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Article

Biomechanics of the run-up and take-off of track and field athletes based on linear regression and factor analysis

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Abstract: The current biomechanical analysis of track and field athletes during run-up and take-off suffers from large errors and poor accuracy in analyzing the relationship between biomechanical variables. To address this problem, this study used the factor analysis model to optimize the linear regression model and analyzed the biomechanics of track and field athletes at different levels based on the optimized model. To verify the new performance of the optimized model, the study compared the model with other models in a comparative test. The outcomes indicated that the prediction accuracy of the model reached 97.6%, and the model took only 1.2s to predict. The model's data detection completeness rate reached 100%, and all the performances were better than other models. The model was then used to analyze the biomechanics during run-up and take-off of athletes of different levels. The analysis results showed that during the run-up and take-off process, the horizontal velocity of the athlete's center of mass first decreased, then increased, and finally decreased again. The maximum horizontal velocity of the national first-class athlete's center of mass was 8.62 m/s. Moreover, the relative center of mass height of athletes gradually increased during the run-up and take-off process. Furthermore, the relative center of mass height of national level athletes reached up to 0.72%, while the reaction force of national level athletes was slightly lower than that of other athletes. It is clear from the aforementioned findings that the suggested optimization model is capable of precisely analyzing track and field players' biomechanics during run-up and takeoff.

Keywords: linear regression; factor analysis; track and field athletes; run-up and take-off; biomechanics

1. Introduction

As people's attention to health is increasing nowadays, the attention of many sports is also rising [1]. Athletics is a general term for an all-around sport program that combines walking, running, jumping, throwing and other sports [2]. Athletes' run-up and take-off can provide athletes with the necessary horizontal speed, vertical speed, and ground reaction force to help track and field athletes achieve better athletic performance [3]. The term "biomechanics" refers to the area of biophysics that uses mechanical concepts and techniques to quantitatively investigate mechanical issues in living things, including systems and entire organisms [4]. Biomechanical analysis of the run-up and take-off process of track and field athletes can help athletes better understand the ground mechanics of the jumping process and optimize the run-up and take-off technique, which can improve the performance and reduce the sports injury [5]. Many scholars have analyzed biomechanics. For example, Ernstbrunner et al. analyzed the biomechanics of paralysis patients and chronic pseudo-paralysis patients by using comparative experiments in order to analyze the significance of biomechanical differences between them. The findings demonstrated that the biomechanics of chronic pseudo-paralyzed patients and paralyzed patients differed significantly [6]. Colella et al. designed to deal with a ultrahigh frequency (UHF) battery-assisted passive Radio Frequency Identification (RFID) technique in order to analyze the biomechanics of human movement. This technique was used in the analysis of biomechanics for experiments, and the results showed that this technique increased the accuracy of the analysis by 21.2% [7]. Nevertheless, the aforementioned biomechanical analysis is still flawed due to the incomplete detection of data at the time of analysis. Furthermore, the relationship between the factors in biomechanics and the outcomes is now impossible to ascertain. Consequently, it is also necessary to optimize the current biomechanical analysis methods [8].

Regression analysis in mathematical statistics is used in the linear regression (LR) model, a statistical analysis technique, to ascertain the relationship between variables [9]. This method is often used in various fields due to its advantages of simplicity and ease of understanding. For example, Singh et al. proposed an LR-based machine learning model in order to analyze the relationship between key performance parameters of product quality. Comparing this model with other models, the results indicated that the model was able to accurately analyze the relationship between performance parameters [10]. However, there will be a high complexity problem in LR due to the large amount of data, and the model needs to be optimized [11]. A statistical method for identifying common factors in a population of variables, factor analysis (FA) lowers the number of variables and tests hypotheses regarding the relationships between them [12]. This method is often used in various fields due to its ability to reduce the dimensionality of the data and to deal with multivariate problems. To examine the impact of congenital and acquired vision impairment on the performance of disabled swimmers and disabled track and field athletes on a global scale, Le Toquin et al. suggested a data analysis method based on the FA approach. The method was compared with other methods and the results showed that the method had an analytical accuracy of 92.1% [13].

In summary, it can be concluded that although there are more biomechanical analysis methods, these methods still have the problems of inaccurate data detection and the relationship between biomechanical variables cannot be analyzed accurately. To solve the above problems, this study organically combines FA and LR models and uses the combined FA-LR model in biomechanical analysis of track and field athletes. The study aims to improve the accuracy of biomechanical analysis and understand the relationship between biomechanical changes and athletic performance. The results of this analysis can help athletes to develop better training measures to improve their athletic performance. The innovation of the study is to extract the common factors from the data by FA method and use the extracted common factors as inputs to the LR model. This can reduce the complexity of the LR model and simplify the calculation.

2. Methods and materials

2.1. LR modeling in conjunction with FA

With the increasing popularity of sports nowadays, many people's attention to track and field is increasing [14]. Athletes in track and field generally use run-up and take-off to increase their free height, so as to better complete various movements.

Research on the biomechanics of run-up and take-off can help athletes optimize their technical movements, improve their training methods, and enhance their athletic performance [15]. LR model is a mathematical regression model to determine the correlation between variables. Using this model, biomechanical information can be extracted from athletes during run-up and take-off. This clarifies the effect of individual biomechanics on athletic performance so that accurate training strategies can be developed with a view to improving the performance of the athlete. The basic flow of the LR model is shown in **Figure 1**.

