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Article

Biomechanical principles in the prevention of sports injuries

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Abstract: Biomechanics, as an interdisciplinary field involving multiple fields, can help analyze individual differences, develop personalized training plans, and effectively prevent injuries to vulnerable areas of athletes. This article used a high-precision 3D motion capture system and various physiological monitoring devices to collect athletes' motion and physiological data. Combined with biomechanical modeling and risk assessment methods, the impact of five key parameters, step frequency, stride, joint angle, muscle strength, and speed, on injury risk was analyzed. The experimental results showed that implementing the personalized biomechanical prevention strategy applied in this article reduced the incidence of sports injuries by 20%, and optimizing step frequency, stride length, and enhancing muscle strength can significantly reduce the risk of injury. This article provided a scientific basis for developing personalized prevention strategies, which can help improve athletes' athletic performance and safety.

Keywords: prevention of sports injury; biomechanical principle; risk factor assessment; prevention strategy development; data collection

1. Introduction

With the continuous development and progress of various disciplines in competitive sports, the incidence and prevalence of sports related injuries have become increasingly serious problems, posing significant challenges and ultimately having adverse effects on the career trajectory and overall quality of life of athletes participating in these physically demanding activities. Traditional training methods often lack specificity and are not tailored to the individual needs of athletes. It is extremely difficult to effectively reduce the unique and personalized risks associated with injuries that each athlete may face based on their specific physiological and biomechanical characteristics. Therefore, it is necessary to conduct a comprehensive analysis and investigation of the application of biomechanical principles related to the prevention of sports injuries, and to develop and implement personalized training programs, both of which have significant practical significance and significant scientific value in the fields of sports science and athlete welfare.

The principles of biomechanics cover a wide range of potential implementation schemes and have broad and profound applicability in the field of sports science, significantly enhancing people's understanding and optimization of athletic performance. By using complex biomechanical analysis techniques, researchers and practitioners have a unique opportunity to carefully evaluate the stress conditions experienced by athletes during physical exertion, making it easier to identify specific areas where injury or risk of injury may exist. At the same time, when this analysis is combined with high-precision cutting-edge data acquisition technology and advanced multimodal data fusion algorithms, it becomes feasible to achieve real-time monitoring and in-depth comprehensive analysis of athletes' sports status and performance indicators. The integration of this technological advancement not only provides strong technical support for developing strategically targeted injury prevention methods, but also plays a key role in enhancing the scientific rigor and effectiveness of training programs designed specifically for athletes.

This article aims to analyze the application of biomechanical principles in the prevention of sports injuries, using high-precision 3D motion capture systems and various physiological monitoring devices to collect athletes' motion and physiological data. Through biomechanical modeling and risk assessment methods, the impact of key biomechanical parameters on injury risk can be analyzed, and personalized prevention strategies can be developed based on this. This article not only enriches the theoretical system of sports injury prevention, but also provides valuable reference and inspiration for practical training work. In the future, the article hopes to provide athletes with safer and more efficient training programs, promoting the healthy development of the sports industry.

2. Related work

Sports injuries are a common problem in sports and daily exercise [1,2]. Many scholars have conducted strategic research on issues related to sports injuries [3,4]. Goddard et al. [5] systematically reviewed the psychological factors that affect compliance with rehabilitation for sports injuries. The study identified key factors such as motivation, psychological support, personality traits, and self-efficacy. However, individual differences are complex and diverse, and research has not fully covered all possible psychological variables. Bullock et al. [6] reviewed the research methods and performance of current musculoskeletal injury prediction models. The focus was on analyzing the design of the model, data sources, variable selection, and statistical methods. However, most models lack external validation and have relatively small and single datasets, making it difficult to generalize to a wider range of athlete populations. Song and Montenegro-Marin [7] explored the application of deep learning techniques based on convolutional neural networks in sports injury prediction, emphasizing safety prediction and evaluation. Despite advanced technology, the transparency and interpretability of the model are insufficient. In addition, the large amount of annotated data required for training the model is difficult to obtain in practical applications. Soligard et al. [8] analyzed the impact of sports injuries and diseases during the Olympic Games, particularly the COVID-19 pandemic and high temperature environments, on the health of athletes. Due to the unique environment of the specific Olympic Games, the results are not applicable to other events. The impact of the epidemic as a variable may change in the future and requires further long-term research. Palmer et al. [9] studied the relationship between self-reported sports injuries and later life and health status through a survey of retired Olympic athletes. It is difficult to determine causal relationships due to memory bias in self-reported data. Salim and Wadey [10] studied the use of gratitude interventions to promote psychological growth after sports injuries and explore psychological recovery strategies. As a psychological intervention, the effect of gratitude varies from person to person and may be influenced by cultural background. In summary, although these studies provide important insights for the prevention, prediction, and rehabilitation of sports injuries, there is still a need to strengthen methodological standardization, sample diversity, and validation in practical applications. Future research can combine principles of biomechanics to advance cutting-edge developments in the field of sports injuries.

