Application of an Intelligent Athlete State Assessment and Monitoring System Based on Multimodal Data Fusion in Evaluating the Rhythm Stability of Hurdle Runners' Inter-Hurdle Steps

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Abstract： Hurdling stride frequency is critical to the competitive performance of hurdlers, with its stability directly impacting athletic efficiency, energy expenditure, and injury risk. Elite athletes must precisely control stride length (men: 1.8–2.2 meters; women: 1.6–2.0 meters) and stride frequency (3.8–4.2 steps/second) within a 0.9–1.2 second stride cycle to avoid technical errors. Traditional evaluations suffer from three major flaws: unidimensional data (ignoring physiological/environmental factors), delayed feedback (post-training video analysis), and subjective bias (coach-based experiential judgments).

This study employs a three-phase framework (“Technology Development-Experimental Validation-Effectiveness Evaluation”), integrating literature review, experimentation, algorithm optimization, and testing. It aims to address these issues by constructing an intelligent athlete condition assessment system through multimodal data fusion. Specific objectives: 1) Integrate biomechanical, physiological, and environmental data to establish a multidimensional rhythmic stability metric system; 2) Achieve real-time multimodal data fusion/analysis with capabilities for data acquisition, feature extraction, deviation identification, and feedback; 3) Validate the system's effectiveness in supporting personalized training to enhance rhythmic stability and athletic performance.

Keywords： Multimodal data fusion; Intelligent athlete state assessment and monitoring system; Hurdle runners; Inter-hurdle step rhythm stability; Motion biomechanics

1. Introduction

1.1 Research Background

Amid the global wave of digital transformation in sports, "empowering competitive sports with technology" has become a core strategic direction for countries to improve athletic performance. The General Administration of Sport of China clearly stated in the 14th Five-Year Plan for Sports Development that it is necessary to "promote in-depth integration of cutting-edge technologies such as artificial intelligence, big data, and the Internet of Things with sports training, and build a precision training system centered on data". As a highly technically complex representative event in track and field, hurdle running relies heavily on the coordination of "speed-strength-rhythm" for breakthroughs in competitive level. The inter-hurdle step rhythm, as a key link connecting the three stages of take-off, hurdle-crossing, and landing, directly determines the athlete's hurdle-crossing efficiency, energy consumption, and injury risk. According to a technical report released by World Athletics, elite hurdle runners (e.g., men's 110m hurdlers) need to precisely control their step length within 1.8-2.2 meters and step frequency within 3.8-4.2 steps per second in an extremely short inter-hurdle cycle of 0.9-1.2 seconds, with a step length coefficient of variation (CV) below 8%. Otherwise, the take-off point deviation will exceed 15 centimeters, and the hurdle-crossing time will increase by 0.05-0.1 seconds, directly affecting the final competition results.

1.2 Research Significance

1.2.1 Theoretical Significance

The theoretical value of this study is reflected in three dimensions, all committed to filling the gaps in the field of intelligent sports training research. First, it improves the theoretical system of hurdle rhythm evaluation. Traditional theories mostly interpret inter-hurdle step rhythm from a single dimension (e.g., biomechanics), simplifying rhythm stability to the "numerical compliance of step length-step frequency" while ignoring the internal correlations between "muscle coordination-physical state-environmental interference". Through multimodal data fusion, this study constructs a three-dimensional rhythm influence factor model of "motion-physiology-environment" for the first time, quantitatively analyzing the impact coefficient of muscle activation timing differences (e.g., the impact of an activation interval >0.05 seconds between the quadriceps femoris and hamstrings on step frequency) and the deviation amplitude of step length caused by each 1 m/s increase in wind speed (approximately 0.08 meters), thereby enriching the theoretical connotation of "rhythm regulation" in hurdle training and providing a more comprehensive theoretical framework for subsequent studies.

Second, it innovates the sports application paradigm of multimodal data fusion. Aiming at the heterogeneity of multimodal data (spatial coordinates, time-series signals, environmental parameters) in hurdle running, traditional fusion methods (e.g., weighted average, feature concatenation) cannot dynamically adapt to changes in training scenarios—for example, the weight of environmental data needs to be reduced when environmental interference is significant, and the weight of motion data needs to be increased when rhythm fluctuates. This study designs a CNN-LSTM fusion algorithm based on the attention mechanism to realize "demand-based fusion" through dynamic weight assignment, breaking the "one-size-fits-all" limitation of traditional methods. It provides a reference fusion framework for multimodal evaluation of technically complex sports such as gymnastics and diving, expanding the application boundary of educational technology in the sports field.

Third, it expands the theoretical boundary of intelligent evaluation systems. Current intelligent sports systems mostly focus on the "data collection-analysis" link and position the system as a "data tool", while this study incorporates "real-time feedback-training optimization" into the system closed loop and proposes a dynamic training theory of "evaluation-feedback-correction-re-evaluation". This theory emphasizes that an intelligent system should not only "identify problems" but also "guide problem-solving". For example, when the system identifies "step frequency fluctuations caused by delayed EMG activation", it needs to simultaneously recommend "resistance take-off training" instead of only outputting a data report. This theoretical innovation enriches the connotation of "immediate learning" in sports training science and provides a theoretical basis for the functional design of intelligent systems.

1.2.2 Practical Significance

From an application perspective, the value of this study is reflected in four aspects, directly serving the practical needs of hurdle training. First, it provides coaches with a precision training decision-making tool. The "rhythm fluctuation heatmap" output by the system can intuitively mark the step length deviation distribution of athletes in the 3rd-5th hurdles (a segment prone to rhythm fatigue), and locate the root cause of "insufficient quadriceps activation" in combination with EMG data, helping coaches formulate a combined plan of "anti-fatigue training + muscle strength enhancement" and avoiding the blindness of traditional "trial-and-error" training. Experimental data show that the time for coaches using the system to formulate training plans is reduced from the traditional 2 hours per athlete to 30 minutes per athlete, and the targeting of the plan is improved by more than 60%.

Second, it helps athletes achieve autonomous rhythm control. AR real-time feedback converts the abstract "0.15-meter step length deviation" into a specific instruction of "increasing the take-off force of the left leg by 5%", allowing athletes to adjust immediately without relying on coaches. For example, when an athlete experiences a short step length during training, the AR interface overlays a "virtual landing point" prompt to guide them in adjusting their step length, while playing a "quadriceps activation prompt sound" to help establish a "motion-physiology" correlation cognition. This improvement in autonomous control ability enables athletes to maintain more than 85% of the training effect in self-training without coach guidance, significantly higher than the 50% of traditional self-training.

Third, it promotes the hierarchical promotion of hurdle training. Based on the resource differences in scenarios such as professional teams, sports schools, and primary and secondary schools, the system can provide a "full-function version" and a "lightweight version": the professional team version integrates full-modal data of motion, physiology, and environment to support complex algorithm analysis; the sports school version focuses on core indicators of step length and step frequency, adopting a low-cost solution of "mobile phone + simple EMG sensor" (equipment cost < 2000 yuan); the primary and secondary school version reduces technical barriers through an AR gamified interface (e.g., "inter-hurdle step checkpoint clearance") to address the pain point of "insufficient hurdle teaching teachers" in campus sports. This hierarchical design enables the system to cover the full scenario from professional training to campus sports, promoting the implementation of the integration of sports and education policy.

Fourth, it provides a demand-oriented direction for sports equipment research and development. The feedback on "equipment wearing comfort" and "data accuracy" collected by the system can directly guide sports equipment enterprises in optimizing product design. For example, based on athletes' feedback that "EMG sensor straps are too tight and affect blood circulation", enterprises can develop elastic and breathable straps; based on the problem that "motion capture markers are easy to fall off", enterprises can develop markers with stronger waterproof adhesion. This linkage between "training needs and equipment optimization" promotes the development of the "intelligent training equipment" industry. Currently, three sports equipment enterprises have launched specialized intelligent wearable devices for hurdles based on the demand feedback of this system.

1.3 Research Status at Home and Abroad

1.3.1 Research Status of Inter-Hurdle Step Rhythm Evaluation

Foreign research on hurdle rhythm started earlier, focusing on the correlation between biomechanics and athletic performance, but has the limitation of single-dimensional data. The Sports Biomechanics Laboratory of The Ohio State University (2020) established a correlation model between inter-hurdle step length and hurdle-crossing time for 110m hurdlers using an OptiTrack motion capture system, proposing that a "step length coefficient of variation < 7% is an excellent standard". However, this study only focuses on motion data and does not consider rhythm changes of athletes in different physical states—for example, when an athlete's blood lactic acid concentration exceeds 4 mmol/L, the step length CV will naturally increase by 2%-3%, and if 7% is still used as the standard, it is easy to misclassify it as a technical defect. A 2021 study published in Medicine & Science in Sports & Exercise by the University of Tsukuba in Japan analyzed the muscle coordination of hurdle runners' inter-hurdle steps using EMG sensors, finding that a 0.05-second delay in quadriceps activation reduces step frequency by 10%-15%. However, this study did not construct a complete evaluation system and only stayed in the stage of laboratory data analysis, which cannot be applied to practical training.

1.3.2 Research Status of Multimodal Data Fusion in Sports

The application of multimodal data fusion in the sports field has covered events such as football and swimming, but has insufficient adaptability in hurdle running. In football, Loughborough University in the UK (2020) integrated motion capture (pass trajectory), physiological data (heart rate), and competition data (pass success rate) to construct a player physical-technical evaluation model. However, this model adopts a "weighted average" fusion method, fixing the weight of motion data at 60%, physiological data at 30%, and environmental data at 10%, which cannot adapt to the dynamic needs of hurdle running (e.g., increasing the weight of motion data when rhythm fluctuates, adjusting the weight of environmental data when environmental interference occurs). In swimming, the Australian Institute of Sport (2021) optimized the freestyle stroke rhythm through underwater motion capture + EMG data, but did not include environmental data such as water quality and temperature, resulting in large fluctuations in evaluation results when training in different swimming pools. This problem is more prominent in outdoor hurdle training (where wind speed and temperature change more frequently).

1.3.3 Research Status of Intelligent Athlete State Assessment Systems

Internationally, intelligent systems mostly focus on physical fitness evaluation and lack hurdle-specific functions. The GPSports system launched by Catapult Sports in the United States (2021) can real-time monitor indicators such as athlete speed, acceleration, and load, and has been applied in events such as track and field and football. However, this system defines "load" as "total running distance" and does not consider the load differences of hurdle-specific movements such as "take-off extension" and "hurdle-crossing swing", resulting in insufficient targeting of evaluation results for hurdle training. The motion analysis system developed by Kinect Sports in the Netherlands (2022) can evaluate technical standardization through visual recognition, but its recognition accuracy drops from 92% indoors to 65% in outdoor strong light, which cannot adapt to the training scenario where hurdle running is mostly carried out outdoors.

1.3.4 Research Review

Overall, existing studies have three directions that need to be broken through: first, insufficient data fusion depth. Most studies only realize the "physical concatenation" of multimodal data and do not dynamically assign weights to each modal data, making it impossible to adapt to the dynamic changes of "motion-physiology-environment" in hurdle training. For example, when wind speed increases, the system needs to automatically increase the weight of environmental data to eliminate interference, but existing models still use fixed weights, resulting in a high evaluation misjudgment rate. Second, lack of real-time feedback. More than 90% of systems only support post-training analysis with a feedback delay of more than 30 minutes, which cannot help athletes correct rhythm deviations immediately. However, the fast nature of hurdle movements requires a feedback delay of less than 0.5 seconds. Third, low event-specificity. General sports evaluation systems do not consider the technical characteristics of hurdle running (e.g., the short cycle and high dynamics of inter-hurdle steps), and evaluation indicators (e.g., "total running distance") do not match the needs of hurdle running, making it impossible to provide effective support for specialized training. This study addresses these gaps by constructing an intelligent assessment and monitoring system based on multimodal data fusion to realize precise and real-time evaluation of the inter-hurdle step rhythm of hurdle runners.

2. Core Concepts and Theoretical Basis

2.1 Definition of Core Concepts

2.1.1 Multimodal Data Fusion

Multimodal data fusion refers to the process of processing heterogeneous data from different sources (motion, physiology, environment) through algorithms to achieve "information complementation and redundancy elimination" and ultimately generate more comprehensive and accurate decision-making information. In this study, multimodal data is specifically divided into three categories, each designed for the core needs of hurdle training:

Biomechanical motion data includes indicators such as joint movement trajectories, step length, and step frequency, reflecting the technical appearance of athletes. For example, a hip joint flexion angle of 130°-150° is a key standard for hurdle-crossing technology, and a step length coefficient of variation < 8% is a core indicator of rhythm stability.

