. Bartsch, et al., "Development and Validation of a Multimodal Neuroimaging Biomarker for Electroconvulsive Therapy Outcome in Depression: A Multicenter Machine Learning Analysis," *Psychological Medicine* 54 (2024): 495–506, https://doi.org/10.1017/S0033291723002040.

[116] S. Poletti, B. Vai, M. G. Mazza, et al., "A Peripheral Inflammatory Signature Discriminates Bipolar From Unipolar Depression: A Machine Learning Approach," *Progress In Neuro-Psychopharmacology & Biological Psychiatry* 105 (2021): https://doi.org/10.1016/j.pnpbp.2020.110136.

[117] Y. Zhang, S. Wang, A. Hermann, R. Joly, and J. Pathak, "Development and Validation of a Machine Learning Algorithm for Predicting the Risk of Postpartum Depression Among Pregnant Women," *Journal of Affective Disorders* 279 (2021): 1–8, https://doi.org/10.1016/j.jad.2020.09.113.

[118] E. M. de Souza Filho, H. C. Veiga Rey, R. M. Frajtag, et al., "Can Machine Learning be Useful as a Screening Tool for Depression in Primary Care?" *Journal of Psychiatric Research* 132 (2021): 1–6, https://doi.org/10.1016/j.jpsychires.2020.09.025.

[119] T. Richter, B. Fishbain, A. Markus, G. Richter-Levin, and H. Okon-Singer, "Using Machine Learning-Based Analysis for Behavioral Differentiation Between Anxiety and Depression," *Scientific Reports* 10 (2020): https://doi.org/10.1038/s41598-020-72289-9.

[120] L. G. Tennenhouse, R. A. Marrie, C. N. Bernstein, and L. M. Lix, "Machine-learning Models for Depression and Anxiety in Individuals With Immune-Mediated Inflammatory Disease," *Journal of Psychosomatic Research* 134 (2020): https://doi.org/10.1016/j.jpsychores.2020.110126.

[121] W. Zhang, H. Liu, V. M. B. Silenzio, P. Qiu, and W. Gong, "Machine Learning Models for the Prediction of Postpartum Depression: Application and Comparison Based on a Cohort Study," *JMIR Medical Informatics* 8 (2020): https://doi.org/10.2196/15516.

[122] B. Wollenhaupt-Aguiar, D. Librenza-Garcia, G. Bristot, et al., "Differential Biomarker Signatures in Unipolar and Bipolar Depression: A Machine Learning Approach," *Australian and New Zealand Journal of Psychiatry* 54 (2020): 393–401, https://doi.org/10.1177/0004867419888027.

[123] E. W. McGinnis, S. P. Anderau, J. Hruschak, et al., "Giving Voice to Vulnerable Children: Machine Learning Analysis of Speech Detects Anxiety and Depression in Early Childhood," *IEEE Journal of Biomedical and Health Informatics* 23 (2019): 2294–2301, https://doi.org/10.1109/JBHI.2019.2913590.

[124] I. Fatima, B. U. D. Abbasi, S. Khan, M. Al-Saeed, H. F. Ahmad, and R. Mumtaz, "Prediction of Postpartum Depression Using Machine Learning Techniques From Social Media Text," *Expert Systems* 36 (2019): https://doi.org/10.1111/exsy.12409.

[125] W. Mumtaz and A. Qayyum, "A Deep Learning Framework for Automatic Diagnosis of Unipolar Depression," *International Journal of Medical Informatics* 132 (2019): https://doi.org/10.1016/j.ijmedinf.2019.103983.

[126] R. Gui, T. Chen, and H. Nie, "The Impact of Emotional Music on Active ROI in Patients With Depression Based on Deep Learning: A Task-State fMRI Study," *Computational Intelligence and Neuroscience* 2019 (2019): https://doi.org/10.1155/2019/5850830.

[127] E. Lin, P. H. Kuo, Y. L. Liu, Y. W. Y. Yu, A. C. Yang, and S. J. Tsai, "A Deep Learning Approach for Predicting Antidepressant Response in Major Depression Using Clinical and Genetic Biomarkers," *Frontiers in Psychiatry* 9 (2018): https://doi.org/10.3389/fpsyt.2018.00290.

