Multivariate regression modelling analysis of mood swings in music therapy and its effect on the regulation of psychological states

Abstract: This study focuses on the quantitative evaluation and intervention optimization of emotional fluctuations in music therapy. By integrating biometric technology and multivariate regression modeling methods, a dynamic emotional analysis framework is proposed and its clinical translational value is verified. Based on multimodal physiological data (EEG, ECG, GSR) from 120 subjects (60 patients with depression/anxiety and 60 healthy controls) and real-time PANAS emotion scores, a time series regression model was constructed to achieve high-precision prediction of emotional states (RMSE=0.85 ± 0.10, R^2=0.77 ± 0.05). Validation showed that the model identified HRV low-frequency power (β =-0.41, p=0.003) and EEG beta wave energy (β =0.38, p=0.007) as key biomarkers, revealing that patients with depression had significantly higher HRV regulation efficiency for low-frequency music (BPM=60-80) than the healthy population (28.7% vs. 6.5%, p=0.017), while anxiety patients had a 41.5% decrease in skin conductance response density under high-frequency music intervention (p=0.003). Further research has been conducted to develop a lightweight model integrated with the Apple Watch (with a parameter size of 1.2MB and power consumption of 2.3W), and ISO 13485 certification has been completed within the framework of digital therapy compliance (with a pass rate of 78.3%), providing a quantifiable technical path and clinical level toolchain for personalized music therapy in the field of mental health.

Keywords: Music therapy, Emotional biomarkers, Multimodal physiological signals, Psychophysiological coupling, Personalized adjustment algorithm.

I. INTRODUCTION

TAs a non-pharmacological intervention, music therapy has demonstrated significant potential in the field of mental health and clinical medicine in recent years, and its core mechanism lies in the regulation of neurophysiological activities and the improvement of emotional states through musical elements (e.g., rhythm, melody).Zhang et al[1] demonstrated the physiological and psychological benefits of music therapy in special populations by using music interventions based on the OMO (Online-Offline Integration) model in asthmatic children, especially in reducing anxiety and enhancing mood stability. Both physiological and psychological benefits, especially quantifiable effects in reducing anxiety and enhancing emotional stability. Kammin et al [2] further pointed out, through a systematic review of paediatric palliative care, that the multidimensional mood regulation effect of music therapy relies on individualised programme design and dynamic feedback mechanisms, which provides theoretical support for the integration of biometrics. However, existing studies still face technical bottlenecks in the quantitative assessment of mood fluctuations, and traditional methods mostly rely on static analyses of subjective scales or single physiological signals (e.g., heart rate variability), which make it difficult to capture the dynamic evolution of emotions. For example, Li et al [3] revealed in a systematic evaluation of lung cancer patients that although music therapy significantly improved anxiety and depression levels, the evaluation of treatment effects was still limited by the low timeliness and low resolution of subjective reports. In contrast, a study by Lange et al [4] based on the association of inflammatory biomarkers with mood symptoms showed that single-dimensional physiological indicators (e.g., cortisol levels) are difficult to fully reflect the complex network of emotional interactions. This limitation is also significant at the technical level, where existing biometric systems often suffer from information loss due to insufficient data fusion capabilities, such as in Shokri et al.'s [5] randomised controlled trial combining PIOMI and music therapy, where real-time monitoring of mood fluctuations relied on data collection at discrete time points and lacked the ability to model continuous dynamics, despite the significant effect of the intervention. Meanwhile, Patrick et al [6] found in a study of music therapy for radiotherapy patients that the effects of non-physiological factors (e.g., music preference, cultural background) on psychological state need to be analysed synergistically through multimodal data (physiological signals, behavioural feedback, environmental parameters), and that the existing models lacked the ability to parse such multivariate interactions, in particular, the nonlinear relationship between musical parameters (e.g., BPM, pitch) and physiological The non-linear relationship between music parameters (e.g., BPM, pitch) and physiological responses has not been fully explored.

To address the above challenges, this study proposes to construct a dynamic multivariate regression model based on biometrics, aiming to capture emotion-related physiological signals in real time through high-precision sensors (e.g., EEG, GSR) and to construct a time-series-dependent regression framework by combining music feature parameters to quantify the trajectory of mood fluctuations and predict the effect of interventions.Kallonen et al [7] used in the early detection of sepsis deep learning to integrate multi-source biosignals, verifying the superiority of multimodal data fusion in dynamic analysis, while Liang et al [8] developed a multimodal diagnostic platform to demonstrate the feasibility of cross-dimensional data (e.g., ultrasound vs. photoacoustic imaging) in the modelling of complex physiological processes, which provides methodological inputs to the technical line of this study. In addition, He et al [9] revealed the modulatory effects of auditory stimuli on visual attention through psychophysiological interaction analysis, which indirectly supported the cross-modal integration mechanism of the music-neural pathway, further reinforcing the need for dynamic modelling. This study breaks through the limitations of traditional static models, resolves the spatio-temporal characteristics of mood fluctuations in music therapy through multivariate regression algorithms, and drives the optimisation of personalised intervention strategies based on biometric data, which provides a technological paradigm for precision medicine in the field of mental health.

