

Application of Artificial Intelligence in Psychological Assessment: Current Status and Challenges

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Abstract: Psychological assessment is an important part of mental health services. Scientific and efficient mental health assessment and intervention are the premise of effective mental health services. Traditional psychological assessment mainly includes psychological tests and clinical interviews. With the rapid development of artificial intelligence and big data technology, psychological assessment is gradually moving towards intelligence. This paper reviews the current application of key technologies of artificial intelligence in psychological assessment, discusses its challenges in psychometric validity, ethics, and technical limitations. The results show that although artificial intelligence has great potential to improve the accessibility, efficiency, and accuracy of psychological assessment, its integration with clinical practice requires careful attention to measurement equivalence, data privacy, algorithmic fairness, and the irreplaceable role of human consultants. Therefore, in the era of artificial intelligence, psychological assessment should continue to develop in the future direction of human-machine collaboration.

Keywords: Artificial intelligence; Psychological assessment; Natural language processing; Machine learning; Human-AI collaboration

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1. Introduction

Psychological assessment is an important part of mental health services. Scientific and efficient mental health assessment and intervention are the premise of effective mental health services. Traditional psychological assessment mainly includes psychological tests and clinical interviews. With the rapid development of artificial intelligence and big data technology, psychological assessment is gradually moving towards intelligence^[1]. With the rapid development of artificial intelligence and big data technologies, psychological assessment is gradually becoming intelligent. Through technologies such as natural language processing, machine learning, and deep learning, data can be collected and analyzed more effectively to achieve accurate

assessment of individual mental health status^[2]. This article will discuss the application status and challenges of AI in psychological assessment, focusing on the two stages of primary screening and diagnosis. By integrating the latest developments and practical challenges in multiple technical fields, this review aims to provide useful insights for understanding the potential and limitations of artificial intelligence in the field of psychological assessment^[3-4].

2. Key AI technologies in psychological assessment

At present, there are more than 60 intelligent psychological assessment systems in the United States, which can provide end-to-end services such as problem analysis, data collection and processing, algorithm modeling, and decision-making recommendations^[5]. Through technologies such as machine learning and deep learning, combined with multimodal data (such as neuroimaging and physiological signals), AI can provide doctors with clearer analysis reports and assist doctors in making more accurate diagnoses^[6]. Previous studies have shown that the accuracy of AI in predicting the incidence of mental disorders in clinical high-risk groups is as high as 79 %^[7]; it can achieve 96 % accuracy in the detection of attention deficit hyperactivity disorder^[8]; and the classification accuracy of schizophrenia was 87 %^[9]. It can be seen that artificial intelligence has been widely used in psychological evaluation and has achieved remarkable results.

At present, the application of artificial intelligence in psychological assessment mainly depends on natural language processing technology, machine learning and deep learning, audio analysis and multimodal technology, data mining technology, and other technologies.

2.1. Application of natural language processing in psychological assessment

Natural language processing (NLP) covers technologies such as speech recognition, sentiment analysis, and text generation, enabling machines to understand, generate, and translate human languages^[4]. Initially, natural language was used in psychological assessment mainly by collecting and analyzing individual social media text data to assess their mental health status. Ophir and his colleagues constructed single-task (STM) and multi-task (MTM) models based on artificial neural network (ANN) to predict the suicide risk reflected by Facebook users' daily language^[10]. Domestic scholars have actively used social media platforms such as Weibo and Zhihu to conduct research on detecting users' depression and suicidal tendencies^[11].

Recent studies have shown that the scope of natural language analysis has expanded from social media to clinical applications. Large language models (LLMs) represent the advanced development of NLP, which are trained on massive data sets to generate natural language texts and understand language meanings, and have enhanced logical reasoning capabilities^[4]. Large-scale language models can conduct structured or free-form psychological interviews, extract symptom information from test responses and media texts, generate targeted follow-up questions, and generate comprehensive psychological assessment reports^[4]. In addition, open answers can be combined with traditional scales, and LLMs can be used to automatically score within the framework of item response theory, which greatly reduces the measurement error of psychological assessment^[4].

