Neurophysiological Mechanisms and Interventions for Subthreshold Depression Integrating Machine Learning Techniques

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Abstract

Depression is a significant factor hindering national mental health. Subthreshold depression (StD) represents a critical prodromal stage of clinical depression; investigating its neurophysiological mechanisms and dynamic developmental patterns is essential for predicting the onset of depression and implementing preventive interventions. To overcome the limitations of previous studies that treated depression as a static, binary diagnostic outcome, this paper adopts the framework of complex dynamical systems theory. Utilizing multi-timescale and multimodal machine learning methods, we explore the close associations and key predictive factors between subthreshold depressive symptoms and neurophysiological characteristics. Furthermore, through longitudinal tracking and neurodynamic network modeling, we examine attractor states and their capacity to predict subsequent depressive onset and phenotypic transformation. Finally, we investigate the preventive intervention effects of Cognitive Behavioral Therapy (CBT) on subthreshold depression and the predictive role of attractor states. The findings serve to elucidate the neurobiological uniqueness of subthreshold depression and provide new perspectives for the development of methods for early identification and precision prevention of depression.

Full Text

Preamble

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1. Introduction

Subthreshold Depression (StD) refers to a clinically significant depressive state that does not meet the full diagnostic criteria for Major Depressive Disorder (MDD). Despite its "subthreshold" status, individuals with StD experience substantial functional impairment, reduced quality of life, and a significantly higher risk of progressing to clinical depression. In recent years, the integration of machine learning (ML) technologies with neurophysiological research has provided new avenues for understanding the complex mechanisms underlying StD and developing personalized intervention strategies.

2. Neurophysiological Mechanisms of Subthreshold Depression

Research into the neurophysiological basis of StD has revealed complex alterations in brain structure and function. Unlike the clear-cut pathologies often seen in MDD, StD is characterized by more subtle, yet pervasive, changes in neural circuitry.

2.1 Functional Connectivity and Neural Networks Studies utilizing functional Magnetic Resonance Imaging (fMRI) have identified significant disruptions in the Default Mode Network (DMN), the Central Executive Network (CEN), and the Salience Network (SN). In individuals with StD, there is often an observed hyper-connectivity within the DMN, which is associated with increased rumination and self-referential processing. Conversely, hypo-connectivity between the CEN and other regulatory regions may explain the cognitive control deficits frequently reported by these individuals.

2.2 Electrophysiological Markers Electroencephalography (EEG) studies have highlighted specific biomarkers associated with StD. For instance, frontal alpha asymmetry—a disparity in alpha wave activity between the left and right hemispheres—has been identified as a potential predictor of emotional dysregulation. Furthermore, event-related potentials (ERPs), such as the P300 and N200 components, show reduced amplitudes during cognitive tasks, suggesting impaired attentional resource allocation and inhibitory control in StD populations.

Figure 1

Figure 1: Figure 1

3. Application of Machine Learning in StD Research

Machine learning offers powerful tools for handling the high-dimensional and heterogeneous data characteristic of neurophysiological studies. By employing advanced algorithms, researchers can move beyond group-level averages to individual-level predictions.

3.1 Feature Extraction and Classification ML techniques, such as Support Vector Machines (SVM), Random Forests, and Deep Learning (DL) architectures, are used to identify the most discriminative neurophysiological features of StD. For example, given a set of features

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摘要

Depression is a significant factor hindering national mental health. Subthreshold depression (SD) represents a critical prodromal stage of clinical depression; investigating its neurophysiological mechanisms and dynamic developmental patterns is essential for predicting the onset of depressive episodes and implementing preventive interventions.

To overcome the limitations of previous research that treated depression as a static, binary diagnostic outcome, this study adopts the framework of complex dynamical systems theory. Utilizing multi-timescale and multi-modal machine learning methods, we first examine the close associations and key predictive factors between subthreshold depressive symptoms and neurophysiological characteristics.

Secondly, through longitudinal tracking and neurodynamic network modeling, we explore attractor states and their capacity to predict subsequent depressive onset and phenotypic transitions. Finally, we investigate the preventive efficacy of Cognitive Behavioral Therapy (CBT) for subthreshold depression and the predictive role of attractor states in treatment response.

The findings of this research serve to elucidate the neurobiological uniqueness of subthreshold depression and provide new perspectives for the development of methodologies for early identification and precision prevention of clinical depression.

关键词

Subthreshold Depression, Attractor States, and Cognitive Behavioral Therapy: Preventive Interventions and Multimodal Machine Learning

Abstract

Subthreshold depression (StD) represents a critical clinical state characterized by depressive symptoms that do not yet meet the full diagnostic criteria for Major Depressive Disorder (MDD). Despite the absence of a formal diagnosis, individuals with StD experience significant functional impairment and face a high risk of progressing to clinical depression. This paper explores the application of multimodal machine learning and dynamical systems theory—specifically the concept of attractor states—to understand the transition dynamics of StD. We further examine the efficacy of Cognitive Behavioral Therapy (CBT) as a preventive intervention designed to shift neural and psychological states away from maladaptive attractors. By integrating heterogeneous data sources, including neuroimaging, physiological signals, and behavioral patterns, we propose a framework for personalized preventive psychiatry.

1. Introduction

Subthreshold depression is increasingly recognized as a major public health concern. While subclinical in nature, its persistence often leads to a "kindling effect," where the brain becomes increasingly sensitized to stress, eventually stabilizing in a pathological state. From the perspective of computational psychiatry, these stable states can be modeled as "attractors" within a high-dimensional landscape of neural and mental activity.

The challenge in treating StD lies in its heterogeneity. Traditional diagnostic tools often fail to capture the subtle physiological and behavioral shifts that precede a major depressive episode. However, recent advances in multimodal machine learning offer a pathway to identify these early warning signals by synthesizing complex datasets. Furthermore, preventive interventions such as Cognitive Behavioral Therapy (CBT) have shown promise in modifying the underlying "basin of attraction," thereby preventing the transition from subclinical symptoms to clinical disorders.

2. Attractor States in Subthreshold Depression

In the context of dynamical systems, an attractor is a set of states toward which a system tends to evolve. In mental health, a healthy state can be viewed as a flexible attractor that allows for resilience and emotional regulation. Conversely, depression can be modeled as a deep, rigid attractor state characterized by persistent negative affect and cognitive biases.

Subthreshold depression represents a precarious equilibrium. While the individual has not yet "fallen" into the deep attractor of MDD, their state space may already be shifting. As the basin of attraction for healthy states narrows, even minor stressors can trigger a transition into a pathological state. Understanding the topology of these states is crucial for determining when and how to intervene.

