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AI IN IMAGING AND THERAPY: INNOVATIONS, ETHICS AND IMPACT: REVIEW ARTICLE

Artificial intelligence in mental healthcare: an overview and future perspectives

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ABSTRACT

Artificial intelligence is disrupting the field of mental healthcare through applications in computational psychiatry, which leverages quantitative techniques to inform our understanding, detection, and treatment of mental illnesses. This paper provides an overview of artificial intelligence technologies in modern mental healthcare and surveys recent advances made by researchers, focusing on the nascent field of digital psychiatry. We also consider the ethical implications of artificial intelligence playing a greater role in mental healthcare.

INTRODUCTION

Mental illnesses are common health conditions that involve changes in emotion, thinking, or behavior, impacting over 1 billion people worldwide per year.[1,2] The global health burden presented by mental illness is substantial, accounting for an estimated 32.4% of years lived with disability through 2016, which is likely an underestimate.[3] This is exacerbated by a chronic and severe shortage of mental health professionals worldwide, further aggravated by the COVID-19 pandemic.[4,5] The psychiatry workforce in the United States alone is projected to experience a shortfall of up to 31,000 by 2024, while rates of depression and anxiety among US adults reached as high as 42.6% at the height of the pandemic, compared to 10.8% before.[4,6,7] Moreover, mental illness was the most costly condition in the USA at $201 billion annually even before the pandemic.[4] To address this urgent need, recent efforts have been devoted toward developing computational approaches to diagnosing and treating mental illnesses. One approach involves incorporating artificial intelligence (AI), with schemes such as digital psychiatry, whose clinical potential is being explored worldwide.[8–13]

From a broader perspective, the advent of AI has changed every aspect of human society. AI aims to create systems that exhibit intelligent behavior and can learn, explain, and advise their users. Machine learning (ML) is a subset of AI that employs statistical models and algorithms to learn features, also known as representations, from large data sets for pattern recognition as well as the importance associated with each feature.[8,14] AI has numerous applications in healthcare, chiefly by way of ML; the most common classes utilized in healthcare are supervised learning, unsupervised learning, and deep learning. Supervised learning algorithms learn associations between features of a labeled input data set such that they can best predict the labels on a previously unseen data set. The researcher must guard against overfitting, which is when the algorithm learns too specifically about one data set and does not generalize well to external samples. Unsupervised learning algorithms discover the underlying structure within a data set instead of predicting labels. They are often used to discern patterns and meaning when labels are not provided.[8] Deep learning algorithms can take in raw data and develop their own representations without human guidance. These representations can be multilayered and are increasingly abstract with every layer. This allows deep learning to learn very complex, non-linear representations of data, making them ideal for discovering intricate structures in high-dimensional data.[8,15]

ML has demonstrated enormous potential for healthcare applications due to the increasing availability of massive data sets of many modalities in recent years.[9,15] Deep learning techniques have received particularly great attention due to their superior performance relative to many classical ML approaches.[9,10,15–19] We conducted a comprehensive literature search encompassing reviews and research articles published between 2017 and 2022 to provide a summary of the latest advancements in the application of AI methods in mental health (Table 1). This paper aims to provide an overview of how AI technologies are being incorporated into mental healthcare, offering insights into their historical progression, current state, and prospects. As shown in Figure 1, the diversity of AI facilitates many possible psychiatric applications. Additionally, we delve into the ethical implications associated with the expanding role of AI in mental health clinics.

OVERVIEW OF AI IN MENTAL HEALTHCARE

In contrast to applications in more physical specialties such as oncology and radiology, the use of AI in mental healthcare has been comparatively modest, as the application presents unique challenges: in contrast to other chronic conditions associated with objective measures such as laboratory tests, mental illnesses have complex pathophysiology that is prone to a higher degree of subjectivity.[8] Available data indicate that rather than adhering to relatively straightforward patterns, mental illnesses are influenced by a complex interplay between genetic, epigenetic, and environmental and social determinants of health.[12] Thus, diagnoses and treatments have a greater reliance on the clinician–patient relationship, often depending on softer skills such as building rapport with the patient and being observant of the patient's emotions and behavior. Consequently, mental health clinical data are often subjective as well, frequently coming in the form of patient statements and clinician notes. This may affect the quality of data labels, which can directly influence model training.[27] Despite these challenges, the field of mental healthcare stands to benefit from AI technologies, which can refine our understanding of mental illnesses with powerful pattern recognition techniques, improve diagnostic accuracy by providing clinical decision-support, and streamline clinical workflow by taking over time-consuming tasks such as writing medical records.[8,27] For instance, natural language processing (NLP) is an AI technique that allows computers to process and analyze human language, holding great potential for applications within mental healthcare as a considerable amount of raw data in the field is in the form of text and conversation.[8]

