AI-Assisted Diagnosing, Monitoring and Treatment of Mental Disorders: A Survey

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Globally, one in seven people has some kind of mental or substance use disorder that affects their thinking, feelings and behaviour in everyday life. People with mental health disorders can continue their normal lives with proper treatment and support. Mental well-being is vital for physical health. The use of AI in mental health areas has grown exponentially in the last decade. However, mental disorders are still complex to diagnose due to similar and common symptoms for numerous mental illnesses, with a minute difference. Intelligent systems can help us identify mental diseases precisely, which is a critical step in diagnosing. Using these systems efficiently can improve the treatment and rapid recovery of patients. We survey different artificial intelligence systems used in mental healthcare, such as mobile applications, machine learning and deep learning methods, and multi-modal systems and draw comparisons from recent developments and related challenges. Also, we discuss types of mental disorders and how these different techniques can support the therapist in diagnosing, monitoring, and treating patients with mental disorders.

CCS Concepts: • **Computing methodologies → Natural language processing**; **Machine learning**; **Artificial intelligence**;

Additional Key Words and Phrases: Mental health; artificial intelligence; large language models; machine learning; natural language processing.

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1 Introduction

Millions of people worldwide are affected by mental disorders that influence their thinking, feeling or behaviour. Mental health is an essential prerequisite for physical and general health. People with mental disorders often require appropriate treatment and support to lead a normal life [1]. Mental healthiness is a condition of well-being in which an individual recognises his or her abilities, can cope with the everyday tensions of life, works productively and can contribute to his or her community. Mental health affects the lives of people with a mental disorder, their professions and the community's productivity. Mental health and resilience are essential to our biological health, human connections, education, work and achieving our potential [2]. The COVID-19 pandemic has significantly impacted people's mental health, in particular groups such as health and other front-line workers, students, people living alone and those with preexisting mental health conditions. Moreover, services for mental, neurological and substance use disorders have been significantly disrupted.

Mental disorders represent disturbances to mental health, often characterised by troubling thoughts, emotions, behaviour and relationships with others. Mental disorders are considered complex to diagnose due to the similarity of symptoms. Regular health inspections of people with severe mental disorders can deter premature death [3]. The difficulty of experts in diagnosing is usually caused by the similarity of symptoms in mental disorders, such as schizophrenia and bipolar disorder. One in four people will experience a mental health problem at some point, and one in six adults have a mental health problem. One in ten children aged between 5 and 16 years has a mental health problem, and many continue to have mental health problems into adulthood. One billion individuals have a mental disorder, and anyone can be impacted. In particular, depression is a leading cause of disability worldwide and significantly contributes to the general global disease burden. Globally, it is calculated that 5% of adults suffer from depression. Half of all such disorders start by the age of 14 years, but most are undetected and untreated [4]. The lost productivity coming from depression and anxiety, two of the most specific mental disorders, costs the international economy US 1 trillion dollars each year. Governments spend 2% of their national health funding on mental health. This has changed little in current years; despite an increase in development assistance for mental health, it has never exceeded 1% of outcome assistance for health [5].

In Europe, 165 million people are affected annually by a disorder or mental disorder. Only a quarter of patients with mental disorders receive treatment, and only 10% have appropriate treatment. Mental disorders have become, in recent years, the leading cause of disability, and it is a significant cause of morbidity in societies. In the particular case of Portugal, Sociedade Portuguesa de Psiquiatria e Saúde Mental reports that more than one-fifth of Portuguese suffer from a psychiatric disorder (22.9%) and that Portugal is the second country with the highest prevalence of psychiatric disorders in Europe, only surpassed by Northern Ireland (23.1%) [6]. Some of the most specific mental health disorders, depression and anxiety, can be treated by talking with therapies, medication, or a combination of both. Generalist health workers can be trained to analyse and treat mental health conditions. For every US$ 1 supported in scaled-up treatment for depression and anxiety, there is a recovery of US$ 5. For every US$ 1 supported in evidence-based treatment for drug addiction, there is a recovery of up to US$ 7 in decreased crime and criminal justice costs [7].

Personalised psychiatry also plays a vital role in predicting mental disorders and improving diagnosis and optimised treatment. The use of **intelligent systems (IS)** is expected to grow in the medical field, and it will continue to pose abundant opportunities for solutions that can help save patients' lives. As it does for many industries, **artificial intelligence (AI)** systems can support mental health specialists in their jobs. Algorithms can explore data much faster than humans, propose possible treatments, monitor a patient's progress, and alert human professionals to concerns [8]. Healthcare organisations have a large quantity of information available, and a significant portion is unstructured and clinically applicable. Researchers are testing how IS can help screen, diagnose and treat mental disorders. To focus this review on recently published literature, we reviewed 97 studies published 2013–2022 (Figure 3) from different literature databases like Google Scholar, **Web of Science (WoS)**, Scopus, IEEE Xplore, PubMed and Science Direct of AI and mental health that used expert systems, novel monitoring systems (e.g., smartphone, video), the app for early detection, networking site and social media platforms to predict, classify or subgroup mental health disorders, including depression, bipolar, **autism spectrum disorder (ASD)**, panic disorder, schizophrenia or other psychiatric disorder.

This survey about diagnosing mental disorders and monitoring mental health is organised as follows: The first section provides the introduction of the problem statement, as well as the objectives and goal of this survey. The second section describes related background mental healthcare, factoid and non-factoid questions and the latest research. The third section describes IS, a brief history of AI in mental health, and the use of AI in mental health to diagnose and monitor patients with mental disorders. In this session, we will also discuss the different **machine learning (ML)** and **deep learning (DL)** methods, mobile applications for mental health and mental health datasets. Finally, we will address AI as assisted decision-making for professionals. The fourth session discusses the approaches used in different works, performance metrics, best classifiers and a brief summary of mental health challenges and limitations. Finally, the conclusions are in the fifth section.

2 Background and Related Work

Mental, physical and social health are vital aspects of any individual's life and are completely interconnected and interdependent to the point that we cannot consider health without mental health. The more we understand this correlation, the clearer it becomes that mental health is central to the well-being of individuals, societies and countries.

2.1 Types of Mental Health Issues and Disorders

The **World Health Organization (WHO)** [3] conceptualises mental health as a 'state of well-being in which the individual realises his or her abilities, can manage with the usual stresses of life, can work constructively and fruitfully and can contribute to their community'. According to [8], mental health is the ability of individuals and all of us to feel, think and operate in ways that improve our ability to enjoy life and deal with our challenges. It is an optimistic sense of emotional and spiritual well-being that appreciates the significance of culture, equity, social justice, interconnections and personal dignity. Mental disorders result from a complex interaction of genetic, biological, personality and environmental factors with the brain as the final common pathway for controlling behaviour, cognition, mood and anxiety. Most mental disorders can be broadly classified as psychoses or neuroses. Psychoses (e.g., schizophrenia and bipolar disorder) are severe mental illnesses distinguished by acute symptoms such as delusions, hallucinations and the inability to objectively evaluate reality. Neuroses are less severe and more treatable illnesses, such as depression, anxiety and paranoia, as well as obsessive-compulsive disorder and **post-traumatic stress disorder (PTSD)** [9].

Mental disorders or illnesses are characterised by altered thinking, mood or behaviour or are associated with significant distress and impaired functioning. The symptoms of mental disorders vary from mild to severe, depending on the type of mental disorder, the individual, the family and the socioeconomic environment. Mental disorders take many forms, including mood disorders, schizophrenia, anxiety disorders, personality disorders, eating disorders and addictions such as substance dependence and gambling. According to World Mental Health

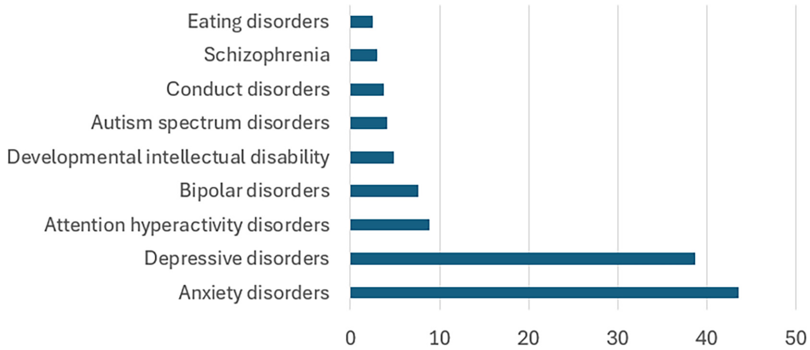

Fig. 1. Number/million with a mental disorder by type, European Region 2019.

Day 2019 [10], based on global data for all ages genders, the most common mental disorders include depression 5.45%, anxiety disorders 3.34%, schizophrenia 1.78%, other mental disorders 1.01%, bipolar disorder 0.99%, conduct disorder 0.56%, intellectual disability 0.51%, autism spectrum 0.5%, eating disorders 0.34% and attention deficit hyperactivity disorder 0.12%, as illustrated in Figure 1.

Among the major diseases, this survey addresses mental disorders such as depressive disorders, panic disorders, bipolar disorders, schizophrenia, anxiety disorders and ASDs and some proposed solutions using AI systems.

Depressive Disorders

Depressive disorders are a primary care disease and are one of the most common categories of psychiatric disorders [11]. The WHO [12] declares depression is a common mental disorder and one of the leading reasons for disability worldwide. Globally, a calculated 264 million people are affected by depression. Depression is a common and severe medical disorder that negatively affects how one feels, thinks and acts [13]. Because of wrong perceptions, nearly 60% of people with depression do not seek medical help. Many sense that the stigma of a mental health disorder is unsuitable in society and may hinder personal and professional life. Depression causes sadness, and a loss of interest in activities once enjoyed. The standard features of all depressive disorders are sadness, emptiness, or irritable mood, attended by somatic and cognitive changes that affect the individual's capacity to function [14].

Bipolar Disorder

The American Psychiatric Association's *Diagnostic and Statistical Manual of Mental Disorders (DSM-5)* [15] describes bipolar disorders as a class of brain disorders that cause severe fluctuation in a person's mood, energy and capacity to function. Bipolar disorder occurs in up to 2.5% of the population [16]. People with bipolar disorder experience great excitement, over-activity, deception, euphoria (mania) and other times of feeling sad and hopeless (e.g., depression). Bipolar disorder is characterised by at smallest one manic/hypo-manic or crossbred episode (mania and depression) with or without a history of influential depression [8].

During the period of mood disorder, three or more of the subsequent symptoms have prevailed and have been present to a considerable degree [16]:

- Inflated self-esteem or grandiosity.
- Reduced need for sleep (e.g., feels rested after only 3 hours).
- More conversational than usual or pressured to keep talking.
- Flight of ideas or subjective knowledge that thoughts are racing.
- Distractibility (i.e., attention is too easily drawn to unimportant or irrelevant external stimuli).
- Addition in goal-directed activity (socially, at work or school, or sexually) or psychomotor agitation.