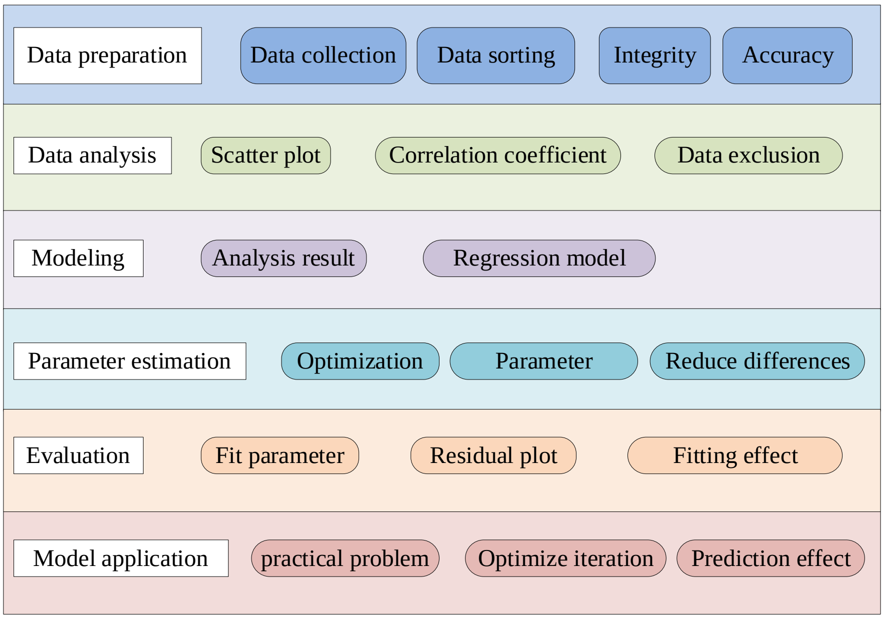


Figure 1. LR basic flow chart.

In **Figure 1**, the LR model first carries out data preparation, i.e., collects and organizes the relevant data to ensure the completeness and accuracy of the data. After that, the collected data are then used to judge the relationship between the independent variables (IDVs) and the dependent variables (DVs) in the data by means of scatter plots or calculating correlation coefficients. The more significant relationships are retained and other data are eliminated to avoid affecting the subsequent analysis of the results. The LR model is established using the analyzed results, and the optimization method is employed to estimate the model parameters in accordance with the actual situation. This is done in order to minimize the discrepancy between the predicted and actual values of the model. The model's fitting effect is then assessed by comparing the residual plots or computing the model's fit parameters. Finally, the model is used in real situations for application and needs to be optimized and iterated according to the actual situation to achieve better prediction results. The basic expression of LR model is shown in Equation (1).

$$y = wx + e \tag{1}$$

In Equation (1), y is the DV. x denotes the IDV. w is the regression coefficient. e denotes the error term. The regression coefficient is calculated as shown in Equation (2).

$$w = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sum(x_i - \bar{x})^2} \tag{2}$$

In Equation (2), $\bar{x}$ and $\bar{y}$ are the means of the IDV and DV, respectively. x_i and y_i represent the IDV and DV of the ith observation. Moreover, the loss function (LF) mean square error is generally used to measure the gap between the predicted value and the true value. Its calculation formula is shown in Equation (3).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3}$$

In Equation (3), $\hat{y}_i$ is the predicted value of the model for y_i. n is the number of samples. When optimizing the model performance, the LF needs to be minimized. The basic idea of minimizing the LF is to use gradient descent to gradually adjust the parameters and reduce the LF to find the optimal solution. The update rule of gradient descent is shown in Equation (4).

$$\begin{cases} w = w - \alpha\dfrac{\partial L}{\partial l} \\ e = e - \alpha\dfrac{\partial L}{\partial e} \end{cases} \tag{4}$$

In Equation (4), α is the learning rate, i.e., the step size of each update. $\frac{\partial L}{\partial w}$ denotes the derivative of the LF with respect to w. $\frac{\partial L}{\partial w}$ denotes the derivative of the LF with respect to b. The above calculation can optimize the LR model to make the model performance optimal. However, in practical applications, due to the high dimensionality of the collected data, more data will lead to the problem of inaccurate prediction results of the LR model, which still needs to be optimized [16]. Whereas, FA modeling is a statistical method that can identify common factors among a group of variables. This method unites the variables that share a common essence into a single factor and uncovers the hidden representative factors among several variables. This can lower the complexity of the model, the number of variables, and the dimensionality of the data [17]. The basic steps of the model are shown in **Figure 2**.

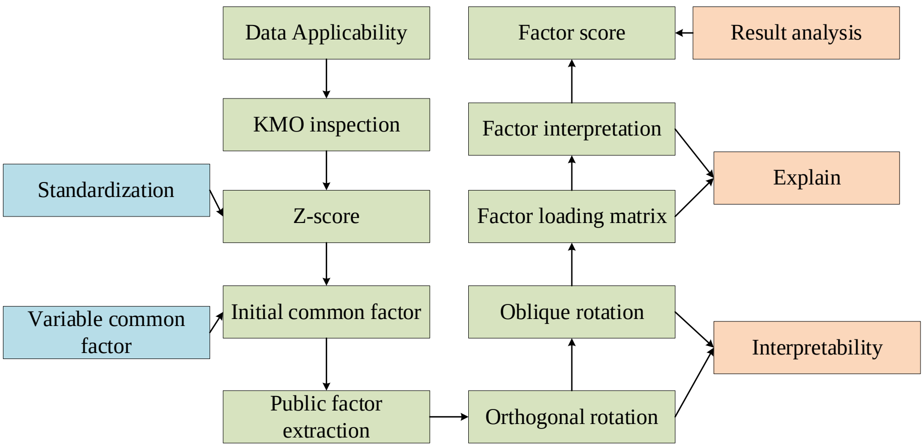


Figure 2. FA model flow chart.