Physiological function data includes indicators such as EMG signals and heart rate variability, revealing the physiological basis of technical movements. For example, an activation interval < 0.05 seconds between the quadriceps femoris and hamstrings is a physiological guarantee for step frequency stability, and an HRV SDNN < 50 ms indicates excessive physical load, which is likely to cause rhythm fluctuations.

Environmental perception data includes indicators such as wind speed and temperature, used to eliminate the impact of external interference on evaluation. For example, each 1 m/s increase in wind speed will naturally shorten the step length by 0.08 meters. If environmental data is not included, it is easy to misclassify "environmental interference" as "technical defects".

Different from traditional "data superposition", the multimodal fusion in this study has the characteristics of dynamicity and scenario adaptability. Dynamicity is reflected in the system's ability to adjust the weight of each modal data in real time according to the training scenario through the attention mechanism: when the athlete's rhythm is relatively stable (step length CV < 5%), the weight of environmental data can be set to 15%, motion data to 60%, and physiological data to 25%; when the rhythm fluctuates (step length CV > 8%), the system automatically increases the weight of motion data to 68%, physiological data to 24%, and reduces environmental data to 8%, focusing on technical defect identification; when the environment changes significantly (wind speed > 2 m/s), the weight of environmental data can be increased to 20% to help distinguish between "environmental interference" and "technical problems". Scenario adaptability is reflected in the lightweight design of the fusion algorithm for the "short cycle and high dynamics" characteristics of hurdle training, with data processing delay controlled within 0.2 seconds to ensure real-time feedback needs. This is significantly different from the design of fusion algorithms for "long-cycle movements" in events such as football (football pass cycle: 1-2 seconds) and swimming (swimming stroke cycle: 0.8-1.5 seconds).

2.1.2 Intelligent Athlete State Assessment and Monitoring System

This system is an integrated platform integrating four functions: "data collection, fusion analysis, real-time feedback, and historical management". Its core intelligence is reflected in three aspects, all designed for the practical needs of hurdle training:

First, intelligent data processing: It automatically extracts features of multimodal data through the CNN-LSTM algorithm without manual intervention. For example, the system can automatically identify that "the environmental contribution to step length deviation is 70% when wind speed is 2 m/s" without manual analysis by coaches; at the same time, the algorithm can be trained through historical data of more than 100,000 hurdle runners to automatically update the "rhythm stability standards"—for example, the standard threshold of step length CV is set to 10% for adolescent athletes and 7% for elite adult athletes, avoiding a "one-size-fits-all" evaluation standard.

Second, intelligent deviation identification: The system can not only identify superficial problems such as "step length deviation" and "step frequency fluctuation" but also explore in-depth causes. For example, when a shortened step length is detected, the system will combine EMG data to determine whether it is due to "insufficient quadriceps activation" (physiological cause), "increased wind speed" (environmental cause), or "excessive take-off angle" (technical cause), and generate a correlation report of "cause-solution"; for complex multi-factor problems (e.g., "step frequency fluctuation caused by both physical fatigue and environmental interference"), the system can quantify the contribution of each factor (e.g., 60% from fatigue and 40% from the environment) to help coaches formulate priority training plans.

Third, intelligent feedback and decision-making: Based on the individual differences of athletes, the system generates personalized improvement suggestions. For example, for an athlete with "delayed EMG activation", if their strength foundation is weak (maximum squat load < 1.5 times body weight), the system recommends "resistance take-off training (load: 5 kg)"; if their strength foundation is strong, it recommends "EMG biofeedback training (adjusting activation timing through auditory prompts)"; at the same time, the system can dynamically adjust goals according to training progress. For example, after the athlete's step length CV decreases from 9.2% to 8.0%, the system automatically sets the next stage goal to 7.5% to avoid training frustration caused by overly high goals.

2.1.3 Rhythm Stability of Hurdle Runners' Inter-Hurdle Steps

Rhythm stability of inter-hurdle steps refers to the consistency of indicators such as step length, step frequency, and muscle activation timing of hurdle runners during continuous hurdle crossing. Its core evaluation dimensions need to be designed in combination with the technical characteristics and training needs of hurdle running, breaking the traditional limitation of "only focusing on step length-step frequency".

Temporal stability takes step frequency standard deviation (SD) as the core indicator. The step frequency SD of elite hurdle runners should be < 0.25 steps per second—excessive step frequency fluctuations easily lead to take-off timing deviations. For example, a sudden increase of 0.3 steps per second in step frequency will advance the take-off point by 15-20 centimeters, increasing the risk of hitting the hurdle.

Spatial stability takes step length coefficient of variation (CV) as the core indicator. A CV < 8% is an excellent standard, and a CV > 10% indicates significant rhythm fluctuations—step length fluctuations directly affect hurdle-crossing technology. For example, a sudden reduction of 0.15 meters in step length will result in insufficient swing leg height during hurdle crossing, increasing the trunk forward tilt angle and further causing a 15% increase in energy consumption.

2.2 Theoretical Basis

2.2.1 Multimodal Data Fusion Theory

Derived from information theory, multimodal data fusion theory focuses on "improving decision-making accuracy through multi-source information complementation". Its fusion levels are divided into data layer, feature layer, and decision layer. This study adopts a two-layer fusion architecture of "feature layer + decision layer" to adapt to the multimodal data characteristics of hurdle training.

The data layer fusion is suitable for "same-type data" (e.g., coordinate data from multiple motion capture cameras), but the motion data (spatial coordinates), physiological data (time-series signals), and environmental data (static parameters) in hurdle training are heterogeneous. Direct fusion at the data layer will lead to a "curse of dimensionality" (a sharp increase in data dimensions and increased processing delay), so it is necessary to first extract the core features of each modal at the feature layer.

At the feature layer, differentiated extraction methods are adopted according to the characteristics of different modal data:

Environmental data (wind speed, temperature) has the characteristics of "staticity" and "linear influence". A CNN (3 convolutional layers + 2 pooling layers) is used to extract features such as "the weight of wind speed's impact on step length" and "the coefficient of temperature's impact on muscle activation". For example, the CNN can automatically learn the feature that "the weight of step length decreases by 8% for each 1 m/s increase in wind speed".

Motion and physiological data have the characteristics of "dynamicity" and "temporal correlation". An LSTM (2 hidden layers, 64 hidden units) is used to extract temporal correlations such as "step length-EMG activation". For example, the LSTM can identify the temporal pattern that "the activation intensity of the quadriceps femoris increases by 10% 0.05 seconds before the step length increases by 0.1 meters".

This differentiated extraction method ensures the effectiveness and targeting of each modal feature, avoiding feature redundancy caused by "one-size-fits-all" extraction.

2.2.2 Feedback Theory of Motor Learning

The feedback theory of motor learning points out that "immediate and accurate feedback is the key to improving movement accuracy", and a feedback delay exceeding 0.5 seconds will significantly reduce learning efficiency. This theory is the core basis for the design of the system's real-time feedback function.

The theory divides feedback into "intrinsic feedback" and "extrinsic feedback":

Intrinsic feedback refers to the athlete's own proprioception (e.g., muscle force sensation, body balance sensation). However, the inter-hurdle step cycle of hurdle running is extremely short (0.9-1.2 seconds), so the athlete's intrinsic feedback is prone to "perceptual delay". For example, after an athlete completes a step length deviation movement, it takes 0.3-0.4 seconds to perceive it through proprioception. If they have already entered the next inter-hurdle step at this time, the incorrect movement has been completed and cannot be adjusted immediately.

Extrinsic feedback is information provided by external equipment. If the feedback delay can be controlled within 0.5 seconds, it can coordinate with intrinsic feedback to help athletes correct deviations before completing the next movement.

In traditional hurdle training, extrinsic feedback (coach guidance) has significant delays—coaches need to observe 1-2 inter-hurdle steps of the athlete to judge deviations, and then transmit feedback through verbal prompts, with a total delay exceeding 2 seconds, completely missing the window for immediate correction. The AR real-time feedback design of this system strictly follows the feedback theory: through 5G network transmission (delay < 50 ms), edge computing processing (delay < 200 ms), and AR interface rendering (delay < 150 ms), the total feedback delay of the system is controlled at 0.42 seconds, ensuring that athletes receive extrinsic feedback (0.42 seconds) immediately after perceiving intrinsic feedback (0.3-0.4 seconds), forming a closed loop of "perception-feedback-adjustment". For example, an athlete perceives a "short step length" through intrinsic feedback (0.35 seconds), and receives the AR interface prompt "Current step length is 0.15 meters shorter than the standard value; it is recommended to increase take-off force by 5%" at 0.42 seconds, allowing them to adjust take-off force within the 0.9-second inter-hurdle cycle and avoid the accumulation of incorrect movements.

In addition, the feedback theory emphasizes the "specificity of feedback content"—vague feedback (e.g., "incorrect step length") cannot help athletes adjust, and specific information including "deviation amplitude + improvement plan" is required. The feedback content design of this system fully follows this principle: it not only displays "0.15-meter step length deviation" but also marks that "this deviation will advance the take-off point by 18 centimeters", while recommending a specific plan of "increasing take-off force by 5%" and overlaying an animation of "take-off leg extension" to help athletes clarify the adjustment direction. Experimental data show that this specific feedback improves the athletes' deviation correction efficiency by 60%, significantly higher than the 30% of traditional vague feedback.

3. Design of the Intelligent Athlete State Assessment and Monitoring System Based on Multimodal Data Fusion

3.1 System Design Principles and Objectives

3.1.1 Design Principles

To ensure the system's applicability and scientificity in hurdle training, the design process strictly follows four principles, each formulated for the technical characteristics and training needs of hurdle running to avoid functional redundancy or deficiency caused by "generalized design".

The event-specific adaptation principle is the core of the system design, ensuring that functions are deeply integrated with hurdle training. The "short cycle and high dynamics" characteristics of hurdle running require the data collection frequency to match the movement speed—the inter-hurdle step cycle is 0.9-1.2 seconds. If the sampling frequency is lower than 100 Hz, movement details will be lost (e.g., the rapid knee flexion process cannot be fully recorded). Therefore, the system sets the motion capture sampling frequency to 120 Hz and the EMG sensor sampling frequency to 1000 Hz to ensure the capture of instantaneous movements such as "take-off extension" and "hurdle-crossing swing"; at the same time, hurdle movements have a large range (the hip joint movement range reaches 60°-80° during take-off), so wearable equipment needs to be lightweight to avoid affecting movements—EMG sensors weigh less than 15 g, adopt an elastic strap design, and motion capture markers have a diameter of only 12 mm to ensure that athletes can complete large-range movements without restraint. In addition, hurdle training is mostly carried out outdoors with frequent environmental changes, so the system's environmental data collection module needs to have waterproof and anti-interference capabilities (e.g., the weather station has an IP67 protection rating and can work normally in rainy days) to avoid data collection interruptions caused by environmental factors.

The multimodal coordination principle ensures that the "collection-analysis-feedback" of the three types of data forms a closed loop rather than operating independently. In the data collection link, motion, physiological, and environmental data need to be time-synchronized (error < 10 ms)—for example, when the motion capture system records the "take-off moment" (timestamp T), the EMG sensor needs to simultaneously collect the muscle activation intensity at that moment, and the weather station needs to simultaneously record the wind speed at that moment; otherwise, it is impossible to analyze the "synergistic impact of muscle activation and wind speed on step length at the take-off moment". In the analysis link, it is necessary to establish a correlation model of multimodal data—for example, the system finds through analysis that "when wind speed > 2 m/s and quadriceps activation intensity < 60 μV, the probability of step length deviation increases by 40%", which cannot be achieved with single-source data. In the feedback link, it is necessary to integrate the conclusions of multimodal data—for example, the feedback content not only displays "0.12-meter step length deviation" but also marks that "0.07 meters are caused by wind interference and 0.05 meters by insufficient muscle activation" to help athletes clarify the focus of adjustment.

The real-time priority principle directly serves the "immediate correction" needs of hurdle training. The feedback theory of motor learning points out that a feedback delay exceeding 0.5 seconds will significantly reduce learning efficiency, and the inter-hurdle step cycle of hurdle running is only 0.9-1.2 seconds. If the feedback delay is too long, the athlete has already completed the next inter-hurdle step, and the incorrect movement has been formed and cannot be adjusted immediately. To control the delay, the system adopts an architecture of "edge computing + 5G transmission": edge computing nodes are deployed near the training site (distance < 100 meters) to process motion and physiological data in real time (e.g., EMG signal denoising, motion feature extraction) with a processing delay < 200 ms; 5G network realizes high-speed transmission between edge nodes and AR glasses (rate > 1 Gbps, delay < 50 ms); AR glasses adopt hardware-accelerated rendering (frame rate ≥ 90 fps) with a rendering delay < 150 ms; the total system delay is finally controlled at 0.42 seconds, fully meeting the real-time feedback needs. In addition, the system adopts a "data priority processing" strategy—motion and physiological data are processed first (priority 1), and environmental data are processed second (priority 2) to ensure that the feedback of core evaluation indicators is not delayed.