Table 1. Symptoms of Panic Disorder

Palpitations	Unsteady	Chest pain or discomfort
Sweating	Trembling or shaking	Nausea or abdominal distress
Shortness of breath	Feelings of choking	Feeling dizzy
Feeling of smothering	Lightheaded or faint	Pounding or accelerated heart rate

—Exaggerated involvement in pleasurable activities with a high possibility for painful consequences (e.g., engaging in unrestrained buying sprees, sexual improprieties, or foolish business investments).

ASD

ASD is a neurodevelopmental condition denoted by deficits in social communication and the presence of restricted interests and repetitive behaviours [17]; other features are atypical patterns of activities and conduct, such as difficulty with the change from one activity to another, a focus on details and unusual reactions to sensations [18]. Autism is an illness that usually starts in infancy, at the latest, in the first 3 years of life. Parents often become concerned because their child is not using words to communicate, even though he or she recites passages from videotapes or says the alphabet. Autism is a heterogeneous condition; no two children or adults with autism have the same profile, but difficulties fall into core domains that are reliably measured and usually consistent across time, even though specific behaviours may change with development [19, 20].

People with autism are usually subject to stigma, intolerance and human rights violations. Care for people with autism needs to be accompanied by actions at community and societal levels for greater accessibility, inclusivity and support.

Panic Disorder

Panic disorder is a typical mental disorder that affects up to 5% of people at some point in life. It is often disabling, especially when complicated by agoraphobia and is associated with substantial functional morbidity and reduced quality of life [21]. According to [22], panic disorder is an anxiety disorder characterised by unexpected and repeated episodes of severe fear accompanied by physical symptoms that may include chest pain, heart palpitations, shortness of breath, dizziness or abdominal distress. Typical features of panic disorders [23] are shows in Table 1:

Schizophrenia

Schizophrenia is a specific reaction to severe anxiety, having its origin in childhood and experienced similarly and reinforced in a later time of life, and it generally affects a motivational use of progressive impairment of the abstract attitude [24]. Schizophrenia is a syndrome: a group of signs and symptoms of unknown aetiology, defined mainly by observed signs of psychosis. Schizophrenia shows paranoid delusions and auditory hallucinations late in adolescence or earlier adulthood in its most common form. These manifestations of the disease have changed little over the past century. Schizophrenia is conceptualised as a psychotic disorder, and this change requires psychotic pathology in the diagnosis [25]. Delusions, hallucinations and disorganised speech are core 'positive symptoms' diagnosed with high reliability and might reasonably be considered necessary for a reliable diagnosis of schizophrenia. People with schizophrenia have two to three times more potential to die earlier than the general population [26].

Schizophrenia is a psychiatric disease with a complex and multi-factorial aetiology resulting from the cumulative effect of several risk factors. Among them, genetic factors reflect the weight of hereditary factors in the genesis of schizophrenia, in which susceptibility to various spectrum diseases is inherited. According to WHO [27], schizophrenia is a psychosis, a type of mental disorder characterised by distorted thinking, perception, feelings, language, sense of self and behaviour. Typical experiences include hallucination: hearing, seeing, or feeling things not there.

Table 2. Summary of Related Survey on Application of AI in Mental Health Context

Reference	Application Scope	Topic Focus
Xishuang et al. [28]	Prevention, diagnosis, treatment of mental illness	NLP, DL techniques and applications
Graham et al. [32]	Predict and classify mental illness	EHRs, mood rating scales, brain imaging data, novel monitoring systems and social media platforms
Garcia-Ceja et al. [31]	Patient monitoring	Sensor data and ML
Gravenhorst et al. [34]	Support therapy and monitoring the current state and development of their mental disorders	Mobile phones
Luxton [33]	Activities in psychological practice and research	Human–computer, augmented reality applications interface
Su et al. [29]	Diagnosis and prognosis	Applications of DL algorithms in mental health outcome research.
Vidhi and Vrushti [30]	Diagnosis and monitoring	Systems for mental health monitoring
This survey	All the above applications and other prevention, diagnosis, monitoring, treatment of mental illness applications	DL, ML techniques, NLP, mobile applications (mhealth), multi-modal systems, applications, performance results and ethical considerations

NLP, natural language processing.

Other everyday experiences include:

—Delusion: selected false beliefs or suspicions not shared by others in the person's culture and firmly held even when there is proof of the opposite.
—Abnormal behaviour: disorganised behaviour such as wandering, mumbling, or laughing to self, strange appearance, self-neglect, or unkempt.
—Disorganised speech: incoherent or irrelevant speech;
—Disturbances of emotions: marked apathy or disconnect between reported emotion and what is observed, such as a facial expression or body language.

2.2 Related Work

There is some research on specific types of AI-assisted diagnosis [28, 30], monitoring [28, 30, 31], predict [32] and treatment [28, 29, 33] applications for mental disorders. In [28], the author explores applications in the prevention, supplementary diagnosis, treatment and rehabilitation of mental illness; the survey also discusses the advantages, shortcomings and opportunities of AI applications in mental disorders to provide references for research related to mental health applications based on AI technology. In [32], the author explores AI and mental health that use **electronic health records (EHRs)**, brain imaging data, novel monitoring systems and social media platforms to predict, classify, or subgroup mental health diseases. In [31], the author gives a survey on mental health monitoring systems using sensor data and ML.

This survey is different from existing ones because its scope is not limited to any specific type of application or algorithms but also to prevent, diagnose, monitor and treat mental illness, as summarised in Table 2 that is not limited to one mental disease. The scope of application of this research includes the diagnosis, monitoring and prevention of various mental problems. The research provides a comprehensive summary and comparison of types of mental disorders and the role of IS in the automatic diagnosis and monitoring of mental disorders.

ML classifiers usually fall into two primary categories: supervised learning and unsupervised learning. We also present several studies that used DL in their approaches. Finally, the research presents a brief discussion and future challenges of IS in aiding the diagnosis and monitoring of patients with mental problems.

2.2.1 Review Method. A critical literature review was performed in this study to define a wide variety of methods of ML, **natural language processing (NLP)**, DL and multi-modal systems to help diagnose, monitor and treat patients with mental disorders and their markers in recent years until 2022 (2013–2022) as shown in Figure 3. The **Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)** [35] method was used to discover and identify relevant articles. Selected articles were identified using the electronic literature search method of Google Scholar, WoS, Scopus, IEEE Xplore, PubMed and Science Direct using the query term combination of the search keywords. Keyword searches for suitable articles include: 'Mental Health', 'Artificial Intelligence', 'Machine Learning', 'classification methods', 'classification problem', 'arrest methods', 'diagnostic methods', 'treatment methods', 'Large Language Models', 'mental health dataset', 'Transformers' and 'Natural Language Processing' in the field of detection, diagnosis, treatment and monitoring of mental illnesses.

The search results were filtered to filter the articles that did not capture such discourse. The screening of articles was based on titles, abstracts and search keywords. The total number of reports collected at the end of the search was 271. After eliminating duplicate articles, the original number was reduced to 198. Based on the title and abstract review, we identified 153 records as eligible and excluded 45 records. The 153 selected articles were read and scanned to eliminate results that did not correlate with the research topic, resulting in 99 articles that we considered relevant to our study.

Ineligible articles were articles that performed text recognition from handwritten datasets, those whose datasets were not in English, articles written before 2013, articles unrelated to mental problems and articles that did not allow downloads. Criteria of Inclusion: articles in the English language, mobile applications, articles that used ML methods, DL methods, NLP methods and a combination of learning methods and articles that do not fulfil any inclusion criterion.

Finally, a total of 99 articles met our eligibility criteria. Most of the reviewed articles were published between 2015 and 2022. To summarise these articles, we grouped them into four categories according to the types of data analysed, including studies of the background of mental health, DL and ML algorithms, mobile applications and studies of mental health datasets. Figure 2 presents a flowchart of the article selection process from the initial search stage to the final number of articles selected.

3 Artificial IS for Mental Health

IS provide a standardised methodological approach to solve critical and relatively complex problems and obtain consistent and reliable results over time [36]. The definition of IS is a complex problem and is subject to a great deal of debate. Independently from the definition, there is not much doubt that AI is an essential basis for building IS [37].

According to Russel and Norvig [38], AI consists of two main directions. One is humanistic AI, which studies machines that think and act like humans and the other is rationalistic AI, which examines machines that can be built on the understanding of intelligent human behaviour [39]. An IS is a system that emulates some aspects of intelligence exhibited by nature. These include learning, adaptability, robustness across problem domains, improving efficiency (over time and/or space), information compression (data to knowledge) and extrapolated reasoning. Doucet et al. [40] declare that an IS refers to different software tools that enable decision-makers to draw on experts' knowledge and decision processes in producing decisions. The first use of AI in the psychological field was the creation of the ELIZA computer program in 1966 [41], a human–computer interface was designed to imitate the empathetic communication style of Carl Rogers psychotherapist [33, 42]. ELIZA used language syntax to provide formulated responses based on a programmed model and only mimicked conversation. Shortly after, PARRY was created by psychiatrist Kenneth M. Colby [33]. The computer program simulated a patient suffering