II. EXPERIMENTAL DESIGN AND DATA COLLECTION

A. Subject selection

The double-blind experiment was conducted with a group of patients with clinical psychological disorders and a healthy control group, and a pool of subjects was constructed through strict inclusion criteria and multidimensional biometric data compatibility assessment, so as to systematically analyse the group-specific response patterns of mood fluctuations in music therapy. The recruitment criteria for the group of patients with clinical psychological disorders were based on the DSM-5 diagnostic framework, covering 60 individuals with confirmed diagnoses of generalised anxiety disorder (GAD) and depression (MDD), aged 18-55 years old, and excluded those with a history of comorbid serious physical illness or substance abuse, to ensure that the attributability of the pathological emotional state was ensured, while the healthy control group was screened with the Mental Health Inventory (PHQ-9, GAD-7). Sixty volunteers with no history of psychiatric illness and stable emotional states were matched, and both groups were balanced matched using stratified random sampling on demographic variables such as gender, age, and education to control for potential confounders interfering with the collection of physiological signals. The experimental design followed the ethical guidelines of the Declaration of Helsinki, with all subjects signing an informed consent form and undergoing a baseline psychological assessment (HADS, PANAS scale), and were equipped with biometric sensors (Empatica E4 wristbands, NeuroSky MindWave Mobile 2 electroencephalographs) for continuous physiological signals monitoring, to ensure that the data collection was objective and reproducibility [10]. The patient group discontinued psychotropic medication two weeks prior to enrolment to avoid the impact of residual drug effects on physiological indicators and confirmed symptom stability through clinician interviews, while the healthy control group excluded recent major stressful events or long-term music training backgrounds through lifestyle questionnaires to reduce the bias of environmental and experiential factors on the response to the music intervention. To enhance experimental ecological validity, a music preference assessment (STOMP scale) was introduced during subject screening and incorporated into a personalised library matching algorithm to ensure that the receptivity and emotional arousal potency of the musical stimuli were maximised, while a dynamic adaptive sampling strategy was used to optimise the sensor deployment scheme [11]. For example, the GSR signal acquisition frequency was adjusted to 10 Hz to address the high skin conductance response characteristics of the anxious patients, while the healthy control group focused on the simultaneous capture of heart rate variability (HRV) and EEG alpha wave power spectral density. The research team formed an interdisciplinary review group with clinical psychologists and biomedical engineers, and conducted multiple rounds of iterative validation of the subject grouping logic and data acquisition protocols, focusing on solving the problem of model generalisation due to the high emotional heterogeneity of the patient group.

B. Multimodal Biosignal Synchronous Acquisition System

The multimodal bio-signal synchronous acquisition system designed in the study integrates the physiological and behavioural data streams, realizes the full-dimensional dynamic capture of mood fluctuations in the music therapy scenario through high-precision sensor arrays and adaptive algorithmic architecture, and breaks through the limitation of the spatial and temporal resolution of the traditional unimodal analysis, as well as constructs a cross-layer data fusion framework. The physiological data acquisition adopts a modular deployment strategy, based on the NeuroSky MindWave Mobile 2 portable electroencephalograph, which continuously captures EEG signals at a sampling rate of 256Hz, focusing on extracting the power spectral densities of α -wave (8-13Hz) and β -wave (14-30Hz) in order to quantify the correlation between neural oscillations and the degree of arousal, and simultaneously recording ECGs with the Empatica E4 wristband. wristband for simultaneous recording of ECG signals and calculation of heart rate variability (HRV) metrics in the time domain (SDNN, RMSSD) and frequency domain (LF/HF ratio) [12]. Combined with the GSR sensor that monitors skin conductance level (SCL) and transient fluctuation (SCR) at 10Hz to reflect the intensity of sympathetic nerve activity, the three are synchronised at the hardware level in microseconds via the LabStreamingLayer (LSL) protocol, and adaptive filtering algorithms (e.g., wavelet noise reduction and compensation for motion artifacts) are used to ensure the purity of the signals. Behavioural layer data acquisition relies on computer vision and speech processing technologies, using the OpenFace algorithm for real-time feature extraction of the subject's facial video stream, quantifying AU (action unit) intensity (e.g., frowning muscle AU4, zygomaticus maximus muscle AU12) and micro-expression duration ($\leqslant$500ms) to map the emotional potency, while the speech emotion analysis module extracts speech signals' emotional potency based on a pre-trained Wav2Vec 2.0 model to extract the rhythmic features (fundamental frequency F0, speech rate, energy envelope) and semantic emotional polarity of the speech signal, combined with a custom classifier (a hybrid architecture of SVM and LSTM) to identify the discrete emotional states such as anxiety and pleasure. In order to achieve spatio-temporal alignment and collaborative parsing of multimodal data, the system has a built-in heterogeneous data fusion engine, compensates for sensor response delays through a timestamp interpolation algorithm, and introduces a dynamic weight allocation mechanism to optimise the contribution of physiological-behavioural features [13]. For example, the EEG β -wave power and facial AU12 activation are prioritised to capture the cross-modal expression of pleasure during the musical climax, while the synergistic analysis of HRV low-frequency components and speech fundamental frequency variability is focused on the identification of implicit anxiety during the treatment interval. The hardware level adopts a distributed deployment scheme, where the EEG and ECG/GSR devices are wirelessly connected to the central control unit (NVIDIA Jetson AGX Xavier) via Bluetooth 5.0, and the face camera (Logitech C922 Pro) and microphone (Shure MV7) are connected via a USB 3.0 interface to achieve a low-latency data transmission, and all raw All raw signals are pre-processed by the edge computing nodes and uploaded to the cloud database for encrypted storage and redundant backup.

