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Artificial intelligence ecosystem for computational psychiatry: Ideas to practice

Xin-Qiao Liu, Xin-Yu Ji, Xing Weng, Yi-Fan Zhang

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Abstract

Computational psychiatry is an emerging field that not only explores the biological basis of mental illness but also considers the diagnoses and identifies the underlying mechanisms. One of the key strengths of computational psychiatry is that it may identify patterns in large datasets that are not easily identifiable. This may help researchers develop more effective treatments and interventions for mental health problems. This paper is a narrative review that reviews the literature and produces an artificial intelligence ecosystem for computational psychiatry. The artificial intelligence ecosystem for computational psychiatry includes data acquisition, preparation, modeling, application, and evaluation. This approach allows researchers to integrate data from a variety of sources, such as brain imaging, genetics, and behavioral experiments, to obtain a more complete understanding of mental health conditions. Through the process of data preprocessing, training, and testing, the data that are required for model building can be prepared. By using machine learning, neural networks, artificial intelligence, and other methods, researchers have been able to develop diagnostic tools that can accurately identify mental health conditions based on a patient's symptoms and other factors. Despite the continuous development and breakthrough of computational psychiatry, it has not yet influenced routine clinical practice and still faces many challenges, such as data availability and quality, biological risks, equity, and data protection. As we move progress in this field, it is vital to ensure that computational psychiatry remains accessible and inclusive so that all researchers may contribute to this significant and exciting field.

Key Words: Computational psychiatry; Big data; Artificial intelligence; Medical ethics; Large-scale online data

Core Tip: This study reviews and integrates the methods and models in the clinical practice of computational psychiatry and constructs a complete and mature Artificial Intelligence ecosystem. The ecosystem for computational psychiatry includes data acquisition, preparation, modeling, application, and evaluation. This approach allows researchers to integrate data from a variety of sources to obtain a more complete understanding of mental health conditions. Despite the continuous development and breakthrough of computational psychiatry, it has not yet influenced routine clinical practice and still faces many challenges, such as data availability and quality, biological risks, equity, and data protection.

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INTRODUCTION

Mental illness is a significant threat to human health, which was especially evident during the coronavirus disease 2019 (COVID-19) pandemic[1,2]. In recent years, artificial intelligence has played an increasingly prominent role in the clinical practice of psychiatry. The birth of computational psychiatry represents not only the inevitable choice to conform to the trend of the fourth industrial revolution but also an important means to solve the real dilemma.

Psychiatry mainly studies the causes, symptoms, and clinical diagnosis of human mental diseases. Computational psychiatry[3] uses computational and mathematical techniques to better understand mental disorders and to develop new treatments. Computational psychiatry is an emerging psychiatry approach that integrates various multidisciplinary approaches, such as psychiatry, neuroscience, machine learning, psychology, statistics, and computer science, to develop quantitative models of mental illness and to assess the effectiveness of different treatments[4]. Specifically, computational psychiatry builds computational models of brain function based on the neurological and cognitive phenomena associated with mental illness, predicts the abnormal degree of mental function, and evaluates the efficacy of treatment by using detailed multidimensional computational models[5,6].

Computational psychiatry includes two approaches: Data-driven computational psychiatry and theory-driven computational psychiatry[6]. Data-driven approaches involve machine learning and big data analytics, and they can improve predictive accuracy in clinical diagnosis, prognosis, and treatment by learning clinical and biological data. The theory-driven approach derives from computational neuroscience and focuses more on constructing models to understand the mechanisms of psychosis[7]. Due to the fact that computational psychiatry is based on mathematics, computer science, biological science, and other deep theories, it has the advantage of multidisciplinary integration[3]. One of the key goals of computational psychiatry is to move beyond the traditional "black box" approach to understanding the brain[8], whereby researchers study the symptoms and behaviors of individuals without fully understanding the underlying mechanisms. By introducing computational and statistical approaches, computational psychiatry has opened the "black box" of pathological mechanisms[9]. Moreover, neural computing functions provide precise algorithmic details for the analysis and solution of specific problems.

Computational psychiatry can identify the pathogenesis of mental diseases from both theory-driven and data-driven aspects, which is the result of the fusion of computational neuroscience and psychiatry [10]; in addition, it has a significant contribution to the diagnosis, treatment, and prevention of mental diseases. Overall, computational psychiatry is a rapidly growing and exciting field that has the potential to revolutionize our understanding of mental illness and to allow for the development of new treatments. By using computational and mathematical techniques to build quantitative models of mental illness, researchers in the field are working to identify the underlying mechanisms of mental illness and to develop more effective treatments.

