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Article

Intelligent Assessment of Athletes' Physical Fitness Data and Optimization of Physical Education Teaching and Training Strategies in the Framework of Multivariate Statistical Analysis

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Abstract: Athletes' physical fitness evaluation is not only an important part of sports work, but also an important part of school education evaluation system. This study carries out a multivariate statistical analysis between the various scores of athletes' sports test and the total score, establishes the regression equation between the total score and the physical form and function, and carries out an intelligent evaluation of athletes' physical quality through the regression model. At the same time, the factors affecting athletes' physical quality were explored based on the regression equation. After analyzing, athletes' physical quality can be assessed based on $\text{Athlete's physical quality}=67.632+0.163\times T1-0.263\times T2+0.063\times T3$. Athletes' physical quality is mainly affected by individual factors and school factors. In this regard, this paper puts forward the optimization strategy of sports teaching and training from three aspects: cultivation mode, teaching method and evaluation mechanism. This is of great practical significance to improve athletes' health and physical quality.

Keywords: correlation analysis; regression model; physical education training; athletes

1. Introduction

With the rapid development of competitive sports and the continuous improvement of the scientific level of sports training, the competition is more and more demanding on the level of athletes' special physical fitness, skills and tactics [1]. However, at present, the training load of athletes lack of scientific intelligent assessment, and the problem of affecting the existing technical and tactical level of athletes to play during the game, through scientific tools and technical means of objective and specific assessment of athletes, effective monitoring of the training process is very necessary [2-4]. Among them, athlete physical fitness data is the focus of monitoring. Athletes' physical fitness data include cardiac function data, central regulation function data and energy metabolism data, in which cardiac function data reflect the ability of athletes to withstand training loads [5]; central regulation data reflect the degree of athletes experiencing exercise fatigue caused by central mechanisms [6]; energy metabolism data reflect the extent to which athletes experience exercise fatigue caused by peripheral mechanisms [7]. Therefore, the monitoring and evaluation of athletes' physical quality data is conducive to coaches' dynamic mastery of athletes' real-time physical function status, which provides data support and theoretical basis for the scientific formulation and timely adjustment of training load programs.

Academics define physical quality as an ability of human activity, which refers to the human body in sports, labor and life, such as strength, speed, endurance, sensitivity and flexibility and other human functional ability [8]. With the deepening of the understanding of the concept of physical fitness, physical fitness is gradually divided into general physical fitness and specialized physical fitness [9]. Most of the existing data assessment of athletes' physical fitness relies on manual experience and a simple statistical analysis framework. For example, Malikov, N et al. noted that the current tests for assessing physical fitness of specialized athletes for different sports are based on the use of only a limited number of traditional parameters, which significantly reduces the efficiency of the biomedical monitoring system and the scientific training process [10]. In their study, Henriques-Neto, D et al. found that the 20m speed test and the standing long jump test, are the best indicators for the effective identification of athletes with athletic potential, however, these tests remain highly subjective [11]. The above methods, although effective in measuring and evaluating athletes' physical fitness data in a small range, are difficult to adapt to oriented large-scale assessment, and there are problems such as lag in the statistical analysis of the assessment results.

With the development of science and technology, on the one hand, the application of the Internet of Things (IoT) technology, wearable monitoring and collection devices have already subverted the traditional data collection methods in athlete training, through such as pressure sensors, accelerometers, gyroscopes, wireless transmission and other types of auxiliary training devices and monitoring systems, artificial intelligence technology has been able to the initial digitization of the assessment of the athlete's physical fitness [12-13]. On the other hand, monitoring systems such as Omega Wave Athletic State Comprehensive Evaluation System, Elite Form Explosive Strength Monitoring System, Gymaware Explosive Strength Testing and Monitoring System, Firstbeat Heart Rate Monitoring System, and so on, have brought about a positive and important impact on high-level athletes in terms of improving the training efficiency, enhancing the training effect, and improving the personalized training program [14-16]. For example, Parrado, E et al. used the Omega Wave Sport system for detecting heart rate variability index data and found that the system was able to collect data without any interference, making heart rate variability analysis easier than [17]. Oleksy, Ł et al. applied the GymAware Linear Sensor to four loads for Land Push Throw (LPT) testing and found that the internal and re-test reliabilities of the tool were very high (ICc=0.97-0.99) and that the device may have important practical applications for strength and conditioning training [18]. However, these tools have a wide range of test indicators with unknown specificity, which do not provide a clear correspondence between athletes' physical fitness and their functional status, and the assessment results are still highly influenced by the personal experience of coaches and administrators.