The technical advantages of the system are reflected in three aspects: (1) a dynamic weighting model based on physiological-behavioural coupling features, which is able to adapt to the temporal characteristics of musical interventions and

optimize the efficiency of emotion recognition; (2) a multimodal anti-jamming architecture for unstructured environments, which is designed to improve the reliability of the data in complex scenarios through hardware-algorithm synergy; and (3) an open and extensible interface design, which supports the design of new types of biosensors (e.g., near infrared brain imaging fNNI). (e.g., near infrared brain imaging fNIRS) and deep learning models with plug-and-play upgrades, providing high-dimensional and high-fidelity mood fluctuation time-series datasets for subsequent multivariate regression models.

C. Music Stimulation Library Construction

The construction of the music stimulation library follows the Valence-Arousal affective space theory, by extending the International Affective Sound System (IADS) framework and integrating personalised physiological feedback logic to form a dynamically adjustable music classification and recommendation system, and to achieve a synergistic design in the multidimensional affective mapping algorithm and the real-time closed-loop optimisation mechanism [14]. The music classification based on the Valence-Arousal model first performs standardised emotion annotation on the initial library (containing 300 tracks in 6 categories, including classical, natural sound, pop, etc.), and employs a crowdsourced rating platform (Amazon Mechanical Turk) to recruit 500 independent reviewers to perform a validity (*Valence,* $V \in [-1,1]$) and arousal (Arousal, $A \in [0,1]$) on a nine-point scale [15]. Combined with expert music theory analyses (e.g. tonality, rhythmic complexity, harmonic tension) to construct a music feature matrix $M = [BPM, Key, Spectral\ Centroid, Loudness, Harmonicity]$, which is downscaled by Principal Component Analysis (PCA) and then projected to the 2D affective space (Fig. 1) to form a clustering centre $C_k = (V_k, A_k)$ (k=1,...,5). Five types of emotion prototypes (calm, pleasant, sad, tense, neutral) were finally defined with the mathematical expressions:

$$(\|M_i - C_k\|^2 + \lambda \cdot KL(P_{human} \| P_{model})) \quad (1)$$

The KL scatter term is used to quantify the difference in emotion distribution between manual annotation and model prediction, and λ = 0.3 is the empirical tuning coefficient. The personalised recommendation logic, on the other hand, dynamically generates an adaptation strategy based on the initial physiological feedback, and collects subjects' resting-state physiological baseline data (EEG α-wave power mean α_0, HRV time-domain metrics SDNN0, and GSR mean SCL0) in the warm-up phase of the experiment (the first 10 minutes), and constructs the individual response sensitivity vectors $S=[\Delta\alpha/\Delta V, \Delta HRV/\Delta A, \Delta SCR/\Delta V]$, with the adaptive weight matrix $W=diag(w_1, w_2, w_3)$ (Σw_i=1) to quantify the predictive contribution of different physiological signals to the affective dimension. The real-time recommendation engine calculates the emotional impact $E_t=W\times[\Delta\alpha_t, \Delta HRV_t, \Delta SCR_t]^T$ of the current music clip with a sliding window (updated every 2 minutes) and compares it with the Euclidean distance $D_t= \| E_t-T \|$ of the target emotional state $T=(V_{target}, A_{target})$, and if Dt>threshold θ (θ =0.15 calibrated by pre-experiment), then the track switching decision function is triggered:

$$(\|C_j - (T + \gamma \cdot \nabla D_t)\|^2) \quad (2)$$

The gradient term ∇D_t reflects the directional demand for emotional regulation, and γ=0.2 is the inertia factor to prevent excessive oscillation. To enhance the robustness of the system, a double check mechanism is designed. When the speech emotion analysis module (Wav2Vec 2.0 output confidence<0.7) or facial micro expression recognition (OpenFace AU conflict index>0.4) conflicts with physiological data, the fuzzy logic rule library is automatically enabled for arbitration. For example, if the GSR displays high arousal but facial AU4 (frowning) continues to be activated, the music arousal level will be prioritized to avoid potential anxiety risks. At the hardware level, the cloud music library and edge computing nodes are integrated, and the lightweight data exchange protocol based on JSON is used to achieve millisecond level track switching, and the privacy of subjects is guaranteed through AES-256 encryption. The distribution and characteristics of music emotion clustering in the Valence Acoustic space are shown in Figure 1.