Although various experimental studies have provided valuable information for understanding and explaining the underlying mechanisms of mental illness[11-13], the development of computational psychiatry is challenged by multiple interactions[14]. For instance, one of the biggest challenges faced by computational psychiatry today is the availability and quality of data. Mental health disorders are complex and multifaceted, and it is difficult to collect data that accurately reflect experiences with the disorders. Another challenge is the interpretability of the results. Many techniques that are used in computational psychiatry are highly complex and even difficult for experts in the field to understand, which makes it difficult for researchers to communicate their findings with others and for clinicians to

apply these findings to actual treatment. Many other problems also need to be solved, such as the technical connection between model development and clinical practice and ethical acceptability. Despite these issues, we remain optimistic about the future of computational psychiatry.

Establishing a complete artificial intelligence ecosystem of computational psychiatry is an effective method to solve the challenges in the clinical practice of psychiatry. In this study, we focus on building an artificial intelligence ecosystem for computational psychiatry to better facilitate the elimination of barriers to clinical practice. This review aims to make a fundamental contribution to shaping the ecosystem and for allowing the modules to be smoothly applied. Moreover, it outlines the responsibilities of the different agents and the linkages between them and builds a loop from data collection to modeling, evaluation, and clinical practice. We plan to sort out and integrate the same and different methods and models in the field, overcome the existing limitations, provide full attention to the role of each subject, and eventually form a complete and mature ecosystem. It is believed that as the field continues to evolve, researchers will eventually find ways to overcome the challenges and make greater advances in our understanding and treatment of mental health conditions.

METHODS

In this review, we used "computational psychiatry", "machine learning", "artificial intelligence", "psychiatry", and "deep learning" as keywords and retrieved the English literature in PubMed (<https://www.ncbi.nlm.nih.gov/pubmed/>) and Web of Science. We also manually screened the retrieved literature according to the relevance of the literature content to the topic and narrowed it down to a more accurate scope.

ARTIFICIAL INTELLIGENCE ECOSYSTEM FOR COMPUTATIONAL PSYCHIATRY

Based on the literature concerning clinical thinking and life cycle management of artificial intelligence projects, we conducted an integrated design of the ecosystem of computational psychiatry. We divided the clinical practice process of computational psychiatry into the following four main stages: data acquisition, modeling preparation, model construction, and application evaluation (Figure 1).

Data collection

One of the strengths of computational psychiatry is its ability to integrate big datasets of various forms to help researchers gain a more complete understanding of a patient's mental health. Thus, the first and most critical step in the artificial intelligence ecosystem for computational psychiatry is data collection. During this process, researchers can select one or more input data that can be measured according to the relevance of the research problem[15]. Common forms include clinical scales, visual data, voice, physiological signals, and Internet of Things data, *etc.* Although there are a wide variety of input data, tool selection should be based on a clear understanding of treatment strategies and the realistic evaluation of clinical effectiveness. Moreover, it should consider the mutual limiting effect of different data acquisition methods and technology operations, as well as the quality of original data and the details of processing methods, which will directly affect the reliability of the tools, and thus affect the effectiveness of clinical application[16,17].

Preparation for modeling

Modeling relies on different theoretical traditions[18]. For example, algorithm engineers are required to follow industry practice rules and conference content, articles, or implicit guidelines related to machine learning, and psychiatrists are bound by rules in the legal and medical fields, such as the National Institute for Health and Clinical Excellence guidelines or the American Psychiatric Association Practice guidelines. In addition, judgments are often made differently depending on the unique personality of the model builder. For example, clinicians' decision-making styles and willingness to take risks have a direct impact on their treatment paths and diagnostic strategies, and conservative and adventurous engineers also exhibit differences in aesthetic awareness and modeling styles. Therefore, the theoretical basis is worth fully preparing before building the model. The second is data preprocessing and quality checking. Since the collected data are often incomplete, as well as the fact that data from heterogeneous data sources may need to be collected, the raw data need to be preprocessed and quality checked to ensure the quality of the data. Only after data cleaning, data integration, data reduction, data transformation, and other processing can standardize data for model construction. The establishment of the compilation environment is also one of the preparatory works of model construction. There are several open source platforms that can be used for training, testing, and benchmarking algorithms based on different design requirements, such as OpenAI Gym[19], which provides a range of tasks, including some classic arcade games including Doom, as well as models, tests, and diagnostic paradigms that can be used for mental illness.

