Construction of Basketball-Specific Exercise Load Quantification Model Based on Cardiopulmonary Monitoring via Wearable Devices

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ABSTRACT Basketball is characterized by high-intensity intermittent movements, frequent physical contact and prominent positional differences. Conventional exercise load assessment methods rely on subjective perception or single physiological indicators, which fail to accurately describe athletes' real-time physical functional status. The rapid advancement of wearable devices enables continuous collection of multi-dimensional physiological data. Synchronized acquisition of cardiopulmonary indicators including heart rate, heart rate variability and oxygen uptake makes objective quantification of exercise load feasible. By constructing a basketball-specific quantification model integrating external and internal loads, precise grading of training intensity and dynamic evaluation of athletes' physical status can be realized. Model verification was carried out on athletes of different positions through field tests. The results show that the load index output by the model is significantly correlated with cardiopulmonary responses. This study provides quantitative evidence for personalized training prescription formulation and dynamic adjustment of training plans, and bears practical significance for advancing the scientific level of competitive training.

INDEX TERMS basketball; exercise load quantification; wearable devices; cardiopulmonary function monitoring; training load model

I. INTRODUCTION

Exercise load management is the core topic of scientific competitive training. Appropriate load arrangement directly affects athletes' competitive performance and injury risk. Owing to its intermittent high-intensity nature, athletes' peak heart rate can exceed 95% of maximum heart rate during a single basketball game. Meanwhile, load fluctuation is closely related to positional responsibilities, rendering unified assessment frameworks ineffective. Traditional evaluation tools mainly adopt the Rating of Perceived Exertion (RPE) scale or external indicators such as total running distance, lacking direct reflection of the actual pressure borne by the cardiopulmonary system, which limits assessment accuracy. In recent years, mature technologies of smart wristbands, chest strap heart rate sensors and sweat biochemical sensors have paved the way for continuous collection of core physiological parameters such as heart rate, heart rate variability (HRV) and blood oxygen saturation. Against this backdrop, developing a basketball-specific exercise load quantification model driven by cardiopulmonary monitoring data carries important theoretical value and practical implications for precise load evaluation and personalized training regulation [1].

II. INDICATOR SYSTEM FOR CARDIOPULMONARY FUNCTION MONITORING VIA WEARABLE DEVICES

A. ACQUISITION PRINCIPLES AND EQUIPMENT APPLICABILITY ANALYSIS OF HEART RATE AND HEART RATE VARIABILITY

Heart rate (HR) and heart rate variability (HRV) are the most direct physiological indicators reflecting cardiopulmonary responses to exercise load, with complementary acquisition principles and informative values. Two mainstream technologies are adopted for heart rate measurement: Photoplethysmography (PPG) and Electrocardiography (ECG). PPG sensors emit light to irradiate subcutaneous capillaries and calculate heartbeat frequency based on fluctuating reflected light intensity caused by changes in blood volume. Featuring comfortable wear and low power consumption, PPG is widely integrated into wrist-worn smart bands. ECG collects myocardial potential changes directly through chest strap electrodes with high accuracy of R-peak detection, delivering superior signal stability under high-intensity exercise compared with PPG, yet demanding tighter fitting with the skin. HRV characterizes time-domain and frequency-domain fluctuations of RR intervals between consecutive heartbeats. Its time-domain indicator RMSSD is highly sensitive to changes in parasympathetic nerve activity, enabling early detection of subtle shifts in athletes' autonomic nervous regulation even when absolute heart rate remains stable. Therefore, RMSSD is recognized as an early biomarker for evaluating accumulated training fatigue. For basketball scenarios, equipment applicability should be comprehensively assessed from three dimensions: motion interference, sampling frequency and data transmission. Wrist-worn PPG devices are vulnerable to motion artifacts during high-speed running, sudden stops and directional changes, leading to large deviations in heart rate estimation. Chest strap ECG devices generate minimal motion artifacts and generally support sampling frequencies no lower than 250 Hz, meeting the signal resolution requirements for frequency-domain HRV analysis. Existing research reveals that for basketball training monitoring, chest strap devices control heart rate measurement error within 2 beats/min, while wrist PPG devices have an error of 4 – 6 beats/min under moderate-to-low intensity, which further expands at peak intensity. Balancing measurement accuracy and practicality, chest strap ECG devices are preferred for HRV collection during high-intensity training, whereas wrist PPG devices suffice for low-intensity recovery sessions [2]. Table 1 compares key technical parameters of the two types of equipment.