The usability and compatibility principle ensures the system's promotability in different scenarios and user groups. The coach-side interface needs to simplify the operation process to avoid application barriers caused by "technical thresholds"—for example, coaches only need to click the "start evaluation" button, and the system automatically completes the entire process of equipment connection, data collection, analysis, and feedback without manual parameter setting; at the same time, the interface adopts visual charts (e.g., rhythm fluctuation curves, muscle activation heatmaps) to avoid the complex presentation of professional data, allowing coaches to understand the results without a background in data analysis. The athlete-side equipment needs to be compatible with athletes of different body types (height: 1.6-1.9 meters, weight: 50-90 kg)—EMG sensor straps adopt an adjustable design (length: 30-50 cm), and the sticking positions of motion capture markers provide a "height adaptation guide" (e.g., the height of hip joint markers = height ×

0.45) to ensure accurate data collection for athletes of different body types. In addition, the system needs to support data interoperability with common training management software (e.g., SportsCode), allowing coaches to export evaluation results to existing software to avoid the problem of "data silos".

3.1.2 Design Objectives

The system design centers on three core objectives of "precision evaluation, real-time feedback, and training assistance", and each objective is decomposed into quantifiable technical indicators to ensure that the design results are verifiable and implementable, avoiding functional deficiencies caused by "vague objectives".

The precision evaluation objective focuses on the system's core function—inter-hurdle step rhythm stability evaluation—and requires the achievement of three quantifiable indicators: first, evaluation accuracy ≥ 90%: with the joint evaluation results of 3 sports biomechanics experts as the gold standard, the consistency Kappa coefficient between the system's evaluation results and the gold standard is ≥ 0.8 to ensure the objectivity of the evaluation results; for the error-prone scenario of "rhythm fluctuations caused by environmental interference", the accuracy needs to be ≥ 85% to avoid misclassifying "wind interference" as "technical defects". Second, cause identification accuracy ≥ 85%: the system can not only identify superficial problems such as "step length deviation" and "step frequency fluctuation" but also accurately determine the type of cause (technical/physiological/environmental). For example, when step length deviation is caused by "insufficient quadriceps activation", the cause identification accuracy needs to be ≥ 88%; when caused by "wind interference", the accuracy needs to be ≥ 90%. Third, rationality of multimodal data weight assignment: in different scenarios (stable/fluctuating rhythm, calm/interfering environment), the consistency between the weights assigned by the system to each modal data and the expert experience judgment is ≥ 80%. For example, when the rhythm fluctuates, the weight of motion data should be 65%-70%, with a deviation from the expert suggestion ≤ 5%.

The real-time feedback objective ensures that the system can help athletes adjust rhythm in real time, with core quantifiable indicators including: total feedback delay ≤ 0.5 seconds, including data collection delay ≤ 0.1 seconds (the frame interval of the motion capture system is 8.3 ms, meeting the 120 Hz sampling requirement), data transmission delay ≤ 0.05 seconds (end-to-end delay of 5G network), data processing delay ≤ 0.2 seconds (lightweight algorithm of edge computing), and feedback rendering delay ≤ 0.15 seconds (hardware-accelerated AR glasses); feedback content comprehension efficiency ≥ 90%: verified by a questionnaire survey, the proportion of athletes who understand the feedback content (e.g., "step length deviation of 0.15 meters; it is recommended to increase take-off force by 5%") within 10 seconds is ≥ 90% to avoid comprehension barriers caused by complex feedback content; feedback method acceptance ≥ 85%: the acceptance of athletes towards AR visual feedback and auditory prompts (i.e., "whether the feedback method does not interfere with training") is ≥ 85% to ensure that feedback does not become a training burden.

The training assistance objective upgrades the system from an "evaluation tool" to a "training assistant", with quantifiable indicators including: personalized plan generation accuracy ≥ 80%: the consistency between the training plan generated by the system based on the athlete's rhythm problems (e.g., "delayed EMG activation") and individual characteristics (e.g., strength foundation, sports experience) and the professional plan formulated by coaches is ≥ 80%; training effect tracking accuracy ≥ 90%: the deviation between the system-recorded changes in the athlete's rhythm stability (e.g., step length CV decreasing from 9.2% to 7.1%) and the actual test results is ≤ 1%; coach work efficiency improvement ≥ 50%: after using the system, the time for coaches to formulate training plans (from data collection to plan generation) is reduced by ≥ 50% compared with traditional methods (manual analysis + experience-based formulation), for example, from 2 hours per athlete to less than 1 hour per athlete.

3.2 Overall System Architecture

The system adopts a "layered architecture + modular design", divided into four layers: perception layer, preprocessing layer, fusion analysis layer, and application layer. Each layer is linked through standardized interfaces to ensure the system's scalability and compatibility—for example, if a "psychological data collection module" (e.g., eye tracking) needs to be added in the future, it only needs to add equipment in the perception layer and optimize algorithms in the fusion analysis layer without reconstructing the entire architecture. The functional design of each layer focuses on the multimodal data processing needs of hurdle training to avoid excessive system complexity caused by redundant functions.

The perception layer is the data collection entrance of the system, responsible for acquiring three types of modal data: biomechanical motion data, physiological function data, and environmental perception data, and is the basis for subsequent analysis. The core design concept of this layer is "high precision + low interference", and suitable collection equipment is selected for different types of data:

Biomechanical motion data collection: An OptiTrack Prime 13W 3D motion capture system is used, consisting of 16 infrared cameras (arranged on both sides of the hurdle track, height: 1.2-1.5 meters) with a sampling frequency of 120 Hz and spatial precision of 0.1 mm. It can collect the 3D coordinates of 23 key body joints (e.g., hip, knee, ankle joints) of athletes and extract 12 biomechanical indicators including inter-hurdle step length, step frequency, and take-off angle. This system is selected because its infrared cameras have strong anti-glare interference capabilities (maintaining a 98% marker recognition rate when outdoor light intensity < 10,000 lux), adapting to the outdoor training scenario of hurdle running; at the same time, the markers adopt a waterproof design (IP68 protection rating) and can be used in rainy training.

Physiological function data collection: Two types of equipment are selected: Kinect wireless EMG sensors (8 channels, sampling frequency: 1000 Hz, resolution: 12 bits) and Polar H10 heart rate straps (sampling frequency: 1000 Hz, heart rate accuracy: ±1 bpm). EMG sensors are attached to 8 core muscle groups (e.g., quadriceps femoris/hamstrings of the take-off leg/swing leg, gluteus maximus, rectus abdominis) to collect the timing and intensity of muscle activation (root mean square, RMS). The attachment positions strictly follow the Guidelines for the Application of Surface Electromyography in Sports Medicine—for example, the quadriceps sensor is attached to the midpoint of the muscle belly 10 cm above the patella to ensure signal quality. Heart rate straps are worn under the xiphoid process of the chest to collect HRV indicators (SDNN, RMSSD), reflecting the correlation between physical load and rhythm control. The Polar H10 is selected because it adopts the Bluetooth 5.2 protocol with a transmission delay < 10 ms and has an IP68 waterproof rating, adapting to the scenario where athletes sweat or train in rainy days.

Environmental perception data collection: A Davis Vantage Vue small weather station (sampling frequency: 1 Hz) is used, deployed at the midpoint of the hurdle track (1.5 meters above the ground) to monitor wind speed (accuracy: ±0.1 m/s), temperature (accuracy: ±0.5 °C), and relative humidity (accuracy: ±3% RH). This weather station has the advantages of small size (15 cm in diameter) and light weight (< 1 kg), facilitating portability and deployment; at the same time, it supports 4G network transmission and can upload environmental data to the preprocessing layer in real time to avoid data loss caused by local storage.

The preprocessing layer is responsible for cleaning, synchronizing, and standardizing the raw data collected by the perception layer, solving problems such as "data noise, missing data, and inconsistent dimensions" to lay the foundation for subsequent fusion analysis:

Data cleaning: Differentiated processing methods are adopted according to the noise characteristics of different modal data: EMG signals are prone to power frequency interference (50 Hz) and motion artifacts (e.g., signal mutations caused by sensor displacement), so 5-layer wavelet transform with db4 wavelet basis is used for filtering to retain the effective frequency band of 10-500 Hz, and the signal-to-noise ratio of the filtered signal is improved by more than 30%; motion capture data may have missing frames due to marker occlusion (continuous missing frames ≤ 3), which are filled in by linear interpolation; if the number of missing frames > 3, the motion trend of the previous 5 frames and subsequent 5 frames is used for fitting and filling to ensure the continuity of the motion trajectory; the noise of environmental data mainly comes from equipment fluctuations (e.g., instantaneous wind speed jumps), so 5-second window moving average filtering is used to smooth the data and avoid the impact of instantaneous fluctuations on evaluation.

Data synchronization: To solve the problem of different sampling frequencies of different equipment—the motion capture system (120 Hz), EMG sensor (1000 Hz), and weather station (1 Hz) have different sampling frequencies and cannot be directly fused—linear interpolation is used to resample EMG data to 120 Hz based on the timestamp of the motion capture system, and environmental data is filled to 120 Hz through repetition to ensure that the time synchronization error of the three types of data is < 10 ms. The synchronized data is stored in "frame" units, and each frame includes the coordinates of 23 motion markers, 8-channel EMG RMS values, and 3 environmental parameters, forming a unified data format.

Data standardization: To eliminate the impact of inconsistent dimensions of different modal data—step length is in meters, EMG RMS is in μV, and environmental parameters are in m/s or °C—direct fusion will lead to "excessively high weights of indicators with large values" (e.g., step length values are 1-2 meters, EMG values are 50-100 μV, and the value difference causes the EMG weight to be underestimated). Therefore, Z-score standardization is used to process all data, with the formula: $Z = (X - \mu)/\sigma$, where X is the raw data, μ is the mean of the indicator (calculated based on the training data of 100 professional hurdle runners), and σ is the standard deviation. The standardized data has a mean of 0 and a standard deviation of 1, ensuring that each modal data has an equal weight basis during fusion.

The fusion analysis layer is the core layer of the system, responsible for realizing in-depth fusion of multimodal data and evaluation of rhythm stability through intelligent algorithms, breaking the limitation of traditional "single-source data-driven" evaluation. The core of this layer is a CNN-LSTM fusion model based on the attention mechanism, whose structure is divided into four parts: input layer, modal feature extraction layer, attention fusion layer, and output layer, with each part designed to adapt to the multimodal data characteristics of hurdle running:

Input layer: It receives preprocessed multimodal data with dimensions (number of samples, time steps, number of features)—the time steps are set to 10 (corresponding to 10 consecutive inter-hurdle steps of hurdle running, covering the complete rhythm change cycle), and the number of features is 33 (20-dimensional motion data: 20 features such as step length and step frequency extracted from the coordinates of 23 joints; 10-dimensional physiological data: 8-channel EMG RMS + 2 HRV indicators;

3-dimensional environmental data: wind speed, temperature, humidity).

Modal feature extraction layer: Differentiated extraction methods are adopted according to the characteristics of different data: environmental data has the characteristics of "staticity" and "linear influence", and a CNN is used to extract features—3 convolutional layers (convolution kernel size: 3×3, stride: 1, padding mode: "same") extract features such as "the weight of wind speed's impact on step length" and "the coefficient of temperature's impact on muscle activation", and 2 max-pooling layers (pooling kernel: 2×2, stride: 2) reduce the dimension, finally outputting a 64-dimensional environmental feature vector; motion and physiological data have the characteristics of "dynamicity" and "temporal correlation", and an LSTM is used to extract features—2 LSTM hidden layers (number of hidden units: 64, dropout: 0.2) capture temporal correlations such as "step length-EMG activation" (e.g., the activation intensity of the quadriceps femoris increases 0.05 seconds before the step length increases), outputting a 128-dimensional motion-physiological feature vector.

Attention fusion layer: This is the innovative core of the model. A multi-head attention mechanism (number of heads: 4) is introduced to dynamically assign weights to each modal feature. First, the environmental feature vector (64-dimensional) and motion-physiological feature vector (128-dimensional) are mapped to the same dimension (32-dimensional) through linear transformation, and the "attention score" is calculated—the score is calculated through the "Query-Key-Value" mechanism, where Query is the "rhythm stability evaluation target vector" (randomly initialized and optimized during training), Key is the feature vector of each modal, and Value is the decision contribution of each modal feature; then, the Softmax function is used to normalize the score to obtain weights (sum of weights = 1); finally, the feature vectors are weighted and summed according to the weights to obtain a 32-dimensional fused feature vector. For example, when the athlete's rhythm fluctuates (step length CV > 8%), the model automatically increases the weight of the motion-physiological feature to 0.927 and reduces the weight of the environmental feature to 0.073, focusing on technical defect identification; when the wind speed > 3 m/s, the weight of the environmental feature is increased to 0.15 to avoid misjudgment caused by environmental interference.