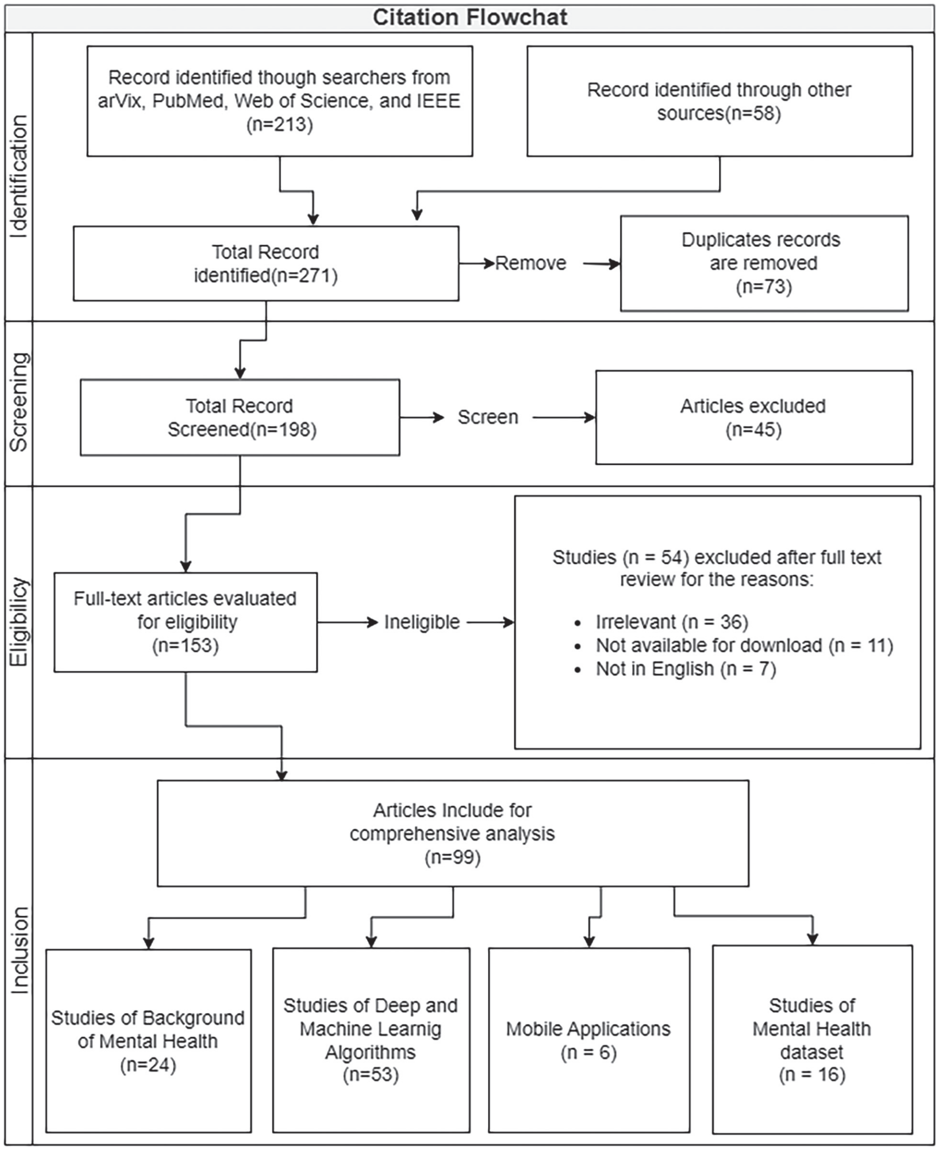

Fig. 2. PRISMA flow diagram: application of AI in a mental health context. In total, 99 studies, in terms of mental health background, deep and ML algorithms, mobile applications and mental health datasets, which met our eligibility criteria, were included in this review.

from paranoid schizophrenia and held conversations, like ELIZA, with its users. PARRY became so realistic that expert psychiatrists had difficulty differentiating PARRY from real-life patients. PARRY has been the closest AI system to pass the **Turing Test (TT)**.

The mathematician Alan Turing proposed the TT to replace the question: ‘Can a machine think?’ Turing’s views have been widely discussed, attacked and defended over and over [43]. At one extreme, Turing’s paper has

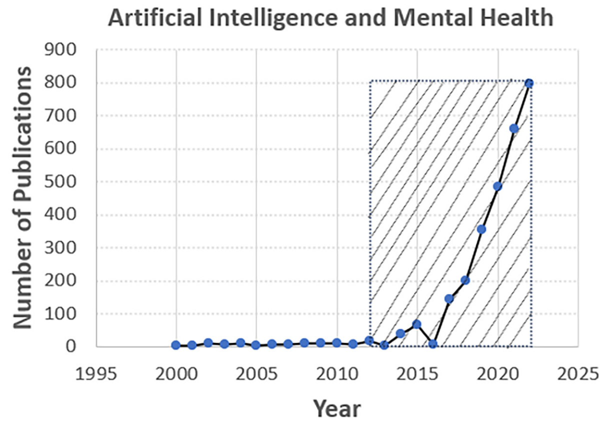

Fig. 3. Statistics on the number of AI and mental health literature in recent years.

been considered to represent the 'beginning' of AI, and the TT has been considered its ultimate goal [42]. The TT is among the many disputed cases in AI, philosophy of mind and cognitive science.

In addition to these more mediatic milestones, the use of AI in mental health remained inexpressive for several decades. On the one hand, AI, in particular ML, was not sufficiently developed; on the other hand, the possibility of accessing and computationally processing medical data on a large scale only became possible in the last two decades. It is only more recently, approximately since 2014, that we have started to see some more concrete research work using AI in mental health [32].

Using AI tools, researchers aim to diagnose (or predict) and monitor mental conditions before reaching the severe stages of mental disorders.

3.1 ML Methods

ML is a branch of AI and computer science that concentrates on using data and algorithms that emulate the process of human learning. How do we identify patterns and induce/abstract knowledge from the environment (data) and make decisions accordingly? ML aims to provide artificial systems with the ability to learn with minimal human intervention and thus adapt quickly to new situations and data. ML classifiers usually fall into two primary categories [53]: *supervised learning* and *unsupervised learning*.

Supervised learning, also known as supervised ML, is described by its use of tagged datasets to train algorithms that classify data or predict effects accurately. Some methods used in supervised learning include linear regression, **random forest (RF)**, logistic regression, **support vector machine (SVM)**, neural networks, **naive Bayes (NB)** and others.

Unsupervised learning, also known as unsupervised ML, applies learning algorithms to induce knowledge from unlabelled data, thus in an autonomous fashion. Typically, these algorithms find hidden patterns in data collections without human intervention. In this category, we can highlight the *k-means clustering*, methods of *probabilistic clustering* and association rules, among others [54, 55].

In the remainder of this section, we further detail some of these algorithms still relevant in different areas of AI and its applications, including naturally the area of *mental health*.

3.1.1 SVM. Most known simply as SVM, this supervised learning algorithm seeks the hyperplane that best separates the data points from different classes. Data are usually represented by n-dimensional points, also called n-dimensional vectors. The data points (vectors) nearest to the potential boundaries are key vectors that help to define the hyperplane during training. An SVM is a statistical model applied for scenarios requiring classification

Table 3. Types of Mental Disorders and Role of the IS

Authors	Disorder Type	Year	Keywords Used	Methodology	Primary Contribution
Jayshree Lavhare [44]	Stress disorder	2021	On-line social networking site, mental disorders detection, feature extracted, and Social network mental disorder classifying	On-line societal network and a random forest classification	ML framework for detecting the **Social Network Mental Disorder Detection (SNMDD)**
Abel and Greis [45]	Bipolar disorder	2019	Bipolar disorder, mental disorders and health literacy	BraPolar: App for remote monitoring of people with bipolar disorder	Detecting fluctuations in mood and behaviour. Indicate early mood changes before the disease reaches extreme functional consequences
Desti Fitriati [46]	Bipolar disorders	2019	Mental disorders, bipolar disorder, early detection of bipolar disorder, back-propagation	Back-propagation algorithm, website and Android app	Conduct an early detection study of bipolar disorder by using screening questionnaire data
Aditya Thota [47]	Stress disorder	2018	Stress prediction, healthcare, ML	ML techniques: Boosting, bagging and decision trees	Using ML methods to develop a model to predict the risk of stress experienced and if treatment is required by an individual
Shahidul Khan et al. [48]	Schizophrenia	2018	Data mining, mental disease, Bangladesh, health data, and classification algorithm	ML Techniques: Random Forest, SVM and K-Neighbor	This model will help the psychiatrist to understand the attributes related to mental disorder patients
Priyanka Dhaka [49]	Anxiety, mood, psychotic, and personality disorder	2016	Mental health, disorders, MongoDB, and extracting	Genetic algorithm	Help us to better understand what treatment works for which kind of patient
Philip and Thomas [50]	Alzheimer disease and dementia	2015	Patient monitoring, mental disorders, sensor technologies, Big Data analytics, psychometric scales	Multimodal systems	Multi-modal systems where patients can be diagnosed, treated and monitored
Sri Mulyana [51]	Schizophrenia and mood disorders	2013	Text processing, NLP, mental disorders, symptoms, and medical record	NLP	Shareasoning computer system to help to diagnose the types of mental disorders and their management
Stefan et al. [52]	Panic disorder	2013	Mobile communication, smartphones, mental disorders, and psychology	Mobile application for people with panic disorder	Treatment for people with panic disorder with and without agoraphobia

Summarising the critical comparisons between the primary contributions of the approaches and review of recently published literature, we included only studies published from 2013 to 2021, corresponding to the upsurge in AI systems publications about mental health.

or regression. SVM is quite efficient and makes decisions efficiently, even in the case of a large dataset. Among all learning algorithms observed in AI for mental health, SVM is the most popular one. In this survey, it was the algorithm used in [48, 56–61].

3.1.2 Decision Tree. The **decision tree (DT)** is a supervised learning method for classification and regression problems. That has a tree-like structure in a leaf node corresponding to a class or a decision node containing a test on some attribute. Each test result has an edge for a sub-tree, and each sub-tree has the same structure as the tree. In a DT, there are two kinds of nodes: decision nodes and Leaf nodes. The latter contains the outcome (the class or value) for a combination of attribute values defined by the path of decision nodes. DT can produce coherent rules without requiring any complex computations. In this survey, DT ranked third in the most used learning methods. It was found in four articles addressing mental health issues [56, 57, 62, 63].

3.1.3 Random Forest. RF is a supervised ML method known as the ensemble classification method; it deals with two types of problems: classification and Regression. The RF algorithm combines the output of multiple DT to generate the final output or for making decisions. By sampling the subsets of the training data, the tree bagging method fits a decision for each tree and aggregates their result. In this survey, RF ranked second in the most used learning methods. It was found in five articles addressing mental health [56–59, 63].

3.1.4 ***K Nearest Neighbour (K-NN).*** The K-NN is one of the most commonly used non-parametric algorithms. It is one of the most straightforward ML algorithms based on supervised learning and can be used for classification and predictive regression problems. K-NN is mainly used for Classification problems, but it can also be used for Regression. K-NN captures all the information of the training data. It assumes the similarity between the new case/data (to be predicted) and available cases (previously observed/learned), assigning the new case into the category most like the available categories on some proximity measure. It is easy to execute and does not make any additional assumptions, but it gets significantly slower with the expansion in the number of independent variables. In this survey, we have observed this technique in three works [48, 56, 63].

3.1.5 Naïve Bayes. NB is an easy but powerful algorithm derived from the Bayes theorem proposed by Thomas Bayes (1701–1761) that is mainly used for building predictive models—used in situations where probabilistic dependencies between datasets are expected, something like $D \Rightarrow C$ meaning that the observation of data configuration in D is likely to produce the outcome/classification in C. For example, D might represent a set of all possible mental diseases' symptoms and C the set of possible diagnostics. In this setting, the Bayes Rule states that

$$\mathbb{P}(C|D) = \frac{\mathbb{P}(C) \cdot \mathbb{P}(D|C)}{\mathbb{P}(D)},$$

where

- $\mathbb{P}(C|D)$ is the posterior probability;
- $\mathbb{P}(D|C)$ is the likelihood of observing data D when class C is certain;
- $\mathbb{P}(C)$ and $\mathbb{P}(D)$ are the prior or marginal probabilities; the normalisation of that evidence under any circumstance.