[128] E. Hochman, B. Feldman, A. Weizman, et al., "Development and Validation of a Machine Learning-Based Postpartum Depression Prediction Model: A Nationwide Cohort Study," *Depression and Anxiety* 38 (2021): 400–411, https://doi.org/10.1002/da.23123.

[129] N. Koutsouleris, D. B. Dwyer, F. Degenhardt, et al., "Multimodal Machine Learning Workflows for Prediction of Psychosis in Patients With Clinical High-Risk Syndromes and Recent-Onset Depression," *JAMA Psychiatry* 78 (2021): 195–209, https://doi.org/10.1001/jamapsychiatry.2020.3604.

[130] H. Byeon, "Development of a Depression in Parkinson's Disease Prediction Model Using Machine Learning," *World Journal of Psychiatry* 10 (2020): 234–244, https://doi.org/10.5498/wjp.v10.i10.234.

[131] S. C. van Bronswijk, S. J. E. Bruijniks, L. Lorenzo-Luaces, et al., "Cross-Trial Prediction in Psychotherapy: External

Validation of the Personalized Advantage Index Using Machine Learning in Two Dutch Randomized Trials Comparing CBT Versus IPT for Depression," *Psychotherapy Research* 31 (2021): 78–91, https://doi.org/10.1080/10503307.2020.1823029.

[132] D. Shin, K. J. Lee, T. Adeluwa, and J. Hur, "Machine Learning-Based Predictive Modeling of Postpartum Depression," *Journal of Clinical Medicine* 9 (2020): 1–14, https://doi.org/10.3390/jcm9092899.

[133] R. Németh, D. Sik, and F. Máté, "Machine Learning of Concepts Hard Even for Humans: The Case of Online Depression Forums," *International Journal of Qualitative Methods* 19 (2020): https://doi.org/10.1177/1609406920949338.

[134] C. Benfares, O. Akhrif, Y. E. B. El Idrissi, and K. Hamid, "A Clinical Support System for Classification and Prediction of Depression Using Machine Learning Methods," *Computational Intelligence* 37 (2021): 1619–1632, https://doi.org/10.1111/coin.12377.

[135] B. Qi, L. M. Fiori, G. Turecki, and Y. J. Trakadis, "Machine Learning Analysis of Blood microRNA Data in Major Depression: A Case-Control Study for Biomarker Discovery," *International Journal of Neuropsychopharmacology* 23 (2020): 505–510, https://doi.org/10.1093/ijnp/pyaa029.

[136] H. S. Alsagri and M. Ykhlef, "Machine Learning-Based Approach for Depression Detection in Twitter Using Content and Activity Features," *IEICE-Transactions on Info and Systems* (2020): 1825–1832, https://doi.org/10.1587/transinf.2020EDP7023.

[137] N. Solomonov, J. Lee, S. Banerjee, et al., "Modifiable Predictors of Nonresponse to Psychotherapies for Late-Life Depression With Executive Dysfunction: A Machine Learning Approach," *Molecular Psychiatry* 26 (2021): 5190–5198, https://doi.org/10.1038/s41380-020-0836-z.

[138] P. Rajpurkar, J. Yang, N. Dass, et al., "Evaluation of a Machine Learning Model Based on Pretreatment Symptoms and Electroencephalographic Features to Predict Outcomes of Antidepressant Treatment in Adults with Depression: A Prespecified Secondary Analysis of a Randomized Clinical Trial," *JAMA Network Open* 3 (2020): https://doi.org/10.1001/jamanetworkopen.2020.6653.

[139] A. B. R. Shatte, D. M. Hutchinson, M. Fuller-Tyszkiewicz, and S. J. Teague, "Social Media Markers to Identify Fathers at Risk of Postpartum Depression: A Machine Learning Approach," *Cyberpsychology, Behavior, and Social Networking* 23 (2020): 611–618, https://doi.org/10.1089/cyber.2019.0746.