In **Figure 2**, the FA model first needs to determine the applicability of FA by determining whether the original variables to be analyzed are suitable for FA, which is generally done using the Kaiser-Meyer-Olkin (KMO) test. After determining this, the different orders of magnitude are standardized using the *z*-score method to avoid errors. Then the common factors of the variables are extracted by solving the initial common factors, i.e., the factor loading matrix. Moreover, the factors need to be rotated by orthogonal or oblique rotation in order to make the variable factors interpretable. After the rotation, the factor loading matrix is interpreted to understand the relationship between each factor and the variable. Finally, the calculation of factor scores is carried out, and the results are used for further analysis. The general model of FA is shown in Equation (5).

$$F(X) = \mu + LF + e_a \tag{5}$$

In Equation (5), $F(X)$ is the opposite vector of measurements. μ denotes the opposite vector of means. L denotes the numerical product vector of the common factor. F denotes the matrix vector of the loadings. e_a is the vector of residuals. In performing the factor rotation, the oblique rotation is shown in Equation (6).

$$Cov = LL^{'} + \psi \tag{6}$$

In Equation (6), ψ is the diagonal matrix and $L^{'}$ is the opposite matrix of L. After that the loading matrix of the factor needs to be calculated to come, which is shown in Equation (7).

$$L = [\sqrt{\hat{\lambda}_1}\hat{e}_1\sqrt{\hat{\lambda}_2}\hat{e}_2\ldots\sqrt{\hat{\lambda}_m}\hat{e}_m] \tag{7}$$

In Equation (7), $\sqrt{\hat{\lambda}_m}\hat{e}_m$ denotes the eigenvalue eigenvector pair of the mAth data. The factor scores are calculated as shown in Equation (8).

$$F = ZC \tag{8}$$

In Equation (8), F denotes the factor score matrix. Z denotes normalized data. C is the factor score coefficient matrix. The score of each factor of the variable factor is obtained by the above calculation. This study combines the FA model with the LR model. The FA model is first utilized to FA the data to refine multiple phase variables into fewer factors and reduce the dimensionality of the original data. As a result, the LR model becomes less complex and has higher prediction accuracy. The basic flow of the optimized FA-LR model is shown in **Figure 3**.

In **Figure 3**, the FA-LR model first inputs the collected data into the FA module first, and applies the FA method to extract the key factors affecting the DV in the data. This eliminates irrelevant data, realizes data dimensionality reduction, and simplifies the data structure. Then, the extracted key factors are used as IDVs in the LR model. It is then used to build the DV according to the actual situation, and the LR model is constructed using the two variables.

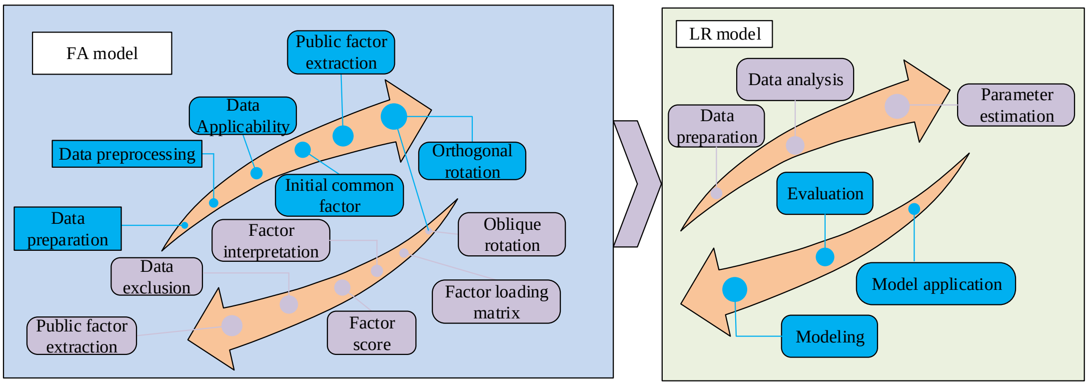


Figure 3. FA-LR model flowchart.

2.2. Biomechanical analysis based on FA-LR modeling

To enhance the accuracy of biomechanical analysis of run-up and take-off for track and field athletes, and thus to improve the athletes' performance, this study utilizes the FA-LR model to analyze the biomechanical changes in run-up and take-off of track and field athletes. The study first collects the main biomechanical indicators of pole vault run-up and take-off. Furthermore, a data analysis system is established through the collected indexes, and the FA-LR model is utilized to clarify the influence of each factor in biomechanics on the athletes' high jump performance, so as to improve the athletes' sports performance. **Figure 4** depicts the flow of the FA-LR model-based biomechanical analysis approach.

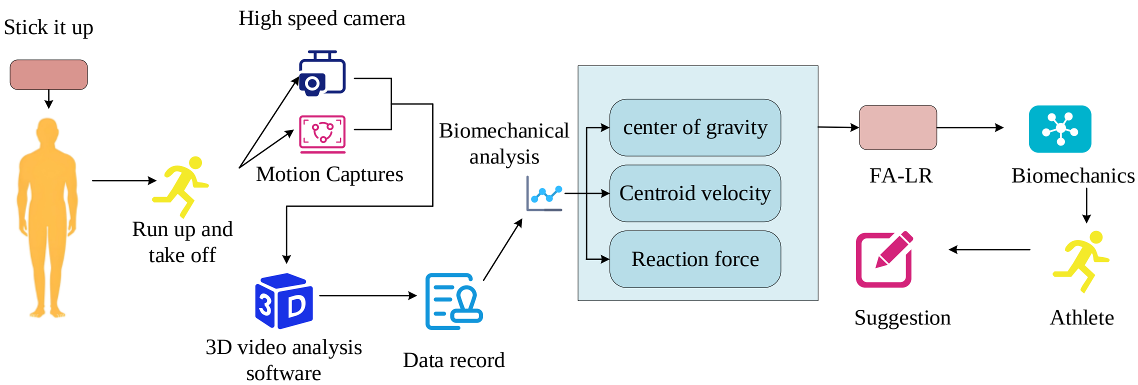


Figure 4. The biomechanical analysis process based on the FA-LR model.

