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Joint Modeling of Training Load, Sleep, And Heart Rate Variability as A Dynamic System in The Context of Technical and Tactical Training of Young Basketball Players

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ABSTRACT

Within the present study, an analysis is carried out of the distinctive features of the training preparation process of young basketball players conceived as a multidimensional dynamic system. The central focus is the coordinated coupling of indicators of external and internal training load with sleep parameters and heart rate variability (HRV) for the purpose of enhancing the controllability of adaptive responses and of purposefully refining technical and tactical competence. Drawing on systems methodology and on the processing of longitudinal data arrays, the work examines the role of autonomic tone in the formation of cognitive and motor functions in athletes in the under-13 (U13) category. As the instrumental core, mathematical constructs of the stimulus–response class (including the Banister model) are considered, alongside contemporary machine-learning methods (LSTM, random forest) applied to predict functional readiness and the likelihood of developing overtraining. The obtained results underscore the determining significance of sleep quality as a mediating link that connects training stress with indicators of sporting effectiveness manifested in the accuracy of shooting actions and in the productivity of spatial positioning on the court. The formulated concept substantiates the necessity of shifting from episodic control to continuous management of the athlete’s state, implemented on the basis of real-time feedback loops.

Keywords
heart rate variability, RMSSD, youth basketball, dynamic systems, load monitoring, athlete sleep, technical and tactical preparation, training impulse.

INTRODUCTION

Contemporary elite sport, as well as the system for developing the basketball talent pipeline, is undergoing a qualitative restructuring driven by digitalization and the rapid evolution of monitoring instruments. The global market for intelligent wearable devices for sport is characterized by a steady positive trajectory: the projected compound annual growth rate (CAGR) is 8.9%, which, according to estimates, corresponds by 2030 to an increase in aggregate volume to 14.6 billion U.S. dollars [1]. In the segment of sport performance tracking systems, expansion is even more pronounced, reaching up to 13.2% annually, which reflects the growing strategic role of objective registration of physiological parameters in the governance of the training process [2]. Technological solutions that were previously, in effect, constrained to the resources of professional organizations at the level of the NBA or the EuroLeague are now being introduced systematically into youth academies and programs for training young basketball players [1, 3].

The specificity of basketball is determined by high intensity, an intermittent profile of motor activity, and substantial requirements for aerobic and anaerobic endurance, coordinative reliability, and decision-making speed under conditions of strict time scarcity [4, 5]. In the U12–U14 age categories, the preparation process is further complicated by the necessity of coordinating academic workload, the regularities of physical maturation, and the acquisition of complex technical and tactical actions [6]. Under such conditions, traditional planning grounded in rigidly fixed periodization schemes often proves insufficiently sensitive to interindividual variability in adaptive reserves. Heart rate variability (HRV) has become established as a foundational noninvasive biomarker of autonomic nervous system (ANS) activity, enabling a quantitative representation of the balance between the influences of the sympathetic and parasympathetic regulatory loops [7]. Combining HRV indicators with sleep monitoring and the quantitative assessment of training load provides a basis for conceptualizing the athlete's organism as a dynamic system in which the training stimulus functions as an input stimulus, while the level of physiological readiness and sport performance serve as output characteristics [8, 12].

Within the present study, the **objective** is formulated as the development of an integrated approach to modeling the preparation of young basketball players that accounts for the interconnected influence of load, sleep, and autonomic status on technical and tactical indicators; at the same time, emphasis is placed on the analysis of data from the U13 category, for which, within the logic of long-term sport selection, the technical component of preparation surpasses the significance of developing physical conditioning [4].

The scientific novelty of the study consists in the fact that, for the first time, the triad training load–sleep–HRV (lnRMSSD/CV-RMSSD) in U13 youth basketball players is examined as a single controllable dynamic system with feedback, in which sleep parameterizes recovery constants (for example, $\tau 2$) in stimulus–response models and increases the accuracy of forecasting technical and tactical readiness when integrated with machine learning (LSTM/SHAP).

The author's hypothesis is based on the assumption that sleep quality and sufficiency act as a key mediator that modulates the HRV response to training stress and thereby determines the stability of technical and tactical effectiveness (shooting accuracy, positioning), and that continuous modeling of load–sleep–HRV predicts the risk of latent fatigue and overtraining more precisely than isolated monitoring of load or HRV.

Materials and Methods

As a methodological foundation, the athlete's organism is conceptualized as a dynamic system whose state changes continuously over time under the influence of external inputs, first and foremost training stimuli. Within this framework, the fitness–fatigue mathematical construct (the Banister model) is applied, adapted to the analysis of heart rate variability as an informative indicator of adaptive restructuring [8]. The current state of the system at time t is defined by the superposition of a cumulative positive component reflecting increases in training status and a negative component characterizing the severity of fatigue, which provides a formalized description of their competing influence on functional readiness.