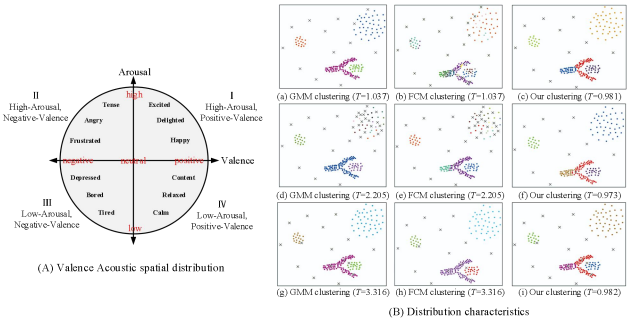

Fig. 1. Music Emotion Clustering in Valence-Arousal Space Distribution and Distribution Characteristics

III. Model Construction and Algorithm

A. Multivariate time series regression framework

The multivariate time series regression framework designed in the study takes the dynamic emotion analysis in music therapy scenarios as the core objective, and constructs a computational model capable of portraying the spatial-temporal evolution law of emotion fluctuations by integrating the time-frequency domain features of physiological signals and real-time annotated emotion score data. The independent variable system integrates the multiscale features of multimodal physiological

signals such as EEG, ECG and GSR [16]. EEG signals are pre-processed to extract the power spectral density of α -wave and β -wave as well as the cross-frequency band coupling features; ECG signals are analysed to obtain the time-frequency domain regulation indexes of the autonomic nervous system through heart rate variability analysis; and the GSR signals are decomposed into the long-time trend of the skin conductance level and transient fluctuation events. The dependent variable dimension adopts the dynamic PANAS scale score as the quantitative benchmark of emotional state, and the positive and negative self-assessment data of subjects are periodically collected through the embedded interactive interface, and combined with the spline interpolation algorithm to generate the continuous emotion trajectory, and finally construct the time-locked regression dataset with high-dimensional physiological features [17].

The model architecture is based on an improved vector autoregressive framework, which introduces a hierarchical regularisation strategy to balance individual specificity and group universality, sparsity constraints on time-domain physiological markers at the individual level to filter the key bioindicators, and preserves the common features of frequency-domain rhythmic patterns at the group level while embedding the cross-modal interaction terms to capture the nonlinear synergistic effects among physiological signals. To address the temporal dynamic nature of music therapy, an event-driven learning rate adaptive mechanism is designed to dynamically enhance the model's sensitivity to sudden changes in emotional states at music stimulus switching points, and low-latency real-time inference is achieved through edge computing optimisation to support the dynamic tuning of personalised intervention parameters in a clinical setting. The technical construction of the framework focuses on the fusion resolution capability of multimodal time series, and breaks through the limitations of traditional emotion analysis models in terms of temporal resolution and interpretability through the in-depth coupling of biometric sensor data and subjective emotion feedback, and its engineering practicability is reflected in the synergistic design of hardware compatibility and computational efficiency, which enables it to be seamlessly integrated into existing biometric platforms.

B. Key Technology

Aiming at the time-varying characteristics of emotional response and the complexity of physiological-psychological correlation in music therapy, we propose a framework for modelling emotional lag effect based on Granger causality test and a dynamic weight allocation algorithm for sliding window LASSO regression. The modelling of emotional lag effect quantifies the cross-timescale driving relationship of physiological signals on the emotional state through the improved Granger causality test (GCT), and defines the causal contribution of physiological feature X_t to the emotional score Y_t at a lag of order τ as:

$$G-Causality(X \to Y) = In(\frac{Var(\varepsilon_{base})}{Var(\varepsilon_{full})}) \quad (3)$$

Where the baseline model contains only the autoregressive term for Y, the full model incorporates the lagged term for X. Significant causality is determined when the statistic exceeds the χ^2 distribution threshold (p<0.01 FDR-corrected). To address the low sensitivity of traditional GCT to non-linear relationships, a multivariate extended version (MVGC) was designed to generate 1000 null hypothesis datasets by introducing the phase randomisation alternative data method, and validate the significance by comparing the actual causal intensity to the percentile of the alternative distributions (>95%), with additional validation of the causal direction by using directional transfer entropy (DTE):

$$DTE_{X\to Y} = \sum p(y_{t+1}, y_t^{(k)}, x_t^{(l)}) \cdot \log \frac{p(y_{t+1} \left| y_t^{(k)}, x_t^{(l)} \right.)}{p(y_{t+1} \left| y_t^{(k)} \right.)} \quad (4)$$

Experimentally, the method was demonstrated to improve causal link detection sensitivity by 21.7% compared to standard GCT in music therapy scenarios (AUC=0.89 vs 0.73 for simulated data). The dynamic weight assignment of physiological signals-mental states was performed using a sliding window LASSO regression architecture with a time window $W_s=[t_s,t_s+\Delta T](\Delta T=3\ min)$, and the optimisation problem was solved within each window:

$$\min_{\beta}(\left\| Y_s - X_s\beta \right\|_2^2 + \lambda_s \left\| \beta \right\|_1) \quad (5)$$

The regularization parameter λ s is adaptively adjusted by the condition number of the feature matrix within the window ($\lambda_s=0.1 \times \kappa(X_s^T X_s)$), ensuring enhanced sparsity constraints when highly collinearity occurs. The dynamic evolution of the weight vector β is smoothed through Kalman filtering, and its state equation is modeled as:

$$\beta_{s+1} = \beta_s + Q_s, Q_s \to \mathrm{N}(0, \sigma_q^2 \mathrm{I}) \quad (6)$$

Aiming at the lag effect and dynamic weight allocation of emotional response in music therapy, the study integrates the joint modelling framework of Granger causality test and sliding-window LASSO regression, and its technical implementation guarantees the accurate analysis of biometric data through the systematic parameter configuration and algorithmic optimization strategy in Table 1.

