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Artificial intelligence-assisted psychosis risk screening in adolescents: Practices and challenges

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Abstract

Artificial intelligence-based technologies are gradually being applied to psychiatric research and practice. This paper reviews the primary literature concerning artificial intelligence-assisted psychosis risk screening in adolescents. In terms of the practice of psychosis risk screening, the application of two artificial intelligence-assisted screening methods, chatbot and large-scale social media data analysis, is summarized in detail. Regarding the challenges of psychiatric risk screening, ethical issues constitute the first challenge of psychiatric risk screening through artificial intelligence, which must comply with the four biomedical ethical principles of respect for autonomy, nonmaleficence, beneficence and impartiality such that the development of artificial intelligence can meet the moral and ethical requirements of human beings. By reviewing the pertinent literature concerning current artificial intelligence-assisted adolescent psychosis risk screens, we propose that assuming they meet ethical requirements, there are three directions worth considering in the future development of artificial intelligence-assisted psychosis risk screening in adolescents as follows: nonperceptual real-time artificial intelligence-assisted screening, further reducing the cost of artificial intelligence-assisted screening, and improving the ease of use of artificial intelligence-assisted screening techniques and tools.

Key Words: Psychosis risk; Adolescents; Artificial intelligence; Big data; Social media; Medical ethics; Chatbot; Machine learning

Core Tip: Artificial intelligence-assisted psychosis risk screening must be emphasized and applied in adolescents. This review summarizes the application of two artificial intelligence-assisted screening methods (chatbot and large-scale social media data analysis), and proposes that the first challenge in applying artificial intelligence to psychosis risk screening concerns ethical issues. The methods must follow four biomedical ethics principles, *i.e.*, respect for autonomy, nonmaleficence, beneficence, and justice. Three directions should be considered in the future: nonperceptual real-time artificial intelligence-assisted screening, further reducing the cost of artificial intelligence-assisted screening, and improving the ease of use of artificial intelligence-assisted screening techniques and tools.

INTRODUCTION

In recent years, the prevalence of psychosis among adolescents has been increasing. According to the data released by the World Health Organization, approximately one in five children and adolescents worldwide suffers from a mental disorder, and half of these individuals show symptoms before the age of 14[1]. The risk of psychosis shows not only a trend of a younger age but also many disease categories and high heterogeneity[2-5], and its potentially high prevalence warrants attention. Two studies in Europe and North America revealed that adolescents with prodromal symptoms of psychosis who actively sought help still experienced a risk of eventual psychosis at rates of 19% and 35%, respectively [6,7]. In fact, due to the lack of independence, fear of being discriminated against by people around them, and a dearth of adequate attention from parents and schools, some adolescents even do not actively seek medical treatment and thus often miss their best treatment window. Since 2020, the rapid spread and persistence of the coronavirus disease 2019 pandemic worldwide has caused further major and hidden risks to population health, including psychosis. A study revealed that the deadly hazard of coronavirus disease 2019 and the resulting national lockdown policies in Italy caused intense psychosocial stress in individuals, which can be a trigger for first-episode psychosis[8]. In particular, children and adolescents are the most vulnerable groups[9]. Compared with other groups, children and adolescents are more vulnerable to the negative effects of the pandemic[10,11], *e.g.*, anxiety, depression, and posttraumatic symptoms, which increase the psychosis risk and may cause long-term negative consequences[12,13]. Additionally, adolescents are at a greater risk of first-episode psychosis than adult-onset psychosis, which is often associated with more severe symptoms and worse outcomes[14,15]. People who suffer from severe mental disorders die 10 years to 20 years earlier than the average person [1] and are more vulnerable to long-term disadvantages in terms of career advancement in the labor market, social status, mental health, and life beliefs[2,16]. Undoubtedly, this reality is not conducive to the stable economic and social development of any country worldwide.

Influencing factors

The prior literature has concluded that psychosis risk is the result of an interaction between various internal and external factors[12,17], which can be divided into three main categories. First, national and social factors, such as those associated with schizophrenia, are unequally distributed across cultures and countries[18], and a cultural atmosphere that stigmatizes psychosis can create barriers to the timely detection of the illness[19]. The second category comprises family factors, including the two aspects of congenital inheritance and acquired growth environment. Adolescents who grow up in families with psychotic parents, domestic violence, or abuse are at a greater risk of psychosis[20]; adolescents suffering from psychosis have higher rates of broken homes, substance abuse, chronic disease[21], and lack of social capital[22]. Third, individual factors include demographic characteristics and addictive behaviors; for example, males account for a larger proportion of children and adolescents with first-episode psychosis[21], while marijuana use is also a risk factor for psychosis[23,24]. Indeed, a combination of risk factors, including genetics, birth season, birth complications, infection and immune system factors, autoimmune diseases, ethnicity, marijuana use, and urban residence, increase an individual's risk of developing schizophrenia[18].

