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Progress in the Application of Wearable Devices in the Prevention and Treatment of Depression/Depressive Tendencies

Hou Yongmei
Department of Psychology, School of Humanity and Administration, Guangdong Medical University, Dongguan, Guangdong Province, China

[Abstract]Background: *Depression is a global health crisis and is currently in an increasingly severe state. The accurate assessment of depression has attracted the attention of medical workers, buttraditional screening and monitoring methods have various drawbacks. Wearable health devices are the emerging products of rapid technological development, providing new ideas for accurate screening and continuous monitoring of depression, and providing reliable basis for intervention in depression.* ***Objective:*** *To clarify the application of wearable devices in the prevention and treatment of depression, and provide reference for scientific research and application of wearable devices.* ***Method:*** *Based on domestic and foreign literature, summarize the research progress on the application of wearable devices in depression screening, evaluation, monitoring, and treatment. The research results show that wearable devices play an important role in the recognition, evaluation, dynamic measurement, and continuous recording of depression. However, at present, the research on wearable devices in depression recognition and evaluation is still in the clinical trial stage and has not been promoted in clinical practice.* ***Conclusion:*** *Based on the needs of clinical work, we should develop more cost-effective, sensitive, and accurate wearable depression assessment devices, continuously monitor patients' depression levels dynamically, in order to provide targeted intervention measures and reduce the adverse effects of depression on patients and society.*

[Keywords] *Depression, wearable devices, assessment, screening, monitoring*

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The Depression Major Report of World Psychiatric Association released by Lancet in 2022 stated that depression is a global health crisis and is currently in an increasingly severe state. Due to the impact of the COVID-19 pandemic, the prevalence rate worldwide has increased by 25% [1]. After 2020, about 5% of adults in the world will suffer from the disease every year, especially young people aged 20-24 years old [2]. The lifetime prevalence of depression among Chinese adults is 3.4% [3].

Depression/depressive tendencies seriously affect individuals' physical and mental health, career development, and quality of life. People are often unwilling to actively seek help due to insufficient awareness of emotional management or personal factors, which has brought significant obstacles to medical management work. The increasingly serious depression have attracted widespread public attention. At present, the scale method is mainly used for depression screening, but this method has disadvantages such as passivity, lag, and poor feedback. How to timely detect individuals' emotional changes, clarify their causes, and intervene as soon as possible to prevent the deterioration of emotional problems is an urgent task that current public health management departments need to solve.

Currently, measures to address mental health issues caused by emotional changes are gradually shifting from post treatment to prevention and screening, such as screening psychological problems through scales, early intervention, and intervention. Zhou Jingjing conducted depression screening on college students through the development of questionnaires and scales, and achieved certain results [4]. However, there are the following shortcomings with screening through scales: first, the measurement of emotions during the diagnostic process mainly relies on the observation of the examiner and the retrospective self-assessment of the subjects, which leads to significant subjectivity and recall bias; second, examinees are required to actively cooperate with the examiner's diagnosis, which requires good cooperation from examinees; final, this approach requires a large number of professionals, but the medical department generally lacks sufficient relevant personnel. So the time interval between two screenings is usually long, and the screening results can only reflect the emotional state of the examineesat a certain point of time, cannot be regularly tracked or monitored at any time, easy to miss serious emotional fluctuations. It is unable to provide more information to help analyze the causes of emotional changes, and also unable to provide more assistance for later treatment and social mental health management. It can be seen that the scale method has drawbacks such as poor data quality, low accuracy, and long delay, which limits its assistance in prevention and treatment work. Therefore, there is an urgent need for a method with high accuracy that can sense people's true emotional changes in work, life, and other aspects at any time, in order to detect depression/depressive tendency in a timely manner and intervene in advance.

