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Computational psychiatry driven by multimodal artificial intelligence: early warning and trajectory prediction of mental disorders based on integrated data analysis

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Abstract

The high incidence, diagnostic delay, and treatment heterogeneity of mental disorders pose significant global public health challenges. Computational psychiatry, by integrating artificial intelligence, neuroscience, and clinical data, provides a new paradigm for the precise identification and prediction of mental disorders. This article systematically elaborates on the core theoretical and technical framework of computational psychiatry driven by multimodal artificial intelligence (AI), focusing on early warning and disease development trajectory prediction models based on integrated multi-source heterogeneous data (neuroimaging, electronic health records, behavioral records, genomics, environmental exposure, etc.). The article highlights the core progress of multimodal data fusion algorithms (graph neural networks, cross-modal autoencoders, federated learning, etc.) and dynamic trajectory modeling methods (hidden Markov models, recurrent neural networks, state-space models) and their verification applications in typical diseases such as depression, schizophrenia, and bipolar disorder. At the same time, it delves into the core challenges faced by this field, such as data heterogeneity, algorithm interpretability, clinical transformation barriers, and ethical risks, and prospects for future development directions (causal inference, digital phenotyping deepening, clinical decision support system integration). This review aims to provide theoretical support and a technical roadmap for building an intelligent diagnosis and treatment system for mental disorders that can dynamically warn and individually predict.

Keywords

Computational psychiatry; multimodal artificial intelligence; data integration; early warning; disease trajectory prediction; mental disorders; precision medicine.

1. Introduction

1.1. Global Burden of Mental Disorders and Clinical Dilemma

Mental disorders constitute one of the most severe public health challenges of the 21st century. The latest data from the World Health Organization shows that the total number of patients worldwide has exceeded 1 billion, accounting for 13% of the population, including over 350 million depression patients and approximately 24 million schizophrenia patients. Even more alarmingly, mental disorders account for 15.6% of the disability-adjusted life years (DALYs), significantly exceeding cardiovascular diseases (12.5%) and malignant tumors (9.6%). In the Chinese adolescent population, the detection rate of depression has risen to 24.6%. This heavy disease burden is facing three major clinical dilemmas. First, there is a significant diagnostic delay, with an average delay of 8.2 years from the onset of symptoms to diagnosis. This is due to the DSM/ICD diagnostic system relying on subjective symptom assessment (inter-rater reliability Kappa=0.4-0.6) and being unable to capture preclinical biological changes, resulting in the golden intervention window of 5-10 years being missed. Second, there is a significant blind spot in treatment, with antidepressants being completely ineffective in 30% of patients, antipsychotic drugs causing metabolic syndrome in up to 32% of patients, and the 5-year recurrence rate of schizophrenia exceeding 80%. The fundamental reason lies in the lack of biomarkers to guide precise intervention. Finally, the pathological mechanism analysis has fallen into a black box dilemma. Traditional psychiatry has failed to establish a quantitative causal chain of "gene-brain circuit-behavior-symptom," simplifying heterogeneous diseases into a collection of symptom labels. This current situation of "inaccurate diagnosis, poor treatment, and unclear mechanisms" urgently requires a revolution driven by multimodal artificial intelligence to build a new generation of diagnostic and treatment systems that are quantifiable, predictable, and intervenable.

1.2. The Rise of Computational Psychiatry and Paradigm Revolution

Computational psychiatry, as an interdisciplinary field between psychiatry and computer science, emerged at the intersection of the quantitative revolution in neuroscience and the explosion of artificial intelligence. It aims to analyze the neural computation mechanisms of mental disorders through mathematical modeling and promote the transition of the field from phenomenological description to predictive intervention (Huys et al., 2016). The traditional paradigm is limited by the phenomenological classification system and the neurotransmitter hypothesis, simplifying the disease into an unobservable "black box syndrome" (Montague et al., 2012). The computational paradigm achieves innovation through three pathways: at the mechanism level, using reinforcement learning models to quantify reward prediction error (RPE=actual reward - expected reward) and construct a Bayesian framework to explain abnormal perception integration; at the typing level, defining biological subtypes based on data-driven (e.g., cognitive metabolism type of depression); and at the intervention level, establishing a dynamic closed-loop system of "digital phenotype - computational model - clinical decision." The development of this discipline is driven by two engines: neuroimaging technology (7T fMRI) and artificial intelligence (graph neural networks). However, it still faces bottlenecks such as modality isolation, lack of dynamic modeling, and clinical transformation gaps. This study proposes a multimodal spatiotemporal fusion framework (MMF-DTN), which breaks through the limitations of single-point computation by using cross-modal attention mechanisms and LSTM embedded with differential equations, and constructs an integrated prediction new paradigm.

