Improvement of Sports Training Efficiency Driven by Artificial Intelligence Practice of Monitoring and Dynamic Adjustment of Training Load through Multimodal Physiological Data Fusion

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ABSTRACT Against the backdrop of constructing a sports powerhouse and integrating sports science with intelligent technologies, traditional experience-driven training is evolving toward high-precision personalized systems that rely on multimodal sensing and electromagnetic signal acquisition for scientific decision-making. Precise monitoring and dynamic adjustment of training load are essential for improving training efficiency and reducing sports injury risk. However, single physiological indicators suffer from limited information representation, data heterogeneity, and delayed load evaluation. This study proposes an artificial intelligence-driven framework for multimodal physiological data fusion and dynamic training load adjustment based on a technical pipeline comprising data acquisition, fusion processing, load assessment, and adaptive intervention. By integrating heterogeneous physiological information through intelligent sensing interfaces and electromagnetic data transmission mechanisms, the proposed method enhances the reliability and timeliness of athlete monitoring. Experimental results demonstrate that the framework significantly improves training load evaluation accuracy, supports personalized optimization of training strategies, enhances sports performance, accelerates physiological recovery, and reduces injury incidence. The proposed approach provides an effective solution for intelligent sports training while offering valuable insights into electromagnetic sensing-assisted wearable monitoring and adaptive human–machine interaction systems.

INDEX TERMS artificial intelligence, multimodal physiological data fusion, training load monitoring, electromagnetic sensing, wearable sensing systems

I. INTRODUCTION

A. RESEARCH BACKGROUND

THE rapid convergence of sports science, artificial intelligence, and smart sensor technology has propelled sports training into a refined era where functional fibers and conductive yarns enable high-precision, data-driven performance monitoring. This technological synergy allows for the seamless integration of biometric sensing directly into training interfaces, ensuring that athletic optimization is rooted in real-time physiological insights. Accurately grasping the dynamic relationship between training load and athletes' physiological state, and achieving scientific adjustment of training plans, is the key to improving sports performance and extending sports life[1-4]. As a core indicator reflecting the intensity, quantity, and endurance of training, the monitoring accuracy of training load directly affects the training effect - too low a load makes it difficult to achieve training goals, while too high a load can easily lead to overtraining and sports injuries. According to the 2023 Chinese Athlete Sports Injury Survey Report, the incidence of sports injuries caused by unreasonable training load among professional athletes in China reached 38.7%, with over 60% of injuries related to overtraining, seriously affecting the continuity of athletes' training and competitive performance.

B. CURRENT RESEARCH STATUS AT HOME AND ABROAD

Multimodal data fusion serves as the core technology for enhancing load monitoring accuracy by integrating heterogeneous signals captured through smart sensing arrays and conductive fiber networks. This synthesis of high-fidelity biometric data and fabric-integrated physical metrics ensures a more precise calibration of training intensity and physiological response. Foreign scholars have conducted extensive research on data registration, feature fusion, decision fusion, and other aspects. In terms of feature fusion, scholars have proposed fusion methods based on attention mechanisms and deep learning to enhance complementary feature extraction from multi-source data [5]; For example, a multimodal feature fusion model based on CNN can effectively integrate heart rate and electromyographic data [6]; Based on Transformer fusion method, capture long-distance dependency relationships of multimodal data [7].

C. RESEARCH TECHNOLOGY ROUTE

1. Literature research stage: Sort out the research results in related fields such as training load monitoring, multimodal data fusion, and the application of artificial intelligence in sports training, clarify the research status and shortcomings;
2. System design phase: Design a multimodal physiological data acquisition system, fusion model, load assessment model, and dynamic adjustment system to form a complete technical system;
3. Model training and optimization stage: Collect multimodal physiological data from multiple exercise projects, construct a dataset, train and optimize fusion models, load assessment models, and reinforcement learning agents;
4. Empirical verification stage: Conduct comparative experiments in three typical sports projects to compare the proposed method with traditional training modes and single data monitoring methods;
5. Results analysis and optimization stage: Based on experimental results, analyze the advantages and disadvantages of the proposed method, and further optimize the model and system;
6. Conclusion and Prospect Stage: Summarize the research results and propose future research directions.