With the development of Cranial nerves, people try to use the head-worn monitoring system to detect EEG signals, so as to sense the mood and stress of the subjects. For example, Patil et al. [5] used the high-order cross of the collected EEG signals as a feature for emotional analysis, which is better than the previous use of statistical features to classify emotions; Aliyu et al. [6] used automatic stack encoder (SAE) and long short term memory/Recurrent neural network (LSTM/RNN) classification methods to classify Electroencephalography (EEG) features of emotions, which reduced the complexity of the model and significantly improves the performance of the classifier. Although the application of EEG in the field of emotion detection has made great progress, and its accuracy is significantly better than the scale evaluation, it is often used to provide important supplementary data for clinical treatment due to the high cost of use and the large volume of the precision instrument, which is inconvenient to carry and requires the participants to participate in specific time and place.

With the rapid development of mobile computing, researchers have begun to attempt to use wearable sensors combined with mobile phones to collect digital biological signals and environmental information of subjects, explore the correlation between perceptual data and daily emotions, and automatically detect emotional states and transitions in daily activities. Ma et al. [7] proposed a daily emotion assessment tool that utilized mobile sensor data such as location, audio, text messages, accelerometers, and light to classify emotions. Sano et al. [8] used Fitbit exercise bracelets to collect behavioral data and monitor the mental health status of college students, and found that dietary habits had a significant impact on stress, sleep, and exercise among college students. Asare [9] used mobile phones and wearable sensors to collect environmental information for depression detection. Helbich [10] found that people's mental health is related to the community they live in, the place they engage in activities, and the environment they experience by collecting geographic and environmental data from the experimenters. The above research converts the data collected by mobile phones into structured spreadsheet data, and then uses traditional Tree Model such as XGBOOST, Random Forest, etc. to process the data, which has achieved good results. However, due to the characteristics of multi-dimensional, large, and sparse data collected by mobile phones, how to obtain implicit high-order feature combinations through feature processing to reveal the interrelationships between features and effectively fuse them is the key to improving prediction accuracy.

Wearable devicesrefer to portable devices that directly attach sensing devices to the body or integrate them into wearable items such as clothing. It combines wearable technology with sensors, integrates Internet, Internet of Things, artificial intelligence, micro sensor and other technologies, changes the traditional mode of sample collection and detection, directly realizes the integration of sample collection and detection, and real-time understanding of physiological functions. It mainly includes smart bracelets, smart watches, smartglasses, smart clothes and other types, with the highest popularity of smart bracelets [11]. Currently, wearable devices have functions such as fitness step counting, sleep indicator monitoring, vibration awakening, sweat secretion, body temperature monitoring, heart rate measurement, and call reminder. Since users usually wear them 24 hours a day, wearable devices can obtain a large amount of users' health data and behavior habits information in real time, store and analyze them through the data platform, and provide necessary information support for users' health monitoring [12, 13]. There are two types of wearable devices used for medical treatment. One is health wearable devices, which can help users track and detect their daily health conditions, such as Fitbit, Xiaomi Mi Band, and the other is designed for certain diseases, such as cancer, diabetes, but due to related medical technology problems, such wearable devices have not been widely promoted [14].

The prototype of wearable devices appeared in the 1960s and 1970s, but due to hardware limitations such as networks and mobile terminals at that time, they did not achieve rapid development. In the past 20 years, with the innovation of hardware [15], software improvement [16], and improvement of network environment [15], wearable devices have undergone rapid changes and are increasingly entering people's lives, and their importance is also increasing day by day.

Mentalhealth problems are usually manifested through physiological reactions, such as sleep, heart rate and eye movements. Therefore, monitoring effectiveness can be achieved by evaluating these indices through intelligent wearable devices. Deng et al. [17] quickly and accurately diagnosed high-risk emotional disorders by comparing the EEG data of individuals with high and low emotional disorders watching different videos. Zhang et al. [18] used support vector machine algorithm to construct a predictive model for identifying anxiety patients by combining EEG data and eye movement data, achieving an accuracy of 82.70%. In addition, emotional stress states can also be detected through indicators such as heart rate and heart rate variability, and relief can be achieved through intervention in heart rate and heart rate variability [19-20]. Drawing on the above research progress, the application of wearable devices in the screening, monitoring, and prevention of depression is also increasing, and its role has been confirmed by a large number of literature[21]. Currently, its main applications are reflected in the following aspects.