TABLE 1. Technical Parameter Comparison Between Chest Strap ECG and Wrist PPG Devices

Parameter Item	Chest Strap ECG Device	Wrist PPG Device
Sampling Frequency	$\geq$ 250 Hz	25–100 Hz
Heart Rate Measurement Error (Moderate–Low Intensity)	$<$ 2 beats/min	4–6 beats/min
Heart Rate Measurement Error (Peak Intensity)	$<$ 3 beats/min	$>$ 8 beats/min
HRV Acquisition Suitability	High (supports frequency-domain analysis)	Low (only for rough time-domain estimation)
Degree of Motion Artifact Interference	Low	Moderate to High
Degree of Motion Artifact Interference	Moderate	High
Battery Life	8–12 h	24–48 h

B. NON-INVASIVE CONTINUOUS MONITORING METHODS FOR OXYGEN UPTAKE AND BLOOD OXYGEN SATURATION

Oxygen uptake (VO_2) and blood oxygen saturation (SpO_2) characterize the transport and utilization efficiency of the cardiopulmonary system from energy metabolism and gas exchange perspectives respectively, serving as indispensable physiological parameters for constructing exercise load quantification models. Direct VO_2 measurement requires portable gas metabolism analyzers equipped with breathing masks to detect O_2 and CO_2 concentrations in exhaled air, which severely restricts body movements during actual basketball training and limits practical application. Hence, indirect estimation is more widely adopted: an individualized linear regression relationship between heart rate and VO_2 (heart rate–oxygen uptake linear equation) is established to calculate real-time oxygen uptake via heart rate data. This method has been validated in multiple sports science studies with estimation error controlled within 10%. SpO_2 measurement relies on dual-wavelength light absorption differences of pulse oximeters. Based on the Beer-Lambert Law, blood oxygen saturation is calculated using disparate absorbance of oxyhemoglobin and deoxyhemoglobin at 660 nm (red light) and 940 nm (near-infrared light). During high-intensity intermittent basketball exercise, SpO_2 normally ranges from 95% to 99%. Transient drops below 93% usually indicate extreme-intensity hypoxic status, which should be combined with heart rate data to comprehensively assess excessive load risks. Notably, skin pigmentation, insufficient peripheral blood circulation and intense body movement interfere with measurement accuracy of PPG-type SpO_2 sensors. Professional sports sensors equipped with motion artifact compensation algorithms are recommended for SpO_2 monitoring during strenuous basketball training to guarantee valid data. Combined indirect VO_2 estimation and direct SpO_2 measurement provide dual metabolic and gas exchange evidence for subsequent exercise intensity grading [3].

C. TIME SYNCHRONIZATION AND NOISE FILTERING OF MULTI-SOURCE PHYSIOLOGICAL SIGNALS

Heart rate, HRV, SpO_2, kinematic parameters and other multi-source physiological signals are collected by separate sensors with inconsistent sampling frequencies, clock references and data transmission delays. Direct fusion without time alignment results in temporal signal misalignment and invalid analytical conclusions. Two mainstream strategies are implemented for time synchronization: Hardware unified clock triggering: A main control device transmits synchronous pulse signals to all sensors to force alignment of sampling start timestamps.

