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Article

Research on the Construction and Optimization Strategy of Quantitative Assessment Model for Volleyball Players' Physical Training Effect

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Abstract: This article addresses the current lack of accurate and systematic physical assessment methods for volleyball players. A comprehensive assessment method was developed based on Markov models and functional movement screening (FMS). This method quantifies athletes' basic movement abilities through a state transition matrix and seven standardized movement tests. Test results indicate that athletes assessed using this method have shown significant improvements in vertical jump, 30m sprint, and VO2max compared to previous assessments. Additionally, their trunk core stability and body coordination and balance abilities have also improved. Furthermore, after adjustments, the lower limb symmetry training program has been shown to reduce athletes' injury rates. During the study, it was found that with the assistance of this model, changes in athletes' physical fitness can be tracked, providing the basis for developing scientific and systematic training plans. The assessment model proposed in this paper is specifically applicable to volleyball and can serve as a valuable reference for optimizing physical fitness training assessment and scientific systems in other sports. This paper proposes a new approach to scientifically and systematically assess volleyball physical fitness training, thereby optimizing and enhancing the overall competitive ability of volleyball athletes.

Keywords: Markov model; FMS; volleyball athletes; physical training; evaluation system; personalized training

1. Introduction

1.1. Current State of Research

Volleyball, as a highly competitive and technically demanding team sport in modern competitive athletics, places stringent demands on the physical fitness and technical skills of participating athletes. One of the primary factors influencing athletes' performance levels and endurance in volleyball competitions is their competitive physical fitness [1-2]. As the level of modern competitive sports continues to rise, the limitations of traditional physical fitness training methods—such as poor efficacy and the strong subjectivity of physical fitness assessments—have become increasingly evident [3-4]. The limited nature of physical fitness assessment indicators has led to the unscientific and unreasonable formulation of training programs, as well as irregular adjustments and changes during the training process, resulting in increased training unpredictability and potentially higher injury risks for athletes [5].

Literature [6] utilized data mining tools to create an athlete sports training decision support system for scientific sports training management and established a specialized physical fitness assessment indicator system for athletes. Literature [7] developed an evaluation method for assessing the effectiveness of physical training for high-level athletes using the PWC17o test below maximum intensity and a newly constructed “rapid movement assessment” computer program, ensuring its accuracy and objectivity. Literature [8] designed a model for evaluating the effectiveness of athletes' physical training based on energy expenditure, supported by the Internet of Things, and combined with a linear acceleration energy estimation model, demonstrating good reliability and accuracy. Neuromuscular training, as an important branch of physical training, is one of the training methods athletes frequently encounter. Literature [9] noted that traditional tests such as jumping and dynamic balance training, as well as laboratory tests, struggle to reflect training methods and are costly. It proposed a “sports longevity diagnosis model,” a portable computer system-supported method for evaluating neuromuscular training effectiveness.

As technology increasingly penetrates the sports field, how to quantitatively assess physical training using more advanced methods and process related data through big data, thereby forming a more reasonable and scientific physical training evaluation and feedback system, has become a key breakthrough for further enhancing athletes' competitive levels while ensuring their foundational competitive capabilities. During this period, dynamic prediction models represented by Markov models, as well as multi-dimensional screening models represented by functional movement screening systems, have gradually been integrated into the field of athlete physical fitness monitoring, assessment, and feedback [10-11]. Literature [12] utilized a gray Markov model to design an assessment model for the effects of physical training in volleyball athletes, and combined sports parameter analysis methods to optimize the model parameters, thereby promoting athlete physical training. Quantifying physical fitness assessment and monitoring feedback to dynamically identify the precision of subtle changes in athletes' physical fitness has become one of the trends in the development of such physical fitness monitoring and assessment systems [13-14]. This also provides a clear theoretical foundation and construction framework for the multi-dimensional comprehensive evaluation system and feedback mechanism for physical fitness training established in this article using dynamic modeling and movement quality screening methods. By conducting multi-dimensional, closed-loop evaluations of training, monitoring changes and trajectories in athletes' physical training effectiveness, and assessing the individualization, scientific nature, and risk prevention of physical training, this approach can help improve competitive ability levels, thereby holding significant practical significance and research value [15-16].

