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A study on modeling the association between students' psychological changes and athletic performance in physical education based on numerical computational methods

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ABSTRACT

Mining the dynamic association between psychological state changes and sports performance is one of the core tasks of physical education towards scientific teaching. In this paper, the data of psychological change indexes of student athletes were collected by scales and the indexes variability was tested. Combined with the principal component analysis to extract the principal component factors of the psychological change index data, construct the correlation coefficient matrix, and calculate the multiple linear regression equations of psychological change and sports performance. The gray correlation model based on the whitening weight function was used to analyze the gray correlation between psychological change and athletic performance, and calculate the influence of the two.Among the 9 psychological indicators, 4 dimensions, such as social evaluation anxiety, had a significant difference with P<0.01. P<0.05 for 2 dimensions such as competition preparation anxiety, there was a difference. In the principal component analysis, the negative and positive psychological dimensions were extracted as principal components, including the 7 psychological indicator components excluding the 2 dimensions. Judging from the regression coefficients and gray correlation calculation results, the 3 psychological indicators of cognitive state anxiety, state self-efficacy, and injury anxiety had the greatest influence on sports performance. Targeted alleviation of cognitive and injury anxiety and improvement of self-confidence can optimize students' sports performance.

Keywords: principal component analysis, multiple linear regression, gray correlation, whitening weight function, sports performance

1. Introduction

The traditional teaching of physical education in schools has always been closely linked to competitive

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sports in society. Nowadays, in the world of competitive sports, when students' learning pressure, mental burden and psychological problems are increasing, and school physical education has to cope with the "examination for higher education", physical education teaching, which is the most important responsibility for students' physical fitness, can not ignore the needs of students' psychological changes. From the perspective of training students to adapt to the needs of internationalized development, the purpose, mission and content of school physical education materials need to be strategically re-conceptualized [1-2]. Physical education, due to its specific site, environment and corresponding sports equipment and other factors, determines the flexibility of teaching methods, diversity, multi-level teaching characteristics different from other disciplines [3-5]. And in the state of the sports environment of secondary school students, facing different physical education teachers, different physical education content, different physical education teaching grounds and other external conditions, its psychological changes will have a direct impact on sports performance [6-8].

Some studies have shown that the psychological ability of athletes is closely related to their physical and technical abilities, which is comprehensively reflected in physical education as the impact of students' psychological state on sports performance [9]. The best athletic performance of secondary school students is usually related to their internal psychological state, such as emotion, self-confidence and anxiety [10]. A good psychological state can effectively motivate students to perform physical training and improve their technical and tactical skills, as well as enable them to perform their sports normally or exceedingly well in daily physical activities [11-12]. In addition to this, in key sport competitions, students experience arousal, anxiety, and other somatic and emotional changes during the competition [13-14]. These emotional reactions usually make students feel nervous and uncomfortable, and in some cases even weak and fearful [15]. At the same time, under stress and anxiety, some students make frequent errors in their performance [16]. How to observe, understand and master students' psychological changes in time in physical education teaching, as well as effectively deal with episodic and emergent events in teaching, is necessary for in-depth investigation.

This paper systematically analyzes the association between students' psychological changes and sports performance. Sixty student-athletes were selected as research subjects, and data on their psychological change indicators were collected through continuous testing of 2 questionnaire scales. The psychological change index data were downscaled by principal component analysis, and some principal component factors were extracted as representatives to study the students' psychological changes. Through regression modeling, the association between the principal component psychological indicators and sports performance of student athletes was analyzed. The gray correlation between psychological changes and sports performance was further analyzed to reveal the most influential psychological change indicators on sports performance.

2. Research methodology and data collection

This chapter determines the object of data collection and specifies the test scale and numerical analysis method chosen for the experiment. The principal component linear relationship between psychological changes and athletic performance of student-athletes is investigated and a gray correlation model is established.

2.1. Experimental design and data sources

2.1.1. Experimental subjects. The participants in this study were 60 student-athletes in sports programs. By athletic level, there were 30 Kenyan and Division I athletes and 30 Division II athletes. By gender, there were 30 male athletes and 30 female athletes.