In the example formulated above, $\mathbb{P}(C|D)$ represents the distribution of the diagnosis taking into account the observed symptoms (D). While $\mathbb{P}(D|C)$ is the distribution of data (symptoms) observed for a given disease ($c \in C$), $\mathbb{P}(C)$ is the distribution of diseases. In learning based on Bayes' formula, one tries to maximise the disease (class) that best fits the observed data (evidence) through the formula:

$$\operatorname*{argmax}_{c \in C} \frac{\mathbb{P}(c) \cdot \mathbb{P}(D|c)}{\mathbb{P}(D)}$$

which is equivalent:

$$\operatorname*{argmax}_{c \in C} \mathbb{P}(c) \cdot \mathbb{P}(D|c).$$

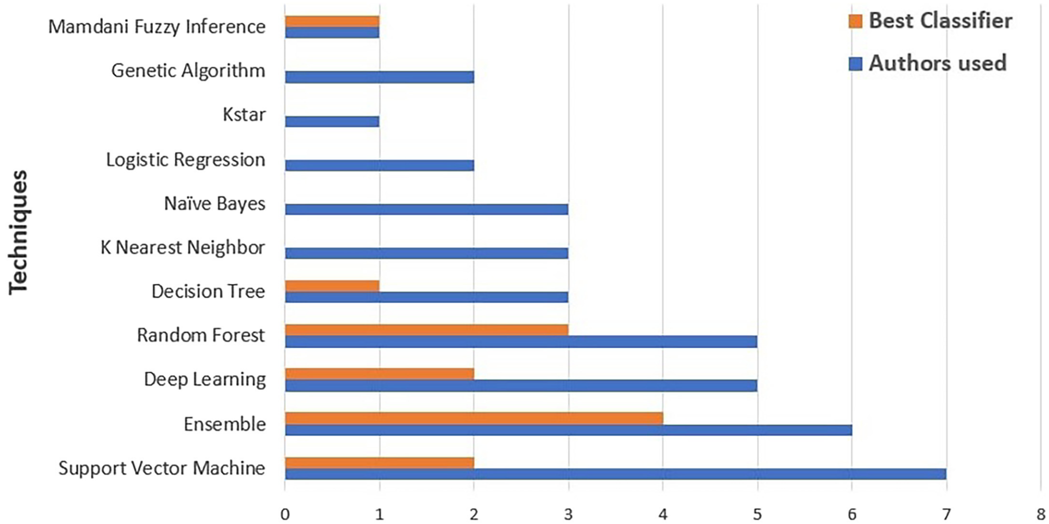

Fig. 4. A comparative analysis of the techniques most used by the authors in their different works and the techniques that had a higher performance based on various metrics. The *x*-axis represents the number of articles in our review.

The *Bayes Rule* and NB are the foundation of many other ML algorithms [64] and are widely used on countless problems. In this survey, we have observed using NB in three works related to mental diseases [57, 59, 62].

3.1.6 Ensemble. Ensemble methods are statistical and computational learning techniques based on human social learning, which involves pursuing input from multiple sources before making any crucial decision. Ensemble methods merge several models to reduce variance and enhance predictions. The ensemble has the particularity of being the studied algorithm with the best classifier in all the cases compared with other techniques used. The popular ensemble methods are bagging and boosting. Even though it is not the most used technique, as can be seen in Figure 4, it was used by the following authors [48, 60, 63, 65, 66].

3.2 DL Methods

DL is the most recent generation of learning algorithms based on neural networks. Architectures containing multiple layers of artificial neurons are carefully engineered to achieve performance breakthroughs in the existing problems. DL discovers complex structures in large datasets by using the back-propagation algorithm [46], which indicates how a machine should modify its inner parameters to compute the representation per layer from the representation in the previous layer [67].

3.2.1 ***Deep Neural Networks (DNNs).*** DNNs is a field of DL, inspired by the structure and functioning of the brain for the construction and training of **artificial neural networks (ANN)**. The evolution of IS, especially AI technologies, has greatly improved the capabilities of clinical expert systems. Recent advancements in Neural Networks, in particular the emergence of modern DL architectures based on **convolutional neural network (CNNs)**, **recurrent neural network (RNNs)**, and *Transformers*, opened new avenues of possibilities in many subfields of AI, including NLP and **Intelligent Image Processing (IIP)**, both being fundamental for the challenges of mental health diagnosis and monitoring. CNN architectures and Transformer models can be integrated to improve the model's ability to understand and interpret the nuanced language patterns associated with psychological assessment and intervention. In the context of COVID-19 for early patient recognition, Irfan et al. [68], using a hybrid deep neural network, obtained a classification accuracy of 99% on test set data. Almalki et al. [69] used AI techniques such as DL to detect suspected Coronavirus patients non-intrusively. In this survey, we have observed methods based on DL in the works of Espinola et al. [57] and Fitriati et al. [46].

3.2.2 Transformers. Transformers have significantly succeeded in many AI fields, such as NLP and computer vision. These fields have demonstrated their effectiveness on fundamental tasks such as classification, detection, segmentation and multi-modal data stream. The transformer is the first transduction model that relies entirely on self-attention to compute models of its input and output without using sequence-aligned RNNs or CNNs [70]. To automatically estimate the level of several symptoms associated with depression at [71], the authors explore the potential of a BERT-based classifier for early detection of self-harm and depression. To identify individuals predisposed to depression based on linguistic and cognitive characteristics in [72], the authors use transformer-based language models such as RoBERTa and self-attention and obtain an accuracy of 96.86.

3.2.3 ***Large Language Models (LLMs).*** LLMs are sophisticated AI systems created to interpret and generate human language. These models use DL techniques based on ANN, which are abstract mathematical models of brains. They use extensive text datasets to learn patterns, semantics and grammar. The LLMs such as Flan-T5 [73], LLaMa [74], Mistral [75] and MentalLLaMa [76] are emerging as potent tools increasingly capable of performing human-level tasks across various research domains, including medicine, education and finance. Due to their adaptability and general-purpose design, LLMs excel at processing and generating text across various topics, providing reassurance about their versatility in different fields. In the context of mental health, using a comprehensive assessment of several LLMs such as Alpaca, Alpaca-LoRA, FLAN-T5, GPT-3.5 and GPT-4, the authors [77] applied various mental health prediction tasks via online text data.

3.3 Mobile Applications for Mental Health

Recently, there has been a proliferation in the use of software applications for medical and health-related purposes. Such applications can be organised according to their functionality. In particular, many mobile applications use cognitive behavioural therapy, mindfulness training, mood monitoring and cognitive skills training to treat depressive symptoms [78]. Such applications are gaining momentum as it has been shown that by enabling users to self-monitor their mood (by periodically reporting their thoughts, behaviours and actions), their emotional self-awareness could be increased, which resulted in the reduction of the symptoms [79]. However, the evidence of efficiency in mental health applications is mixed. Indeed, the study of 22 mobile mental health applications presented in [80] found that they were only effective in users who had self-reported mild-to-moderate depression but had no significant impact on patients with major depression, bipolar or anxiety disorders.

To improve medication adherence among patients with schizophrenia over 24 weeks [81], the author created a new AI platform for mobile devices. The study showed that the adherence rate was 89.7% (with a standard deviation of 24.92) for individuals using the AI platform, compared to 71% (with a standard deviation of 24.92) for those receiving modified directly observed therapy while taking nicotinic receptor agonists. In [52] Stegemann et al. developed a GET.ON PAPP, a mobile application for panic disorder that integrates an internet-based treatment into daily life. The program can be used by people with panic disorder with and without agoraphobia. In [82], Festersen et al. developed a Re:Mind; a mobile application designed to treat bipolar disorder patients. Re:Mind can be used by both patients and medical personnel. In Re:Mind, patients can proactively enter personal health-related data, display it, manage their medicaments and prescriptions and communicate with their physicians. The impact of mobile technology on health can be far-reaching and cost-effective: digital content can be accessed, stored, manipulated and transmitted at an affordable price, in real-time, from anywhere, anytime.

3.4 Mental Health Datasets

The authors in [83] propose a **virtual assistant (VA)** as a first contact point for depressed or discouraged users. The VA should be able to provide motivational and affirming responses and offer users a safe environment in which to share their thoughts and anonymously ask for help and advice. To address these different aspects, they created a large-scale dataset, MotiVAte, consisting of dyadic conversations between the depressed user and the VA (conveying hope and motivation). The proposed dataset is evaluated using state-of-the-art generative models. Empirical results based on automatic and human evaluation are presented. According to the authors, this is the first application of natural language generation in the mental health domain.

Depression is a common mental illness that must be detected and treated early to avoid serious consequences. There are many methods and modalities for detecting depression that include a physical examination of the person. However, diagnosing mental health based on social media data is more effective because it avoids these physical examinations. In addition, people can express their emotions well on social media, so it is desirable to diagnose their mental health based on data from social media. Although many systems detect a person's mental illness by analysing their social media data, determining the degree of depression is also essential for further treatment. All existing systems are designed to detect depression based on texts in social networks. Although depression detection is more important, depression-level detection is equally important. The study in [84] developed a baseline dataset that identifies the degree of depression as 'non-depressed', 'moderately depressed' and 'severely depressed' based on posts in social media. The dataset can also be augmented by considering images and text to provide more accurate detection.

The research community has observed a significant increase in identifying mental health problems and their causes through social media analysis. Authors in [85] present a new dataset for **causal analysis of mental health problems in social media posts (CAMS)**, a dataset of 5,051 instances to categorise direct causes of mental disorders based on users' mentions in their posts. Their contribution to causal analysis is twofold: causal interpretation and causal categorisation. An annotation scheme for this causal analysis task is presented. The effectiveness of their scheme is demonstrated on two different datasets: (i) by examining and annotating 3,155 Reddit posts and (ii) by re-annotating the public SDCNL dataset of 1,896 instances for interpret-able causal analysis and then combining these data to form the CAMS dataset and make this resource publicly available with the associated source code: https://github.com/drmuskangarg/CAMS.

The **Distress Analysis Interview Corpus (DAIC)** [86] contains clinical interviews to support the diagnosis of mental disorders such as anxiety, depression and post-traumatic stress disorder. Interviews are conducted by humans, agents and autonomous agents, and participants include both sufferers and non-sufferers. The data collected included audio and video recordings, numerous questionnaire responses and verbal and nonverbal characteristics. The corpus was used to develop an automated interview agent and research the automatic detection of mental health problems.

ETAD corpus [87] is the first Chinese dataset on depression. It contains the audio responses of 162 volunteers to three emotion-related questions. The text transcripts were extracted from the audio, manually corrected and inserted into the EATD corpus. Given the lack of public multimedia data on depression, the EATD corpus provides valuable data for psychologists and computational researchers studying depression.