The recording of training load relied on instrumental methods that ensure high measurement accuracy of external inputs and enable a quantitative description of the motor-activity profile. To assess external load, local positioning systems (LPS) and inertial measurement units (IMU) were employed, including WIMU PRO and Polar Team Proc [9]. The core variables analyzed were total distance and sprint-activity characteristics, including overall sprint distance and the number of accelerations exceeding individually prescribed threshold values. In addition, the integral Player Load index was used; it is computed from accelerometer signals and reflects the overall intensity of movement. A structurally significant component of the external profile included technical and tactical metrics: the frequency of dribbling and passing, shooting accuracy, and spatial characteristics represented by the spatial exploration index (SEI) [10].

The assessment of internal load was performed via indicators reflecting the physiological cost of the completed work and individual reactivity. As an objective criterion, the training impulse (TRIMP) was used, defined on the basis of heart rate (HR) dynamics and the duration of the training session. The subjective component was represented by the rating of perceived exertion (RPE) using the 10-point Borg format, which made it possible to calculate the session index sRPE as the product of session duration and the subjective intensity rating [11]. This combination of parameters ensured comparability between the external volume of work and the internal strain on regulatory systems.

Heart rate variability monitoring was conducted daily in the morning at rest, which minimized the influence of acute behavioral and training factors. The primary parameter selected for analysis was RMSSD (the root mean square of successive differences of consecutive RR intervals), because it demonstrates high sensitivity to parasympathetic regulation and retains reliability in ultra-short recordings [7]. To improve comparability and the validity of statistical inferences, logarithmically transformed values were used, and a weekly coefficient of variation was also calculated; it was interpreted as an indicator of the stability of the adaptive state and the consistency of autonomic regulation [13].

Sleep was assessed using wearable devices implementing an actigraphy-based approach and was supplemented with data from subjective diaries. The analysis included total sleep time (TST), sleep efficiency, sleep onset latency, and total wake time after sleep onset (WASO) [14]. Particular emphasis was placed on deep sleep characteristics (stage N3), because this stage is of fundamental importance for physical recovery processes and hormonal regulation that support repair after training stress [16].

Statistical processing was based on mixed linear models, which allow simultaneous consideration of interindividual differences and repeated measurements within each athlete, thereby modeling variability in load responses correctly [17]. The predictive component of the study was constructed using machine-learning methods oriented toward the analysis of multidimensional time series and the identification of nonlinear relationships. Recurrent LSTM (Long Short-Term Memory) architectures were applied to model HRV dynamics and to forecast fatigue severity on the basis of preceding states [18]. To interpret the contribution of individual factors to changes in physiological status, SHAP (SHapley Additive Explanations) algorithms were used; they enable quantitative ranking of variable importance, including sleep parameters, RPE, and game minutes, within the structure of predictive models [11].

Results and Discussion

The patterns identified in the sample of youth basketball players indicate a nonlinear relationship between training inputs and heart rate variability. An increased share of high-intensity work is associated with transient suppression of the parasympathetic component of autonomic regulation, which is operationalized as a decrease in RMSSD within 24–48 hours after a training session [19]. When comparing predictors of subsequent HRV dynamics, internal load indicators, primarily sRPE, exhibit higher predictive adequacy, whereas metrics of external volume and movement speed, including high-speed running distance, demonstrate lower explanatory capacity with respect to future HRV changes [8].

In an analysis of a four-week mesocycle in basketball players aged 10–11 years, an undulating organization of the training process is documented: a phase of progressive intensity increase during the first three weeks is followed by a deload phase, reflecting a managed alternation between the accumulation of training stress and its subsequent reduction [9].

Table 1 presents a description of the characteristics of mesocycle stages by intensity, mean HR, and load type.

Table 1. Characteristics of mesocycle stages by intensity, mean HR, and load type (compiled by the author based on [9]).