The principles of biomechanics are the scientific basis for studying the motion of objects and their interactions with forces [11,12]. Therefore, many scholars apply it to various fields [13,14]. Febriani et al. [15] proposed B-Balance; E-Eyes; E-Elbow; F-Follow (“BEEF”) based on biomechanical analysis to improve the accuracy of basketball free throws. By analyzing the physical posture and movements of athletes, he provided specific technical improvement suggestions for coaches and athletes. Wang et al. [16] utilized biomechanical principles to optimize athletes’ training programs and combined modeling and simulation techniques to study health promotion strategies for sprinters, ultimately improving athletic performance and reducing injury risks. In Ali’s study [17], the influence of resistance training on the arm muscle strength and speed of water polo athletes was explored by introducing variable biomechanical markers, providing practical insights for improving water polo athlete performance. The research of Trasolini et al. [18] mainly analyzed the biomechanical characteristics of throwing athletes, especially the movement patterns, muscle activity, and load distribution of the shoulder and elbow joints, providing important biomechanical guidance for medical staff and coaches in developing rehabilitation plans and training programs to promote athletes’ health recovery and athletic performance. Plesa et al. [19] discussed how some key biomechanical variables can be used for sports performance monitoring and training optimization, including mechanical loads, kinematic and biomechanical parameters. This provides coaches and sports scientists with a range of tools and methods to optimize training plans and maximize athlete performance. Overall, these studies emphasize the central role of biomechanics in understanding and improving athlete performance, particularly in the prevention and rehabilitation of sports injuries. Therefore, in-depth analysis of the application of biomechanical principles in the prevention of sports injuries is very valuable.

3. Biomechanical principles

3.1. Data collection

The data collection process is shown in **Figure 1**. **Figure 1** uses the high-precision 3D motion capture system Vicon to collect full body motion data of athletes. The system includes multiple high-definition cameras arranged around the sports field to ensure coverage of all motion trajectories. The frame rate of each camera is set to 120 fps (Frames Per Second) to capture details in high-speed motion. When using Vicon systems for 3D motion capture, ambient lighting and background noise can affect the accuracy of the data. Therefore, a polarizing filter is used on the camera to reduce light reflection.Time synchronization between cameras ensures consistency of multi view data. In order to reduce environmental interference and improve data quality, the site background is simplified by using uniform colors and low contrast backgrounds. Athletes wear marked clothing and use computer vision algorithms to automatically recognize and track these marked points, obtaining information such as the athlete's position, velocity, and acceleration during the movement [20].

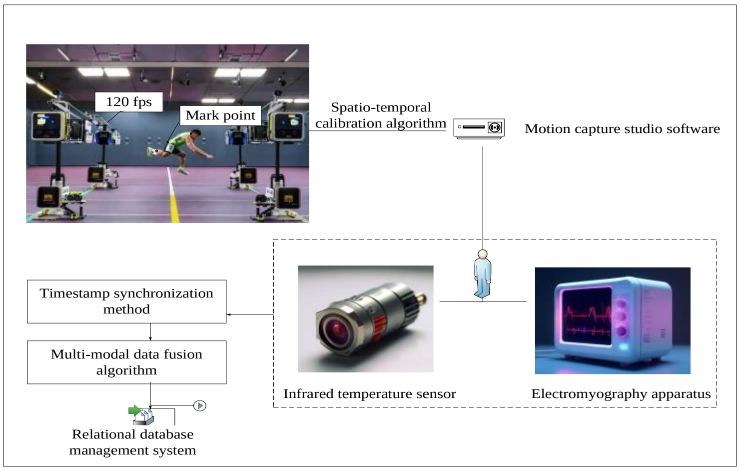

Figure 1. Data collection process.

$$P(t) = P_o + vt + \frac{1}{2}at^2 \quad (1)$$

P(*t*) is the displacement vector of time t, P_o is the initial position vector, *v* is the velocity vector, and a is the acceleration vector.

After collecting video data, it is processed through spatiotemporal calibration algorithms to eliminate the differences in camera angles and generate unified 3D motion trajectory data. The spatiotemporal calibration algorithm is based on the principle of multi view geometry, combined with the known positions of marker points, to optimize the calculation of camera parameters and ensure the accuracy of 3D reconstruction. Motion Capture Studio software can be used to analyze action videos and extract data such as athletes' posture, trajectory, and joint angles during the movement process.