3. Multimodal Machine

1 研究意义

Major Depressive Disorder (MDD) is a high-incidence mental illness with a lifetime prevalence of approximately 15%, affecting hundreds of millions of people worldwide. It is associated with increased suicide risk and mortality, serving as one of the primary causes of the global public health burden [?, ?]. MDD is characterized by persistent low mood and the loss of interest or pleasure, accompanied by adverse outcomes, role dysfunction, high recurrence rates, and social-psychological difficulties [?, ?]. Previous research has sought to clarify risk factors for the onset of depression; however, these findings have largely been limited to identifying predictors through clinical and demographic data. Such static predictors fail to capture the highly dynamic nature of psychopathology over time [?, ?]. Departing from the traditional concept of depression as a fixed set of underlying symptoms, an increasing number of researchers view it as a complex network of features that unfolds and evolves dynamically over time, manifesting phenomenologically as a longitudinal continuum [?, ?, ?]. Accordingly, research methodologies in psychopathology have conceptualized mental disorders as complex dynamic systems of interacting symptoms. This perspective suggests that individuals typically progress from complete health to MDD through a subthreshold state or a clinical high-risk phase, known as Subthreshold Depression (StD) [?, ?, ?]. StD is defined as the simultaneous presence of two or more depressive symptoms for most or all of the time for at least two weeks, resulting in social dysfunction, in individuals who do not meet the diagnostic criteria for mild depression, major depression, or dysthymia [?, ?]. Analyses of community samples, high-risk individuals, and medical patients by [?, ?] found that individuals with StD consistently face a higher risk of developing MDD. Longitudinal studies indicate that MDD can be traced back to a subthreshold state. For instance, [?, ?] reviewed previous research and found that 18.9% of adults with StD convert to MDD during follow-up periods, noting that stricter definitions of StD and longer follow-up durations lead to higher conversion rates. Consequently, StD serves as a significant high-risk factor for MDD [?, ?, ?].

According to the *Diagnostic and Statistical Manual of Mental Disorders* (DSM-5) developed by the American Psychiatric Association, StD and MDD are not discrete categories but rather different stages along a continuum of symptom severity. Furthermore, individuals with StD are similar to those with MDD across many important dimensions, including clinical presentation, social functioning, psychiatric and physical comorbidities, and sleep electroencephalogram (EEG) patterns [?, ?]. Researchers argue that effectively distinguishing between different stages of depression is a critical issue for predicting the dynamic progression of the disease [?, ?, ?]. However, the unique neurophysiological characteristics that distinguish different stages (StD vs. MDD) have not been systematically analyzed. Moreover, machine learning methods based on multimodal neurophysiological data have yet to be effectively evaluated within StD populations. Constructing multimodal neurophysiological feature indices combined with machine learning to predict transitions from the current stage (e.g., StD) to other stages—identifying who will subsequently develop the disorder, who will not, and who might recover spontaneously—represents a research direction well worth exploring.

According to complex dynamic systems theory, the "attractor" is a crucial concept used to measure a system's ability to return to its original state after being subjected to external perturbations [?, ?, ?, ?]. Attractor states exist on a continuum from stable to unstable. A stable state is relatively robust and persistent, whereas an unstable state suggests the system may transition into another state; the strength of the attractor describes the probability of the system returning to its original equilibrium. In psychopathology, attractor states persist across an individual's varying symptom presentations, including healthy, StD, and MDD phases [?, ?]. For example, in healthy individuals, external stress may cause a temporary dip in mood, but the system eventually returns to a state of mental health, indicating a stable attractor. Conversely, during the StD phase—the ultra-high-risk stage for MDD—individuals are more prone to a sudden transition into a depressive state, reflecting an unstable attractor.

During the transition toward major depression, an individual's internal global system may undergo sudden, discontinuous shifts (mutations between attractor states). Between these states lies the clinical high-risk stage of subthreshold depression, where the attractor is in an unstable phase [?, ?, ?, ?]. Although the severity of symptoms in the subthreshold state does not yet meet the clinical diagnostic criteria for MDD, it serves as a high-risk phase for onset and a critical transition period for longitudinal change. Exploring the attractor states of this important StD phase to predict future depressive symptoms and state transitions can help reveal the relationship between internal systemic homeostasis and longitudinal disease patterns. Ultimately, this approach may

facilitate the prediction of depressive onset and personalized precision prevention [?, ?, ?]. From the perspective of precision medicine, the importance of StD lies not only in its status as a disabling condition requiring treatment but also in its role as a high-risk precursor to MDD—a risk that may be mitigated through preventive intervention.

A recent meta-analysis indicates that current interventions for individuals with StD generally offer significant benefits. In particular, Cognitive Behavioral

Therapy (CBT) may be one of the most effective interventions for StD [?, ?]. Active intervention with CBT can help modify an individual' s core beliefs and information-processing biases while reducing emotional dysregulation [?, ?]. However, it remains unclear whether the efficacy of preventive interventions for StD can be predicted in advance by attractor states. Therefore, from the perspective of complex dynamic systems theory, this study explores the preventive intervention effects of CBT on StD and the predictive role of internal system attractor states as reflected by corresponding neurophysiological mechanisms.

2.1 抑郁的复杂动力系统理论

The pathological process of depression is inherently highly dynamic and variable. Over time, symptoms and risks undergo significant changes at both the micro-level (hourly and daily) and the macro-level (monthly and yearly), manifesting as fluctuations in depressive symptoms and the consolidation or resolution of different clinical stages. Traditional static and univariate predictive models lack the capacity to adequately predict the complex, dynamic patterns of symptom change exhibited by individuals. Consequently, it is crucial to understand these dynamic transitions and their underlying neurophysiological mechanisms from a multi-temporal perspective based on complex dynamical systems theory [?, ?, ?, ?]. The complex dynamical systems framework is regarded as a means of integrating broad patterns into coherent models, and it is used to verify whether the dynamic changes of certain characteristics can predict the developmental stages of psychopathology [?, ?, ?, ?, ?].

According to complex dynamical systems theory, a system can transition dynamically between different stable states. When a system is in a stable state—including both healthy and depressed states—its internal elements are closely interconnected, utilizing reinforcement and inhibition feedback loops to maintain dynamic equilibrium. However, when a system reaches a point where a minor perturbation can trigger a massive shift, it enters an opposite and persistent state; for example, external stress may cause an individual to transition from a healthy state to a state of depression. Before a critical transition in the system' s stable state occurs, it may be accompanied by a weakening of attractor strength (i.e., an unstable state). This manifests as specific variables becoming early warning signals at the level of temporal dynamics. Corresponding indicators can reflect a gradual slowing in the system' s recovery speed from minor disturbances, a phenomenon known as critical slowing down [?, ?, ?, ?], which facilitates the personalized prediction of depressive transitions [?, ?, ?, ?, ?]. Common indicators of early warning signals for the onset of depression include an increase in autocorrelation and variance among internal system elements, as well as increased emotional correlation [?, ?, ?]. [?] monitored the mental states of individuals at high risk for psychopathology (such as mood disorders) continuously for six months to measure critical slowing down; the results indicated that critical slowing down could predict whether an individual' s upcoming symptom transition would trend toward remission or exacerbation. [?] explored instanta-

Figure 1

Figure 2: Figure 1

neous emotional states and depression severity in individuals during a high-risk phase of state transition while reducing antidepressant dosages. They found that a sharp increase in the autocorrelation of the mental state "low mood" predicted an exacerbation of depressive symptoms in the following month. For individuals undergoing treatment for depression, research has found that some participants exhibit a significant increase in emotional autocorrelation levels before symptoms improve, suggesting that the remission process of depressive symptoms induced by psychotherapy also follows complex dynamical systems theory. Thus, we can hypothesize that, compared to healthy individuals, the internal systems of subthreshold depressed individuals in a high-risk state may be in an unstable condition. Specifically, during intensive repeated measurements of their neurophysiological characteristics, an increase in early warning signals from a complex dynamical systems perspective may be detected, clinically manifesting as an increase in depressive symptoms and a higher rate of conversion to clinical depression.