The rapid development of technologies such as big data, artificial intelligence and intelligent acquisition provides technical support for analyzing athletes' physical fitness data using deep learning [19]. Li, Y and Li, X input the physical fitness data into a deep learning model for analysis in order to target personalized intelligent training programs, and established a rule-based reasoning mechanism for physical test data collection, physical fitness assessment, and information management to improve physical fitness [20]. Gao, D and Shen, J fused deep learning algorithms and big data techniques to develop a multimodal data fusion framework that integrates multimodal data, including physical fitness data, sleep quality mental health status and basic physiological parameters, to provide a comprehensive, accurate and intelligent assessment of comprehensive physical fitness [21]. Galán-Mercant, A et al. proposed two different deep learning architectures (Convolutional Self-Encoder and Convolutional Neural Networks) to extract acceleration data features, and according to the results of the study the two proposed methods were able to assess the physical fitness and functional health of individuals with a very high level of accuracy [22]. Omarov, B et al. explored the process of development, testing and application of deep learning models for monitoring the physical fitness of individuals with the help of convolutional neural networks (CNN) to track, analyze and assessing the physical fitness ability of individuals for the physical exercises they perform, and demonstrated through empirical evidence that the deep learning system outperforms traditional methods in terms of accuracy, speed and monitoring efficiency, and bridges the gap to more personalized and effective physical education and training programs [23]. Liang, H et al. addressed the limitations of traditional physical fitness assessment methods and proposed to utilize deep learning to comprehensively assess individuals' physical activities, cognitive tasks, emotional responses, and social interactions through a multi-attribute user assessment model, which has the characteristics of automation, objectivity, and scalability, thus improving the level and efficiency of physical fitness assessment [24].

The study was based on multivariate statistical analysis for intelligent assessment of athletes' physical quality and optimization of physical education and training strategies based on the factors affecting athletes' physical quality. The growth and development indexes of 500 athletes were measured by height, weight, lung capacity, standing long jump, 50m run, seated forward bending, pull-ups (boys)/sit-ups (girls), and endurance running. The regression equation between physical fitness and body form function was constructed. The factors affecting athletes' physical quality were studied through regression analysis. Finally, the optimization strategy of sports teaching and training is proposed according to the analysis results.

2. Research Objects and Methods

2.1. Subjects of study

The study used stratified randomized cluster sampling method with age as the sampling unit. Those who had diseases of heart, liver, spleen, kidneys and other major organs, those who were physically crippled or deformed, those who were acutely ill or who had suffered from acute illnesses such as high fever, diarrhea and other acute illnesses within 1 month that had not yet recovered their physical strength, and female students who were in the period of menstruation were excluded. Athletes aged 23-28 years old were selected as study subjects, totaling 500, including 320 boys and 180 girls.

2.2. Data acquisition

Growth and development indicators such as height (T1), weight (T2), lung capacity (T3), standing long jump (T4), 50m run (T5), seated forward bending (T6), pull-ups (boys)/sit-ups (girls) (T7), and endurance running (1000m run for boys/800m run for girls) (T8) were measured in the athletes. Nutritional status classification in this study was calculated based on the height and weight of the athletes in the physical measurement data, and the body mass index (BMI) = weight (kg)/height^2 (m^2). The total score of the physical test was equal to the sum of the individual scores according to the weights, and the weights of the physical test indexes were as follows: BMI accounted for 15%, lung capacity accounted for 15%, 50m run accounted for 20%, seated body flexion accounted for 10%, standing long jump accounted for 10%, pull-ups (male)/1min sit-ups (female) accounted for 10%, and 1000/800m run accounted for 20% [25]. The nationally standardized “Athletes' Physical Fitness and Health Research Athletes' Questionnaire” was used for the survey, which included basic information of the athletes, sleep time, nutritional status, physical activity-related behaviors, and attitudes toward physical activity.