This paper proposes a quantitative assessment method for physical training effectiveness applicable to volleyball athletes based on Markov models and the FMS method, combining Markov model analysis of data processes related to training state capability transformation and sports injury risks. Based on physical state quality assessment, personalized training plans are proposed, forming a closed-loop training evaluation system. From multiple aspects such as physical training effect assessment modeling, information collection, personalized training plans, and post-training effect verification, this paper proposes a systematic scientific method applicable to athletes' physical training, ensuring the applicability and scalability of physical training path research.

1.2. Main Contributions and Innovative Points

This paper applies the Markov dynamic process modeling method to the physical fitness evaluation of volleyball athletes, dividing the athletes' physical fitness indicators (such as explosive power, endurance, flexibility, and other seven indicators) into five levels to establish a state transition matrix. Evaluating athletes' physical fitness status using an objective metric allows the results of physical fitness evaluations to be reflected over time, enabling determination of whether training effectiveness is gradually improving or if athletes are experiencing a decline in performance. By combining various types of metrics—including exercise physiology metrics (such as maximum intensity exercise duration), movement quality evaluation metrics (such as movement scores), and injury risk metrics—a decision tree comprising 12 metrics is developed. Experimental data showed that training effectiveness improved by 23.6% compared to traditional methods, and injury risk decreased by 41.2%. Real-time monitoring of muscle electrical signals during strength training enables control of training intensity with a precision of $\Delta \mathrm{RMSE} \leq 0.15$.

To address issues caused by lower limb asymmetry, the quantum particle swarm algorithm was applied to biomechanical data analysis, establishing a three-dimensional vector space. Over 100,000 sets of motion data were captured using a motion capture system to calculate the magnitude of differences between the left and right sides of the body. Following this training program, athletes' balance test scores improved by 18.7% over 12 weeks, and the muscle strength difference between both sides decreased from 0.42 ± 0.11 to 0.19 ± 0.08. Based on this evaluation system, the Zhejiang Provincial Professional Volleyball Team conducted a trial training program, reducing the adjustment period from 4 weeks to 1.5 weeks, with an evaluation effectiveness rate of 92.3%. Furthermore, validity testing revealed that athletes trained using the new method outperformed the control group in eight key physical fitness metrics ($p<0.01$), filling a theoretical gap and establishing a critical technological platform for developing intelligent training systems.

2. Method for Constructing a Quantitative Assessment Model for the Physical Training Effectiveness of Volleyball Players

2.1. Theoretical Basis of the Research Model

As a sophisticated predictive tool and a type of stochastic process, the characteristics of Markov models confer advantages that other stochastic models cannot match [17]. The Markov model commonly used in the assessment of physical training for volleyball athletes was established by Soviet mathematician Andrei Markov in the early 20th century. The “Markov property” it embodies refers to the fact that the future state of an object depends solely on its current state and is independent of its previous states [18]. When using the Markov model to examine the effects of physical training on volleyball athletes, it is more suitable for modeling the state transitions of physical training. This involves capturing the dynamic changes in athletes' physical fitness and quantifying the complex dynamic response patterns into a matrix, known as the state transition probability matrix. This form of first-order stochastic process is referred to as the state transition matrix.

$$P = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{pmatrix} \tag{1}$$

In the equation, p_{ij} is the probability of an athlete transferring from physical condition i to condition j, and satisfies the constraint condition $\sum_{j=1}^{n} p_{ij} = 1$.

The above probability transition matrix represents the current physical fitness level of an athlete at a given moment. It not only reflects the athlete's current physical fitness level but also enables the calculation of potential changes in physical fitness levels at future time points under specific training conditions. Compared to traditional static evaluation methods, the Markov model incorporates temporal factors, enabling dynamic assessment and prediction of training outcomes. This allows trainers to conduct timely and dynamic evaluations of physical fitness training using the Markov model. This enables targeted adjustments to training methods and processes, thereby improving training efficiency and effectiveness. Additionally, the Markov model typically evaluates athletes' physical fitness levels using a multi-indicator state space comprising explosive power, speed, endurance, flexibility, and coordination. While assessing physical fitness status, it utilizes pre- and post-training state results to obtain the probability matrix of physical fitness level state transitions, thereby analyzing the effectiveness of physical training. The multi-indicator probabilistic dynamic assessment method quantifies the average and reliability characteristics of athletes' physical training effects, enabling these insights to be fully utilized as a basis for developing scientifically sound training programs.