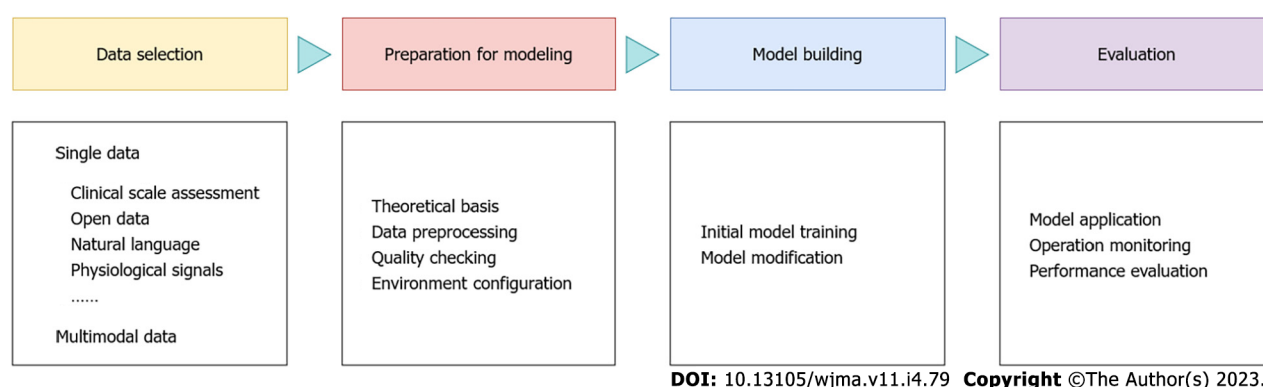


Figure 1 Framework for modeling artificial intelligence ecosystems.

Model building

The first two steps in the computational psychiatry ecosystem both serve the third step; specifically, after collecting and processing the corresponding data in the theoretical context, the next step involves normative model building[20-22]. This step is divided into two parts: initial model training and model modification. Machine learning[23-27] is often used in model training to recognize emotional states[28], to detect mood swings[29], and to diagnose mental diseases[30]. There are two main types of machine learning: supervised learning and unsupervised learning. Supervised learning uses categorization and regression to learn from examples of existing labels. This method is often used to build classifiers to distinguish healthy people from sick people or to build predictive models. Washington *et al*[31] designed Guesswhat, which is a smartphone game for emotional data collection. They trained a pediatric emotion classification convolutional neural network classifier to recognize children's expressions, such as sadness, surprise, disgust, happiness, and neutral expressions. Their results demonstrated the value of mobile digital health. Although mood classifiers have made remarkable progress in automatic emotion recognition, the computational cost of existing models is too high. Banerjee *et al*[32] optimized the design of the machine learning model. The MobileNet-V2 network that they trained on ImageNet achieved a balanced accuracy rate of 65.11% and an F1 score of 64.19% on CAFE. Through optimization techniques, machine learning models can achieve greater accuracy and lighter weight. Unsupervised learning[33,34] is a classification method that does not require human data classification but automatically divides the structure based on the inherent distribution characteristics of datasets. In addition, clustering methods are often used in unsupervised learning. Regardless of which training method is used, professional school education and clinical training are needed. For example, clinicians require training in psychiatric education based on clinical case studies (fictional or nonfictional), and machine learning engineers require systematic schooling and professional experience. Finally, the initial model is reasonably built.