Evidently, the clinical application of early warning signals from complex dynamical systems can provide an important predictive pathway for the dynamic process of subthreshold depression transitioning into clinical depression. Furthermore, it offers theoretical support for preventive interventions and identifies targeted intervention points for critical transitions in subthreshold depressive symptoms.

presents a schematic diagram of the dynamic course of depression [?, ?]. This figure illustrates that individuals transitioning from a completely healthy state typically pass through a subthreshold depression stage. [FIGURE:2] provides a visualization of the stability of the internal system [?, ?, ?, ?]. In this model, the ball represents the current state, the basin in which it resides represents the current attractor, and other basins represent alternative attractors.

2.2 抑郁状态与多模态机器学习

In the conceptualization of depression as a complex dynamical system, an individual is viewed as a multidimensional complex system composed of interacting components—such as behavior, emotion, and cognition—which characterize the system through their joint dynamical patterns over time [?, ?, ?, ?]. With the advancement of dynamical systems concepts and research techniques, researchers have begun to consider the complexity and dynamics of the pathophysiology of depression. By employing multimodal rather than unimodal machine learning techniques, they can measure the autonomic nervous system, brain function, and external manifestations of depressed individuals. This approach allows for the integrated prediction of depressive states and developmental trajectories, facilitating the discovery of neurophysiological markers that accurately predict the condition.

The use of actigraphs and mobile applications to perform multimodal measurements—including voice, facial expressions, and emotional states—in both depressed and healthy populations has revealed that the fusion of all modalities yields superior predictive performance for depression diagnosis compared to any single modality. Meta-analytic reviews further indicate that depression prediction models integrating multimodal data types significantly outperform models based on a single dimension of data. Furthermore, machine learning is capable of resolving disease risks, trajectories, and potential influencing factors that are otherwise difficult to characterize clinically [?, ?].

The combination of multimodal data and machine learning techniques enables continuous, precise, and objective assessments without the direct involvement of clinicians [?, ?]. It is evident that integrating multimodal data with machine learning allows researchers to observe depressive states more closely and track targetable neurophysiological markers alongside the dynamic onset of depression. Ultimately, this synergy facilitates feature fusion, classification, and the precise quantification of depressive states.

2.2.1 抑郁的

Neurophysiological Modality Measurement

Depression, as an affective disorder, is characterized by key alterations in autonomic nervous system activity, which reflect its underlying pathophysiology [?, ?, ?]. Among these measures, Heart Rate Variability (HRV)—a measure of the variation in time intervals between adjacent heartbeats—reflects the regulatory activity of the autonomic nervous system, including both the sympathetic and parasympathetic branches. Consistent evidence suggests that HRV reflects the severity of depressive symptoms [?, ?, ?]. A study utilizing wearable devices for long-term monitoring of the relationship between depression severity and heart rate changes found that individual depression severity was negatively correlated with daytime HRV. Furthermore, significant differences in HRV were observed between mild depression and moderate-to-severe depression during both daytime and nighttime. [?, ?] collected three-minute resting-state electrocardiogram (ECG) data from individuals with subthreshold depression and healthy controls. By calculating HRV parameters in both time and frequency domains, they found that individuals with subthreshold depression exhibited lower HRV compared to healthy controls, specifically in the standard deviation of NN intervals (SDNN) and high-frequency (HF) power indicators. Researchers suggest that lower HRV is associated with higher levels of depression and emotional instability [?, ?, ?]. It may serve as a predictor of psychological resilience and reflect an individual' s emotional regulation capacity [?, ?]. Thus, HRV not only reflects current depressive states and symptom severity but is also associated with an increased risk of developing clinical depression.

Electrodermal activity (EDA) is another sensitive physiological indicator of sympathetic nervous system activity. Specifically, the signal strength of Skin Potential (SP) reflects changes in the quantity of superoxide free radicals within connective tissues, providing electrophysiological insights into autonomic arousal.

Skin potential has emerged as a potential biomarker for clinical diagnosis [?, ?]. Some studies have incorporated the difference in skin potential between resting and task states into decision tree classification models, finding this metric effective in distinguishing individuals with depression from healthy controls. [?, ?] recruited patients with depression to complete clinical assessments, cognitive function tests, laboratory examinations, and task-based skin potential measurements. Compared to the healthy control group, depressed individuals exhibited abnormal skin potential characteristics during free-viewing tasks, positive and negative emotion recognition, semantic stimulation, emotion induction, and contextual intervention tasks. Furthermore, using these data to construct disease discrimination models yielded high accuracy in distinguishing the depressed group from the healthy group. Consequently, skin potential represents a feasible method for objective assessment and holds promise as a potential biomarker for diagnosing depressive states.

During the pathogenesis of depression, the body releases excessive cortisol into the brain, leading to a reduction in the volume of the prefrontal cortex. This structural change results in functional abnormalities in emotional control and decision-making behavior [?, ?, ?]. Electroencephalography (EEG), which offers millisecond-level temporal resolution, is used to record the brain' s neurophysiological activity and diagnose various mental disorders [?, ?, ?]. By performing non-invasive assessments [?, ?], establishing reliable neuroelectrophysiological markers through EEG data, and conducting longitudinal monitoring of brain physiological health, researchers may provide effective strategies for clinical diagnosis and disease management.

A significant portion of current research on potential neural markers for depression or subthreshold depression focuses on brain dynamics, reporting predictive indicators such as time-domain signal features, frequency-domain network connectivity, and microstates. Research on the time-domain features of depression indicates that Event-Related Potential (ERP) components are widely considered to reflect the processing of pleasant or unpleasant emotions. Compared to healthy individuals, those with depression exhibit reduced amplitudes when facing pleasant stimuli, which is significantly correlated with symptom severity [?, ?, ?]. Meta-analyses based on randomized controlled trials show that ERP amplitudes are significantly lower in depressed groups compared to healthy controls, suggesting that these components may be important biomarkers for depression detection [?, ?]. Recent analyses of frequency-domain network connectivity indicate that the power of specific frequency bands in the prefrontal and medial occipital cortex during resting-state with eyes open is a predictor of depression.

[?, ?] found through meta-analysis that depression is characterized by abnormal resting-state functional connectivity, specifically reduced connectivity within the frontoparietal network. Simultaneously, there is decreased connectivity between neural systems involved in cognitive control and those involved in emotional processing, reflecting deficits in emotional regulation. [?, ?] utilized resting-state data from individuals with subthreshold depression to explore connectivity across various frequency domains, finding that these individuals exhibited higher functional connectivity in specific bands compared to healthy controls.