2.2. Applications of machine learning and deep learning in psychological assessment

Machine learning (ML), as the core technology of artificial intelligence, enables machines to automatically improve performance through data and experience without explicit programming^[4]. Previous studies

have shown that machine learning can extract biomarkers from physiological data to assist psychological assessment ^[12]. Machine learning helps to identify and extract neurobiological markers from complex brain data, and provides important support for neuropathological studies of various mental disorders such as addiction, schizophrenia, social anxiety, and attention-deficit/hyperactivity disorder ^[13–16]. In addition, machine learning can predict the behavior of individuals by identifying their emotional tendencies ^[17].

2.3. Application of audio-visual and multimodal technology in psychological assessment

Audio and video technologies assess users' mental health mainly by capturing and analyzing individual voice, intonation, fluency, coherence, and facial expressions. Previous studies have collected clinical speech data from patients with unipolar depression, bipolar disorder, and healthy controls, and compared them with speech databases in the laboratory environment. It was found that the recognition accuracy of this technology was 73.33 % ^[18]. In addition, gait information extracted from the video has an accuracy of more than 80 % in predicting individual emotions ^[19]. Combining facial and speech data has also been shown to be as accurate as 90 % in identifying patients with post-traumatic stress disorder (PTSD) ^[20].

Computer vision (CV) interprets visual information through image classification, target detection, and image segmentation. In psychological assessment, it can observe the subject's posture and behavior, analyze facial expressions, and score the observation items on the rating scale, allowing the computer to perform the test and score the performance test ^[4].

2.4. The application of data mining and big data processing technology in psychological assessment

Data mining is a technical method for extracting useful information and knowledge from large datasets, identifying data patterns, trends, and relationships through techniques such as cluster analysis, association rule mining, and anomaly detection ^[21]. Existing research has shown that big data processing technology, combined with Internet plus, AI, and VR technologies, can provide mental health services including assessment screening, risk prediction, psychological counseling, and clinical treatment. By integrating diverse data sources, it can surpass the scalability and continuous mental health monitoring potential of traditional clinical scenarios, providing a new paradigm for psychological assessment ^[4].

3. Challenges and ethical considerations

3.1. Technical limitations

On the one hand, there is a fundamental difference between the cognitive understanding ability of artificial intelligence and the human psychological process, which is also the inherent limitation of artificial intelligence in psychological assessment. Human psychological activity is a nonlinear open system with uncertainty and randomness, which is difficult to predict by algorithms ^[3]. On the other hand, artificial intelligence lacks real empathy. Previous studies have shown that although the score of empathy response generated by artificial intelligence may be higher than that of human response, it is an understanding response at the cognitive level, not a real emotional experience ^[22]. Therefore, artificial intelligence can simulate cognitive empathy through pattern recognition and response generation, but emotional empathy cannot be replicated by algorithmic systems ^[23]. In psychological assessment work, the establishment of a treatment alliance is the cornerstone of effective psychological intervention, which requires visitors to think

that counselors are similar to themselves in physical and emotional aspects. No matter how complex the artificial intelligence system is, it is impossible to replicate this basic interpersonal relationship.

3.2. Privacy protection and data security

The application of artificial intelligence in psychological assessment involves the collection and analysis of highly sensitive personal information. The possibility of data leakage will bring a huge psychological burden, thus undermining the therapeutic relationship. Even with detailed informed consent procedures, the risk of unauthorized data access remains a key issue ^[24].

3.3. Algorithmic bias and fairness

The performance of artificial intelligence depends largely on the quality and representativeness of training data. When the dataset is biased or fails to fully represent diverse social groups, artificial intelligence may continue and amplify social prejudice, resulting in unfair results in psychological assessment ^[3].

3.4. Professional role transformation

With the popularity of artificial intelligence, artificial intelligence may play a greater role in basic psychological services and preliminary assessments, which may affect the demand for human consultants. However, studies have shown that human-machine collaboration can improve the therapeutic effect ^[25]. Psychological counseling practitioners should actively master the basic knowledge of artificial intelligence to enhance their human-machine collaboration capabilities, while also improving irreplaceable skills such as empathy and complex case management capabilities.