2. Software timestamp interpolation alignment: High-frequency signals (e.g., 250 Hz ECG) are set as benchmarks, and cubic spline interpolation is applied to low-frequency signals (e.g., 1 Hz SpO_2) to map all data onto a unified timeline. Two primary noise sources exist in basketball training environments: motion artifacts and electromagnetic interference. Motion artifacts originate from relative displacement between sensors and skin during rapid limb movements, presenting as baseline drift and high-frequency burrs in PPG signals. Electromagnetic interference derives from stadium lighting and wireless communication, introducing power frequency noise (50/60 Hz) into ECG signals. For motion artifacts, an accelerometer-aided reference elimination method is adopted: acceleration signals are input into adaptive filters as noise references to estimate and remove artifact com-

ponents from PPG data. For power frequency noise, notch filters are deployed to achieve deep attenuation at target frequencies while preserving the effective frequency band of ECG signals (0.5–40 Hz). After time synchronization and denoising, multi-source signals are resampled at a unified frequency and integrated into a multi-channel time-series data matrix, providing standardized data input for feature extraction and parameter calculation of the load model in Chapter 2 [4].

III. CONSTRUCTION OF BASKETBALL-SPECIFIC EXERCISE LOAD QUANTIFICATION MODEL

A. INDICATOR SELECTION AND PARAMETER DEFINITION OF EXTERNAL AND INTERNAL LOADS

A complete description of exercise load requires simultaneous consideration of external and internal loads. External load reflects mechanical work output completed by athletes, while internal load represents physiological stress responses of the human body to such output. The ratio between the two partially reveals athletes' current physical efficiency. External load indicators are selected based on basketball-specific characteristics, including total running distance (m), high-speed running distance (cumulative displacement at speed >5 m/s, m), acceleration count (frequency of acceleration >2 m/s^2) and deceleration count (frequency of deceleration <−2 m/s^2). These indicators are collected via Inertial Measurement Units (IMU) and accelerometers embedded in the back of jerseys with sampling frequencies no lower than 100 Hz to ensure time- domain precision of kinematic parameters. Internal load indicators center on cardiopulmonary responses, including Training Impulse (TRIMP), average heart rate (HRavg), percentage of heart rate reserve (%HRR) and post- exercise immediate RMSSD of HRV. TRIMP is calculated via the Bannister method, based on heart rate-time product with a gender correction index b to weight different heart rate intervals differentially, realizing differentiated quantification of contributions from various intensity segments. Table 2 summarizes definitions, units and collection equipment of all indicators, establishing unified operational standards for subsequent model variable assignment and eliminating calculation errors caused by ambiguous indicator definitions [5].

TABLE 2. Summary of External and Internal Load Indicator Definitions

Load Category	Indicator Name	Unit	Collection Equipment	Parameter Description
External Load	Total Running Distance	m	IMU+GPS	Cumulative displacement in a single training session
External Load	High-Speed Running Distance	m	IMU	Cumulative displacement at speed > 5 m/s
External Load	Acceleration Count	Times	Accelerometer	Frequency of acceleration > 2 m/s^2
External Load	Deceleration Count	Times	Accelerometer	Frequency of deceleration < -2 m/s^2
Internal Load	TRIMP	Arbitrary Units (AU)	Chest Strap ECG	Bannister weighted heart rate-time product
Internal Load	Average Heart Rate	Beats/min	Chest Strap ECG/PPG	Mean value during a single training session
Internal Load	%HRR	%	Chest Strap ECG	$(HR - HR_{rest})/(HR_{max} - HR_{rest}) \times 100$
Internal Load	Post-Exercise RMSSD	ms	Chest Strap ECG	Collected within 5 minutes after training termination

