112056_Auto_Edited.docx

WORD COUNT	2869	TIME SUBMITTED	18-NOV-2025 06:14PM
		PAPER ID	119075958

Name of Journal: *World Journal of Psychiatry*
Manuscript NO: 112056
Manuscript Type: MINIREVIEWS

Innovations and approaches in depression detection *via* functional near-infrared spectroscopy: A minireview

Li WT *et al*. Depression detection *via* fNIRS

Abstract

Depression, a leading contributor to global disability, lacks objective diagnostic biomarkers. This review evaluates functional near-infrared spectroscopy (fNIRS) as a portable neuroimaging tool for depression detection, highlighting its algorithmic innovations and clinical translation potential. Machine learning techniques effectively decode hemodynamic patterns of the prefrontal cortex during emotional or cognitive tasks to achieve high classification accuracy in controlled studies. Clinically, fNIRS identifies prefrontal cortex hypoactivation as correlated with symptom severity and tracks neuroplasticity during psychotherapy. However, heterogeneity across symptom subtypes, cultural backgrounds, and age groups limits the generalizability of the model. Technical challenges include signal noise from motion artifacts and interference from superficial tissues. Future research should prioritize standardized multicenter trials, multimodal integration to enhance biomarker specificity, and interpretable artificial intelligence frameworks for clinical translation. fNIRS demonstrates unique advantages for scalable, noninvasive depression screening but necessitates rigorous validation to transition from research to point-of-care applications. This review provides insights into the optimization of fNIRS-based tools for precision psychiatry.

Key Words: Depression; Functional near-infrared spectroscopy; Machine learning; Cognitive tasks; Verbal fluency tasks

Li WT, Wan YM, Miao W, Zhong R, Gao Q, Wang QX, Zheng YS. Innovations and approaches in depression detection via functional near-infrared spectroscopy: A minireview. *World J Psychiatry* 2025; In press

Core Tip: Functional near-infrared spectroscopy shows great potential in depression research: It captures prefrontal oxygenation deficits at rest and emotional/cognitive activation abnormalities during tasks, offering quantifiable biomarkers for diagnosis, differentiation, and severity assessment. Despite challenges like limited spatial

resolution and unstandardized tasks, combining with advanced algorithms and large samples may enable its key role in early screening, mechanism analysis, and precise treatment, advancing objective, quantitative diagnosis.

INTRODUCTION

Depression, particularly major depressive disorder (MDD), has evolved into a global mental health crisis with a wide range of impacts[1]. According to the World Health Organization, approximately 350 million people worldwide are affected by depression, and this number is projected to grow exponentially in the future[2,3]. Symptoms of depression are diverse, and in severe cases, psychotic symptoms and suicidal thoughts may occur, significantly increasing the risk of unnatural death[4,5]. The diagnosis of MDD relies primarily on clinicians' reference to classification systems, such as the International Classification of Diseases and Related Health Problems, 10th Revision, or the Diagnostic and Statistical Manual of Mental Disorders, 5th Edition[6,7]. The diagnosis often depends on the clinician's subjective assessment and clinical experience[8]. Mental symptoms are polymorphic and often overlap in various diseases, making accurate diagnosis extremely difficult[9]. Moreover, owing to the limitations of diagnostic tools, erroneous or ineffective results are often given to people with cognitive impairments[10].

Functional near-infrared spectroscopy (fNIRS) has emerged as a promising technology in neuroscience and mental health research[11,12]. The principle of fNIRS is that when specific regions of the brain are activated, changes occur in the cerebral blood flow, volume, and oxygenation[13]. By measuring the absorption of near-infrared light by hemoglobin in the brain tissue, fNIRS can detect changes in oxygenated (HbO), deoxygenated (HbR), and total hemoglobin, thereby providing insights into brain function[14]. It is a noninvasive, portable, and relatively inexpensive technology, making it suitable for various scenarios, including clinical settings and large-scale population studies[12-15]. The core pathological mechanism of depression involves functional abnormalities in multiple brain regions, and fNIRS can be used to monitor

key regions[16,17]. The dorsolateral and ventromedial prefrontal cortices are brain regions associated with emotional regulation and cognitive control[18]. Patients with depression typically exhibit decreased blood oxygen levels in the prefrontal cortex (PFC), indicating reduced activity of neural circuits responsible for emotional regulation[19]. The default mode network, which includes the posterior cingulate cortex, precuneus, and related regions, shows excessive activity at rest[20]. Current research indicates that there is dysregulation in neural processing during self-referential cognition[21], the amygdala shows excessive activity in emotional processing, and the regulatory control of the PFC over the amygdala is weakened[22]. This imbalance may disrupt emotional homeostasis, contributing to depressive symptoms[23,24]. Several existing studies have analyzed the principles of depression and brain mechanisms using statistical correlation analysis[25].