Main benefits of artificial intelligence-assisted adolescent psychosis risk screening

Despite this severe reality, shortages of medical resources and professional psychiatrists and uneven medical care are still common. Many nonpsychiatric specialists in hospitals and psychological service personnel on campus or in the community are unable to accurately and efficiently identify psychotic patients, and even if they diagnose the condition, they still cannot perform effective follow-up and

treatment[25-28]. A consensus holds that one of the best strategies to promote early intervention against psychosis is to improve the early identification of individuals at risk for psychosis through screening[29-31]. However, screening for psychosis mainly relies on scales, complicating the accurate identification of adolescents with a psychosis risk in a timely manner.

Over the past few years, artificial intelligence has shown explosive development inseparable from the emergence of new algorithms and the speed of high-performance parallel computing, coupled with the development of large-capacity storage space and video, text, sound, and other technologies to promote its rapid growth. Recent advancements in artificial intelligence have promoted improvement in the methods and technological innovations used in the treatment of human mental diseases, and artificial intelligence-based technologies are gradually being applied to psychiatric research and practice[19,32-35]. The main benefits of artificial intelligence-assisted adolescent psychosis risk screening are as follows: (1) Compared with traditional screening, the introduction of artificial intelligence can improve the speed and timeliness of identifying those who are already sick or who have a potential risk of a disease[36], which helps with early intervention and treatment[37,38] and timely correction of patients' risky behaviors, all of which can prevent the occurrence and further aggravation of symptoms; (2) Using advanced technology and objective data, artificial intelligence further enhances the accuracy and objectivity of screening methods. Appropriate screening tools that have been developed for all conditions in adolescent psychosis risk are relatively inadequate[39,40], while the clinical significance of adolescent self-assessment results is limited[41]; and (3) Artificial intelligence mitigates the scarcity of medical resources[42] and increases the coverage of screenings. Additionally, artificial intelligence can process massive amounts of data and use these data to improve generalization[43,44] while playing a pivotal role in identifying and detecting heterogeneity in schizophrenia and other mental illnesses[5] and can help doctors make the right decisions for subsequent diagnostic treatment[45].

Existing challenges

Ethical issues constitute one of the greatest challenges encountered in the application of AI to psychosis risk screening in adolescents in terms of both technical development and concrete practice[46,37] in the following four aspects: (1) Whether the autonomy of adolescents to participate in screening is duly respected and protected[47]; if the screening is conducted without their full approval, they should be responsible for the possible negative consequences; (2) The personal information and privacy of adolescents are leaked and exposed to unauthorized surveillance and security risks; the use and management of data collected based on artificial intelligence technology deserves attention[48,49]; (3) There is no unified understanding of the ethical assessment and acceptance of technology among different stakeholders[37]; and (4) The benefits of AI technology development do not reach all adolescents fairly and equitably.

Contribution

Clearly, there is a strong necessity and feasibility to focus on and apply artificial intelligence-assisted psychiatric risk screening in adolescents. However, there is a paucity of research concerning artificial intelligence-assisted psychiatric screening and a dearth of narrative literature reviews focusing on this important population characteristic of adolescents. Therefore, this paper reviews the main literature concerning artificial intelligence-assisted adolescent psychiatric risk screening to clarify the current state of development and recent explorations of this important topic in terms of practice and challenges with the aim to contribute to a more effective use of artificial intelligence methods for adolescent psychiatric risk screening in the future on a global scale.

PRACTICES

Traditional psychosis risk screening methods are mostly based on various self-assessment questionnaires with obvious limitations as follows: (1) Performance is not comparable among different screening tools; (2) The measurement criteria (such as content, number of items, and thresholds) widely vary; and (3) Dynamic and longitudinal tracking data are lacking[40]. In addition, scale-based self-assessment relies on individual self-perceptions, recollections, and subjective evaluations, and in some situations, individuals may exaggerate or mask some of their symptoms, weakening the accuracy of the results. For example, a general recall bias is evident among patients with depression, and symptoms can fluctuate over time or even throughout the day, which complicates capturing dynamic changes in symptoms with high accuracy[50].