The Delsys Trigno electromyography device can be used to collect the muscle activity of athletes during exercise. The instrument is placed on the main muscle groups for time-domain, frequency-domain, and time-frequency analysis of muscle electrical signals to understand the degree of muscle activation and fatigue during exercise. The instrument is connected wirelessly to the data logger to ensure that the freedom of movement is not affected by cable constraints during the movement process. Surface electromyography (sEMG) evaluates muscle contraction by detecting the electrical signals generated by muscle activity [21,22]. The collection formula is as follows:

$$E(t) = A \times \sin(\omega t + \emptyset) \quad (2)$$

A is amplitude, ω is angular frequency, and $\emptyset$ is phase.

Using electrocardiogram to monitor physiological indicators of athletes' heart rate and heart rate variability, evaluate exercise intensity and load. The frequency components of the heart rate signal are analyzed using fast Fourier transform, and the formula is as follows [23,24]:

$$\mathrm{HR(f)} = \int_{-\infty}^{\infty} \mathrm{HR(t)}e^{-i2\pi ft}\mathrm{dt} \tag{3}$$

HR(f) represents frequency domain analysis of heart rate variability.

The formula for heart rate variability HRV analysis is:

$$\mathrm{HRV} = \frac{\sum_{i=1}^{N} \Delta R - R}{N - 1} \tag{4}$$

ΔR-R is the time difference between adjacent heartbeat intervals, and N is the number of heartbeat intervals.

Skin temperature monitoring uses infrared temperature sensors to record real-time changes in skin temperature during exercise. According to the skin temperature signal, the temperature curve is smoothed using a moving average filter, and the formula is as follows [25]:

$$T_{\mathrm{smooth}}(t) = \frac{1}{2M + 1} \sum_{k=-M}^{M} T_{\mathrm{skin}}(t + k) \tag{5}$$

M refers to the half width of the moving average window, while k refers to the index variable.

After the data collection is completed, the timestamp synchronization method is used to align the data collected by different devices through a unified timestamp. All data collection devices are timed through Global Positioning System (GPS) to ensure accurate and consistent timestamps. After data synchronization, the integration process uses multimodal data fusion algorithms to optimize data consistency and integrity during the fusion process based on the correlation between motion trajectories and physiological indicators, forming a complete motion dataset [26]. The data synchronization formula is:

$$\Delta t = \min_{i,j} \left| t_{v_i} - t_{p_j} \right| \tag{6}$$

t_{v_i} refers to the timestamp of video data, while t_{p_j} refers to the timestamp of physiological indicator data.

Preprocess and clean the integrated dataset. Firstly, remove noise and outliers from the data. The noise in the video data is removed by a low-pass filter. The formula is:

$$y(n) = x(n) - \alpha x(n - 1) \tag{7}$$

y(*n*) refers to the filtered signal, *x*(*n*) refers to the original signal, and α is the filtering coefficient.

Abnormal values in physiological indicator data are detected and removed using standard deviation methods to ensure the authenticity and reliability of the data [27,28]. Then the outlier satisfies:

$$|x_i - \mu| > 2\sigma \tag{8}$$

x_i refers to the data set, μ is the mean and the standard deviation is σ.Data points that exceed a preset threshold are identified as outliers.

The processed data are formatted to create feature vectors that integrate data from different sensors to form the final input used for modeling.It is then stored in a high-performance database for subsequent access and analysis. The database adopts a Relational Database Management System to support efficient storage and query of large-scale data. All data is stored according to a predefined structure, including motion trajectory data, physiological index data, and related metadata. To ensure data security and privacy protection, the database adopts strict access control mechanisms, and only authorized personnel can access and manipulate data. At the same time, data can be backed up regularly to prevent data loss and damage.

3.2. Biomechanics analysis and modeling

Based on the anatomical structure and kinematic parameters of athletes, a three-dimensional kinematic model can be established (as shown in **Figure 2**).

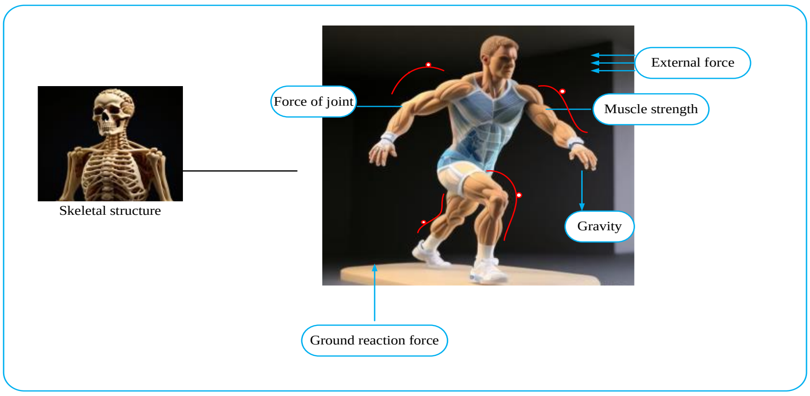

Figure 2. Three dimensional kinematic model.