The TILES-2018 dataset (Tracking Individual performance with Sensors, the Year 2018) [88] comes from a prospective longitudinal study with an intensive multi-modal assessment of workers and their environment to understand the dynamic relationships between individual differences, work and well-being and the contexts in which they appear. The aim is to support the development and validation of sensor-based methods for assessing workers' well-being and work performance over time. The data were collected in partnership with Keck Hospital at the University of Southern California to directly follow 212 workers who volunteered to participate in the study over ten weeks, both on and off the job. Biobehavioural data was continuously and passively collected throughout the study using wearable devices (bracelets, smart underwear, audio clip recorders, Bluetooth badges and personal smartphones). These data streams were combined with environmental and behavioural data from **Internet of Things (IoT)** devices and applications that recorded personal smartphone usage. To link sensor data to interesting constructs, participants also completed an initial series of online and daily surveys aimed at identifying individual difference variables (e.g., personality, intelligence, socioeconomic status), states and psychological traits (e.g.,

Table 4. Overview of Dataset Presented in This Study

Dataset	Instances	Data-Type	Source	Year	Reference
MotiVAte	4,000	Dialogue	Multiple	2021	[83]
Depression SM	20,008	Text	Reddit	2022	[84]
CAMS	5,051	Text	Reddit	2022	[85]
DAIC	24,348	Multi-modal	Interviews	2014	[86]
ETAD	162	Audio and text	Counselling	2022	[87]
TILES	212	Sensors and multi-modal	Wearable devices	2018	[88]
MAIKI	48	Sensors and multi-modal	Mobile phones	2022	[89]

SM, social media.

positive and negative affect, anxiety, stress, fatigue, psychological flexibility, psychological capital), health and well-being (e.g., sleep, physical activity, cardiovascular exercise, smoking and alcohol consumption, health-related quality of life, and life satisfaction) and work behaviour (e.g., performance, organisational, civic behaviour, counterproductive work behaviour, work engagement, perceived support and stressors).

The MAIKI [89] is a real-world longitudinal dataset that was collected as part of the MAIKI project [90], which collected different active and passive data modalities, e.g., telephone data, GPS data or different questionnaires, from 48 patients over 3 months. The study procedures were approved by the ethics committee of the Friedrich-Alexander University of Erlangen-Nuremberg (385_20B). During the study period, there were days when data were not collected from some participants. This was because some individuals did not complete a diary for each day. A brief comparison of datasets discussed above is given in Table 4.

3.5 Assisted Decision-Making for Professionals

3.5.1 Factoid and Nonf-Factoid Questions. Issues related to mental health are usually complex and very subjective for each individual. People going through the same experiences deal uniquely and individually. Usually, in psychiatry, patients deal with questions that can help them understand their situation and thus determine their condition. These questions can be separated into two main categories: factoid and non-factoid questions. Factoid questions have specific answers that can be looked up and have a basis for determining a correct answer. For example, the factoid questions comprise a significant fraction of all user queries submitted to search engines [91]. The question 'What is the capital of Portugal?' is a factoid question as there is only one capital of Portugal, Lisbon. The related questions to mental health are not direct, so they often involve other processes. Non-factoid questions ask open-ended questions and may not have one clear answer [42]. They are open-ended questions requiring complex answers, like descriptions, opinions, or explanations, which are primarily passage-level texts [92]. An example of a non-factoid question may be: 'how do you feel about your new cell phone?'

Mental health questions are open-ended and do not have one exact answer. For instance, if a person asks him or herself, 'Why do I have PTSD?' the answers will vary among those with PTSD. One may experience PTSD due to domestic violence or rape, while another may have PTSD from seeing a friend die in combat in the army. Diagnosis of mental disorders is difficult to pinpoint one root cause, and many symptoms overlap in different disorders, making it hard to diagnose mental disorders. Doctors, nurses, psychiatrists must trust their patients to give the correct symptoms to indicate what is wrong. The symptoms signs are even harder to pinpoint, especially if someone is not looking for the signs. These reasons make it difficult for AI systems to give feedback, let alone humans [42, 93].

Table 5. Comparison of Various Automatic Mental Diagnosis Solutions

Author	Automatic Diagnosis Tool	Accuracy
Chen et al. [56]	The authors used different ML methods (SVM, logistic regression, DT, K-NN, and RF) to the automatic diagnosis of ADHD.	73%
Jaiswal et al. [58]	The authors showed how computer vision can detect ADHD and ASD based on video analysis of a person's behaviour.	96%
Dharun et al. [63]	The authors used ML algorithms to detect stress in working employees and found features contributing to mental stress.	75.13%
Husain et al. [97]	The authors adopt a random forest approach to identifying hidden patterns and relationships that can be used for predicting generalised anxiety disorder.	90%
Agnes et al. [98]	The authors used a smartphone-based sensor system and developed an early warning system to find the changes in the states of bipolar disorder patients.	97%

ADHD, attention deficit hyperactivity disorder.

3.5.2 Diagnostic and Prediction Tools. Diagnosis is an essential initial step in the treatment of mental disorders. One defiance for clinicians in making diagnoses is that patient exchanges only offer a snapshot of an individual's mental state, yet mood conditions are dynamic and fluctuate over time. Currently, psychiatric examination of patients includes observation of their mental state and subjective self-report questionnaires. These approaches are subjective, difficult to repeat and time-consuming [94]. The therapist can be aided in his/her diagnosis by AI systems that simulate practitioners' reasoning capacities. As such, the artificial diagnosis can confirm the intuition of the health professional or alert him/her to a possible difference. The artificial system can act as advice for a second colleague.

Students at Columbia University and the New York State Psychiatric Institute have developed a ML system capable of predicting if a person at risk of developing psychosis caused by schizophrenia will develop the condition with 90% accuracy by analysing his or her speech, which can exhibit telltale signs of the condition. Also, IBM researchers developed an ML speech classifier with 79% accuracy in predicting psychosis onset in those with clinically high-risk [95, 96]. In addition to helping with diagnosis, such tools may support monitoring patients' progress. Table 5 shows the literature review about automatic mental diagnosis solutions.

3.5.3 Monitoring. To support the therapist in his/her diagnosis of patients, monitoring systems have been developed that identify specific verbal and non-verbal descriptors which can manifest mental disorders. In mental health, monitoring mood and mental health outside the clinical setting is the written record that patients keep throughout the treatment process, such as a diary. All but the most extreme psychiatric care takes position in an outpatient setting, so additional monitoring in the community would offer significant benefits. Early detection and prevention of relapse can considerably impact outcomes [94].

AI can be integrated with other technologies, such as sensors and mobile applications, to continuously monitor patients, clinicians/therapists or researchers to view changes and symptom trajectories over time. Another characteristic of monitoring is medication adherence, which is an issue in all chronic health issues and may exceptionally be so in mental health disorders; the calculations of non-adherence to antipsychotic prescriptions meander from 20% to 89% for patients with schizophrenia or bipolar condition [94, 99], medication being an essential part of the treatment of these patients. Table 6 synthesises the literature review about automatic mental monitoring solutions.

Table 6. A Brief Comparison of Automatic Monitoring Solutions for Mental Disorders

Author	Monitoring tool
Valenza et al. [100]	Monitored through the smartphone and a sensorised t-shirt, the authors developed bipolar an m-Health application for remote monitoring of patients with bipolar disorder, detecting fluctuations in mood and behaviour.
Upkar Varshney [101]	An IT-enabled framework to support mental health monitoring. This includes comprehensive monitoring of patients for symptoms, behaviour, and medication compliance.
Ha et al. [102]	To monitor electroencephalography, hemoencephalography, and heart rate variability for accurate mental health monitoring, the authors proposed a multi-modal mental management system in the shape of the wearable headband and earplugs.
Muhammad et al. [103]	Using the IoT Long Range technology, the authors propose a system design for the tracking and monitoring of mental disorder patients.
Philip Moore et al. [50]	The authors implemented multi-modal systems where patients can be diagnosed, treated, and monitored. The systems incorporate triage and treatment capabilities in both hospital settings while monitoring the community.

4 Discussion

In this session, we identify the algorithms used by different studies and their performance. SVM, DL, RF and Ensemble method are among the most used algorithms. In the performance comparison, the ensemble algorithms performed best in all the implemented studies. This is due to the amount of data used in the different studies. The datasets presented balancing problems in their studies due to data limitations. As an assisted decision-making aid for professionals in diagnosis, SVM, RF and DT were the most implemented for monitoring and treatment; in the different studies, they used a combination of sensors, ML algorithms and mobile devices. We compared several ML techniques and which algorithms performed best, as shown in Figure 4.

A wide variety of mental health conditions have been researched, but the limited availability of open source datasets restricts many. Frequently studied mental conditions include stress disorder [44, 47, 63, 86], bipolar disorder [45, 46, 82, 98, 100], schizophrenia [48, 51, 59, 81, 94, 95, 104], anxiety disorder [49, 60, 80, 86, 97, 104], and depression: [61, 66, 71, 72, 80, 84, 86, 87, 89, 104].

New IS that, through visual perception, correctly interpret the patient's emotional states and can interact with him verbally are crucial for the new *automatic therapies*. With NLP, IIP, ML and all their associated areas, we have a plethora of tools to start with predictive modelling of these diseases through the treatment of large volumes of already existing data, in addition to the more specific ones that will prove to be relevant in the future. There are a significant number of data science problems in this field that need to be addressed. Even more, each specific clinical context will require special attention regarding data analysis. Nowadays, these areas already provide several important algorithms that can identify patterns and trends, predicting target classifications through supervised and unsupervised learning. Many such algorithms have been extensively used to diagnose or detect the prevalence of mental disorders.

For performance assessment of models and systems, authors use various metrics to perform a comparative analysis of different algorithms in terms of several parameters like *accuracy*, *recall*, *precision*, *F1-score*, *specificity*, and so on. All these metrics are calculated based on the confusion matrix. Some algorithms may perform more useful with improving accuracy and precision, while others may perform better in decreasing errors. Table 7 shows a comparative performance analysis of the different works we have observed for diagnosing and monitoring

Table 7. Comparative Analysis of ML and Best Classifier Algorithms

Author	Problems Addressed	Techniques Used	Metrics	Best Classifier
Astari et al. [46]	Bipolar disorder	Back-propagation algorithm	-	Back-propagation algorithm
Chen et al. [56]	ADHD	SVM, Logistic Regression, DT, K-NN, and RF.	Accuracy, AUC score	RF
Dhaka [49] and Johari	Anxiety disorder, mood disorder, psychotic disorder, personality disorder	Genetic algorithm	Accuracy, precision	Genetic algorithm
Dooshima et al. [62]	General	NB, DT	Accuracy, precision	DT
Espinola et al. [57]	Major depressive	MLP, NB, SVM, DT, RF, Bayes Net, Regression	Accuracy, Kappa, sensibility and specificity	SVM
Jayshree and Kulkarni [58]	SNMDD	SVM and RF	Precision, recall, F1-score and accuracy	RF
Kamal et al. [59]	Schizophrenia, autism and PTSD	RF, XGboost, NB, SVM	Precision, recall, F1-score	XGboost
Khan et al. [48]	General	RF, SVM, KNN	Recall, precision	RF
Makhija et al. [65]	General	Sentence embedding, ensembling kstar, MLP	Accuracy	Ensemble
Ming-Yi and Chih-Ying [60]	Anxiety	Ensemble and SVM	Precision and recall	Ensemble
Parameswaran et al. [61]	Depression	Viola Jones face detection algorithm, Gabor filter, SVM	Accuracy, sensitivity specificity, Precision F1-score, false positive rate	SVM
Silvana et al. [104]	Schizophrenia paranoid, phobia, depression, anxiety, OCD and anti-social	Mamdani fuzzy inference	Accuracy	Mamdani fuzzy inference
Tasnim et al. [66]	Depression	Network, gradient boosting tree	Accuracy, precision-recall	DNN
Thota and Dranu [63]	General	Logistic regression, K-NN, DT, RF, bagging, boosting	Accuracy, false positive rate, precision, AUC Score	Boosting

MLP, multilayer perceptron; OCD, obsessive-compulsive disorder.

mental disorders. It focuses on the authors' techniques and the algorithms with the best classifier. For depression studies, the MLP algorithm presents significant results compared to other classical algorithms.