[140] M. Helbich, J. Hagenauer, and H. Roberts, "Relative Importance of Perceived Physical and Social Neighborhood Characteristics for Depression: A Machine Learning Approach," *Social Psychiatry and Psychiatric Epidemiology* 55 (2020): 599–610, https://doi.org/10.1007/s00127-019-01808-5.

[141] R. Razavi, A. Gharipour, and M. Gharipour, "Depression Screening Using Mobile Phone Usage Metadata: A Machine Learning Approach," *Journal of the American Medical Informatics Association* 27 (2020): 522–530, https://doi.org/10.1093/jamia/ocz221.

[142] K. S. Na, S. E. Cho, Z. W. Geem, and Y. K. Kim, "Predicting Future Onset of Depression Among Community Dwelling Adults in the Republic of Korea Using a Machine Learning Algorithm," *Neuroscience Letters* 721 (2020): https://doi.org/10.1016/j.neulet.2020.134804.

[143] Z. Yang, C. Chen, H. Li, L. Yao, and X. Zhao, "Unsupervised Classifications of Depression Levels Based on Machine Learning Algorithms Perform Well as Compared to Traditional Norm-Based Classifications," *Frontiers in Psychiatry* 11 (2020): https://doi.org/10.3389/fpsyt.2020.00045.

[144] Y. Liu, R. Admon, M. S. Mellem, et al., "Machine Learning Identifies Large-Scale Reward-Related Activity Modulated by Dopaminergic Enhancement in Major Depression," *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging* 5 (2020): 163–172, https://doi.org/10.1016/j.bpsc.2019.10.002.

[145] A. Zhdanov, S. Atluri, W. Wong, et al., "Use of Machine Learning for Predicting Escitalopram Treatment Outcome From Electroencephalography Recordings in Adult Patients With Depression," *JAMA Network Open* 3 (2020): E1918377, https://doi.org/10.1001/jamanetworkopen.2019.18377.

[146] M. Zhao and Z. Feng, "Machine Learning Methods to Evaluate the Depression Status of Chinese Recruits: A Diagnostic Study," *Neuropsychiatric Disease and Treatment* 16 (2020): 2743–2752, https://doi.org/10.2147/NDT.S275620.

[147] L. Cui, C. Wang, Z. Wu, et al., "Symptomatology Differences of Major Depression in Psychiatric Versus General Hospitals: A Machine Learning Approach," *Journal of Affective Disorders* 260 (2020): 349–360, https://doi.org/10.1016/j.jad.2019.09.030.

[148] H. Kim, S. H. Lee, S. E. Lee, S. Hong, H. J. Kang, and N. Kim, "Depression Prediction by Using Ecological Momentary Assessment, Actiwatch Data, and Machine Learning: Observational Study on Older Adults Living Alone," *JMIR mHealth and uHealth* 7 (2019): https://doi.org/10.2196/14149.

[149] R. Pearson, D. Pisner, B. Meyer, J. Shumake, and C. G. Beevers, "A Machine Learning Ensemble to Predict Treatment Outcomes Following an Internet Intervention for Depression," *Psychological Medicine* 49 (2019): 2330–2341, https://doi.org/10.1017/S003329171800315X.

[150] J. Gong, G. E. Simon, and S. Liu, "Machine Learning Discovery of Longitudinal Patterns of Depression and Suicidal Ideation," *PLoS One* 14 (2019): https://doi.org/10.1371/journal.pone.0222665.

[151] B. Besteher, C. Gaser, and I. Nenadić, "Machine-learning Based Brain Age Estimation in Major Depression Showing No Evidence of Accelerated Aging," *Psychiatry Research Neuroimaging* 290 (2019): 1–4, https://doi.org/10.1016/j.pscychresns.2019.06.001.

[152] X. Li, X. Zhang, J. Zhu, et al., "Depression Recognition Using Machine Learning Methods With Different Feature Generation Strategies," *Artificial Intelligence in Medicine* 99 (2019): https://doi.org/10.1016/j.artmed.2019.07.004.

[153] S. N. Kasthurirathne, P. G. Biondich, S. J. Grannis, S. Purkayastha, J. R. Vest, and J. F. Jones, "Identification of Patients in Need of Advanced Care for Depression Using Data Extracted From a Statewide Health Information Exchange: A Machine Learning Approach," *Journal of Medical Internet Research* 21 (2019): https://doi.org/10.2196/13809.