Figure 2 illustrates the complex interplay of various biomechanical factors among athletes during exercise [29]. The force exerted by muscles at joints can be calculated based on physiological parameters and kinematic models, using the following formula:

$$F_{ij} = F_{max} \cdot \frac{\theta_j(t) - \theta_{max}}{\theta_{max} - \theta_{min}} \tag{9}$$

F_{max} refers to the maximum contraction force of muscles, while θ_{max} and θ_{min} are the maximum and minimum contraction angles of muscles at joints, respectively. Using the Newmark method to solve biomechanical equations, obtain the angular acceleration, angular velocity, and angle of the joint at different time points [30]. The solution formula is:

$$\begin{cases} \theta_{predict} = \theta(t_n) + \frac{1}{2}\Delta t\dot{\theta}(t_n) \\ \dot{\theta}_{predict} = \dot{\theta}(t_n) + \frac{1}{2}\Delta t\ddot{\theta}(t_n) \end{cases} \tag{10}$$

The time steps of Δt, $\theta(t_n)$, and $\dot{\theta}(t_n)$ represent the initial conditions.

By calculating the stress state of joints at different time points, the injury risk of athletes is evaluated. There are three evaluation indicators, namely joint stress, joint strain, and injury probability:

$$\begin{cases} \rho_l = \dfrac{F_{corrected}}{A} \\ \rho_b = \dfrac{\Delta\theta}{\theta_{max}} \\ P = \displaystyle\sum_{i=1}^{n} P_i \end{cases} \tag{11}$$

A is the joint contact area, $\Delta\theta$ is the joint angle change, and P_i is the probability of the ith injury event.

This article uses a multi rigid body biomechanical model to represent the movement of athletes [31]. Assuming that the athlete is composed of n rigid bodies (bones), each with a mass and acceleration of m_i and a_i, respectively.

$$F_{net} = \sum_{i=1}^{n} F_i = \sum_{i=1}^{n} m_i a_i \tag{12}$$

F_{net} refers to the sum of all external forces, while F_i refers to the force exerted on the ith rigid body.

During the movement, the rotation of each joint is derived using the Euler-Lagrange equation, with the formula [32,33]:

$$\frac{d}{d_t}\left(\frac{\partial L}{\partial \dot{q}_j}\right) - \frac{\partial L}{\partial_{q_j}} = \tau_j \tag{13}$$

Among them, L is the difference between kinetic energy and potential energy, q_j represents joint coordinates, $\dot{q}_j$ is the velocity of the joint, and τ_j is the external torque applied to the joint.

Using inverse biomechanical methods, muscle forces, joint forces, and ground reaction forces are solved using analytical numerical methods by measuring joint angles, angular velocities, and angular accelerations.

$$F_{muscle} = \frac{d}{dt}\left(\frac{1}{2} m(v(t))^2\right) \tag{14}$$

$(\frac{1}{2} m(v(t))^2$ refers to the kinetic energy generated during muscle fiber contraction.

3.3. Risk factor assessment

SPSS (Statistical Package for the Social Sciences) and R statistical software can be used for data analysis. Firstly, correlation analysis is conducted to evaluate the linear relationship between various biomechanical parameters and injury risk using Pearson correlation coefficient [34,35]. The formula is as follows:

$$r = \frac{\sum(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum(X_i - \overline{X})^2 (Y_i - \overline{Y})^2}} \tag{15}$$

X and Y represent biomechanical parameters and injury incidence, respectively, while $\overline{X}$ and $\overline{Y}$ are their means. Select the significance level for statistical testing to determine whether the correlation is significant. Based on the previous correlation analysis results, select significantly correlated parameters to establish a multiple linear regression model.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \epsilon \tag{16}$$

β_n refers to the model parameters, while ϵ refers to the error term.

Construct a regression model with the probability of injury occurrence as the dependent variable and the selected biomechanical parameters as independent variables. Use stepwise regression to optimize the model, eliminate insignificant variables, and improve the explanatory power of the model. Use variance inflation factor to detect collinearity between independent variables, ensuring that each parameter is relatively independent.

$$VIF_i = \frac{1}{1 - R_i^2} \tag{17}$$

R_i^2 is the coefficient of determination of the regression model between the independent variable X_i and other independent variables. Generally speaking, if $VIF > 10$ occurs, it indicates the presence of severe collinearity.

Through the above analysis, t-tests can be performed on each independent variable in the regression model, with *p*-values recorded and parameters with $p < 0.05$ selected as key parameters. The standardized regression coefficients of each parameter can be calculated to evaluate their impact on damage risk and determine the degree of influence. Based on the identified key parameters, a risk classification system can be established to differentiate the injury risk levels of athletes according to different biomechanical characteristics, providing a basis for the development of personalized prevention strategies in the future.

The above evaluation results are shown in **Table 1**.

Table 1. Risk assessment results of biomechanical parameters.