In **Figure 4**, the FA-LR model for biomechanical analysis of the athlete run-up and take-off requires the use of a high-speed camera or motion capture system to record the athlete's run-up and take-off. To ensure the complete capture of the athlete's run-up and take-off, two high-speed cameras with a sampling frequency of 200Hz will be used, which are placed on the right back side and right front side of the pedals respectively. Moreover, before the start of the experiment, the athlete's body needs to be labeled with points in order to better record the data of the athlete's key points. After that, the athlete completes the run-up and take-off movements, and the video data captured are analyzed by the 3D video analysis software, which mainly analyzes the biomechanical indexes such as the athlete's body center of gravity, center of mass (CM) velocity, CM height and ground reaction force. The velocity and acceleration of the point of mass are calculated through the dynamic Equation, and the mechanical changes during the jump are analyzed. Then the obtained data are input into the FA-LR model to analyze the influence of various biomechanical indexes on the athletes. Finally, according to the analysis results, the influence of the CM velocity and jump angle on the results during the assisted running and jumping process is analyzed. This can provide reasonable guidance and suggestions to the athletes to help them improve their sports performance. The formula for calculating the CM velocity of the athlete is shown in Equation (9).

$$v = \frac{\sum_a m_a v_a}{\sum_a m_a} \tag{9}$$

In Equation (9), m_a is the mass of the ath mass point. $\sum_a m_a$ denotes the total mass of the athlete's number of mass points. v_a is the velocity of the ath mass point. The CM acceleration is calculated as shown in Equation (10).

$$a = \frac{\sum_a m_a a_a}{\sum_a m_a} \tag{10}$$

In Equation (10), a_a is the acceleration of the ath mass. Moreover, the specific application principle of FA-RL module in biomechanical analysis model is shown in **Figure 5**.

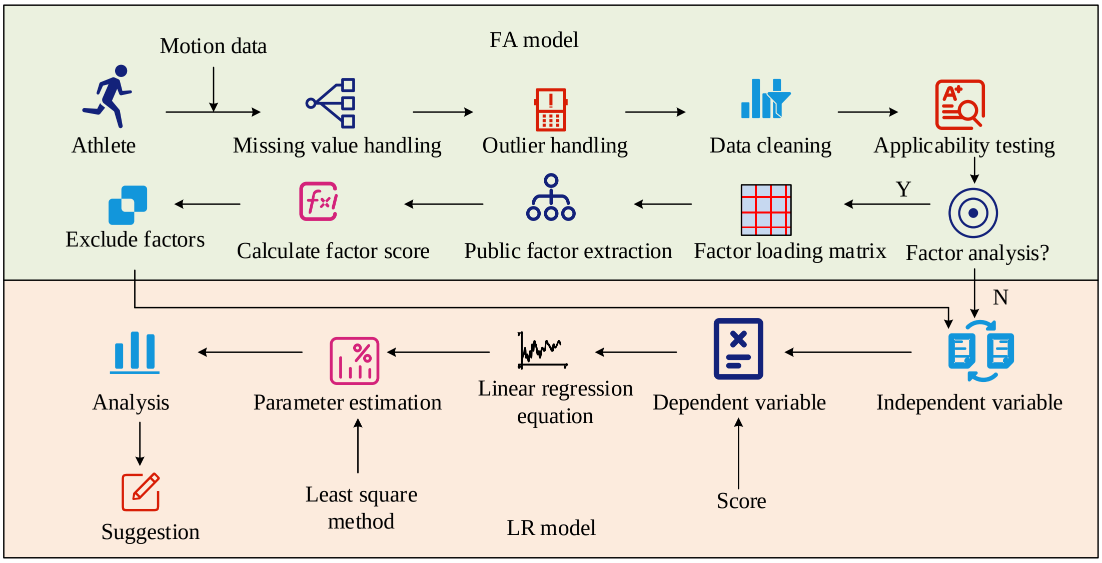


Figure 5. Application principles of the FA-LR module.

In **Figure 5**, the FA-LR model needs to first collect all the motion data when the athlete performs the assisted high jump in the actual biomechanical analysis. The collected data are pre-processed with missing data values, outliers and data cleaning. Secondly, using the applicability test, the collected data are tested to see if they can be analyzed using FA. If the test results satisfy the conditions, the data will be subjected to FA. if not, the unsatisfied data will be directly subjected to LR modeling. In FA, each data collected from the athletes are used as different factors, and the loading matrix of each factor is calculated to extract the male factors. Moreover, the factor scores of each sample are calculated, and those with scores less than the minimum requirement are excluded to reduce the subsequent calculations. The factor score is represented by the cumulative variance contribution rate of the factors, and its calculation formula is shown in Equation (11).

$$\rho = \sum_{i=1}^{n} \left(\frac{T}{\sum_{i=1}^{n} T} \times 100\%\right) \tag{11}$$

In Equation (11), n represents the total number of factors, T represents the eigenvalues of the factors, and ρ is the cumulative variance contribution rate. If $\rho > 80\%$, the factor can be extracted and used as an analytical factor in biomechanics. Then the obtained factor scores are used as the IDVs in the LR model, and the results of athletes' run-up and take-off are used as the DVs, so as to construct the LR equation. It then utilizes the least squares method to estimate the parameters of the regression equation. Finally, the regression equation is used to evaluate the degree of influence of each factor on the DV and to predict the sports results, and practical suggestions are made based on the prediction results. Among them, when performing outlier processing, Gaussian mixture model (GMM), which is able to deal with high-dimensional data and complex data structure, is chosen to process the data with outliers due to the high dimensionality and complex data structure of the collected sports data. The basic idea of this method is to determine whether a sample belongs to an outlier class by setting up a threshold and a posteriori probability, and after determining the outliers, the outliers are removed. The a posteriori probability is calculated as shown in Equation (12).

$$v_a = j \middle| x_a, \theta_j \tag{12}$$

In Equation (12), v_a denotes the posterior probability. j denotes the data category. x_a denotes the sample. θ denotes the parameter set of the mixture components. In this process, the total body energy of the athlete is calculated as shown in Equation (13).

$$E_T = E_1 + E_2 + E_3 + E_4 \tag{13}$$

In Equation (13), E_T denotes the total energy of the body. E_1 is the neutral potential energy (PE) of the body. E_2 denotes the kinetic energy (KE) of the human body. E_3 is the sagittal plane angular KE of the body. E_4 denotes the angular KE of the torso around the longitudinal axis.

