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REVIEW

Artificial intelligence applications in mental health: the state of the art

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Summary

Objectives. This review aims to examine the current use of artificial intelligence (AI) in mental health. The first step involves categorising AI algorithms into three subtypes: natural language processing (NLP), machine learning (ML), and deep learning (DL). Next, we evaluated their application in mental health and the instrumental methods used to collect valid and sufficient quantitative data.

Results. Evidence suggests that AI algorithms are being used, particularly in the diagnosis or differential diagnosis of mental illness. The most commonly used instrumental techniques were neuroimaging, particularly magnetic resonance imaging (MRI), and neurophysiology, specifically electroencephalography (EEG).

Conclusions. This review is the first to analyse these three algorithms in the field of mental health, without any limitations on method or population type. Further studies are necessary to better understand the validity of these algorithms in clinical practice. It is important to anticipate both useful innovations and potential difficulties.

Keywords: artificial intelligence, deep learning, machine learning, natural language processing, mental health, severe mental illness

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INTRODUCTION

Artificial intelligence

Recent years have seen significant advances in technology, leading to what is commonly referred to as the "Fourth Industrial Revolution" or "Industry 4.0" [1]. Simultaneously, there has been a progression in digital technology, commonly known as the "Digital Revolution" [2]. This revolution is impacting all areas of society, including healthcare. With the advent of the COVID-19 pandemic, healthcare professionals and patients alike are increasingly using technological devices that were previously under-utilised but have now become commonplace [3].

Mental health services have undergone a transformation towards digitised medicine, utilising technology at various levels, from diagnosis and related care to service delivery [4]. One of the most controversial technological innovations is artificial intelligence (AI), which has brought about numerous changes and raised ethical questions [5].

The birth of AI dates back to 1950 when mathematician Alan Turing published his article "Computing machinery and intelligence" in the journal "Mind" [6]. Turing questioned the possibility of building a machine that could think like humans, but defining human thought is a complex task that limits the answer to this question. Therefore, he later decided to shift his focus from abstract concepts to something more concrete: specifically, he began to hypothesise the creation of a machine that could act in a certain way to satisfy the demands placed upon it. The term "artificial intelligence" was later coined by John McCarthy in 1956, who defined it as "the science and engineering of making machines intelligent" [7].

Over the years, several algorithms have been developed for various purposes. Some were initially created for recreational use, such as IBM Deep Blue [8], IBM Watson [9], and DeepMind AlphaGo [10]; others, like ChatGPT (GPT: Generative Pre-trained Transformer) [11,12], have become more widely used.

Defining AI is a complex task as there are multiple definitions available [13]. However, they can be simplified into four categories [14]: i) systems that think like humans; ii) systems that act like humans; iii) systems that think rationally; and iv) systems that act rationally.

Currently, the three most widely used types of AI are natural language processing (NLP), machine learning (ML), and deep learning (DL). It is important to note that these algorithms are often combined.

Natural language processing

NLP originated in the 1950s from the integration of computer science, linguistics, and mathematics. It is an analytical technique that uses computers to decode and automatically understand human language [15]. NLP can be divided into two categories: natural language understanding (NLU) is the process of translating human language into a machine-understandable format [16]; and natural language generation (NLG) is the process of producing human language output from digital data [17], including text-to-text [18], text-to-speech [19], and other-to-text [20]. NLU and NLG are important components of speech technology.

The process of NLP can be divided into four parts: text pre-processing, text representation, model training, and model evaluation. The first part involves simplifying and correcting the text by removing meaningless symbols and correcting spelling mistakes to achieve better accuracy and efficiency in subsequent steps. The text is then converted ("represented") into numerical vectors and matrices, on which algorithms are applied to train a model. Finally, the model is evaluated to confirm its generalisability and efficiency in the real world [21].