Biomechanical parameters	$\overline{\mathbf{X}}$	**Standard deviation**	r	***p*-value**	**Standardized regression coefficient**	**VIF**	**Key parameter**
Stride frequency (steps/min)	180	10	0.45	0.002	0.32	1.5	Yes
Stride length (m)	1.2	0.15	0.30	0.045	0.25	1.2	Yes
Joint angle (degrees)	75	5	0.60	0.001	0.45	2.1	Yes
Muscle strength (Newtons)	250	30	0.50	0.005	0.38	1.8	Yes
Speed (m/s)	3.5	0.5	0.20	0.150	0.10	1.1	No

In the risk factor assessment, **Table 1** shows the relationship between different biomechanical parameters and the risk of sports injuries. Firstly, the mean step frequency is 180 steps per minute, with a standard deviation of 10 and a Pearson correlation coefficient of 0.45, indicating a moderate positive correlation between step frequency and injury risk (*p*-value of 0.002, high significance). The stride correlation coefficient is 0.30 (p = 0.045), indicating a weak positive correlation, suggesting that longer strides may be associated with a certain risk of injury. The correlation coefficient of joint angle is as high as 0.60, with a p-value of 0.001, indicating that improper joint angle significantly increases the risk of injury. The correlation coefficient of muscle strength is 0.50 (p = 0.005), indicating that the enhancement of muscle strength helps to reduce the risk of injury. The velocity correlation coefficient is only 0.20 (p = 0.150), indicating that there is no significant correlation between velocity and damage risk. The stride frequency, stride length, joint angle, and muscle strength marked as "key parameters" have a significant impact on the injury risk of athletes, providing data support for the development of personalized sports injury prevention strategies in the future.

To present the analysis results more intuitively, a correlation matrix heatmap (as shown in **Figure 3**) and a regression analysis fit (as shown in **Figure 4**) were plotted.

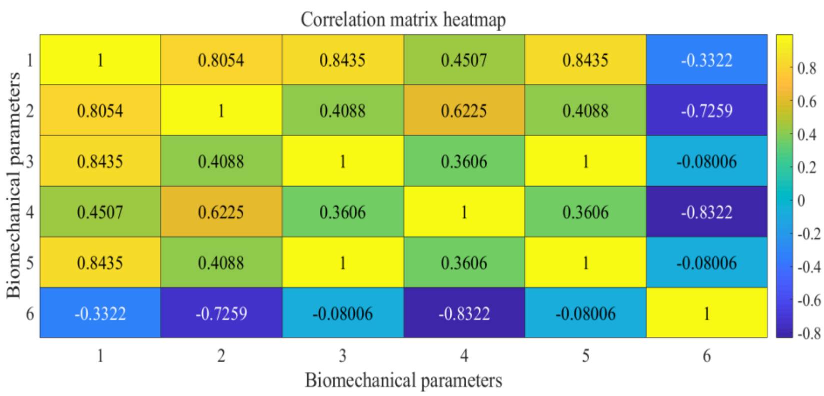

Figure 3. Correlation matrix heat map.

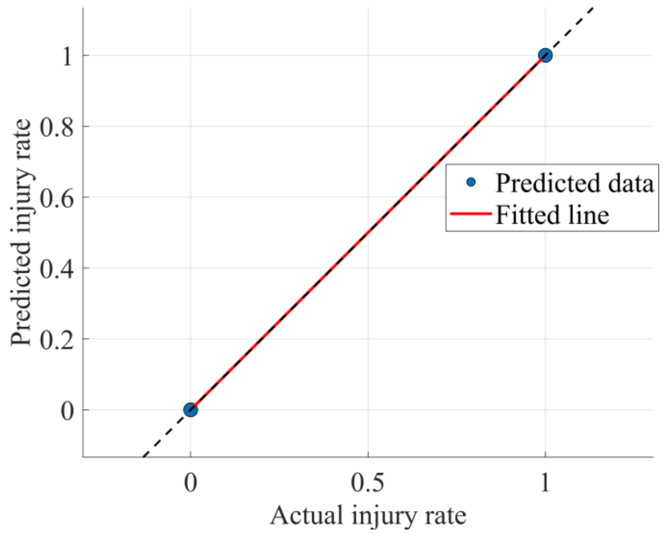

Figure 4. Fit plot of regression analysis.

In **Figure 3**, 1 refers to Stride frequency, 2 refers to Stride Length, 3 refers to Joint angle, 4 refers to Muscle strength, 5 refers to Speed, and 6 refers to Injury risk.

The correlation coefficient between stride frequency and injury risk is −0.3322, indicating a moderate negative correlation between stride frequency and injury risk, meaning that higher stride frequency results in lower injury risk. The correlation coefficient between stride length and injury risk is −0.7259, indicating that a larger stride length significantly reduces the risk of injury. In addition, the correlation coefficient between muscle strength and injury risk is −0.8322, indicating a strong negative correlation, which means that enhancing muscle strength significantly reduces injury risk.