AI can be highly beneficial when predicting mental health issues, creating personalised treatment strategies and ensuring compliance [105]. However, it also brings typical challenges requiring cooperation between AI researchers and healthcare employees. It's an emerging field that includes other dimensions of various modalities; hence, there are fusion and hybrid models, and so on, and no one solution is applicable in all scenarios.

4.1 Challenges and Limitations

The complexity of using IS for areas such as mental health mainly focuses on subjective questions present in treating patients with mental problems. This subjectivity often becomes so complex for the surrounding elements (e.g., patient and psychiatrist). As previously discussed, factoid questions and non-factoid questions, IS, when involved in a diagnostic patient with a mental disorder, will have to deal with non-factoid questions [42, 91], many of which are the basis for the study of sciences such as philosophy and psychology science. However, IS are generally more accurate than humans and may support enhanced decision-making [106]; just as with a human practitioner, AI systems are exposed to mistakes in judgement and incorrect risk inspection [107]. In the case of diagnosis, many other factors (besides the question-and-answer process) should be considered as part of this process. For example, most systems we study do not deal with subjective issues at the level of voice tone, sign language and other aspects of the patient's physical condition.

Another field of this study that should be considered is the cases of technologies related to patient monitoring. The first aspect focuses on using electronic equipment to monitor patients with mental problems. On the one hand, it helps the psychiatrist monitor the patient's processes in real time. Still, on the other hand, this equipment can increase the index of addiction to the use of electronic equipment by patients.

Using IS to offer diagnostic and monitoring treatment services brings new complexities related to legal and ethical issues in psychological practice. These issues need to be carefully addressed to ensure that the benefits are maximised without causing harm. For instance, systems accessible over the internet, like current avatar systems, can offer services across different legal jurisdictions [33]. Legal and ethical considerations include obtaining informed consent, ensuring safety and transparency, addressing algorithmic bias and rights and safeguarding data privacy. Legal concerns also encompass evaluating safety and effectiveness, addressing liability and providing data protection and privacy. IS have the potential to significantly enhance the delivery of healthcare services and support various public health interventions. However, ethical principles and human rights must remain central to these systems' design, implementation and use.

5 Conclusion

An IS is increasingly a part of digital medicine and will contribute to mental health research and practice. Many techniques like NLP, multi-modal systems, ML and AI algorithms have significantly contributed to building models/solutions to diagnose and monitor societal mental disorders. This survey observed that no particular techniques are suitable in all situations, and several other factors can contribute to the technique's performance. Different techniques show high accuracy and precision with fewer error rates according to different circumstances. So, we must choose a specific technique or classifier for each domain of interest without getting stuck on one particular technique. Although none of the techniques can necessarily solve all problems, whether for diagnosis, monitoring, or treatment, with interactive studies, applied methods and results that obtained the best classifications, we can consider that ML algorithms such as SVM, DL, RF, DT, and essential ensemble algorithms such as bagging and boosting have shown the potential to be applied for diverse mental health-related issues.

The practice of mental health for the care of patients and the help of psychiatrists for diagnosis and monitoring can be improved with the advancement of IS. This is by collaborating with diverse professionals such as data scientists, computer engineers and health professionals. The aim should be to focus on the assistive part of AI instead of replacing the professionals with IS. The future of IS in mental healthcare is promising. The data source for training IS for mental disorders could become more consistent if we add data from multiple sources. So far, most of the data have been obtained from interview questionnaires. As part of future work, we propose the construction of a hybrid system to detect the majority and severity of mental disorders in people through body language and multi-modal data. The detention and mental health process deals with multiple data sources. This system can be used by mental health professionals for therapeutic intervention.

References

[1] Department of Health. 2020. *No health without mental health: A cross-government mental health outcomes strategy for people of all ages-* Analysis of the Impact on Equality, volume 00. Department of Health.

[2] Kavitha Kolappa, David C. Henderson, and Sandeep P. Kishore. 2013. No physical health without mental health: Lessons unlearned?. *Bull World Health Organization* 91, 1 (2013), 3–3A.

[3] HMG/DH. 2015. No health without mental health: A cross-government mental health outcomes strategy for people of all ages. *WHO*. Retrieved from https://assets.publishing.service.gov.uk/media/5a7c2248e5274a1f5cc75fcd/dh_124514.pdf

[4] Bettina van Wylich-Muxoll. 2015. Mental health in an unequal world. World Mental Health Day 2021. *WHO* 12, 2, 00–00. Retrieved from https://www.consaludmental.org/publicaciones/Mental-health-Unequal-World.pdf

[5] WHO. 2020. World Mental Health Day 2021- The economic cost. Retrieved from https://www.who.int/key-messages

[6] João Marques Teixeira. 2020. Perturbação Mental em Números. Retrieved from https://www.sppsm.org/informemente/guia-essencial-para-jornalistas/perturbacao-mental-em-numeros/

[7] WHO. 2021. No health without mental health- A cross-government mental health outcomes strategy for people of all ages. Retrieved from https://www.who.int/campaigns/world-mental-health-day/2021

[8] Government of Canada. 2006. The human face of mental health and mental illness in Canada. Retried from https://www.phac-aspc.gc.ca/publicat/human-humain06/pdf/human_face_e.pdf

[9] Britannica. 2022. Mental disorder summary. Retrieved from https://www.britannica.com/summary/mental-disorder

[10] Ranjive Mahajan and Shruti Verma. 2021. An assessment of the impact of Covid-19 on the mental health of medical students across various medical colleges of Punjab. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3796917

[11] American Psychiatric Association. 2015. *Depressive Disorders: DSM-5® Selections*. American Psychiatric Publishing.

[12] World Health Organization. 2021. *Depression: Definition*. WHO.

[13] Robert Rakel. 1999. Depression. *Primary Care* 26 (1999), 211–214. DOI: https://doi.org/10.1016/S0095--4543(08)70003--4

[14] Suma P. Chand, Hasan Arif, and Rose M. Kutlenios. 2021. Depression (Nursing). *Europe PMC*, 12, 33760492 (2021), 9–8.

[15] Darrel A. Regier, Emily A. Kuhl, and David J. Kupfer. 2013. The DSM-5: Classification and criteria changes. *World Psychiatry* 12, 2 (2013), 92–98.

[16] Jessica Truschel. 2019. *Bipolar Definition and DSM-5 Diagnostic Criteria*. Retrieved from https://www.psycom.net/bipolar-definition-dsm-5/

[17] Michael J. Asken, Dave Grossman, and Loren W. Christensen. 2013. American Psychiatric Association. Diagnostic and Statistical Manual of Mental Disorders. *Therapy* 45, 10 (2013), 2317–2325.

[18] World Health Organization. 2013. *Meeting report: Autism spectrum disorders and other developmental disorders: From raising awareness to building capacity*. World Health Organization.

[19] Catherine Lord, Edwin H. Cook, Bennett L. Leventhal, and David G. Amaral. 2000. Autism spectrum disorders. *Neuron* 28, 2 (2000), 355–363.

[20] Holly Hodges, Casey Fealko, and Neelkamal Soares. 2020. Autism spectrum disorder: Definition, epidemiology, causes, and clinical evaluation. *Translational Pediatrics*, 9, Suppl 1 (2020), S55.

[21] Peter P Roy-Byrne, Michelle G Craske, and Murray B Stein. 2006. Panic disorder. *The Lancet*, 368(9540), 1023–1032.

[22] National Institute of Mental Health. 2017. Transforming the understandingand treatment of mental illnesses. National Institute of Mental Health. Retrieved from https://www.nimh.nih.gov/

[23] R. Nicholas Carleton, Sophie Duranceau, Mark H. Freeston, Paul A. Boelen, Randi E. McCabe, and Martin M. Antony. 2014. "But it might be a heart attack": Intolerance of uncertainty and panic disorder symptoms. *Journal of Anxiety Disorders* 28, 5 (2014), 463–470.

[24] Silvano Arieti. 1955. Interpretation of schizophrenia. *American Psychological Association* 522, 7321 (1955), 98–99.

[25] Rajiv Tandon, Wolfgang Gaebel, Deanna M. Barch, Juan Bustillo, Raquel E. Gur, Stephan Heckers, Dolores Malaspina, Michael J. Owen, Susan Schultz, Ming Tsuang, Jim Van Os, and William Carpenter. 2013. Definition and description of schizophrenia in the DSM-5. *Schizophrenia Research* 150, 1 (2013), 3–10.

[26] Thomas Munk Laursen, Merete Nordentoft, and Preben Bo Mortensen. 2014. Excess early mortality in schizophrenia. *Annual Review of Clinical Psychology*, 10, 425–448.