2.3. Research methodology

In this paper, according to the “Physical Fitness Standard for Athletes (Trial Program)” and “Implementation Measures of <Physical Fitness Standard for Athletes (Trial Program)>” formulated by the Ministry of Education of the People's Republic of China and the General Administration of Sport of the People's Republic of China, the athletes were tested for their physical fitness and health status. The data obtained were analyzed and processed using multivariate statistical methods. The mathematical statistics tool used was SPSS.

2.4. Questionnaire design

The evaluation index system of physical fitness influencing factors of athletes designed in this paper is shown in Table 1. They are analyzed from three aspects: individual, school and social policy.

Table 1. Evaluation index system of athletes' physical quality influence factors

Primary indicator	Secondary indicator
Individual	Knowledge of physical quality (X1)
	Skills (X2)
	Habit (X3)
	self-control (X4)
	Exercise number (X5)
School	Development balance (X6)
	School rules (X7)
	Exercise level (X8)
	Site facilities (X9)
	Health knowledge course (X10)
Social policy	Government guidelines (X11)
	Supervises (X12)
	Measures (X13)

In order to design an evaluation index system of the factors affecting athletes' physical quality that can be put into practical use, this study adopts the expert ranking method for the calculation of index weights. A high degree of consistency in the views of experts is a prerequisite for the use of the expert ranking method, and it is also an important criterion for the evaluation index system of high reliability. In order to further calculate the weights of indicators, this study uses mathematical statistics method, internal consistency test by SPSS22.0, and the questionnaire survey method for the test of content validity. The Clonbach coefficients of the expert elicitation questionnaires for the athletes' physical literacy evaluation indicators were all above 0.7, which indicates that the internal consistency of the questionnaires in this study is good. Therefore, the physical literacy evaluation index system for upper elementary school students constructed in this study has good reliability and can meet the basic requirements of the study. According to the evaluation standard of I-CVI, when the number of evaluators is more than 5, the I-CVI should not be lower than 0.78. The I-CVI values of the indicators in this paper are all greater than 0.78, and the content validity is extremely high. It can be concluded that the physical literacy evaluation index system of athletes designed in this study has good content validity.

The assignment of questionnaire items adopts a combination of a two-level evaluation standard of "yes" or "No" and a five-level Likert evaluation standard of "very poor", "relatively poor", "average", "relatively good", and "very good". The five-level evaluation indicators range from "very poor" to "very good" and are assigned values of 1 to 5 respectively. Among the two-level evaluation indicators, "None" is assigned 1 and "has" is assigned 2.

The questionnaires were distributed to 500 athletes selected in the previous section, and 480 valid questionnaires were retrieved, with a valid questionnaire recovery rate of 96%.

In order to better understand the physical health status of the athletes, the data situation is now descriptive statistics. The statistical quantities of 8 observation indexes such as height, weight, lung capacity, standing long jump, 50m running of male and female athletes are shown in Table 2. The mean values of male and female body measurements were 76.32 and 77.64 respectively.Through the descriptive analysis of the mean trend of the statistics of the eight indicators, in which the standard error of the sample describes the degree of dispersion of the sample mean, and the smaller the degree of dispersion of the sample mean indicates that the sample represents the reliability of the whole, it can be seen that, in addition to the standard error of the indicator of lung capacity is greater than 0.3, the standard error of the other seven indicators is greater than zero less than 0.3, indicating that the sample of this study is homogeneous, scientific and representative, indicating that the sample is approximately normally distributed. To sum up, the eight observation indexes of height, weight, lung capacity and standing long jump are all representative and can fully satisfy the inferential analysis of athletes' physical quality.