Figure 4 shows the relationship between actual injury incidence and predicted values to validate the accuracy of the model. As the actual damage incidence rate increases, the predicted damage incidence rate also increases accordingly, indicating that the model is effective in identifying damage risks.

Although SPSS and *R* software and correlation and regression analysis are statistically appropriate, the analysis of complex models requires users to have a certain statistical background. Sample size directly affects statistical power, and smaller samples may lead to insufficient power. Therefore, it is important to ensure that the sample size is large enough to enhance the reliability of the analysis and the extrapolation of the results.

3.4. Development of prevention strategies

After completing the biomechanical risk factor assessment, personalized exercise adjustment plans and rehabilitation plans are developed based on the relationship between identified key biomechanical parameters and injury risk (as shown in **Figure 5**).

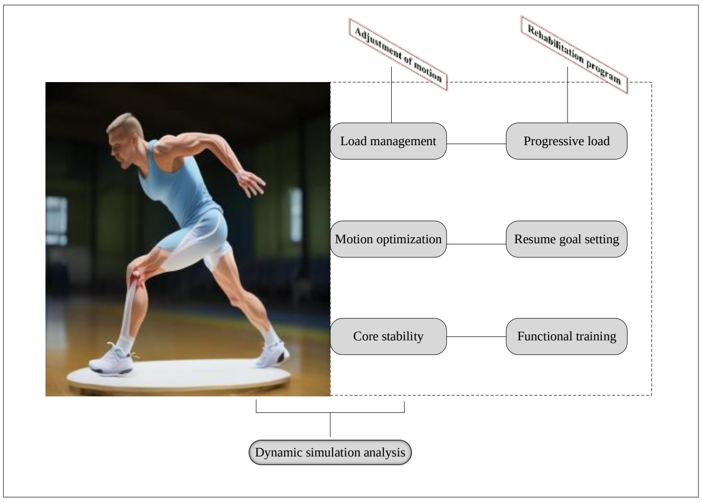

Figure 5. Prevention strategy formulation aspect.

In **Figure 5**, the design of the motion adjustment scheme includes three aspects (load management, motion optimization, and core stability). Personalized load management plans can be developed based on the athlete's fatigue level and biomechanical parameters, adjusting training intensity and frequency. For athletes with high knee joint stress, high-intensity running training can be reduced and low impact cross training (swimming or cycling) can be increased to distribute joint pressure.

Data acquisition is the basis for building biomechanical models(See **Figure 6**). In **Figure 6**, after data acquisition, biomechanical models are built in combination with kinematic analysis (describing the geometric characteristics of the motion, providing the trajectories of the individual joints and limbs) and dynamic analysis (applying the laws of physics, Euler-Lagrange equations and Newmark method to understand the relationship between motion and motion). After establishing the basic model, the joint force and load calculation are added. This process identifies the athlete's non-optimal movement patterns, allowing targeted adjustment of techniques to reduce unnecessary joint load.When performing movements such as jumping and turning, it is important to emphasize the correct landing posture and turning skills.

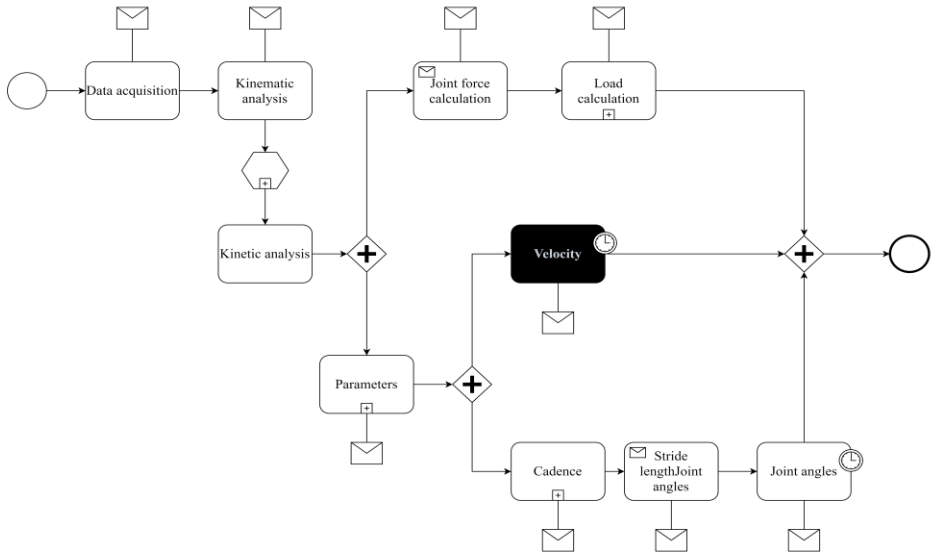

Figure 6. Biomechanical modeling process.