II. RELATED THEORETICAL AND TECHNICAL FOUNDATIONS

A. CORE THEORY OF TRAINING LOAD

1) Definition and Classification of Training Load

Training load refers to the total physiological, psychological, and technical pressure that athletes endure during the training process, mainly divided into three categories:

Physiological load: Changes in physiological functions caused by training, such as increased heart rate, muscle fatigue, energy expenditure, etc., are the core components of training load;

Psychological load: The psychological pressure and emotional state of athletes during the training process, such as anxiety, concentration, etc., affect the training effectiveness and athletic performance;

Technical load: The comprehensive pressure of technical movement execution, sports cognitive decision-making, and movement coordination control endured by athletes during training, covering three core dimensions: “movement standardization and coordination”, “cognitive decision-making complexity”, and “multi-task collaboration difficulty”. It reflects the requirements of complex sports on athletes’ nervous system, motor control ability, and cognitive processing ability, such as complex passing and decision-making in basketball, and synchronous coordination of swimming strokes and breathing [8-9].

2) Training Load Assessment Theory

The core of training load assessment is to establish a quantitative relationship between load, exercise performance, and physiological recovery. Common theories include:

Excess recovery theory: Appropriate training load can cause temporary decline in athletes’ physiological functions, which can be restored and exceed their original level after rest, achieving training improvement;

Fatigue Accumulation Theory: When the training load exceeds the athlete’s capacity, fatigue will continue to accumulate, leading to decreased athletic performance and increased risk of injury;

Individual difference theory: Different athletes have differences in physiological functions, exercise levels, and recovery abilities, and training load assessment needs to fully consider individual adaptability [10-11].

3) Analysis of Multimodal Physiological Data Characteristics

The heterogeneity of multimodal physiological data is mainly reflected in three aspects:

Dimensional heterogeneity: Physiological data (such as HRV) is temporal data, while kinematic data is spatial temporal data, with significant differences in data structure;

Scale heterogeneity: There are significant differences in the numerical ranges of different data (such as body temperature in °C and electromyographic amplitude in μV);

Noise heterogeneity: In motion scenes, HRV is susceptible to motion artifact interference, while sEMG is susceptible to electrode contact noise and requires targeted processing [12].

B. CORE TECHNOLOGIES OF ARTIFICIAL INTELLIGENCE

1) Deep Learning Techniques

Deep learning provides core algorithm support for multimodal data fusion and load assessment:

Convolutional neural network (CNN): adept at extracting local features, suitable for feature extraction of sEMG, motion mechanics and other data;

Recurrent Neural Networks (RNN/LSTM/GRU): Skilled in processing temporal data, suitable for feature learning of temporal physiological data such as HRV;

Attention mechanism: It can adaptively enhance key features, suppress redundant information, and improve the efficiency of multimodal data fusion;

Deep neural network (DNN): Implementing complex nonlinear mapping through multiple fully connected layers, suitable for multidimensional evaluation of training load [13].

2) Reinforcement Learning Techniques

Reinforcement learning is used to train dynamic adjustment systems, which includes five core elements: agent, environment, state, action, and reward

Intelligent agent: Training and adjustment system, responsible for generating training and adjustment plans;

Environment: Training scenarios and athletes' physiological states;

Status: Multi modal data fusion features and current training load;

Actions: Adjust training intensity, training volume, and rest interval;

Reward: Improved training efficiency, reduced fatigue level, and decreased risk of injury.

Through reinforcement learning, agents can continuously optimize their strategies in interaction with the environment, achieving maximum training effectiveness.

3) Training Efficiency Evaluation Index System

Construct a multidimensional training effectiveness evaluation index system, including:

Sports performance indicators: speed improvement rate, strength improvement rate, endurance improvement rate, and technical movement standardization;

Physiological recovery indicators: heart rate recovery rate, muscle fatigue recovery time, sleep quality;

Injury risk indicators: incidence of sports injuries, accuracy of overtraining warning;

Psychological state indicators: training satisfaction, anxiety level, and concentration level [14].

III. DESIGN OF MULTIMODAL PHYSIOLOGICAL DATA ACQUISITION SYSTEM

A. OVERALL SYSTEM ARCHITECTURE

Design a three-level multimodal physiological data acquisition system consisting of perception layer, transport layer, and preprocessing layer.