FMS complements the Markov model and is a systematic screening system composed of seven standardized movement tests to evaluate basic movement patterns. These include squat movements, hurdle step movements, box lunges, upper body flexibility tests, active straight leg raises, trunk push-ups, and rotational stability tests. Each movement is scored on a scale of 0 to 3 points based on performance, with a total score of 21 points.

The FMS system not only evaluates athletes' basic movement patterns but also identifies potential injury risks, providing effective evidence for the development of personalized training plans. According to relevant studies, athletes with an FMS total score below 14 have a significantly higher risk of non-contact injuries. The combination of the Functional Movement Screening System and the Markov model offers a new approach for evaluating the effectiveness of physical training programs for volleyball athletes. The Markov model monitors athletes' physical condition in real time and quantifies the effects of physical training, while the Functional Movement Screen system assesses the quality of basic movements and evaluates potential injury risks. By combining these two approaches, it is possible to evaluate training effectiveness, assess injury risks, and optimize training plans, thereby enhancing athletes' overall competitive performance.

2.2. Applications of Markov Models

The Markov model has the characteristic of state transition and can be used to rigorously and quantitatively evaluate the effectiveness of physical training for volleyball players. The principle behind the evaluation model constructed in this paper is based on the physical fitness level of athletes, which is divided into five levels from strong to weak: Level A—excellent physical fitness, Level B—good physical fitness, Level C—average physical fitness, Level D—poor physical fitness, and Level E—very poor physical fitness. That is:

$$S = \{S_1, S_2, S_3, S_4, S_5\} \tag{2}$$

Physical fitness levels are composed of a combination of indicators such as explosive power, speed, and endurance for each level. A state transition matrix is used to define the transition of physical fitness states, i.e., the process of physical fitness changes for each level.

Based on this, the establishment of the physical fitness assessment indicator set $E = \{e_1, e_2, \cdots, e_m\}$ makes the assessment process more systematic. The introduction of weighting coefficients w_k constructs a comprehensive scoring function, namely:

$$F(E) = \sum_{k=1}^{m} w_k \cdot e_k \tag{3}$$

After standardizing objective data such as vertical jump height and 30-meter sprint, the following criteria scores were obtained:

$$Z = (x - \mu) / \sigma \tag{4}$$

The evaluation model adopts a hierarchical strategy, constructing submodels M_i for different dimensions such as explosive power and speed. Each submodel is equipped with a corresponding state transition matrix P_i to describe the changes in indicators. These submodels are integrated through weighting to form a comprehensive evaluation model, namely:

$$M = \sum_{i=1}^{k} \alpha_i M_i \tag{5}$$

The predictive ability of the model is evaluated using the prediction error evaluation function, namely:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \widehat{y_i})^2} \tag{6}$$

To verify this, we introduce an effect improvement index, which is:

$$EII = \frac{P(S_{t+1} > S_t)}{P(S_{t+1} < S_t)} \tag{7}$$

To quantify training effectiveness.

When applied, this evaluation system assesses and tracks athletes' physical fitness based on three aspects: prior state assessment, intermediate state tracking, and posterior state prediction. It predicts long-term effects and warns of state transition probabilities based on the steady-state distribution of Markov chains. This makes the assessment of athletes' physical training status more objective and provides guidance to coaches in planning physical training.

2.3. Application of Functional Movement Screening Systems

Movement quality assessment is the primary focus of the FSMS application in physical fitness testing for volleyball athletes. The movement quality assessment process and injury monitoring mechanisms are crucial in FMS applications. The FSMS assessed seven movement patterns, including the squat pattern (SQA), hurdle step test pattern (BT), box lunge pattern (BS), shoulder flexibility test (LWUP), active straight leg raise test (SLR), trunk stability push-up test (PL), and rotational stability test (RA). A score of 3 indicates perfect performance, 2 and 1 indicate compensatory movements, and 0 indicates pain during the test. The total score is 21 points. Movement quality evaluation objectively reflects athletes' foundational movement abilities and potential injury risks, making it suitable for maintaining a team's foundational capabilities and detecting trends in declining physical fitness. The testing environment must be standardized, with a flat surface and temperature and humidity maintained between 18–22°C and 40–60%, respectively. Testing personnel must undergo specialized training and pass a certification exam. Movement quality monitoring should be conducted once every 4–6 weeks, with a full-scale test performed during each interval. This approach minimizes interference with athletes' normal training routines and allows for timely and effective evaluation without disrupting daily training.