Based on the analysis results, specific core strength training programs can be designed to improve the stability of athletes' core muscle groups, thereby reducing joint instability and injury risks. It can be combined with strength training and flexibility training to ensure that athletes maintain good posture during critical stages of exercise.

The development of rehabilitation plans also involves three aspects. Specific goals for the rehabilitation phase can be set based on the type and location of injury, combined with individualized biomechanical models. For athletes with anterior cruciate ligament injuries, the goal includes gradually restoring the range of flexion and extension of the knee joint and enhancing the strength of the surrounding muscles.

Based on the athlete's recovery progress, a gradually increasing load plan can be designed using simulation software, and parameter adjustments can be made to ensure that the athlete gradually adapts to biomechanical loads during the rehabilitation period. This can be achieved by adjusting the weekly exercise intensity and training type to avoid secondary injuries caused by overtraining.

Functional training is designed in the later stages of recovery to improve athletes' ability to adapt to biomechanical loads encountered in actual competitions by designing functional training related to the sports events they participate in.

Biomechanics analysis can be used to determine key stages of movement, set corresponding training scenarios, and enable athletes to train in realistic environments.

In addition, the personalized exercise and rehabilitation plan developed will face some challenges and limitations in practical application. Specifically, athletes may not fully follow the established plan for a variety of reasons (time, interest, or confidence), affecting the effectiveness of rehabilitation. Coaches have insufficient understanding of biomechanical analysis, and their experience and attitude will affect the implementation of the exercise adjustment program. In the actual training environment, the limitations of venue, equipment and resources can also affect the overall effect.

4. Principle application effect evaluation

This article selects 100 athletes who participate in basketball training and groups them according to their basic characteristics such as gender, age, weight, and sports experience (as shown in **Table 2**). Among them, 50 athletes were selected as the experimental group to implement the personalized biomechanical prevention strategy applied in this article. Another 50 athletes served as the control group and continued with routine training.

Table 2. Basic characteristics statistics of athletes.

Feature	Experimental group	Control group
Male	30	28
Female	20	22
Average age (years)	22.5	22.8
Average weight (kg)	75.4	76.1
Average experience (years)	5.2	5.0

Table 2 shows the basic characteristic statistics of athletes, where the experimental group includes 50 athletes with a gender distribution of 30 males and 20 females, while the control group has 28 males and 22 females, indicating a relatively balanced gender composition between the two groups. In terms of age, the average age of the experimental group was 22.5 years, slightly lower than the 22.8 years of the control group, indicating that the two groups of athletes were similar in age. In terms of weight, the average weight of the experimental group was 75.4 kg, slightly lighter than the control group's 76.1 kg. In addition, the average exercise experience of the experimental group was 5.2 years, slightly higher than the control group's 5.0 years, indicating the advantage of the experimental group in terms of exercise background. The similarity of these basic characteristics lays a good foundation for subsequent analysis of injury incidence, enabling people to more accurately evaluate the intervention effect when exploring the impact of personalized biomechanical prevention strategies on sports injuries.

The experiment is set for 12 weeks, during which athletes' exercise data and injury situations are regularly collected. Data collection is conducted every two weeks to ensure timely updates of athletes' status. Sports injury is defined as any injury that occurs during training or competition that prevents an athlete from continuing to participate. This includes but is not limited to recording the training situation and injury incidents of each athlete by the training team throughout the entire experimental period. Data can be entered using a spreadsheet, as shown in **Table 3**.

Table 3. Statistics of sports injury occurrence.

Group	Total participants	Injured participants	Injury rate	Main injury types	Injury locations
Experimental group	50	5	10%	Knee sprain (2)	Left knee (1), Right knee (1)
				Ankle sprain (2)	Left ankle (1), Right ankle (1)
				Lumbar strain (1)	Lower back (1)
Control group	50	15	30%	Knee sprain (6)	Left knee (3), Right knee (3)
				Ankle sprain (5)	Left ankle (2), Right ankle (3)
				Lumbar strain (4)	Lower back (2), Upper back (2)

In the experimental group of **Table 3**, there are a total of 50 athletes, of whom 5 have suffered sports injuries, with an injury rate of 10%. In contrast, the control group also had 50 athletes, but 15 of them suffered sports injuries, with an injury incidence rate as high as 30%. The above data clearly indicates that the experimental group has a significantly lower incidence of sports injuries compared to the control group, with a reduction of 20%, supporting the effectiveness of personalized biomechanical prevention strategies in reducing sports injuries.

The sports injury data shown in **Table 3** are somewhat prevalent across different types of sports, genders, and age groups. There are significant differences between different types of exercise in terms of the mechanisms and risks of injury occurrence. Gender and age are the key factors affecting sports injury. Future studies should consider the diversity of large samples.