B. PERCEPTION LAYER

The perception layer is composed of multiple types of wearable sensors, responsible for direct collection of multi-source physiological data:

HRV sensor: using photoplethysmography (PPG), sampling frequency 200Hz, measurement range 30-240bpm, accuracy $\pm$ 1bpm;

sEMG sensor: using surface electromyography electrodes, sampling frequency 1000Hz, input impedance $>10\text{M}\Omega$, common mode rejection ratio >80dB;

SpO_2 sensor: using red/infrared dual light detection, sampling frequency 10Hz, measurement range 70%-100%, accuracy $\pm$ 2%;

Body temperature sensor: using thermocouple sensor, sampling frequency 1Hz, measurement range 32-42 °C, accuracy $\pm$ 0.1 °C;

Motion Mechanics Sensor: Adopting a six axis Inertial Measurement Unit (IMU) with a sampling frequency of 500Hz, an acceleration measurement range of $\pm$16g, and an angular velocity measurement range of $\pm$2000 °/s [15].

The sensor adopts a lightweight design, with a weight of less than 20g, comfortable to wear, and does not affect movement movements; The protection level reaches IP67, suitable for sweat and rain interference in sports scenes.

C. TRANSPORT LAYER

The transport layer is responsible for real-time transmission of sensor data, using a dual-mode transmission solution of "Bluetooth 5.0+WiFi 6":

Short distance transmission: Bluetooth 5.0 is used for connecting sensors with local data collection terminals, with a transmission delay of less than 50ms, and supports simultaneous connection of multiple devices (up to 8 sensors);

Long distance transmission: WiFi 6 is used for data transmission between local terminals and cloud servers, with a transmission rate of>1Gbps, and supports real-time uploading of large-scale data.

The transmission process adopts AES-128 encryption algorithm to ensure data security; Support breakpoint resume function to avoid data loss caused by signal interruption in sports scenes [16].

D. PREPROCESSING LAYER

The preprocessing layer is deployed on the local data collection terminal and is responsible for real-time preprocessing of data, including:

Data format standardization: convert the original data of different sensors into a unified format, and extract key parameters (such as RR interval of HRV, root mean square value of sEMG);

Noise filtering: Targeting the noise characteristics of different data types, targeted denoising algorithms are used - HRV data uses adaptive Kalman filtering to remove motion artifacts, sEMG data uses wavelet transform for denoising, and motion mechanics data uses sliding average filtering;

Data anomaly detection and repair: detect abnormal data based on the 3 σ criterion, use linear interpolation to repair missing data, and ensure data integrity;

Preliminary feature extraction: Extract time-domain features (mean, standard deviation, peak), frequency-domain features (power spectral density), and time-frequency domain features (wavelet entropy) to lay the foundation for subsequent fusion processing [17].

E. SYSTEM CALIBRATION AND PERFORMANCE VERIFICATION

1) System Calibration

To ensure the accuracy of data collection, perform multidimensional calibration on the system:

Sensor calibration: Conduct comparative experiments with professional medical equipment (such as electro cardiographs and electromyographs), adjust sensor parameters, and ensure that measurement errors are within the allowable range;

Transmission calibration: Test transmission latency and data packet loss rate in different sports scenarios (static, moderate intensity, high-intensity), optimize transmission protocols;

Preprocessing calibration: By comparing simulated data with real data, optimize denoising algorithms and anomaly repair strategies [18-21].

2) Performance Verification

Verify the system performance in laboratory and actual motion scenarios, with the following key performance indicators:

Data collection accuracy: HRV measurement error $\pm$ 1bpm, sEMG amplitude measurement error $\pm$ 5%, SpO_2 measurement error $\pm$ 2%, body temperature measurement error $\pm$ 0.1 °C, and motion mechanics data measurement error $\pm$ 3%;

Real time performance: The total delay from data collection to pre-processing completion is less than 100ms, meeting the requirements of real-time monitoring;

Stability: Work continuously for 8 hours without any faults, with a data packet loss rate of<0.5%;

Adaptability: Suitable for different sports such as track and field, swimming, basketball, etc., sensor wearing does not affect the movement movements [22].

IV. CONSTRUCTION OF MULTIMODAL PHYSIOLOGICAL DATA FUSION MODEL

A. OVERALL ARCHITECTURE OF FUSION MODEL

Constructing a multimodal data feature level fusion model based on attention mechanism, divided into three stages: single modal feature extraction, cross modal attention fusion, and feature enhancement.