Table 2. Descriptive statistics of physical quality of athletes

Gender		T1/cm	T2/kg	T3/ml	T4/m	T5/s	T6/cm	T7	T8/min	Test score
Male	M	178.6	74.1	4563.6	1.9	8.3	69	25	2.6	76.32
	SD	5.6	8.4	563.41	0.63	1.63	11	6	0.3	7.63
	SE	0.06	0.3	6.34	0.01	0.13	0.06	0.1	0.01	0.06
	Bias	-0.11	0.53	0.11	1.06	0.86	0.06	0.01	0.14	-0.36
	Peak	1.06	1.33	1.05	0.63	0.23	0.41	0.01	1.63	1.52
Female	M	168.5	58.6	3963.4	1.8	9.3	76	45	3.2	77.64
	SD	4.9	8.1	553.1	0.59	1.59	10	5	0.2	7.42
	SE	0.05	0.21	6.25	0.04	0.05	0.27	0.03	0.05	0.03
	Bias	0.31	0.42	0.15	1.04	0.77	0.04	0.06	0.21	-0.36
	Peak	1.03	1.34	1.23	0.53	0.26	0.42	0.06	1.74	0.05

3. Results and analysis

3.1. Assessment of athletes' physical fitness

3.1.1. Independent samples t-test

(1) Independent sample t-test for each indicator of male athletes

The independent sample test for each index of male athletes is shown in Table 3. The T-values of the eight observed indicators such as height, weight, lung capacity, standing long jump and 50m run were -8.44, -23.01, -53.84, 18.53, -50.84, -26.92, 22.53, 18.53, and the significance was less than 0.05, that is, the male athletes had highly significant differences in each indicator.

Table 3. Male athletes are tested independently of each index

	F	Sig.	T	DF	Sig(2-side)	MD	SD	95% confidence interval	
								Lower limit	**Upper limit**
T1	22.19	0	-8.44	10835	0	-1.02	0.12	-1.25	-0.79
T2	50.23	0.001	-23.01	10836	0	-3.96	0.16	-4.31	-3.63
T3	6.84	0	-53.84	10836	0	-592.94	10.99	-613.86	-570.73
T4	1.911	0.006	18.53	10835	0	6.74	0.36	6.04	7.44
T5	11.84	0	-50.84	10841	0	-590.34	15.99	-609.16	-565.73
T6	198.78	0	-26.92	10838	0	-3.25	0.11	-3.43	-2.97
T7	5.91	0.005	22.53	18410	0	10.74	6.32	11.06	13.42
T8	2.911	0	18.53	10381	0	7.74	3.32	7.04	10.44

(2) Independent sample t-test for each indicator of female athletes

The independent sample test for each index of female athletes is shown in Table 4. The T-values of eight observed indicators such as height, weight, lung capacity, standing long jump and 50m run of the athletes were 9.63, -16.45, -16.42, -13.42, -52.34, -53.61, 22.24 and 17.63, and the significance of all of them was 0.000 less than 0.05, that is, the indicators of female athletes had highly significant differences.

Table 4. Female athletes are tested independently of each index

	F	Sig.	T	DF	Sig(2-side)	MD	SD	95% confidence interval	
								Lower limit	**Upper limit**
T1	79.63	0	9.63	18643	0	0.86	0.09	0.63	0.93
T2	8.12	0.001	-16.45	18964	0	-1.63	0.14	-1.94	-1.53
T3	153.42	0	-16.42	18642	0	-106.42	6.43	-116.42	-92.64
T4	26.42	0	-13.42	18643	0	-2.63	0.26	-2.96	-1.96
T5	16.52	0.003	-52.34	10243	0	-563.51	15.08	-52.18	-56.79
T6	106.41	0	-53.61	18641	0	-4.53	0.18	-4.63	-3.65
T7	63.54	0	22.24	14130	0	15.54	6.88	11.63	12.64
T8	2.63	0.002	17.63	14083	0	6.54	3.85	7.09	16.34

3.1.2. Correlation analysis

Based on the data, the degree of correlation between the total score and weight, lung capacity and height, as well as between the total score and the scores of each subtest was analyzed using correlation analysis.