3. Results

3.1. Performance analysis of the FA-LR model

To analyze the superiority of the forecasting performance of the FA-LR model, the study conducts comparative experiments between the FA-LR model and the LR model before optimization, grey forecast model (GM), and autoregressive integrated moving average model (ARIMA). During the experiment, analyze the environmental configuration first, the experiments are conducted using the Iris dataset, which contains 150 data samples divided into 3 classes, 50 data in each class, and each data contains 4 attributes. Conduct experiments in different experimental environment configurations to analyze the performance of the FA-LR model. The results are shown in **Table 1**.

Table 1. Performance comparison of FA-LR models configured in different environments.

Environment	Intel Core i5 8GB	Intel Core i5 4GB	Intel Core i3 4GB	Intel Core i3 8GB
Time	1.2 s	2.7 s	3.8 s	3.2 s
Space occupancy rate	57.6%	65.4%	69.8%	59.8%
Resource utilization rate	87.6%	79.3%	65.5%	76.4%
Stability	83.5%	78.9%	65.1%	69.7%

According to **Table 1**, using an Intel Core i5 8GB computer configuration during the experiment can optimize the performance of the FA-LR model. According to **Table 1**, using an Intel Core i5 8GB computer configuration during the experiment can optimize the performance of the FA-LR model. So, the environmental configuration during the experiment is shown in **Table 2**.

Table 2. Experimental environment configuration.

Environment	Index	Model number
Hardware environment	OS	Windows10
	Processing element	Intel Core i5
	EMS memory	8GB
Software environment	Matlab Version	Matlan R2023
	Python Version	Python4.0
	PyTorch Version	PyTorch2.0
	SPSSAU	SPSSAU23.0

The performance of the four models is analyzed. **Figure 6** displays the four models' forecast outcomes.

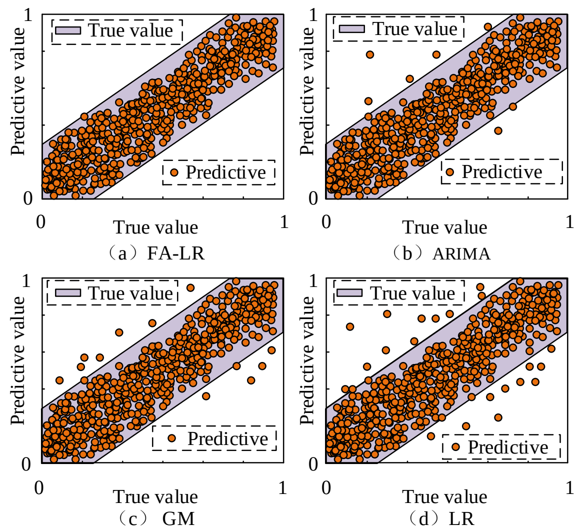
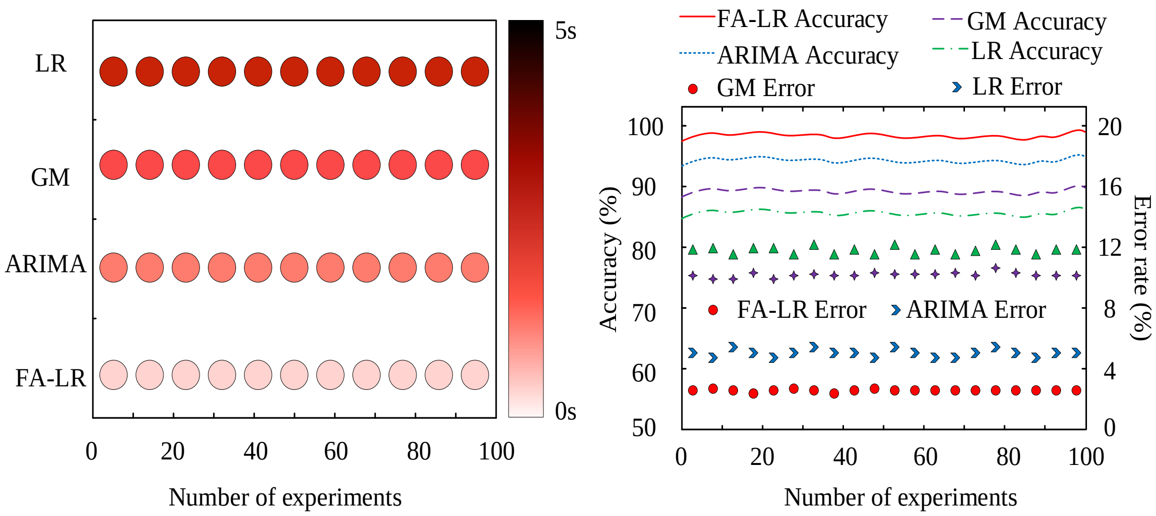


Figure 6. Comparison of model prediction performance.

In **Figure 6**, among the four models, the FA-LR model has the best prediction effect, and the values predicted by this model are within the range of true values. However, the prediction effect of ARIMA on the data is lower than the FA-LR model, and some of the values predicted by ARIMA and GM are not within the range of the true values, i.e., there are still some errors in the prediction of ARIMA. The LR model, on the other hand, has the largest gap between the predicted values and the true values, with more predicted values that are not within the range of the true values. From this result, it can be concluded that the prediction of the FA-LR model proposed in the study is optimal. The prediction time consuming and prediction accuracy of the four models are shown in **Figure 7**.