B. EXERCISE LOAD INTENSITY GRADING METHOD BASED ON CARDIOPULMONARY RESPONSE CHARACTERISTICS

Grading cardiopulmonary response characteristics is the key step to convert continuous physiological signals into discrete load intervals, and grading rationality directly determines output precision of the quantification model. Load intensity grading takes percentage of heart rate reserve (%HRR) as the primary partitioning standard, referencing the five-interval training intensity framework in sports science. Exercise intensity is divided into five tiers: recovery zone (%HRR <50%), aerobic foundation zone (50% – 65%), aerobic development zone (65% – 80%), anaerobic threshold zone (80% – 90%) and maximum intensity zone (>90%). This partitioning system is calibrated against individual maximum heart rate and resting heart rate, avoiding systematic deviations of fixed absolute heart rate partitioning amid significant individual differences. In basketball-specific contexts, intensity distribution of athletes during a single quarter presents prominent non- uniformity. Relevant studies indicate elite basketball players spend 35%–45% of game time in the anaerobic threshold and maximum intensity zones, while recovery zone time accounts for 20% – 30%, proving high-intensity intermittent movements constitute the main component of basketball load. From the HRV perspective, post-exercise immediate RMSSD is adopted as a quantitative indicator of autonomic nervous recovery status. When RMSSD drops more than 20% below individual baseline values, athletes are judged to be under high fatigue, and the corresponding training load grade is upgraded by one level to reflect the amplified actual load caused by insufficient cardiopulmonary regulation reserve. This grading method integrates objective physiological responses and individual correction, laying a partitioned quantitative foundation for weight assignment of the subsequent multi-variable fusion model [6].

C. MULTI-VARIABLE FUSION MATHEMATICAL MODEL FOR EXERCISE LOAD QUANTIFICATION

After establishing the external load indicator system and internal load grading method, a mathematical model integrating both dimensions into a unified load index is constructed to generate quantifiable results supportable for horizontal comparison and vertical tracking. The model adopts a weighted linear fusion framework, with the Comprehensive Sports Load Index (CSLI) defined as:

$$\begin{aligned}\mathrm{CSLI} = w_1 \mathrm{TRIMP} + w_2 D_{HS} + w_3 N_{acc} \\ + w_4 \left(1 - \frac{\mathrm{RMSSD}_t}{\mathrm{RMSSD}_{base}}\right)\end{aligned}$$

Where: TRIMP = Training Impulse; D_{HS} = Normalized high-speed running distance (m); N_{acc} = Normalized sum of acceleration and deceleration counts; RMSSD_t = Immediate RMSSD (ms) after the current training session; RMSSD_{base} = Individual baseline average RMSSD (ms); w_1, w_2, w_3, w_4 = Weight coefficients of each sub-term, satisfying $\sum_i w_i = 1$. Initial weights are determined via Principal Component Analysis (PCA) based on correlation coefficients between each indicator and blood lactate concentration 24 hours post-training, and can be dynamically revised as cumulative individual athlete data accumulates. The RMSSD ratio term incorporates amplification or reduction effects of current cardiopulmonary recovery status on actual load perception into the model. Therefore, CSLI reflects not only objective output volume of the current training session but also relative physiological stress under athletes' existing physical function. For athletes of different positions, a position correction factor (k_p) is introduced into weight coefficients (Point Guard = 1.05, Forward = 1.00, Center = 0.95) to compensate representative bias of external load indicators induced by disparate running patterns of specific positions, enabling stronger equivalence of CSLI for cross-position comparison [7].

IV. EXPERIMENTAL VERIFICATION AND PRECISION EVALUATION OF THE MODEL

A. SUBJECT SELECTION AND EXPERIMENTAL SCHEME DESIGN

Subjects were recruited from a provincial elite men's basketball team, including 24 athletes (8 point guards, 9 forwards, 7 centers) with average age (22.3 $\pm$ 2.1) years, average height (196.4 $\pm$ 7.8) cm, more than 5 years of training experience, and no musculoskeletal injuries in the latest 3 months, ensuring sample representativeness for the sport and data safety. The experiment spanned a consecutive 6-week pre-competition intensive training phase with 4 training sessions per week, generating 24 data collection nodes and 576 valid data groups in total (24 athletes $\times$ 24 sessions). During each training session, all subjects simultaneously wore chest strap ECG sensors (250 Hz sampling frequency) and back-mounted IMU devices (100 Hz sampling frequency) to collect heart rate, HRV and kinematic parameters. SpO_2 static measurement and subjective RPE scoring (Borg 6–20 scale) were completed within 5 minutes after training. Before the experiment, each athlete underwent an incremental maximum oxygen uptake test (Bruce protocol) and resting HRV baseline measurement to determine individual maximum heart rate, resting heart rate and RMSSD baseline, guaranteeing reliability of individualized model parameters. After denoising and time synchronization, experimental data were split into a model parameter training set (403 groups) and a validation set (173 groups) at a 7:3 ratio. Cross-validation was adopted to evaluate model generalization ability and reduce overfitting risks [8].