1. Depression monitoring for different populations

1.1Monitoring depression in single household elderly

Apilot study [22] aims to predict the depressed mood of single household elderly from unobtrusive monitoring of their daily life. A wearable band with multiple sensors has been selected for monitoring elderly people. Depression questionnaire has been surveyed periodically to be used as the labels. Instead of working with depression patients, the researchers recruited 14 single household elderly people from a nearby community. The wearable band provided daily activity and biometric data for 71 days. From the data, a depressed mood prediction model was generated, and multiple features from the collected sensor data were exploited for model generation. One general model is generated to be used as the baseline for the initial model deployment. Personal models are also generated for model refinement. The general model has a high recall of 80% in an MLP model. Individual models achieved an average recall of 82.7%.

1.2 Monitoring of depressionrisk of working population

Rykov et al [23] conducted a cross-sectional study of 290 healthy working adults to examine the predictive ability of digital biomarkers and detect risk of depression in a working population, based on sensor data from consumer-grade wearables. Participants wore Fitbit Charge 2 devices for 14 consecutive days and completed a health survey, including screening for depressive symptoms using the 9-item Patient Health Questionnaire (PHQ-9), at baseline and 2 weeks later. A range of known and novel digital biomarkers were extracted to characterize physical activity, sleep patterns, and circadian rhythms from wearables using steps, heart rate, energy expenditure, and sleep data. Associations between severity of depressive symptoms and digital biomarkers were examined with Spearman correlation and multiple regression analyses adjusted for potential confounders, including sociodemographic characteristics, alcohol consumption, smoking, self-rated health, subjective sleep characteristics, and loneliness. Supervised machine learning with statistically selected digital biomarkers was used to predict risk of depression (ie, symptom severity and screening status). Varying cutoff scores from an acceptable PHQ-9 score range were used to define the depression group and different subsamples for classification, while the set of statistically selected digital biomarkers remained the same. For the performance evaluation, researchers used k-fold cross-validation and obtained accuracy measures from the holdout folds. A total of 267 participants were included in the analysis. The mean age of the participants was 33 (SD 8.6, range 21-64) years. Out of 267 participants, there was a mild female bias displayed (n=170, 63.7%). The majority of the participants were Chinese (n=211, 79.0%), single (n=163, 61.0%), and had a university degree (n=238, 89.1%). This study found that a greater severity of depressive symptoms was robustly associated with greater variation of nighttime heart rate between 2 AM and 4 AM and between 4 AM and 6 AM; it was also associated with lower regularity of weekday circadian rhythms based on steps and estimated with nonparametric measures of interdaily stability and autocorrelation as well as fewer steps-based daily peaks. Despite several reliable associations, rich evidence showed limited ability of digital biomarkers to detect depression in the whole sample of working adults. However, in balanced and contrasted subsamples comprised of depressed and healthy participants with no risk of depression (ie, no or minimal depressive symptoms), the model achieved an accuracy of 80%, a sensitivity of 82%, and a specificity of 78% in detecting subjects at high risk of depression.

1.3Monitoring depression in college students

Sleep disturbances are associated with both the onset and progression of depressive disorders. It is important to capture day-to-day variability in sleep patterns. Lim et al [24] used sleep efficiency, measured with wearable devices, as an objective indicator of daily sleep variability to detect the depression level. The total sample consists of 100 undergraduate and graduate students, 60% of whom were female. All were divided into three groups (with major depressive disorder, mild depressive symptoms, and controls). Self-report questionnaires were completed at the beginning of the experiment, and sleep efficiency data were collected daily for 2 weeks using wearable devices. The results showed that more marked daily variability in sleep efficiency significantly predicted levels of depression and anxiety, as did the average person-level covariates (longer time in bed, poorer quality of life, lower extraversion, and higher neuroticism).