DEPRESSION DETECTION *via* fNIRS

Applications of fNIRS in depression research

Research on the use of fNIRS for depression detection involves multilevel explorations from basic research to clinical practice[36]. In addition to resting and task states, fNIRS applications in depression detection also include natural contexts and mixed states. fNIRS has unique advantages compared to traditional technologies such as functional magnetic resonance imaging and electroencephalography, making it suitable for the long-term monitoring of natural environments[26,27]. As a chronic mental illness[28], depression can be monitored using fNIRS in natural settings, such as clinical consulting rooms, laboratories, and homes[29].

Studies have demonstrated that, based on the detection of abnormal resting-state brain function, low oxygenation levels in the PFC of patients at rest are positively correlated with the severity of depression, which can serve as a potential marker for distinguishing patients with depression from healthy individuals[30]. Regarding abnormal emotional and cognitive responses in task states, the brain region activation patterns of patients with depression differed significantly from those of healthy

individuals[31]. During executive function tasks, the amplitude of blood oxygen changes in the PFC of patients is significantly lower than that observed in healthy individuals. The degree of such abnormalities is correlated with the degree of cognitive impairment, which can be used as a supplementary indicator for diagnosis. For the dynamic monitoring of treatment effects and prediction of therapeutic efficacy, fNIRS can track changes in brain activity in patients with depression during drug therapy, psychotherapy, or physical therapy, providing an important basis for efficacy evaluation and the adjustment of individualized treatment plans[32].

In research on depression in special populations, by monitoring the prefrontal activity of adolescents during social interaction tasks using fNIRS, it was found that the activation of the ventrolateral PFC in patients was significantly reduced when facing peer evaluation, revealing the neural basis behind social anxiety and providing targets for early intervention[33]. fNIRS can monitor brain activity in elderly patients at the bedside. Studies have found that the reduction in blood oxygen levels in their PFC is closely related to cognitive decline, providing evidence for the comorbidity mechanism of geriatric depression with cognitive impairment[34]. For treatment-resistant depression, fNIRS can identify unique brain activity patterns in patients who are unresponsive to conventional treatments, thus providing a basis for personalized treatment.

fNIRS is also often used in combination with other technologies such as scale assessment, electroencephalography, and behavioral tasks. The specific applications of fNIRS in depression research, from the exploration of objective diagnostic markers to the dynamic monitoring of treatment effects and the analysis of neural mechanisms of core symptoms to targeted research on special populations, all reflect its unique value[35]. fNIRS is an ideal tool for depression detection due to its low cost and high portability, its ability to process high-dimensional data in combination with technologies like machine learning, its contribution to objective diagnosis, treatment effect monitoring, and mechanism research of depression, as well as its compatibility with various other technologies.

Resting-state depression detection

The resting state refers to the brain activity state of the subjects without specific tasks. Analysis of blood oxygen signals in regions such as the PFC and default network revealed baseline functional abnormalities in patients with depression. Xu *et al*[37] conducted a study of 34 patients with MDD and 30 healthy controls using fNIRS. During a 10-minute resting-state detection, they found that patients with MDD exhibited stronger brain network integration and lower local efficiency of occipital hub nodes. Zhu *et al*[38] used fNIRS to detect the resting-state activity in the PFC of 28 patients with adjustment disorder (AD) and 30 healthy controls. They found that connectivity within the PFC and between symmetric hemispheres was reduced in AD patients, and that connection strength was negatively correlated with depressive symptoms, indicating that fNIRS can characterize AD neuropathology[38]. Wong *et al*[53] used fNIRS to measure the dorsolateral PFC in 70 subjects and found that patients with depression receiving combined acupuncture and antidepressant therapy exhibited improved depressive symptoms and stronger resting-state functional connectivity in the dorsolateral PFC compared with those treated with antidepressants alone. Lin *et al*[54] recruited 37 patients and 49 healthy controls to investigate the association between the resting-state prefrontal network and cognitive function in patients with depression and insomnia using fNIRS. They found that these patients exhibited impaired prefrontal cortical functional connectivity, which is closely linked to cognitive function[54].