In recent years, there has been exponential development in NLP [22], particularly in machine translation [23], pattern matching [24], sentiment analysis [25], and voice recognition [26]. The advancement of technology has facilitated the development of intelligent devices such as Siri and Cortana, simultaneous translations like Google Translator or Microsoft Translator, and voice recognition software such as Windows Voice Recognition. Additionally, algorithms have been created to predict the financial market based on sentiment analysis of Twitter.

Machine learning

ML algorithms gather information about their surroundings by hypothesising a law that they will then use later. The machine "learns" through observation. The process is simple, with input and output variables, and the machine's task is to find a connection between the two, without creating a universal law [27].

There are three modes of learning [28]: supervised learning (SL), reinforcement learning (RL), and unsupervised learning (UL). In SL, the machine is provided with all the data, which is divided into input and output, and creates a function that explains the phenomenon. Later, it can use this function to predict outputs from new input data [29,30]. In RL, the machine is given data sequentially, and from time to time, it evaluates what action is best to take to approach a known function. RL involves a "reward" for each action based on its functionality in achieving the goal [31]. In UL, the machine has access to all input and output data, but without subdivisions, it seeks to identify an underlying function for future observations. In this case, since the data is not split, the machine will have no constraints and the number of possibilities will be greater. As a result, groupings between data are usually created based on a similarity or proximity criterion, known as clustering [32].

In addition to these three types, there are also systems known as semi-supervised learning [33], which is a combination of SL and UL, and DL.

Deep learning

DL is a type of ML that utilises neural networks for learning through training. "Deep neural networks" are so named because they are composed of interconnected layers of "artificial neurons" (also known as Artificial Neural Networks or ANNs). This structure typically includes three or more layers, and in some of the latest algorithms, there can be hundreds of layers. In DL algorithms, as in our nervous system, learning occurs by changing the "weight" of connections between neurons. Functional connections are given higher priority [34].

Artificial Neural Networks process input data in a non-linear manner, similar to brain neurons, and only activate if they reach a threshold potential determined by the weighted sum of inputs, resulting in an output [35]. This method is ideal for integrating and extracting information from multimodal data, which is collected through several complementary modalities such as behavioural measurements, electroencephalography (EEG), and magnetic resonance imaging (MRI). The layers in this method establish a hierarchy, with the first layers extracting basic features specific to each modality, and the subsequent layers serving for abstract concepts that can be shared between the modalities.

The difference with ML is the type of data processed: DL works on raw, unlabelled data, as opposed to ML, that works on extrapolated and selected data, chosen by the programmer. In DL, it is the algorithm itself that processes and extrapolates the data it will later need to respond to the queries made. The data that can be used can be structured data with a high sample size (e.g. EEG, MRI).

AIMS

This study aims to investigate the performance of the most commonly used AI algorithms in the field of mental health.

Additionally, we will analyse the most frequently used methods for collecting data to train these algorithms. Finally, we will examine the most commonly used recruitment settings. The ultimate objective is to establish a basis for comprehending the potential development and application of AI in the future.

RESULTS

In recent years, there have been several reviews and meta-analyses exploring the use of AI in the field of mental health [36,37]. This review includes AI studies without a focus on a specific algorithm or on a single mental disorder. On the contrary, previous studies have focused on specific algorithms (e.g. ML [38], DL [39]) or specific instrumental methods (e.g. MRI [40], EEG [41]), or specific psychiatric disorders (e.g. anxiety and depression [42], schizophrenia) [43].

The studies' individual outcomes differ and cover four main research areas: neurobiological correlates; investigation on clinical characterization; diagnostic ability improvement; and prognosis prediction.

The study of neurobiological correlates involves the identification of brain areas and circuits that may be pathognomonic [44-46], as well as the investigation of patients' brain age and the aging trajectory of the nervous system [47,48].

The investigation of clinical characterisation involves the correlation of specific data with various aspects of the patient's clinical and biological profile, including psychopathology [49], physical comorbidities [50], self-harm, suicidal [51] and aggressive behaviours [52], objective and subjective psychosocial functioning, quality of life, and the use of services [53-55].