THE PAST: PRELIMINARY APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN MENTAL HEALTHCARE

In spite of a growing number of studies, AI in mental healthcare remains at the preliminary stage.[8,11,27] Studies tend to focus on proof of concept, with limited exploration of clinical validity and generalizability, which is not unique when adapting AI to a new domain. Two main applications that have been most explored are disease diagnosis and treatment response prediction.[8,10]

With regards to diagnosis, early detection of mental illnesses is critical to improving the quality of mental healthcare and our understanding of mental illnesses. AI has demonstrated potential in mental health clinical decision-support, capturing aspects of mental illness that a clinician may not notice. The heterogeneity and multidimensionality of many neuropsychiatric conditions frustrate the development of comprehensive diagnostics and motivate data-driven approaches that leverage computational power.[26] As Graham et al note in their review of AI in mental healthcare, supervised learning, and NLP are the most common AI techniques in mental health studies. Depression was the most commonly studied condition.[8] Deep learning has arguably demonstrated the greatest potential among all AI and ML methods applied to mental healthcare so far. Su et al note that there is a growing number of studies using deep learning models for studying mental health outcomes, with multiple studies developing promising disease risk prediction models using both clinical and non-clinical data.[9] Squarcina et al's review of studies using deep learning in the prediction of depression treatment response found promising accuracies around 80%; however, weaknesses include small sample sizes and results that may be difficult to interpret.[18]

THE PRESENT: BUILDING LARGER AND MORE HETEROGENOUS DATA SETS

Despite many studies achieving high accuracy scores, the greatest limitation of current research on AI in mental healthcare is the lack of large, high-quality data sets that represent a diverse set of mental phenotypes. Further, current psychiatric clinical data are based on primarily symptom-based diagnostic frameworks founded on social constructs, such as the *Diagnostic and Statistical Manual of Mental Disorders* (DSM-V). These data may not be reliable predictors of mental illnesses.[12]

Current literature indicates that the field is moving towards elucidating the pathophysiology of mental illnesses by discovering associations with more objective indicators such as biomarkers. Kalmady et al exemplify this shift toward biologically informed diagnoses by demonstrating accurate classification of schizophrenia using fMRI images. They employed an ensemble model that imitates brain connectivity structure, achieving 87% accuracy on a data set of 174 subjects.[22] Sharma and Verbeke extracted 28 biomarkers from a Dutch database and explored associations between them and four different anxiety disorders, using several different ML approaches. Their group found associations between their chosen biomarkers and all four anxiety disorders but conceded that future work would need to focus on larger, more diverse data sets (since they only focused on Dutch citizens, limiting generalization to other countries), validating their findings through clinical research, and expanding their biomarker selection.[30] The issue of symptom heterogeneity also complicates diagnoses and necessitates additional stratification of disease subtypes, which should correspond to biological phenotypes. Drysdale et al published work that lays the foundations for further work of this type in depression, a profoundly heterogeneous condition, where they clustered patients into different depression subtypes using a multisite fMRI data set of 1188 patients, finding four connectivity-based subtypes of depression.[20] A more promising direction that considers biological associations as well as heterogeneity appears to be multimodal data integration as exemplified by Rahaman et al, who built a deep

Table 1. Summary of selected publications on AI in mental healthcare (2017–2022).