[?, ?] further utilized a Support Vector Machine (SVM) classification method embedded with a Recursive Feature Elimination (RFE) algorithm, discovering that functional connectivity in the fronto-centro-parietal network contributes significantly to the classification and identification of subthreshold depression. As electrophysiological markers, EEG microstates can not only capture emotional fluctuations but also reveal the severity of depression [?, ?]. Recent studies have found that in both subthreshold depression and clinical depression, microstate characteristics—such as duration, coverage, and transition rates—exhibit abnormalities. These may reflect reduced connectivity strength or disruptions within brain networks [?, ?, ?]. Peripheral physiological signals, such as facial expressions and voice, are also considered potential novel biomarkers for depression [?, ?, ?]. Because these signals are easily accessible and capture authentic behavioral and emotional responses in natural states, many researchers have utilized computer vision and other methods for automated diagnosis [?, ?]. Research on depressive expressions and behavioral patterns has found that, compared to healthy individuals, patients with depression typically exhibit fewer smiles, reduced mouth movement, and less eye contact, alongside more melancholic facial expressions, frowning, downward gaze, and non-specific fixation [?, ?]. Additionally, there is a significant correlation between acoustic features and depression severity; analyzing speech signals and their variations allows for the exploration of an individual' s emotional and psychological state. Studies have shown that depressed patients exhibit distinct vocal characteristics, such as slower speech rates and monotonic, pessimistic tones [?, ?, ?]. In clinical settings, the use of objective neurophysiological indicators can improve early identification of high-risk populations, enabling targeted preventive interventions. However, previous research has largely focused on neurophysiological abnormalities in major depressive disorder, often overlooking the unique value of subthreshold depression for early screening and prevention. Consequently, the exploration of the neurophysiological mechanisms of subthreshold depression remains insufficient.

There remains significant potential to uncover neurophysiological abnormalities in subthreshold depression by integrating multimodal data, including skin potential, audio, and video signals.

2.2.2 抑郁诊断与机器学习

The application of machine learning in the field of depression has provided unprecedented opportunities for addressing clinical diagnosis, monitoring dynamic disease progression, and adjusting treatment strategies [?, ?]. A substantial body of research has utilized traditional machine learning methods—such as logistic regression, support vector machines, and Naive Bayes—to analyze data primarily derived from questionnaires and self-reports to assist in clinical decision-making [?, ?, ?]. To process more complex signal data, including speech and video, deep learning methods such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) have been applied to depression screening and auxiliary diagnosis, effectively improving both accuracy and robustness.

For instance, Zhang proposed an improved method based on Empirical Mode Decomposition (EMD) that better captures subtle variations, thereby effectively enhancing the precision of early depression screening. Regarding specific depression video datasets (e.g., AVEC2013, AVEC2014), Jazaery and Guo proposed an RNN-based approach to extract spatial and temporal features from subjects performing free-response tasks, allowing for more refined regression predictions of depression severity. Furthermore, Shen and Yang developed a model based on Long Short-Term Memory (LSTM) networks; by utilizing an emotional audio-text corpus for automated detection, they demonstrated the capability of multimodal data—combining audio and textual information—to improve detection accuracy. Additionally, other researchers have integrated multiple modalities by designing attention-based multimodal fusion networks to process audio and video signals for depression assessment.

Consequently, this study intends to employ machine learning techniques combined with multimodal data for model construction. The objective is to improve the accuracy of clinical screening and prediction across different stages of depression—including healthy states, subthreshold depression, and clinical depression—thereby achieving automated and large-scale detection capabilities.

2.3 认知行为疗法对抑郁的预防性干预

The positive intervention effects of psychotherapy on depression have been widely confirmed. Research has further demonstrated that preventive measures targeting subthreshold depression can facilitate the remission of depressive symptoms (Hao et al., 2023; He et al., 2022; Legemaat et al., 2021;

Cuijpers et al., 2023). As a primary psychological intervention for treating depression, Cognitive Behavioral Therapy (CBT) has been shown to induce positive shifts in emotional bias at both behavioral and neural levels. This is likely because CBT directly targets negative schemas and cognitive biases while enhancing top-down control within the executive and dorsal attention networks (Hao et al., 2023; Kalsi et al., 2017; Sankar et al., 2018). Meta-analytic studies indicate that CBT effectively alleviates symptoms of subthreshold depression, with significant preventive intervention effects observed in both adolescents and adults (Cuijpers et al., 2014). In follow-up studies, psychotherapy significantly reduced the incidence of future clinical depression in adults with subthreshold symptoms (Cuijpers et al., 2021) and demonstrated superior relapse prevention compared to pharmacotherapy (Vittengl et al., 2009). To date, the evaluation of psychotherapeutic efficacy for depression is no longer limited to questionnaires and clinical diagnoses; an increasing number of studies have expanded to using neurophysiological indicators to determine the reduction in symptom severity following intervention (Watts et al., 2022; C., 2022). Simultaneously, Dynamic Systems Theory provides a powerful framework for exploring the impact of psychotherapy on the pathology of depression, allowing for a more comprehensive capture of the dynamic changes in depressive states among individuals receiving treatment. According to complex dynamic systems theory, psychotherapy may shift or disrupt the stability of attractors during the treatment process (Hayes & Andrews, 2020). For instance, the primary measures of CBT involve introducing corrective information and skills to provide the external stimulus interference necessary to facilitate the transition from a subthreshold depressive phase to other states. Given that the subthreshold depression phase is inherently unstable, CBT as a preventive intervention may help the system strengthen healthier attractors, thereby increasing the likelihood of the attractor state shifting from a subthreshold unstable state to a healthy stable state.

3 问题提出

The dimensional perspective of psychopathology posits that the difference between subthreshold depression and major depressive disorder (MDD) is quantitative rather than qualitative, suggesting that the two share similar underlying structures and treatment responses [?, ?, ?]. Neurophysiological evidence further demonstrates a significant degree of overlap in brain region activation between subthreshold depression and MDD [?, ?]. Clinically, the two conditions appear similar, both manifesting as personal distress and functional decline [?, ?, ?].

Clinical relevance is also reflected in prognostic outcomes. Research indicates that, compared to healthy individuals, those with subthreshold depressive symptoms are significantly more likely to subsequently develop MDD than their healthy counterparts [?, ?]. These findings collectively support the view that subthreshold depression represents a transient stage along a continuum between health and clinical depression. Consequently, elucidating targetable neurophysiological markers during the subthreshold phase holds promise for early detection and effective preventive interventions. However, there is still a lack of understanding regarding the neurophysiological mechanisms and targetable predictive markers of subthreshold depression from the perspective of complex dynamical systems. Therefore, based on the complex dynamical systems theory of depression and focusing on the high-risk stage of subthreshold depression, this study explores whether neurophysiological features can serve as objective biomarkers to assist researchers in the early screening and model construction for high-risk individuals who may progress to MDD.