[27] Assen Jablensky, Norman Sartorius, Gunilla Ernberg, Martha Anker, Ailsa Korten, John E. Cooper, Robert Day, and Aksel Bertelsen. 1992. Schizophrenia: manifestations, incidence and course in different cultures a world health organization ten-country study. *Psychological Medicine Monograph Supplement*, 20 1–97.
[28] Xishuang Feng, Maorong Hu, and Wanhui Guo. 2022. Application of artificial intelligence in mental health and mental illnesses. In *Proceedings of the 3rd International Symposium on Artificial Intelligence for Medicine Sciences*, 506–511.
[29] Chang Su, Zhenxing Xu, Jyotishman Pathak, and Fei Wang. 2020. Deep learning in mental health outcome research: A scoping review. *Translational Psychiatry* 10, 1 (2020), 116.
[30] Vidhi Mody and Vrushti Mody. 2019. Mental health monitoring system using artificial intelligence: A review. In *Proceedings of the 2019 IEEE 5th International Conference for Convergence in Technology (I2CT)*, pages 1–6. DOI: https://doi.org/10.1109/I2CT45611.2019.9033652
[31] Enrique Garcia-Ceja, Michael Riegler, Tine Nordgreen, Petter Jakobsen, Ketil J. Oedegaard, and Jim Tørresen. 2018. Mental health monitoring with multimodal sensing and machine learning: A survey. *Pervasive and Mobile Computing*, 51 (2018), 1–26.
[32] Sarah Graham, Colin Depp, Ellen E Lee, Camille Nebeker, Xin Tu, Ho-Cheol Kim, and Dilip V Jeste. 2019. Artificial intelligence for mental health and mental illnesses: An overview. *Current Psychiatry Reports* 21 (2019), 1–18.
[33] David D. Luxton. 2014. Artificial intelligence in psychological practice: Current and future applications and implications. *Professional Psychology: Research and Practice* 45, 5 (2014), 332.
[34] Franz Gravenhorst, Amir Muaremi, Jakob Bardram, Agnes Grünerbl, Oscar Mayora, Gabriel Wurzer, Mads Frost, Venet Osmani, Bert Arnrich, Paul Lukowicz, and Gerhard Tröster. 2015. Mobile phones as medical devices in mental disorder treatment: an overview. *Personal and Ubiquitous Computing* 19 (2015), 335–353.
[35] David Moher, Alessandro Liberati, Jennifer Tetzlaff, Douglas G Altman, and PRISMA Group*. 2009. Preferred reporting items for systematic reviews and meta-analyses: The Prisma Statement. *Annals of Internal Medicine* 151, 4 (2009), 264–269.
[36] Terry Anthony Byrd and Richard D. Hauser. 1991. Expert systems in production and operations management: Research directions in assessing overall impact. *The International Journal of Production Research* 29, 12 (1991), 2471–2482.
[37] Imre J. Rudas and János Fodor. 2008. Intelligent systems. *International Journal of Computers, Communications & Control* 3, 3 (2008), 132–138.
[38] Stuart Russell and Peter Norvig. 1995. *Prentice Hall Series in Artificial Intelligence*. Prentice Hall, Englewood Cliffs, NJ.
[39] Kalmanje Krishnakumar. 2003. Intelligent systems for aerospace engineering-an overview. *National Aeronautics and Space Administration Moffett Field CA AMES Research* (2003). Retried from https://ntrs.nasa.gov/api/citations/20020065377/downloads/20020065377.pdf
[40] Mary S. Doucet and Thomas A. Doucet. 2003. Public accounting firms. In Hossein Bidgoli (Ed.), *Encyclopedia of Information Systems*, Elsevier, 601–606. DOI: https://doi.org/10.1016/B0-12-227240-4/00143-X
[41] Jerry W. O'Dell and James Dickson. 1984. Eliza as a "therapeutic" tool. *Journal of Clinical Psychology* 40, 4 (1984), 942–945.
[42] Michelle C Ausman. 2019. Artificial intelligence's impact on mental health treatments. In *Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society*, pages 533–534, ACM.
[43] Ayse Pinar Saygin, Ilyas Cicekli, and Varol Akman. 2000. Turing test: 50 years later. *Minds and Machines* 10, 4 (2000), 463–518.
[44] Jayshree N. Lavhare and M. A. Kulkarni. 2021. Mental disorders detection using social networking sites. In *Proceedings of the 2021 3rd International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)*. IEEE, 113–117.
[45] Abel González Mondéjar, Greis Francy M. Silva-Calpa, Alberto Barbosa Raposo, and Daniel C. Mograbi. 2019. Brapolar: An m-health application for remote monitoring of people with bipolar disorder. In *Proceedings of the 2019 IEEE 7th International Conference on Serious Games and Applications for Health (SeGAH)*. IEEE, 1–8. DOI: https://doi.org/10.1109/SeGAH.2019.8882469
[46] Desti Fitriati, Febri Maspiyanti, and Fairuz Astari Devianty. 2019. Early detection application of bipolar disorders using backpropagation algorithm. In *Proceedings of the 2019 6th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI)*. IEEE, 40–44.
[47] U Srinivasulu Reddy, Aditya Vivek Thota, and A. Dharun. 2018. Machine learning techniques for stress prediction in working employees. In *Proceedings of the 2018 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*. IEEE, 1–4. DOI: https://doi.org/10.1109/ICCIC.2018.8782395
[48] Shahidul Islam Khan, Ariful Islam, Akther Hossen, Taiyeb Ibna Zahangir, and Abu Sayed Md. Latiful Hoque. 2018. Supporting the treatment of mental diseases using data mining. In *Proceedings of the 2018 International Conference on Innovations in Science, Engineering and Technology (ICISET)*. IEEE, 339–344. DOI: https://doi.org/10.1109/ICISET.2018.8745591
[49] Priyanka Dhaka and Rahul Johari. 2016. Big data application: Study and archival of mental health data, using mongodb. In *Proceedings of the 2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT)*. IEEE, 3228–3232.
[50] Philip Moore, Andrew Thomas, Tarik Qassem, Nik Bessis, and Bin Hu. 2015. Monitoring patients with mental disorders. In *Proceedings of the 2015 9th International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing*. IEEE, 65–70. DOI: https://doi.org/10.1109/IMIS.2015.15
[51] Sri Mulyana, Sri Hartati, Retantyo Wardoyo, and Subandi. A processing model using natural language processing (NLP) for narrative text of medical record for producing symptoms of mental disorders. In *Proceedings of the 2019 4th International Conference on Informatics and Computing (ICIC)*, IEEE, 1–6.

[52] Stefan Kleine Stegemann, Lara Ebenfeld, Dirk Lehr, Matthias Berking, and Burkhardt Funk. 2013. Development of a mobile application for people with panic disorder as augmentation for an internet-based intervention. In *Proceedings of the 2013 Federated Conference on Computer Science and Information ystems*, 1331–1337.

[53] IBM Cloud Education. 2021. *Machine Learning*. IBM.

[54] Nong Ye. 2013. *Data Mining: Theories, Algorithms, and Examples*. CRC press.

[55] Christopher M. Bishop and Nasser M. Nasrabadi. 2006. *Pattern Recognition and Machine Learning*. Springer.

[56] Tianhua Chen, Grigoris Antoniou, Marios Adamou, Ilias Tachmazidis, and Pan Su. 2021. Automatic diagnosis of attention deficit hyperactivity disorder using machine learning. *Applied Artificial Intelligence* 12, 2 (2021), 1–13.

[57] Caroline Wanderley Espinola, Juliana Carneiro Gomes, Jessiane Mônica Silva Pereira, and Wellington Pinheiro dos Santos. 2021. Detection of major depressive disorder using vocal acoustic analysis and machine learning—An exploratory study. *Research on Biomedical Engineering* 37, 1 (2021), 53–64.

[58] Shashank Jaiswal, Michel F Valstar, Alinda Gillott, and David Daley. 2017. Automatic detection of ADHD and ASD from expressive behaviour in rgbd data. In *Proceedings of the 2017 12th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2017)*. IEEE, 762–769.

[59] Anam Nasir, Khurram Aslam, Subhan Tariq, and Mian Farhan Ullah. 2020. Predicting mental illness using social media posts and comments. *International Journal of Advanced Computer Science and Applications* 11, 7 (2020). Retrieved from https://thesai.org/Publications/ViewPaper?Volume=11&Issue=12&Code=IJACSA&SerialNo=71

[60] Ming-Yi Chang and Chih-Ying Tseng. Detecting social anxiety with online social network data. In *Proceedings of the 2020 21st IEEE International Conference on Mobile Data Management (MDM)*, IEEE, 333–336.

[61] Namboodiri Sandhya Parameswaran and D Venkataraman. 2019. A computer vision based image processing system for depression detection among students for counseling. *Indonesian Journal of Electrical Engineering and Computer Science* 14, 1 (2019), 503–512.

[62] Mhambe Priscilla Dooshima, Egejuru Ngozi Chidozie, Balogun Jeremiah Ademola, Olusanya Olayinka Sekoni, and Idowu Peter Adebayo. 2018. A predictive model for the risk of mental illness in nigeria using data mining. *International Journal of Immunology* 6, 1 (2018), 5–16.

[63] U. Srinivasulu Reddy, Aditya Vivek Thota, and A. Dharun. 2018. Machine learning techniques for stress prediction in working employees. In *Proceedings of the 2018 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*. IEEE, 1–4.

[64] Tom M. Mitchell and Tom M Mitchell. 1997. *Machine Learning*. McGraw-Hill, New York.

[65] Deepali J. Joshi, Mohit Makhija, Yash Nabar, Ninad Nehete, and Manasi S. Patwardhan. 2018. Mental health analysis using deep learning for feature extraction. In *Proceedings of the ACM India Joint International Conference on Data Science and Management of Data*. ACM, 356–359.

[66] Mashrura Tasnim and Eleni Stroulia. 2019. Detecting depression from voice. In *Canadian Conference on Artificial Intelligence*. Springer, 472–478.

[67] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. 2015. Deep learning. *Nature* 521, 7553 (2015), 436–444.

[68] Muhammad Irfan, Muhammad Aksam Iftikhar, Sana Yasin, Umar Draz, Tariq Ali, Shafiq Hussain, Sarah Bukhari, Abdullah Saeed Alwadie, Saifur Rahman, Adam Glowacz, and Faisal Althobiani. Role of hybrid deep neural networks (HDNNs), computed tomography, and chest x-rays for the detection of covid-19. *International Journal of Environmental Research and Public Health*, 18(6):3056, 2021.

[69] Yassir Edrees Almalki, Abdul Qayyum, Muhammad Irfan, Noman Haider, Adam Glowacz, Fahad Mohammed Alshehri, Sharifa K Alduraibi, Khalaf Alshamrani, Mohammad Abd Alkhalik Basha, Alaa Alduraibi, and Faisal Althobiani. 2021. A novel method for Covid-19 diagnosis using artificial intelligence in chest x-ray images. *Healthcare* 9, 522.

[70] Chenguang Wang, Mu Li, and Alexander J. Smola. 2019. Language models with transformers. arXiv:1904.09408. Retrieved from https://arxiv.org/abs/1904.09408

[71] Rodrigo Martínez-Castaño, Amal Htait, Leif Azzopardi, and Yashar Moshfeghi. 2021. Bert-based transformers for early detection of mental health illnesses. In *Experimental IR Meets Multilinguality, Multimodality, and Interaction: 12th International Conference of the CLEF Association, CLEF 2021, Virtual Event*. Springer, 189–200.

[72] Srishti Verma, Rakesh Chandra Joshi, Malay Kishore Dutta, Stepan Jezek, and Radim Burget. 2023. AI-enhanced mental health diagnosis: Leveraging transformers for early detection of depression tendency in textual data. In *Proceedings of the 2023 15th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT)*. IEEE, 56–61.

[73] Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Yunxuan Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, Albert Webson, Shixiang Shane Gu, Zhuyun Dai, Mirac Suzgun, Xinyun Chen, Aakanksha Chowdhery, Alex Castro-Ros, Marie Pellat, Kevin Robinson, Dasha Valter, Sharan Narang, Gaurav Mishra, Adams Yu, Vincent Zhao, Yanping Huang, Andrew Dai, Hongkun Yu, Slav Petrov, Ed H. Chi, Jeff Dean, Jacob Devlin, Adam Roberts, Denny Zhou, Quoc V. Le, and Jason Wei. 2024. Scaling instruction-finetuned language models. *Journal of Machine Learning Research* 25, 70 (2024), 1–53.