Authors	Publication type	Type of AI application	Data type	Study cohort	Discoveries	Limitations	Year of publication
Drysdale et al.(2021)[20]	Study	Clustering	fMRI images	1,118 subjects	Clustering fMRI images can divide depression into four novel subtypes based on brain connectivity	Needs replication on single-site sample; phenotyping is not extensive and uniform enough	2017
Cearns et al.(2019)[21]	Review	N/A	N/A	N/A	Machine learning in psychiatry is promising but still early – methods should be tested alongside clinicians to provide realistic expectations of integration into practice	Clinical data sets are usually small, necessitating novel approaches to training models on smaller data sets	2019
Graham et al.(2019)[8]	Review	N/A	N/A	N/A	Depression is the most studied mental illness; supervised learning and natural language processing are the most common techniques; studies largely achieve high accuracy but should be considered early proofs-of-concept	Large, high-quality data sets are needed; deep learning methods increasingly needed to handle such complex data	2019
Kalmady et al.(2019)[22]	Study	Classification	fMRI images	174 subjects	Model based on one MRI modality can accurately classify drug-naive schizophrenia patients	May not generalize well; small single-site sample	2019
Durstewitz et al.(2019)[10]	Review	N/A	N/A	N/A	Deep learning methods are suited to the complex relationships within psychiatric data and have shown convincing results in diagnosing dementia and ADHD	Low sample size and single-site data sets challenge generalizability; deep networks are less interpretable	2019
Garrido et al.(2019)[23]	Review	N/A	N/A	N/A	Depressed patients prefer and engage more with game-like interventions and relatable, interactive content	Interventions need to be much more appealing to young people; use interventions must be supported by institutions	2019
Hariman et al.(2019)[24]	Review	N/A	N/A	N/A	Rapid advances in technologies are changing psychiatry practice such that more patients will gain access to mental healthcare	Provider training on digital psychiatry technologies should be updated; experts and institutions should provide ethics guidance	2019
Lovejoy et al.(2019)[25]	Review	N/A	N/A	N/A	New diagnostic, monitoring, and treatment tools may improve patient outcomes and reduce clinician workload	Regulation is needed to address ethical and privacy concerns	2019
Tai et al.(2019)[12]	Review	N/A	N/A	N/A	For psychiatry, AI provides viable options for modeling at-risk patients and personalizing and developing treatments	Small and poorly standardized data sets that rely on few diagnostic frameworks	2019
Chandler et al.(2020)[14]	Review	N/A	N/A	N/A	Policy is needed to ensure trust in AI methods such that they become viable to psychiatry	A lack of data sharing and standardization can slow AI development	2019
Washington et al.(2020)[26]	Review	N/A	N/A	N/A	Development of AI diagnostics for autism indicate the complexity of mental conditions and set the stage for future digital psychiatry to development	Standardized image and video data sets are needed for rapid progress, while preserving privacy	2019
Su et al.(2020)[9]	Review	N/A	N/A	N/A	A growing number of studies use deep learning models and are achieving promising results	Small sample sizes; existing data sets rely on clinician judgment; mental health is heterogenous, requiring multimodal approaches; deep models are less interpretable; associating diagnosis with intervention remains challenging	2020
Lee et al.(2021)[27]	Review	N/A	N/A	N/A	AI technologies hold great promise in supporting the diagnosis and treatment of psychiatric disorders	Data quality matters in model training; closed-source models hamper progress; AI must address ethical concerns such as bias, privacy, and transparency	2021
Jacobs et al.(2021)[28]	Study	N/A	N/A	220 subjects	Clinicians interacting with AI tools may not necessarily perform better than each one individually	Study was conducted in a hypothetical environment; medication combinations or non-medication treatments were not included	2021
Squarcina et al.(2021)[18]	Review	N/A	N/A	N/A	Deep learning methods are promising in predicting psychiatric treatment response	Small sample sizes; limited interpretability of results	2021
Lipschitz et al.(2022)[29]	Review	N/A	N/A	N/A	Digital mental health interventions have varying engagement and lacks reporting standards	A lack of standardization around studying digital mental health interventions limits the ability to draw conclusions	2021
Ray et al.(2022)[11]	Review	N/A	N/A	N/A	AI-based interventions demonstrate promise in supporting the analysis, forecast, and treatment of mental health conditions	Collaboration between providers, ethicists, engineers, and other experts is necessary to accomplish AI's full potential	2021