A substantial body of research suggests that not all cases of subthreshold depression inevitably transition into clinical onset; instead, symptoms may improve or persist in a high-risk mental state [?, ?]. Understanding which high-risk individuals will transition from a subthreshold state to clinical depression, as well as the underlying dynamic mechanisms of this transition, is crucial for early screening and precision prevention. From the perspective of complex dynamical systems, how does the stability of the internal system in individuals with subthreshold depression predict subsequent symptom transformation and neurophysiological changes? To address this question, longitudinal tracking of subthreshold individuals can reveal the dynamic characteristics of depression onset at the individual level. Furthermore, the construction of corresponding models can help researchers predict which individuals are likely to transition from a subthreshold state to full-blown clinical depression. By uncovering the dynamic process of onset, targeted prevention for subthreshold individuals can provide timely, personalized precision medical measures, thereby reducing the incidence of depression [?, ?]. Nevertheless, evidence regarding the impact of cognitive behavioral therapy on subthreshold transition—supported by complex dynamical systems theory and neurophysiological predictive indicators—remains scarce. Moreover, it is unclear whether preventive interventions for subthreshold individuals can be accurately predicted through attractor states. Based on these gaps, this study proposes a series of research frameworks to address the aforementioned issues.

4 研究构想

The general approach of this study follows the path of "multimodal characteristic assessment → attractor state monitoring → preventive intervention" for subthreshold depression. By integrating multi-temporal, multi-dimensional, and multimodal data with machine learning, we aim to elucidate the neurophysiological mechanisms and attractor states of subthreshold depression and, based on these findings, implement preventive interventions. First, this study utilizes multimodal data to explore differences in symptoms and mechanisms between individuals with subthreshold depression and healthy individuals at the group level, thereby identifying key predictive neurophysiological indicators of subthreshold depression.

Simultaneously, we will employ multimodal data combined with machine learning to construct a neurodynamic network model for subthreshold depression. This model will be used to identify depressive symptoms and neurobiological features, followed by cross-group and cross-individual validation. Secondly, to address which states of subthreshold depression are likely to transition into clinical depression, we will adopt an Ecological Momentary Assessment (EMA) strategy combined with longitudinal follow-up at the individual level. This will allow us to investigate the relationship between the attractor states of individuals with subthreshold depression, their subsequent transition to clinical depression, and the accompanying changes in neurophysiological characteristics. Furthermore, building upon previous work [?], this study intends to construct a complex dynamical system model for individuals with subthreshold depression. By combining ordinary differential equations (ODEs) with Graph Neural Networks (GNNs), we will learn continuous-time dynamics on neural networks in a data-driven manner to construct a neurodynamic network model.

Specifically, the dynamic changes of graph node features over time are modeled as differential equations, providing the following description of the dynamics of depression:

$$(\ )\ =\ (\ (\ ),\ ,\ ,\ )$$

Node information includes multimodal representations such as emotion, physiology, behavior, sleep, symptoms, and clinical diagnosis. Let $\mathcal{G}$ represent the network of multimodal data, and let θ denote the neural network parameters. This study performs future state prediction based on discrete-time sampling; specifically, we predict the node state at any future time point based on the states from the initial time to the current time, as follows:

In the above equation, h_0 represents the node state at the initial time, while h_t represents the node state at time t. To ensure that Graph Convolutional Networks (GCNs) can efficiently and rapidly solve the aforementioned integral, we will build upon recent advances in the fields of neurodynamics and machine learning.

Specifically, we will conduct continuous-time neurodynamic network modeling based on neighborhood aggregation of graph nodes [**?**, **?**]. The proposed approach will specifically employ aggregation operations based on graph convolutions.

$$+1 = (\ \tilde{}\ -1\ 2\ \tilde{}\ \tilde{}\ -1\ 2\ \ )$$

The hidden representation of node features in the l-th layer of a Graph Convolutional Network (GCN) is denoted as $H^{(l)}$, where σ represents a non-linear activation function, D is the degree matrix of the graph, and A is the adjacency matrix. The update process for node feature representations in an L-layer GCN is defined such that, through L layers of graph convolutional operations, the feature of node i evolves from its initial state $h_i^{(0)}$ to a representation that integrates aggregated information from its multi-order neighborhood.

Integrating this with the dynamical description of depression, the state of a node at time t can be expressed as:

$$(\ ) = (\ 0\ ) + \int (\ \tilde{}\ -1\ 2\ \tilde{}\ \tilde{}\ -1\ 2\ (\ )\ )$$

The model updates node states by aggregating information from neighboring nodes, thereby enhancing the efficiency and stability of the integral solution. Baseline models are constructed using ecological momentary assessment (EMA) data and longitudinal data collected during the subthreshold depression phase to determine individual thresholds or control limits. These limits define the boundaries within which an individual remains in their current attractor state, provided they continue to conform to the current neurodynamic network model. Finally, whereas previous evaluations of preventive interventions for subthreshold depression have relied largely on clinical diagnostic outcomes, this study explores the effects of Cognitive Behavioral Therapy (CBT) on the transition of subthreshold depression from a commonality dimension. By utilizing depressive symptoms and neurophysiological characteristics as objective evaluation indices for intervention efficacy, we further elucidate the predictive role of an individual's attractor state on future transitions in subthreshold depression status through the construction of the aforementioned predictive models.

Depressive Feature Extraction and Model Construction via Multimodal Machine Learning

The framework includes a text encoding module, a video encoding module for processing audio-visual features and signals, and a neurophysiological module for analyzing neurophysiological signals. These components feed into a multimodal feature fusion and classification module to output predictive classifications.

Stability Analysis and Transition of Subthreshold Depression

This stage involves instantaneous assessment and measurement (continuous data collection over N days) to support predictive model construction and stability analysis.

Cognitive Behavioral Therapy Intervention for Subthreshold Depression

The intervention phase integrates predictive model construction with instantaneous assessment measurements, comparing the treatment group against a waitlist (WL) control group through repeated instantaneous assessments.

4.1 抑郁的神经生理特征及模型建构

Study 1 focuses on the dynamic developmental stages of depression, selecting healthy individuals, individuals with subthreshold depression (StD), and patients with major depressive disorder (MDD) as research subjects. This study aims to explore the uniqueness of the neurophysiological characteristics of individuals with subthreshold depression using multimodal data and machine learning techniques, followed by model fitting. Participants from both school and community populations were recruited through offline campus recruitment, online advertisements, and community postings. The recruitment categories included healthy, subthreshold depressed, and clinically depressed individuals, ensuring that at least 50 participants in each category met the inclusion criteria. All participants were adults within the age range of 18 to 60 years, with balanced gender distribution, no intellectual disabilities, fluent Chinese language skills, the ability to complete questionnaires and experimental tasks, and voluntary participation. Socio-demographic data, including employment status, marital status, income level, and education level, were collected to ensure no significant differences in demographic characteristics between groups at baseline [?, ?, ?, ?]. Participants were required to complete depression symptom assessments.

The study involved relevant self-reports, diagnostic interviews, and multimodal data collection. Portable smartwatches and audio-video recorders were utilized to record neurophysiological multimodal data from healthy, subthreshold depressed, and clinically depressed individuals.

By reviewing and summarizing the features that differentiate healthy individuals from those with depression across various modalities, the neurophysiological features to be explored in this study are presented in .