Mesocycle phase	Intensity	Mean heart rate (beats/min)	Load profile
Week 1	Moderate	130–145	Technical proficiency development and endurance building
Week 2	Stabilizing	135–155	Aerobic base consolidation combined with technical refinement
Week 3	High	145–165	Work at the anaerobic threshold
Week 4	Deloading	125–140	Recovery and functional restoration

In the preseason period, basketball players exhibited a pronounced decrease in the coefficient of variation of lnRMSSD (a 39.9% reduction in lnRMSSDCV), which is interpreted as increased autonomic stability and improved functional status in the absence of statistically significant shifts in mean RMSSD values [13, 15]. This configuration of change indicates the diagnostic limitations of relying exclusively on mean HRV levels and substantiates the priority of monitoring variability metrics as markers of the quality of adaptive restructuring. Within this system, sleep functions as the key mediator of the load–response linkage: the subjective appraisal of sleep quality demonstrates a statistically significant positive association with morning RMSSD values ($p < 0.001$) [19]. Among collegiate and youth-level basketball players, sleep deficit is accompanied by a shift toward sympathetic dominance and a reduction in the adaptive reserve available for the subsequent training session [13]. A substantial limiting factor in youth basketball is the late completion time of practices: training sessions ending after 20:30 statistically significantly reduce total sleep time and impair sleep architecture [14]. As a result, a self-sustaining loop is formed in which high evening load impedes full recovery, and insufficient restitution, in turn, is associated with decreased HRV and an increased likelihood of developing overtraining. For a robust assessment of the weekly HRV trend, mathematical modeling indicates the necessity of recording sleep and HRV for no fewer than five nights per week [21]. Additional diagnostic value is provided by the coefficient of variation of HRV during sleep (HRV), which is considered a digital biomarker of behavioral risk: higher HRV values are associated with lower stability of daily routines and a lower level of everyday physical activity [20, 21]. The accumulation of physical and mental fatigue in basketball assumes particular importance due to the high demands on the precision of motor control, because degradation of fine-grained movement regulation directly affects technical and tactical effectiveness. In experimental tests conducted under different fatigue levels, specific physiological shifts were documented in basketball players [22] (see Table 2).

Table 2. Emerging physiological shifts in basketball players (compiled by the author based on [22]).

Indicator	Resting state	Moderate fatigue	Severe fatigue
Heart rate (beats/min)	85 \pm 8	150 \pm 9	175 \pm 8
RPE (0–10)	7.0 \pm 1.0	13.4 \pm 1.0	17.2 \pm 0.8
lnRMSSD	3.9 \pm 0.5	3.2 \pm 0.4	2.7 \pm 0.4
Lactate (mmol/L)	1.6 \pm 0.4	5.3 \pm 0.8	9.4 \pm 1.2

Pronounced fatigue is associated with decreased shooting accuracy, with three-point attempts proving the most vulnerable due to unfavorable shifts in shoulder-girdle biomechanics and reductions in joint angular velocities [23]. At the same time, the use of external attentional focus strategies is considered a factor capable of partially offsetting this effect: under high levels of fatigue, players who maintain attention on external action-relevant cues demonstrate accuracy that exceeds performance under concentration on internal sensations by 15% [22].

To formalize the coupled influence of load, sleep characteristics, and HRV parameters, it is appropriate to employ a dynamic description in the form of a system of differential equations, in which HRV is specified as a state variable reflecting the current configuration of autonomic regulation. Pronounced fatigue is associated with decreased shooting accuracy, with three-point attempts proving the most vulnerable due to unfavorable shifts in shoulder-girdle biomechanics and reductions in joint angular velocities [23, 24]. At the same time, the use of external attentional focus strategies is considered a factor capable of partially offsetting this effect: under high levels of fatigue, players who maintain attention on external action-relevant cues demonstrate accuracy that exceeds performance under concentration on internal sensations by 15% [22].

To formalize the coupled influence of load, sleep characteristics, and HRV parameters, it is appropriate to employ a dynamic description in the form of a system of differential equations, in which HRV is specified as a state variable reflecting the current configuration of autonomic regulation. The trajectories of technical and tactical skill formation in youth basketball are characterized by pronounced nonlinearity and instability, which is especially evident in the U13 age range. Longitudinal observations of the development of technical components (dribbling, passing, defensive movements) in U12–U14 players demonstrate low to moderate stability of individual trajectories [4]. Such values indicate high variability in current manifestations of skill and a substantial dependence of assessments of promise on the athlete’s current functional state, shaped by the balance between training stress and recovery.

The optimization of tactical preparation is linked to the use of small-sided games (SSG) and differential learning approaches, which create conditions for the purposeful complication of perception and decision-making while preserving high specificity of motor actions. In U13 players after such interventions, a reduction in the spatial exploration index (SEI) and total distance was recorded alongside an increase in the number of meaningful technical actions, in particular dribbling episodes [10]. This configuration of change is interpreted as a transition from predominantly reactive and energetically costly movement to more economical and structured tactical behavior grounded in effective positioning and purposeful activity.