4. Conclusion

This paper systematically expounds the application status and challenges of artificial intelligence technology in psychological assessment. Artificial intelligence provides a revolutionary opportunity to improve the efficiency and accuracy of psychological assessment. However, the deep integration of artificial intelligence (AI) and psychological assessment faces multiple fundamental challenges, which require that the clinical application of AI in the field of psychological assessment must be based on strict technical verification, strict ethical governance, and clear division of responsibilities. In addition, the popularity of artificial intelligence will inevitably reshape the professional role of human consultants, which requires human consultants not only to strengthen irreplaceable human capabilities such as empathy and complex case management, but also to cultivate human-machine collaboration skills and capabilities. Only by maintaining a dynamic balance between technological innovation and humanistic care can psychological assessment work achieve high-quality development.

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References

- [1] Ren P, Wang Y, Liu DY, et al., 2022, Intelligent Application of Mental Health Assessment and Intervention. *Journal of Beijing Normal University (Social Science Edition)*, 2022(4): 150–160.
- [2] Yao F, Wang X, Wei ZD, et al., 2024, Research Progress of Artificial Intelligence in Psychological Assessment. *Science and Technology Review*, 42(23): 70–78.
- [3] Li WT, 2025, Opportunities and Challenges of Artificial Intelligence in Psychological Counseling and Treatment Services. *Psychology Newsletter*, 8(2): 93–98.
- [4] Cheng MB, Hu XT, Zhou XQ, et al., 2025, Development and Prospect of Intelligent Psychological Assessment. *Chinese Journal of Clinical Psychology*, 2025(6): 1206–1211. <https://doi.org/10.16128/j.cnki.1005-3611.2025.06.014>
- [5] Zhang P, 2020, The Application of AI Technology in College Students' Psychological Assessment. *China Education Informatization*, 2020(10): 90–93.
- [6] Luxton DD, 2016, Chapter 1 — An Introduction to Artificial Intelligence in Behavioral and Mental Health Care, in *Artificial Intelligence in Behavioral and Mental Health Care*. Academic Press, San Diego, 1–26. <https://doi.org/10.1016/B978-0-12-420248-1.00001-5>
- [7] Corcoran CM, Carrillo F, Fernández-Slezak D, et al., Prediction of Psychosis across Protocols and Risk Cohorts Using Automated Language Analysis. *World Psychiatry: Official Journal of the World Psychiatric Association (WPA)*, 17(1): 67–75. <https://doi.org/10.1002/wps.20491>
- [8] Jaiswal S, Valstar MF, Gillott A, et al., 2017, Automatic Detection of ADHD and ASD from Expressive Behaviour in RGBD Data. 2017 12th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2017). 2017: 762–769. <https://doi.org/10.1109/FG.2017.95>
- [9] Kalmady SV, Greiner R, Agrawal R, et al., 2019, Towards Artificial Intelligence in Mental Health by Improving Schizophrenia Prediction with Multiple Brain Parcellation ensemble-learning. *NPJ Schizophrenia*, 5(1): 2. <https://doi.org/10.1038/s41537-018-0070-8>
- [10] Ophir Y, Tikochinski R, Asterhan CSC, et al., 2020, Deep Neural Networks Detect Suicide Risk from Textual Facebook Posts. *Scientific Reports*, 10(1): 16685. <https://doi.org/10.1038/s41598-020-73917-0>
- [11] Tian X, Batterham P, Song S, et al., 2018, Characterizing Depression Issues on Sina Weibo. *International Journal of Environmental Research and Public Health*, 15(4): 764. <https://doi.org/10.3390/ijerph15040764>
- [12] Lee J, Robert W, 2018, Neuromarkers for Mental Disorders: Harnessing Population Neuroscience. *Frontiers in Psychiatry*, 2018(9): 242. <https://doi.org/10.3389/fpsy.2018.00242>
- [13] Luijten M, Schellekens AF, Kühn S, et al., 2017, Disruption of Reward Processing in Addiction: An Image-Based Meta-analysis of Functional Magnetic Resonance Imaging Studies. *JAMA Psychiatry*, 74(4): 387–398. <https://doi.org/10.1001/jamapsychiatry.2016.3084>
- [14] Crossley NA, Mechelli A, Ginestet C, et al., 2016, Altered Hub Functioning and Compensatory Activations in the Connectome: A Meta-Analysis of Functional Neuroimaging Studies in Schizophrenia. *Schizophrenia Bulletin*, 42(2): 434–442. <https://doi.org/10.1093/schbul/sbv146>
- [15] Brühl AB, Delsignore A, Komossa K, et al., 2014, Neuroimaging in Social Anxiety Disorder—A Meta-analytic Review Resulting in a New Neurofunctional Model. *Neuroscience and Biobehavioral Reviews*, 2014(47): 260–