[154] A. Zandvakili, N. S. Philip, S. R. Jones, A. R. Tyrka, B. D. Greenberg, and L. L. Carpenter, "Use of Machine Learning in Predicting Clinical Response to Transcranial Magnetic Stimulation in Comorbid Posttraumatic Stress Disorder and Major Depression: A Resting State Electroencephalography Study," *Journal of Affective Disorders* 252 (2019): 47–54, https://doi.org/10.1016/j.jad.2019.03.077.

[155] K. Zhao and H. C. So, "Drug Repositioning for Schizophrenia and Depression/Anxiety Disorders: A Machine Learning Approach Leveraging Expression Data," *Journal of Biomedical and Health Informatics* 23 (2019): 1304–1315, https://doi.org/10.1109/JBHI.2018.2856535.

[156] R. Dinga, A. F. Marquand, D. J. Veltman, et al., "Predicting the Naturalistic Course of Depression From a Wide Range of Clinical, Psychological, and Biological Data: A Machine Learning Approach," *Translational Psychiatry* 8 (2018): https://doi.org/10.1038/s41398-018-0289-1.

[157] J. Wallert, E. Gustafson, C. Held, et al., "Predicting Adherence to Internet-Delivered Psychotherapy for Symptoms of Depression and Anxiety After Myocardial Infarction: Machine Learning Insights From the U-CARE Heart Randomized Controlled Trial," *Journal of Medical Internet Research* 20 (2018): https://doi.org/10.2196/10754.

[158] A. Kautzky, M. Dold, L. Bartova, et al., "Refining Prediction in Treatment-Resistant Depression: Results of Machine Learning Analyses in the TRD III Sample," *The Journal of Clinical Psychiatry* 79 (2018): https://doi.org/10.4088/JCP.16m11385.

[159] K. Schultebraucks, V. Yadav, A. Y. Shalev, G. A. Bonanno, and I. R. Galatzer-Levy, "Deep Learning-Based Classification of Posttraumatic Stress Disorder and Depression Following Trauma Utilizing Visual and Auditory Markers of Arousal and Mood," *Psychological Medicine* 52 (2022): 957–967, https://doi.org/10.1017/S0033291720002718.

[160] J. Mehltretter, C. Rollins, D. Benrimoh, et al., "Analysis of Features Selected by a Deep Learning Model for Differential Treatment Selection in Depression," *Frontiers in Artificial Intelligence* 2 (2020): https://doi.org/10.3389/frai.2019.00031.

[161] J. Oh, K. Yun, U. Maoz, T. S. Kim, and J. H. Chae, "Identifying Depression in the National Health and Nutrition Examination Survey Data Using a Deep Learning Algorithm," *Journal of Affective Disorders* 257 (2019): 623–631, https://doi.org/10.1016/j.jad.2019.06.034.

[162] M. Helbich, Y. Yao, Y. Liu, J. Zhang, P. Liu, and R. Wang, "Using Deep Learning to Examine Street View Green and Blue Spaces and Their Associations With Geriatric Depression in Beijing, China," *Environment International* 126 (2019): 107–117, https://doi.org/10.1016/j.envint.2019.02.013.

[163] J. F. Dipnall, J. A. Pasco, M. Berk, et al., "Why So GLUMM? Detecting Depression Clusters Through Graphing Lifestyle-Environs Using Machine-Learning Methods (GLUMM)," *European Psychiatry* 39 (2017): 40–50, https://doi.org/10.1016/j.eurpsy.2016.06.003.

[164] P. Tripathi, M. A. Ansari, F. Akhtar, et al., "Automatic Epileptic Seizure Detection Based on the Discrete Wavelet Transform Approach Using an Artificial Neural Network Classifier on the Scalp Electroencephalogram Signal," *Computational Intelligence in Healthcare Applications* (2022): 157–173, https://doi.org/10.1016/B978-0-323-99031-8.00012-0.