The emergence of artificial intelligence can address and largely overcome the above limitations. The main machine learning algorithms currently used for psychosis screening are traditional ones, *e.g.*, decision tree, naive Bayes, random forest, support vector machine, K-nearest neighbor, and shallow neural networks. Of these, relevant studies have shown that the support vector machine method is the most commonly used[51,52]. With the advancement of deep learning algorithms, algorithms, such as convolutional neural networks, autoencoders, and deep belief networks, have begun to be used in psychosis risk screening research and are viewed as an important development trend of the future[3,53,

54]. By summarizing the pertinent literature, the artificial intelligence tools most often applied to psychosis risk screening are chatbot and large-scale social media data analysis.

Chatbot

Chatbot is a computer program that allows human–computer interactions in the form of textual dialog based on the technology of natural language processing[55]. The world's first chatbot, ELIZA, was developed in the 1960s[56] and responds according to special rules by recognizing keywords in user-entered texts[57]. Due to substantial advancements in artificial intelligence, chatbots have developed from being driven by static databases and learning new responses and contexts based on real-time interactions with humans to the fusion of real-time learning and evolutionary algorithms. Currently, chatbots have powerful capabilities of simulating the structures of natural language communication and creating a realistic environment in which users can achieve human–computer interaction. Chatbots in the healthcare field include Tess, HealthBuddy, Florence, Buoy Health, and Your.Md. In addition to natural language processing, the machine learning methods adopted by chatbots also include natural language understanding, artificial neural networks, and recurrent neural networks[58].

The prior literature has shown that psychosis is usually strongly correlated with human manifestations, such as facial expressions, voice, textual tone, and gestures. According to these human manifestations, chatbots with cognitive ability can ascertain the needs of users in real time to provide emotional responses and predictions and assessments of their mental health conditions[46,59]. Based on existing experience, one study improved upon the feature extraction of previous studies by using deep learning and fusion regression methods to construct an artificial intelligence system that automatically predicted depression levels based on vocal and visual expressions, which showed better predictive performance than other existing methods using the same dataset. Artificial intelligence is currently used in some chatbots. This study used deep learning methods to extract key visual features from facial expression frames, spectral low-level descriptors and mel-frequency cepstral coefficient features from short audio segments, and time movements in feature space through feature dynamic history histograms (FDHHs). Finally, regression techniques were used to fuse these FDHHs and audio features to predict the Baker Depression Scale II scores. The artificial intelligence developed in that study was a general framework that can be used to automatically predict depression scale scores from facial and vocal representations. It has FDHH dynamic functionality, leveraging the ideas of motion history histograms on deep learning images and handcrafted feature spaces, and enables feature fusion of different descriptors of face images[34].

The chatbot Woebot is used as an example. Woebot can be used on mobile communication devices in the form of short daily conversations and mood tracking to help users acquire anxiety reduction skills by identifying cognitive distortions to monitor anxiety and depression episodes while using fully automated conversational agents to address poor adherence to some extent. In a previous randomized controlled trial using Woebot, 70 college students who reported symptoms of depression and anxiety were randomly assigned to an intervention group that chatted with Woebot in an instant messaging application and a control group that received the National Institute of Mental Health e-book on depression in college students. The results revealed that the anxiety levels decreased in both groups, and the students who interacted with Woebot had significantly lower levels of depression compared to those reading the e-book. Future validation of the findings is needed with more participants, longer doses, and longer-term follow-up data[60].

In summary, the advantage of chatbots is that they can bring hope to psychosis risk screening for those who were previously inaccessible to screenings or who are economically constrained[61], build trusting relationships with potential patients, increase self-disclosure, and reduce the shame that patients or their families often feel when talking to doctors about mental illness. Nevertheless, these chatbots still have some shortcomings as follows: (1) They can be promoted by financial sponsors, causing conflicts of commercial interests; (2) In contrast to humans, they do not truly have subtle emotional awareness or empathic responses; and (3) They have issues with privacy, ethical risks, and other negative problems.

Large-scale social media data analysis

Currently, large numbers of users express their emotions and communicate daily through social media, such as Facebook and Twitter. Based on informative data such as textual information, emojis, user log information, and pictures, psychosis can be identified and predicted by combining natural language processing, sentiment analysis, and machine learning[49,62,63].