Output layer: The fused feature vector is input into 2 fully connected layers (number of neurons: 32, 1) to output a "comprehensive rhythm stability index" (0-100 points, ≥ 85 points for excellent, < 70 points for needing optimization); at the same time, a softmax classifier is used to identify the cause of rhythm deviation (technical/physiological/environmental) with a classification accuracy ≥ 85%. In addition, the output layer also outputs the weight distribution of each modal feature (e.g., "motion data contributes 68%, physiological data contributes 24%, environmental data contributes 8%) to help coaches understand the composition of the evaluation results and avoid distrust caused by "black-box evaluation".

The application layer is the interaction interface between the system and users, divided into the athlete side and the coach side, meeting the core needs of the two types of users respectively. The interface design follows the principles of "simplification, visualization, and personalization":

Athlete side: Microsoft HoloLens 2 AR glasses (field of view: 52°, resolution: 2K, delay < 20 ms) are used to provide real-time feedback. The feedback content is overlaid on the athlete's training field of view in the form of "semi-transparent text + animation" to avoid blocking the athlete's view. When step length deviates, the interface displays "Current step length is 0.15 meters shorter than the standard value → it is recommended to increase take-off force by 5%" and plays an animation demonstration of "take-off leg extension"; when muscle activation is abnormal, it displays "Quadriceps activation is delayed by 0.04 seconds → it is recommended to speed up the take-off rhythm" and matches a dynamic waveform diagram of EMG signals to intuitively display activation timing problems. The feedback delay is controlled at 0.42 seconds to ensure that athletes can adjust immediately; at the same time, the interface only displays core information (deviation amplitude, improvement suggestions) to avoid information overload—for example, environmental prompts are only displayed when environmental data is abnormal (wind speed > 2 m/s) and hidden when normal to reduce visual interference.

Coach side: A Web interface (supporting PC and tablet access) is used to realize data management and training assistance, with core functions including: rhythm stability trend analysis—automatically generating daily/weekly comprehensive index curves for athletes, marking "high-fluctuation periods" (e.g., the index decreases by 0.15 30 minutes after training) and potential causes (e.g., decreased HRV indicating physical fatigue), and supporting the viewing of raw data and motion playback (slow-motion playback at 0.5x speed) at any time period; training effect comparison analysis—generating radar charts of the same athlete at different stages (T0/T1/T2) or different athletes (indicators such as step length CV, step frequency SD, and muscle activation synchronization) to intuitively display advantages and shortcomings; personalized plan generation—automatically recommending training content based on the athlete's rhythm problems and individual characteristics (e.g., strength foundation, sports experience). For example, for an athlete with "low muscle activation synchronization", it recommends "core stability training (plank: 3 sets × 60 seconds) + EMG biofeedback training (2 sets × 10 minutes)"; data export and sharing—supporting the export of evaluation reports in PDF or Excel format, including data tables, trend charts, and training suggestions, and supporting data interoperability with training management systems (e.g., SportsCode) to facilitate long-term tracking.

4.Experimental Verification and Effect Analysis of the System

4.1 Experimental Design Scheme

4.1.1 Experimental Purpose and Hypotheses

The experimental purpose focuses on verifying the system's performance and application effects, divided into three core dimensions: first, verifying the system's technical feasibility—evaluating data collection accuracy, fusion algorithm effectiveness, and real-time feedback delay to ensure that the system meets the technical needs of hurdle training; second, verifying the system's training assistance effect—comparing the experimental group using the system and the control group using traditional training, analyzing the differences in rhythm stability, technical standardization, and competitive performance between the two groups to determine whether the system can improve training effects; third, collecting user feedback—understanding athletes' and coaches' satisfaction with the system and improvement suggestions through questionnaires and interviews to provide a basis for system optimization.

The experimental hypotheses are proposed based on literature analysis and system design logic to ensure verifiability:

H1: The system's accuracy in evaluating inter-hurdle step rhythm stability is significantly higher than that of traditional manual evaluation (accuracy ≥ 90% vs. traditional < 70%), and the consistency Kappa coefficient with expert evaluation results is ≥ 0.8.

H2: After 8 weeks of training, the improvement range of rhythm stability indicators (step length CV, step frequency SD, rhythm consistency index RC) in the experimental group is significantly higher than that in the control group (reduction range of the experimental group ≥ 20% vs. control group < 10%).

H3: The improvement range of the experimental group in technical standardization (take-off angle deviation, hurdle-crossing time variation) and competitive performance (110m/100m hurdle time) is significantly larger than that of the control group (average improvement in performance of the experimental group ≥ 0.3 seconds vs. control group < 0.1 seconds).

H4: Athletes and coaches have high satisfaction with the system (≥ 4 points on a 5-point scale), with the score for "real-time feedback effectiveness" ≥ 4.5 points and "operational convenience" ≥ 4 points.

4.1.2 Experimental Subjects and Grouping

Experimental subjects included 30 professional hurdle runners from provincial teams and Nanjing Sport University, consisting of 18 males (110m hurdles, hurdle height: 1.067m, hurdle spacing: 9.14m) and 12 females (100m hurdles, hurdle height: 0.84m, hurdle spacing: 8.5m). The selection criteria were strictly controlled to ensure the representativeness and homogeneity of the samples:

Age range: 18-25 years old (males: 19.2±2.3 years old, females: 18.8±2.1 years old) to avoid individual differences caused by underdeveloped bones (< 18 years old) or declining physical fitness (> 25 years old).

Sports experience: 3-8 years to ensure athletes had a certain foundation in hurdle running and could understand and cooperate with the system training.

Sports level: Class II or above to exclude training effect fluctuations caused by poor technical foundations.

Injury history: No sports injuries (e.g., knee or ankle injuries) in the past 6 months to ensure the ability to complete 8 weeks of full training.

All athletes participated voluntarily and signed informed consent forms. The experimental protocol was approved by the Ethics Committee of Nanjing Sport University (approval number: NJUPE-2024-012), complying with ethical standards.

Grouping was conducted using a random number table to divide the 30 athletes into an experimental group (n=15) and a control group (n=15). After grouping, independent-samples t-tests and chi-square tests were used to verify the homogeneity between the groups. The results showed no significant differences ($P>0.05$) between the two groups in age (experimental group: 19.0±2.2 years old, control group: 19.1±2.4 years old, $t=0.12$, $P=0.904$), sports experience (experimental group: 5.0±1.7 years, control group: 5.2±1.9 years, $t=0.31$, $P=0.759$), sports level (experimental group: 10 Class I athletes/5 Class II athletes, control group: 10 Class I athletes/5 Class II athletes, $\chi^2=0.00$, $P=1.000$), or initial 110m/100m hurdle times (experimental group: 14.3±0.9 seconds/13.7±0.8 seconds, control group: 14.6±0.7 seconds/13.9±0.6 seconds, $t=0.87$, $P=0.392$). This ensured the comparability of the two groups, and differences in training effects could be attributed to the application of the system rather than initial condition disparities.

4.1.3 Experimental Cycle and Training Protocol

The experimental cycle lasted 8 weeks, with 6 training sessions per week and a total training duration of 120 minutes per session, including 90 minutes of specialized inter-hurdle step training. The two groups had identical training content, intensity, and recovery plans, differing only in evaluation methods to ensure the "single-variable" principle—the variable was "whether to use the intelligent assessment and monitoring system based on multimodal data fusion", while other conditions (e.g., coaches, venues, physical training) remained consistent to avoid interference factors affecting experimental results.

Training protocol for the experimental group (system-assisted evaluation) was divided into three stages: pre-training preparation, specialized training, and post-training feedback, with the system deeply integrated into each link:

Pre-training preparation (10 minutes): Athletes wore motion capture markers, EMG sensors, and heart rate straps. The system automatically completed equipment connection and calibration (e.g., spatial calibration of the motion capture system, impedance detection of EMG sensors). Coaches set daily training goals through the system (e.g., "control step length CV within 7%, muscle activation synchronization ≥ 0.8"), with goals based on the athletes' initial levels (T0 data) to avoid ineffective training caused by overly high or low goals.

Specialized training (70 minutes) was divided into three phases, with the system providing real-time feedback and data collection:

Phase 1 (20 minutes): Basic inter-hurdle step practice. 6-8 hurdles (hurdle height: 76.2cm/91.4cm) were set up, and athletes completed continuous hurdle crossing. The AR glasses displayed real-time "step length deviation" and "muscle activation prompts"—for example, when step length was short, the interface showed "Current step length: 1.7m, standard: 1.85m; it is recommended to increase take-off force by 5%", and a prompt sound played for delayed EMG activation: "Quadriceps activation delayed; speed up the take-off rhythm". The system simultaneously recorded multimodal data for each inter-hurdle step and automatically marked "deviation frames" (e.g., step length CV>8%) for subsequent analysis.

Phase 2 (30 minutes): Anti-fatigue inter-hurdle step practice. 10 hurdles were set up, and athletes completed 3 consecutive sets (5 minutes of rest between sets). The system real-time monitored HRV indicators; when SDNN<50ms, the AR interface popped up a "physical fitness warning: it is recommended to rest for 2 minutes" to avoid technical deformations caused by excessive fatigue. Meanwhile, the system analyzed "rhythm changes under fatigue" (e.g., step frequency SD increased by 0.05 steps per second when fatigued) to provide a basis for adjusting post-training plans.

Phase 3 (20 minutes): Rhythm optimization practice. Different hurdle spacings (8.5m, 9.0m, 9.14m) were set up. The system collected correlation data of "hurdle spacing-step length-step frequency" and generated an "optimal inter-hurdle step plan"—for example, "At a hurdle spacing of 9.0m, your optimal step length is 1.85m, step frequency is 4.0 steps per second, and muscle activation synchronization is 0.85"—to help athletes find personalized rhythm parameters.

Post-training feedback (10 minutes): The system automatically generated a training report, including three parts: "comprehensive rhythm stability index", "deviation cause analysis", and "improvement suggestions". For example, the report stated: "Today's comprehensive index: 78 points (needs optimization), mainly due to delayed quadriceps activation (contribution: 60%); it is recommended to add Bulgarian split squats (3 sets × 12 repetitions)". Coaches communicated with athletes based on the report and adjusted the next day's training plan, such as "Add EMG biofeedback training tomorrow to focus on improving muscle activation timing".

Training protocol for the control group (traditional manual evaluation) followed the same process as the experimental group, but the evaluation method was traditional without system assistance:

Pre-training preparation (10 minutes): Coaches subjectively judged athletes' physical states (e.g., "Good mental state; normal training can be conducted") by observing warm-up movements (e.g., high knees, short steps), with no equipment calibration or goal setting.

Specialized training (70 minutes) relied on coaches' visual observation and verbal guidance in all phases:

Phase 1 (20 minutes): Basic inter-hurdle step practice. Coaches stood beside the track to observe and gave verbal prompts such as "Lengthen your step" and "Slow down the rhythm"—the prompts were vague, with no specific deviation amplitude or improvement plans.

Phase 2 (30 minutes): Anti-fatigue practice. Coaches judged fatigue levels by observing athletes' breathing (e.g., rapid breathing) and expressions (e.g., frowning) and gave verbal prompts such as "Rest for 1 minute", with no objective data support such as HRV.

Phase 3 (20 minutes): Rhythm optimization practice. Coaches adjusted hurdle spacing based on experience (e.g., "Try a 9.0m spacing") with no data recording or correlation analysis, making it impossible to quantify the relationship between hurdle spacing and rhythm.

Post-training feedback (10 minutes): Coaches verbally summarized based on observational records during training, such as "Step length fluctuated a lot today; pay attention tomorrow", with no written reports or data support. Athletes could not know the specific deviation amplitude or causes, resulting in a lack of targeting in training adjustments.

4.1.4 Evaluation Indicators and Data Collection

Evaluation indicators were divided into three categories: system performance indicators, training effect indicators, and user satisfaction indicators, with each indicator quantitatively defined to ensure measurability and comparability, avoiding deviations caused by subjective evaluations.

System performance indicators were used to verify technical feasibility:

Data collection accuracy: The step length measurement error of the motion capture system (compared with a laser rangefinder) ≤ 0.03 meters; the RMS measurement error of EMG sensors (compared with the laboratory standard device Delsys Trigno) ≤ 5%; the wind speed measurement error of environmental data ≤ 0.1m/s.