[165] J. Kambeitz, S. Goerigk, W. Gattaz, et al., "Clinical Patterns Differentially Predict Response to Transcranial Direct Current Stimulation (tDCS) and Escitalopram in Major Depression: A Machine Learning Analysis of the ELECT-TDCS Study," *Journal of Affective Disorders* 265 (2020): 460–467, https://doi.org/10.1016/j.jad.2020.01.118.

[166] M. J. A. Fazmiya, A. Sultana, M. B. Bin Heyat, et al., "Efficacy of a Vaginal Suppository Formulation Prepared with Acacia Arabica (Lam.) Willd. Gum and Cinnamomum Camphora (L.) J. Presl. In Heavy Menstrual Bleeding Analyzed Using a Machine Learning Technique," *Frontiers in Pharmacology* 15 (2024): 1–23, https://doi.org/10.3389/fphar.2024.1331622.

[167] A. Sultana, W. Begum, R. Saeedi, et al., "Experimental and Computational Approaches for the Classification and Correlation of Temperament (Mizaj) and Uterine Dystemperament (Su'-I-Mizaj Al-Rahim) in Abnormal Vaginal Discharge (Sayalan Al-Rahim) Based on Clinical Analysis Using Support Vector Mach," *Complexity* 2022 (2022): 1–16, https://doi.org/10.1155/2022/5718501.

[168] S. Qayyum, A. Sultana, M. B. Bin Heyat, et al., "Therapeutic Efficacy of a Formulation Prepared with Linum usitatissimum L., Plantago Ovata Forssk., and Honey on Uncomplicated Pelvic Inflammatory Disease Analyzed With Machine Learning Techniques," *Pharmaceutics* 15 (2023): 643, https://doi.org/10.3390/pharmaceutics15020643.

[169] H. J. Tsai, W. C. Yang, S. J. Tsai, C. H. Lin, and A. C. Yang, "Right-side Frontal-Central Cortical Hyperactivation Before the Treatment Predicts Outcomes of Antidepressant and Electroconvulsive Therapy Responsivity in Major Depressive Disorder," *Journal of Psychiatric Research* 161 (2023): 377–385, https://doi.org/10.1016/j.jpsychires.2023.03.023.

[170] D. Adhikari, W. Jiang, J. Zhan, D. B. Rawat, and A. Bhattarai, "Recent Advances in Anomaly Detection in Internet of Things: Status, Challenges, and Perspectives," *Computer Science Review* 54 (2024): https://doi.org/10.1016/j.cosrev.2024.100665.

[171] W. Zhang, J. Xie, Z. Zhang, and X. Liu, "Depression Detection Using Digital Traces on Social Media: A Knowledge-Aware Deep Learning Approach," *Journal of Management Information Systems* 41 (2024): 546–580, https://doi.org/10.1080/07421222.2024.2340822.

[172] S. Choudhary, M. Kumar Bajpai, and K. Kumari Bharti, "Spatio-Temporal Features Based Deep Learning Model for Depression Detection Using Two Electrodes," *Measurement Science and Technology* 35 (2024): 086015, https://doi.org/10.1088/1361-6501/ad4dc0.

[173] K. Yeul Kim, Y. bo Yang, M. ra Kim, J. Kim, and J. S. Park, "Predicting Early Depression in WZT Drawing Image Based on Deep Learning," *Expert Systems* (2024): https://doi.org/10.1111/exsy.13675.

[174] Y. Liu, X. Ding, S. Peng, and C. Zhang, "Leveraging ChatGPT to Optimize Depression Intervention Through Explainable Deep Learning," *Frontiers in Psychiatry* 15 (2024): https://doi.org/10.3389/fpsyt.2024.1383648.

[175] S. Nasim, A. Sami Al-Shamayleh, N. Thalji, et al., "Novel Meta Learning Approach for Detecting Postpartum Depression Disorder Using Questionnaire Data," *IEEE Access* 12 (2024): 101247–101259, https://doi.org/10.1109/ACCESS.2024.3427685.

[176] N. Farruque, R. Goebel, S. Sivapalan, and O. R. Zaïane, "Depression Symptoms Modelling From Social Media Text: an LLM Driven Semi-Supervised Learning Approach," *Language Resources and Evaluation* (2024): https://doi.org/10.1007/s10579-024-09720-4.