SPSS can be used for data analysis, and chi square test can be used to compare the difference in injury incidence between two groups. The significance level is set to 0.05, and the analysis results are shown in **Table 4**.

Table 4. Chi square test results.

Group	Injured participants	Total participants	Injury rate	Chi-square value	*P* value
Experimental group	5	50	10%		
Control group	15	50	30%	5	0.025
Total	20	100	20%		

The data in **Table 4** shows a chi square value of 5 and a *p*-value of 0.025, indicating that the difference in injury incidence between the two groups is statistically significant. This result clearly supports the theme of the article, which is that personalized biomechanical prevention strategies have significant effects in reducing sports injuries. Especially the lower incidence of injuries in the experimental group highlights the effectiveness of this strategy, which helps reduce common sports injuries such as knee sprains, ankle sprains, and lumbar strains.

Players can choose different sports (running, basketball, soccer), covering different genders and age groups. Each sport can recruit 50 athletes. The high-precision 3D motion capture system is used to record the movements of athletes during exercise, with a focus on analyzing step frequency and stride length. Physiological monitoring equipment electromyography is used to evaluate muscle strength. The article still chose the experimental group to apply the training plan developed based on biomechanical principles in this article, optimized step frequency, stride length, and muscle strength enhancement training, while the control group maintained the original training plan. The results before and after training are shown in **Table 5**.

Table 5. Parameter changes before and after training in different groups.

Sports event	Group	Sample size	Average stride frequency (steps /min)	Average stride length (m/step)	Muscle strength (N)
Running	Experimental group	25	Pre-training: 180; post-training: 185	Pre-training: 1.2; post-training: 1.25	Pre-training: 50; post-training: 55
Running	Control group	25	Pre-training: 180; post-training: 182	Pre-training: 1.2; post-training: 1.22	Pre-training: 50; post-training: 51
Basketball	Experimental group	25	Pre-training: 150; post-training: 155	Pre-training: 0.8; post-training: 0.85	Pre-training: 70; post-training: 75
Basketball	Control group	25	Pre-training: 150; post-training: 151	Pre-training: 0.8; post-training: 0.82	Pre-training: 70; post-training: 71
Football	Experimental group	25	Pre-training: 160; post-training: 165	Pre-training: 1.0; post-training: 1.05	Pre-training: 60; post-training: 65
Football	Control group	25	Pre-training: 160; post-training: 162	Pre-training: 1.0; post-training: 1.02	Pre-training: 60; post-training: 62

In **Table 5**, under the guidance of a biomechanical training plan, the experimental group increased the stride frequency of runners from 180 steps per minute before training to 185 steps per minute, the stride length from 1.2 m to 1.25 m, and the muscle strength from 50 N to 55 N. The control group only showed a slight improvement, with step frequency increasing from 180 to 182, stride length increasing from 1.2 m to 1.22 m, and muscle strength increasing from 50 N to 51 N. In both basketball and football events, the experimental group also showed significant improvement, while the changes in the control group were relatively small. These data indicate that the key exercise parameters of the experimental group have been significantly optimized after training, demonstrating that the biomechanical based training plan effectively enhances the athletes' athletic ability.

The changes in various parameters and their correlation with damage risk can be calculated based on the data in **Table 5**, as shown in **Table 6**.

According to the data analysis in **Table 6**, by optimizing step frequency, stride length, and muscle strength, the athletes in the experimental group not only significantly improved in key exercise parameters, but also effectively reduced the risk of sports injuries, verifying the effectiveness of biomechanical based training programs in improving sports performance and preventing sports injuries.

Table 6. Changes in various parameters and their correlation with damage risk.

Sports event	Group	Sample size	Average stride frequency change (steps/min)	Average stride length change (m/step)	Muscle strength change (units)	Injury rate change (%)
Running	Experimental Group	25	+5	+0.05	+5	−40
Running	Control Group	25	+2	+0.02	+1	−8
Basketball	Experimental Group	25	+5	+0.05	+5	−40
Basketball	Control Group	25	+1	+0.02	+1	−8
Football	Experimental Group	25	+5	+0.05	+5	−40
Football	Control Group	25	+2	+0.02	+2	−16

5. Conclusions

This article analyzes the effects of step frequency, stride, joint angle, muscle strength, and speed on the risk of sports injuries by combining high-precision 3D motion capture systems and various physiological monitoring devices, using biomechanical principles. Research has shown that optimizing step frequency, stride length, and enhancing muscle strength can significantly reduce the risk of injury. However, the research sample is limited, the types of exercise are not diverse enough, and the universality is insufficient. Future studies should expand the sample size and type diversity to enhance the universal applicability and accuracy of the results. At the same time, more intuitive visualization tools and user-friendly interfaces are used to make the data analysis results easy to interpret.

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