2.1.2. Motor Cognitive Trait Anxiety Scale test. In this study, we used the Cognitive Trait Anxiety Scale for Athletics (Anxiety C scale, or CCTA-C questionnaire at the time of the test), which is divided into six dimensions of cognitive trait anxiety for athletics (i.e., social appraisal anxiety, preparation for the competition, athletic performance anxiety, failure anxiety, opponent's strength anxiety, and injury anxiety), and the measure was primarily designed to measure athletes' pre-competition cognitive trait anxiety for athletics. The scale was quantified by means, standard deviations and Cronbach's a reliability coefficients for these six dimensions.

2.1.3. Competition State Anxiety Measurement Scale test. In this study, the Competitive State Anxiety Questionnaire (CSAI-2 scale) was used as a test tool. Competition state anxiety was divided into cognitive state anxiety, somatic state anxiety and state self-confidence. The CSAI-2 scale consists of 27 questions, and participants are asked to choose one of the four options that meets the level they feel at the moment, out of four options: "not at all", "somewhat", "moderate", and "very strong". The higher the score, the higher the cognitive state anxiety, the higher the somatic state anxiety and state self-confidence.

In this paper, a questionnaire survey was implemented on 60 student-athletes based on the combination of research objectives and expert recommendations. A total of 60 questionnaires were distributed, 60 were recovered, and 60 questionnaires were valid, with a validity rate of 100%.

2.2. Numerical analysis methods

2.2.1. Principal component analysis. Principal Component Analysis (PCA) is an unsupervised dimensionality reduction method which is widely used in multiple linear regression analysis. The purpose of principal component analysis is to find linear combinations of a small number of predictors that can be used to reflect information from the original data without losing too much information. This statistical method solves the problem of multicollinearity by converting a broad set of correlated variables into a smaller number of uncorrelated variables, which are called principal components.

Let X be a $n \times p$ matrix, where n is a number of observations and p is a set of predictor variables $X_1, X_2, \ldots, X_p$, where X denotes random observations of $X_1, X_2, \ldots, X_p$. The goal of principal component analysis is to select a subset of predictor variables that reflects most of the information in the original data set, and an important step involves solving the covariance matrix of the data to obtain the eigenvalues and eigenvectors. Let σ_{ij} denote the covariance of the variables X_i and X_j in the data matrix, and the matrix (σ_{ij}) can be written as Σ, which is denoted as the variance-covariance array. The values of the diagonal elements of the matrix Σ are the variance of X_i and the covariance matrix Σ is a symmetric square matrix.

The principal components (PCs) of principal component analysis (PCA) are linear combinations of the original variables $x_{i1}, x_{i2}, \ldots, x_{ip}$, denoted as $\sum a_i x_i$, where a_i is the scalar. If $\sum |a_i| = 1.1$, the principal component is a normalized linear combination of the original predictor variables in the data matrix. The principal component analysis method solves the problem of variable correlation by selecting a series of orthogonal principal components, that is, all principal components are uncorrelated with each other, the first principal component PC1 is uncorrelated with PC2, PC2 is uncorrelated with PC3, and so on. There are two commonly used methods for solving principal components:

1) Eigen-decomposition based on covariance matrix to solve principal components. Assuming that the eigenvalues of the covariance matrix Σ of X are $\lambda_1, \lambda_2, \ldots, \lambda_p$, where $\lambda_1 > \lambda_2 > \ldots > \lambda_p$, and each of the eigenvalue The corresponding orthogonal eigenvectors are $b_1, b_2, \ldots, b_p$, then the i th principal component $t_i = x_{i1}b_{i1} + x_{i2}b_{i2} +$, $i = 1, 2, \ldots, n$, and p is the number of predictor variables. The number of principal components k is selected based on the cumulative variance contribution rate $\sum_{i=1}^{k} \lambda_{i=1}^{k} \lambda_i$, which ultimately results in a cumulative contribution rate of the first k principal components of $\geq 75\%$.