(a) Predicting time consumption

(b) Prediction accuracy and error rate

Figure 7. Comparison of model prediction performance.

In **Figure 7a**, among the four models, the FA-LR model takes the shortest time to make a prediction, which is only 1.2 s. The prediction time taken by the ARIMA, GM, and LR models are 2.1 s, 3.2 s, and 4.3 s, respectively, which are higher than that of the FA-LR model. In **Figure 7b**, the prediction accuracy of FA-LR model reaches 97.6%, and the error rate of this model is only 3.4%. The prediction accuracy of ARIMA is only 93.6%, and the prediction accuracy is slightly lower than that of ARIMA. Whereas, the prediction accuracies of GM and LR models are 88.5% and 86.7%, respectively. The prediction accuracies are all lower than 90% and the error rates are all higher than 10%. From this result, it can be concluded that the proposed FA-LR model has the shortest prediction time and the highest prediction accuracy. Then the four models are compared for image data detection integrity. The results are shown in **Figure 8**.

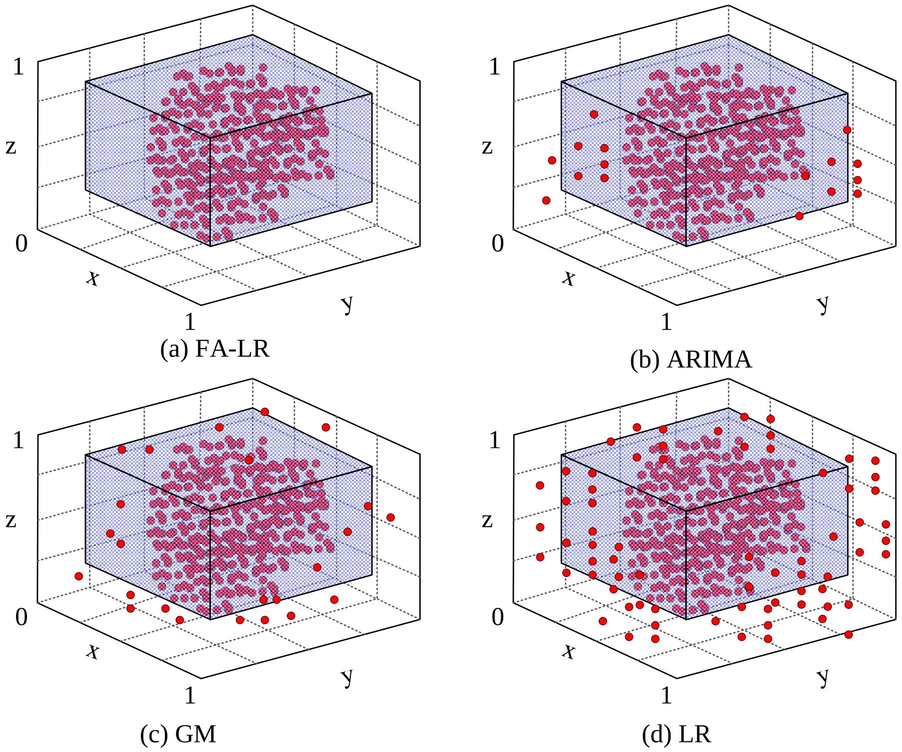


Figure 8. Model data detection integrity.

In **Figure 8**, among the four models, the FA-LR model has the highest data detection integrity. All the data can be detected and the detection integrity rate reaches 100%. While ARIMA, GM and LR models also have data omission when detecting the experimental data, and the detection integrity rate is lower than FA-LR model. From the above experiments, it can be concluded that all the performances of the FA-LR model proposed in the study are better than other current data prediction models. Accordingly, this study employs the FA-LR model to examine the biomechanics of track and field athletes during the run-up and take-off phases. The objective is to enhance the athletes' comprehension of their own biomechanical alterations through the analysis of the model, thereby facilitating more optimal execution of the run-up and take-off maneuvers and ultimately leading to enhanced athletic performance.

3.2. Biomechanical analysis of run-up and take-off in track and field athletes

After the performance of the model is examined, the model is used to analyze the biomechanics of track and field athletes during run-up and take-off maneuvers. A sample of 300 athletes is selected for the experiment. Among them, 100 are national level athletes, 100 are intermediate level track and field athletes and 100 are junior level athletes. The biomechanics of the three levels of athletes are analyzed by FA-LR model. Firstly, the correlation between different biomechanical variables during the run-up and take off process was analyzed, and the results are shown in **Figure 9**.

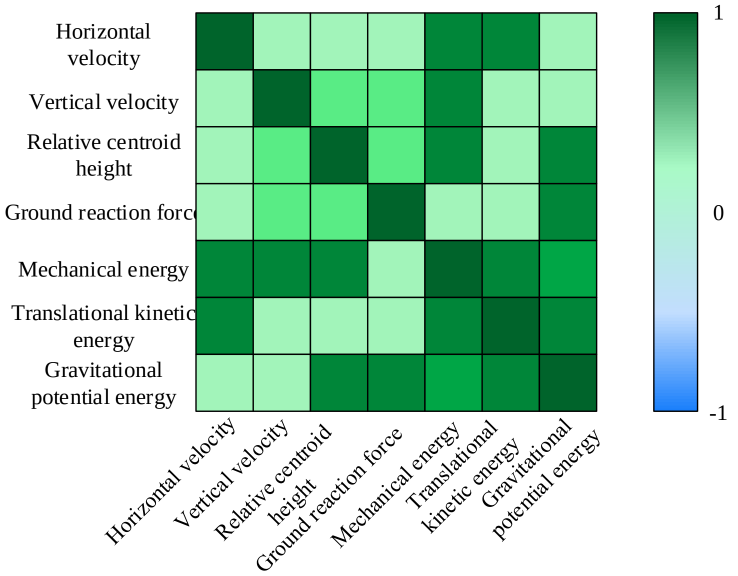


Figure 9. Correlation analysis between biomechanical variables.