Task-state of depression detection

Compared with resting-state detection, task-state detection induces specific brain region activities through designed standardized tasks and detects neural abnormalities in dimensions such as emotion, cognition, and social function, which is the mainstream form of current research. Gao *et al*[39] studied 27 patients with MDD and 24 healthy controls during facial emotion recognition tasks. They found that the hemodynamic

changes in the left PFC and between bilateral prefrontal cortices detected by fNIRS can provide reliable predictive indicators for the clinical diagnosis of depression[39]. Manelis *et al*[40] observed 33 patients with depression and 20 healthy controls during an emotional intensity rating task. They found that compared with healthy controls, depressed patients demonstrated lower activation in the right PFC when identifying happy facial expressions. Wan *et al*[41] recruited 37 patients with MDD and 34 healthy controls to participate in three groups of emotion recognition cognitive tasks. They found that patients with MDD had lower accuracy in distinguishing sad emotional cues from neutral and happy ones. Lee *et al*[42] compared the functional activity in the prefrontal region measured by fNIRS in 28 patients with seasonal affective disorder and 27 healthy controls during cognitive tasks. The results indicated that the reduction in right frontopolar PFC activity in the healthy control group was greater than that in the seasonal affective disorder group; there were also significant differences in orbitofrontal cortex activity[42].

Lyu *et al*[43] recruited 110 MDD patients and 106 healthy controls to perform verbal fluency tasks. They found that compared to healthy controls, MDD patients had significantly reduced changes in the right inferior frontal gyrus, and the functional language lateralization to the left in the inferior frontal gyrus was significantly increased. Mao *et al*[44] recorded fNIRS data from 289 patients with MDD and 178 healthy controls who performed verbal fluency tasks to assess cognitive deficits and conduct early screening for MDD. Yang *et al*[45] used fNIRS to detect brain functional activity in recurrent MDD and healthy control groups, and found that the average activation in the frontal and temporal lobes of the MDD group was lower. Yang *et al*[46] studied 50 patients with MDD and 20 healthy controls, and collected fNIRS data during four tasks (emotional pictures, verbal fluency, finger movement, and negative emotional picture description). They found that differences in activation patterns and functional connectivity characteristics between patients with MDD and healthy controls were closely related to the selected tasks.

Machine learning based detection methods

The data processing stage involves preprocessing raw fNIRS signals to eliminate noise and artifacts, which includes applying bandpass filtering to eliminate physiological interference, motion correction techniques to address head movement artifacts, and normalization to ensure consistency across subjects. This was followed by segmentation of the time-series data into epochs corresponding to specific experimental conditions or resting-state periods. For feature extraction, both temporal and spatial characteristics of the fNIRS signals were analyzed, where temporal features such as mean, variance, and skewness of HbO and HbR hemoglobin concentrations were computed. Spatial features were derived from connectivity patterns between different brain regions using correlation or coherence measures, and dimensionality reduction techniques such as principal component analysis were applied to identify the most discriminative features for depression classification. The data processing stage involves preprocessing raw fNIRS signals to eliminate noise and artifacts, which includes applying bandpass filtering to eliminate physiological interference, motion correction techniques to address head movement artifacts, and normalization to ensure consistency across subjects. This was followed by segmentation of the time-series data into epochs corresponding to specific experimental conditions or resting-state periods.

For feature extraction, both temporal and spatial characteristics of fNIRS signals were analyzed, and temporal features such as the mean, variance, and skewness of HbO and HbR hemoglobin concentrations were computed. Spatial features were derived from connectivity patterns between different brain regions using correlation or coherence measures. Dimensionality reduction techniques, such as principal component analysis, were applied to identify the most discriminative features for depression classification. In model construction, machine learning algorithms or deep learning models are trained on the extracted features for classification, with performance evaluated through cross-validation and metrics such as accuracy, sensitivity, and specificity[52]. Interpretability techniques, such as SHapley Additive exPlanation values or feature importance analysis, were employed to identify brain regions and functional

connectivity patterns that were most predictive of depression, thereby enhancing the clinical applicability of the approach. All articles are summarized in Table 1[27,47-51,55,56].

Yu *et al*[47] proposed a graph neural network-based method using fNIRS data from 96 subjects. They combined the temporal and spatial features of fNIRS data for automatic depression recognition, achieving good performance in depression identification. Shao *et al*[48] proposed a cross-modal data augmentation-based fNIRS-driven depression recognition architecture that converted fNIRS data into pseudo-sequential activation images using a stimulus task-driven data pseudo-sequential method, achieving a binary classification accuracy of 0.905. Huang *et al*[49] collected fNIRS data from 140 subjects and applied a combined denoising method using complete ensemble empirical mode decomposition and adaptive noise wavelet thresholding. The proposed model effectively distinguished between mild and severe depression with an accuracy of 92.8%. Kim *et al*[50] conducted a study on 30 adolescents with MDD aged 13-19 years to explore the relationship between their fNIRS data during the Stroop test and suicide risk. Wang *et al*[51] conducted research on fNIRS in depression and proposed time and frequency domain feature extraction and deep neural network recognition methods. They found that patients with depression exhibited weaker brain connectivity and lower prefrontal activation levels.