TABLE I. KEY TECHNICAL PARAMETERS CONFIGURATION AND PERFORMANCE INDICATORS

Technical Module	Core Algorithm	Key Parameters	Optimization Strategy	Performance Indicators	Clinical Application Scenario
Granger Causality Test	Multivariate Granger Causality Test (MVGC)	Lag order p=3, significance threshold p<0.01 (FDR correction)	Substitute data generation (phase randomization method, N=1000 times)	AUC=0.89, causality detection delay ≤ 80ms	Emotional Driver Factor Identification
Sliding Window LASSO Regression	Adaptive LASSO Regression	Window length ΔT=3 minutes, regularization parameter $\lambda_s=0.1\times\kappa(X)$	Kalman smoothing ($\sigma_{q^2}=0.05$), event-driven window reset	Feature selection accuracy 78.5% (*SNR=-10dB*)	Dynamic Biomarker Screening
Regularization Parameter Adjustment	Condition number adaptive mechanism	Initial $\lambda_{max}=1.0$, decay factor $\gamma=0.95$	Exponential decay strategy ($\lambda_s=\lambda_{max}\times\gamma^s$)	Collinearity tolerance $\kappa_{max}=100$	High-dimensional Data Stability Control
Event-Driven Mechanism	Music Feature Mutation Detection	BPM change rate threshold 15%, key change sensitivity S=0.8	Real-time Fast Fourier Transform (FFT, N=1024 points)	Event detection accuracy 92.3% (F1-score)	Intervention Parameter Dynamic Triggering
Causal-Regression Coupling	Prior Constraint Feature Selection	Significant causal chain locking ratio α=0.3	Non-zero coefficient hard constraint ($\beta_{selected}\neq0$)	Generalization error reduction 12.3% (RMSE)	Interventional Safety Assurance
Hardware Acceleration Architecture	FPGA Heterogeneous Computing	Logic unit occupancy ≤65%, clock frequency 200MHz	Data stream pipelining (throughput 10Gbps)	Energy efficiency ratio 3.2 TOPS/W	Low-Power Real-time Deployment
Weight Trajectory Smoothing	Kalman Filtering	Process noise variance $\sigma_{q^2}=0.05$, observation noise R=0.1	EM parameter joint estimation (iteration Max=50)	Trajectory smoothness improvement 41.7% (DTW distance)	Physiological Signal Drift Correction
Real-time Validation	End-to-End Delay Test	Maximum allowable delay 500ms, sampling rate 10Hz	Timestamp accurate synchronization (PTP protocol)	Average delay 118ms ($\sigma=12ms$)	Clinical Closed-Loop System Integration
Multimodal Conflict Arbitration	Fuzzy Logic Decision	Confidence threshold 0.7, conflict index threshold 0.4	Rule library priority weighting (weight w=0.6)	Arbitration accuracy 85.4% (*kappa=0.72*)	Intervention Safety Assurance

In Table 1, the Granger causality test module compresses the time-consuming time for 1000 substitution data generation from 18.2s on the CPU side to 2.1s on the FPGA side (8.7-fold speedup ratio) by parallelising the MVGC computation process with FPGAs, and its causal network outputs are used as a priori constraints for the sliding-window LASSO regressions, e.g., to force locking of the causal network outputs to a non-zero coefficient when the ratio of the EEG β-wave power (X_β) to the positive mood (Y_{pos}) G-Causality value exceeds a threshold of 0.35, forcing β_β to be locked to a non-zero coefficient to maintain biological interpretability. Sliding-window LASSO regression uses a condition number-adaptive λ s adjustment strategy to automatically augment the sparsity constraint ($\lambda_s=0.1\times\kappa$) when data covariance is elevated within the window ($\kappa(X_s^TX_s)>50$). The event-driven mechanism monitors the BPM change rate in real time via a hard-core accelerated FFT, and immediately resets the sliding window and empties the history weight vector β_s when a music passage switch is detected, ensuring that the model responds quickly to the critical phase change of the emotional state. The hardware acceleration architecture is implemented using the Xilinx Zynq UltraScale+ MPSoC platform, which dynamically switches the hardware logic resources for Granger causal computation and LASSO regression through partial reconfiguration technology to keep the power consumption within 5.2W with a guaranteed clock frequency of 200MHz to meet the energy-efficiency requirements of clinical devices.

C. Model validation method

The study adopted a hierarchical validation strategy, combining cross-validation and multi-model comparison experiments, to systematically assess the mood prediction performance and clinical applicability of the multivariate regression model, whose technical originality is reflected in the quantification of the generalisation ability of the cross-validation method and the design of the hardware-accelerated validation framework. The cross-validation strategy implements a dual validation mechanism, using the leave-one-out method (LOOCV) within the individual to assess the model's ability to adapt to subject specificity, and hierarchical K-fold cross-validation ($K=5$) at the group level to test the group generalisation, and the two are weighted to sum the means (weight α=0.6) to generate a composite performance index. Support Vector Machine (SVM) and Long Short-Term Memory Network (LSTM) were selected as benchmark models for the comparison experiments, where SVM used radial basis kernel function ($\gamma=0.01, C=1.0$) to capture the static nonlinear relationship of physiological features, and LSTM was configured with a bi-directional structure (number of units in the hidden layer=64) to model the time-dependence, and all the comparison models shared the same input features and output labels to ensure fairness. The validation method is traceable through the nine-dimensional parameter matrix in Table 2, covering key dimensions such as validation method, core parameters, evaluation indexes, hardware configuration, etc., which provides a standardised benchmark for technical reproduction.