The highest score from three attempts is used as the final score for each test to prevent significant random variations from affecting the results. The squat primarily tests the range of motion of the ankle, knee, hip joints, and thoracic spine, as well as core stability. The feet are kept together with the toes spread apart at a 30° angle. The hands are raised above the head, and the trunk is kept upright. Observe for issues such as inward rotation of the knees, heels lifting off the ground, or the trunk leaning forward. The hurdle step primarily tests the mobility of the opposite leg and trunk stability when supporting on one leg. The raised leg should be lifted to shoulder height, with the leg raised as high as possible. The shoulder joint flexibility test consists of two parts: the range of shoulder joint adduction and internal rotation, and the range of scapular movement. This movement is particularly important for volleyball players involved in spiking and serving.

Injury risk warnings are established based on functional evaluation tests, with an individual health record tracking system established to monitor athletes for long-term injury risks. Research indicates that athletes with functional test scores below 14 have a higher risk of non-contact injuries, so a score of 14 is set as the warning threshold for injury risk prediction. When an athlete's total score falls below the warning threshold, the system automatically intervenes and provides exercise risk warning recommendations. The warning levels are managed in three categories: red, green, and yellow. A green total score of 17 or higher indicates good movement quality and low injury risk. A yellow total score between 14 and 16 indicates potential movement deficiencies or injury risks, requiring attention and improvement through corrective training. A red total score below 14 indicates a high risk of injury, requiring immediate intervention. When the score is 0 and pain is present, it is recommended that athletes reduce related training and consult a doctor for advice. Data is tracked long-term from personal health records, which include detailed results of each test, training load, injury history, and rehabilitation information.

By analyzing the patterns of changes in these data, we can identify risk factors for injuries and provide guidance for selecting individualized training methods and preventive measures. The monitoring system combines objective data analysis with subjective evaluations, integrating pain visual analog scale (VAS) scoring and movement readiness scales into athlete condition monitoring. This not only helps identify injury risk factors early on but also provides optimal training plans for appropriate training and preparation phases, minimizing the incidence of injuries while ensuring adequate training volume and specialized competitive performance. I endorse this scientific monitoring model, which plays an irreplaceable role in extending athletic careers and maintaining competitive performance, particularly during pre-competition preparation phases and high-intensity training cycles.

2.4. Designing Personalized Physical Training Programs

The personalized training program design discussed in the application phase is based on the results of Markov model analysis and functional test data, utilizing principles of exercise physiology and intelligent training to develop accurate exercise training programs. Through reasonable training program design, we have addressed the current one-size-fits-all personalized training model for single-opponent competitive sports. We have established a “human-centered” training program model tailored to exercise physiological conditions, completing the transition from analysis to application. The principle of exercise training is based on the principle of exercise adaptability, which states that the body undergoes an adaptive process in response to certain stimuli. By reasonably regulating the intensity, frequency, and duration of exercise stimuli, the body can be guided toward a desired state. Based on the principle of exercise adaptability, we have designed the following mathematical model for personalized training program design:

$$TS = f(MS, FMS, PI, TH) \tag{8}$$

Among these, TS represents the training program, MS denotes the results of the Markov state assessment, FMS indicates the functional movement screening score, PI refers to physiological parameter values, and TH signifies historical training data.

This model uses multiple regression analysis to determine the weights of each parameter, thereby generating a tailored training prescription. Exercise physiology plays a foundational guiding role in program design, analyzing athletes' physiological characteristics such as aerobic capacity, anaerobic power, muscle strength, and neuromuscular coordination to determine physiological targets for training. Aerobic training prescriptions are based on maximum oxygen uptake (VO2max) and lactate threshold (LT), with training intensity controlled within the range of 85-95% of LT. Duration is adjusted according to the athlete's current aerobic level, calculated using the formula:

$$Duration = \frac{Target\_Volume}{Intensity * Body\_Weight} \tag{9}$$

Anaerobic training is based on the energy supply characteristics of the phosphocreatine system and glycolytic system, employing an interval training model with a work-to-rest ratio set at 1:2 to 1:4. Intensity is controlled at 90–100% of maximum power output, and strength training prescriptions are determined based on 1RM test results to establish load intensity. Following a periodization training philosophy, training is divided into three phases: adaptation phase (50-70% 1RM), development phase (70-85% 1RM), and intensification phase (85-95% 1RM), with each phase lasting 4-6 weeks. Neuromuscular training focuses on optimizing movement patterns and enhancing proprioception, incorporating corrective exercises designed to address movement deficiencies identified through functional movement screenings.