Computational psychiatry seeks to develop quantitative, mechanistic models of psychiatric disorders [35] that can help researchers better understand the biological and cognitive processes that lead to these disorders. A key benefit of computational models is that they can help researchers generate testable hypotheses about the underlying mechanisms of mental disorders. For example, reinforcement learning models of addiction[36,37] can be used to generate hypotheses about specific brain regions and pathways associated with addiction, as well as types of interventions that may be effective in treating addiction. The model, which is based on principles of neuroscience and psychology, suggests that addiction is caused by a disorder in the brain's reward system, which leads to obsessive behavior and a loss of control over behavior. Another benefit of computational models in psychiatry is that they can help researchers assess the effectiveness of different treatment options. For example, the cognitive-affective neural circuit model of depression[38] can be used to evaluate the efficacy of different antidepressants or psychotherapy based on predictions of their effects on basic brain circuits associated with depression. The model, which is based on evidence from neuroscience and psychology, proposes that depression is caused by the disequilibrium of the brain's emotional and cognitive processing systems, which leads to symptoms such as low mood, reduced negative thinking, and reduced motivation. However, regardless of how good the model is, there is room for improvement. As more theoretical background is accumulated in clinical practice, updated data will be incorporated into the model[39, 40]. Moreover, the model will expose more practical problems in clinical application; thus, it needs to be constantly adjusted and modified to adapt to new challenges.

Evaluation

Computational psychiatry is not currently used clinically, but it has the potential to inform new clinical interventions and treatments for mental illness to help guide the treatment of mental disorders. For example, clinicians can use computational models to assess an individual's brain activity and symptoms

to choose the most appropriate treatment for them. By using computational and mathematical models to better understand the underlying mechanisms of these diseases, researchers in the field can identify potential targets for intervention and assess the likely effects of different treatment options. However, more research is needed to fully understand the clinical potential of computational psychiatry and to develop the necessary tools and techniques to apply it in the clinical setting. Given the complexity of psychiatric disorders, future applications should be subject to enhanced regulatory oversight of clinical practice, as well as the evaluation and post hoc analysis of actual clinical benefits and model performance[41].

DATA SOURCES OF COMPUTING PSYCHIATRY

Based on the review of the existing studies, we conclude that data sources mainly include the following methods: scales, public data, language, physiological signals, blood, multimodal data, *etc.* (Table 1). This paper will discuss some of these categories.

Scales

Clinical scales[42-45] are one of the most widely used tools in clinical evaluation, and mature scales include the World Health Organization-Quality of Life-Brief (WHO-QoL-Bref), cognitive function test, Hamilton Depression Scale, Autism Diagnostic Observation Schedule, Hamilton Anxiety Scale, Fibromyalgia and Chronic Fatigue Rating Scale, *etc.* Large datasets accumulated through electronic medical records[46] facilitate the determination of goals by using computational methods. Self-reported digital scales[47,48] are used in the following manner. Researchers load the quantitative list of questions into the app, allow users to answer questions by using smart devices, and ultimately screen for symptoms based on the answers. This approach relies on mobile technology rather than traditional clinical scales.

Large-scale online data

Dubois *et al*[49] used a large online sample to demonstrate an association between human exploration strategies and impulse psychiatry, which not only demonstrated that impulsivity is associated with specific forms of exploration but also explored links between impulsivity and other psychiatric dimensions. Moreover, Nam *et al*[50] used machine learning and web analysis to identify factors associated with depression from national population surveys. Nielsen *et al*[51] discussed how large multisite public datasets contribute to the application of machine learning in psychiatry. Furthermore, Hu *et al*[52] collected users' text expressions on social platforms (such as Weibo) as data sources to predict their depression symptoms. Artificial intelligence (especially big data)[53] plays a vital role in health care, thus demonstrating its significant potential in applications[54].

Images and videos

Research indicates that psychiatric patients have different color vision and are less able to discriminate between colors than ordinary people. Therefore, the color recognition of images can be used to examine the difference between psychiatric patients and control groups or as a prognostic diagnosis. Shen *et al* [55] reviewed the paintings of 281 patients with chronic schizophrenia and 35 patients with healthy controls and used a series of computational analyses to scan and process the images. The results showed that color paint images have the potential to be used as a clinical diagnostic and prognostic tool for patients with chronic schizophrenia. The video data collected by the camera exhibit a large deviation, which is caused by noise in the natural environment. Moreover, existing studies provide optimized schemes through data collection pipelines, feature engineering, and data expansion strategies. The standard diagnosis for autism spectrum disorders takes several hours and assesses 20 to 100 behaviors (*e.g.*, eye contact, social smiling, *etc.*). Leblanc *et al*[56] introduced feature replacement methods to analyze family videos to establish the diagnosis of autism. They rated 140 videos of children on YouTube, filled in missing values by using feature replacement methods, and optimized the performance of the autism detection classifier. Dynamic feature replacement methods are superior to traditional methods in terms of performance and can reduce the impacts of missing values on video diagnosis[56]. Furthermore, Tariq *et al*[57] used mobile devices to classify videos by machine learning and labeled video features. This method ensures the accuracy of assessment and improves the speed of diagnosis.