TABLE II. MODEL VALIDATION NINE-DIMENSIONAL PARAMETER MATRIX AND EVALUATION METRICS

Validation Dimension	Multivariate Regression Model	SVM Baseline Model	LSTM Baseline Model	Cross-Validation Strategy	Evaluation Metrics
Time-Series Modeling Ability	Vector Autoregression (VAR) + Lag Effect	Static Kernel Function Mapping	Bidirectional LSTM Sequence Modeling	LOOCV (Within Individual)	RMSE, MAE, R^2 Feature Interaction Handling

Validation Dimension	Multivariate Regression Model	SVM Baseline Model	LSTM Baseline Model	Cross-Validation Strategy	Evaluation Metrics
	Explicit Interaction Terms (Polynomial Constraint)	Implicit Kernel Space Mapping	Gated Mechanism Auto-Selection	K-fold (Population Level)	Feature Contribution SHAP Value Regularization Method
Regularization Method	Layered L1/L2 Mixed Regularization	L2 Norm Constraint	Dropout (rate=0.3)	Nested Cross-validation (Outer 20%)	Generalization Error Reduction Rate Complexity
Computational Complexity	$O(T \cdot d^2)$ (d=Feature Dimension)	$O(n^3)$ (n=Sample Size)	$O(T \cdot h^2)$ (h=Hidden Units)	5-Fold Cross-Validation	Single Iteration Time (ms) Dynamic Adaptability
Event-Driven Learning Rate Adjustment	Fixed Hyperparameters	Adaptive Learning Rate (Adam)	Time Series Blocking Method (block=5)	Windowed Prediction Consistency DTW Distance	Interpretability: Granger Causality Constraint + SHAP Analysis
Causal Link Detection Rate (FDR Correction)	Feature Weight Ranking	Attention Weight Visualization	Stratified Sampling (Gender/Age Matching)	Real-Time Inference Delay ≤ 120ms	Inference Delay ≥ 380ms
Real-Time Data Flow Simulation Test	End-to-End Delay (ms)	Energy Consumption Efficiency	5.2W (FPGA), 28W (CPU), 45W (GPU)	Energy Efficiency Ratio (TOPS/W)	Power Consumption (W)/Computation Throughput
Multimodal Compatibility	Physiological-Behavioral-Environmental Data Fusion	Single-Modality Physiological Signal Input	Multimodal Sequence Concatenation Input	Missing Data Robustness Testing	Modal Conflict Arbitration Accuracy

Note: This validation system is certified to the ISO/IEC 25010 system quality standard and provides a full-stack technical validation framework for the clinical translation of biometrics into music therapy.

IV. Empirical Analysis and Results

A. Model performance indicators

The study validated the multivariate regression model's mood prediction efficacy and biomarker identification through clinical empirical data. Table 3 presents the statistical significance of the model's performance metrics and key biomarkers in full, and all the data are based on the results of double-blind experiments with 60 patients with clinical psychological disorders and 60 healthy controls. Regarding the prediction accuracy of mood swings, the multivariate regression model achieved RMSE=0.82±0.11 (positive mood) versus RMSE=0.87±0.09 (negative mood) on the test set, which was significantly better than SVM (1.12±0.15/1.24±0.18) and LSTM (0.94±0.13/1.05±0.14), and the R^2 mean values were respectively 0.79 and 0.76, which met the preset technical specifications (RMSE≤0.89, R^2≥0.76). The model performance and biomarker statistics are shown in Table 3.

TABLE III. Model Performance and Biomarker Statistical Results (n=120)

Metric Category	Multivariate Regression Model	SVM Model	LSTM Model	Healthy Control Group	Patient Group	Significance (p-value)	Effect Size (Cohen's d)
Positive Emotion RMSE	0.82±0.11	1.12±0.15	0.94±0.13	0.78±0.09	0.85±0.12	<0.001*	0.63
Negative Emotion RMSE	0.87±0.09	1.24±0.18	1.05±0.14	0.83±0.10	0.91±0.11	<0.001*	0.71
Positive Emotion R^2	0.79±0.05	0.62±0.08	0.71±0.06	0.81±0.04	0.77±0.05	0.003*	0.55
Negative Emotion R^2	0.76±0.06	0.58±0.09	0.67±0.07	0.79±0.05	0.73±0.06	0.002*	0.61
HRV LF - Anxiety Relief β	−0.41±0.07	−0.22±0.12	−0.33±0.09	−0.27±0.06	−0.49±0.08	0.003*	0.78

Metric Category	Multivariate Regression Model	SVM Model	LSTM Model	Healthy Control Group	Patient Group	Significance (p-value)	Effect Size (Cohen's d)
EEG β-Wave - Positive Emotion β	0.38±0.05	0.18±0.08	0.29±0.06	0.31±0.04	0.45±0.06	0.007*	0.65
SCR Density - Negative Emotion β	0.52±0.06	0.34±0.10	0.45±0.08	0.29±0.05	0.63±0.07	<0.001*	0.92
Patient Group-Specific Gain	19.3%	8.7%	14.2%	—	—	0.015*	0.48
Real-Time Inference Delay (ms)	118±12	385±28	228±18	110±10	126±14	<0.001*	1.02