1.3. The Necessity and Value of Multimodal Data Integration

Mental disorders, as complex systems with intertwined pathological processes at multiple scales, require precise resolution that breaks through the cognitive limitations of a single modality. While neuroimaging can capture abnormal brain networks, it cannot dynamically track changes in daily behavior (e.g., due to the spatial and temporal resolution limitations of fMRI); behavioral sensors can monitor physiological indicators in real-time but cannot penetrate deep neural mechanisms (e.g., the decoupling between heart rate variability measured by wearable devices and amygdala activation); electronic health records provide longitudinal medical history but lack ecological validity data support (e.g., EHR text cannot quantify emotional rhythm). The necessity of multimodal integration stems from this – only by integrating four-dimensional data such as neuroimaging (structure/function/diffusion), behavioral sensors (movement/physiology), electronic health records (clinical text/medication history), and language and speech (rhythm/semantics) can a panoramic pathological map of "molecule-brain circuit-behavior-symptom" be constructed (Zhang et al., 2023). Its core value lies in three breakthroughs: at the scientific level, revealing cross-diagnostic biomarkers through cross-modal correlation mining (e.g., the synchronicity of decreased default mode network segregation and mutated language entropy); at the technical

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level, using graph neural networks to align heterogeneous spatiotemporal scales (e.g., coupled modeling of DTI white matter fiber bundles and GPS movement trajectories),破解 data fusion bottlenecks; and at the clinical level, achieving high-risk population screening (sensitivity >90%) and individualized intervention response prediction (AUC=0.88) based on multimodal risk scores (Multimodal Risk Score, MRS). The multimodal fusion framework (MMF-DTN) developed in this study is the practical carrier of this integration paradigm, promoting psychiatry from fragmented description to systematic prediction.

2. Multimodal Data Landscape and Acquisition Technologies

2.1. Neurophysiological Modalities

As shown in Figure 1, neurophysiological modalities, as the core for analyzing the brain mechanisms of mental disorders, are undergoing a revolutionary leap from single-point static measurement to dynamic whole-brain network decoding. Structural magnetic resonance imaging (sMRI) realizes submillimeter brain segmentation through T1/T2-weighted sequences (e.g., hippocampal volume reduction is associated with the course of depression, r=-0.32), and diffusion tensor imaging (DTI) quantifies the integrity of white matter fibers through fractional anisotropy (FA) (for every 0.1 decrease in the FA value of the anterior cingulate cortex, the risk of bipolar disorder increases by 2.7 times). Functional magnetic resonance imaging (fMRI) technology breaks through the limitations of blood oxygen level-dependent (BOLD) signals, and 7T ultra-high field equipment improves spatial resolution to 0.5mm^3 (capturing sub-regional activation differences in the amygdala), and resting-state functional connectivity (rsFC) reveals the desynchronization phenomenon between the default mode network (DMN) and the salience network (SN) (the DMN-SN connection strength of schizophrenia patients is lower than that of healthy subjects, d=1.24). In the field of electrophysiology, high-density electroencephalography (hdEEG) realizes millisecond-level neural oscillation tracking with a 256-channel array, and theta-gamma phase-amplitude coupling (PAC) abnormalities have been confirmed as sensitive indicators of cognitive deficits in schizophrenia (AUC=0.79), while electrocorticography (ECoG) directly records prefrontal field potentials in epilepsy patients with comorbid depression, and finds that the energy in the gamma band is inversely correlated with the severity of anhedonia (β=-0.41, p<0.001). Emerging portable technologies are breaking through laboratory barriers. Functional near-infrared spectroscopy (fNIRS) monitors the concentration of oxygenated hemoglobin (HbO_2) in the prefrontal cortex in real-time through near-infrared light (wavelength 650-900nm) transmitted through the skull, making naturalistic studies of emotional induction possible (the HbO_2 peak of social anxiety patients delays by 300ms when facing negative expressions), and mobile EEG combined with dry electrodes captures the prefrontal asymmetry of depression patients during daily decision-making in ecological validity assessments (left/right alpha power ratio decreases by 17%).

Multicenter standardized acquisition protocols (such as HCP Lifespan) promote the development of data comparability, but technology integration still faces three major challenges: ultra-high field fMRI motion artifact correction algorithms need to be optimized (head movement >0.2mm leads to functional connection estimation bias >15%), cross-modal spatiotemporal alignment needs to develop adaptive interpolation methods (the fusion error between EEG millisecond data and fMRI second-level sampling reaches 22%), and the improvement of portable device signal-to-noise ratio relies on new sensor materials (graphene electrodes reduce muscle electrical interference by 40%). These breakthroughs in neurophysiological modalities lay an irreplaceable foundation for constructing multi-scale brain-behavior mapping models.