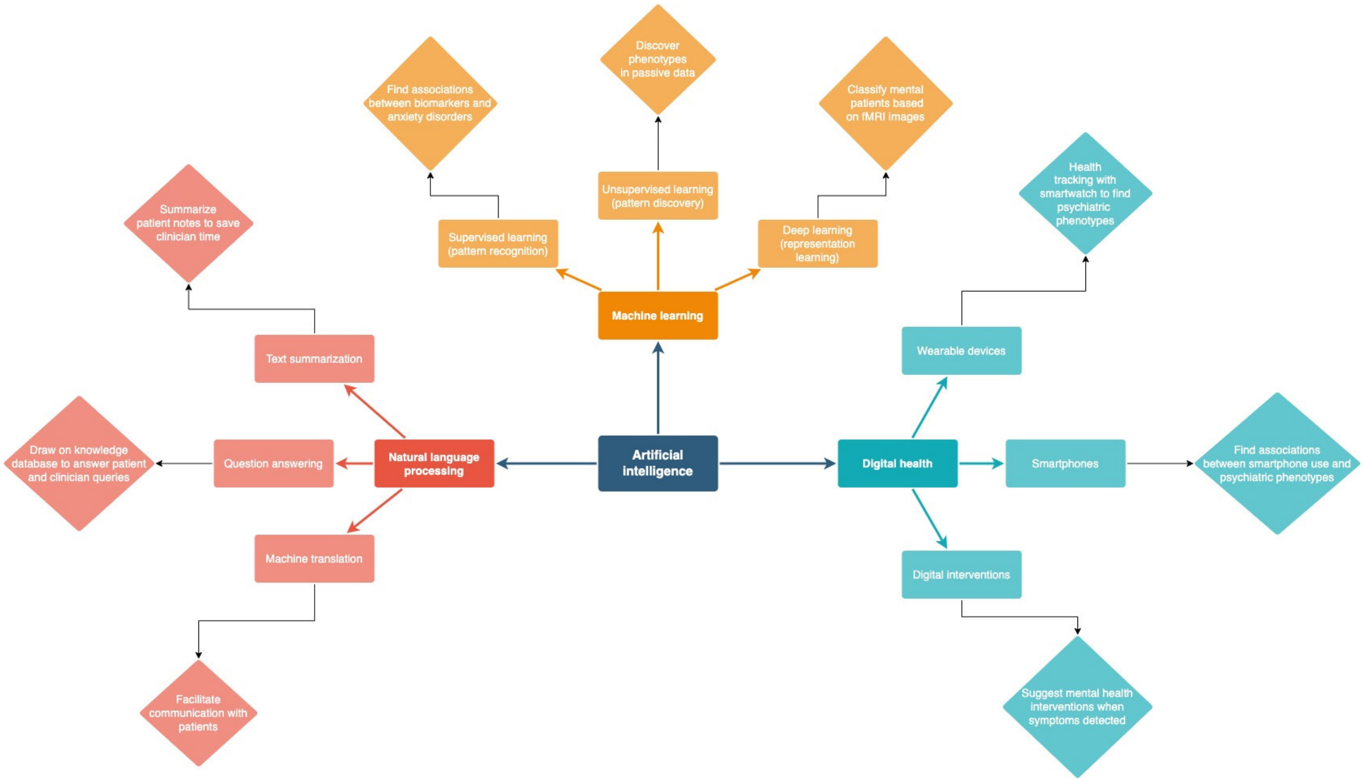
(Continued)

Table 1. (Continued)

Authors	Publication type	Type of AI application	Data type	Study cohort	Discoveries	Limitations	Year of publication
Sharma and Verbeke (2021)[30]	Study	Supervised (classification and regression)	Clinical data	11,081 subjects	Found associations between 28 biomarkers and four anxiety disorders	Focused on Dutch citizens, limiting generalization	2021
Araya et al. (2021)[31]	Study	Smartphone-delivered digital intervention app	Clinical data	880 subjects	App usage successfully reduced depressive symptoms	Enhanced care for high-risk patients likely affected results; digital intervention was supported by nurses; app *vs* nurse contributions cannot be distinguished	2021
Rahaman et al.(2021)[32]	Study	Supervised (classification)	Multimodal	437 subjects	Blending data modalities achieves better accuracy	Small sample size	2021
Torous et al.(2021)[13]	Review	N/A	N/A	N/A	Digital psychiatry methods (interventions, smartphone data, social media, virtual reality, and chatbots) all demonstrate early promise in mental healthcare	Better understanding of user engagement with these methods is needed; provider training for prescribing these methods should be improved; policy should allow for more flexibility in adopting new clinical innovations	2021
Price et al.(2022)[33]	Study	Unsupervised (clustering)	Actigraphy data	77 subjects	Passive movement data contains psychopathologic phenotypes	Small sample size	2022
Straczkiewicz et al.(2022)[34]	Study	Supervised (classification)	Clinical and movement data	24 subjects	Demonstrated feasibility of quantifying medication adherence in mentally ill patients using smartphones	Small sample size; limited adoption of study app	2022
Lakhtakia et al.(2022)[35]	Study	Supervised (classification)	Clinical data	60 subjects	Demonstrated feasibility of monitoring symptoms of and phenotyping schizophrenia patients using a smartphone app in a global context	Small sample size; study impacted by COVID-19	2022

AI, artificial intelligence.