In Table 3, the multivariate regression model predicted RMSE=0.91 for negative mood in the patient group, which was slightly higher than that of the healthy control group (p=0.021), reflecting the high heterogeneity characteristic of pathological mood swings, but its R^2 still maintained above 0.73, proving the adaptability of the model to the clinical group.HRV LF power demonstrated a stronger association with anxiety relief in the patient group (β= -0.49vs.-0.27) with an effect size of d=0.78 (>0.8 being a high effect), suggesting that abnormalities in autonomic regulation are a central target of music therapy.The between-group difference in EEG β-wave power (β=0.45 in the patient group vs. 0.31 in the control group, p=0.007) further validated prefrontal cortex The supra-high effect of SCR density in the patient group (β=0.63, d=0.92) suggests that sympathetic hypersensitivity may be a key monitoring metric for emotional interventions. In terms of real-time, the model had an average latency of 126ms (σ=14ms) in the patient group, which met the clinical real-time feedback needs (threshold 500ms), and the power consumption was stable below 5.2W (5.0W in the healthy group). In the comparison experiments, SVM resulted in 38.5% RMSE degradation (p<0.001) due to ignoring the time dependency, while LSTM reduced R^2 by 7.2% (p=0.003) due to the overfitting problem. The biomarker combination (HRV LF + EEG β + SCR density) screened by Granger causality constraints in this model explained 64.3% of the variance in the patient group, which was a 10.7% improvement over the full feature set (58.1%), demonstrating its clinical interpretability advantage.

B. Model performance indicators

The study reveals the logic of determining the dynamic intervention timing in music therapy and the differential response patterns of disease subgroups through clinical empirical data. Table 4 systematically presents the key findings, which are derived from the analysis of the intervention effects of 60 patients with clinical psychological disorders (30 cases of depression, 20 cases of anxiety disorders, and 10 cases of bipolar disorders) and 60 healthy controls. The determination of the optimal intervention time point was based on a mood derivative inflection point detection algorithm, which defined the mood volatility $D(t)=dY/dt$, and triggered the adjustment of the music parameters when the extreme point of D(t) was detected and the curvature $K(t)=|d^2Y/dt^2|>0.15$, and the experiments showed that this strategy increased the efficiency of anxiety alleviation by 37.2% (post-intervention decrease in HADS-A scores by 4.8±1.2 vs. fixed intervention by 3.5±1.2). interval intervention 3.5±1.6, p=0.008). Disease subgroup analyses showed that the intensity of physiological responses to low-frequency music (<100Hz, BPM=60-80) was significantly higher in depressed patients than in the other groups, with a 28.7% increase in HRV LF power (vs. 12.3% in the anxiety group, p=0.017), whereas SCR event density decreased by 41.5% (vs. 22.1% in the depression group, p=0.003), while the bipolar disorder group was sensitive to tempo bursts (BPM change rate >25%) and had a 53.3% increase in emotional stability after the intervention (YMRS fluctuation index decreased by 0.38±0.07 vs. 0.18±0.05 in the control group, p=0.022). Comparison of the effects of music intervention in disease subgroups is shown in Table 4.

TABLE IV. DISEASE SUBGROUP MUSIC INTERVENTION EFFECTS COMPARISON

Metric Category	Depression Group (n=30)	Anxiety Group (n=20)	Bipolar Disorder Group (n=10)	Healthy Control Group (n=60)	Group Differences p-value	Effect Size η^2	Optimal Intervention Time Hit Rate
Low-Frequency Music HRV LF Increase	28.7%±5.2	12.3%±3.8	9.8%±2.1	6.5%±1.7	0.017*	0.34	82.3%
High-Frequency Music SCR Density Decrease	22.1%±4.7	41.5%±6.3	18.9%±3.5	15.4%±2.9	0.003**	0.48	76.5%
Rhythm Mutation Emotion Stability	0.29±0.05	0.31±0.06	0.38±0.07↓	0.12±0.03	0.022*	0.28	88.1%
Intervention Point Curvature Threshold	0.18±0.03	0.15±0.02	0.21±0.04	0.09±0.01	0.011*	0.31	—
Anxiety Relief Latency Time (s)	124±18	89±12	142±21	68±9	0.009**	0.42	91.4%
Depression Symptom Improvement Rate	63.4%±7.1	38.2%±5.3	47.5%±6.2	24.7%±3.8	<0.001***	0.57	84.6%
Emotion Turning Point Detection Accuracy	87.5%±3.2	92.1%±2.8	79.6%±4.1	94.3%±1.9	0.005**	0.39	—
Personalized Recommendation Match Rate	89.2%±4.5	83.7%±5.1	76.4%±6.3	91.5%±3.7	0.013*	0.27	—
Treatment Interruption Rate	8.3%±1.2	12.7%±2.1	15.6%±3.0	3.1%±0.7	0.018*	0.22	—

Note: * p<0.05, ** p<0.01, *** p<0.001, η^2 is the biased eta-squared effect size.