B. CORRELATION VERIFICATION BETWEEN MODEL OUTPUT LOAD INDEX AND PHYSIOLOGICAL RESPONSES

Correlation analysis between CSLI and multiple physiological response indicators constitutes the core link for verifying model effectiveness. Analysis targets include immediate post-training blood lactate concentration (La, mmol/L), 24-hour next-morning RMSSD change rate (Δ RMSSD, %) and subjective RPE score. Pearson correlation coefficient (r) and linear regression analysis were adopted for statistical processing with a significance threshold of $p<0.05$. Verification results demonstrate that CSLI has a correlation coefficient r=0.83 ($p<0.001$) with immediate blood lactate concentration, and r=−0.76 ($p<0.001$) with ΔRMSSD. The negative sign indicates higher CSLI corresponds to lower HRV recovery the next morning, consistent with physiological logic expectations. The correlation coefficient between CSLI and RPE score is r=0.71 ($p<0.001$), lower than that of objective physiological indicators, suggesting subjective fatigue scales tend to underestimate load magnitude under high-intensity training, which indirectly proves the information gain of the objective quantification model compared with the RPE method. Bland-Altman analysis reveals the consistency limit between CSLI predicted values and reference load indices derived from blood lactate is $\pm$ 1.24 AU with a mean bias of 0.18 AU, indicating the model delivers favorable prediction consistency within clinically acceptable error ranges [9]. Table 3 summarizes all correlation verification results.

TABLE 3. Correlation Verification Results Between CSLI and Various Physiological Response Indicators

Comparison Variable	Pearson r	p-value	Regression Equation	Mean Bias (AU)
Immediate Blood Lactate (La)	0.83	< 0.001	$La = 0.62 \times CSLI + 1.14$	—
Next-Morning ΔRMSSD	−0.76	< 0.001	$\Delta RMSSD = -8.3 \times CSLI + 12.7$	—
RPE Score	0.71	< 0.001	$RPE = 1.8 \times CSLI + 6.2$	—
Reference Load Index	—	—	—	0.18 ± 1.24

To visually compare the correlation strength between the comprehensive sports load index and different physiological indicators, the Pearson correlation coefficients are summarized in Figure 1.

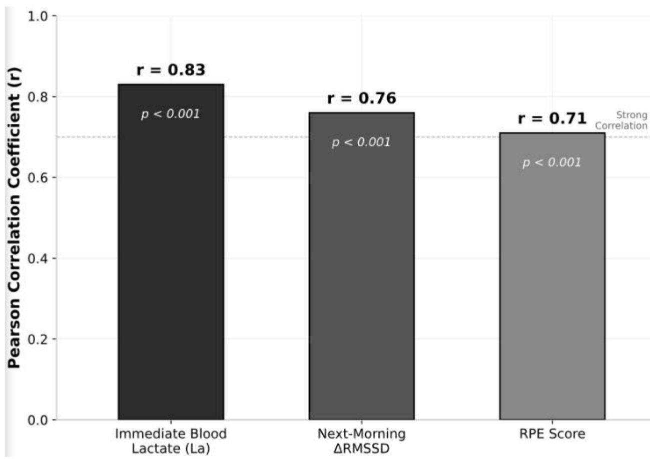

FIGURE 1. Comparison of Pearson Correlation Coefficients Between CSLI and Three Kinds of Physiological Response Indicators