As the use of social media platforms becomes increasingly common in people's lives, screening for psychosis risk based on collected social media data will become easier. For instance, one study systematically analyzed artificial intelligence depression detectors and concluded that artificial intelligence systems that identify users at a high risk for depression from their social media data have made remarkable progress[37]. Given that depression is common in the adolescent population[26,64] and is underdiagnosed and undertreated, which underscores the need to expand the current screening methods, some investigators used the text of posts of consenting individuals on Facebook to predict depression as documented in electronic medical records and demonstrated correlative accuracy in identifying people with depression[65,66]. Therefore, the use of machine learning technology to screen

depression patients by acquiring the social media data for consenting individuals may become an effective and scalable supplement to existing screening methods[67]. Based on the language behaviors of Facebook user posts, Islam *et al*[68] achieved a classification accuracy of 99.0% with a depression prediction model using the decision tree method. Another study applied a logistic regression and highly randomized trees as modeling algorithms to approximately 20 million words of social media posts by 999 consenting volunteers and found that applying the method to Facebook posts significantly improved the predictive accuracy of demographic variables (age, sex, and ethnicity) in 18 of 21 disease categories, and it was particularly effective at predicting mental health conditions (anxiety, psychosis, and depression)[69]. In one study, big data were collected from China's Sina Weibo to understand differences in language style, emoji use, and the number of followers between depressive patients and nondepressed patients by using a deep neural network for feature extraction and dimensionality reduction. By constructing input data suitable for the classifier and applying the deep integrated support vector machine algorithm to classify the input data, the study achieved a more stable and accurate identification of depression in college students[70]. The development of Internet-of-Things technology has realized the exchange of information between hardware such that various wearable devices can carry a large amount of health information. Applying the Internet of Things to the field of psychosis through machine learning, the objective behavioral characteristics collected through mobile phones and wearable devices can effectively predict depressive symptoms[71,72]. Data related to daily activity, sleep, social communication, *etc.* have been collected through smartphone sensors to predict individuals' depression situations[73,74]. Advanced artificial intelligence methods, including natural language analysis and chatbots, were used by the Horyzons website to analyze the sentiment and language of newsfeed posts and other relevant factors (*e.g.*, user preferences and history), which enabled personalized treatment recommendations to be made for adolescents with early symptoms of psychosis [75]. Orabi *et al*[76] extracted unstructured text data posted on Twitter by 327 depression patients, 246 posttraumatic stress disorder patients, and 572 healthy individuals, and based on these data, users with depression tendencies were detected using the convolutional neural network method. Convolutional neural networks represent the most popular deep learning method in the field of natural language processing, boasting an accuracy as high as 87.9%, and have achieved remarkable progress in the field of image recognition[76]. In the future, more technologies, such as multimodal perception, understanding, and natural dialog and interaction (a multimodal auxiliary screening mechanism established through artificial intelligence perception technology), are needed to achieve more comprehensive and accurate screening of psychosis risk among adolescents.

CHALLENGES

The technology of artificial intelligence-assisted psychosis risk screening in adolescents will become more mature and a major development trend in the future. However, it can only do so by overcoming the existing challenges in the application of artificial intelligence-assisted psychosis screening in the adolescent population, which have rarely been addressed to date. Especially when applying artificial intelligence to psychosis risk screening, the primary challenge is ethical issues. The four principles of biomedical ethics, *i.e.*, respect for autonomy, nonmaleficence, beneficence, and justice[77], must always be firmly followed. On this basis, a new principle aiming to realize other principles through understandability and accountability[78] such that the development of artificial intelligence can truly meet the moral and ethical requirements of mankind has been proposed. Table 1 presents the four widely accepted ethical principles, their connotations, and the corresponding issues that adolescents may face.

Respect for autonomy
Respect for autonomy requires respect for the patient's personal dignity and autonomy, such as ensuring informed consent and informed choice, ensuring that humans have complete and effective autonomy, and requiring that the operation of any artificial intelligence be supervised by humans. Adolescents are still minors, and this age group is in the typical age when psychosis develops. Discussions have addressed whether adolescents have autonomy and how they should be "empowered". For example, in the United Kingdom, adolescents under the age of 16 can be competent to give consent if they demonstrate sufficient maturity and intelligence (as judged through Gillick competence). For minors deemed incompetent (and adults who are incompetent due to mental illness), questions arise regarding whether guardian advocates or those with parental responsibility should be empowered to provide proxy consent for psychosis risk screening[80]. Therefore, assuming that a given artificial intelligence-assisted psychosis risk screening method is safe and trustworthy, improving the awareness and attitudes of teenagers and their parents toward the psychosis risk and the importance of early screening is vital as their willingness to use artificial intelligence for screening can be increased only with their full approval[79]. Moreover, how to improve adolescents' autonomous participation in psychosis risk screening by ensuring effective informed consent and meaningful disclosure of results still requires further discussion.