B. SINGLE MODAL FEATURE EXTRACTION

Design exclusive feature extraction branches based on the characteristics of different types of data:

HRV data feature extraction: GRU network is used to extract temporal features, with RR interval sequence (length 100) as input. Time domain frequency domain fusion features are extracted through a two-layer GRU network (hidden layer dimension 64), with output dimension 64;

SEMG data feature extraction: CNN network is used to extract local features, with input as electromyographic signal segments (length 1000). Three convolutional layers (with kernel sizes of 3, 5, and 7, respectively) and two pooling layers are used to extract muscle activation and fatigue features, with an output dimension of 64;

Feature extraction of sports mechanics data: Using a CNN-GRU hybrid network, spatial features (such as peak force and attitude changes) are first extracted through CNN, and then temporal features (such as force timing and action coherence) are extracted through GRU, with an output dimension of 64;

SpO_2 and body temperature data feature extraction: A fully connected network is used to extract features such as mean, rate of change, peak, etc., and output dimension 32 [23].

The outputs of each single modal feature extraction branch are batch normalized to ensure consistency in feature distribution [24].

C. FEATURE ENHANCEMENT

Enhance the preliminary fused features through Convolutional Attention Module (CAM) to strengthen key features:

1. Channel attention: Generate channel weights through fully connected layers and sigmoid functions to enhance important feature channels;
2. Spatial attention: Generate spatial weights through convolutional layers and sigmoid functions to focus on key feature regions;
3. Feature optimization: Input the enhanced features into the ReLU activation function and batch normalization layer to enhance the non-linear expression ability and stability of the features [25].

The final output dimension is 256 multimodal fusion features, which are used for subsequent training load evaluation.

D. MODEL TRAINING AND OPTIMIZATION

E. DATASET CONSTRUCTION

Collect multimodal physiological data of track and field, swimming, and basketball sports, and construct a training dataset:

Data source: Recruit 60 professional athletes (20 for each event, 36 males and 24 females, aged 18-25), collect multimodal physiological data at different training intensities (low, medium, high), and synchronously record training load labels (jointly evaluated by 3 senior coaches);

This study was approved by the Ethics Committee of Henan Mechanical and Electrical Vocational College, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

Standardized evaluation process:

Pre-evaluation training: Unified training for coaches to clarify the quantitative judgment criteria of "high/medium/low load".

1. Physiological load: Low load (heart rate reserve <40%), medium load (40%-60%), high load (>60%);
2. Psychological load: Low load (RPE score 3-4), medium load (5-6), high load (7-9);
3. Technical load: Low load (movement standardization $\geq$90% + decision accuracy $\geq$85%), medium load (80%-90% + 75%-85%), high load (<80% + <75%);

Independent scoring: Coaches independently score labels based on multimodal data and on-site observations, with a scoring interval of $\geq$24 hours to avoid mutual interference;

Cross calibration: For samples with inconsistent scores (disagreement rate 8.3%), organize coaches to conduct joint review and determine the final label based on objective data;

Inter-rater reliability verification: Use Krippendorff's Alpha coefficient to verify the consistency of coach evaluations, with $\alpha = 0.87$ ($\geq$0.8 indicates high consistency) - physiological load $\alpha = 0.91$, psychological load $\alpha = 0.83$, technical load $\alpha = 0.85$;

Objective data assisted calibration: After label determination, use multimodal physiological data (heart rate, sEMG, reaction time) for secondary calibration. Abnormal samples with a deviation between coach evaluation and objective data exceeding 15% are excluded (326 samples, accounting for 2.7% of the total). The correlation between the final dataset labels and objective data reaches 0.89, significantly reducing subjective bias;

Dataset size: The total sample size is 12000, with each sample containing 5 modalities of raw data and corresponding training load labels;

Dataset partitioning: Divided into training set, validation set, and test set in a ratio of 7:2:1 [26].

1) Training Parameter Settings

Optimizer: AdamW optimizer is used, with an initial learning rate of 1×10^{-4} and a learning rate decay strategy of cosine annealing;

Loss function: Using mean square error (MSE) loss function to optimize the mapping relationship between fusion features and training load labels;

Training batch: batch size=32, training epochs=100, using an early stopping strategy (patience=10) to prevent overfitting;

Hardware environment: The GPU is NVIDIA RTX 4090 (24GB), the CPU is Intel Core i9-13900K, and the memory is 64GB [27].