Language

Automated speech analysis has been used in psychiatric diagnosis[58,59] and learns baseline interview data through machine learning algorithms to predict mental illness. Carrillo *et al*[60] conducted baseline autobiographical interviews with patients and transcribed them by using machine learning algorithms to predict the effectiveness of psilocybin for depression. The combination of machine learning with automated speech algorithms[61] contributes new ideas for the prediction and diagnosis of psychiatry. Moreover, the acquisition of language is relatively mild compared to acquiring intrusive data and

Table 1 Data sources for computational psychiatry

Module	Category
Single data	Clinical scales[42,45], electronic medical records[46], and digital scales[47,48] large online sample[49], national population surveys[50], and large multisite public datasets[51] Images[55] and videos[56,57] Language[62] and baseline interviews[60] Emotional faces[63,64], electrocardiogram[65], electroencephalogram[68-70], magnetoencephalogram[71], and magnetic resonance imaging[72,73,75] Human motion bone data[79] Blood[81,85]
Multimodal data	Multimodal data[45,86,89]

supports self-testing by users[62]. Computational linguistics combined with artificial intelligence provides a good aid to clinical diagnosis and risk monitoring.

Physiological signals

Physiological signals include emotional faces[63,64], electrocardiogram[65], electroencephalogram (EEG)[66-69], magnetoencephalogram[71], and functional magnetic resonance imaging (fMRI)[72-77]. There are two main methods to collect biological signals: invasive and noninvasive methods. Noninvasive data acquisition is commonly used, including electroencephalogram and functional magnetic resonance imaging. In recent years, physiological signals have been increasingly used to measure emotional responses. Compared with audiovisual data, physiological signals provide more detailed and real information. However, there are too many interference factors in the collection process of physiological signals, and the processing mechanism is more complex.

Human motion bone data

The clinical and scientific value of full body movement assessment has been increasingly recognized, and it is often used in the diagnosis of cerebral palsy. Previous studies were mostly based on computer vision[78]. However, during the process of sorting out the relevant studies, we noticed an interesting experimental study[79]. From the perspective of full body kinematics, the team built a machine-learning model to establish the purpose of automatic recognition and classification of depression. They used Kinect to capture human motion bone data, conducted experiments with four machine learning tools (including a support vector machine, logistic regression, random forest, and gradient lift), and finally utilized the evaluation and classification of patients with depression and without depression. This experimental study allows us to demonstrate the auxiliary role of kinematics in the identification of depression. However, when motion capture equipment is used to record the joint skeleton data of participants in motion, the captured data often contain noise due to the influence of the environment and sensor accuracy, which limits the accuracy of the data.

Blood

Biomarkers[80] are a group of proposed markers in recent years related to cell growth, proliferation, and disease occurrence, and they can be used to reflect drug reactions during pathological processes or after therapeutic interventions. Wagh *et al*[81] reviewed gene expression studies based on peripheral blood to identify gene expression biomarkers for schizophrenia. According to a genome-wide association study (GWAS), C-reactive protein (CRP) which is a biomarker of chronic inflammation, in the blood is likely associated with an increased risk of major depression; however, it is also correlated with a decreased risk of anorexia nervosa, obsessive-compulsive disorder, and schizophrenia[82]. By examining RNA, researchers can determine the patient's current state of anxiety, depression, and mania[83]. Moreover, despite the differences in population characteristics, analysis methods of gene expression, and nature of the research, the results still proved the validity of blood-based gene expression. Fernandes *et al*[84] used a machine learning algorithm composed of peripheral blood immunoinflammatory biomarkers and cognitive biomarkers in the diagnosis of bipolar disorder and schizophrenia with clinical effectiveness. The manner in which machine learning is combined with pharmacogenomic data provides a new way to predict patients with major depression. In a systematic review of recent advances in machine learning and pharmacogenomics studies, Bobo *et al*[85] demonstrated the effectiveness of pharmacogenomics in predicting short-term antidepressant responses and suggested that the prediction of treatment outcomes may depend on background factors that cannot be captured by machine learning algorithms.