DISCUSSION

The application of fNIRS in depression research provides a novel perspective for addressing core challenges in current depression diagnosis and treatment. Existing studies have shown that by detecting changes in cerebral regional blood oxygen dynamics, fNIRS can capture specific neural activity patterns in patients with depression during the resting and task states, providing potential biomarkers for objective diagnosis, treatment monitoring, and mechanism analysis of depression. Machine learning is revolutionizing depression research with fNIRS. Algorithms ingest multichannel prefrontal hemodynamic responses during verbal fluency or emotional

tasks, learning subtle hypo-or hyper-activation patterns to classify patients *vs* controls with acceptable accuracy. Feature selection and deep networks handle high-dimensional, noisy fNIRS data, identifying biomarkers tied to pathophysiology. Regression models further predict symptom severity and treatment response, supporting personalized care. The low cost and portability of fNIRS enable large, ecologically valid datasets.

The rapid development of machine learning technology has injected strong impetus into fNIRS-based depression recognition. By deeply mining the temporal dynamic laws of cerebral blood oxygen changes and the spatial distribution characteristics of brain region activation contained in fNIRS data, high-precision automatic recognition of depression can be realized to significantly improve diagnostic efficiency and objectivity. The integrated analysis of time-series patterns and spatial topological structures of fNIRS data using machine learning algorithms can accurately locate abnormal brain function regions in patients with depression and effectively distinguish brain function differences between patients and healthy individuals by constructing multidimensional feature classification models, providing data support for the study of the pathological mechanism of depression. This opens new avenues for early screening, accurate diagnosis, and personalized treatment plan formulations for depression.

LIMITATIONS

Despite the promising advances, several limitations must be acknowledged. First, the spatial resolution of fNIRS remains inferior to that of fMRI, restricting its capacity to probe subcortical structures critically involved in depression, such as the amygdala or hippocampus. Second, variability in experimental protocols (*e.g.*, task design, duration, and channel configurations) undermines the comparability and reproducibility of cross-study findings. Third, most existing models are trained on relatively small, homogeneous samples, limiting their generalizability across diverse populations, ethnicities, and clinical subtypes. Additionally, fNIRS signals are susceptible to motion artifacts, physiological noise, and systemic variations, which can confound the

interpretation of hemodynamic responses. The interpretability of machine learning models also remains a challenge; while they achieve high accuracy, the clinical translation of these "black-box" systems requires clearer neurobiological correlates. Finally, longitudinal studies are scarce, and the utility of fNIRS in tracking long-term treatment outcomes or predicting relapse has yet to be fully established. Addressing these limitations through standardized protocols, multimodal validation, and larger multi-center cohorts will be essential for translating fNIRS into a reliable clinical tool.

CONCLUSION

fNIRS has demonstrated significant potential for application in depression research. It can capture the low oxygenation characteristics of the PFC in depressed patients at rest and activation abnormalities in brain regions related to emotional processing and cognitive function during task states, providing quantifiable biomarkers for the objective diagnosis of depression, which helps distinguish patients from healthy individuals and evaluate disease severity and cognitive deficits. Although there are current challenges, such as limited spatial resolution and insufficient standardization of task paradigms, combined with advanced algorithms and large-sample studies, fNIRS is expected to play a crucial clinical role in early screening, mechanism analysis, and precise treatment of depression, promoting the transformation of depression diagnosis from subjective to objective and quantitative assessment.

112056_Auto_Edited.docx

ORIGINALITY REPORT

2%
SIMILARITY INDEX

PRIMARY SOURCES

1	storage.googleapis.com Internet	21 words — 1%
2	Xinyu Lin, Shanling Ji, Zhuoyan Shan, Lifeng Wang, Xinxiu He, Ranran Xue, Xiuzhen Jia, Xia Liu, Hao Yu. "The association between resting-state prefrontal network and cognitive function in depressed patients with insomnia", Neuroscience, 2025 Crossref	18 words — 1%
3	www.turkpsikiyatri.com Internet	16 words — 1%

EXCLUDE QUOTES	ON	EXCLUDE SOURCES	< 15 WORDS
EXCLUDE BIBLIOGRAPHY	ON	EXCLUDE MATCHES	< 15 WORDS