2) Singular value decomposition (SVD) is a commonly used matrix decomposition method. The specific steps of using singular value decomposition for matrix A are: firstly, calculate the eigenvalues and corresponding eigenvectors of AA^T, unitize these eigenvectors, and merge them into matrix U; then calculate the eigenvalues and corresponding eigenvectors of A^TA, unitize these eigenvectors, and merge them into matrix V; Finally, solve for the square root of the eigenvalues of AA^T or A^TA to form a matrix D with the above values as diagonal elements. Then, for the matrix $A_{m\times n}$, the singular value decomposition is expressed as:

$$A = UDV^T \tag{1}$$

where U is the left singular matrix containing the orthogonal vectors; D is the diagonal matrix, where the elements on the diagonal are called the singular values, and the other elements are 0.1; and $0;V^T$ is the right singular matrix, which also contains the orthogonal vectors. The principal components are denoted as $Y = XU$.

2.2.2. Gray correlation analysis. Gray correlation analysis is an effective method for quantitative and ranking analysis among factors for uncertain systems with incomplete information or less data. As a very active branch of gray system theory, its basic idea is to judge the degree of connection between different sequences according to the geometry of sequence curves. This paper is based on Dunn's correlation as the foundation of gray correlation analysis, and improved according to the characteristics of the research problem, constructed an interval gray correlation model based on the typical whitening weight function. The following paper will introduce the basic definition and calculation steps of Dunn's correlation degree.

Let the system behavior sequence be:

$$\begin{aligned} X_0 &= \left(x_0(1), x_0(2), \cdots, x_0(n)\right) \\ X_1 &= \left(x_1(1), x_1(2), \cdots, x_1(n)\right) \\ &\cdots\cdots \\ X_i &= \left(x_i(1), x_i(2), \cdots x_i(n)\right) \\ &\cdots\cdots \\ X_m &= \left(x_m(1), x_m(2), \cdots x_m(n)\right) \end{aligned} \tag{2}$$

For $\xi \in (0,1)$, let:

$$\begin{aligned} &\gamma\left(x_0(k), x_i(k)\right) \\ &= \frac{\min_i \min_k \left|x_0(k) - x_i(k)\right| + \xi \max_i \max_k \left|x_0(k) - x_i(k)\right|}{\left|x_0(k) - x_i(k)\right| + \xi \max_i \max_k \left|x_0(k) - x_i(k)\right|} \end{aligned} \tag{3}$$

$$\gamma\left(X_0, X_i\right) = \frac{1}{n}\sum_{k=1}^{n} \gamma\left(x_0(k), x_i(k)\right) \tag{4}$$

Then $\gamma\left(X_0, X_i\right)$ is said to satisfy the four basic axioms of gray correlation analysis, where ξ is called the discrimination coefficient of gray correlation analysis and $\gamma\left(X_0, X_i\right)$ is called the gray correlation degree of the sequence X_0 and X_i with the gray correlation.

The gray correlation degree $\gamma\left(X_0, X_i\right)$ is usually abbreviated as γ_{0i}, k, and the correlation coefficient at k points $\gamma\left(x_0(k), x_i(k)\right)$ is abbreviated as $\gamma_{0i}(k)$. According to the above definitions and formulas, the calculation steps of gray correlation under Dunn's correlation principle can be obtained.

Step1 Find the initial value image (or mean value image) of each system sequence.

$$X_i{}' = \frac{X_i}{x_i(1)} = \left(x_i{}'(1), x_i{}'(2), \cdots, x_i{}'(n)\right), i = 0, 1, 2, \cdots, m \tag{5}$$

Step2 Find the sequence of absolute values of the difference between the corresponding components of the initial value image (or mean value image) of the sequence X_0 and X_i, denoted:

$$\Delta_i(k) = \left|x_0{}'(k) - x_i{}'(k)\right|, \Delta_i = \left(\Delta_i(1), \Delta_i(2), \cdots, \Delta_i(n)\right), i = 1, 2, \cdots, m \tag{6}$$