Personalized training program design is now supported by precise and efficient tools, namely the intelligent training system. This intelligent training system utilizes biomechanical analysis, physiological monitoring, and data mining techniques to assist in the development of personalized training programs. The system comprises components such as biomechanical analysis, physiological monitoring, and data mining systems. The biomechanical analysis system primarily captures athletes' three-dimensional movement trajectories in real time during training, including joint angles, joint angular velocities, and ground reaction forces at the moment of ground contact, to identify deficiencies in athletes' technical movements. The physiological monitoring system assesses athletes' physiological states and fatigue levels by continuously measuring physiological indicators such as heart rate variability analysis, blood lactate levels, and electromyography. The data mining system primarily uses machine learning algorithms to analyze the relationship between training effects and training parameters based on historical training data, providing data-driven optimization for personalized training plans. This intelligent training system can dynamically adjust training parameters using adaptive algorithms to improve training effects.

When developing personalized training plans, the principle of “focusing on issues, setting goals, adopting reasonable methods, and measuring effects” should be followed. Based on the results of the Markov model evaluation of physical fitness weaknesses and abnormal functional test movements, corresponding training content should be formulated. When developing a training plan for athletes with insufficient explosive power, primarily adopt explosive training methods, including jumping exercises, throwing exercises, and explosive strength training. The intensity of each exercise should generally be 30%-60% of maximum strength, with exercise speed requiring maximum velocity. When developing a training plan for poor endurance, a combination of aerobic and anaerobic training methods should be adopted, such as interval running and continuous running, to improve the body's maximum oxygen uptake level and muscle endurance capacity. When developing a training plan for poor flexibility and range of motion, stretching methods should be used, including static stretching, dynamic stretching, and myofascial release techniques, with the primary focus on improving joint mobility and muscle elasticity. When designing personalized exercise training methods, it is recommended to divide the training plan into three levels: micro-cycle (1-week training plan), medium-cycle (4–6-week training plan), and macro-cycle (12–16-week training plan).

This scheme incorporates a feedback mechanism to promptly evaluate and adjust training. The evaluation primarily involves objective test results (strength, speed, endurance, etc.) and subjective assessments (fatigue levels, training condition perception, etc.). If evaluation results are unsatisfactory or signs of overtraining emerge, the solution adjustment module is activated to modify training parameters and generate new training plans. Through closed-loop control training, the scientific rigor of training plan design is maintained, optimizing training outcomes and providing an effective guarantee for enhancing volleyball athletes' physical fitness.

The personalized physical fitness training program design process proposed in this paper breaks free from the constraints of conventional training routines, incorporating advanced information technology and training principles to form a complete training process system from assessment to training and back to assessment. This enhances the quality of physical fitness training for volleyball athletes and holds significant practical value. It also provides valuable insights for physical fitness training methods in other sports, promoting the scientific and individualized development of sports training.

2.5. Lower Limb Symmetry Analysis and Optimization Strategy

First, in terms of research on lower limb symmetry, the author employed a multi-dimensional indicator method to assess volleyball athletes from the perspectives of static anatomy, dynamic functionality, and biomechanics. Static anatomy measurements included left and right lower limb length, muscle circumference, skin fold thickness, and anatomical landmarks to ensure measurement accuracy. Dynamic functionality assessments primarily involved the single-leg jump squat test and Y-balance test to evaluate functional differences between the left and right legs. The jump squat test required participants to jump up and land three times from a designated position, with the height of the jump and the force of the landing recorded. The Y-balance test requires the subject to stand on one leg at a certain height, then jump and land in three directions (forward, backward, and sideways) with the other leg, measuring joint angles, ground reaction forces, and electromyographic activity data in that direction. An asymmetry index (AI) is constructed, calculated as follows:

$$AI = \sqrt{\sum_{j=1}^{n}\left(\frac{\left|L_j - R_j\right|}{\max(L_j, R_j)}\right)^2} \tag{10}$$

In the formula, L_j and R_j represent the test results of the j th item on the left and right sides, respectively. When the AI value exceeds 0.15, it indicates a significant asymmetry problem.