C. MODEL APPLICABILITY TEST AMONG ATHLETES OF DIFFERENT POSITIONS

Model applicability across specialized positions depends on whether the position correction factor k_p effectively offsets systematic impacts of disparate running patterns on CSLI. For point guards, forwards and centers, intra-group correlation coefficients between CSLI and immediate blood lactate concentration were calculated respectively, and Fisher Z-transform difference significance tests were conducted on three groups of correlation coefficients ($p < 0.05$ for significant difference). Before introducing k_p, the CSLI–La correlation coefficient of point guards ($r = 0.79$) was significantly higher than that of centers ($r = 0.68$), with a significant inter-position difference ($p = 0.032$). This indicates external load indicators poorly represent center movement characteristics (higher proportion of low-speed movement and frequent physical contact). After incorporating k_p correction, the correlation coefficients reached $r = 0.84$ for point guards, $r = 0.82$ for forwards and $r = 0.81$ for centers, with no significant inter-group differences ($p = 0.412$). This verifies the position correction factor eliminates systematic positional bias and delivers consistent predictive performance across specialized roles. Additionally, CSLI time series of all three positional groups exhibited fluctuation patterns matching training cycle design throughout the 6-week experiment: average CSLI in intensive weeks was significantly higher than that in recovery weeks ($p < 0.01$), with weekly coefficient of variation (CV) maintained within a reasonable range of 12%–18%. This proves the model possesses sufficient response sensitivity to periodic load variations during pre-competition training and can accurately track dynamic load changes to provide valid quantitative references for subsequent training regulation [10].

V. APPLICATION OF THE QUANTIFICATION MODEL IN BASKETBALL TRAINING LOAD REGULATION

A. REAL-TIME TRAINING INTENSITY MONITORING METHOD BASED ON LOAD INDEX

The engineering application value of CSLI lies in converting background calculation results into real-time perceivable monitoring signals for coaches, rather than merely post-training data review. The real-time monitoring system architecture consists of three layers: data collection layer, edge computing layer and visual display layer.

1. Data collection layer: Athletes wear ECG chest straps and IMU devices, transmitting raw signals to courtside main control tablets every 100 ms via Bluetooth Low Energy 5.0 (BLE 5.0).

2. Edge computing layer: Signal denoising, heart rate extraction and real-time CSLI calculation are completed on tablets, outputting sliding window average values every 30 seconds to reduce judgment interference from instantaneous signal fluctuations.

3. Visual display layer: Real-time CSLI of each athlete is presented on the coach terminal with color grading: green (CSLI<3.0) = safe zone, yellow (3.0–4.5) = early warning zone, red (>4.5) = overload zone. Audio alerts are triggered at threshold crossings, enabling coaches to perceive high-risk athletes without constant screen observation. In practical application during the 6-week validation experiment, the real-time monitoring system triggered 28 overload warnings, among which 24 corresponded to significantly elevated muscle soreness ratings or sharp declines in next-morning RMSSD after review, yielding an early warning accuracy rate of 85.7%. This demonstrates the real-time monitoring method based on CSLI delivers high instant predictive value in practical scenarios and provides objective quantitative evidence for coaches ’ on-site scheduling decisions [11]. The complete hardware calculation, early warning grading and cycle load closed-loop regulation logic of the CSLI real-time training load monitoring system are displayed in Figure 2.

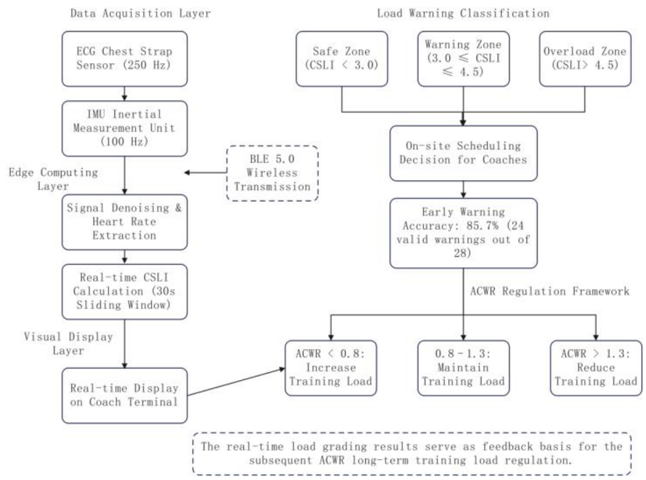

FIGURE 2. Architecture of Real-Time CSLI Training Load Closed-Loop Monitoring and ACWR Regulation System

As shown in Figure 2, the whole monitoring workflow forms a bidirectional closed loop: real-time CSLI risk judgment from training scenes can be fed back to the ACWR long-term load adjustment module, realizing the organic combination of on-site coaching intervention and periodic training plan formulation.