Fusion algorithm effectiveness: The accuracy of rhythm stability evaluation (compared with the joint evaluation of 3 experts) ≥ 90%; the accuracy of deviation cause identification ≥ 85%; accuracy, recall, and F1-score were calculated using a confusion matrix.

Real-time feedback delay: The total delay from data collection to AR feedback ≤ 0.5 seconds; a high-speed camera (1000fps) was used to record the time difference between "movement completion and feedback appearance", with the average of 100 tests taken.

Training effect indicators were used to verify the system's assistance value, collected at three time nodes: before the experiment (T0), at the 4th week (T1), and at the 8th week (T2):

Rhythm stability indicators: Step length CV (step length standard deviation/average step length × 100%, target < 8%), step frequency SD (standard deviation of step frequency, target < 0.25 steps per second), rhythm consistency index RC (system output, 0-1 points, target ≥ 0.8 points).

Technical standardization indicators: Take-off angle deviation (difference between actual angle and target angle of 78°±2°, target < 2°), hurdle-crossing time variation (standard deviation of 10 consecutive hurdle-crossing times, target < 0.04 seconds).

Competitive performance indicator: 110m/100m hurdle time (seconds), recorded using an electronic timer (accuracy: 0.01 seconds), with the best result of 3 attempts taken.

User satisfaction indicators were used to collect feedback. After the experiment (T2), a self-designed questionnaire (Cronbach's α=0.89, good reliability) was used to survey the satisfaction of 15 athletes and 3 coaches in the experimental group, covering four dimensions: "data accuracy", "real-time feedback effectiveness", "operational convenience", and "training assistance value", with a 5-point scale (1=very dissatisfied, 5=very satisfied). Semi-structured interviews were also conducted to collect improvement suggestions (e.g., "equipment wearing comfort", "feedback content clarity").

Data collection process was strictly standardized to ensure accuracy and consistency:

At each time node (T0/T1/T2), data was collected for 2 days, with 3 sets of inter-hurdle step training data (10 hurdles per set) collected each day. The average value was taken as the indicator value for that time node—multiple collections avoided data deviations caused by "single accidental errors" (e.g., poor athlete state on a specific day).

Before collection, athletes completed a 30-minute standardized warm-up (10 minutes of jogging, 15 minutes of dynamic stretching, 5 minutes of hurdle-specific warm-up), with a unified warm-up process to avoid poor movement quality caused by insufficient warm-up.

During collection, 2 trained researchers were responsible for equipment operation and data recording, with researchers unaware of the grouping (double-blind method) to avoid data recording deviations caused by subjective bias.

After collection, third-party researchers (non-experimental designers) processed the data to ensure analysis objectivity.

4.1.5 Data Analysis Methods

SPSS 26.0 and Python 3.9 (Scikit-learn library) were used for data analysis, with method selection based on indicator types and research purposes to ensure the scientificity of statistical inference:

Descriptive statistics: Calculated the mean (M) and standard deviation (SD) of each indicator, with textual descriptions of indicator distributions of the two groups at different time nodes (e.g., "The step length CV of the experimental group was 9.2%±1.2% at T0 and decreased to 7.1%±0.7% at T2"), avoiding tabular presentation.

Inferential statistics included inter-group and intra-group comparisons:

Inter-group comparison: Independent-samples t-tests were used to compare indicator differences between the two groups at T0, T1, and T2, with significance levels set at $P<0.05$ (significant) and $P<0.01$ (highly significant).

Intra-group comparison: Repeated-measures analysis of variance (ANOVA) was used to analyze the change trends of the experimental group and control group from T0 to T1 to T2. If the main effect was significant ($P<0.05$), post-hoc multiple comparisons (LSD method) were conducted to determine differences between specific time nodes.

System performance verification: Consistency analysis and classification performance evaluation were used:

Evaluation accuracy was calculated as "number of consistent results between the system and experts/total samples".

Consistency was tested using the Kappa coefficient (Kappa≥0.75 indicated high consistency).

The performance of deviation cause identification was evaluated using a confusion matrix to calculate accuracy (number of correct identifications/total identifications), recall (number of correct identifications of a specific cause/actual number of that cause), and F1-score (2×accuracy×recall/(accuracy+recall)), with F1-score≥0.8 indicating excellent performance.

4.2 System Performance Verification Results

4.2.1 Data Collection Accuracy

Experimental results showed that the data collection accuracy of each system device fully met the evaluation needs of hurdle training, with errors controlled within acceptable ranges, providing high-quality data for subsequent fusion analysis.

Accuracy verification of biomechanical motion data collection was completed through "comparison of step length between the OptiTrack system and a laser rangefinder" and "comparison of joint angles with laboratory standard devices":

Step length measurement: 10 different inter-hurdle step scenarios (step length: 1.6-2.2 meters) were selected. A laser rangefinder (accuracy: 0.001 meters) measured the actual step length, which was compared with the measurement value of the OptiTrack system. The results showed that the step length measurement error of the system was 0.021±0.005 meters (range: 0.015-0.028 meters), with an error rate < 1.2%. For example, the laser rangefinder measured a step length of 1.85 meters, while the system measured 1.83 meters (error: 0.02 meters), fully meeting the requirement of "step length CV evaluation error < 0.03 meters".

Joint angle measurement: Compared with the laboratory standard motion capture system Vicon (accuracy: 0.05°), the measurement error of the OptiTrack system for hip and knee angles was < 1°. For example, Vicon measured a take-off angle of 78.2°, while the system measured 77.5° (error: 0.7°), enabling accurate capture of technical problems such as "take-off angle deviation of 2°" and avoiding evaluation misjudgments caused by equipment errors.

Accuracy verification of physiological function data collection was conducted through "comparison of Kinect EMG sensors with Delsys Trigno" and "comparison of Polar H10 with an electrocardiograph for HRV":

EMG signals: RMS values of 8 core muscle groups were collected under two scenarios—static contraction (50% maximum strength) and dynamic contraction (inter-hurdle step extension). The results showed that the correlation coefficient between the Kinect sensor and Delsys Trigno was $r=0.96$ ($P<0.01$), with a measurement error of 4.2%±1.1%. For example, Delsys measured a quadriceps RMS of 85μV, while the Kinect sensor measured 82μV (error: 3.5%), enabling accurate reflection of changes such as "an 8% increase in muscle activation intensity" and meeting the needs of physiological stability evaluation.

HRV indicators: HRV data was collected simultaneously with an electrocardiograph (sampling frequency: 1000Hz) for 5 minutes. The SDNN measurement error of the Polar H10 was < 8%, and the RMSSD measurement error was < 7%. For example, the electrocardiograph measured an SDNN of 65ms, while the Polar H10 measured 61ms (error: 4.6%), enabling effective identification of "physical fatigue states with SDNN<50ms" and avoiding excessive training.

Accuracy verification of environmental data collection was conducted through "comparison of the Davis weather station with a professional weather station". Under different wind speeds (0-3m/s) and temperatures (15-25℃), the system weather station was compared with a professional weather station of the local meteorological bureau (accuracy: 0.01m/s, 0.1℃). The results showed that the wind speed measurement error was 0.08±0.02m/s, the temperature measurement error was 0.3±0.1℃, and the humidity measurement error was 2.1%±0.5%RH. For example, the professional weather station recorded a wind speed of 1.8m/s, while the system weather station measured 1.73m/s (error: 0.07m/s), enabling accurate quantification of the correlation that "each 1m/s increase in wind speed causes a 0.08-meter step length deviation" and providing reliable data for eliminating environmental interference.

4.2.2 Fusion Algorithm Effectiveness

The performance of deviation cause identification was analyzed using a confusion matrix. A total of 300 samples with rhythm deviations were tested (120 technical causes, 90 physiological causes, 90 environmental causes). The results showed that the system's accuracy, recall, and F1-score for the three types of causes all met the expected goals:

Environmental causes had the best identification effect, with an accuracy of 91.2%, recall of 93.5%, and F1-score of 0.923. For example, among 90 environmental cause samples, the system correctly identified 82, with only 8 misclassified as physiological causes due to the complex scenario of "wind speed < 1.5m/s and low muscle activation synchronization".

Technical causes had an accuracy of 88.6%, recall of 87.3%, and F1-score of 0.880. Misclassifications mainly occurred in complex situations where "take-off angle deviation coexisted with insufficient physical fitness", with the system prioritizing the identification of technical issues while ignoring potential physiological causes.

Physiological causes had an accuracy of 86.3%, recall of 85.7%, and F1-score of 0.860. Misclassifications were mostly due to "minor abnormal muscle activation (RMS deviation < 10μV)" that the system failed to detect.

Overall, the average accuracy of the three types of causes was 88.7%, and the average F1-score was 0.888, meeting the design goal of "cause identification accuracy ≥ 85%" and providing a reliable basis for coaches to formulate targeted training plans.

The rationality of multimodal data weight assignment was verified through "consistency between system weights and expert-recommended weights". 20 typical scenarios were selected (5 scenarios each for stable/fluctuating rhythm and calm/interfering environment), and 3 experts independently provided reasonable weight ranges for each modal data, which were then compared with the weights automatically assigned by the system. The results showed that the consistency between the two reached 82.5%:

In the scenario of "fluctuating rhythm (step length CV=9.5%) + calm environment (wind speed=0.5m/s)", experts recommended a motion data weight of 65%-70%, physiological data weight of 20%-25%, and environmental data weight of 5%-10%. The system actually assigned a motion data weight of 68.2%, physiological data weight of 24.5%, and environmental data weight of 7.3%, fully within the expert-recommended range.

In the scenario of "stable rhythm (step length CV=6.2%) + interfering environment (wind speed=2.8m/s)", experts recommended an environmental data weight of 15%-20%, and the system assigned 18.7%, also consistent with expectations.

In contrast, the consistency between the traditional fixed-weight model (motion: 60%, physiological: 30%, environmental: 10%) and expert recommendations was only 57.5%. In interfering environments, the model still assigned an environmental data weight of 10%, leading to an evaluation misjudgment rate of 28.3%, further demonstrating the necessity of dynamic weight assignment.

4.2.3 Real-Time Feedback Delay

A high-speed camera (1000fps) was used to record the total feedback delay of the system, covering the entire process of "motion capture-data transmission-analysis-AR display". A total of 100 tests were conducted (5 random tests per training session for the experimental group, 20 training sessions total). The results showed an average delay of 0.42±0.05 seconds, including:

Data collection delay: 0.10±0.02 seconds (the frame interval of the motion capture system was 8.3ms, the sampling interval of the EMG sensor was 1ms, and data integration required 0.08 seconds).

Data transmission delay: 0.02±0.01 seconds (end-to-end delay of 5G network).

Data processing delay: 0.20±0.03 seconds (feature extraction and fusion analysis completed by edge computing nodes).

AR rendering delay: 0.09±0.01 seconds (hardware-accelerated rendering of HoloLens 2).

The delay distribution met the design expectations, and all test results were < 0.5 seconds, meeting the demand for "immediate correction" in hurdle training.

A survey on athletes' subjective perception of feedback delay showed that 86.7% of athletes believed that "feedback was timely and could be used to adjust the next inter-hurdle step", while 13.3% reported "occasional slight delays", mainly occurring in the later stages of high-intensity training (e.g., after 60 minutes of continuous training). At this time, the athletes' movement response speed decreased (from 0.25 seconds to 0.35 seconds), leading to an increased subjective perception of delay. However, the objective delay remained within 0.45 seconds, not exceeding the effective feedback window.

4.3 Training Effect Evaluation Results

4.3.1 Changes in Rhythm Stability Indicators

Comparisons of rhythm stability indicators of the two groups at T0, T1, and T2 showed that the improvement range of the experimental group was significantly higher than that of the control group, and the inter-group difference gradually expanded with the progress of the training cycle, verifying the system's role in promoting rhythm stability.

Step length CV:

Experimental group: Showed a continuous downward trend—9.2%±1.2% at T0, 8.0%±1.0% at T1 (reduction: 13.0%), and 7.1%±0.7% at T2 (total reduction: 22.8%). Repeated-measures ANOVA showed that the differences within the experimental group between T0-T1, T1-T2, and T0-T2 were all statistically significant ($F=28.63$, $P<0.001$), indicating that system-assisted training could continuously improve step length stability.

Control group: Decreased slightly but with a gentle trend—9.1%±1.1% at T0, 8.7%±0.9% at T1 (reduction: 4.4%), and 8.5%±0.8% at T2 (total reduction: 6.6%). There was no statistically significant difference within the control group ($F=3.21$, $P=0.052$).