Figure 1. AI technologies and their potential applications in mental healthcare. AI, artificial intelligence.



learning framework that fuses neuroimaging and genomic data to capture the interaction between latent features and evaluates their complementary information in characterizing schizophrenia. The authors believe this heterogeneous approach better reflected the complexity of neurological disorders and helped them achieve 88% accuracy on a data set of 437 subjects.[32]

To further improve model generalizability, large multisite data sources are needed. While proposing a deep learning clinical decision-support system that helps select effective treatments for depression, Benrimoh et al outlined the necessity of training their model on large, diverse data sets from various groups and institutions, and the practical considerations that arise.[16] To that end, attention has been turning to a new category of data generation on a global scale, spurred on by global events.

THE FUTURE: THE POTENTIAL OF DIGITAL PSYCHIATRY

Digital health, a promising avenue of biomedical data generation, has grown in popularity across the medical field over the past few years, greatly accelerated by the COVID-19 pandemic. Digital health is especially relevant to mental healthcare, where it is known as digital psychiatry, owing to its unrivaled ability to increase accessibility to care. Even prior to the pandemic, a review by Hariman et al predicted that despite a lack of direct evidence, rapid advances in technology would soon revolutionize mental healthcare. They suggested incorporating technology training into medical and psychiatric curricula, convening expert panels to discuss applications of technology in mental health practice, launching more clinical trials in conjunction with technology companies to test new interventions and iron out ethical issues such as data privacy, and forming an international committee on digital psychiatry with the participation of international psychiatry associations.[24] Current literature makes it clear that there is increasing interest in digital psychiatry; a recent review by Torous et al identifies a growing number of studies exploring the potential of smartphones and other wearables, social media, virtual reality, and chatbots in digital psychiatry.[13]

Improve diagnoses using AI

Digital psychiatry can help improve diagnoses by discovering patterns that a clinician may not notice. In a first-of-its-kind study utilizing naturalistic, passively collected movement data, Price et al applied cluster analysis to identify distinct behavioral phenotypes within actigraphy data that corresponded to depression and schizophrenia. They utilized unlabeled raw minute-level actigraphy data from three groups over 1 week: individuals with schizophrenia ($N = 23$), individuals with depression ($N = 22$), and controls ($N = 32$) to find distinct movement patterns in patients with different psychiatric diagnoses. Though their study demonstrates the potential of pattern discovery to better understand multidisorder motor differences, the authors acknowledge several limitations, chiefly the small size of their sample, which was drawn from a single institution.[33]

Improve treatment adherence

Digital psychiatry can also help monitor treatment adherence. Straczkiewicz et al demonstrated the feasibility of quantifying psychotropic medication adherence among patients with serious mental illness by combining smartphone digital phenotyping and digital medication data in a longitudinal pilot study.[34] Digital psychiatry also shows promise for public health surveillance on a much wider scale. A first-episode psychosis study performed in the USA and India demonstrated the feasibility and acceptability of a smartphone app for symptom monitoring, cognitive assessments, and digital phenotyping in a global context.[35]

Digital interventions with AI

In addition, digital health can expand the reach of interventions. Two randomized controlled trials conducted in separate cohorts by Araya et al showed that a smartphone-delivered intervention over 6 weeks successfully reduced depressive symptoms in both cohorts at 3 months among people with diabetes and/or hypertension.[31] However, it should be noted that mental health interventions are in their early stages and are continuously evolving; more trials are needed to validate their clinical significance. A systematic review conducted by Garrido et al suggested that although digital interventions provide tangible benefit, they may only be clinically significant when their use is highly supervised. The authors note the importance of improving patient engagement.[23] Many ongoing trials are testing digital interventions of increasing complexity among patients with various psychiatric diagnoses.[36–40]

Wearable devices

Furthermore, wearable devices are experiencing a surge in popularity. These devices collect data on various aspects such as sleeping patterns, physical activity, and heart rate variations. This information is then utilized to evaluate the user's mood and cognitive state, opening possibilities for early detection of mental health issues. By promoting early intervention and prevention of these diseases, wearable devices, with the aid of AI algorithms, are paving the way for innovative approaches to mental healthcare.

