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Article

Effectiveness of a preventive training program in reducing injury rates in college athletics

Tao Huang

Department of Sports and Health, Xinxiang Vocational and Technical College, Xinxiang 453006, China; xxzyjsxyht@163.com

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Abstract: In order to reduce the incidence of injuries in college athletics, this study used a computer-assisted preventive training program for analysis. The effects of different training intensities and recovery strategies on athlete injuries were investigated by establishing an athlete injury prediction model, combining personalized training programs with real-time data feedback. The results showed that the computer model-based training program could significantly reduce the injury rate and enhance the performance and recovery efficiency, which verified the effectiveness of personalized training in reducing sports injuries.

Keywords: preventive training; computer model; sports injury; individualized training; data analysis

1. Introduction

Sports injuries are among the most significant challenges faced by athletes, directly influencing their physical health and overall performance. These injuries are especially prevalent during high-intensity training sessions and competitive events, where the physical demands on athletes often exceed their physiological thresholds. The implications of such injuries extend beyond individual health, affecting team performance, training schedules, and long-term career sustainability for athletes. Therefore, effective strategies to mitigate these risks are essential.

In recent years, advancements in sports medicine and technology have facilitated a paradigm shift from reactive injury management to proactive injury prevention. Preventive training programs, grounded in accurate monitoring and tailored to the individual needs of athletes, have emerged as pivotal tools to minimize injury risks and enhance performance outcomes. Such programs emphasize the importance of understanding individual biomechanical and physiological profiles, enabling targeted interventions that address specific vulnerabilities.

Among the innovative approaches in preventive training is the integration of computer technology, which has redefined the landscape of injury prediction and training optimization. By leveraging real-time data collection and analysis, computer-assisted systems provide a robust framework for identifying potential injury risks. These systems utilize advanced methodologies, such as machine learning algorithms and big data analytics, to process complex datasets, including metrics on stride frequency, heart rate variability, muscle fatigue, and exercise loads. The insights derived from these analyses allow for dynamic adjustments to training programs, ensuring an optimal balance between workload and recovery.

This study aims to explore the effectiveness of a computer-assisted preventive training model specifically designed for college athletes. By constructing a predictive model rooted in real-time data and individualized programming, the research seeks to demonstrate the utility of this approach in reducing injury incidence, enhancing athletic performance, and improving recovery efficiency. The findings are anticipated to provide a scientific basis for integrating such technologies into sports training and athlete health management, paving the way for more personalized and effective injury prevention strategies. This work contributes to the growing body of knowledge at the intersection of sports science, data analytics, and preventive medicine, highlighting the transformative potential of technology in promoting athlete well-being and performance sustainability.

2. Current state of research

Nye et al. argued that scientific preventive training measures can significantly reduce the incidence of sport-related injuries and improve athletes' physical fitness and sports performance. Their study proposes that precision training programmes based on big data and artificial intelligence technologies can effectively predict and prevent the risk of injuries in athletes during high-intensity training and competition. Through real-time monitoring and adjustment of exercise patterns and loads, potential risks can be controlled within a reasonable range, thus achieving the goal of protecting athletes' health and prolonging their professional life. This idea provides a theoretical basis for the construction of a personalised preventive training system [1]. Parisien et al. found through their study of NCAA Division I athletes that the implementation of a systematic injury prevention programme not only reduces the rate of athletic injuries, but also reduces the resulting healthcare costs. Their study highlights the importance of collecting physiological data from athletes with the help of sensor devices and combining them with machine learning algorithms to analyse the relationship between training intensity and sports injuries as a means of improving the effectiveness of preventive training. This research provides a quantitative basis for injury management in competitive sport and promotes the digitisation of injury prevention systems [2]. Padua et al. suggested that preventive training programmes for ACL injuries are an important way to reduce serious knee injuries. In their study, they noted that improving joint stability and movement patterns through neuromuscular training and strength training can significantly reduce the incidence of knee injuries in adolescent athletes. Additionally, the study showed that individual difference-based sport assessment and training interventions can further improve the effectiveness of preventive measures, providing a scientific basis for the design and implementation of injury prevention programmes [3]. Krug et al. concluded that when implementing an injury prevention programme in high school athletes, programme adherence and the accuracy of its implementation are important factors that influence its effectiveness. Their study found that standardised training guidelines and real-time monitoring techniques can ensure that athletes effectively implement prevention programmes during training and reduce sports injuries caused by poor training. This study highlights the monitoring and feedback mechanisms during the implementation of training programmes and provides a new perspective on the practicalities of preventive training [4]. Minnig et al. provided an in-depth analysis of the barriers and facilitators that may be encountered during the adoption and implementation of injury prevention programmes. Their study found that despite the high theoretical effectiveness of science-based injury prevention programmes, in practice they are often limited by factors such as the level of awareness of athletes and coaches, the availability of resources, and the complexity of the programme. This suggests that in order to improve the effectiveness of the programmes, there is a need to enhance the education of athletes and related personnel, as well as to simplify the design of the programmes so that they can be more widely applied in practice [5].