[177] A. V. Sokolov and H. B. Schiöth, "Decoding Depression: A Comprehensive Multi-Cohort Exploration of Blood DNA Methylation Using Machine Learning and Deep Learning Approaches," *Translational Psychiatry* 14 (2024): 287, https://doi.org/10.1038/s41398-024-02992-y.

[178] P. V. Narayanrao, K. Kohirker, T. S. Preeth, and P. L. S. Kumari, "Depression Symptom Identification Through Acoustic Speech Analysis: A Transfer Learning Approach, Trait," *Du Signal* 41 (2024): 165–177, https://doi.org/10.18280/ts.410113.

[179] A. M. Chekroud, R. J. Zotti, Z. Shehzad, et al., "Cross-trial Prediction of Treatment Outcome in Depression: A Machine Learning Approach," *The Lancet Psychiatry* 3 (2016): 243–250, https://doi.org/10.1016/S2215-0366(15)00471-X.

[180] B. Hosseinifard, M. H. Moradi, and R. Rostami, "Classifying Depression Patients and Normal Subjects Using

Machine Learning Techniques and Nonlinear Features From EEG Signal," *Computer Methods and Programs in Biomedicine* 109 (2013): 339–345, https://doi.org/10.1016/j.cmpb.2012.10.008.

[181] N. Koutsouleris, L. Kambeitz-Ilankovic, S. Ruhrmann, et al., "Prediction Models of Functional Outcomes for Individuals in the Clinical High-Risk State for Psychosis or With Recent-Onset Depression: A Multimodal, Multisite Machine Learning Analysis," *JAMA Psychiatry* 75 (2018): 1156–1172, https://doi.org/10.1001/jamapsychiatry.2018.2165.

[182] R. Fulmer, A. Joerin, B. Gentile, L. Lakerink, and M. Rauws, "Using Psychological Artificial Intelligence (Tess) to Relieve Symptoms of Depression and Anxiety: Randomized Controlled Trial," *JMIR Mental Health* 5 (2018): e64, https://doi.org/10.2196/mental.9782.

[183] I. Nouretdinov, S. G. Costafreda, A. Gammerman, et al., "Machine Learning Classification With Confidence: Application of Transductive Conformal Predictors to MRI-Based Diagnostic and Prognostic Markers in Depression," *NeuroImage* 56 (2011): 809–813, https://doi.org/10.1016/j.neuroimage.2010.05.023.

[184] M. J. Patel, C. Andreescu, J. C. Price, K. L. Edelman, C. F. Reynolds, and H. J. Aizenstein, "Machine Learning Approaches for Integrating Clinical and Imaging Features in Late-Life Depression Classification and Response Prediction," *International Journal of Geriatric Psychiatry* 30 (2015): 1056–1067, https://doi.org/10.1002/gps.4262.

[185] M. R. Islam, M. A. Kabir, A. Ahmed, A. R. M. Kamal, H. Wang, and A. Ulhaq, "Depression Detection From Social Network Data Using Machine Learning Techniques," *Health Information Science and Systems* 6 (2018): 1–12, https://doi.org/10.1007/s13755-018-0046-0.

[186] B. Ay, O. Yildirim, M. Talo, et al., "Automated Depression Detection Using Deep Representation and Sequence Learning with EEG Signals," *Journal of Medical Systems* 43 (2019): https://doi.org/10.1007/s10916-019-1345-y.

[187] S. Jiménez-Serrano, S. Tortajada, and J. M. García-Gómez, "A Mobile Health Application to Predict Postpartum Depression Based on Machine Learning," *Telemed. e-Health* 21 (2015): 567–574, https://doi.org/10.1089/tmj.2014.0113.

[188] J. F. Dipnall, J. A. Pasco, M. Berk, et al., "Fusing Data Mining, Machine Learning and Traditional Statistics to Detect Biomarkers Associated With Depression," *PLoS One* 11 (2016): 1–23, https://doi.org/10.1371/journal.pone.0148195.