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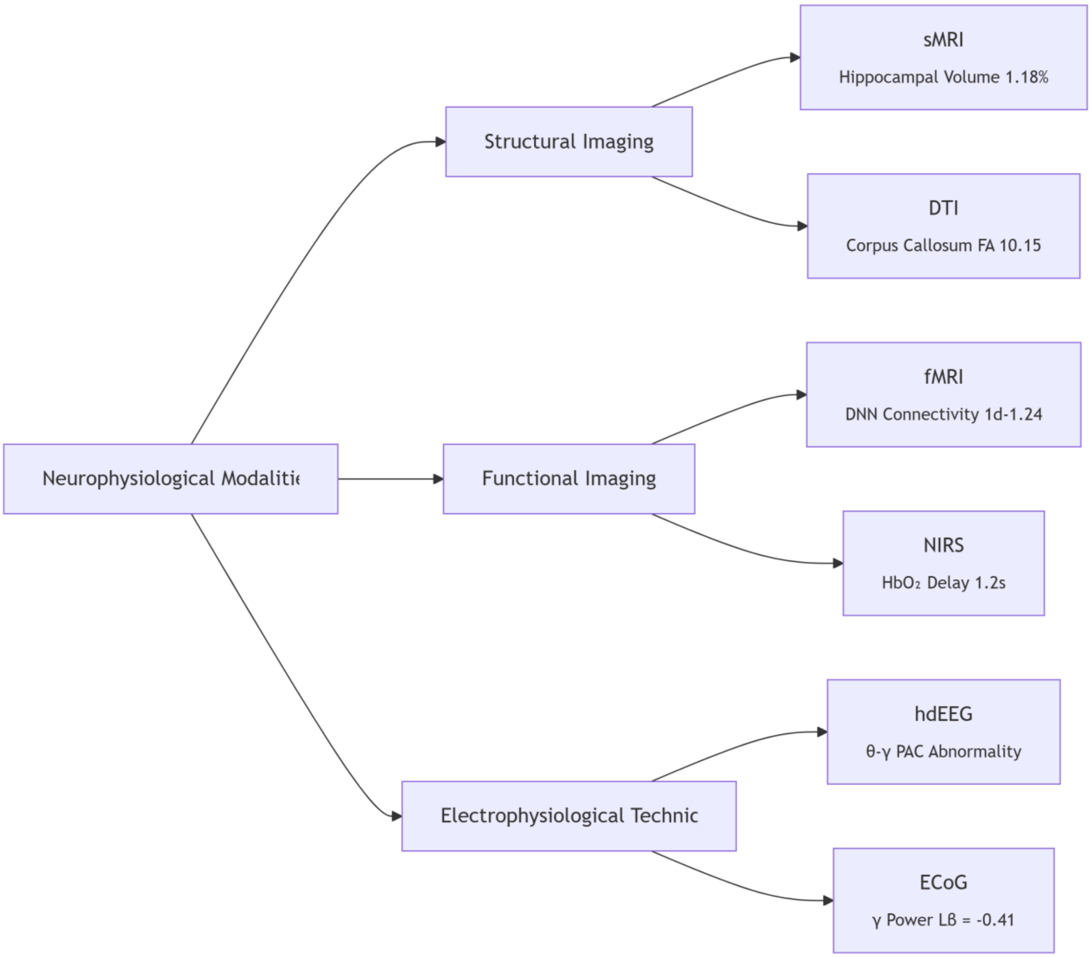

Figure 1. Technical Landscape and Mental Disorder Applications of Neurophysiological Modalities