1.4Monitoring of depression and suicidal ideation among medical interns

In this study [25], medical interns (N = 2881; 57 % female; 58 % White) were recruited from over 300 US residency programs. Interns completed a pre-internship assessment of depression, were given Fitbit wearable devices, and provided daily mood ratings (scale: 1-10) via mobile application during the study period. Three-step hierarchical logistic regressions were used to predict depression and SI at the end of the first quarter utilizing pre-internship predictors in step 1, Fitbit sleep/step features in step 2, and daily diary mood features in step 3. The results showed that passively collected Fitbit features related to sleep and steps had negligible predictive validity for depression, and no incremental predictive validity for SI; however, mean-level and variability in mood scores derived from daily diaries were significant independent predictors of depression and SI, and significantly improved model accuracy. The limitations of this study are as following: work schedules for interns may result in sleep and activity patterns that differ from typical associations with depression or SI,and the SI measure did not capture intention or severity.

2.Monitoring of various clinical depression states

2.1Monitoring of severe depression

Sato et al. [26] developed a novel MDD screening system based on sleep-induced autonomic nervous responses. The proposed method only requires a wristwatch device to be worn for 24 h. heart rate variability (HRV) was evaluated via wrist photoplethysmography (PPG). However, previous studies have indicated that HRV measurements obtained using wearable devices are susceptible to motion artifacts. Sato et alpropose a novel method to improve screening accuracy by removing unreliable HRV data (identified on the basis of signal quality indices (SQIs) obtained by PPG sensors). The proposed algorithm enables real-time calculation of signal quality indices in the frequency domain (SQI-FD). A clinical study conducted at Maynds Tower Mental Clinic enrolled 40 MDD patients (mean age, 37.5 ± 8.8 years) diagnosed on the basis of the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition, and 29 healthy volunteers (mean age, 31.9 ± 13.0 years). Acceleration data were used to identify sleep states, and a linear classification model was trained and tested using HRV and pulse rate data. Ten-fold cross-validation showed a sensitivity of 87.3% (80.3% without SQI-FD data) and specificity of 84.0% (73.3% without SQI-FD data). Thus, SQI-FD drastically improved sensitivity and specificity.

By using a wearable sensor that monitors 3-dimensional acceleration and HRV simultaneously, Woo et al [27] examined the activity and HRV indices in depressive episode of mood disorders. Participants were 19 patients (13 major depressive disorder [MDD] and 6 bipolar depression; 11 females) and 18 controls (9 females) matched for age and ethnicity (all Japanese) who completed 3 consecutive days of all-day monitoring by a small and light device attached to the chest. Activity magnitude was significantly reduced, while lying/resting time was increased in depressed patients, compared with controls; when males and females were examined separately, male, but not female, patients showed significant reduction in activity; HRV indices such as R-R interval and high-frequency power (a parameter for the parasympathetic system) were significantly decreased in patients than in controls; significant differences in activity and HRV indices were seen only in males; sympathetic load during sleep significantly correlated with damped rest-activity rhythm in depressed patients. The limitations of this study are as following: the number of participants was small, and the majority of the participants were taking psychotropic medications.

2.2Monitoring of refractory depression

Qualitative methods were used to conduct interviews with 19 patients (4 male; 15 female) diagnosed with treatment-resistant depression undergoing transcranial magnetic stimulation (TMS) treatment for depression. The results of reflexive thematic analysis showthathealthy sleep and physical activity levels are interlinked and reduce depressive symptoms as well as improving well-being and physical health, and a Fitbit is useful to enhance physical activity, self-awareness, motivation, healthier lifestyles and effective sleep [28].

2.3Examining stress as a predictor of remitted depression

Residual symptoms and stress are the most reliable predictors of relapse in remitted depression. Prevailing methodologies often do not enable continuous real-time sampling of stress. Thus, little is known about day-to-day interactions between residual symptoms and stress in remitted depression. In preparation for a full-scale trial, Whiston et al [29] conducted an experiment aimed to pilot a wrist-worn wearable electrodermal activity monitor: ADI (Analog Devices, Inc.) Study Watch for assessing interactions between physiological stress and residual depressive symptoms following depression remission. Thirteen individuals remitted from major depression completed baseline, daily diary, and post-daily diary assessments. Self-reported stress and residual symptoms were measured at baseline and post-daily diary. Diary assessments required participants to wear ADI's Study Watch during waking hours and complete self-report questionnaires every evening over one week. Sleep problems, fatigue, energy loss, and agitation were the most frequently reported residual symptoms. Average skin conductance responses (SCRs) were 16.09 per-hour, with an average of 11.30 hours of wear time per-day. Increased residual symptoms were associated with enhanced self-reported stress on the same day. Increased SCRs on one day predicted increased residual symptoms on the next day.