[189] A. Sultana, K. Rahman, M. B. Bin Heyat, F. Akhtar, and A. Y. Muaad, "Role of Inflammation, Oxidative Stress, and Mitochondrial Changes in Premenstrual Psychosomatic Behavioral Symptoms With Anti-Inflammatory, Antioxidant Herbs, and Nutritional Supplements," *Oxidative Medicine and Cellular Longevity* 2022 (2022): 3599246, https://doi.org/10.1155/2022/3599246.

[190] M. B. Bin Heyat, F. Akhtar, M. A. Ansari, et al., "Progress in Detection of Insomnia Sleep Disorder: A Comprehensive Review," *Current Drug Targets* 22 (2020): 672–684, https://doi.org/10.2174/1389450121666201027125828.

[191] M. B. Bin Heyat, F. Akhtar, M. H. Khan, et al., "Detection, Treatment Planning, and Genetic Predisposition of Bruxism: A Systematic Mapping Process and Network Visualization Technique," *CNS & Neurological Disorders-Drug Targets* 20 (2020): 755–775, https://doi.org/10.2174/1871527319666201110124954.

[192] F. Akhtar, J. P. Li, M. B. Bin Heyat, et al., "Potential of Blockchain Technology in Digital Currency: A Review," in *2019 16th International Computer Conference on Wavelet Active Media Technology and Information Processing* (Chengdu, China, December 2019), 85–91, https://doi.org/10.1109/ICCWAMTIP47768.2019.9067546.

[193] F. Akhtar, M. Belal Bin Heyat, A. Sultana, et al., "Medical Intelligence for Anxiety Research: Insights From Genetics, Hormones, Implant Science, and Smart Devices With Future Strategies," *WIREs Data Mining and Knowledge Discovery* (2024): e1552, https://doi.org/10.1002/widm.1552.

[194] H. M. Zeeshan, M. B. Bin Heyat, M. A. Bin Hayat, et al., "Progress and Research Trends in Lumpy Skin Disease Based on the Scientometric Assessment-A Review," *Annals of Animal Science* (2024): https://doi.org/10.2478/aoas-2024-0091.

[195] F. Akhtar, P. K. Patel, M. B. Bin Heyat, et al., "Smartphone Addiction Among Students and its Harmful Effects on Mental Health, Oxidative Stress, and Neurodegeneration Towards Future Modulation of Anti-Addiction Therapies: A Comprehensive Survey Based on SLR, Research Questions, and Network Visualization," *CNS & Neurological Disorders-Drug Targets* 22 (2022): 1070–1089, https://doi.org/10.2174/1871527321666220614121439.

[196] P. Kokol, H. Blažun Vošner, and J. Završnik, "Application of Bibliometrics in Medicine: A Historical Bibliometrics Analysis," *Health Information and Libraries Journal* 38 (2021): 125–138, https://doi.org/10.1111/hir.12295.

[197] M. Norris and C. Oppenheim, "The H-Index: A Broad Review of a New Bibliometric Indicator," *Journal of Documentation* 66 (2010): 681–705, https://doi.org/10.1108/00220411011066790.

[198] R. Tomaszewski, "Visibility, Impact, and Applications of Bibliometric Software Tools Through Citation Analysis," *Scientometrics* 128 (2023): 4007–4028, https://doi.org/10.1007/s11192-023-04725-2.

[199] A. Ninkov, J. R. Frank, and L. A. Maggio, "Bibliometrics: Methods for Studying Academic Publishing," *Perspectives on Medical Education* 11 (2022): 173–176, https://doi.org/10.1007/s40037-021-00695-4.

[200] M. B. Bin Heyat, *Insomnia: Medical Sleep Disorder & Diagnosis*, 1st edition (Hamburg, Germany: Anchor Academic Publishing, 2016), https://www.anchor-publishing.com/document/337729.

[201] J. V. B. Benifa, C. Chola, A. Y. Muaad, et al., "FMDNet: An Efficient System for Face Mask Detection Based on Lightweight Model During COVID-19 Pandemic in Public Areas," *Sensors* 23 (2023): 6090, https://doi.org/10.3390/s23136090.