Step3 Find the maximum value of $\Delta_i(k) = \left|x_0{}'(k) - x_i(k)\right|, k = 1, 2, \cdots, n; i = 1, 2, \cdots, m$, $k = 1, 2, \cdots, n$; $i = 1, 2, \cdots, m$ and the minimum value, respectively, are denoted:

$$M = \max_i \max_k \Delta_i(k), \quad m = \min_i \min_k \Delta_i(k) \tag{7}$$

Step4 Calculate the association coefficient of the sequence.

$$\gamma_{0i}(k) = \frac{m + \xi M}{\Delta_i(k) + \xi M}, \quad \xi \in (0,1)$$
$$k = 1, 2, \cdots, n; i = 1, 2, \cdots, m \tag{8}$$

Step5 Calculate the average of all sequence correlation coefficients, which is the gray correlation between the system behavior sequence and the system feature sequence.

$$\gamma_{0i} = \frac{1}{n}\sum_{k=1}^{n}\gamma_{0i}(k), \quad i = 1, 2, \cdots, m \tag{9}$$

3. Data analysis and discussion of results

This chapter collects data related to psychological changes and athletic performance of student athletes by means of questionnaires. The psychological indicators were tested for differences to determine whether the selected psychological indicators were usable or not. The data related to psychological indicators are subjected to principal component analysis, the principal component factors are extracted, the matrix of component score coefficients is calculated and the multiple regression model with athletic performance is constructed. Gray correlation analysis and modeling of psychological change indicators and sports performance, to determine the correlation between the two and to analyze the results.

3.1. Comparison of Variability in Psychological Indicators of Student-Athletes

The CCTA-C questionnaire and CSAI-2 scale were used to follow up the psychological changes and athletic performances of the selected 60 fitness and Division I athletes and Division II athletes for a period of one year. 30 fitness and Division I athletes were in group 1, and 30 Division II athletes were in group 2. Differences in athleticism and athletic performances existed between the two student-athletes' groups. The student-athletes in the 2 groups were invited to fill out test scales before each of the 6 competitions, and valid data were collected on 6 occasions. The data were analyzed for differences. Table 1 shows the results of the comparison of the differences in psychological indicators of student athletes at different levels. From the results, the 2 groups of student-athletes with different levels of sports and sports performance showed significant differences in 4 dimensions of social evaluation anxiety, injury anxiety, somatic state anxiety, and state self-confidence (P<0.01); in 3 dimensions of game preparation anxiety, opponent strength anxiety, and cognitive state anxiety (P<0.05); and in 2 dimensions of athletic level play anxiety and failure anxiety, no differences existed (P>0.05). Bodybuilders and Division I athletes have better athletic level and athletic performance, have lower somatic state anxiety, stronger state self-confidence, but at the same time are more anxious in pre-competitive preparations and are more concerned about the social evaluation of themselves. Division II student-athletes were less athletic and less athletic than fit and Division I student-athletes, and were more likely to be anxious due to the strength of the other team, as well as anxious due to a lack of clarity about their perceived state. All student-athletes were concerned about their level of athletic performance and the likelihood of failure in competition. Overall, student-athletes of different athletic levels and athletic performances differed in various psychological indicators, allowing for an in-depth analysis of the data collected.

Table 1. Comparison of student-athlete psychological indexes

Scale	Dimensionality	Group	Quantity	Mean value	Standard deviation	Z	P
CCTA-C	Social evaluation anxiety	1	20	4.08	1.01	-2.64	0.007**
		2	40	3.60	1.26		
	Race preparation anxiety	1	28	4.12	0.62	-3.11	0.01*
		2	32	3.36	0.34		
	Competitive level play anxiety	1	27	3.66	1.09	-1.27	0.200
		2	33	3.92	1.35		
	Failure anxiety	1	30	3.45	1.44	-1.95	0.246
		2	30	3.73	1.52		
	Power anxiety	1	21	3.55	1.24	-0.52	0.05*
		2	39	4.21	0.99		
	Injury anxiety	1	23	3.60	0.93	-2.84	0.003**
		2	37	4.10	1.20		
CSAI-2	Cognitive state anxiety	1	25	3.63	1.03	-1.31	0.015*
		2	35	4.05	1.21		
	Somatic state anxiety	1	18	3.33	0.59	-0.90	0.009**
		2	42	4.16	1.07		
	State confidence	1	25	2.37	0.71	-1.63	0.008**
		2	35	3.51	1.22		