(1) Results of correlation analysis

The proximity matrix of total performance with height, weight and lung capacity is shown in Figure 1. It can be seen that $r_{\text{Total score}\cdot T3}=0.623$, $r_{\text{Total score}\cdot T1}=-0.362$, $r_{\text{Total score}\cdot T2}=0.356$, suggesting that athletes' physical fitness has the highest correlation with lung capacity, followed by body weight, and negatively correlated with height.

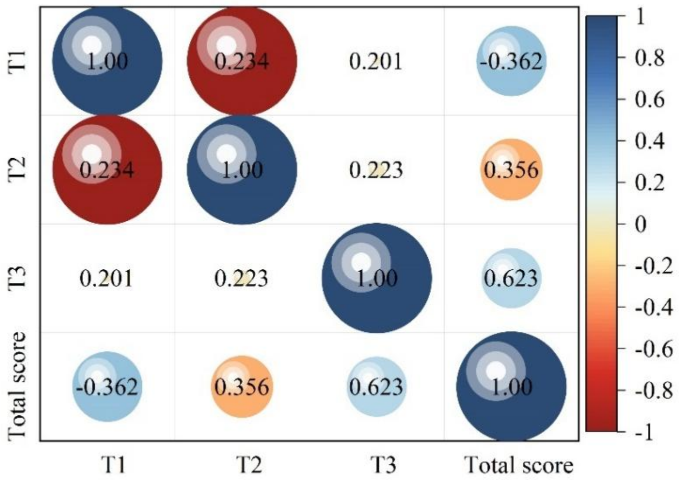

Figure 1. The total results and the adjacent matrix of T1, T2 and T3.

The proximity matrix between the total score and the scores of each subtest is shown in Figure 2. It can be seen that $r_{\text{Total score}\cdot T4}=0.328$, $r_{\text{Total score}\cdot T5}=0.163$, $r_{\text{Total score}\cdot T6}=0.122$, $r_{\text{Total score}\cdot T7}=0.659$, $r_{\text{Total score}\cdot T8}=0.512$, indicating that athletes' physical fitness was positively correlated with all subtests, with the greatest correlation with seated forward bending and endurance running (1000m run for boys/800m run for girls).

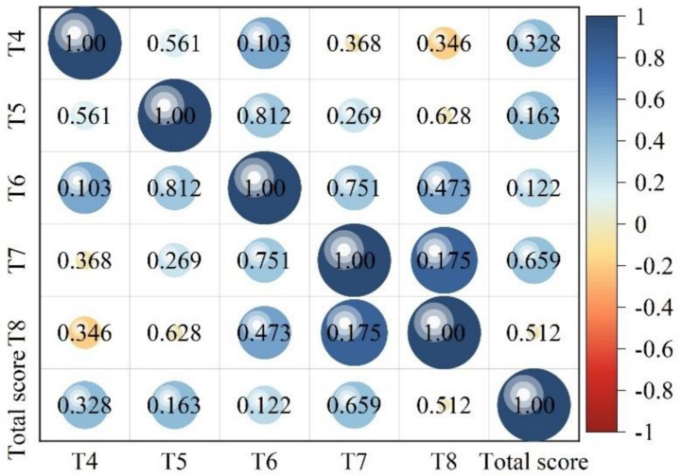

Figure 2. The total results and the performance of the test scores.

(2) Conclusion of distance-related analysis

From the results of the above analysis, we can draw the corresponding conclusions: in terms of the physical fitness level of this group of athletes, the greatest influence on the total performance of the test is the lung capacity, followed by height and finally weight. This means that the most important weights in the overall performance are those tests that are very relevant to lung capacity, i.e. pull-ups (boys)/sit-ups (girls) and endurance running. In terms of the individual test scores, the greatest impact on the overall score was in the pull-ups (boys)/sit-ups (girls) test, followed by the endurance run and the standing long jump. This conclusion coincides with the above conclusion that two of the top three items that have the greatest impact on overall performance are related to lung capacity, which is a further illustration of the above conclusion. Therefore, we should pay attention to this in the actual physical education process.