[74] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini,

Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurelien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. 2023. Llama 2: Open foundation and fine-tuned chat models. arXiv:2307.09288. Retrieved from https://arxiv.org/abs/2307.09288

[75] Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, Lélio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timothée Lacroix, and William El Sayed. 2023. Mistral 7b. arXiv:2310.06825. Retrieved from https://arxiv.org/abs/2310.06825

[76] Kailai Yang, Shaoxiong Ji, Tianlin Zhang, Qianqian Xie, Ziyan Kuang, and Sophia Ananiadou. 2023. Towards interpretable mental health analysis with large language models. arXiv:2304.03347. Retrieved from https://arxiv.org/abs/2304.03347

[77] Xuhai Xu, Bingsheng Yao, Yuanzhe Dong, Saadia Gabriel, Hong Yu, James Hendler, Marzyeh Ghassemi, Anind K. Dey, and Dakuo Wang. 2024. Mental-llm: Leveraging large language models for mental health prediction via online text data. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 8, 1 (2024), 1–32.

[78] Pooja Chandrashekar. 2018. Do mental health mobile apps work: evidence and recommendations for designing high-efficacy mental health mobile apps. *Mhealth*, 4 (2018). Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5897664/

[79] Sylvia Deidre Kauer, Sophie Caroline Reid, Alexander Hew Dale Crooke, Angela Khor, Stephen John Charles Hearps, Anthony Francis Jorm, Lena Sanci, and George Patton. 2013. Self-monitoring using mobile phones in the early stages of adolescent depression: Randomized controlled trial. *Journal of Medical Internet Research* 14, 3 (2013), e1858.

[80] Joseph Firth, John Torous, Jennifer Nicholas, Rebekah Carney, Abhishek Pratap, Simon Rosenbaum, and Jerome Sarris. 2017. The efficacy of smartphone-based mental health interventions for depressive symptoms: A meta-analysis of randomized controlled trials. *World Psychiatry* 16(3), 287–298, 2017.

[81] Earle E Bain, Laura Shafner, David P Walling, Ahmed A Othman, Christy Chuang-Stein, John Hinkle, and Adam Hanina. 2017. Use of a novel artificial intelligence platform on mobile devices to assess dosing compliance in a phase 2 clinical trial in subjects with schizophrenia. *JMIR mHealth and uHealth*, 5(2), e7030.

[82] Pia Lyck Festersen and Andrea Corradini. 2014. Re: Mind: A mobile application for bipolar disorder patients. In *Proceedings of the 2014 4th International Conference on Wireless Mobile Communication and Healthcare - Transforming Healthcare Through Innovations in Mobile and Wireless Technologies (MOBIHEALTH)*,343–346. DOI: https://doi.org/10.1109/MOBIHEALTH.2014.7015981.

[83] Tulika Saha, Saraansh Chopra, Sriparna Saha, Pushpak Bhattacharyya, and Pankaj Kumar. 2021. A large-scale dataset for motivational dialogue system: An application of natural language generation to mental health. In *Proceedings of the 2021 International Joint Conference on Neural Networks (IJCNN)*, 1–8, 2021. DOI: https://doi.org/10.1109/IJCNN52387.2021.9533924

[84] Kayalvizhi Sampath and Thenmozhi Durairaj. 2022. Data set creation and empirical analysis for detecting signs of depression from social media postings. In *Proceedings of the Computational Intelligence in Data Science: 5th IFIP TC 12 International Conference, ICCIDS 2022, Virtual Event*, March 24–26, Revised Selected Papers, 136–151. Springer.

[85] Muskan Garg, Chandni Saxena, Veena Krishnan, Ruchi Joshi, Sriparna Saha, Vijay Mago, and Bonnie J. Dorr. CAMS: An annotated corpus for causal analysis of mental health issues in social media posts. arXiv:2207.04674. Retrieved from https://arxiv.org/abs/2207.04674

[86] Jonathan Gratch, Ron Artstein, Gale Lucas, Giota Stratou, Stefan Scherer, Angela Nazarian, Rachel Wood, Jill Boberg, David DeVault, Stacy Marsella, David Traum, Skip Rizzo, and Louis-Philippe Morency. 2014. The distress analysis interview corpus of human and computer interviews. Technical report, University of Southern California Los Angeles.

[87] Ying Shen, Huiyu Yang, and Lin Lin. 2022. Automatic depression detection: An emotional audio-textual corpus and a gru/bilstm-based model. In *ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 6247–6251.

[88] Karel Mundnich, Brandon M. Booth, Michelle l'Hommedieu, Tiantian Feng, Benjamin Girault, Justin L'hommedieu, Mackenzie Wildman, Sophia Skaaden, Amrutha Nadarajan, Jennifer L. Villatte, Tiago H. Falk, Kristina Lerman, Emilio Ferrara, and Shrikanth Narayanan. 2020. Tiles-2018, a longitudinal physiologic and behavioral data set of hospital workers. *Scientific Data* 7, 1 (2020), 354.

[89] Xiangheng He, Andreas Triantafyllopoulos, Alexander Kathan, Manuel Milling, Tianhao Yan, Srividya Tirunellai Rajamani, Ludwig Küster, Mathias Harrer, Elena Heber, Inga Grossmann, David D. Ebert, and Björn W. Schuller. 2022. Depression diagnosis and forecast based on mobile phone sensor data. In *Proceedings of the 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 4679–4682.

[90] Alexander Kathan, Andreas Triantafyllopoulos, Xiangheng He, Manuel Milling, Tianhao Yan, Srividya Tirunellai Rajamani, Ludwig Küster, Mathias Harrer, Elena Heber, Inga Grossmann, David D. Ebert, and Björn W. Schuller. 2022. Journaling data for daily phq-2 depression prediction and forecasting. In *Proceedings of the 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 2627–2630.

[91] Iulian Vlad Serban, Alberto García-Durán, Caglar Gulcehre, Sungjin Ahn, Sarath Chandar, Aaron Courville, and Yoshua Bengio. 2016. Generating factoid questions with recurrent neural networks: The 30m factoid question-answer corpus. arXiv:1603.06807. Retrieved from https://arxiv.org/abs/1603.06807

[92] Helia Hashemi, Mohammad Aliannejadi, Hamed Zamani, and W. Bruce Croft. 2020. Antique: A non-factoid question answering benchmark. *Advances in Information Retrieval* 12036,166.

[93] Mohammad Kadkhoda and Hoorie Jahani. 2012. Problem-solving capacities of spiritual intelligence for artificial intelligence. *Procedia-Social and Behavioral Sciences* 32 (2012), 170–175.

[94] Christopher A. Lovejoy. 2019. Technology and mental health: The role of artificial intelligence. *European Psychiatry*, 55 (2019), 1–3.

[95] Adrienne Lafrance. 2015. Computers can predict schizophrenia based on how a person talks. *The Atlantic* (*2015*). Retrieved from https://www.theatlantic.com/technology/archive/2015/08/speech-analysis-schizophrenia-algorithm/402265/

[96] Cheryl M. Corcoran, Facundo Carrillo, Diego Fernández-Slezak, Gillinder Bedi, Casimir Klim, Daniel C. Javitt, Carrie E. Bearden, and Guillermo A. Cecchi. 2018. Prediction of psychosis across protocols and risk cohorts using automated language analysis. *World Psychiatry* 17, 1 (2018), 67–75.

[97] Wahidah Husain, Lee Ker Xin, Nur'Aini Abdul Rashid, and Neesha Joth. 2016. Predicting generalized anxiety disorder among women using random forest approach. In *Proceedings of the 2016 3rd International Conference on Computer and Information Sciences (ICCOINS)*. IEEE, 37–42.

[98] Agnes Grünerbl, Amir Muaremi, Venet Osmani, Gernot Bahle, Stefan Oehler, Gerhard Tröster, Oscar Mayora, Christian Haring, and Paul Lukowicz. 2014. Smartphone-based recognition of states and state changes in bipolar disorder patients. *IEEE Journal of Biomedical and Health Informatics*, 19 (1), 140–148.

[99] Ulrike Stentzel, Neeltje van den Berg, Lara N Schulze, Thea Schwaneberg, Franziska Radicke, Jens M. Langosch, Harald J. Freyberger, Wolfgang Hoffmann, and Hans-Jörgen Grabe. 2018. Predictors of medication adherence among patients with severe psychiatric disorders: findings from the baseline assessment of a randomized controlled trial (Tecla). *BMC Psychiatry* 18, 1 (2018), 1–8.

[100] Gaetano Valenza, Antonio Lanatà, Rita Paradiso, and Enzo Pasquale Scilingo. 2014. Advanced technology meets mental health: How smartphones, textile electronics, and signal processing can serve mental health monitoring, diagnosis, and treatment. *IEEE Pulse* 5, 3 (2014), 56–59. DOI: https://doi.org/10.1109/MPUL.2014.2309582

[101] Upkar Varshney. 2009. A framework for wireless monitoring of mental health conditions. In *Proceedings of the 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, 5219–5222.

[102] Unsoo Ha, Yongsu Lee, Hyunki Kim, Taehwan Roh, Joonsung Bae, Changhyeon Kim, and Hoi-Jun Yoo. 2015. A wearable EEG-HEG-HRV multimodal system with simultaneous monitoring of tES for mental health management. *IEEE Transactions on Biomedical Circuits and Systems* 9, 6 (2015), 758–766.

[103] Nur Hayati and Muhammad Suryanegara. 2017. The IOT lora system design for tracking and monitoring patient with mental disorder. In *Proceedings of the 2017 IEEE International Conference on Communication, Networks and Satellite (Comnetsat)*, IEEE, 135–139.

[104] Meza Silvana, Ricky Akbar, Derisma, Mia Audina, and Firdaus. 2018. Development of classification features of mental disorder characteristics using the fuzzy logic Mamdani method. In *2018 International Conference on Information Technology Systems and Innovation (ICITSI)*, IEEE, 410–414.

[105] Paulina Cecula, Jiakun Yu, Fatema Mustansir Dawoodbhoy, Jack Delaney, Joseph Tan, Iain Peacock, and Benita Cox. 2021. Applications of artificial intelligence to improve patient flow on mental health inpatient units-narrative literature review. *Heliyon*, 7, 4. Retrieved from https://www.cell.com/heliyon/fulltext/S2405-8440(21)00729-5?_returnURL=https%3A%2F%2Flinkinghub.elsevier.com%2Fretrieve%2Fpii%2FS2405844021007295%3Fshowall%3Dtrue

[106] Gloria Phillips-Wren. 2013. Intelligent decision support systems. *Multicriteria Decision Aid and Artificial Intelligence: Links, Theory and Applications*, Michael Doumpos, Evangelos Grigoroudis (Eds.), 25–44.

[107] Osonde A. Osoba, William Welser IV, and William Welser. 2017. *An intelligence in our image: The risks of bias and errors in artificial intelligence*. Rand Corporation.

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