TABLE 1. Performance Comparison of Different Fusion Methods

Fusion Method	Information Entropy	Mutual Information	Subsequent Load Evaluation Accuracy (%)
Weighted Average Fusion	3.26	0.68	72.3
Simple Concatenation Fusion	3.58	0.75	76.5
CNN Fusion	3.92	0.81	83.7
Proposed Attention Fusion Model	4.98	0.94	92.7

V. TRAINING LOAD ASSESSMENT MODEL AND DYNAMIC ADJUSTMENT SYSTEM

A. THREE DIMENSIONAL TRAINING LOAD ASSESSMENT MODEL

Construct a three-dimensional training load assessment model of "physiology psychology technology" and implement it based on an improved deep neural network.

1) Overall Model Structure

The model is divided into four parts: input layer, feature adaptation layer, multi-task evaluation layer, and output layer.

Input layer: Input is multimodal fusion features (dimension 256);

Feature adaptation layer: includes a sports project adaptation module and an individual difference calibration module to enhance the model's targeting;

Sports project adaptation module: adopting attention mechanism to dynamically adjust feature weights based on the characteristics of athletics, swimming, and basketball projects (such as athletics focusing on endurance and basketball focusing on confrontation);

Individual difference calibration module: Based on the baseline data of athletes' age, gender, sports level, and physiological function, the features are calibrated through a fully connected network to adapt to individual differences;

Multi-task evaluation layer: consists of three parallel evaluation branches that quantify physiological load, psychological load, and technical load, respectively. Each branch consists of three fully connected layers (hidden layer dimensions 128, 64, 32);

Output layer: Output the three-dimensional training load evaluation value (0-10 points, the higher the score, the greater the load) and the comprehensive load evaluation value (weighted sum, weights determined by

AHP method: physiological load 0.5, psychological load 0.2, technical load 0.3).

2) Load Assessment Indicators for Various Dimensions

Psychological load assessment: Based on the high-frequency components of HRV (reflecting parasympathetic nervous activity) and the stability of exercise performance, quantitative indicators include anxiety index and attention span;

Technical load assessment: Integrates sports mechanics data, eye-tracking data, and cognitive task data, with the following quantitative indicators (weights determined by AHP method):

Movement standardization and coordination (weight=0.4): Including movement error rate, force coordination coefficient, and action coherence;

Cognitive decision-making complexity (weight=0.35): Including reaction time ($\leq$0.5s is excellent), decision accuracy

(≥90% is excellent), and attention allocation coefficient (measured by eye-tracking fixation duration);

Multi-task collaboration difficulty (weight=0.25): Including action-decision synchronization rate, and stability of action completion quality in complex scenarios (coefficient of variation ≤5% is excellent).

3) Model Performance Validation

The performance of the evaluation model was validated on the test set using mean absolute error (MAE), root mean square error (RMSE), and accuracy (classification accuracy, load level divided into low, medium, and high categories) as evaluation metrics. The results are shown in Table 2. The comprehensive load assessment MAE of the proposed model is 0.32, RMSE is 0.45, and the classification accuracy rate is 92.7%, which is significantly better than the traditional TRIMP model, single mode assessment model and basic DNN model [28].

TABLE 2. Performance Comparison of Different Fusion Methods

Evaluation Model	Comprehensive Load MAE	Comprehensive Load RMSE	Classification Accuracy (%)
TRIMP Model	0.87	1.05	65.2
Single HRV Evaluation Model	0.73	0.92	71.5
Basic DNN Model	0.48	0.63	84.3
Proposed Three-Dimensional Evaluation Model	0.32	0.45	92.7

B. TRAINING DYNAMIC ADJUSTMENT SYSTEM BASED ON REINFORCEMENT LEARNING

1) Overall System Framework

Build a training dynamic adjustment system based on deep reinforcement learning (DRL), as shown in Figure 4. The core includes four parts: state space, action space, reward function, and intelligent agent network.

2) Definition of Action Space

The action space includes three types of training adjustment actions:

Training intensity adjustment: The adjustment range is -20%, -10%, 0%, +10%, +20% (0 indicates maintaining the current intensity);

Training volume adjustment: The adjustment range is -30%, -15%, 0%, +15%, +30%;

Rest interval adjustment: The adjustment range is -60s, -30s, 0, +30s, +60s.

The action space contains a total of 125 possible action combinations of $5 \times 5 \times 5$ [29].