3.1.3. Regression analysis

Based on the data obtained, regression analysis was carried out with the total test score as the dependent variable and lung capacity, height and weight as the independent variables to establish regression equations between them in order to seek quantitative relationships between these factors and the total score.

The regression coefficients of to using stepwise regression method [26] are shown in Table 5. From the data in the table, the following regression equation can be obtained:

$$\text{Athlete's physical quality}=67.632+0.163\times T1-0.263\times T2+0.063\times T3 \tag{1}$$

Table 5. Regression coefficient.

	Nonnormalized coefficient		Normalization factor	T	Sig.
	Value of undetermined coefficients	**SE**	**Beta**		
Constant	67.632	14.63	-	4.635	0
T1	0.163	0.096	0.163	1.963	0
T2	-0.263	0.063	-0.163	-4.634	0
T3	0.063	0.001	0.369	3.652	0.006

The normal P-P probability plot of the standardized residuals obtained using stepwise regression is shown in Figure 3. The sample data are all normally distributed, indicating that the model in this paper can be analyzed by linear regression.

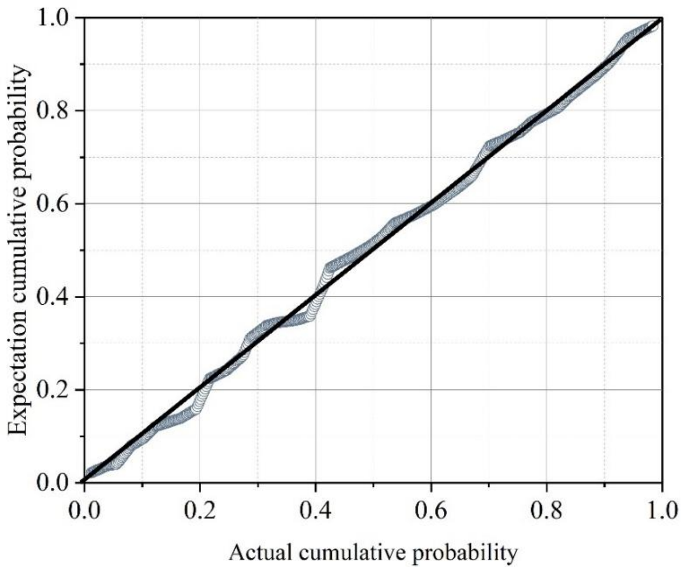

Figure 3. Standardized residual normal P-P probability diagram.

From the above regression results, we can get the relationship between athletes' physical fitness and height, weight and lung capacity. If you want to improve the physical fitness of athletes, you must reduce your weight, grow taller and increase your lung capacity. But for an adult, if you want to make the body grow taller quickly through physical exercise is impossible, but for a body fat, low test scores for students, reduce weight to increase lung capacity is very feasible. But for the light weight students, if you want to improve physical fitness, the main thing is to strengthen the physical exercise to increase lung capacity.

3.2. Analysis of Factors Influencing Athletes' Physical Fitness

The regression equation constructed in the previous section can effectively assess the physical fitness of athletes, and this chapter will continue to use multivariate statistical analysis to explore the factors affecting the physical fitness of athletes and optimize the current sports teaching and training strategies based on the results of the analysis.

The physical fitness test data of the sampled samples were converted into corresponding scores and graded. A four-level scoring standard was used, with test scores below 60 as failing, 60~69 as passing, 70~89 as good, and above 90 as excellent. The distribution of athletes' physical fitness test scores is shown in Table 6. Most of the athletes' physical fitness was good (61.67%), and a small number of athletes' physical fitness test scores failed (8.33%).

Table 6. The athletes' physical quality test scores are distributed.

	Tot	Excellence	Good	Passing	Inferior lattice
People	480	58	296	86	40
Proportion	100%	12.08%	61.67%	17.92%	8.33%

3.2.1. Correlation analysis of influencing factors

The correlation coefficient is the basis of the regression equation and the factors are correlated and analyzed to prepare the follow-up accordingly. The regression model made is meaningful when the correlation between variables is high. The correlation coefficient test of the factors affecting athletes' physical fitness is shown in Figure 4. It can be seen that there is a certain degree of correlation between the factors, which indicates that the predictors are correlated with the performance and can be analyzed by regression.