3.2. Principal Component Analysis of Psychological Indicators for Student-Athletes

3.2.1. Results of KMO and Bartlett's test for psychometric data. Psychological indicator data of 9 dimensions were selected for principal component factor analysis. According to the preliminary analysis results, the indicator data of 2 dimensions of competitive level play anxiety and failure anxiety were excluded from it. Table 2 shows the results of KMO and Bartlett's test for the psychological indicator data, where N=420.As can be seen from Table 2, the KMO sampling suitability test statistic is 0.77, indicating that the overlap of information in the data of the above indicators is high and the correlation is large.The Bartlett's test chi-square value is 142.45, and the p-value is 0.005, which is at an extremely significant level. Both test results indicate that the above data indicators are suitable for principal component analysis.

Table 2. Psychological indicators POMS data KMO and Bartlett test results

KMO and Bartlett tests		
KMO sample appropriateness measure		0.77
Bartlett sphericity test	Approximate chi-square	142.45
	Degree of freedom	20.00
	Significance	0.005

3.2.2. Results of total variance interpretation of data on psychological indicators. Further, the total variance test was performed on the selected psychological indicator data to determine the effectiveness of the factor analysis of the indicator data used. Table 3 shows the results of total variance explained for the psychological indicator data. As can be seen from Table 3, based on the eigenvalues greater than 1, the 2 factors extracted together explained 72.20% of the total variance of the psychological indicator data. Overall, the analyzed indicator data had less information loss and the effect of factor analysis was more satisfactory, which can be used to study the association between psychological changes and athletic performance in student athletes.

Table 3. Total variance interpretation of psychological indicator data

Total variance interpretation						
Ingredient	Initial eigenvalue			Extract the sum of squared loads		
	Total	Percent variance	Accumulation (%)	Total	Percent variance	Accumulation (%)
1	3.70	52.01	52.01	3.70	52.01	52.01
2	1.75	20.19	72.20	1.75	20.19	72.20
3	0.82	9.70	81.90			
4	0.69	8.55	90.45			
5	0.57	5.11	95.56			
6	0.43	2.00	97.56			
7	0.35	1.41	98.97			
8	0.22	0.82	99.79			
9	0.10	0.21	100.00			

3.2.3. Results of Principal Component Extraction for Psychological Indicator Data. Figure 1 is a diagram of the data components of the psychological indicators. As can be seen from Figure 1, the six dimensions of social evaluation anxiety, match preparation anxiety, opponent strength anxiety, injury anxiety, cognitive state anxiety, and somatic state anxiety have high loadings on the first factor, which can be further categorized as negative psychological dimensions based on the nature of these dimensions. The state self-efficacy has high loadings on the second factor and can be further categorized as a positive psychological dimension based on the dimensions based on the nature of the dimensions. The dimensional factor distribution can be clearly seen based on the component diagram. Therefore, the principal components of the psychological indicator data are named negative psychological dimension (F1) and positive psychological dimension (F2). The component score coefficients were social evaluation anxiety (X1) (0.68,0.039), match preparation anxiety (X2) (0.43,-0.111), opponent strength anxiety (X3) (0.81,-0.197), injury anxiety (X4) (0.72,-0.289), cognitive state anxiety (X5) (0.57,0.044), somatic state anxiety (X6) (0.6,-0.149), state self-efficacy (X7) (0.10,0.930). From this, a matrix of coefficients of scores of components of psychological indicators of student-athletes can be constructed for subsequent correlation analysis.