3.Exploration of influencing factors on the efficacy of severe depression

In this study [30], 40 participants with MDD provided actigraphy data using wearable devices for one week after initiating antidepressant treatment in a randomized, double-blind, placebo-controlled trial. Their depression severity was calculated pretreatment, after one week and eight weeks of treatment. This study assesses the relationship between parametric and nonparametric measures of circadian rhythm and change in depression. Results showed significant association between a lower circadian quotient (reflecting less robust rhythmicity) and improvement in depression from baseline following first week of treatment (estimate = 0.11, $F = 7.01$, $P = 0.01$). There is insufficient evidence of an association between circadian rhythm measures acquired during the first week of treatment and outcomes after eight weeks of treatment. Despite this lack of association with future treatment outcome, this scalable, cost-effective biomarker may be useful for timely mental health care through remote monitoring of real-time changes in current depression.

4. The application of wearable devices in the treatment of depression

There is not much relevant research and a lack of detailed reports. Swedish medical device company Flow Neuroscience has developed a head-worn wearable product for adult depression patients. The main function of this product is to stimulate the left frontal lobe of the brain, which mainly controls emotional cognition, through continuous low level signals. When used in conjunction with the application software, it can reduce drug side effects; Neurolifef, an Israeli digital healthcare company, is committed to developing a head-worn device that can treat migraines, depression, insomnia, etc. It utilizes stimulation of brain nerves to regulate brain substance secretion, thereby alleviating patient symptoms [31]. A company in San Francisco, USA has designed an intelligent health bra patch that can regulate users' emotions. They need simply to place the bra patch near the heart to check heart rate variability at any time.The bra patchwill use tactile vibrations to send feedback information to users when heart rate variability is abnormal, reminding them to adjust their emotions through breathing. According to official data, this product can effectively improve heart rate variability by about 140%, anduserscan view these data on the supporting APP to understand their own information. Antonio et al. [32] developed a wearable monitoring system, which combined the embedded breathing piezoresistive sensor with ordinary T-shirt to collect and identify the ECG, heart rate variability, respiratory activity and other data of patients with mental disorders. Through the use evaluation of 10 patients with bidirectional affective disorder, it proved that the data and information visualization function can help doctors make clinical decisions.

5.Comparative study on the monitoring effect of wearable devices and other approaches

5.1Comparison of different analysis approaches (multimodal analysis and unimodal analysis)

Ahmed et al [33] presents a machine learning (ML) approach that utilizes retrospectively collected data-derived consumer-grade wearables for passive detection of depression severity. The experiments conducted in this work reveal that multimodal analysis of physiological signals in terms of their discrete wavelet transform (DWT) features exhibit considerably better performance than unimodal scenarios.

5.2 Comparison with self-reported results

In a longitudinal study [34], the participants provided daily mood (valence and arousal) scores and collected data using their smartphones and Oura Rings. The researchers computed daily aggregations of mood, sleep, physical activity, phone usage, and GPS mobility from raw data to study the differences between the depressed and non-depressed groups and create population-level Machine Learning classification models of depression. They found statistically significant differences in GPS mobility, phone usage, sleep, physical activity and mood between depressed and non-depressed groups. An XGBoost model with daily aggregations of mood and sensor data as predictors classified participants with an accuracy of 81.43% and an area under the curve of 82.31%. A support vector machine using only sensor-based predictors had an accuracy of 77.06% and an area under the curve of 74.25%.