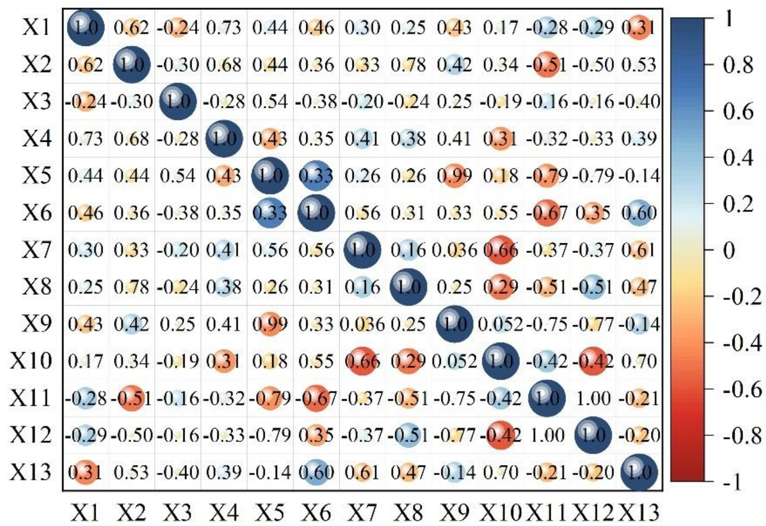

Figure 4. Test of correlation coefficient of athletes' physical quality factors.

3.2.2. Regression modeling and analysis

Multiple comparisons of factors affecting athletes' physical quality are shown in Table 7. Note * denotes P < 0.05, ** denotes P < 0.01, and *** denotes P < 0.001.It can be seen that individual factors, school factors, and social policy factors all have a significant effect on athletes' physical fitness.

Table 7. Factors of physical quality of athletes.

	MD	SD	Sig.	95% confidence interval	
				Lower limit	Upper limit
Individual	0.362*	0.063	0.001***	0.14	0.53
School	-0.369*	0.063	0.036**	-0.56	-0.16
Social policy	0.369*	0.063	0.000***	0.13	0.52

In order to explore the corresponding influence rate of the factors affecting athletes' physical fitness, regression analysis was used for interpretation. The explanatory power of the model is shown in Table 8. a, b, and c denote the regression equation models constructed after the introduction of the independent variables individual factors, school factors, and social policy factors respectively. Individual factors among the factors affecting athletes' physical fitness can explain 2.6% of the physical test scores, the explanatory power rises to 3.5% by adding the school factors, and there is no change in the explanatory power by adding the social policy factors. It reflects that school factors and individual factors have a greater influence on athletes' physical fitness.

Table 8. Model explanatory force.

Model	R	R^2	ΔR^2
1	0.158[a]	0.26	0.026
2	0.163[b]	0.35	0.034
3	0.186[c]	0.35	0.034

After interpreting the equation model, it is also necessary to verify the overall significance of the fitted equation, the test results are shown in Table 9.The F value is 6.635 and the significance level of the model is 0.000, which indicates that the regression model is meaningful.

Table 9. The overall significance of the fitting equation

Model	Sum of squares	Freedom	Mean square	F	Sig.
Regression	43.152	18	0.452	6.635	0.000
Residual error	7.624	642	0.075	-	-
Total	53.143	452	-	-	-

The significance levels of the influential factors are shown in Table 10. It shows that the individual factors that entered the model were: knowledge of physical fitness, skill acquisition, habits, self-control, and number of exercise sessions, and the school factors were: developmental balance, school rules and regulations, level of promotion of exercise, field facilities, and health literacy programs, all of which had significance levels greater than 0.05.

Table 10. Significance level of influencing factors.