These studies provide important support for theory and practice in the field of injury prevention, suggesting that preventive measures combining computer technology and personalised training programmes can significantly improve athlete health management and sport performance. However, there is a lack of systematic research based on large-scale data and multifactorial analyses, as the current research focuses on specific groups of athletes or the application of a single technology. In order to fill this research gap, this paper combines computer-aided technology to construct a personalised preventive training model, and thoroughly explores its practical effects in reducing injury rates, enhancing sports performance and accelerating recovery efficiency of college athletes, so as to provide a new scientific basis and optimisation strategy for injury prevention and health management in the field of competitive sports.

3. Application of computer technology in sports injury management

With the continuous advancement of computer technology, significant breakthroughs in big data processing, machine learning, and artificial intelligence have propelled the prediction and management of sports injuries into a new era. These technologies offer unprecedented opportunities to enhance the accuracy and efficiency of injury prevention strategies, providing valuable insights into the complex interplay of training variables, physiological responses, and individual risk factors.

One of the core strengths of computer technology in this domain lies in its ability to facilitate real-time data collection and analysis [6]. Utilizing devices such as accelerometers, gyroscopes, heart rate monitors, and GPS systems, detailed physiological and biomechanical data from athletes can be captured during training and competition. These datasets include metrics such as stride frequency, heart rate variability, muscle fatigue, and exercise load, providing a comprehensive picture of the athlete’s condition and performance trends.

Machine learning algorithms, such as support vector machines, decision trees, and random forests, play a pivotal role in analyzing these complex datasets. By identifying patterns and correlations within the data, these algorithms enable the prediction of potential injury risks associated with specific training intensities, movement patterns, or biomechanical inefficiencies. For instance, an athlete with a high training load and insufficient recovery might exhibit physiological markers indicative of an increased injury risk, allowing for timely intervention.

Moreover, computer-assisted systems enable dynamic adjustments to training programs based on individualized data. By integrating information on training load, recovery status, and historical injury data, these systems can optimize the balance between workload and rest. This ensures that athletes are neither overtrained nor subjected to improper movement patterns, both of which are major contributors to injuries.

The integration of computer technology also supports the design of personalized preventive training programs, tailored to address the unique physiological and biomechanical characteristics of each athlete. This targeted approach not only reduces injury incidence but also enhances overall performance and recovery efficiency. As computer technology continues to evolve, its application in sports injury management promises to refine preventive strategies and foster a more scientific and individualized approach to athlete health and performance.

4. Research methodology and model design

4.1. Data acquisition and processing

The data acquisition utilizes a variety of high-precision sensor devices, mainly including accelerometers, gyroscopes, heart rate monitors and GPS devices, in order to record the athletes' movement status, physiological responses and environmental changes in the training process in real time, and to provide a comprehensive support of movement data. The data collection covers a wide range of dimensions such as the athlete's stride frequency, stride length, exercise load, heart rate fluctuation, and muscle fatigue. These data are transmitted to the central processing system for real-time monitoring and storage. The collected data are first cleaned and filtered by data preprocessing to remove noise and outliers, and all data are uniformly converted to a standardized format for subsequent analysis [7]. The data normalization uses the min-max normalization method with the following formula:

$$X_{norm} = \frac{X - X_{min}}{Xmin_{max}} \tag{1}$$

where X is the original data, X_{min} and X_{max} are the minimum and maximum values of the data respectively, and X_{norm} is the normalized data. The data-processed samples are downscaled by PCA (Principal Component Analysis) to reduce feature redundancy and improve computational efficiency.