Limitations

However, researchers should exercise caution, keeping in mind that digital psychiatry is nascent. It should be noted that most of these studies have small sample sizes, which limits their generalizability. Larger and more heterogeneous trials are needed to evaluate clinical significance. Moreover, there is currently a lack of standardization within digital psychiatry. A recent review by Lipschitz et al points out that engagement with digital mental health interventions is heterogeneous and often underreported, resulting from a lack of reporting standards. They suggest adopting a set of reporting guidelines to specify the minimum necessary information when reporting randomized controlled trials.[29]

ETHICAL CONSIDERATIONS

As the field moves towards larger data sets and models, it is noteworthy in a broader context that mental healthcare has been slower to adopt AI technologies in the clinic, owing to concerns over safety and trustworthiness. As Cearns et al note, psychiatry has long relied on statistical inference over prediction and has experienced significant problems with methodology translation. Though ML is well-suited to psychiatric applications, studies have reported varying degrees of accuracy, which has raised concerns about the veracity of findings. Several reviews have called for a closer look at the ethical issues underpinning the hesitancy and uncertainty around incorporating AI in mental healthcare.[8,21,27]

AI trustworthiness

Researchers should keep in mind that AI clinical decision-support tools may be inaccurate and can negatively influence clinicians. Jacobs et al found that incorrect AI recommendations may adversely impact clinician treatment selections, challenging the assumption that clinicians interacting with AI would perform better than clinicians or AI algorithms individually. They presented 220 clinicians with patient vignettes that did or did not include an ML-produced treatment recommendation and an explanation of the recommendation. Their results indicated that interacting with these recommendations did not significantly improve treatment selection accuracy compared to decisions made independently. Furthermore, interacting with an incorrect recommendation significantly reduced treatment selection accuracy, and explanations did not address overreliance on imperfect ML algorithms.[28]

Model interpretability and transparency

Although ML models have achieved high performance in healthcare applications, they can be difficult to interpret semantically in a given clinical setting, which some have warned hampers understanding of their underlying mechanisms and can seed doubt in their judgments.[10,14] Others argue that while research into the inner workings of "black box" models should continue, insisting on transparency before clinical application can stifle innovation and may not be a productive endeavor. Chandler et al point out that the meaning of interpretability and transparency can vary across domains, and even for clinicians, what constitutes a sufficient explanation of a model may not align directly with clinical constructs. Instead, they and others suggest that researchers focus on the more realistic goal of focusing on transparency by providing high-level explanations of the model's selection process, the statistics of the training data, the training process, and any underlying assumptions. On the clinical and regulatory side, they also advocate for rigorous quality and safety evaluations prior to clinical deployment, close validation and monitoring after deployment, and medical education that incorporates AI.[14,21,41]

Data security and informed consent

As Lovejoy et al note, healthcare data, especially mental healthcare data, are highly sensitive due to the high risk of stigmatization. Data disclosures are frequent and the increasing role of computation and AI in mental healthcare must be accompanied by strict data protection standards and regulations. While the most rigorous protections should be implemented for patients, they must also be sufficiently informed of the risk behind sharing their data with research groups.[25] Even promising initiatives such as federated learning, which may provide a solution for the problem of insufficient data by enabling collaborative learning without centralizing data, carry inherent risks that patients must be acutely aware of.[42]

CONCLUSIONS

Mental healthcare is undergoing a much-needed disruption by way of AI, but progress has been hampered by a lack of large, high-quality heterogeneous data sets. Digital health technologies represent a promising addition to the computational and clinical toolkit, expanding the reach of care and simplifying public health surveillance. However, as technologies evolve, open questions remain about the ethics of integrating AI into the clinic. Researchers, clinicians, and regulators should continue to collaborate closely such that patient protection is of paramount importance as AI plays a greater role in mental healthcare.

AUTHOR CONTRIBUTIONS

KWJ performed the review and composed the manuscript. GX conceived the review and provided guidance. QL and YX reviewed the manuscript and provided constructive input.

COMPETING INTERESTS

Author declear no competing interests

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