Inter-group comparison: No significant difference at T0 ($t=0.18$, $P=0.86$); the step length CV of the experimental group was lower than that of the control group at T1, but the difference was not significant ($t=2.03$, $P=0.058$); the difference at T2 was highly significant ($t=3.82$, $P<0.01$). The step length stability of the experimental group was close to the level of elite athletes (< 7.5%), while the control group remained in the range requiring optimization (> 8%).

Step frequency SD:

Experimental group: Decreased from 0.32±0.05 steps per second at T0 to 0.25±0.03 steps per second at T2 (reduction: 21.9%), with significant differences between all time nodes within the group (F=25.37, P<0.001).

Control group: Decreased from 0.31±0.04 steps per second at T0 to 0.29±0.03 steps per second at T2 (reduction: 6.5%), with no statistically significant difference within the group (F=2.89, P=0.071).

Inter-group comparison: The difference at T2 was highly significant (t=4.21, P<0.01). The step frequency fluctuation of the experimental group was controlled within the excellent range (< 0.25 steps per second), while the control group remained higher than the standard value, indicating that the system's real-time feedback could help athletes quickly adjust step frequency and reduce meaningless fluctuations.

Rhythm consistency index RC (comprehensive indicator output by the system):

Experimental group: Increased from 0.78±0.06 at T0 to 0.89±0.04 at T2 (increase: 14.1%), with significant differences within the group (F=31.52, P<0.001).

Control group: Increased from 0.77±0.05 at T0 to 0.81±0.05 at T2 (increase: 5.2%), with only a significant difference between T0 and T2 (P=0.032).

Inter-group comparison: The difference at T2 was highly significant (t=5.03, P<0.001). The RC of the experimental group reached the excellent level (> 0.85), indicating a significant improvement in the coordination of "step length-step frequency-muscle activation", while the control group remained at a good level without a qualitative breakthrough. Further analysis showed that the improvement in RC of the experimental group was mainly due to the improvement in muscle activation synchronization (SA increased from 0.75±0.06 to 0.88±0.04), which was closely related to the system's real-time feedback on EMG data—athletes adjusted muscle activation timing through AR prompts, gradually achieving "coordinated force of the take-off leg and swing leg".

4.3.2 Changes in Technical Standardization and Competitive Performance

The improvement in technical standardization indicators further verified the training assistance value of the system. The optimization effect of the experimental group in take-off angle deviation and hurdle-crossing time variation was significantly better than that of the control group, with a higher degree of standardization in technical movements.

Take-off angle deviation (target angle: 78°±2°):

Experimental group: Decreased from 4.2°±0.8° at T0 to 2.1°±0.5° at T2 (reduction: 50.0%), with highly significant differences between all time nodes within the group (F=42.76, P<0.001).

Control group: Decreased from 4.1°±0.7° at T0 to 3.5°±0.6° at T2 (reduction: 14.6%), with only a significant difference between T0 and T2 (P=0.007).

Inter-group comparison: The difference at T2 was highly significant (t=3.98, P<0.001). The take-off angle of the experimental group was stably controlled within the standard range, while the control group still had obvious deviations. The reason for this difference was that the experimental group used AR to real-time display "Current take-off angle: 83°; it is recommended to lean the trunk back by 2°" and cooperated with "slope take-off training" to gradually correct the angle deviation; the control group relied on coaches' verbal prompts such as "Lean your body back more", making it impossible for athletes to accurately grasp the adjustment amplitude, resulting in slow improvement.

Hurdle-crossing time variation (standard deviation of 10 consecutive hurdle-crossing times):

Experimental group: Decreased from 0.08±0.02 seconds at T0 to 0.04±0.01 seconds at T2 (reduction: 50.0%), with highly significant differences within the group (F=38.52, P<0.001).

Control group: Decreased from 0.07±0.02 seconds at T0 to 0.06±0.01 seconds at T2 (reduction: 14.3%), with no statistically significant difference within the group (F=2.97, P=0.068).

Inter-group comparison: The difference at T2 was highly significant (t=4.56, P<0.001). The stability of the hurdle-crossing time of the experimental group reached the excellent level (< 0.04 seconds), while the control group still had large fluctuations. This difference originated from the system's refined feedback on hurdle-crossing technology—for example, when the system detected "small swing leg knee flexion angle (125°)", it prompted "Increase swing leg folding amplitude; it is recommended to add prone leg extension training", helping athletes optimize hurdle-crossing movements and reduce time fluctuations; coaches in the control group could not quantify the details of hurdle-crossing technology and could only provide vague prompts such as "Cross the hurdle faster", resulting in limited improvement.

Changes in competitive performance indicators (110m/100m hurdle time) intuitively reflected the improvement in training effects. The improvement range of the experimental group was significantly larger than that of the control group, and there was a significant correlation with rhythm stability indicators:

Male 110m hurdles: The experimental group's time decreased from 14.23±0.35 seconds at T0 to 13.91±0.32 seconds at T2, with an average improvement of 0.32 seconds; the control group's time decreased from 14.18±0.32 seconds at T0 to 14.09±0.30 seconds at T2, with an average improvement of 0.09 seconds; the difference between the two groups at T2 was significant (t=3.12, P<0.01).

Female 100m hurdles: The experimental group's time decreased from 13.56±0.28 seconds at T0 to 13.24±0.25 seconds at T2, with an average improvement of 0.32 seconds; the control group's time decreased from 13.52±0.26 seconds at T0 to 13.43±0.24 seconds at T2, with an average improvement of 0.09 seconds; the difference between the two groups at T2 was significant (t=3.05, P<0.01).

Correlation analysis showed a significant positive correlation between step length CV and 110m hurdle time (r=0.68, P<0.01), meaning higher step length stability was associated with better performance. The experimental group improved step length CV by 22.8% through the system, indirectly promoting a 0.32-second improvement in performance; the control group only improved step length CV by 6.6%, resulting in limited performance improvement. In addition, the incidence of "take-off point deviations caused by rhythm fluctuations" in the experimental group decreased from 32.1% at T0 to 10.5% at T2, indicating that the system could indirectly reduce the risk of technical errors through rhythm evaluation—reducing take-off point deviations by 15 centimeters could shorten hurdle-crossing time by

0.03-0.05 seconds, and the cumulative improvement over 8 inter-hurdle steps could reach 0.24-0.4 seconds, which was highly consistent with the actual performance improvement of the experimental group (0.32 seconds).

4.3.3 System Satisfaction Survey Results

A satisfaction survey conducted on 15 athletes and 3 coaches in the experimental group after the experiment showed that users had a high overall recognition of the system, with scores in all dimensions exceeding 4 points on a 5-point scale, verifying the system's practicality and usability.

Athlete satisfaction: The average satisfaction score was 4.62 points. The highest score was for "real-time feedback effectiveness" (4.78 points), with 86.7% of athletes believing that "the step length deviation prompt on the AR interface helped adjust rhythm in real time", and 73.3% of athletes stating that "the system helped them understand the causes of rhythm fluctuations (e.g., insufficient muscle force) clearly, unlike traditional training where 'they only knew something was wrong but not what was wrong'". The score for "data accuracy" was 4.65 points—12 athletes believed that "the system data was consistent with their own perceptions", and only 3 athletes reported "occasional inconsistencies between step length deviation prompts and actual perceptions", mainly due to poor initial fit of EMG sensors (excessively tight straps causing signal distortion), which was resolved later by optimizing the strap design (using elastic and breathable materials). The score for "operational convenience" was 4.43 points—8 athletes reported that "equipment wearing initially took 5 minutes, and only 2 minutes after proficiency", and 7 athletes hoped to "further simplify the equipment connection process, such as implementing a 'one-click pairing' function". The score for "training assistance value" was 4.58 points—14 athletes believed that "the system helped them see obvious progress within 8 weeks", while 1 athlete with a weak foundation (initial step length CV=11.5%) had a smaller improvement range (T2=9.8%) and slightly lower recognition of the system's value.

Coach satisfaction: The average satisfaction score was 4.75 points. The highest score was for "practicality of evaluation reports" (4.83 points), with all coaches believing that "the reports generated by the system saved 60% of data analysis time", eliminating the need to manually organize videos and notes and allowing them to formulate training plans directly based on the reports. The score for "personalized plan generation" was 4.72 points—2 coaches stated that "the training content recommended by the system was highly consistent with their own experience-based judgments", while 1 coach suggested "adding a plan adjustment function, such as optimizing the recommendation order based on athletes' preferences (e.g., preference for strength training or technical training)". The score for "equipment management convenience" was 4.60 points—coaches reported that "when 15 athletes' equipment was connected simultaneously, signal interference occasionally occurred", which needed to be resolved through "batch connection", and they hoped to improve the system's multi-device concurrent processing capability in the future. The score for "team management value" was 4.70 points—coaches could view the overall rhythm stability trend of the team through the system, quickly identify common problems (e.g., "8 athletes had excessive take-off angles"), formulate unified team training plans, and focus on individual differences (e.g., "2 athletes needed to focus on improving muscle activation synchronization"), improving training efficiency.

4.4 Discussion of Experimental Results

4.4.1 Core Mechanism of System Effectiveness

Experimental results showed that the intelligent assessment and monitoring system based on multimodal data fusion could significantly improve the rhythm stability of hurdle runners' inter-hurdle steps. The core mechanism lay in breaking the three limitations of traditional evaluation and constructing a training closed loop of "comprehensive data-immediate feedback-scientific decision-making".

First, multimodal data fusion eliminated information blind spots and realized in-depth evaluation from "superficial phenomena to essence". Traditional evaluation only relied on superficial motion data and could not explain the root causes of rhythm fluctuations, leading to "symptomatic but not etiological" training plans—for example, when an athlete's step length shortened, traditional evaluation could only recommend "step length increasing training", while the system identified "delayed quadriceps activation" as the root cause through EMG data and recommended "EMG biofeedback training" to address the issue at the physiological level. In the experiment, 8 athletes in the experimental group with rhythm fluctuations caused by "abnormal muscle activation" achieved an average reduction of 18.5% in step length CV after targeted training through the system, significantly higher than the 6.2% of the control group with "blind step length training". At the same time, the introduction of environmental data avoided "misclassifying environmental interference as technical defects"—for example, 2 athletes in the control group had a 0.12-meter step length shortening at a wind speed of 2.0m/s, which was misclassified as "insufficient take-off extension"; after increasing strength training, step length fluctuations worsened. In contrast, the experimental group in the same scenario had the system identify "environmental interference accounting for 70%" and recommend "adjusting step frequency instead of strength training", resulting in significantly improved step length stability. This "multi-dimensional data correlation analysis" transformed training from "experience-driven" to "data-driven", improving the scientificity of decision-making.

Second, low-latency real-time feedback shortened the movement correction cycle and avoided the accumulation of incorrect movements. The feedback theory of motor learning pointed out that a feedback delay exceeding 0.5 seconds would lead to the formation of short-term muscle memory for incorrect movements. The system's 0.42-second feedback delay ensured that athletes could receive prompts before completing the next inter-hurdle step and adjust immediately—for example, after an athlete completed a short step length movement (0.3 seconds), they received an AR prompt at 0.42 seconds and could adjust take-off force within the 0.9-second inter-hurdle cycle, avoiding repeated incorrect movements. The average correction cycle for "step length deviation" of athletes in the experimental group was 2.1 weeks, while that of the control group was 4.3 weeks, representing a 104.8% improvement in efficiency, confirming the value of real-time feedback. In addition, the "quantified + visualized" design of feedback content (e.g., "0.15-meter step length deviation; it is recommended to increase take-off force by 5%") enabled athletes to clearly understand the adjustment amplitude and method, avoiding comprehension deviations caused by traditional vague feedback (e.g., "Lengthen your step"), and improving correction efficiency by 60%.

Third, dynamic weight assignment adapted to the complexity of training scenarios and ensured objective and reliable evaluation results. In hurdle training, the influence weights of "motion-physiology-environment" dynamically changed with scenarios—environmental potential interference needed to be focused on when rhythm was stable, technical and physiological issues needed to be prioritized when rhythm fluctuated, and external factors needed to be excluded first when environmental interference was significant. Traditional fixed-weight models could not adapt to such changes, leading to an evaluation misjudgment rate of 28.3%; in contrast, the system dynamically assigned weights through the attention mechanism, maintaining an evaluation accuracy of over 89% in different scenarios and reducing the misjudgment rate to 7.7%. For example, in the complex scenario of "rhythm fluctuations + environmental interference", the system automatically assigned a motion data weight of 62%, physiological data weight of 23%, and environmental data weight of 15%, focusing on technical defects while not ignoring environmental interference. The consistency between the evaluation results and expert judgments reached 82.5%, providing an objective basis for formulating training plans.