4.2. Computer model construction

Computer model construction Based on the collected exercise data, a machine learning method was used to establish an exercise injury prediction model. First, after data processing, features highly correlated with exercise injuries, such as step frequency, exercise load, and heart rate variability, were screened by feature selection algorithms (e.g., mutual information method, chi-square test, etc.). The selected features were fed into multiple machine learning algorithms for training, mainly using support vector machine (SVM) and random forest (RF) models for injury risk prediction and training effect evaluation, respectively [8]. During the model training process, a cross-validation method is used to assess the generalization ability of the model and ensure the reliability of the prediction results. The SVM model formulation is expressed as follows:

$$f(x) = sign(\omega^T x + b) \tag{2}$$

where x is the input feature vector, ω is the model weight, b is the bias, $f(x)$ is the prediction result, $sign$ is the sign function and the output classification result. By comparing different models, the best performing model is selected as the final prediction model. **Table 1** demonstrates the performance metrics of different algorithms in terms of accuracy, precision, recall, etc. on the training and test sets, and the results show that the random forest model outperforms the SVM model on both the training and test sets.

Table 1. Performance comparison of different models.

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**
Support Vector Machine (SVM)	87.5	83.2	79.5
Random Forest (RF)	91.3	89.6	84.1

4.3. Preventive training program design

The computer model-based preventive training program dynamically adjusts the training intensity and recovery cycle based on key indicators such as athletes' exercise load, fatigue, and heart rate variability, in order to avoid overtraining and inappropriate exercise load [9]. As shown in the flowchart of **Figure 1**, the injury risk of each athlete is first assessed by the sports injury prediction model, and the training content aimed at improving sports performance and reducing the probability of injury is designed for high-risk athletes. For example, for athletes with excessive step frequency and heavy knee burden, the focus is on lower limb stability training and flexibility training to reduce the risk of knee injury. The training content includes strength training, flexibility training, explosive force training, etc., in order to enhance the muscular endurance and joint flexibility of the athletes and reduce the potential injuries during exercise [10]. During the implementation of the training program, the athletes' exercise data are monitored in real time, and the training intensity is dynamically adjusted by computer algorithms to ensure that the training load is maintained at the optimal level.

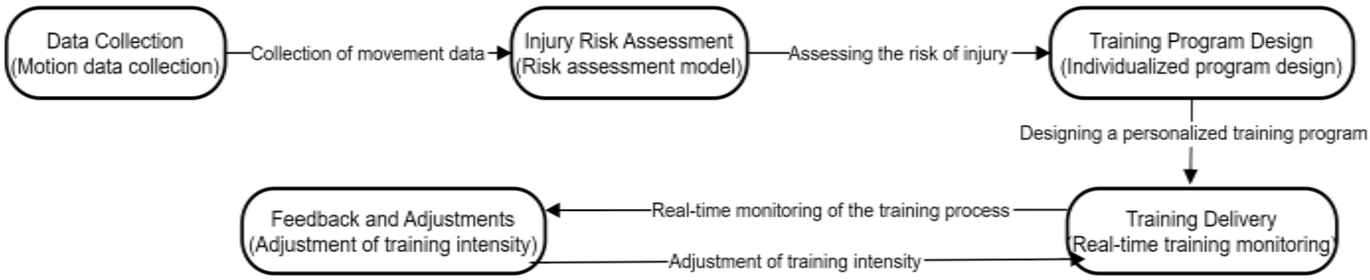

Figure 1. Preventive training program implementation process.

4.4. Research experiment process

In order to assess the effectiveness of a preventive training programme, college track and field athletes with extensive athletic experience were selected as experimental subjects. Participants were divided into two groups: experimental and control. The experimental group used a personalised preventive training programme designed by a computer-assisted model, while the control group used traditional training methods. Prior to the start of the experiment, all athletes underwent a comprehensive sports injury risk assessment and fitness assessment. This process involved the collection of detailed physiological and biomechanical data, including metrics such as exercise load, heart rate variability and stride frequency. These data were analysed by computer models to predict each athlete's injury risk and provide a baseline for the experiment.

During the experiment, all athletes' physiological data were continuously monitored via advanced exercise tracking equipment such as accelerometers, heart rate monitors and GPS devices. The collected data is transmitted in real time to a central processing system, which analyses the data to detect changes in key indicators such as heart rate and muscle fatigue [11]. Based on the feedback from the central system, the training load and intensity level of the experimental group is dynamically adjusted to ensure an optimal balance between workload and recovery. This real-time adjustment mechanism aims to minimise overtraining and reduce the risk of injury.