Model	Unnormalized coefficient		Normalization factor	T	Sig.
	B	SE	Beta		
Constant	1.147	0.134	-	2.391	0.003
X1	0.109	0.213	-0.174	0.351	0.001
X2	-0.037	0.137	-0.352	-0.772	0.003
X3	0.01	-0.086	-0.291	-10.371	0.045
X4	-0.052	-0.182	0.22	-0.602	0.027
X5	0.108	-0.455	0.323	0.572	0.054
X6	-0.004	-0.186	-0.345	0.243	0.078
X7	0.157	-0.307	-0.139	10.918	0.028
X8	-0.044	0.604	0.024	-10.717	0.084
X9	-0.075	-0.071	0.43	-0.115	0.089
X10	-0.008	-0.42	-0.087	0.586	0.067
X11	0.135	0.6	0.364	10.63	0.279
X12	-0.723	0.005	-0.525	-20.614	0.211
X13	0.188	0.188	-0.112	-0.314	0.322

In conclusion, athletes should focus on optimizing their strategies both individually and at school when training for physical education.

4. Optimization of physical education and training strategies

4.1. Adoption of a creative training model

To the athletes, the sports teaching strategy of "changing the soup without changing the medicine" greatly discourages the athletes' enthusiasm and participation in sports learning. Therefore, in the process of formulating teaching strategies and teaching plans, physical education teachers should adopt a “creative” mode of teaching and training to address this problem, and mobilize athletes to participate in the formulation and promotion of teaching strategies through “student-specific” physical education teaching strategies, which will greatly promote the liberalization and promotion of athletes' physical education learning. This will greatly promote the liberalization and enthusiasm of athletes' sports learning. This will also effectively promote the transformation and development of sports.

4.2. Utilization of information technology to support teaching and learning

In the background of information technology, sports teaching and training, teachers should effectively use information technology to assist classroom teaching, enrich the form of classroom teaching, and stimulate athletes' interest in learning. Teachers can use the network to collect some resources about sports skills teaching, in the classroom for the athletes to play, the use of vivid pictures and videos to attract athletes, enhance the enthusiasm of athletes to participate in the classroom. At the same time, under the background of information technology, it can expand the athletes' knowledge horizons and cultivate the athletes' innovative thinking ability. Take “basketball” as an example, teachers can use information technology to play videos about basketball skills for athletes, so that athletes can deeply understand the basketball skills [27]. In addition, teachers can also show athletes some clips of basketball confrontation and how to apply these skills in basketball confrontation. In this way, after watching, athletes can train in groups, cooperate with each other to actively learn basketball skills, and improve the efficiency of exercise in the sports classroom.

4.3. Improving evaluation mechanisms

Sports teaching and training inevitably involves the problem of teaching evaluation, in the actual teaching process, the vast majority of physical education teachers are difficult to objectively and positively evaluate the teaching of athletes, which to a certain extent makes the athletes do not agree with the teaching and training of physical education teachers, thus affecting the development and improvement of the teaching of sports. Therefore, physical education teachers should continuously improve the teaching evaluation mechanism in the teaching process, and make objective and reasonable evaluation of athletes' learning ability and participation degree, in order to mobilize athletes' learning participation. At the same time, teachers also need to constantly reflect on their own teaching process in order to make it “keep pace with the times”, to promote the development and improvement, so as to make “physical education” subject teaching become a real subject education, rather than “perfunctory” physical training. Physical education is not a “perfunctory” physical training.

5. Conclusion

This paper studies athletes' physical quality and physical quality influencing factors through regression analysis and draws the following conclusions:

(1) Intelligent assessment of athletes' physical quality data can be based on Athlete's physical quality=67.632+0.163 $\times T1 - 0.263 \times T2 + 0.063 \times T3$ (T1, T2, and T3 denote height, weight, and lung capacity, respectively).

(2) Athletes' physical fitness is related to their individual and school factors. It is mainly affected by physical fitness knowledge, skill mastery, habit, self-control, number of exercise sessions, developmental balance, school rules and regulations, degree of promotion of exercise, venue facilities, health knowledge programs, and other factors.

(3) When conducting sports teaching and training, teachers should develop personalized training strategies, and can adopt information technology to assist classroom teaching and enrich the form of classroom teaching. After the completion of teaching, the training of athletes should be effectively evaluated, so as to promote the perfect development of sports teaching and training.

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