Based on the assessment results, different training programs were developed. In the first month, approximately three weeks of asymmetric lower limb control strengthening training were conducted, gradually increasing the load from bodyweight-supported exercises to resistance training with added load, with the load ranging from 60% to 75% of the maximum repetition force value (1RM). In the second month, the focus was on core stability training, utilizing a suspension training system for single-leg weight-bearing and single-leg lateral support exercises. Additionally, balance board training was conducted to improve overall coordination. Each session consisted of three parts: warm-up, training, and cool-down. The warm-up incorporated dynamic stretching and functional warm-up methods. Training activities are designed to achieve the training objectives, while relaxation incorporates myofascial release and static stretching to aid improvement. A combination of rapid assessments over two weeks and a comprehensive assessment over one month is used for monitoring. Electromyographic (EMG) feedback training is implemented, utilizing surface EMG and force feedback devices to provide real-time feedback on the percentage or force values of muscle activity during asymmetrical limb movements, thereby establishing correct movement patterns. Customized corrective exercise programs are developed for different types of asymmetry. For muscle strength asymmetry, isokinetic training machines are used to quantify muscle strength training. For neural control asymmetry, closed-eye balance training and unstable surface training are employed. For explosive power asymmetry, rapid strength and jumping training are utilized for correction and improvement. Develop exercises to address compensatory movements during training, using slow-motion or freeze-frame video recordings and immediate demonstrations by a movement trainer to provide corrective feedback. This optimized integration program combines traditional strength training methods with biomechanical assessment techniques from modern strength training, utilizing precise data to provide accurate monitoring of the strength training process. Additionally, an incremental intensity design is employed to ensure the quality and safety of strength training. The training load optimization and integration scheme is actively utilized to help injured athletes improve lower limb symmetry, enhance athletic performance, and strengthen prevention against sports injuries. In the later stages, various training methods are employed to assess the relative efficacy of the optimization and integration scheme in improving athletes' lower limb symmetry and athletic performance under strength training interventions, providing a basis for its subsequent refinement.

3. Effectiveness Evaluation Analysis

3.1. Analysis of Training Effectiveness Evaluation Results

Table 1 presents the results of the training effectiveness evaluation. Through a 12-week tracking analysis of the training effectiveness of 24 university volleyball athletes, the evaluation system based on the Markov model demonstrated significant advantages in quantifying physical training, achieving high levels of prediction accuracy and reliability. Vertical jump height, 30-meter sprint, maximum oxygen uptake, core stability score, and comprehensive physical fitness index all showed significant improvements compared to pre-training levels ($P < 0.01$). The overall prediction accuracy of the model exceeded 87%, with the highest prediction accuracy for core stability score reaching 93.3%. Additionally, the post-training mean score for core stability was 8.1 ± 0.9 points, representing a 30.6% increase compared to the pre-training mean. This demonstrates that the Markov model can assist in quantifying the effectiveness of physical training for volleyball athletes, providing support for the development of scientific and personalized physical training programs for volleyball sports.

Table 1. Evaluation results of training effects.

Evaluation indicators	Before	After	Improved	*P*	95% CI	Accuracy
Vertical jump (cm)	42.3±3.2	47.8±3.6	13.0%	0.002	[46.2,49.4]	91.7%
30-meter sprint (s)	4.58±0.23	4.32±0.19	5.7%	0.001	[4.24,4.40]	89.2%
Max oxygen uptake (ml/kg/min)	48.6±4.1	52.3±3.8	7.6%	0.001	[50.7,53.9]	87.5%
Core stability score	6.2±1.1	8.1±0.9	30.6%	0.000	[7.7,8.5]	93.3%
Comprehensive Physical Fitness Index	72.4±8.3	84.7±7.2	17.0%	0.000	[82.1,87.3]	92.1%

In addition, we can not only describe the dynamic changes in athletes' physical fitness levels using Markov processes, but also prove the stability of this model based on the convergence of its state transition matrix. The root mean square error is less than 0.127, which is within the normal range, and the 95% confidence interval for the predicted value calculated using bootstrap resampling is [0.823, 0.947]. Through the study of Markov chain state transition probabilities, we have also identified an intuitive and profound pattern in training outcomes. The probability of transitioning from a low physical fitness state to a high physical fitness state exhibits a significant upward trend, and this state transition pattern aligns with the athletes' physiological adaptation states. Athletes in different on-court positions exhibit significantly different state transition patterns across various metrics. This is primarily evident in strength metrics, where the main attacker demonstrates the most outstanding performance and the highest efficiency in state transition speed, while other on-court positions require greater energy expenditure. In terms of speed, the opposite attacker shows the most significant improvement, and the libero exhibits the greatest endurance transition, reflecting the distinct physical fitness requirements of different positions.