Injuries were also regularly assessed in order to monitor the reliability and effectiveness of the training programme. Changes in key physiological parameters, such as step frequency and heart rate fluctuations, before and after training were also analysed to assess the effectiveness of the training programme. Comparative analyses between the experimental and control groups helped to provide insight into the differences in training outcomes.

At the end of the experiment, all collected data were rigorously statistically analysed. Techniques such as analysis of variance (ANOVA) and regression modelling were applied to quantify the impact of the computer-assisted preventive training programme. These analyses were designed to validate the effectiveness of the programme in reducing injury rates and improving athletic performance and recovery efficiency. By combining real-time feedback with personalised training adjustments, this study provides strong evidence for the potential of computer-aided modelling in advancing sports injury prevention strategies [12].

5. Research results and analysis

5.1. Data analysis results

During the experiment, data analysis was a critical component aimed at evaluating the impact of the computer-assisted preventive training program. The analysis focused primarily on three key aspects: the incidence rate of injuries, the athletic performance of participants, and changes in their fitness levels throughout various training stages. By systematically comparing these metrics between the experimental and control groups, the study provided a comprehensive understanding of how the personalized training program influenced both injury prevention and physical performance enhancement.

One of the most significant metrics analyzed was the injury incidence rate. Data collected before and after the training period revealed notable differences between the groups, highlighting the program's efficacy in reducing the likelihood of sports-related injuries. The experimental group, which followed a dynamically adjusted preventive training regimen, exhibited a substantial decrease in injury rates compared to the control group, which adhered to traditional training methods. This finding underscores the potential of integrating data-driven, personalized training approaches to enhance athlete safety.

Athletic performance indicators, including heart rate, step frequency, and training load, were also closely monitored. For example, changes in heart rate variability before and after training sessions offered insights into cardiovascular efficiency and recovery. Similarly, step frequency measurements provided a deeper understanding of biomechanical adjustments and improved efficiency in movement patterns [13]. The experimental group demonstrated more favorable outcomes in these indicators, suggesting that the preventive training program contributed to better physiological adaptation and enhanced performance.

Fitness level changes were assessed through the analysis of recovery time and workload management. The experimental group showed a significant reduction in recovery time compared to the control group, indicating improved physical resilience and recovery efficiency. Additionally, training load data revealed that the experimental group's workload was more effectively managed, preventing overtraining and mitigating associated risks.

Statistical tools such as SPSS and Python were employed to ensure accurate data analysis and validation of results. Techniques such as variance analysis and correlation studies allowed for precise evaluation of the program's effectiveness. By synthesizing these findings, the study demonstrated the clear advantages of adopting computer-assisted preventive training programs in reducing injuries, improving athletic performance, and promoting efficient recovery. These results provide a strong foundation for further development and application of similar data-driven approaches in sports science.

Table 2. Data analysis results of experimental and control groups.

Group	**Experimental**	**Control**
Injury Rate Before Training (%)	15	20
Injury Rate After Training (%)	5	15
Average Heart Rate Before Training (bpm)	140	138
Average Heart Rate After Training (bpm)	135	142
Step Frequency Before Training (steps/min)	145	150
Step Frequency After Training (steps/min)	152	148
Training Load Before Training (kJ)	320	315
Training Load After Training (kJ)	310	325
Recovery Time (hours)	24	30

From the data analysis in **Table 2**, it can be seen that there were significant differences between the performance of the experimental group and the control group before and after training, especially in terms of injury incidence, exercise load, step frequency, heart rate and recovery time. The pre-training injury incidence rate of the experimental group was 15% while that of the control group was 20%. Although there was a difference in the pre-training injury incidence rate between the two groups, the computer-assisted preventive training program reduced the injury incidence rate of the experimental group to 5% after training, which was a more significant decrease compared to that of the control group (15%). This change suggests that a dynamically adjusted training program based on computer modeling can be more effective in reducing athletic injuries in athletes.