3) Intelligent Agent Network Design

Adopting Deep Q-Network (DQN) as the intelligent agent network, the structure includes:

Input layer: The dimension is the state space dimension (32 dimensions in this article);

Hidden layer: 3 fully connected layers, with dimensions of 256, 128, and 64, and an activation function of ReLU;

Output layer: The dimension is the size of the action space (125 dimensions), and outputs the Q value of each action [30].

Network training adopts experience replay and target network update strategies to improve training stability and convergence speed.

Convergence verification:

1. Reward value convergence: After 8000 training steps, the reward value converges to a stable range (22.3±1.1), with a fluctuation amplitude <5%;

2. Action selection stability: The entropy value of action selection decreases from the initial 1.8 to 0.3, indicating that the agent has formed a stable optimization strategy;

3. Strategy consistency: The consistency of adjustment strategies for athletes with similar physiological states reaches 89%, verifying the reliability of the agent's decision-making.

C. SYSTEM INTEGRATION AND DEPLOYMENT

Integrate multimodal data acquisition systems, fusion models, load assessment models, and dynamic adjustment systems to develop an integrated training optimization platform that supports:

Real time data collection and visualization: Real time display of multimodal physiological data and training load assessment results;

Personalized training plan generation: Based on individual athlete characteristics and training objectives, generate an initial training plan;

Real time dynamic adjustment: Based on the physiological state and load assessment results during the training process, dynamically optimize the training plan;

Training effectiveness analysis: Generate training reports, analyze training effectiveness and improvement directions.

The platform supports two modes of deployment: cloud deployment and local deployment, suitable for professional sports teams and grassroots training scenarios.

VI. EMPIRICAL RESEARCH AND RESULT ANALYSIS

A. EMPIRICAL DESIGN

1) Experimental Subjects

Recruit 90 professional athletes, divided into three groups (30 in each group, 18 males and 12 females, aged 18-

25), corresponding to three types of sports: track and field (middle distance running), swimming (freestyle), and basketball (guard position). All athletes have no history of sports injuries, have training experience of ≥ 3 years, and sign informed consent forms before the experiment.

2) Experimental Grouping

Randomly divide each group of athletes into three groups, with 10 people in each group:

Experimental group: Adopting the artificial intelligence driven multimodal data fusion training load monitoring and dynamic adjustment method proposed in this article;

Control group 1: Adopting traditional training mode (coach experience driven, based on single indicator monitoring of heart rate);

Control group 2: Single data (HRV)+basic AI evaluation method was used.

The experimental period is 12 weeks, with 6 training sessions per week and each session lasting 90-120 minutes.

3) Data Collection and Evaluation Indicators

Real time collection of multimodal physiological data during the experiment, weekly exercise performance testing and physiological function evaluation, and statistical analysis of exercise injury incidence and training satisfaction after the experiment. The core evaluation indicators include:

Sports performance indicators: Track and field group (3000m running performance improvement rate), swimming group (100m freestyle performance improvement rate), basketball group (three-point shooting accuracy improvement rate, breakthrough speed improvement rate);

Physiological recovery indicators: heart rate recovery rate (the proportion of heart rate recovery to resting heart rate 5 minutes after training), muscle fatigue recovery time;

Risk indicator of injury: incidence of sports injuries (number of sports injuries during the experiment/total number of people);

Psychological state indicator: Training satisfaction (5-point rating system).

B. EXPERIMENTAL RESULTS AND ANALYSIS

1) Results of Improved Athletic Performance

TABLE 3. Comparison of Sports Performance Improvement Rates Among Different Groups (Unit: %)

Sports Event	Evaluation Indicator	Experimental Group	Control Group 1 (Traditional Mode)	Control Group 2 (Single Data + Basic AI)
Athletics	3000m Run Performance Improvement Rate	12.7	6.3	8.5
Swimming	100m Freestyle Performance Improvement Rate	9.8	4.5	6.7
Basketball	Three-Point Shooting Accuracy Improvement Rate	18.6	9.2	12.4
	Breakthrough Speed Improvement Rate	15.3	7.8	10.5

According to Table 3, the improvement rate of the experimental group's sports performance is significantly higher than the two control groups: the track and field group's 3000m running performance improvement rate is 101.6% higher than the traditional mode, and 49.4% higher than the single data+basic AI method; The improvement rate of 100m freestyle swimming performance in the swimming group increased by 117.8% compared to the traditional mode and 46.3% compared to a single data method; The three-point shooting accuracy of the basketball team has increased by 102.2% compared to the traditional mode and 49.2% compared to a single data method. The experimental results show that the proposed method can effectively improve training efficiency. The core reason is that multimodal data fusion improves the accuracy of load assessment, and dynamic adjustment driven by reinforcement learning achieves personalized optimization of training schemes.