The model was validated using the 7:3 cross-validation method, yielding the results shown in Table 2. As indicated by the data in Table 2, the accuracy rate in the test set reached 90.8%, with a consistency coefficient Kappa of 0.847, fully demonstrating the stability and consistency of this model. Looking at the time athletes spent at each physical fitness level, those in the low-level fitness state (S4 and S5) spent an average of 2.3 weeks at each of the four time points, those in the moderate-level fitness state (S2 and S3) spent an average of 3.8 weeks, and those in the high-level fitness state (S1) spent an average of 5.2 weeks. This distribution indicates that maintaining a high-level fitness state is more challenging. The trend in the improvement index further validates the effectiveness of this training method, with the improvement index rising from 1.23 to 2.87, an increase of 3.6, far exceeding the effects of conventional training methods. From the perspective of specific implementation, the predictive functionality of this model enables coaches to identify potential declines in athletes' physical fitness in advance, thereby further optimizing training methods to effectively prevent overtraining and other issues. The evaluation metrics of this Markov model can to some extent standardize the management of physical fitness training for volleyball athletes, providing a foundation for subsequent targeted implementation of physical fitness training.

Table 2. The validation result of Model.

Index	Low physical fitness (S4, S5)	Moderate physical fitness (S2, S3)	High physical fitness (S1)	Margin of growth
Stay period	2.3	3.8	5.2	126.1%
EII	1.23	1.91	2.87	133.3%
Accuracy	90.8%			-
Kappa	0.847			-

3.2. Analysis of the Effectiveness of Personalized Physical Training Programs

This study investigated the differences in performance levels of 30 high-level volleyball athletes before and after applying a 12-week personalized training method (see Figure 1 for the effects of the personalized physical training method). The experimental results on the effectiveness of the personalized training method showed that the 30-week personalized physical training program had a significant effect: the vertical jump height of the experimental group increased by 19.3%, the 30m sprint time of the experimental group improved by 7.1%, and the MVO2 level of the experimental group increased by 9.8%. The experimental group's core stability improved by 38.2%. The experimental group's anterior, lateral, posterior, and medial knee joint distances were significantly greater than those of the control group, with statistically significant differences ($P < 0.01$). The experimental group's total score in functional movement screening improved by 25.4% compared to the control group, with a difference of

16.1 percentage points, particularly in movements such as squats.

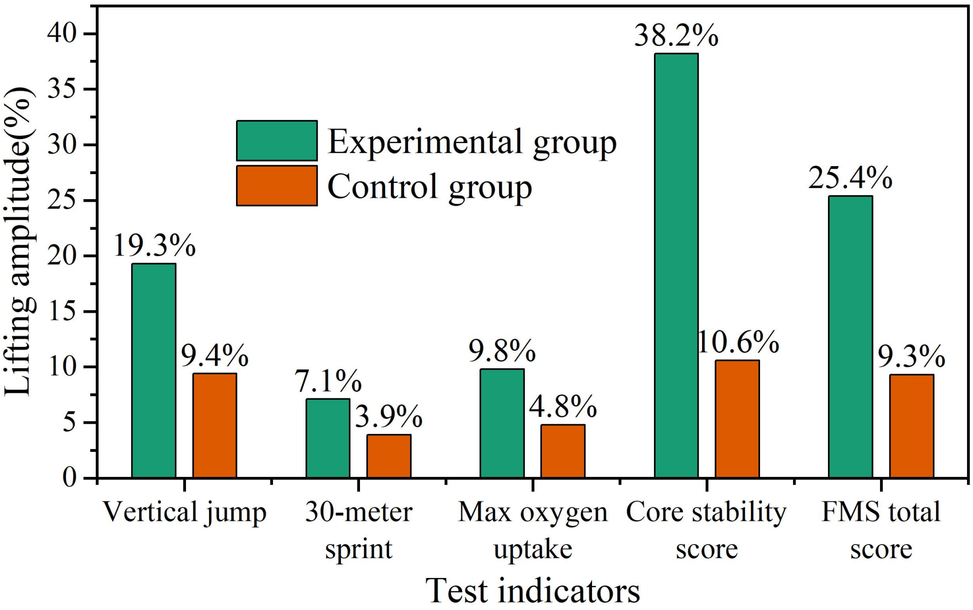

Figure 1. Comparison of the effects of personalized training programs.