Multimodal data

In addition to collection methods of single data, multimodal datasets are increasingly used in psychiatry, such as the use of clinical scale evaluation and resting-state functional magnetic resonance imaging (MRI) to establish a prediction model of mood disorders, anxiety, and anhedonia[45], as well as a machine learning framework based on multimodal neuropsychiatric data to predict the responses of patients with schizophrenia to treatment[86]. Chen *et al*[87] conducted a comprehensive review of the practice of machine learning combined with neuroimaging in psychiatry, which emphasized the importance of multimodal data and the extraction of multimedia information. Data were collected through a combination of electronic questionnaires, standard clinical care record reviews, and device output analysis[88]. Although this statistical method integrating multimodal data demonstrates advantages over the general methods of single data, it is usually prone to overfitting and poor generalization[89]. The method of how to avoid these problems should be further explored in the future.

CHALLENGES OF COMPUTATIONAL PSYCHIATRY

The building of an AI ecosystem for computational psychiatry currently faces multiple challenges, which can be broadly divided into three categories: technical factors, cost and context, and ethical challenges. In this section, each challenge is explained separately.

Technical factors

It is important to note that computational psychiatry is still in its early stages, and there are many challenges that must be overcome. The most fundamental challenge is technical difficulty. Examples include data availability and quality, data transparency[90], technology openness, and professional integration. The quality of the raw data and the details of the processing are directly related to the interpretation of the results. One primary way to address this challenge is to increase collaboration with experts in other fields, such as computer science and engineering. By combining their expertise, researchers can develop new algorithms and tools to better handle the complex datasets associated with mental health research. Automation, rigor, and standardization of treatment methods[16] is another manner to advance the field of computational psychiatry, which can help to ensure that the results of computational research are replicable and can be generalized to a wider population. Due to the fact that "data-driven" research is based on the analysis and application of data, the transparent presentation of data results without bias and selectivity is the norm that researchers must follow. In response, there is a need to develop an interpretable, transparent, and universally applicable scientific review framework [91] to ensure the feasibility of using AI in psychiatry. Although the rapid development of artificial intelligence approaches has made up for the shortcomings of traditional mental illness research methods, thus identifying increasingly more information related to brain function, it must be stated that mental illness researchers and clinicians know very little about computational technology methods[92, 93]. It is recommended that there should be improvements in the computational literacy of neuroscientists and mental health professionals[94] while also leveraging the talent development role of higher education to bring more people with cross-disciplinary professional backgrounds into the field. Another note about computational psychiatry is the importance of ensuring that the field remains accessible and inclusive. As computing becomes more widely used in mental health research, it is important that these technologies are not just reserved for the best-funded or best-known researchers. Instead, an open and inclusive approach should be taken to provide researchers from diverse backgrounds and institutions with the tools and resources that are needed to conduct computational psychiatry research. It is also important for researchers to engage with policy-makers and advocacy groups[95] to ensure that findings from computational psychiatry are translated into practical applications.

Costs and different theoretical backgrounds

The costs mentioned in this section include time costs[18] and labor costs, which are uncontrollable factors that should be considered in clinical modeling. Due to the wide range of projects contained in the ecosystem, the system operation needs to be repeatedly monitored, evaluated, adjusted, and optimized, thus requiring a large amount of time. Moreover, there are many participating roles in each link, and there are cost consumption problems in coordination and communication management. For example, a team of clinicians may accept social and institutional pressures, and there may be conflicts between experienced mature doctors and novice decision-makers. The intersection and unification of viewpoints under different theoretical backgrounds in interdisciplinary cooperation also require coordination and compromise. Second, the reasonable match between professional salary structure and working style will also affect the clinical practice effects. In addition to the abovementioned overt factors, some individuals have raised concerns about the use of computational techniques in studies of mental health conditions, wherein they have argued that these methods may oversimplify complex phenomena and ignore important environment-specific factors. We also need to consider whether the modeling state of computational psychiatry follows the natural trajectory of core neurobiology[3] and whether computational psychiatry is detached from the developmental background of the field of psychiatry. When we

discuss the development of psychiatry with sophisticated AI approaches, we must not lose sight of the core purpose of disease treatment.