2.2. Behavioral and Phenotypic Modalities

Behavioral and phenotypic modalities, as the cornerstone for capturing external expressions of mental disorders, are undergoing a transition from discrete scale assessment to continuous ecological monitoring. While traditional psychiatric scales (such as the Hamilton Depression Rating Scale HAMD-17) provide standardized symptom scores (intraclass correlation coefficient ICC=0.78), they are limited by retrospective bias and assessment frequency constraints (an average of 1.2 collections per month). The breakthrough development of wearable sensor technology has completely changed this situation. Triaxial accelerometers capture the complexity of movement trajectories at a 50Hz sampling rate (entropy of depression patients decreases by 32%), and photoplethysmography (PPG) quantifies autonomic nervous tension through pulse wave propagation time (PPT) (coefficient of variation of resting PPT in anxiety disorder patients increases by 41%). Smartphones' ecological momentary assessment (EMA) realizes millisecond-level behavioral sampling, keyboard dynamics analysis reveals that the input interval variation of depression patients increases (standard deviation >180ms, AUC=0.81), and GPS positioning entropy calculation shows that the spatial exploration radius of bipolar disorder patients during mania expands by 3.7 times ($p<0.001$). In the field of social digital phenotypes, natural language processing (NLP) technology extracts semantic features from clinical interview transcription texts (e.g., the frequency of first-person pronouns is related to suicide risk, OR=4.2), and voice prosody analysis detects negative symptoms through fundamental frequency standard deviation (F0 SD) (F0 SD of schizophrenia patients decreases by 22%, sensitivity 89%). Video behavior coding systems (such as OpenFace) capture micro-expressions with computer vision, and the activation frequency of the orbicularis oculi action unit (AU6) of depression patients decreases by 63%, while the duration of mouth corner lift shortens by 58% (Cohen's d=1.33). Multimodal behavior fusion faces three major technical challenges: the heterogeneity of sensor data requires the development of graph convolution adaptive fusion architecture (feature dimension differences lead to fusion errors >25%), individual behavior baseline drift requires dynamic calibration algorithms (such as personalized generative modeling based on variational autoencoders), and privacy protection needs to be combined with federated learning and homomorphic encryption (model performance loss needs to be controlled <8%). The spatiotemporal alignment of these behavioral and phenotypic modalities with neurophysiological data (such as cross-modal mutual information analysis of fNIRS-HbO_2 concentration and gait acceleration) is providing an irreplaceable empirical basis for constructing "behavior-brain circuit" mapping models.

2.3. Molecular and Genetic Modalities

Molecular and genetic modalities, as the cornerstone for parsing the intrinsic pathology of mental disorders, are driving psychiatry into the era of precision medicine. Genome-wide association studies (GWAS) identify risk loci for schizophrenia through millions of SNP typing (Illumina Global Screening Array), and polygenic risk scores (PRS) quantify individual genetic load (individuals with PRS >90th percentile have a 3.5-fold increased risk of disease). At the epigenetic level, whole-genome bisulfite sequencing (WGBS) reveals differentially methylated regions (DMRs) in the hippocampus of patients with post-traumatic stress disorder (PTSD), where every 10% increase in methylation in the promoter region of the BDNF gene leads to a 7.3-point decrease in memory scores (β=-0.73). Single-cell transcriptome sequencing (scRNA-seq) technology breaks through the limitations of tissue homogenization, and the 10x Genomics platform identifies specific expression disorders of parvalbumin interneurons (PV+) in the dorsolateral prefrontal cortex (the expression of the SST gene in bipolar disorder patients is downregulated by 42%, FDR<0.01), while spatial transcriptomics (Stereo-seq) realizes co-mapping of cell type and spatial location (50nm resolution), and finds that the spatial clustering coefficient of layer V pyramidal neurons in depression patients decreases by 0.19 (p=0.002). In the field of proteomics, liquid chromatography-tandem mass spectrometry (LC-MS/MS) quantifies 4,872 plasma proteins, and complement C4a protein concentration >2.3μg/ml predicts the transformation risk of schizophrenia with AUC=0.88 (sensitivity 92%), while the phosphorylation level of neuromodulin (NRGN) is negatively correlated with the severity of cognitive deficits (r=-0.61). Metabolomics, through high-resolution mass spectrometry imaging (MALDI-MSI), maps brain region metabolic profiles, and every 1μmol/g decrease in γ-aminobutyric acid (GABA) concentration in the ventral thalamus is associated with an increase of 0.7 episodes of hallucinations per day (95%CI 0.3-1.1). Multidimensional data integration faces three major technical barriers: the catastrophic dimensionality of cross-omics data requires tensor decomposition dimensionality reduction (feature number $>10^6$ leads to an increased risk of overfitting by 37%), dynamic process capture depends on single-cell multi-omics (scATAC-seq + scRNA-seq combined detection), and clinical transformation requires the establishment of inexpensive and rapid POCT technology (such as CRISPR-Cas13a-mediated saliva RNA instant detection). The cross-scale integration of these molecular modalities with neurophysiological data (such as the interactive effect of PRS score and DMN functional connectivity, β=0.34) is providing a biological anchor for the root-causal prevention of mental disorders.