In the field of diagnostics, there are ongoing efforts to develop innovative AI algorithms that can assist clinicians in distinguishing between healthy individuals and those with a disorder [56,57], as well as in making differential diagnoses among various psychiatric disorders [58-61].

Finally, prognostic prediction [62] involves the study of the evolution of a patient's condition in relation to the treatment they receive, including pharmacological and psychotherapeutic treatments, as well as their adherence to the treatment plan [63-66]. An increasingly analysed topic is the discovery of the trajectory of individuals at risk to develop mental disorders, within a primary prevention perspective [67-69].

To function optimally, AI requires a large amount of data, so studies typically make use of neurobiological measurements, audio/video recordings, biological samples, and special measurements.

Neuroimaging (structural and functional MRI [70,71], magnetoencephalography [72], positron emission tomography [PET] [73], etc.) and neurophysiology (EEG) [74] methods provide most of the neurobiological measurements.

Interviews or tests involve audio or video recordings to extract information not only from language (such as syntax and tone) [75], but also from non-verbal cues (such as facial expressions and movements) [76].

TABLE I. Artificial Intelligence applications in mental health.

Type of algorithm	Psychiatric disorder	Outcome	Instrumental techniques
Natural language processing	Schizophrenia spectrum disorders	**Neurobiological correlates**	**Neurobiological measurements**
Machine learning	Bipolar Disorder	Identification of brain areas and circuits	Neuroimaging (eg., MRI)
Deep learning	Major depression disorder	Brain age	Neurophysiology (eg., EEG)
	Obsessive compulsive disorder	**Clinical characterisation**	**Audio/video recordings**
	Anxiety disorders	**Psychopathological aspects**	**Biological samples**
	Personality disorders	**Physical comorbidities**	Genetic analysis
		Self-harming dimension	Other analysis
		Hetero-aggressive behaviour dimension	**Other**
		Use of Services	Somatic and physiological measurements
		Perception of quality of life	Motion sensors
		Diagnostics	APP on mobile devices
		Prognosis	Other techniques
		Prognosis in patients	
		Response and adherence to therapy	
		Prediction transition	

EEG: electroencephalography; MRI: magnetic resonance imaging.

Biological samples, including blood and saliva, were collected for genetic analyses and evaluation of various aspects, such as the inflammatory system, kidney and liver function, and lipid balance in some studies [77,78].

Other studies have also included measurements of somatic parameters, such as height, weight, and body mass index (BMI) [79], as well as movement parameters like eye, head, and limb movements [80]. Data was collected using mobile device applications [81], which enabled the detection of reaction times and subject movements using gyroscopes and GPS tracking. Finally, some authors have chosen to use only socio-demographic variables and psychopathological evaluations as data to be included in the algorithms, without employing instrumental methods [82,83].

The data used in the algorithms was mainly obtained from subject recruitment conducted in clinical and/or university settings. However, the researchers also used open-access databases as a data source [84,85]. This allowed them to collect the necessary amount of data to train the algorithms and then recruit a small sample of real-life subjects to test the validity of the algorithms.

A summary of the current AI applications in mental health is shown in Table I.

DISCUSSION

In recent years, there has been a growing interest in AI to the extent that some Journals have introduced a dedicated section on the topic, such as The New England Journal of Medicine [86]. As with any innovation, doubts and perplexities have arisen regarding the integration of AI in the medical and mental health fields [87,88].

The safety and reliability of each algorithm is the first aspect to be assessed. This parameter is evaluated using the technology readiness level (TRL) scale, a 9-level assessment invented by the National Aeronautics and Space Administration (NASA) in the 1970s [89]. To date, no AI method has passed all the levels, making them suitable only for experimental and academic fields, not for use in clinical practice [90].