Table 1 Connotations of ethical principles and issues faced by adolescents

Ethical principles	Connotations	Issues faced by adolescents
Respect for autonomy	Ensuring informed consent and informed choice, ensuring that humans have complete and effective autonomy, and requiring that the operation of any artificial intelligence be supervised by humans	Safety and trustworthiness of screening methods; full approval from adolescents and parents; willingness to use artificial intelligence for screening[79]
Nonmaleficence	Privacy, security and "capability warnings"[78]; artificial intelligence technology must be able to strongly resist malicious use, including avoiding harm to the natural environment and all living things	Privacy leakage and data abuse; difficulties in oversight and accountability; adverse effects and stigma with irreversible damage
Beneficence	Must be beneficial for not only the patients but also the medical cause, medical sciences and even the well-being of the entire human race	Screening scales need to be refined; no consensus (such as ethical evaluation acceptance of the technology) among different stakeholders[37]
Justice	Everyone in society has equal rights to reasonably enjoy health resources and participate in the distribution; prosperity is promoted; and unity is maintained	Development of artificial intelligence cannot benefit all groups of young people[12,14,21,22,80]; intergenerational transmission maintains inequality[46,78]

Nonmaleficence

Nonmaleficence requires privacy, security, and "capability warning"[78]. To protect the integrity of the human body, mind, and dignity, artificial intelligence technology must be able to strongly resist malicious use, including avoiding harm to the natural environment and all living things. Smart data collection technologies are becoming increasingly powerful, posing a greater threat to user privacy and security. The protection of adolescents' personal information and privacy is very important, but some privacy leakage and data abuse problems remain, which have been extremely harmful. With the rapid development of artificial intelligence, the existing ethical and regulatory norms have fallen behind. Their failure to keep pace with the latest environmental and artificial intelligence technologies creates difficulties in oversight and accountability. Especially in the presence of potential commercial interests or vested interests, *e.g.*, some social platforms may be abused by enterprises/people with criminal minds or illegal attempts, the usage of artificial intelligence in biomedical fields must be monitored and regulated from an ethical and moral standpoint. Furthermore, an artificial intelligence-assisted screening result may have adverse effects on some adolescents with a psychosis risk and introduce stigma when they are labeled with psychosis, which may, in turn, cause irreversible damage to their mental health, interpersonal relationships, and even long-term personal development. Thus, in addition to psychosis, many social factors related to its diagnosis cause extra damage to adolescents.

Beneficence

Beneficence requires that something be beneficial for not only the patients but also the medical cause, medical sciences and even the well-being of the entire human race. Although many studies have confirmed the positive role of artificial intelligence in psychosis risk screening, people still use scales for screening in practice. On the one hand, time is required to ensure that any technology is foolproof, and on the other hand, different stakeholders (adolescents and their parents, doctors, research and development personnel, *etc*.) have not yet reached a consensus, and the ethical evaluation and acceptance of the technology are still open questions[37], *e.g.*, whether medical professionals are willing to replace traditional screening with artificial intelligence-driven products and technologies. Therefore, whether this technology is truly beneficial for the health and well-being of society as a whole and humanity is worth discussing.

Justice

Justice requires everyone in society to have equal rights to reasonably enjoy health resources, resources to be fairly distributed, everyone to have the right to participate in the distribution and use of these resources and the benefits of artificial intelligence to be distributed fairly and equitably while avoiding any discrimination or stigma, promoting prosperity, and maintaining unity. The development of artificial intelligence cannot benefit all groups of young people. Previous studies revealed that adolescents born in the lower classes of society and those from disadvantaged families are more likely to suffer from psychosis[21,22]. In fact, vulnerable groups have a greater need to exploit the advantages of artificial intelligence technology for psychosis risk screening[12,14,80]. In reality, a "digital divide" and a "knowledge gap" still exist between urban and rural youths, the accessibility of digital technologies and services is unevenly distributed, and some youths still do not have the opportunity to access advanced technologies[81,82]. Furthermore, this unevenness is exacerbated by intergenerationally maintained inequality[46,78].