Neurophysiological Feature Indicators: - Speech features: Prosodic features, voice quality features, and spectrum-based features [?, ?, ?]. - Facial features: Smile duration and frequency, mouth activity, facial expressions, frowning, gaze shifting, and attention. - Electrodermal activity (EDA): Skin conductance level (SCL), skin conductance response (SCR), non-specific skin conductance response (NS-SCR), and habituation. - Heart rate variability (HRV): Mean heart rate, frequency-domain indicators (LF/HF), and time-domain indicators (RMSSD) [?, ?, ?]. - Electroencephalogram (EEG): Frequency-domain indicators (Alpha, Gamma) [?]; Microstate indicators (state, duration, coverage, transition rate) [?, ?]. - Sleep: Sleep duration, sleep onset time, and sleep offset time [?].

This study employed a two-stage method for participant screening and grouping. First, the Chinese version of the Patient Health Questionnaire-9 (PHQ-9) [?, ?] was used to identify healthy participants with scores of 5 or below. Second, participants with scores above 5 underwent the Mini-International Neuropsychiatric Interview (MINI) [?] to differentiate between subthreshold depression and clinical depression. The clinical diagnostic interview is a semi-structured interview designed based on diagnostic manuals, conducted by licensed psychiatrists [?]. If a participant exhibited symptoms at or above the level of mild depression on the PHQ-9 but did not meet the MINI diagnostic criteria, they were classified as having subthreshold depression or being in a clinical high-risk state. If the participant' s scale score was at or below the mild depression threshold, they were classified as healthy. If the PHQ-9 indicated depressive symptoms and the MINI diagnostic interview confirmed a diagnosis of depression, the participant was classified as being in a clinical state of depressive episode. Exclusion criteria for all participants included: pregnancy, lactation, or non-use of contraception; a lifetime history of psychosis or bipolar disorder; drug dependence or substance abuse within the past six months, or the use of any medication to treat depression; unstable psychiatric or medical conditions requiring hospitalization; a history of epilepsy; ongoing physical, pharmacological, or psychological therapy; and significant suicide risk.

Multi-platform recruitment of participants; application of exclusion criteria; Ecological Momentary Assessment (EMA) strategy; participant screening and classification; exclusion of those unable to complete the experiment; implementation of the EMA strategy.

Figure 1

Figure 3: Figure 1

PHQ-9 $\leq$ 5: Healthy

Multimodal Phenotyping: Questionnaire measurements; Neurophysiological signals.

实验

Experiment 3: Audio and Video Signals

1. Introduction

The objective of this experiment is to explore the fundamental principles and processing techniques associated with audio and video signals. In the modern digital era, audio and video data constitute the vast majority of internet traffic. Understanding how these signals are captured, digitized, compressed, and transmitted is essential for developing advanced multimedia applications and machine learning models. This section focuses on the mathematical representation of signals and the transformation processes required to move between the time and frequency domains.

2. Signal Representation and Processing

Audio signals are typically represented as one-dimensional functions of time, denoted as $s(t)$. In digital systems, these are sampled at a specific frequency f_s to produce a discrete sequence $s[n]$. Video signals, conversely, are multi-dimensional, involving spatial coordinates (x, y) and a temporal component t. A video frame can be represented as a matrix of pixel intensities $I(x, y)$, and a video sequence as $V(x, y, t)$.

2.1 Fourier Analysis To analyze the spectral content of these signals, we employ the Discrete Fourier Transform (DFT). For a discrete signal of length N, the transform is defined as:

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-j\frac{2\pi}{N}nk}$$

This allows us to identify the dominant frequencies within an audio clip or the spatial frequency components within a video frame. In practical applications, the Fast Fourier Transform (FFT) is utilized to reduce computational complexity from $O(N^2)$ to $O(N \log N)$.

3. Audio Signal Analysis

During the experimental procedure, we recorded a sample audio signal and performed Short-Time Fourier Transform (STFT) to generate a spectrogram. The spectrogram provides a visual representation of the frequency spectrum of a signal as it varies with time.

$$\mathrm{STFT}\{x[n]\}(m,\omega) = \sum_{n=-\infty}^{\infty} x[n]w[n-m]e^{-j\omega n}$$

where $w[n]$ is a window function (such as a Hamming or Hann window) used to segment the signal into quasi-stationary frames. This analysis is crucial for tasks such as speech recognition and acoustic scene classification.

4

分析

Hypothesis testing was conducted through data analysis. Post-test tracking within the Flow Chat was included in Studies 2 and 3. This study collected multimodal data, including interview data, from participants across different groups, specifically focusing on the subthreshold depression group.

All participants completed interviews to assess their depressive status. The study measured the severity of participants' depressive and anxiety symptoms. The Patient Health Questionnaire (PHQ-9) was used to assess the severity of depressive symptoms. This scale consists of 9 items, requiring participants to indicate the frequency of depression-related symptoms over the past two weeks, scored on a four-point Likert scale. Anxiety symptoms were measured using the Generalized Anxiety Disorder 7 (GAD-7) scale to assess symptom severity. This scale consists of 7 items, requiring participants to indicate the frequency of anxiety-related symptoms over the past two weeks, also scored on a four-point Likell scale.

The Positive and Negative Affect Schedule (PANAS; [**?**, **?**]) was employed to measure the real-time emotional states of the participants.

The neurophysiological data included both resting-state and task-state recordings. Participants were seated in a quiet, soundproof room, and their neurophysiological signals were collected after the EEG cap was properly fitted. For resting-state data collection, participants were first asked to close their eyes and then to open them and fixate on a crosshair in the center of a computer screen; they were instructed to remain awake and in a state of mind-wandering throughout the duration [**?**, **?**]. Task-state data were collected using the Emotional Conflict Task. This is a classic paradigm for assessing emotional conflict and its regulation, and it has been widely applied in research concerning depression and intervention efficacy [**?**, **?**, **?**].

Stimuli were selected from the Chinese Facial Affective Picture System, consisting of happy and angry emotional images, along with corresponding happy and angry emotional words. Image processing software was used to overlay red emotional words onto the images. An "congruent condition" occurred when the valence of the facial expression matched the emotional word, while an "incongruent condition" occurred when the valences conflicted. The experiment consisted of an equal number of congruent and incongruent trials. Regarding the task procedure, each stimulus was presented for 1 second with an inter-stimulus interval of 1,000 milliseconds. Facial expressions, gender, emotional words, and response keys were balanced using a pseudo-randomized method. Stimuli were presented in the center of the screen, with all participants maintained at a distance of approximately 60 cm from the screen, their eyes aligned with the upper third of the display.

Electrodermal activity (EDA) and heart rate data were also collected. Electrodes for the EDA device were attached to the participant' s middle finger and left wrist, with data transmitted via Bluetooth to a corresponding monitoring application. Similarly, a professional smartwatch was used to collect heart rate, sleep duration, and physical activity acceleration data. EDA and heart rate data were collected during the interviews and the resting state, ensuring temporal synchronization across modalities.

Audio and video data were recorded throughout the process. During the interviews, high-definition cameras were used to record facial expressions and voice data. During the resting-state and task-state sessions, cameras continued to record facial expression information.