280. <https://doi.org/10.1016/j.neubiorev.2014.08.003>

- [16] Plichta MM, Scheres A, 2014, Ventral–striatal Responsiveness during Reward Anticipation in ADHD and its Relation to Trait Impulsivity in the Healthy Population: A Meta-Analytic Review of the fMRI Literature. *Neuroscience & Biobehavioral Reviews*, 2014(38): 125–134. <https://doi.org/10.1016/j.neubiorev.2013.07.012>
- [17] Wang YY, Zhan JE, Chen ZL, et al., 2021, Application of Machine Learning in Psychometrics. *Computer Knowledge and Technology*, 17(3): 204–206. <https://doi.org/10.14004/j.cnki.ckt.2021.0183>
- [18] Williamson JR, Young D, Nierenberg AA, et al., Tracking Depression Severity from Audio and Video Based on Speech Articulatory Coordination. *Computer Speech & Language*, 2019(55): 40–56. <https://doi.org/10.1016/j.csl.2018.08.004>
- [19] Zhao N, Zhang Z, Wang Y, et al., 2019, See your Mental State from Your Walk: Recognizing Anxiety and Depression through Kinect-recorded Gait Data. *PLOS ONE*, 14(5): e0216591. <https://doi.org/10.1371/journal.pone.0216591>
- [20] Schultebraucks K, Yadav V, Shalev A Y, et al., 2022, Deep Learning-based Classification of Posttraumatic Stress Disorder and Depression Following Trauma Utilizing Visual and Auditory Markers of Arousal and Mood. *Psychological Medicine*, 52(5): 957–967. <https://doi.org/10.1017/S0033291720002718>
- [21] Liu T, Hou Q, Huang YX, 2022, Research on Mental Health Assessment of College Students Based on Big Data Driven. *Information Technology*, 2022(10): 41–45. <https://doi.org/10.13274/j.cnki.hdzj.2022.10.007>
- [22] Ovsyannikova D, De Mello VO, Inzlicht M, 2025, Third-party Evaluators Perceive AI as more Compassionate than Expert Humans. *Communications Psychology*, 3(1): 4–14. <https://doi.org/10.1038/s44271-024-00182-6>
- [23] Matan RB, Hadar A, Huppert J, et al., 2024, Considering the Role of Human Empathy in AI-driven Therapy. *MIR Mental Health*, 2024(11): e56529. <https://doi.org/10.2196/56529>.
- [24] Iwaya LH, Babar MA, Rashid A, et al., 2023, On the Privacy of Mental Health Apps: An Empirical Investigation and its Implications for App Development. *Empirical Software Engineering*, 28(1): 2–43. <https://doi.org/10.1007/s10664-022-10236-0>
- [25] Sharma A, Lin IW, Miner AS, et al., 2023, Human–AI Collaboration Enables more Empathic Conversations in Text-based Peer-to-peer Mental Health Support. *Nature Machine Intelligence*, 5(1): 46–57. <https://doi.org/10.1038/s42256-022-00593-2>

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