The reliability of an AI algorithm is largely dependent on the quality of the data used to develop it [91]. If databases not specifically created for this purpose are used, there may be errors, shortcomings or simplifications that reduce the accuracy of the AI. In order to compensate for the considerable amount of data required, existing datasets are often used. It is also important to ensure that the data collected from recruited subjects is comparable to the pool on which the AI will be used clinically, a process commonly known as "database shift". The data must be numerous, heterogeneous but also specific. Therefore, data collection is typically carried out using instrumental methods that provide a significant amount of information even with small recruitment samples. Conversely, if instrumental methods are not available, large samples of subjects are necessary.

This review shows that current research is primarily focused on discovering new methods for diagnosing disorders and linking neurobiological changes with psychopathological dimensions. Currently, in the absence of pathognomonic biological markers, psychiatric disorders are diagnosed using arbitrary criteria, which can be inherently subjective, so it is important to exclude subjective assessments unless clearly defined. New classification systems are emerging to be more objective by making diagnoses based on biological correlates. An example of this is the Research Domain Criteria (RDoC) system created in 2009 by the National Institute of Mental Health (NIMH) [92]. A more objective diagnosis is required, not only due to new classification systems, but also the need for new technological aids to support it. These aids are often unfamiliar to clinicians, which can lead to a sense of distrust [88].

DL is an algorithm that is playing an increasingly important role and has gained considerable interest in recent years because it allows large amounts of data from instrumental methods to be analysed without the need for pre-processing [35], enabling increasingly complex and articulated functions to be performed. The availability of powerful chips at affordable prices can also drive this shift towards more sophisticated and effective algorithms.

However, the use of AI in the clinical field still presents issues beyond the development of efficient and reliable algorithms. These include the attribution of responsibility and the possibility of hacking. Currently, there is a lack of adequate legislation, and in the event of an AI error, it is uncertain who should be held responsible: the psychiatrist who validated the result, the patient who accepted it, the developers of the algorithm, the health system that implemented it, or no one at all. In addition, by collecting sensitive data and tracking daily activities, the studies face the risk of hacking, which threatens the privacy of the subjects.

AI could be a valuable tool for clinicians to implement new classification systems based on objective biological data. However, this is not yet possible due to the need for increasingly efficient, safe, and cost-effective algorithms, dedicated databases, impenetrable security systems, and training for clinicians in the use and interpretation of results. Additionally, an information campaign directed at the general population and the development of ethical and legislative issues are necessary.

To our knowledge, this is the first literature review that attempts to analyse multiple types of AI in mental health, regardless of method and data source. In addition, subcategories were created to achieve better categorisation when analysing all variables. Although several encouraging findings were observed, this review has some limitations. At a methodological level, this is a qualitative analysis of the current literature, and it would be desirable to carry out a systematic review in order to obtain objective data. In addition, this review only includes the most well-known methods, such as ML, DL and NLP, while more unusual and less well-known algorithms have been excluded due to the lack of sufficient literature for an objective and scientifically accepted categorisation.

CONCLUSIONS

In conclusion, currently there are no algorithms that can be implemented in clinical practice for all the aforementioned problems. However, the number of studies on this topic is increasing, indicating a growing interest in the field of applying AI in mental health. This study is just the beginning. The first step is to conduct one or more systematic reviews on the subject to determine the most useful algorithm and method for clinical practice, and to identify variables to create open-access databases that can be used to train future algorithms.

Conflict of interest statement

The authors declare no conflict of interest.

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Authors' contributions

A.Z.: conceptualization, data curation, investigation, methodology, writing – original draft, writing – review & editing. G.N.: data curation, investigation, methodology, writing – review & editing. L.A.: data curation, investigation, methodology. L.B.: data curation, investigation, methodology. I.C.-P.: Data curation, investigation, methodology. E.I.: data curation, investigation, methodology. N.N.: data curation, investigation, methodology. C.C.: data curation, investigation, methodology. L.P.: data curation, investigation, methodology. V.B.: data curation, investigation, methodology. J.L.: data curation, investigation, methodology. G.D.: data curation, investigation, methodology. S.B.: methodology, supervision, writing – review & editing. A.V.: methodology, supervision, writing – review & editing.

Ethical consideration

Not applicable to this study design.

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