5.3Comparison of wearable devices and questionnaire screening results

A study [35] included 55 adolescents with symptoms of depression aged 12 to 17 years. Each participant was passively monitored through smartphone sensors and Fitbit wearable devices for 24 weeks. Passive sensors collected call, conversation, location, and heart rate information daily. Following data preprocessing, 67% (37/55) of the participants in the aggregated data set were analyzed. Weekly Patient Health Questionnaire-9 surveys answered by participants served as the ground truth. Regression-based approaches were applied to predict the Patient Health Questionnaire-9 depression score and change in depression severity. These approaches were consolidated using universal and personalized modeling strategies. The universal strategies consisted of Leave One Participant Out and Leave Week X Out. The personalized strategy models were based on Accumulated Weeks and Leave One Week One User Instance Out. Linear and nonlinear machine learning algorithms were trained to model the data. The results showed that personalized approaches performed better on adolescent depression prediction compared with universal approaches, the best models were able to predict depression score and weekly change in depression level with root mean squared errors of 2.83 and 3.21 respectively, following the accumulated weeks personalized modeling strategy. The feature importance investigation showed that the contribution of screen-, call-, and location-based features influenced optimal models and were predictive of adolescent depression.

5.4Comparison of automatic recording from wearable devices and objective physical activity data

Yokoyama et al [36] analyzed time-series patterns of physical activity intensity measured by a wearable device and investigated the relationship between its model parameters and depression-related behaviors. Sixty-six individuals used the wearable device for one week and then answered a questionnaire on depression-related behaviors. A seasonal autoregressive integral moving average (SARIMA) model was fitted to the individual-level device data and the best individual model parameters were estimated via a grid search. Out of 64 hyper-parameter combinations, 21 models were selected as optimal, and the models with a larger number of affiliations were found to have no seasonal autoregressive parameter. Conversely, about half of the optimal models indicated that physical activity on any given day fluctuated due to the previous day's activity. In addition, both irregular rhythms in day-to-day activity and low-level of diurnal variability could lead to avoidant behavior patterns.

6.The use of wearable devices in patients with depression

AbdAlrazaq et al [21] searched 8 electronic databases (MEDLINE, PsycINFO, Embase, CINAHL, IEEE Xplore, ACM Digital Library, Scopus, and Google Scholar), and found that of 69 studies included in the review, two-thirds used wearable AI for depression, whereas the remaining studies used it for anxiety. The most frequent application of wearable AI was in diagnosing anxiety and depression; however, none of the studies used it for treatment purposes. Most studies targeted individuals aged between 18 and 65 years. The most common wearable device used in the studies was Actiwatch AW4 (Cambridge Neurotechnology Ltd). Wrist-worn devices were the most common type of wearable device in the studies. The most commonly used category of data for model development was physical activity data, followed by sleep data and heart rate data.

Onyeaka et al [37] found that about 1 in 3 adults with depression use WD, and several sociodemographic and technology factors are significant predictors of WD adoption and willingness to share WD data with clinicians, include age, gender, education status, and previous experience with technology.

Lee et al [38]thinks that it is necessary to overcome several issues, including limited types of collected data, reliability, user adherence, and privacy concerns.

7.Prospect

To sum up, depression detection through wearable data is more intelligent,convenient, effective and economical. In this study, a literature survey was conducted of research into the development and use of wearable devices in patients with depression. We collected 32 studies that had investigated wearable devices for assessment, monitoring, or prediction of depression. In this report, we examine the sensors of the various types of wearable devices (e.g., actigraphy units, wristbands, fitness trackers, and smartwatches) and parameters measured through sensors in people with depression among various population and at variousstages. In addition, we comparedthe monitoring effectiveness between wearable devices and other tools, and suggest the challenges of using wearable devices in the field of depression. Real-time objective monitoring of symptoms and novel approaches for diagnosis and treatment using wearable devices will lead to changes in management of patients with depression. During the process, it is necessary to overcome several issues, including limited types of collected data, reliability, high cost, incomplete interactive functions, low acceptance of styling, varying levels of social acceptance, user adherence, and privacy concerns [39-41].

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