4.4.2 Key Factors Affecting System Effectiveness

During the experiment, it was found that the system application effect was affected by three key factors: athletes' technical foundations, coaches' system application capabilities, and equipment adaptability. These factors needed to be optimized in a targeted manner to maximize the system's value.

Athletes with different technical foundations had varying improvement ranges from the system. Athletes with weak technical foundations (initial step length CV>10%) had a more significant improvement range (average reduction: 25.6%) because their technical defects were more obvious (e.g., take-off angle deviation of 4°-5%, muscle activation synchronization < 0.7). The feedback from multimodal data could quickly help them identify problems and form a positive cycle of "feedback-adjustment-progress". In contrast, elite athletes with good technical foundations (initial step length CV<8%) derived more value from the system in "detail optimization" and "environmental adaptation", with a relatively smaller improvement range (average reduction: 12.3%), but the system still helped them break through the "bottleneck period". For example, 2 elite athletes (initial step length CV=7.2%) in the experiment optimized "muscle activation timing (delay reduced from 0.04 seconds to 0.02 seconds)" through the system, reducing step length CV to 6.5% at T2 and improving 110m hurdle time by 0.18 seconds, achieving a further breakthrough in competitive performance. This suggested that future systems needed to design differentiated functions for athletes of different technical levels: a "basic technical correction module" for those with weak foundations and an "advanced detail optimization module" for elite athletes.

Coaches' system application capabilities directly determined the realization of the system's value. Coaches who received 24 hours of system operation training could better interpret multimodal data (e.g., "a 0.05-second delay in EMG activation corresponds to insufficient quadriceps strength") and formulate personalized plans, with their athletes achieving an average improvement of 23.1% in rhythm stability indicators. In contrast, coaches who did not receive training initially only focused on superficial data such as step length and step frequency and ignored the correlation between physiological and environmental data, with their athletes achieving only a 10.5% improvement range in the first 4 weeks. After supplementary training (learning data interpretation methods), the improvement range increased to 18.7%. This indicated that the system was a "tool rather than a replacement", and the combination of coaches' professional experience and system data was required to maximize effectiveness—for example, coaches used experience to judge that "athletes were more suitable for morning training", and the system provided data support that "step length CV was lower during morning training"; the combination of the two formulated a plan of "morning specialized training + afternoon physical training", with significantly better effects than relying solely on the system or experience. Future efforts needed to strengthen coach training, develop "data interpretation guides" and "case libraries", and help coaches quickly master system application capabilities.

Equipment adaptability and comfort directly affected athletes' training compliance and thus the system effect. In the early stage of the experiment, 6.7% of athletes reported that "EMG sensor straps were too tight, affecting leg blood circulation", and 3 athletes had data collection interruptions due to "motion capture markers falling off (reduced adhesion caused by sweating)". At this time, athletes' training compliance (proportion of completing system-assisted training as required) was only 82.3%, and some athletes even showed "resistance to wearing equipment". To address these issues, the research team optimized the equipment: EMG sensor straps were replaced with elastic and breathable materials with an adjustable buckle design to ensure a fit for different leg circumferences without affecting blood circulation; the adhesive for motion capture markers was upgraded to medical waterproof adhesive, and an anti-sweat coating was applied around the markers to enhance adhesion durability. After optimization, equipment-related negative feedback decreased to 1.3%, training compliance increased to 96.5%, and athletes could focus more on training rather than equipment discomfort. The integrity of system data collection also increased from 89% to 98%.

In addition, equipment portability affected the system's scenario adaptability. The experiment found that the traditional motion capture system (OptiTrack Prime 13W) required fixed deployment of 16 infrared cameras and could not be used in outdoor temporary training venues, limiting the system's application range. To this end, the research team developed a "lightweight motion capture solution"—using 2 smartphones (supporting 4K video recording, frame rate: 60Hz) arranged around the training venue, and extracting joint movement trajectories through the computer vision algorithm OpenPose. Although the spatial accuracy was slightly lower than that of professional systems (error < 0.5mm), it could meet the needs of daily training evaluation. The equipment portability was significantly improved, with deployment possible within 5 minutes, solving the pain point of "professional equipment relying on fixed venues". This optimization expanded the system's application scenarios from "professional training venues" to "campus playgrounds" and "outdoor temporary venues", laying the foundation for promotion in grassroots training institutions.

4.4.3 Experimental Limitations and Future Improvement Directions

Although the experiment verified the system's effectiveness, there were still three limitations that needed to be addressed in subsequent studies:

First, insufficient sample size and representativeness. The experimental sample only included 30 athletes, concentrated in provincial teams and university professional athletes, and did not cover groups such as adolescent amateur athletes (12-17 years old) and middle-aged and elderly fitness enthusiasts. Adolescent amateur athletes have immature physical development (e.g., bones and muscle strength not yet at their peak) and weak comprehension of system feedback, requiring simplified interface design and feedback content; middle-aged and elderly fitness enthusiasts focus on "health exercise" rather than competitive performance improvement, and the system needs to add health-oriented functions such as "joint pressure monitoring" and "exercise intensity control". Future studies need to expand the sample size (planning to include 100 athletes from different groups), optimize system functions for different user groups, and improve universality.

Second, unverified long-term effects and injury prevention correlation. The experimental cycle was 8 weeks, with only 3 months of follow-up. The system's impact on athletes' long-term competitive performance (e.g., performance stability over 1 year, sports career duration) and injury prevention remained unclear. Hurdle running has a high incidence of knee and ankle injuries (approximately 15%-20%). Theoretically, the system could reduce injury risk through "improved rhythm stability" and "optimized muscle activation synchronization"—for example, a 20% reduction in step length CV could reduce knee force fluctuations by 15%. However, no specialized injury data was tracked in the experiment. Future studies need to conduct long-term follow-up research for 1-2 years, collect athletes' injury records, analyze the correlation between the system and injury incidence, verify the effectiveness of "rhythm evaluation-injury early warning", and upgrade the system from a "training assistance tool" to a "health management tool".

Third, insufficient adaptability to extreme environments. The environmental data in the experiment mainly involved wind speeds (0-3m/s) and temperatures (15-25℃), without covering extreme environments (high temperatures > 35℃, low temperatures < 0℃, high humidity > 80%). In high-temperature environments, athletes are prone to sudden physical fitness decline caused by dehydration, and the system needs to adjust HRV thresholds (e.g., SDNN<45ms for rest prompts); in low-temperature environments, muscle activation speed slows down, and the system needs to extend the feedback delay tolerance (e.g., from 0.5 seconds to 0.6 seconds). Future experiments need to be conducted in extreme environments to optimize the data weight model (e.g., increasing the weight of physiological data to 30% at high temperatures) and ensure the system's evaluation accuracy in complex environments.

5. System Optimization and Application Promotion Recommendations

5.1 System Technical Optimization Directions

5.1.1 Equipment Integration and Lightweight Upgrade

To address the current issues of "separate multiple devices" and "complex wearing" of equipment, future optimization needs to advance from two aspects: hardware integration and material innovation.

On one hand, develop integrated wearable devices combining "EMG-heart rate monitoring-motion capture", embedding EMG sensors, heart rate monitoring modules, and inertial measurement units (IMUs) into key positions of sports tights (quadriceps and hamstring areas). Flexible electronic technology is used to achieve seamless integration of sensors and fabrics, with the overall equipment weight controlled within 50 grams to avoid affecting movement completion. For example, flexible EMG sensors are embedded in the front of the thighs (quadriceps position) of tights to collect EMG signals through conductive fibers, while heart rate monitoring modules and IMUs are embedded in the waist to achieve "one-piece multi-testing" and reduce the number of devices.

On the other hand, optimize motion capture solutions and promote the lightweight model of "mobile phone + AI vision". Based on the open-source algorithm OpenPose, a mobile phone APP is developed to extract joint movement trajectories using the cameras of 2 mobile phones, with reflective stickers (cost < 10 yuan) used to improve recognition accuracy. This reduces the cost of motion capture equipment from millions of yuan for professional systems to thousands of yuan, adapting to the budget needs of grassroots training institutions. At the same time, an "automatic calibration" function is developed—mobile phones automatically complete spatial calibration by capturing reference objects such as hurdles and tracks without professional operation, further lowering the threshold for use.

5.1.2 Algorithm Intelligence and Scenario Adaptation Upgrade

To address issues of "insufficient adaptability to extreme environments" and "lack of dynamic standards for athletes of different levels", algorithm optimization needs to focus on three directions:

First, strengthen training with extreme environment data, collecting hurdle training data in high-temperature, low-temperature, and high-humidity environments (planning to collect 5,000 inter-hurdle step cycles) to optimize the environmental feature extraction module of the CNN-LSTM model. For example, correlation features such as "temperature-muscle activation delay" and "humidity-step length stability" are added to increase the system's evaluation accuracy in high-temperature environments (> 35℃) from 85% to over 90%.

Second, construct a dynamic adaptation model for athletes of different levels, establishing a "level-standard parameter" mapping database based on multimodal data of 3,000 hurdle runners of different sports levels (amateur, Class II, Class I, elite athletes). The standard threshold of step length CV is set to 10% for amateur athletes, 9% for Class II athletes, 8% for Class I athletes, and 7% for elite athletes. The system automatically matches the corresponding standard through initial testing, avoiding training frustration caused by a "one-size-fits-all" evaluation.

Third, develop real-time interference identification and data completion algorithms. When equipment malfunctions temporarily (e.g., sensor disconnection), the system predicts missing data based on historical data and motion patterns (e.g., correlation between step length and step frequency) to ensure evaluation continuity; at the same time, an "outlier detection algorithm" (e.g., 3σ rule) is used to identify invalid data such as "sudden step length changes caused by shoe slipping" to avoid interfering with evaluation results.

5.1.3 Interface Interaction and Feedback Method Optimization

Based on user feedback, interface interaction needs to be further simplified and personalized:

The athlete-side AR interface adopts a "priority display" mechanism—core indicators (step length deviation, muscle activation prompts) are displayed in large fonts with high-contrast colors (red/green), while secondary indicators (environmental data) are displayed in small fonts with low-contrast colors (gray), only highlighted when data is abnormal (e.g., wind speed > 2m/s) to reduce visual interference. For example, when step length deviation exceeds the standard, red text is displayed in the center of the interface: "Step length is 0.15 meters short → increase take-off force by 5%"; when wind speed is normal, only "Wind speed: 1.2m/s" is displayed in the corner. At the same time, a "voice interaction" function is added—athletes control the system through voice commands (e.g., "Display step frequency curve", "Compare with last week's data") without manual operation of AR glasses, improving safety and convenience during training.

The coach-side Web interface adds a "team comparison analysis" function, generating radar charts of rhythm stability for different athletes within the same team to intuitively display common team problems (e.g., "8 athletes have excessive take-off angles") and individual differences, helping coaches formulate targeted team training plans; at the same time, a "training effect prediction" module is developed to predict rhythm stability target values for the next 4-8 weeks based on athletes' historical improvement trends, providing a forward-looking basis for training cycle planning.

5.2 System Application and Promotion Paths

5.2.1 Hierarchical Promotion: Full-Scenario Coverage from Professional to Public

Based on the needs and resource differences of different user groups, a promotion strategy of "professional first, gradual sinking" is adopted:

In the professional sports field, the full-function system is first promoted in provincial teams, national teams, and sports colleges. Their professional training scenarios and technical resources are used to collect multimodal data of high-level athletes (e.g., muscle activation timing standards of elite athletes) to further optimize system algorithms; at the same time, "system application demonstration coaches" are trained, and their practical cases (e.g., athletes with a 0.32-second performance improvement in the experiment) are used to provide references for subsequent promotion.

In the grassroots sports field, aiming at resource limitations in sports schools and primary and secondary schools, a "simplified system" is developed—focusing on core indicators of step length, step frequency, and take-off angle, adopting a low-cost solution of "mobile phone + simple EMG sensor" (equipment cost < 2,000 yuan), with the interface simplified to "data display + basic feedback" (e.g., "Step length is short; it is recommended to increase take-off force") to lower the application threshold. For example, primary and secondary schools can collect students' step length data through a mobile phone APP, achieve motion capture with simple reflective stickers, and the system automatically generates a "rhythm score" to help physical education teachers conduct hurdle teaching.

In the public fitness field, an "entertainment experience system" is developed, transforming hurdle training into a "checkpoint game" through AR technology (e.g., "Unlock the next level by completing 10 standard inter-hurdle steps"). The interface adopts a cartoon design, and feedback content is simplified to "correct/incorrect" prompts to attract adolescents to participate; at the same time, a "health monitoring" function (e.g., joint pressure early warning) is added to adapt to the needs of middle-aged and elderly fitness groups, promoting hurdle running from "professional competitions" to "public fitness venues".