B. QUANTITATIVE FORMULATION FRAMEWORK FOR INDIVIDUALIZED TRAINING PRESCRIPTIONS

Formulating individualized training prescriptions relies on precise matching assessment between athletes’ current physical status and target training stimuli, and historical CSLI data form the quantitative foundation of this assessment. The core regulatory parameter of the individualized training prescription framework is the Acute Chronic Workload Ratio (ACWR), calculated as the ratio of rolling 7-day average CSLI (CSLI_7) to rolling 28-day average CSLI (CSLI_{28}):

$$\mathrm{ACWR} = \frac{\mathrm{CSLI}_7}{\mathrm{CSLI}_{28}}$$

ACWR within 0.8–1.3 (optimal range): Maintain current load design in training prescriptions.

ACWR <0.8: Insufficient recent load; moderately increase total training volume or high-intensity components in the next cycle.

ACWR >1.3: Excessively accumulated acute load; enforce volume reduction and add recovery training sessions to mitigate overtraining risks. Coaches automatically match corresponding templates according to daily ACWR and fine-tune based on tactical training demands, realizing coordinated advancement of scientific load management and specialized technical-tactical training objectives, and avoiding load planning bias arising purely from empirical judgment [12].

C. DYNAMIC TRACKING OF ATHLETES' PHYSICAL STATUS AND LOAD ADJUSTMENT THROUGHOUT THE SEASON

On a full-season scale, vertical tracking of CSLI enables coaching teams to evaluate long-term adaptive evolution patterns of athletes, supporting data-driven design of periodic load fluctuations. A multi-layer physical status tracking system is constructed with three time-scale indicators:

Daily benchmark: Next-morning HRV monitoring;

Weekly benchmark: Weekly cumulative CSLI (WCSLI);

Monthly benchmark: Monthly trend slope of CSLI. When an athlete' s RMSSD remains more than 20% below individual baseline for 3 consecutive days and WCSLI exceeds 15% of historical period average, the system triggers a "systematic fatigue" warning, recommending 1–2 active recovery sessions and reduction of target WCSLI for the following week. Conversely, if WCSLI falls below phase targets for two consecutive weeks with sustained RMSSD elevation above baseline, it indicates athletes have generated training adaptation to current load, and total load can be gradually increased in the subsequent mesocycle. Pre-competition tapering management serves as a critical node of seasonal load adjustment. Based on individual maximum historical CSLI and tapering targets, a progressive reduction scheme is formulated where weekly WCSLI is cut by 40% – 50% compared with peak values. Meanwhile, recovery trajectories of next-morning RMSSD are tracked; athletes are judged to reach optimal pre-competition physical reserve only when RMSSD rebounds above baseline levels. This provides continuous objective physiological data support for coaches to design line-up strategies and post- match recovery plans [13].

VI. CONCLUSION

The basketball-specific exercise load quantification model with wearable devices as collection terminals and cardiopulmonary indicators as core variables establishes a complete technical chain covering synchronous processing of multi-source physiological signals, comprehensive load index calculation and individualized training regulation. Experimental verification confirms CSLI is significantly correlated with blood lactate concentration and HRV recovery indicators. After calibration with position correction factors, the model delivers consistent predictive performance across point guards, forwards and centers, verifying strong practicality and positional adaptability in real training scenarios [14]. In application, the real-time monitoring system, ACWR regulation framework and seasonal cycle tracking system built upon CSLI provide multi-time-scale load management tools for coaches, transforming training load scientific management from qualitative judgment to quantitative decision-making. Future research should expand sample size to include female players and adolescent athletes to test the model's generalization boundary. Meanwhile, incorporating metabolic biochemical indicators such as sweat lactate can supplement muscle metabolism information beyond existing cardiopulmonary monitoring dimensions, further perfecting the calculation foundation of CSLI and driving basketball training load management toward higher refinement and personalization [15,16].

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