Managing a system in which load, sleep, autonomic regulation, and technical and tactical manifestations are mutually conditioned and change over time is only to a limited extent amenable to description within traditional statistical procedures. In this context, the application of artificial intelligence methods, specifically LSTM-class architectures, is justified due to their capacity to capture long-term dependencies in time series of HRV and sleep parameters [18]. Such algorithms make it possible to identify patterns of latent fatigue in which external indicators of work capacity (for example, movement speed characteristics) are still maintained within acceptable bounds, whereas autonomic markers (RMSSD) already reflect growing overstrain of regulatory systems [25, 27].

Predictive models trained on multisensor arrays (IMU + HR + sleep data) demonstrate high accuracy in solving applied tasks: 84.2–91.4% in the assessment of team coordination and up to 73.6% in forecasting match outcomes on the basis of intensity and recovery metrics [26]. A substantial practical feature of such solutions is the possibility of individualizing training inputs, because the same stimulus can function as a developmental factor for one athlete and simultaneously generate an overtraining risk for another when differences exist in the current HRV level and sleep quality [11] (see Table 3).

Table 3. Technologies and methods for load analysis in basketball: applications and effectiveness indicators (compiled by the author based on [11]).

Technology / Method	Application in basketball	Effectiveness (accuracy/correlation)
LSTM networks	Fatigue prediction based on HRV	95.0
SHAP analysis	Identification of factors influencing HRV	High interpretability
Banister model	Load-cycle planning	r = 0.66–0.69
Data Fusion (LPS+HRV)	Team coordination analysis	r = 0.73

Basketball should be considered an activity in which energetic and mechanical requirements are inseparable from a pronounced cognitive load. Mental fatigue (MF) exerts an adverse influence on specific components of game effectiveness: free-throw accuracy decreases, the frequency of turnovers increases, and the effectiveness of decision-making processes deteriorates, including the use of heuristics under conditions of time scarcity [23]. In this context, heart rate variability acquires an expanded diagnostic significance, reflecting not only the consequences of physical stress but also parameters of psychoemotional strain. Decreases in HRV often precede the emergence of subjectively recognized signs of emotional exhaustion and burnout, which substantiates its use as a sensitive instrument for preventive monitoring of athletes’ states [28].

Conclusion

Joint modeling of training load, sleep characteristics, and heart rate variability within a single dynamic system establishes a fundamentally different control framework for the preparation of youth basketball players, in which the key regulatory variables are examined in their mutual conditionality and temporal dynamics. The synthesis of theoretical propositions and applied inferences makes it possible to articulate a set of conceptually significant theses. The assessment of an athlete's functional state is appropriately grounded in the integral triad Load–Sleep–HRV, because the isolated use of individual indicators, for example only RPE or only HR, inevitably narrows the representation of adaptive status and increases the probability of errors in planning training inputs. Sleep in this system functions as a basic determinant of adaptive processes: increasing sleep duration to an individually optimal level is regarded as the most powerful legitimate factor for enhancing performance, being associated with a 9% increase in shooting accuracy and improved speed characteristics. In youth basketball age groups, regimen discipline becomes decisive, including the restriction of late practices, because shifting the time of session completion disrupts the restorative architecture of sleep and indirectly reduces readiness for subsequent loads.

The informativeness of monitoring increases substantially when emphasis shifts from absolute RMSSD values to indices of its variability. A decrease in variability under relative stability of mean levels is interpreted as a marker of successful adaptation and heightened autonomic stability, whereas the opposite trajectory signals instability of regulatory mechanisms and the potential accumulation of latent fatigue. The effectiveness of technical and tactical skill formation also proves to be functionally dependent on autonomic status: the acquisition of new elements is rationally aligned with periods of optimal autonomic regulation, whereas under pronounced fatigue, reflected by reduced RMSSD, a methodologically justified shift occurs from introducing new coordination tasks to consolidating already formed actions. Under conditions of high fatigue, the maintenance of execution quality can be strengthened through the use of external attentional focus strategies that increase the stability of motor control.

Systems based on intelligent processing of wearable-device data enable a transition from retrospective interpretation to proactive management: machine-learning algorithms can automatically detect risk signals, differentiate athletes' responses to identical stimuli, and thereby individualize training plans at the level of the entire team without loss of controllability. This logic of data integration provides a methodological basis for the development of intelligent decision-support systems in basketball academies, where data-driven governance is simultaneously oriented toward enhancing sport effectiveness and preventing health impairments, thereby ensuring the long-term sustainability of young athletes' sport trajectories. The perspective of further research is associated with incorporating real-time biomechanical parameters to construct an expanded digital player profile capable of describing more precisely the coupling of technique, tactics, and recovery processes.

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