5.2.2 Ecosystem Construction: University-Enterprise Cooperation and Resource Integration

Long-term system promotion requires integrating resources from sports colleges, sports equipment enterprises, and technology companies to form a collaborative ecosystem of "industry-university-research-application":

First, deepen university-enterprise cooperation and jointly develop "intelligent hurdle equipment" with sports equipment enterprises (e.g., Li-Ning, Anta), connecting the system's data interface with intelligent spikes and sportswear. Intelligent spikes are embedded with pressure sensors to collect landing buffer data, which is fused with the system's motion data to evaluate the correlation between "landing technology and joint protection"; intelligent sportswear is embedded with flexible sensors to achieve "wearing = collection" without additional equipment. For example, Anta can optimize the conductive performance of sportswear fabrics based on the system's EMG data needs to ensure sensor signal quality.

Second, cooperate with technology companies to optimize the technical architecture, collaborating with enterprises such as Huawei and Microsoft to use their 5G and edge computing technologies to improve system real-time performance. Huawei's 5G modules can reduce data transmission delay to less than 5ms, and Microsoft's Azure edge computing nodes can control data processing delay within 100ms, reducing the total system feedback delay from 0.42 seconds to 0.3 seconds; at the same time, the field of view of Microsoft HoloLens 3 is expanded from 52° to 80% to optimize the visible range of AR feedback and avoid blocking athletes' views.

Third, construct a data sharing platform, led by sports colleges to establish a "hurdle training big data center", integrating training data from professional teams, sports schools, and primary and secondary schools to form a hurdle database of "different levels-different scenarios", providing data support for system algorithm iteration and training plan optimization; at the same time, federated learning technology is used to achieve data sharing while protecting data privacy, avoiding the risk of raw data leakage.

5.2.3 Policy Support: Standard Formulation and Talent Training

Standardized system promotion requires policy guidance and standard support:

On one hand, jointly formulate the "Application Specifications for Intelligent Hurdle Athlete Evaluation Systems" with the General Administration of Sport of China, clarifying the system's technical requirements (e.g., motion capture accuracy, feedback delay), data security standards (e.g., data encryption, privacy protection), and training plan formulation principles (e.g., adjusting training content based on EMG data) to ensure application standardization across different regions and users. For example, the specifications clearly state that "step length measurement error $\leq$ 0.03 meters" and "feedback delay $\leq$ 0.5 seconds" to avoid evaluation effects being affected by low-quality equipment and non-standard operations.

On the other hand, strengthen teacher training and cooperate with sports colleges to offer "intelligent training system operation courses", covering data interpretation, equipment operation, and plan formulation. The courses adopt a "theory + practice" training model—theoretical courses explain the correlation logic of multimodal data (e.g., relationship between EMG activation and step length), and practical courses conduct system application drills on training grounds (e.g., adjusting athletes' step frequency through AR feedback). Each training session lasts 24 hours, and certificates are issued after passing assessments. At the same time, an "online training platform" is established, providing video tutorials, case libraries, and online Q&A to facilitate grassroots coaches to learn at any time and solve the problem of "conflicts with centralized training schedules".

5.3 Future Research Directions

5.3.1 Expanding Evaluation Dimensions: Integrating Psychological and Health Data

The current system focuses on "technical-physiological-environmental" data; future research needs to expand to psychological and health dimensions to construct a more comprehensive evaluation system.

In terms of psychological data, eye tracking technology (e.g., lightweight eye trackers) is introduced to collect athletes' attention distribution during training (e.g., whether excessive focus on hurdles causes body leaning backward), analyzing the correlation between "attention concentration and rhythm stability". For example, step length CV increases by 5%-8% when attention is distracted, and the system prompts "Focus on the landing point" through AR; at the same time, the high-frequency power (HF) of HRV is used to analyze athletes' anxiety states—HF<$20ms^2$ indicates high anxiety levels, and the system recommends "4-7-8 breathing exercises" to relieve stress.

In terms of health data, joint pressure monitoring is added (e.g., collecting knee force data through intelligent knee pads). When the force exceeds a safety threshold (e.g., 8 times body weight), the system prompts "Adjust landing buffer movements" to prevent injuries; at the same time, sleep data (e.g., sleep duration and quality collected through smart bracelets) is combined to analyze the correlation between "insufficient sleep and rhythm stability"—step length CV increases by 10% when sleep < 6 hours, and the system recommends "Extend rest time" to achieve integrated evaluation of "training-health-psychology".

5.3.2 Integrating Digital Twins: Constructing Virtual Training Scenarios

Digital twin technology provides new possibilities for "virtual-real integration" in hurdle training. Future research needs to construct digital twins of hurdle runners, generating 1:1 virtual models of athletes based on multimodal data (motion, physiology, environment) to realize a closed loop of "virtual training-real feedback".

In virtual training scenarios, coaches can adjust virtual environment parameters (e.g., wind speed, hurdle height, opponent rhythm) to test athletes' adaptability—for example, simulating extreme scenarios of "wind speed 3m/s + 5cm increase in hurdle height" to observe rhythm changes of virtual models and formulate response plans in advance; at the same time, virtual models are used to simulate "energy consumption of different rhythm plans" (e.g., energy consumption difference between step frequency 4.0 steps per second and 4.2 steps per second), recommending "energy-efficient" rhythm parameters for athletes.

In addition, digital twins can be used for "technical review"—reproducing rhythm deviations in real training (e.g., take-off angle deviation of 3°) in virtual models, and helping athletes intuitively understand "energy consumption caused by deviations" through slow-motion and force analysis functions, improving the initiative of technical improvement.

5.3.3 Ethics and Security: Data Privacy Protection

With the expansion of the system's data collection range, data security and privacy protection have become important issues. Future research needs to construct a protection system from both technical and institutional aspects:

At the technical level, blockchain technology is used for data certification to ensure that training data cannot be tampered with—each training data of athletes generates a unique hash value, which is uploaded to a blockchain platform to trace the source and usage records of data; at the same time, "data desensitization" technology is used to remove sensitive information such as athletes' names and ID numbers and replace them with anonymous codes to avoid identity leakage.

At the institutional level, the "Specifications for the Use of Hurdle Training Data" are formulated, clarifying the scope of data use (only for teaching and training, not for commercial development), access rights (coaches can only view data of their own students, administrators require dual authorization), and retention period (non-critical data is automatically deleted after 3 years); at the same time, athletes are granted "data control rights" to view, correct, and delete their own data at any time and refuse collection of irrelevant data (e.g., facial images are not collected unless necessary), ensuring the legality and ethical compliance of data collection and use.

6. Research Conclusions and Outlook

6.1 Research Conclusions

Through a research process of "system development-experimental verification-effect analysis", this study deeply explored the application of an intelligent athlete state assessment and monitoring system based on multimodal data fusion in evaluating the rhythm stability of hurdle runners' inter-hurdle steps, drawing the following core conclusions:

Multimodal data fusion breaks through the limitations of traditional inter-hurdle step rhythm evaluation. By integrating three types of data—"motion biomechanics-physiological functions-environmental perception"—the system constructs a "comprehensive rhythm stability index" (including step length CV, step frequency SD, muscle activation synchronization SA, and rhythm consistency index RC), breaking the limitations of single-source data evaluation. Experimental verification shows that the system's accuracy in evaluating inter-hurdle step rhythm stability reaches 92.3%, significantly higher than traditional manual evaluation (63.7%), and the Kappa coefficient for consistency with sports biomechanics experts' evaluation results is 0.82 (P<0.01). It can accurately locate the root causes of rhythm fluctuations (technical/physiological/environmental), with a more comprehensive evaluation dimension and more objective results.

The system's intelligent algorithms and real-time feedback significantly improve the rhythm stability of hurdle runners' inter-hurdle steps. The CNN-LSTM fusion model based on the attention mechanism dynamically optimizes data weights to avoid misjudgments from single-modal data; AR real-time feedback (delay: 0.42 seconds) helps athletes adjust rhythm deviations immediately, shortening the "cognition-action correction" cycle. After 8 weeks of experiments, the rhythm stability indicators (step length CV, step frequency SD) of the experimental group decreased by more than 20%, and the average 110m/100m hurdle time improved by 0.32 seconds, significantly better than the control group (reduction range: 6.6%-6.5%, performance improvement: 0.09 seconds), proving that the system can effectively improve the rhythm stability and competitive performance of hurdle runners.

The system has good practicality and adaptability. Lightweight equipment (EMG sensors weigh < 15g) has minimal interference with athletes' movements; interface interaction is visualized (e.g., rhythm fluctuation heatmaps, AR step length prompts), lowering the threshold for data interpretation; at the same time, the system can adapt to athletes of different technical levels (adolescents/elites), meeting diverse needs through dynamic standard adjustment and personalized plan generation. The average satisfaction of athletes and coaches in the experimental group with the system reached 4.62 points and 4.75 points (on a 5-point scale), respectively, and 86.7% of athletes believed that the system "helped quickly locate rhythm problems", verifying the system's practicality and usability.

System application requires combining coaches' professional capabilities and equipment optimization. Experiments show that athletes guided by coaches who received system training achieved a 23.1% improvement in rhythm stability indicators, significantly higher than those guided by coaches who did not receive training (10.5%); equipment adaptability (e.g., strap comfort, marker adhesion) affects athletes' training compliance, which increased from 82.3% to 96.5% after optimization. This indicates that the system is a "tool rather than a replacement", and its effectiveness can only be maximized when combined with coaches' professional capabilities and equipment optimization.

6.2 Future Outlook

6.2.1 Technology Integration: Upgrading to an "Intelligent Coach"

In the next 5-10 years, with the maturity of artificial intelligence and digital twin technology, the system will upgrade from an "assessment and monitoring tool" to a "full-process intelligent coach":

On one hand, based on athletes' digital twins, the system can simulate the effects of different training plans (e.g., energy consumption difference between step frequency 4.0 steps per second and 4.2 steps per second) and automatically generate "personalized training plans". For example, for athletes with "low muscle activation synchronization", it recommends "core stability training (3 sets × 60 seconds) + EMG biofeedback training (2 sets × 10 minutes)" and dynamically adjusts the load according to training progress.

On the other hand, natural language processing technology is introduced to enable the system to interact with athletes and coaches through voice, answering training questions (e.g., "Why did my step length suddenly shorten") and analyzing competition videos (e.g., "Causes of rhythm deviations at the 5th hurdle in the last competition"), realizing full-process intelligence of "training-evaluation-review" and reducing reliance on manual work.

6.2.2 Scenario Expansion: Extending to Multiple Track and Field Events

The multimodal data fusion concept and technical framework of the system can be extended to track and field events such as sprinting, long jumping, and triple jumping, with only adjustments to data collection plans and evaluation indicators required based on event characteristics:

In sprinting, focusing on "step frequency-step length coordination" and "start reaction", evaluation indicators are adjusted to "step frequency stability", "start reaction time", and "muscle explosive force"; in long jumping, focusing on "run-up rhythm-take-off connection", additional indicators such as "run-up step length stability" and "muscle activation synchronization at take-off" are added.

In the future, an "intelligent state assessment platform for track and field athletes" can be constructed to realize "one set of equipment for multi-event evaluation", reducing equipment procurement costs for sports training institutions and providing data support for training transfer between track and field events (e.g., applying rhythm training experience from hurdle running to sprinting), promoting the overall intelligent upgrading of track and field training.

6.2.3 Ecosystem Construction: Contributing to Building a Sports Power

Digital technology is an important support for building a sports power. The promotion and application of the system will drive the transformation of hurdle training from "experience-driven" to "data-driven", improving the international competitiveness of China's hurdle events. At the same time, the system's application in campus sports and public fitness can address issues such as "insufficient hurdle teaching teachers" and "unscientific public training": primary and secondary schools can conduct hurdle teaching through the simplified system to cultivate adolescents' interest in sports; public fitness groups can participate in hurdle running through the entertainment system to improve physical fitness.

In the future, the system will be integrated into a broader "digital sports ecosystem", linking with the youth sports training system, campus sports curriculum, and sports industry to become an important node connecting competitive sports, campus sports, and public fitness, providing technical support and practical paradigms for building a sports power.

In conclusion, the intelligent athlete state assessment and monitoring system based on multimodal data fusion provides an innovative solution for evaluating the rhythm stability of hurdle runners' inter-hurdle steps. Its value lies not only in improving training efficiency and competitive performance but also in promoting the digital and scientific transformation of sports training. Through continuous optimization in balancing technology and humanity, the system will become an important force in the development of sports intelligence, helping to cultivate a new generation of athletes with both exquisite skills and scientific training thinking.

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