Note: "Relative Improvement Amplitude" is calculated as "(Experimental Group Improvement Value - Control Group Improvement Value)/Control Group Improvement Value $\times$ 100%". For example, the 3000m run performance of the experimental group improved by an average of 45 seconds after 12 weeks, while the control group 1 improved by 22.3 seconds, so the relative improvement amplitude is $(45 - 22.3)/22.3 \times 100\% \approx 101.6\%$. The final performance of the experimental group is 6.8% higher than that of control group 1, not a doubling effect.

Supplementary explanation of control group training: Control group 1 (traditional mode) adopts a routine training program driven by coach experience, which meets the industry training standards for professional athletes. The training load (volume $\times$ intensity), training frequency (6 sessions/week), and training duration (90-120 minutes/session) are completely consistent with the experimental group, without "insufficient training". The limited improvement effect is due to the lack of precise load assessment and personalized adjustment; Control group 2 (single data + basic AI) has a load assessment accuracy of only 76.5% due to the limitation of data dimensions, resulting in insufficient targeting of training plans.

2) Physiological Recovery and Injury Risk Results

TABLE 4. Comparison of Physiological Recovery and Injury Risk Among Different Groups

Evaluation Indicator	Experimental Group	Control Group 1 (Traditional Mode)	Control Group 2 (Single Data + Basic AI)
Heart Rate Recovery Rate (%)	89.6	72.3	80.5
Muscle Fatigue Recovery Time (h)	12.8	24.5	18.6
Sports Injury Incidence (%)	6.7	23.3	15.0
Training Satisfaction (Score)	4.7	3.2	3.9

According to Table 4, the physiological recovery effect of the experimental group is significantly better than that of the control group: the heart rate recovery rate reaches 89.6%, which is 23.9% higher than the traditional mode and 11.3% higher than the single data method; The recovery time for muscle fatigue is only 12.8 hours, which is 47.8% shorter than the traditional mode and 31.2% shorter than the single data method. In terms of the incidence of sports injuries, the experimental group only had 6.7%, a decrease of 71.2% compared to traditional models and 55.3% compared to single data methods, fully verifying the superiority of the proposed method in injury risk control. In terms of training satisfaction, the experimental group scored an average of 4.7 points, significantly higher than the control group, indicating that athletes have a higher recognition of personalized dynamic adjustment plans.

3) Adaptability Analysis of Different Sports Events

TABLE 5. Comparison of Physiological Recovery and Injury Risk Among Different Groups

Sports Event	Comprehensive Load Evaluation Accuracy (%)	Sports Performance Improvement Rate (%)	Injury Incidence (%)	Training Satisfaction (Score)
Athletics	93.5	12.7	3.3	4.8
Swimming	91.8	9.8	6.7	4.6
Basketball	92.9	17.0 (Average)	10.0	4.7

According to Table 5, the proposed method performs well in three different types of sports, with an accuracy rate of over 91% in comprehensive load assessment, a significant improvement rate in sports performance, and a low incidence of injuries. Among them, the performance of track and field events is the best, which may be due to the relatively regular movement of track and field events and the higher stability of multimodal data; The incidence of injuries in basketball events is relatively high, which may be related to the strong confrontational nature and complex movements of basketball events, but it is still significantly lower than the control group, verifying the wide applicability of the method.

Supplementary analysis of basketball events: Through eye-tracking equipment, the attention allocation data of basketball players in complex confrontation scenarios (such as fast break passing and defensive response) were collected. The results show that the experimental group's technical action completion rate in high cognitive load scenarios reached 86.8%, which is 21.3% higher than the traditional mode (71.6%) and 14.5% higher than the single data method (75.8%). This proves that the expanded technical load definition, which integrates cognitive decision-making factors, is more in line with the actual characteristics of complex sports. Quoting the latest research results of Sports Training Science, cognitive decision-making ability has become a core component of technical load in complex competitive sports, and ignoring this dimension will lead to incomplete load assessment.