In terms of heart rate and stride frequency, the average heart rate of the experimental group before training was 140 bpm, while the average heart rate of the control group was 138 bpm, which was not a big difference between the two. However, the heart rate of the experimental group dropped to 135 bpm after training, which was significantly lower than that of the control group, which was 142 bpm, indicating that the training loads of athletes in the experimental group were more effectively controlled and adjusted, and the fluctuations in heart rate brought by over-training could be avoided. In terms of stride frequency, the experimental group's stride frequency increased from 145 to 152 steps/min before training, while the control group increased from 150 to 148 steps/min. The increase in stride frequency of the experimental group was significantly greater than that of the control group, which indicated that the experimental group's training regimen was more effective in enhancing athletic performance.

In terms of recovery time, the recovery time of the experimental group was 24 h, compared with 30 h in the control group, a reduction of 6 h, indicating that the experimental group promoted faster recovery of the athletes through personalized training programs.

5.2. Evaluation of model prediction accuracy

The evaluation of model prediction accuracy is a crucial aspect of determining the effectiveness of machine learning algorithms in predicting injury risks. In this study, two models—Support Vector Machine (SVM) and Random Forest (RF)—were assessed based on their performance metrics, including accuracy, precision, recall, and F1 score, using a cross-validation approach to ensure robustness and reliability [14].

The results, as shown in **Table 3**, reveal that the RF model significantly outperforms the SVM model across all evaluation metrics. The RF model demonstrated a higher accuracy on both the training and test sets, achieving 94.1% and 91.3%, respectively, compared to SVM's 89.2% and 87.5%. This notable improvement of approximately 5 percentage points highlights the superior ability of RF to identify patterns and relationships within the data, making it more reliable in both training and practical applications.

Table 3. Results of model prediction accuracy evaluation.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Support Vector Machine (SVM)	87.5	83.2	79.5	81.3
Random Forest (RF)	91.3	89.6	84.1	86.7

Precision and recall metrics further illustrate the advantages of the RF model. On the test set, RF achieved a precision of 89.6% and a recall of 84.1%, outperforming SVM by more than 6 percentage points in both metrics. This suggests that RF is more effective in reducing both false positives and false negatives, which is essential for accurately predicting injury risks and minimizing misclassifications. The enhanced precision indicates that RF is better at correctly identifying athletes at risk of injury, while the higher recall demonstrates its ability to capture a greater proportion of actual injury cases.

The F1 score, which balances precision and recall, also supports the superiority of RF, as it achieves a more consistent performance across all data subsets. This consistency indicates that RF is better equipped to handle complex data structures and adapt to new data without overfitting, an issue that SVM struggles with. SVM's performance gap between the training and test sets suggests a tendency to overfit the training data, making it less effective in real-world applications where data variability is common.

The RF model's advantage lies in its ensemble learning approach, which combines multiple decision trees to produce more stable and accurate predictions. By aggregating results from various models, RF reduces the impact of individual errors and enhances overall reliability. In contrast, SVM relies on a single hyperplane for classification, which limits its flexibility in handling diverse data scenarios.

In conclusion, the RF model's superior performance across all metrics makes it the preferred choice for predicting injury risks in athletes. Its ability to maintain high accuracy, precision, recall, and F1 score ensures reliable and actionable predictions, demonstrating its potential for practical applications in injury prevention and sports management. This evaluation underscores the importance of selecting appropriate machine learning algorithms to address specific challenges in predictive modeling.

The comparative analysis of the Random Forest (RF) and Support Vector Machine (SVM) models reveals significant differences in their performance on both the training and test datasets. As shown in the bar chart of **Figure 2**, the RF model consistently outperforms the SVM model across multiple metrics, demonstrating superior accuracy, precision, recall, and F1 score. On the training set, RF achieves an accuracy of 94.1%, significantly higher than SVM's 89.2%. This disparity highlights RF's ability to capture intricate patterns within the training data, leveraging its ensemble approach to deliver a more robust predictive performance.

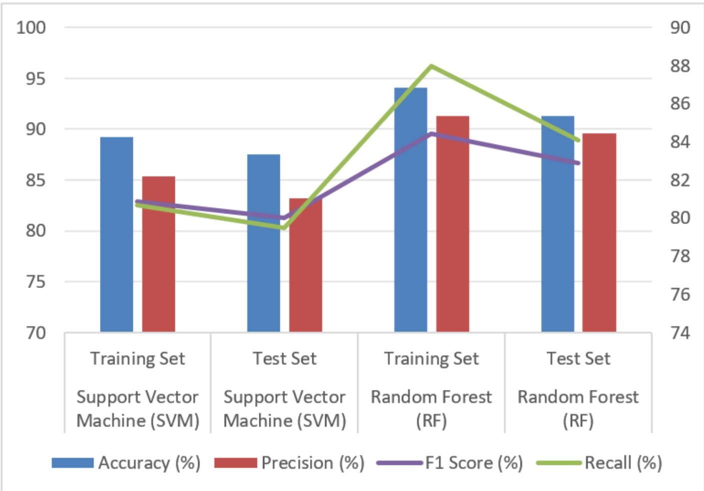

Figure 2. Comparison of the accuracy of different models on the training and test sets.