The study first employed one-way Analysis of Variance (ANOVA) to examine differences in age, years of education, and questionnaire scores among the healthy control, subthreshold depression, and clinical depression groups. Chi-square tests were used to compare the gender distribution between groups. ANOVA was also utilized to analyze differences in neurophysiological data, with age, gender, and years of education included as covariates to reveal the unique neurophysiological characteristics of subthreshold depression. Subsequently, machine learning was used to construct depression classification models based on the multimodal data. The machine learning model utilized feature extraction modules combining deep learning methods, such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, to encode feature vectors for questionnaire text, audio-video data, and neurophysiological signals. These multimodal feature encodings were fused using an attention-based multimodal feature fusion module. Finally, a Multi-Layer Perceptron (MLP) was trained as a classification model to generate predictive outputs for depression diagnosis based on the fused multimodal features.

This study hypothesizes that there are specific neurophysiological indicators capable of distinguishing between healthy individuals, those with subthreshold depression, and those with clinical depression. It is expected that the degree of abnormality in these neurophysiological indicators will correlate positively with the severity of depression.

Furthermore, the continuity of the depressive stages may be reflected in the continuity of these neurophysiological indicators. Additionally, it is hypothesized that after modeling multimodal indicators using machine learning, the multimodal neurophysiological data will demonstrate more accurate performance in predicting depression categories (healthy, subthreshold depression, and clinical depression) compared to single-modality data.

4.2 阈下抑郁的吸引子状态预测动态转化

Based on the theory of complex dynamical systems, Study 2 selects individuals with subthreshold depression (SD) as the research subjects, treating them as a multidimensional complex system. By employing an Ecological Momentary Assessment (EMA) strategy combined with neurodynamic networks, this study explores the unique joint dynamical patterns and attractor states of SD individuals. Furthermore, it investigates the development of depressive symptoms and neurophysiological characteristics over time using longitudinal tracking data. Previous research has indicated that individuals with subthreshold depression may transition along a depression continuum toward major depression, revert to a healthy state, or remain in a subthreshold state \cite{van_{{{de}}{{leemput}}}{2014}}. Building upon these findings, this study aims to clarify the relationship between the attractor states of SD individuals and the increased risk of future depressive onset.

The recruitment and screening criteria for participants with subthreshold depression are identical to those in Study 1. Participants are required to complete questionnaires, interviews, and multimodal data collection, voluntarily participating in the study and completing long-term follow-up surveys. To explore the attractor states of SD individuals, an instantaneous assessment strategy is used to analyze time series of emotions (happiness, contentment, sadness, and anxiety), depressive states, and heart rate. The overall emotional state of the individual is obtained through experience sampling methods, using structured diaries to record assessments within the context of daily life \cite{van_{{{de}}{{leemput}}}{2014}, myin_{{{germeys}}{{2009}}}, husen{2016}}. Participants wear digital wristwatches programmed to use stratified random sampling to trigger signals between 10:00 AM and 10:00 PM. These signals prompt participants to complete self-assessment forms at that moment, which include current context, 7-point Likert scale emotional ratings, and depression-related characteristics.

Information is collected as peripheral physiological signals. The self-assessment forms measure the position of four emotions—happiness, contentment, anxiety, and sadness—on an emotional scale, which is treated as the individual' s "emotional score" at a specific time point. Participants are typically required to perform self-assessments daily for several consecutive days.

Following the assessment period, multimodal data collection is conducted using the same content as in Study 1. This stage is defined as the baseline period. Follow-up records of depression severity and multimodal data collection are completed at four follow-up measurements after the baseline, with each interval lasting approximately three months over a one-year period. The follow-up content remains consistent with Study 1.

This study obtains the stability levels of individual attractor states by modeling longitudinal time-series data—including emotions, heart rate, and depressive symptoms—using neurodynamic networks. Taking the emotional system as an example, a three-level data structure is created as model input: the four emotions are nested within measurement time points, which are in turn nested within individuals. Data such as emotions and depressive symptoms are input into the model in this manner to establish a neurodynamic network model for calculating attractor states. Furthermore, the study investigates whether the current level of state stability can predict the subsequent depressive states and neurophysiological characteristics of SD individuals.

A combination of measures is used to determine the individual' s depressive state (healthy, subthreshold depression, or clinical depression). Neurophysiological characteristics include the individual' s audio-visual features, galvanic skin response (GSR), heart rate characteristics, as well as sleep and physical activity data. This study hypothesizes that lower stability coefficients in the time series of emotions, heart rate, and depressive symptoms in SD individuals will correlate with a higher likelihood of worsening depressive symptoms or an increased incidence of major depression during follow-up, accompanied by changes in multimodal neurophysiological features. Additionally, the constructed neurodynamic network model is expected to effectively predict the future transition of depressive symptoms in subthreshold individuals.

4.3 认知行为疗法

Based on the aforementioned research foundations and integrated with complex dynamical systems theory, Study 3 utilizes changes in depressive symptoms and neurophysiological characteristics as objective assessment indicators to investigate the intervention effects of Cognitive Behavioral Therapy (CBT) on subthreshold depression. Furthermore, this study aims to elucidate the early predictive role of individual attractor states on the future transition effects of subthreshold depression states.

The recruitment and screening criteria for participants with subthreshold depression are identical to those in Study 1. Eligible participants were randomly assigned to a cognitive behavioral intervention group or a control group. Following the methodology of [?, ?], a randomized controlled trial (RCT) was employed to explore the preventive effects of CBT on individuals with subthreshold depression and its impact on corresponding multimodal neurophysiological features.

Through longitudinal tracking and monitoring, this study examines whether the preventive intervention of CBT for subthreshold depression can reduce the likelihood or severity of its conversion into Major Depressive Disorder (MDD). It further explores whether these intervention effects align with the complex dynamical systems theory of depression. Participants volunteered for the study and were required to complete questionnaires, interviews, and multimodal data collection, as well as long-term follow-up surveys.

The study utilizes the "Coping With Depression" (CWD) course [?, ?] for group cognitive behavioral therapy, specifically the version adapted by Cuijpers [?, ?]. This is a highly structured depression therapy consisting of ten weekly sessions, each lasting 120 minutes. The content includes empirically validated intervention components such as psychoeducation, cognitive restructuring, behavioral activation, and relapse prevention. The CBT sessions are led by psychologists and experienced social workers. Each session requires two group leaders, consisting of licensed counselors or psychiatrists and graduate students under their supervision. Each group comprises 8–12 participants. The control group consists of participants on a waitlist who do not receive the intervention immediately but are invited to participate after the experiment concludes. Regarding outcome assessment, given that interventions for subthreshold depression aim to reduce the risk of developing clinical depression, randomized follow-up intervals were established. Measurements were taken pre-intervention, immediately post-intervention, and at six-month and twelve-month follow-ups. The multimodal measurement tasks and analytical methods used in this study are consistent with those in Study 2.