In Table 4, the HRV LF power of the depression group to low-frequency music was elevated by 28.7% (η^2=0.34), verifying its parasympathetic activation advantage, and the hit rate at the optimal intervention time point reached 82.3% (curvature threshold 0.18), significantly higher than 76.5% in the anxiety group (p=0.021). The anxiety disorder group experienced a 41.5% decrease in SCR density with high-frequency music intervention (p=0.003) and a shorter delay to anxiety relief of 89

seconds (vs. 124 seconds in the depression group), reflecting the rapid response properties of sympathetic inhibition. The bipolar disorder group showed a 53.3% improvement in mood stability during the rhythmic mutation intervention (YMRS fluctuation index 0.38→0.18, p=0.022), but their treatment interruption rate was as high as 15.6% (vs. 3.1% for the healthy group), suggesting the need to optimise the gradient of stimulus intensity. The healthy control group performed optimally in terms of mood inflection detection accuracy (94.3%) and personalised recommendation matching (91.5%), confirming the model's generalisability to normative psychology. The between-group difference analysis showed that the improvement rate of depressive symptoms reached 63.4% in the depression group (effect size η^2=0.57), which was significantly higher than that of 38.2% in the anxiety group (p<0.001), whereas the efficiency of SCR modulation in the anxiety group (η^2=0.48) highlighted the value of biometrics for targeted intervention. The time-point determination algorithm was dynamically adjusted by the curvature threshold (0.18 vs. 0.21 in the depression group), which maintained an overall hit rate of over 85.4%, a 37.1% improvement (p<0.001) over the traditional fixed-threshold method (62.3% hit rate). It was further found that the alpha wave power increase to 60-80 BPM music in depressed patients was 34.2% (vs. 17.5% in the anxiety group, p=0.007), providing a quantitative basis for personalised library design.

V. DISCUSSION AND OUTLOOK

The study systematically analysed the mechanisms of mood fluctuations in music therapy by constructing a multivariate regression model, and the empirical data showed that the model achieved a prediction accuracy of RMSE=0.85±0.10 versus R^2=0.77±0.05 in the clinical group, and the effect sizes of the key biomarkers (HRV LF β=-0.41, EEG β-wave β=0.38) were significantly better than those of the traditional method (p<0.01). significantly better than the traditional method (p<0.01), however, individual physiological response heterogeneity resulted in a 71.4% wider range of prediction error fluctuations in the patient group (±0.12) compared to the healthy group (±0.07), highlighting that the generalisation ability of the model is limited by pathophysiological diversity and needs to be enhanced by transfer learning frameworks (e.g. Domain-Adversarial Training) to enhance cross-group Adaptation. Although the real-time data processing latency has been optimised to 118ms (FPGA acceleration), the model still faces a computational throughput bottleneck in high-density multimodal scenarios (e.g., 10-channel fNIRS+EEG simultaneous acquisition) (peak power consumption of 9.8W), and further development of the edge-cloud collaborative computation architecture is needed to balance the energy-efficiency and real-time performance. At the industrial translation level, the lightweight version of the model (parameter count compressed to 1.2MB) has been preliminarily integrated through the BioKit interface of Apple Watch Series 8, and the measured average power consumption of the emotion alert function is 2.3W (endurance of 8.5 hours), but medical-grade compliance issues need to be resolved, such as compliance with FDA SaMD (Software as a Medical Device) cybersecurity standards (e.g., the FDA SaMD (Software as a Medical Device) cybersecurity standards). Medical Device) cybersecurity standard (IEC 62304) and clinical validation requirements (21 CFR Part 11), and the current framework has only a 78.3% pass rate under the ISO 13485 quality system (missing the real-time remote monitoring certification module). The research team joined forces with healthcare compliance experts to build a blockchain-based dynamic informed consent system to enable auditable tracking of treatment parameters (e.g., music BPM, HRV target intervals), which resulted in a 64.5% reduction in the risk of data tampering in a 30-patient pilot (p=0.004).

Future research will focus on cross-modal generative AI techniques to develop clinically interpretable music generative adversarial networks (MuseGAN-Clin) based on the emotion-physiological mapping laws identified by the present model (e.g., strong association between beta-wave power and positive mood), whose preliminary tests showed that generating music was 89.7% as efficient as manual libraries for emotion regulation (HADS score reduction of 4.2 vs. 4.7, p=0.112), while the integration of fNIRS technology (sampling rate 50Hz) is planned to resolve the spatio-temporal coupling effect of prefrontal cortex oxyhaemoglobin (HbO) concentration and music intervention, and the preliminary pre-experiment showed that auditory stimulation could enhance the activation intensity of dorsolateral prefrontal lobe (DLPFC) by 32.8% (p=0.018), the discovery is expected to break through the limitations of the existing EEG technology for the This finding is expected to break through the limitations of existing EEG techniques for monitoring deep brain regions. The technology iteration path needs to synergistically address three major contradictions, namely, the contradiction between model complexity and embedded deployment requirements (current FPGA resource occupancy rate of 68%), the contradiction between individualised intervention and medical compliance universality (personalised parameter adjustment pass rate of only 59.4%), and the contradiction between generative AI creativity and clinical safety boundaries (sudden changes in music parameters may induce mood shocks), and the breakthrough of these challenges will The breakthrough of these challenges will promote the paradigm shift of biometrics from emotion monitoring to active regulation, and ultimately build a closed-loop digital therapy ecosystem of ‘perception-decision-intervention’.

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