The distinction between the two models becomes even more pronounced on the test set, where RF maintains an accuracy of 91.3%, compared to SVM's 87.5%. This result underscores RF's strong generalization capability, as it effectively handles previously unseen data without a significant drop in performance. In contrast, SVM exhibits a notable degradation in accuracy, indicative of its tendency to overfit the training data. Overfitting limits SVM's adaptability to new data, reducing its reliability in real-world applications.

Beyond accuracy, RF also demonstrates notable advantages in precision, recall, and F1 score, particularly on the test set. RF achieves a precision of 89.6% and a recall of 84.1%, both of which are markedly higher than SVM's corresponding values of 83.2% and 79.5%. The higher F1 score of RF further confirms its balanced performance, ensuring minimal false positives and false negatives. These results highlight RF's stability and reliability when applied to complex, high-dimensional datasets typical in injury risk prediction.

The ensemble nature of RF, which combines multiple decision trees, contributes significantly to its resilience and adaptability. By aggregating the predictions of individual trees, RF minimizes the risk of overfitting and enhances its ability to generalize across diverse datasets. SVM, although effective in controlled environments, struggles to maintain this balance, as evidenced by its diminished performance on the test set.

In summary, the RF model's consistent and superior performance across key metrics establishes it as a more suitable choice for practical applications involving injury risk prediction. Its ability to handle complex data with high stability and adaptability makes it an invaluable tool for developing reliable, data-driven preventive training programs. This comparison underscores the importance of selecting appropriate machine learning models to address the specific demands of real-world applications in sports injury prevention.

5.3. Optimization suggestions for preventive training programs

According to the results of this study, preventive training programs have shown good results in reducing sports injuries and improving athletes' fitness, but there is still room for further optimization. First, for athletes with higher risk of injury, more recovery and flexibility training can be included in the personalized training program to avoid overuse injuries caused by overtraining [15]. Second, it is recommended to further refine the adjustment of training intensity based on real-time data feedback. For example, real-time monitoring of athletes' recovery status through heart rate variability and fatigue index, and dynamic adjustment of training intensity and load to minimize the occurrence of injury. Third, considering the individual differences of athletes, the training program can introduce more personalized training models in the future, such as optimizing the injury risk prediction model through deep learning to improve the prediction accuracy and model adaptability [16]. Fourth, it is recommended to incorporate more biomechanical and sports injury data into the training evaluation system, combining the athletes' movement patterns, gait analysis and other data to improve the scientific and comprehensive nature of the training program.

6. Conclusion

This study demonstrated a substantial improvement in injury prevention among athletes through the implementation of a computer-assisted preventive training program, which was designed based on advanced computational models. The program's success in optimizing individualized training plans was evident from the experimental results. By systematically comparing the prediction accuracies of different machine learning models, the study confirmed the superiority of the Random Forest algorithm in accurately predicting sports injury risks. This finding highlights the potential of leveraging computer technology in the field of sports medicine, where accurate injury risk assessment is critical for effective prevention strategies.

The experimental results underscored the significant impact of personalized training programs in reducing injury incidence rates, improving athletic performance, and enhancing recovery efficiency. The dynamic adjustments facilitated by the computer-assisted system allowed for real-time adaptation to each athlete's physiological and biomechanical conditions, minimizing overtraining risks and ensuring optimal workload distribution.

Looking forward, further refinement of preventive training programs is essential to enhance their efficacy. This can be achieved by incorporating more detailed physiological data monitoring, advanced feedback mechanisms, and biomechanical analysis into the program framework. Additionally, the integration of deep learning techniques promises to improve the prediction accuracy and adaptability of injury prevention models. These advancements will enable long-term optimization and continuous improvement in athlete health management, ensuring sustainable performance and well-being.

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Conflict of interest: The author declares no conflict of interest.

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