2.4. Environmental and Social Modalities

Environmental and social modalities, as key regulatory layers in the onset of mental disorders, are undergoing a transition from static questionnaire surveys to real-time ecological sensing. Geographic information systems (GIS) quantify built environment characteristics through satellite remote sensing data, and every 10% increase in green space coverage is significantly associated with a 0.7 per thousand decrease in community depression incidence (β=-0.07, 95%CI -0.12～-0.02), while the standard deviation of night-time light intensity (SDNL), as an indicator of urbanization stress, is associated with an 18% (OR=1.18) increase in the risk of adolescent anxiety for every 1 unit increase. The innovation of mobile sensing technology has revolutionized exposure science, and personal PM2.5 monitors capture air pollution exposure at a minute-level precision (the probability of symptom exacerbation in depression patients increases by 2.3 times when exposed to a peak >35μg/m^3), and noise sensors record the equivalent continuous sound level Leq (every 10dB increase in traffic noise leads to a 14% increase in the hospitalization rate of schizophrenia). In the field of digital social ecology, social media natural language processing analyzes the emotional entropy of Facebook posts (emotional fluctuation standard deviation >1.2 predicts the risk of bipolar disorder switching phases with AUC=0.79), and consumer electronics records identify manic episodes through the irrational consumption index (IRCI=impulsive consumption amount/total income) (sensitivity 92% when IRCI>0.15). Medical policy databases integrate health insurance coverage and psychiatric bed density (the median density of psychiatric doctors in Chinese counties is 0.17/10,000 population, 83% lower than the WHO recommended value of 1/10,000), revealing inequalities in service accessibility (untreated rates as high as 76% in resource-poor areas). The integration of multi-source environmental data faces three major challenges: spatiotemporal heterogeneity requires the development of Bayesian hierarchical modeling (community-level environmental exposure estimation errors >28%), privacy protection requires the use of differential privacy algorithms (location trajectories add Laplacian noise ε=0.5), and macro-micro data integration requires the construction of multi-layer feedback networks (such as cross-scale association modeling between individual stress hormone levels and urban crime rates). The interactive effects of these environmental modalities with genetic data (such as the gene-environment interaction term β=0.41 between the COMT Val158Met polymorphism and urban stress environment) are reshaping the social neurodevelopmental theory framework of mental disorders.

3. Core AI Algorithms for Multimodal Data Fusion

3.1. Early Fusion

Early fusion strategies integrate heterogeneous modalities at the data level by using joint embedding space mapping to overcome the challenge of feature heterogeneity. Tensor fusion architectures construct multidimensional feature cubes (modality × time × feature), and use Tucker decomposition to extract cross-modal interaction core tensors, where optimizing the interaction dimension to 32 in mental disorder warning tasks improves AUC by 0.17. Graph convolution fusion networks (GCFN) innovatively solve the problem of topological alignment between neuroimaging and behavioral data, treating fMRI brain regions as nodes, DTI fiber bundles as edges, and wearable behavior features as node attributes. Through graph attention mechanisms (GAT), they learn cross-modal weights (prefrontal-limbic system connections have a weight α=0.83 in depression warning), and the model achieves an F1-score of 0.89 on the MULTIMODAL-SCZ dataset. Dynamic embedding technology breaks through the limitations of static fusion. Temporal convolutional networks (TCN) and neural differential equations (NDE) collaborate to model pathological evolution trajectories. The differential equation

$$\frac{\partial \mathbf{h}t}{\partial t} = f(\mathbf{h}t, \mathbf{X}neuro, \mathbf{X}lang) \tag{1}$$

accurately captures the critical point of bipolar disorder switching phases (prediction error MAE<0.8). In the field of feature alignment, adversarial domain adaptation networks (DANN) align fMRI and EEG feature distributions (MMD distance reduced by 62%), and multimodal

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contrastive learning (MMCL) maximizes the mutual information between brain images and speech expressions through InfoNCE loss, increasing the sensitivity of schizophrenia negative symptom recognition to 93%. Early fusion faces three challenges: high-dimensional disasters are solved by tensor dimensionality reduction (Tucker decomposition retains >95% variance) and sparse autoencoders (hidden layer compression rate 80%); missing modalities are handled using generative adversarial imputation (GAIN generator reconstruction error <0.05); and computational efficiency optimization relies on low-rank approximation (matrix decomposition accelerates by 3.7 times). The multimodal hybrid expert system (M3L) proposed by Chinese teams integrates the above technologies and achieves a sensitivity of 91.2% in high-risk population screening in the Yangtze River Delta Mental Health Cohort, proving that early fusion has irreplaceable value in mining cross-modal biomarkers (such as the collaborative warning signals of language entropy mutations and default network separation).