As shown in **Figure 9**, during the run-up and takeoff process, the correlation between the horizontal velocity of the athlete's center of mass and the vertical velocity of the center of mass, the relative height of the center of mass, the ground reaction force, and the gravitational potential energy is low, while the correlation between the athlete's gravitational potential energy, translational kinetic energy, and mechanical energy is high. And there is a high correlation between the mechanical energy of athletes and the horizontal velocity, vertical velocity, and relative height of the center of mass. Then, the CM horizontal and vertical velocities of the athletes during the whole process of run-up and take-off are compared. The results are shown in **Figure 10**.

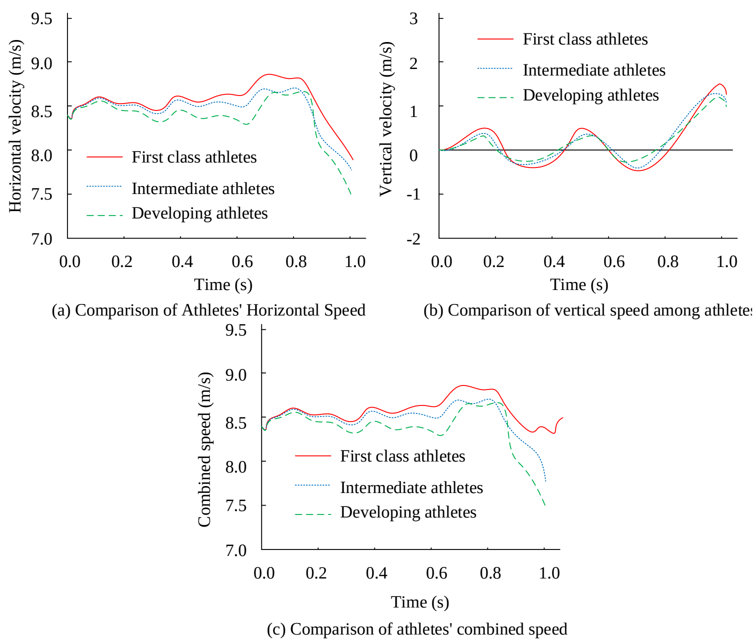


Figure 10. Speed changes during athlete's run-up and take-off process.

In **Figure 10a**, the horizontal velocity of the CM of track and field athletes during run-up and take-off shows a small decreasing trend in the early stage, increasing in the middle stage, and decreasing in the late stage. Moreover, the horizontal velocity of CM of national level athletes is greater than that of intermediate level athletes and junior level athletes. In **Figure 10b**, the vertical velocity of the CM of track and field athletes shows insignificant changes in the early stage with low fluctuation. However, in the late stage, the vertical velocity of the CM of the athletes increases. Furthermore, the final velocity of CM vertical velocity of national level athletes is higher than that of other athletes. In **Figure 10c**, the change of CM combined velocity during athlete's run-up and take-off is the same as the change of CM horizontal velocity. Then the relative CM height and ground reaction force during the athlete's run-up and take-off are analyzed. The results are shown in **Figure 11**.

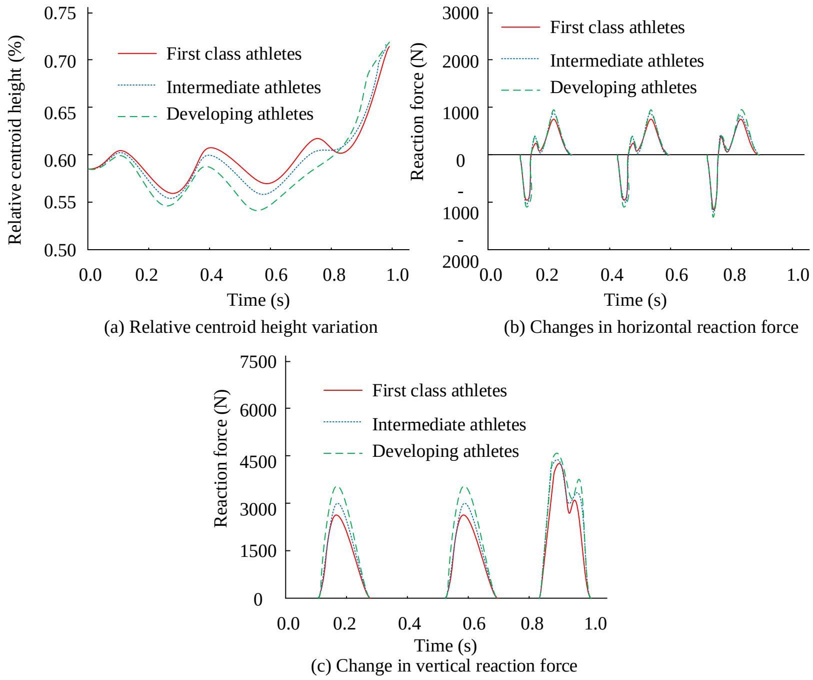


Figure 11. Comparison of relative CM height and ground reaction force of athletes.

In **Figure 11a**, during run-up and take-off, the relative CM height of the athletes has been fluctuating up and down in the early stage, and then the relative CM height gradually increased in the late stage. Furthermore, the relative CM height of national level athletes in the early stage is higher than that of other athletes. However, the relative CM height of national level athletes in the late stage is lower than that of other athletes. In **Figure 11b**,**c**, the athletes' reaction forces in both the horizontal and vertical directions show periodic changes. In the early and middle periods, the changes in the athletes' reaction forces are approximately the same. In the late stage, the athletes' reaction forces are higher than those in the early and middle stages. Moreover, the horizontal and vertical reaction forces of the national level athletes are slightly lower than those of the other athletes. Finally, the changes of mechanical energy, translational KE and gravitational Potential energy (PE) of the athletes are analyzed. The results are shown in **Table 3**.