Ethical challenge

In addition, there are ethical issues with the use of computing in mental health research[96,97]. The application of AI to psychiatry needs to consider AI ethical issues, including respecting patient autonomy by providing adequate consent[70,98], data ownership, the ignoring of conscious experience, privacy protection[99], and equity[100]. An ethically acceptable manner[101,102] is an obstacle to the transformation of computational psychiatry from theory to practice. Some researchers have argued that the use of these techniques can lead to biased or discriminatory results, especially if the algorithm is not properly trained or verified. In the practice of treating and predicting mental illness, we call upon researchers and health care professionals to approach patients with rigorous optimism concerning the principles of kindness[103], harmfulness, respect for autonomy and justice[42], and prevention of ethical issues from the aspects of communication, consent, and contrast[104]. According to four basic ethical principles (respect, no harm, benefit, and justice), researchers should fully respect the independent will of data providers when collecting and using data, as well as pay attention to the protection of their personal privacy and process data anonymously. In addition, the participants' rights and interests should be the first priority. Justice and fairness should be adhered to. Moreover, informed consent should be obtained, and the process should be open and fair. Although we are aware that computational AI approaches (such as machine learning) can have a profound impact in psychiatry, there are still no applications that constitute standard clinical practice. The early consideration of these ethical challenges and the establishment of standards and requirements to eventually allow for the early use of the benefits of AI for mental health care should be enacted. Despite these concerns, we remain convinced that the potential benefits of computational psychiatry far outweigh the risks[105]. By properly using AI to study mental health conditions, researchers can gain a more comprehensive and nuanced understanding of mental illness, which could ultimately lead to better treatments.

LIMITATIONS

There were several limitations to this study. First, all of the relevant literature that was analyzed in this paper is in English and does not cover studies in other languages (such as Chinese, Korean, Japanese, and German). Thus, the coverage of the research may still be insufficient. Second, this paper is only a summary of the research in related fields, which cannot be applied to clinical treatment. This review only collates extensive research on data sources, tools, and model frameworks in computational psychiatry and does not use explicit methods, such as systematic reviews, nor does it address substantive clinical outcomes.

CONCLUSION

This paper builds an artificial intelligence ecosystem for computational psychiatry by reviewing the literature, including the following four stages: data acquisition, preparation for modeling, model building, and application evaluation. In terms of data acquisition, we discussed different data acquisition methods and data forms and summarized single data source methods, such as scale, open data, language, and physiological signals, as well as multimodal data statistical methods combining different types of data. In terms of preparation for modeling, we explored constraints from both the clinician and algorithm engineer industry norms and emphasized the importance of data preprocessing and quality testing. For model building, we proposed two steps of normative modeling (initial model training and model modification) and discussed supervised learning and unsupervised virtual seats in machine learning. Finally, based on the relevant theory and experience, we prospectively assessed the aspect of application evaluation and clarified the complexity and necessity of model performance evaluation and post analysis.

In conclusion, computational psychiatry is a promising field that has the potential to revolutionize our understanding and treatment of mental health conditions. In recent years, research on computational psychiatry has produced many good results. For example, it has made profound theoretical breakthroughs in the integration of computer science, biology, psychiatry, statistics, and other disciplines. In addition, it has allowed for the performance of more in-depth research in the use of computing and mathematical techniques to explain mental diseases and has made many attempts and modifications in data collection, model construction, and other aspects. It is worth mentioning that this field has accumulated a rich amount of data, with data originating from traditional clinical scale evaluations to the application of big data, from language to EEG, and from a single dataset to multimodal data, which provides a solid foundation for future clinical practice.

However, it should not be ignored that computational psychiatry is still in its early stages and experiences of technical challenges, such as data quality and tool openness, cost issues (such as role conflict and development cycle), and ethical challenges (such as data privacy, respect, and equity). More work will need to be performed to realize its full potential to ensure that existing discoveries are eventually translated into clinical applications. Specifically, the need for an artificial intelligence ecosystem for computational psychiatry can help researchers clarify their work, build on it, further develop better algorithms and techniques to analyze complex datasets, establish more rigorous and standardized experimental methods, and collaborate with policy-makers and advocacy groups to ensure that the findings of computational psychiatry are translated into practical applications. When considering that the use of artificial intelligence needs to experience a series of ethical problems caused by computing technology, the establishment of relevant application standards and moral guidelines should be emphasized in the future. Moreover, future research should focus on the integration of computational psychiatry with other disciplines, such as psychology, neuroscience, and genetics. By combining multidisciplinary and multidisciplinary expertise, researchers can gain a more comprehensive understanding of the crux of mental illness and develop more effective treatments and interventions.

FOOTNOTES

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