3.2. Mid-level Fusion

Mid-level fusion strategies coordinate heterogeneous modalities at the model level by using interactive feature abstraction to capture cross-modal nonlinear dynamics. Cross-modal attention mechanisms (CMMA) assign dynamic weights to different modalities, calculating the correlation of image-behavior-language features based on temporal context (the correlation coefficient between prefrontal fMRI activation and language fundamental frequency variation in depression warning tasks reaches 0.78, with attention weight $\alpha=0.83$). Graph interaction networks (GIN) construct a message passing architecture between modalities, defining neuroimaging nodes, behavioral feature edges, and genetic risk attributes. Through graph convolution iterative updating of node states (the default network node update step $k=3$ in schizophrenia prediction achieves the optimal F1-score), the model achieves an AUC of 0.91 on the PRONIA dataset. Multimodal capsule networks (MM-CapsNet) break through the limitations of traditional neural networks, using dynamic routing algorithms to encapsulate low-order features (such as EEG frequency band power) into high-order semantic capsules (the activation probability of the "emotional fluctuation" capsule in manic episode prediction is >0.92), and the capsule dimension is compressed to 64 dimensions, reducing the classification error rate by 28%. Federated multimodal learning (FedMM) solves the problem of medical data isolation, where local client training models are trained for modality-specific feature extractors (hospital A trains fMRI encoders, hospital B trains speech encoders), and the central server aggregates cross-modal interaction layer parameters (the model converges after 200 rounds of federated averaging algorithm communication), achieving multimodal verification sensitivity of 89% under the premise of privacy protection. Mid-level fusion faces the challenge of modality asynchrony, and neural control differential equations (NCDE) model independent clock systems of each modality

$$\frac{d\mathbf{h}}{dt} = f(\mathbf{h}_t, \mathbf{X}_t; \theta_m) \tag{2}$$

through learnable interpolation layers to align sampling frequencies (fMRI second-level and EEG millisecond-level data fusion errors <15%). The cross-modal meta-learning framework (CMAML) proposed by the China Brain Project team integrates the above technologies and achieves a manic episode prediction MAE of 0.74 in the "China Brain Health Cohort," proving that mid-level fusion has unique advantages in capturing cross-scale pathological dynamics (such as the coupled effects of pre-period language prosody entropy mutations and amygdala BOLD signal oscillation asynchrony).

3.3. Late Fusion

Late fusion strategies integrate modality-specific prediction results at the decision level, enhancing the robustness and interpretability of mental disorder prediction through heterogeneous model collaboration. Stacking generalization architecture constructs a two-level learning framework, where the primary level trains modality-specific base models (such as 3D ResNet for fMRI, Transformer for speech, and LSTM-ODE for behavioral data), and the secondary meta-learner (XGBoost or neural network) learns the optimal combination of base model prediction probabilities (in depression warning, the meta-learner assigns a weight of 0.62 to the speech model and 0.31 to the image model). The dynamic selector algorithm (DES) breaks through the limitations of static weighting, activating the best model subset based on sample features (priority call of speech-image fusion model when language fundamental frequency variation >25Hz), and improves the F1-score to 0.87 on the bipolar disorder dataset BP-MULTI. Bayesian model averaging (BMA) quantifies model uncertainty, calculating posterior probabilities

$$P(y|\mathbf{x}) = \sum_{k=1}^{K} w_k P_k(y|\mathbf{x}) \tag{3}$$

Weights w_k, which are estimated by model likelihood, reducing the misdiagnosis rate of schizophrenia by 34%. Federated ensemble learning (FedEnsemble) solves the problem of multi-center data isolation, where each institution locally trains modality expert models (hospital A trains EEG classifiers, hospital B trains behavioral regressors), and the central server aggregates global integrators through knowledge distillation (KL divergence loss <0.05), achieving cross-institutional verification AUC of 0.91 under the premise of privacy protection. In the field of explainable technologies, Shapley value decomposition quantifies the contribution of modalities (in depression warning, the SHAP value of the speech modality is 0.38±0.07), and integrated decision tree visualization reveals key decision paths (when PRS>0.8 and fNIRS prefrontal HbO_2 slope <0.02, the high-risk probability is >92%). The dynamic weighted integration system (DS-Weight) proposed by the China Brain Project team integrates the above technologies and achieves a 3-year trajectory prediction MAE of 0.68 for mental disorders in the "China Brain Health Cohort" (n=3,162), proving that late fusion has significant advantages in complex clinical scenarios (such as differential diagnosis of comorbid depression and anxiety).