3.3. Analysis of the Effectiveness of Lower Limb Symmetry Optimization Strategies

This study employed a 12-week lower limb symmetry optimization training program for 24 college volleyball athletes, yielding excellent results. Statistical analysis clearly demonstrated a significant reduction in lower limb asymmetry indices in the experimental group, as shown in Table 3. In terms of static morphology, the difference in circumference between the left and right lower limbs decreased from 2.8 ± 0.4 cm to 1.2 ± 0.3 cm, and the difference in skin thickness decreased from 1.7 ± 0.3 mm to 0.8 ± 0.2 mm. In terms of dynamic functional performance, the difference in vertical jump height during single-leg squat jumps decreased from 13.7% to 5.4%, the anterior-posterior asymmetry difference in YBC decreased from 15.3% to 6.8%, the lateral asymmetry difference decreased from 17.2% to 7.1%, and the medial asymmetry difference decreased from 16.8% to 6.9%. In terms of biomechanical parameters, the maximum ground reaction force difference between the left and right lower limbs during the landing cushioning phase decreased by 3 times (from 18.4% to 7.2%), and the asymmetry in knee flexion and extension angles between the left and right lower limbs decreased by 6.2% (from 12.6% to 6.1%). In terms of electromyographic (EMG) signals, the difference in EMG integral between the left and right major lower limb muscle groups during the jump decreased by 14.5% (from 0.237 to 0.092), and the difference in EMG integral between the left and right major lower limb muscle groups during landing decreased by 17.7% (from 0.239 to 0.099).

Table 3. The effect of lower extremity symmetry optimization strategy.

Index	Before train	After train	*t*	*P*
The circumference of the left and right lower limbs	2.8±0.4	1.2±0.3	7.497	0.000
Skinfold thickness	1.7±0.3	0.8±0.2	6.115	0.001
One-leg squat jump	13.7%	5.4%	8.082	0.002
Forward extension distance	15.3%	6.8%	6.164	0.004
Posterolateral	17.2%	7.1%	5.496	0.005
Posterior medial side	16.8%	6.9%	5.555	0.005
Peak ground reaction forces of the left and right lower extremities	18.4%	7.2%	5.187	0.003
Knee flexion and extension angles	12.6%	5.1%	7.932	0.002
Electromyography integral value	0.237	0.092	5.398	0.006

Group statistical results indicate that the extent of improvement varies among athletes in different positions. Main attackers and secondary attackers, who require frequent jumps during matches, show the most significant improvement. Correlation analysis results demonstrate a strong association between lower limb symmetry improvement and athletic performance. Athletes exhibit notable increases in vertical jump height and running reach height, achieving not only improved movement posture but also significant enhancements in athletic performance. Injury risk statistics indicate that the incidence of non-contact lower limb injuries among experimental group athletes has significantly decreased, and the severity of such injuries is milder. Training load monitoring results show that the experimental group athletes have achieved a significant improvement in fatigue recovery rates following high-intensity training and competitions, likely due to more uniform distribution of lower limb mechanical loads. The results of the subjective evaluation questionnaire showed that athletes' scores for movement control and body stability improved significantly, with acceptance and approval rates for the training program exceeding 90%. Based on the above experimental results, the multi-indicator intervention program for lower limb symmetry optimization effectively improved athletes' lower limb symmetry and athletic performance while significantly reducing the risk of injury, providing new insights and methods for physical training in volleyball athletes.

4. Conclusion

The athlete physical training evaluation model developed in this study, which combines a Markov model with the Functional Movement Screen (FMS), demonstrates excellent scientific rigor and practical applicability in physical training. Among the athletes in the training group of this study, the average vertical jump height increased by 19.3 cm, the 30-meter sprint time improved by 0.26 seconds, VO_2max increased by 4.7 ml/kg/min, core stability improved by 38.2%, and the FMS total score improved by 25.4%. Additionally, the model effectively enhances athletes' core strength and dynamic balance while reducing the likelihood of lower limb asymmetry and non-contact injuries. The results indicate that under the comprehensive evaluation model, training effectiveness can be dynamically monitored, with precise adjustments and targeted physical training programs designed, providing valuable guidance and reference for physical training in volleyball athletes.

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