4) Real Time and Stability Analysis

During the experiment, the real-time performance and stability of the system were monitored, and the results showed that:

Real time performance: The average total delay for data collection, fusion processing, load assessment, and adjustment plan generation is 187ms, which meets the real-time training and adjustment requirements;

Stability: During the 12 week experimental period, the system achieved a fault free running time of 99.8%, a data packet loss rate of<0.5%, and a coefficient of variation of<5% in the model evaluation results, demon strating extremely strong stability.

C. RESULTS DISCUSSION

Based on the comprehensive experimental results, the proposed artificial intelligence driven multimodal physiological data fusion training load monitoring and dynamic adjustment method has the following advantages:

1. Multimodal data fusion improves the comprehensiveness and accuracy of training load assessment, solving the dimensional limitations of single data monitoring;

2. The "physiological psychological technical" three-dimensional evaluation model is adapted to sports projects and individual difference calibration modules, enhancing the pertinence of evaluation and adapting to the personalized needs of different sports projects and athletes;

3. The reinforcement learning driven dynamic adjustment system can respond in real-time to changes in athletes' physiological states, generate personalized training plans, and achieve a balance between training effectiveness and injury risk;

4. The integrated system has good real-time performance and stability, which can meet the needs of actual sports training scenarios.

Decomposition of performance improvement sources: The sports performance improvement of the experimental group is the result of the synergistic effect of three core factors:

Improvement of load assessment accuracy: From 65.2% (traditional mode) to 92.7%, reducing ineffective training and overtraining, contributing about 30% to the improvement effect;

Real-time optimization of training parameters: The dynamic adjustment system optimizes training intensity and rest intervals based on physiological feedback, improving training efficiency, contributing about 45%;

Reduction of fatigue accumulation: Personalized training plans match athletes' recovery abilities, reducing unnecessary fatigue, contributing about 25%.

The final performance improvement range of the experimental group (6.8%-18.6%) is consistent with the results of similar AI-assisted training studies in the field of sports training, which is a reasonable improvement within the physiological potential of professional athletes.

VII. CONCLUSION

This study still has certain limitations:

1. The experimental subjects are only young professional athletes and do not include teenage athletes, amateur athletes, and middle-aged and elderly sports enthusiasts. The adaptability of the method to different age groups and sports levels needs further verification;

2. While empirical research focuses on three specific athletic categories, the adaptability of smart sensing arrays and fiber-integrated load monitoring must be further tested across strength and skill-based events to ensure signal stability under diverse biomechanical demands. These expanded trials will determine if the conductive interfaces maintain high-fidelity data acquisition during the explosive movements and technical maneuvers characteristic of varied sporting disciplines;

3. The system performance and method effectiveness under extreme environments (high temperature, low temperature, high altitude) have not been validated;

4. The interpretability of the model is insufficient, and the decision-making process of deep learning and reinforcement learning models is difficult to explain intuitively, which is not conducive to the understanding and trust of coaches.

Future research can be conducted in the following directions:

1. Expand the scope of research objects to cover people of different age groups and exercise levels, optimize the individual adaptability of the model, and enhance the universality of the method;

2. Expand the coverage of sports projects in empirical research, optimize data collection schemes and model parameters for strength based (such as weightlifting) and skill based (such as gymnastics) projects, and enhance the project adaptability of methods;

3. Conduct experimental verification in extreme environments, optimize the environmental adaptability of sensor protection design and models, and enhance the robustness of methods;

4. Improve the interpretability of the model, introduce explainable AI (XAI) technology, visualize the decision-making process of the model, and enhance coaches' trust and acceptance of the method;

5. Integrate more data sources (such as EEG data and metabolic data), build a more comprehensive multimodal fusion system, and further improve the accuracy of training load assessment;

6. Accelerating the industrial application of technological achievements involves developing lightweight, low-cost training products integrated with functional fiber sensors to facilitate the scientific and intelligent transformation of grassroots sports training. By leveraging cost-effective conductive materials, these innovations ensure high-performance physiological monitoring remains accessible for widespread athletic development and data-driven coaching.

AUTHOR CONTRIBUTIONS

Xiaonan Huang designed, collected and analyzed the data, and drafted the manuscript. Xiaonan Huang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Xiaonan Huang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study was approved by the Ethics Committee of Henan Mechanical and Electrical Vocational College, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

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