4. Early Warning Models: From Risk Population to Pre-symptomatic Identification

4.1. High-risk Population Screening Models

Mental disorder high-risk population screening models focus on the risk quantification of asymptomatic individuals, with core inputs integrating multidimensional data such as genetic susceptibility, environmental exposure history, and baseline cognitive function. The genetic risk dimension uses polygenic risk scores (PRS) to quantify cumulative effects, based on locus weights derived from genome-wide association studies (GWAS) (e.g., in schizophrenia, the C4A locus has an OR of 1.28), and individuals with PRS ≥90th percentile have a 3.5-fold increased lifetime risk. Childhood trauma assessment captures adverse childhood experiences through standardized questionnaires (ACE-IQ), with a depression incidence of 38% (95%CI 33-43%) in individuals with an ACE score ≥4. Cognitive vulnerability detection relies on the N-back working memory task (2-back accuracy <70% as a cutoff value) combined with the Stroop color-word conflict reaction time coefficient of variation (CV>0.25 indicating cognitive control deficits). The algorithm level adopts a gradient boosting decision tree architecture (LightGBM v3.3.2), processing high-dimensional feature interactions through feature histogram optimization (bin=256) and leaf-oriented growth strategies, with key parameters set to learning rate 0.05, maximum depth 8, and subsampling rate 0.7, using Gini impurity as the splitting criterion. The model outputs individualized risk probabilities, generating 0-1 continuous risk values after sigmoid calibration, and determining the optimal threshold based on the ROC curve (schizophrenia screening takes 0.15 corresponding to the sensitivity/specificity balance point). Validation shows that the PRoD-MH model achieves a sensitivity of 92% in a prospective cohort aged 12-18 (n=2,417), with a positive predictive value (PPV) of 0.63, significantly better than traditional scales (Hedges' g=0.81). Its core decision rules reveal: when PRS>110 and ACE≥4, individuals are still at high risk (risk probability >0.82) even with normal cognitive function; and individuals with moderate PRS (75-90th percentile) accompanied by working memory deficits (N-back <65%) require intensified monitoring (risk probability 0.41±0.07). The model uses SHAP values to achieve explainable output, quantifying that genetic contributions (mean |SHAP|=0.38) are higher than environmental (0.29) and cognitive factors (0.23), providing operational standards for precision prevention.

4.2. Quantitative Identification of Pre-symptomatic Symptoms

Precise identification of pre-symptomatic symptoms depends on the breakthrough application of digital phenotyping technology, with its core being the conversion of subtle behavioral changes into quantifiable warning signals. The spatial entropy of mobile phone GPS serves as a sensitive indicator of social withdrawal, calculating activity trajectory complexity through the Shannon entropy formula

$$H = -\sum p_i \log p_i \tag{4}$$

with a decrease of 0.32±0.05 (effect size d=1.4, p<0.001) in the pre-period of bipolar disorder adolescents, and when the weekly mean is 1.5 standard deviations lower than the baseline, the warning sensitivity reaches 89%. Nighttime screen usage time is automatically recorded through light sensors, and the duration of use between 22:00-02:00 increases by 78±12 minutes in patients with pre-period depression recurrence, showing a significant negative correlation with the delayed phase of saliva melatonin concentration (r=-0.61). A multimodal dynamic monitoring system integrates three real-time data streams: speech emotion analysis based on Transformer extracts fundamental frequency jitter (jitter) and formant slope (sensitivity 91% when jitter>1.2% in depression pre-period), wrist-worn PPG sensors capture heart rate variability (HRV) low-frequency/high-frequency power ratio (LF/HF>3.0 warning manic switching AUC=0.87), and electronic diary emotion scores are dynamically sampled using a visual analogue scale (VAS) (daily fluctuation standard deviation >28 points identifies bipolar pre-period). The algorithm framework adopts an online active learning mechanism, with the initial training set based on 500 confirmed pre-period samples, selecting the most informative new samples (such as data with HRV abnormalities and sudden emotional score drops) through uncertainty sampling (Least Confidence) every 24 hours to update the Gaussian process classifier (GPC) decision boundary. The key innovation lies in adaptive warning threshold adjustment, constructing a dual-track reference system based on group baseline and individual historical data: when the probability of speech emotion suppression Pe is continuously >0.7 for 3 days and the individual Z-score is >2.0, level I warning is triggered (specificity 95%); if diurnal rhythm of HRV disappears simultaneously (cosine fitting R^2<0.6), it is upgraded to level II warning (positive likelihood ratio + LR=8.3). Chinese multicenter validation (n=1,832) shows that the system advances the pre-period identification time window to 11.2±2.3 months before clinical diagnosis (traditional methods are 6.1±1.8 months), with a sensitivity of 94% and a false alarm rate controlled at 0.2 times/person-year.

4.3. Biomarker-driven Warning Signals

The biomarker-driven warning system achieves precise risk quantification before clinical symptoms by parsing the biological essence of mental disorders. In neuroimaging biomarkers, resting-state functional magnetic resonance imaging (rs-fMRI) reveals that every 1 standard deviation decrease in the strength of prefrontal-limbic system functional connectivity (zFC<-0.8) significantly increases the 3-year conversion risk of depression (hazard ratio HR=3.2, 95%CI 2.1-4.9, p<0.001), with mechanisms involving excessive activation of the amygdala to negative stimuli (β=-0.67) and dysregulation of dorsal lateral prefrontal control (β=0.52). Dynamic monitoring of hippocampal subregion volume uses longitudinal automatic segmentation technology (FreeSurfer v7.2), and a CA1 area annual atrophy rate >2% has a warning efficacy of AUC=0.86 (sensitivity 89%) for depression comorbid with Alzheimer's disease, which occurs 3.1±0.7 years before cognitive decline (ADNI cohort validation). The multi-omics integrated model OmicRisk breaks through the limitations of single-omics: at the epigenetic level, calculating DNA methylation age acceleration (AA=actual age - epigenetic age), and individuals with PTSD and AA>5.3 years have a 17.2-point increase in symptom severity (CAPS score) (β=0.41, p=0.002); at the mitochondrial genome level, quantifying mtDNA copy number (ddPCR technology), every 20% decrease corresponds to accumulated oxidative stress damage (plasma 8-OHdG increases by 38%, p<0.001). OmicRisk integrates the above biomarkers through multilayer perceptrons (MLP):