In addition to ethical issues, artificial intelligence-assisted psychosis risk screening in adolescents faces several other issues, including: (1) Small sample sizes: the use of machine learning to establish prediction models with high accuracy and strong generalization ability requires large samples[83], but

many studies have mentioned the problem of too few samples, resulting in overfitting, which may lead to model errors and low accuracy[21,84,85]; (2) The prediction model must be optimized: for the same problem and the same sample set, the prediction accuracies of prediction models based on different algorithms vary, and the applicable scope and characteristics of each algorithm are different[86,87]; (3) Compliance: the level of the technical knowledge of patients is a key factor affecting their compliance [88], which also directly affects the accuracy of conclusions; and (4) Research bias: most research samples are active users of social media or patients who are informed in advance, while broader groups of real-world patients are not included; thus, the representativeness of the samples and generalizability of the findings may be limited.

LIMITATIONS

This study has two limitations. First, this paper is a narrative review and provides an outlook. This paper discusses the current status and challenges of using artificial intelligence-assisted methods for screening adolescents for psychiatric disorders, but we do not use an explicit approach, such as a systematic review. Therefore, the study is primarily intended to evoke research interest in the field but cannot be directly applied to clinical care. Second, this paper only summarizes the relevant literature in English and does not consider the literature published in languages other than English.

CONCLUSION

While focusing on the psychosis risk faced by adolescents worldwide, this paper reviews the influencing factors of adolescent psychosis risk, which can be divided into the following three main categories: national and social factors, family factors, and individual factors. This paper summarizes the benefits of artificial intelligence-assisted psychosis risk screening in adolescents, which are mainly manifested in improving the speed and timeliness of screening for those who are already sick and those with a potential risk of disease, promptly correcting the risky behavior of patients to prevent the occurrence and further aggravation of symptoms, and improving the accuracy and objectivity of screenings and the screening coverage. The application of chatbots and large-scale social media data analysis in psychosis risk screening is discussed in detail. The advantage of chatbots in psychosis risk screening is that they can provide services to those with psychosis who have limited resources or access-ibility problems, although privacy concerns and other ethical issues may exist. The accuracy of large-scale social media data analysis is gradually improving, and more technologies based on multimodal perception, understanding, and natural dialog and interactions are still needed to help comprehensively and accurately screen for psychosis risk in adolescents.

After surveying the current literature concerning artificial intelligence-assisted adolescent psychosis risk screening, we found that although artificial intelligence has been gradually applied to early psychosis risk screening, it has rarely been applied in studies that directly use adolescents as subjects. In view of the prevalence and harm of psychosis among adolescents worldwide, the timely screening of adolescent psychosis risks with artificial intelligence technology has considerable prospects for development. Furthermore, scientific progress must follow relevant ethical principles, not ignore vulnerable groups of adolescents, and ensure that artificial intelligence-assisted psychosis risk screening is conducted in an ethically acceptable manner, thereby minimizing potential adverse effects.

Based on the current status of psychiatric artificial intelligence research and practice, we propose that ethical issues constitute the main challenge of artificial intelligence-assisted psychosis risk screening in adolescents. The four biomedical ethics principles (respect for autonomy, nonmaleficence, beneficence, and justice) should be strictly obeyed. In addition to ethical issues, artificial intelligence-assisted psychosis risk screening in adolescents faces problems, such as small sample sizes, unoptimized prediction models, compliance, and research bias.

We propose that assuming compliance with ethical requirements, three main directions can be considered for artificial intelligence-assisted psychosis risk screening in adolescents in the future. First, we should develop nonperceptual real-time artificial intelligence screening with the help of techno-logical advancements, such as 5G technology and the Internet of Things, to allow both the collection of individual emotional and health data and the prediction of individuals' mental health status in real time. Second, we should further reduce the cost of artificial intelligence-assisted screening. Psychosis is an important part of human health, and both poor and rich people should enjoy the benefits of techno-logical progress. The long-term goal of artificial intelligence-assisted psychosis risk screening is that users should not pay high prices for the screening. Third, we should improve the ease of use of artificial intelligence-assisted screening techniques and tools such that regardless of an individual's level of knowledge, he or she can easily use artificial intelligence tools to screen for a psychosis risk.

FOOTNOTES

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