Table 3. Energy changes during athletes' run-up and take-off process.

Time	Energy (J)	0.2 s	0.4 s	0.6 s	0.8 s	1.0 s
First class athletes	Mechanical energy	3575	3570	3640	3574	3000
	Translational kinetic energy	2950	2900	3078	2974	2498
	Potential energy	512	532	539	553	570
Intermediate athletes	Mechanical energy	3500	3498	3570	3510	2965
	Translational kinetic energy	2790	2720	2910	2780	2389
	Potential energy	489	500	510	523	534
Developing athletes	Mechanical energy	3321	3200	3400	3149	2890
	Translational kinetic energy	2680	2600	2790	2598	2200
	Potential Energy	469	498	500	509	527

In **Table 3**, during run-up and take-off, the athlete's mechanical and hydrodynamic energies first decrease and then increase, and then decrease again after reaching the maximum value. However, the gravitational PE of the athletes in the run-up and take-off process has been increasing. Moreover, the mechanical energy, translational KE and gravitational PE of the national level athletes are higher than those of the intermediate level athletes and junior level athletes. From this result, it can be concluded that athletes should improve their performance by increasing their mechanical energy, translational KE and gravitational PE. In general, to achieve enhanced performance, athletes should augment their CM horizontal velocity, vertical velocity, and combined velocity during the run-up and take-off phases, while concurrently reducing their relative CM height and horizontal and vertical reaction forces.

4. Discussion and conclusion

To accurately analyze the current biomechanics of track and field athletes during run-up and take-off, the FA model was combined with the LR model, and a FA-LR model was designed in this study. The FA-LR model was employed to examine the biomechanics of track and field athletes during the run-up and take-off phases. The objective was to utilize the findings of this analysis to enhance training methodologies for athletes and to elevate their athletic performance. The study first analyzed the superiority of the proposed FA-LR model and compared the FA-LR model with the ARIMA, GM and LR models in a comparative experiment. The outcomes indicated that the prediction accuracy of the FA-LR model, ARIMA, GM, and LR model were 97.6%, 93.6%, 88.5%, and 86.7%, respectively. Moreover, the prediction of this FA-LR model took only 1.2 s, which was much lower than the 2.1 s of ARIMA, 3.2 s of GM, and 4.3 s of LR model. All the performances of the FA-LR model were better than the comparison models. So using this model can analyze the biomechanical changes of track and field athletes in a timely manner, provide real-time feedback during the training process, and help athletes provide better training measures and improve competition results. The above results were similar to those of D'Urso et al. This may be due to the fact that the FA-LR model could perform a complete detection of the data to be detected by the FA method and extract the common factors in the data.

As a result, the model's prediction accuracy may increase and its complexity may decrease [18].

After testing the performance of the FA-LR model, the biomechanics of the athletes during run-up and take-off were analyzed using the model. The results revealed that the horizontal velocity of the CM and the sum velocity of the CM of the athletes were similar during run-up and take-off, both of which decreased first, then increased, and finally decreased. The horizontal velocity of the CM and the sum velocity of the CM of the national level athletes were slightly larger than those of the second level athletes and the junior level athletes. Vertical CM velocity of the athletes fluctuated low in the early stage, but increased sharply in the late stage. Furthermore, the CM vertical velocities of the national level athletes were eventually higher than those of the other athletes. This result was similar to that of Zou et al. [19]. This result indicated that the athletes should increase their speed in all directions of their CM when performing run-up and take-off. Then the athletes' relative CM height and ground reaction force were compared. The results indicated that the relative CM height of the national level athletes was consistently higher than that of the other athletes, but their horizontal reaction force as well as their vertical reaction force were lower than that of the other athletes. This result was similar to that of Roupa's team [20]. The reason for this result may be that first level athletes have a relatively coordinated stride frequency and step length during the run-up and takeoff process, with an average increase in stride frequency and step length. The center of mass can achieve a large horizontal velocity, vertical velocity, and composite velocity. First level athletes can also control their running speed, body center of gravity, and core strength to prevent excessive reaction force from affecting jumping distance and height. It can be concluded that athletes should increase their relative CM height and decrease their horizontal and vertical reaction forces during run-up and take-off in order to improve their athletic performance. In addition, this study also found that athletes' mechanical energy and translational kinetic energy first decrease and then increase during the run-up and takeoff process, which is similar to the research results of Hu et al. on volleyball athletes' run-up and takeoff [21]. And during this process, the athlete's gravitational potential energy continued to increase, which coincides with the results of the Van Oeveren team [22]. The fundamental reason for this result is that during the run-up, the athlete's takeoff speed is increased, thereby increasing the translational kinetic energy. When the athlete reaches the highest point, the speed begins to decrease, and the kinetic energy begins to decrease; As the height increases, kinetic energy is continuously converted into gravitational potential energy. However, when the FA-LR model was employed for analysis in this study, it was only able to accurately assess the linear relationship between the biomechanical variables. The model was not yet capable of accurately analyzing some nonlinear relationships. In the future, the model should be optimized using other intelligent algorithms or artificial intelligence so that it can accurately analyze data with nonlinear relationships.

The results demonstrate that the FA-LR model, as proposed in the study, is an effective tool for analyzing the biomechanics of athletes and for suggesting enhanced training methods based on the analysis results. Track and field athletes should maintain a stable body posture during the run-up and takeoff process, pay attention to their balance and coordination, and increase their center of mass horizontal velocity, vertical velocity, and composite velocity to ensure maximum strength during takeoff. And grasp the body posture during the airborne and landing phases, reduce the horizontal and vertical reaction forces, and improve athletic performance. In addition, the FA-LR model proposed in the study cannot accurately analyze some nonlinear relationships. The FA-LR model relies on specific data distributions, namely the relationship between independent and dependent variables, to establish the model, which may have limitations in some biomechanical analyses. In the future, data matching can be used to reduce the model's dependence on data format.

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