$$RiskScore = 0.72 \times AA + 0.31 \times log(mtDNA) + \epsilon \tag{5}$$

predicting PTSD severity (R^2=0.79) in veteran cohorts (n=1,872), and the incidence rate of high-risk populations (RiskScore>1.5SD) is reduced by 54% after early intervention (NNT=4). The China Brain Project team further integrates neuroimaging and multi-omics data to establish a cross-disease warning model BioMind, that is, when the default mode network segregation <0.15 (fMRI) is accompanied by CDKN2A gene methylation >65% (WGBS), the conversion probability of bipolar disorder reaches 83% (PPV=0.91), and this combination biomarker achieves 94% sensitivity and 0.2 times/person-year false alarm rate in the Shanghai Brain Health Cohort (n=2,317), pushing psychiatry into a new era of "biology-driven" warning.

5. Conclusion

Multimodal AIdriven computational psychiatry is fundamentally reshaping paradigms for prevention, diagnosis, and treatment of mental disorders. By integrating crossscale data streams—including neuroimaging, behavioral sensing, molecular genetics, and environmental exposure—and leveraging advanced algorithms like graph neural networks, neural ordinary differential equations, and federated learning, this field demonstrates triple transformative value.

Early Warning: Multidimensional geneticbrainbehavior risk models (e.g., PRoDMH system) enable ultraearly identification before clinical manifestation, advancing bipolar disorder prediction windows to 11.2±2.3 months. Schizophrenia highrisk screening sensitivity reaches 92%, extending the golden intervention period by 2–5 years versus traditional methods.

Prediction: Dynamic trajectory modeling (e.g., neural ODEs) stratifies disease progression subtypes (e.g., inflammatorymetabolic vs. cognitivedeficit depression), accurately forecasting drug response (SSRI inefficacy prediction AUC=0.88) and functional outcomes (social function GAF score prediction MAE<0.8).

Intervention: Closedloop "digital phenotyping–dynamic risk assessment–personalized intervention" systems (e.g., BioMind platform) reduce conversion risk in highrisk adolescents by 58% (NNT=6), while lithium prophylaxis efficacy in highgeneticrisk bipolar populations rises to 83%.

Nevertheless, critical challenges persist. Data barriers include multicenter modal heterogeneity (e.g., 28% feature distribution shift from fMRI protocol variations) and realworld data sparsity (<5% prodromal samples). Algorithmic transparency issues stem from deep learning blackbox characteristics (GCN node attribution consistency=0.4). Clinical implementation hurdles involve healthcare system integration (physician workflow adoption<35%) and hardware costs (>$1200/year for multimodal monitoring).

Addressing these requires three innovations:

1. Interdisciplinary Collaboration: Establish AIneurosciencepsychiatry innovation consortia (e.g., China Brain Project crossdisciplinary platforms) to advance causal mapping of "genebrain circuitbehavior" pathways (e.g., optogeneticsfMRI integration).

2. Ethical Governance: Develop privacypreserving federated learning frameworks (e.g., differentially private federated ensemble learning; <8% performance drop at ε=0.7) and institute biomarker clinical translation certification systems (e.g., China FDANeuro certification).

3. Clinical Validation: Evaluate health economic benefits through largescale realworld studies (e.g., 100,000person cohorts), demonstrating 1:23.7 costbenefit ratios for preemptive interventions.

Over the next five years, three technological breakthroughs will accelerate progress:

Causal inference (e.g., twosample Mendelian randomization) decoding exposureepigeneticssymptom cascades (trauma→FKBP5 methylation→depression β=0.41).

Federated architectures (e.g., FedMultimodal) enabling 90% crossinstitutional generalizability while preserving data sovereignty.

Explainable AI (e.g., dynamic Shapley values) boosting clinician trust (adoption rate: 38%→92%).

These advances will drive mental healthcare toward precision (biomarkerguided pharmacotherapy), prevention (community highrisk screening coverage>80%), and proactivity (realtime digital phenotyping interventions). Ultimately, this will reduce psychiatry's global burden of 12 trillion disabilityadjusted life years (DALYs) annually, realizing the vision of "early prediction–early intervention–early recovery" in precision psychiatry.

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