The study first employs repeated measures Analysis of Variance (ANOVA) to compare changes in depression severity and status between the intervention group and the waitlist control group during the follow-up period. Subsequently, the stability coefficients of time-series data (such as mood) before and after follow-up are calculated to represent individual attractor state levels, allowing for an exploration of changes in these attractor states pre- and post-intervention. Finally, the study explores at the individual level whether changes in attractor states mediate the effects of CBT on depressive symptoms and multimodal neurophysiological characteristics.

This study hypothesizes that individuals with subthreshold depression undergoing CBT will exhibit a reduction in depression severity or a decrease in the rate of conversion to clinical depression, accompanied by changes in multimodal features. It is further hypothesized that the attractor state can accurately predict positive intervention outcomes for subthreshold depressive symptoms and corresponding neurophysiological indicators. Simultaneously, by constructing a depression prediction model, the study investigates the predictive role of individual attractor states on the transition effects of future subthreshold depression states following CBT intervention.

5 理论建构

A Dynamical Systems Framework for Predicting Preventive Interventions of Cognitive Behavioral Therapy on Subthreshold Depression

In the context of Cognitive Behavioral Therapy (CBT), the process by which individuals acquire corrective information and cognitive skills can be conceptualized as the application of external perturbations to a dynamical system through clinical intervention. As an individual' s information-processing biases diminish and emotional dysregulation decreases, the system transitions away from its current unstable state toward a stable, healthy equilibrium [?, ?].

Building upon this framework, the present predictive hypothesis proposes that if CBT effectively facilitates the transition of individuals with subthreshold depression toward a healthy state, the post-intervention attractor state can serve as a robust predictor for the trajectory and severity of both depressive symptoms and neurophysiological characteristics over subsequent periods. This hypothesis aims to be empirically validated through the integration of multi-temporal, multi-dimensional, and multimodal machine learning methodologies.

Subthreshold depression (StD) is closely related to the formation and development of clinical depression and is accompanied by abnormalities in neurophysiological indicators. From the perspective of complex dynamical systems, the StD state may be a critical transition point determining the progression toward clinical depression. This study hypothesizes that Cognitive Behavioral Therapy (CBT) may further alleviate the severity of depressive symptoms by enhancing the stability of the state' s attractor, and that these changes can be predicted using neurophysiological features.

This study features three primary innovations. First, as a prodromal stage of depression, subthreshold depression is characterized by emotional disorders such as pessimism and anhedonia; however, not every individual in a subthreshold state eventually develops clinical depression. Therefore, identifying key predictive factors at this stage provides a vital entry point for early screening and intervention. Based on this, the present study systematically elucidates the neurophysiological mechanisms of subthreshold depression. We utilize machine learning algorithms for multimodal feature extraction and conduct cross-population, independent cohort, and cross-classification (healthy, subthreshold depression, and clinical depression) validations from multiple perspectives. This approach confirms the robustness of neurophysiological features by comparing differences across different stages of the depression continuum.

Second, this study operates within the framework of complex dynamical systems, viewing an individual' s behavior, emotion, cognition, and physiology as an interacting, multidimensional complex system. Considering that the system exhibits unique joint dynamical patterns at different stages (healthy, subthreshold depression, and clinical depression) as it evolves over time, this research innovatively employs neurodynamic network models to construct this dynamical system.

This system aims to reveal the pathological complexity and systemic stability of depression, thereby enabling the precise prediction of the dynamic development of depressive states.

Regarding the research methodology, this study utilizes longitudinal tracking to advance a dynamic model that employs internal attractor states of subthreshold depression to predict both the transition to clinical depression and changes in neurophysiological characteristics. By adopting the conceptual framework of "Attractor States –Multimodal Feature Changes," and leveraging the advantages of multimodal data systems alongside longitudinal tracking, this research attempts to elucidate the relationship between the internal stable states of an individual' s system and changes in modal features.

Furthermore, the study seeks to identify the core modal features driving the progression from subthreshold depression to clinical depression, while revealing the critical role of internal states. Ultimately, this work provides essential data support from longitudinal tracking to advance the field of precision medicine for depression.

Finally, this study explores subthreshold depression as a potential target for intervention, elucidating the positive impact of this psychological treatment on both the clinical manifestations and neurophysiological characteristics of depressive disorders. By focusing on this critical state, we further compare the differences in treatment effects between groups. Simultaneously, we clarify intervention strategies for identifying depressive states and improving depressive symptoms. This approach demonstrates the theoretical and clinical advantages of integrating psychopathology with neurophysiology.

Based on the theory of complex dynamical systems, the transition from subthreshold depression (StD) to a healthy state can be predicted in advance by observing changes in attractor states. This study aims to investigate the specific symptoms of subthreshold depression and their underlying neurophysiological mechanisms at the neurophysiological level. By utilizing machine learning techniques for multimodal feature extraction, cross-classification, and cross-group validation, this research seeks to verify that subthreshold depression—as a high-risk stage for clinical depression—can provide specific characteristic targets for preventive interventions. Furthermore, through longitudinal tracking, this study aims to confirm that the attractor levels of subthreshold depression can serve as a predictor for subsequent depressive outcomes.

The study aims to evaluate the predictive capacity of subthreshold depression states and their corresponding multimodal neurophysiological features. The ultimate goal is to elucidate whether the relief of symptoms following therapy, as well as the associated transitions in multimodal neurophysiological characteristics, can be predicted through the internal attractor states of the individual system.

This research overcomes the limitations of evaluating treatment efficacy based solely on clinical symptoms. By utilizing neurophysiological features as objective biomarkers and introducing complex dynamical systems, this approach enables earlier and more precise dynamic predictions of therapeutic outcomes. Such advancements assist clinicians in making timely adjustments to preventive intervention strategies.

The research results will provide an artificial intelligence approach for analyzing the neurobiological uniqueness of subthreshold depression. This approach is driven by complex dynamical systems theory and integrates multimodal machine learning, offering unique insights for the development of methods for early identification and precision prevention.

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Neurophysiological echanisms and nterventions of ubthreshold

d epression by i ntegrating m achine l earning t echniques

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bstract: Major Depressive Disorder (MDD) poses a substantial threat to national mental health.

Subthreshold depression, serving as a crucial prodromal stage of MDD, is of great value for investigating the neurophysiological features and its dynamic developmental patterns, as well as their potential for improving prediction of MDD onset. Past researc h is limited in treating MDD as a static, singular diagnostic entity. The current research, grounded in complex dynamic systems theory, explores multi temporal and multi modal machine learning techniques to explore the intricate relationships between subth reshold depressive symptoms and neurophysiological characteristics, as well as to identify key predictive factors. Additionally, through longitudinal tracking and neurodynamic network modeling, the study investigates attractor states and their predictive c apacity for subsequent MDD onset and characteristic transitions. Additionally, the current study explores the preventive efficacy of cognitive behavioral therapy for subthreshold depression and the predictive role of attractor states. The research aims to clarify the neurophysiological features and its dynamic developmental patterns of subthreshold depression, hoping to inform the development of effective early screening and selective prevention strategies of

Keywords

Subthreshold Depression; Attrac ; Cognitive behavioral Therapy; Preventive

Intervention; Multi - modal Machine Learning