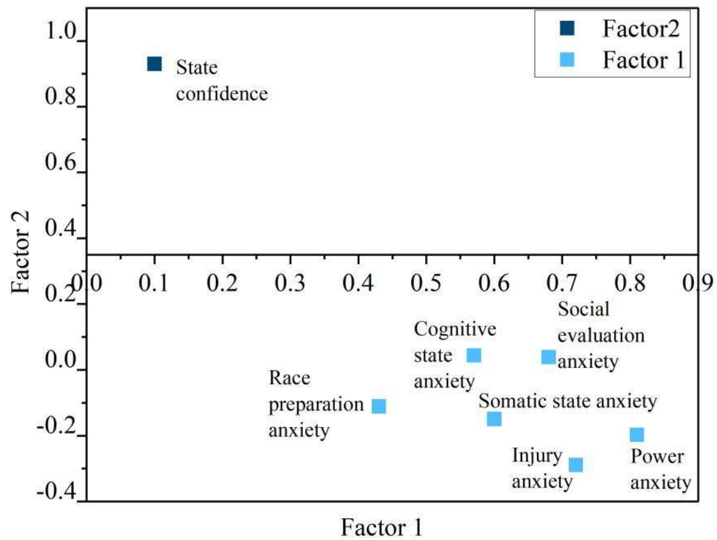

Fig. 1. Psychological index data component diagram

3.3. Principal Component Correlation Analysis of Psychological Indicators and Athletic Performance

3.3.1. Association between state self-efficacy and years of athletic experience. Taking the positive psychological dimension of state self-confidence in the principal components as an example, it was determined whether there was an association between the extracted principal components of psychological change and student athletes' sports performance. Table 4 shows the description of the association between the state self-confidence of student athletes with different years of athletic training. Different years of training lead to differences in student-athletes' athletic performance, which in turn also has an impact on psychological changes before, during and after the competition. From the analysis of the results in Table 4, it can be found that the factor of years of training had a significant main effect on state self-confidence, which differed among student-athletes with different years of training. Student-athletes with 5.5 and 4 years of training had the highest mean values of state self-confidence, 19.23 and 18.45, respectively, which could be attributed to the moderate number of years of training, as well as the moderate number of athletic competitions they participated in, and thus presented a better psychological attitude and enthusiasm for themselves and for the competition at the same time. It can be seen that there is a correlation between the extracted principal components of psychological changes and the athletic performance of student athletes, which can be further analyzed by constructing regression equations.

Table 4. Association between different training years and state self-confidence

Training years	MEAN value	STD value	N
3	11.52	1.80	5
3.5	14.86	7.91	3
4	18.45	6.62	5
4.5	14.00	7.23	4
5	14.67	12.51	4
5.5	19.23	10.66	9
6	14.26	11.25	10
6.5	14.18	8.23	15
7	18.02	11.54	5

3.3.2. Multiple regression equations for psychological change and athletic performance. In this study, the athletic performance of student-athletes was represented by the results of six competitions in which they participated during the year. Table 5 shows the results of regression coefficients calculated between changes in psychological indicators and athletic performance. Accordingly, the multiple regression equation between psychological changes and athletic performance was established.

According to the multiple regression model A=b1+b2x1+b3x2+b4x3+...

Substitute the contents of item B in the unstandardized coefficients in Table 5 into the multiple regression model:

A=-560.486-7.457X1-18.885X2-1.473X3+6.695X4+34.764X5-13.442X6+12.234X7.

Based on the unstandardized regression coefficients, it is concluded that among the dimensions of psychological changes, the greatest influence on athletes' performance is cognitive state anxiety (X5), state self-confidence (X7), and injury anxiety (X4), and the least influence is the preparation for competition anxiety (X2). From this result, it can be preliminarily concluded that in the principal component analysis, student-athletes' cognitive accuracy and self-confidence about their athletic level and athletic performance affect their athletic performance during the actual competition; and anxiety about injuries that result in the inability to continue to participate in athletic competitions exacerbates the effect on athletic performance even further. Since student-athletes are required to complete tasks assigned by their coaches on time and on schedule regardless of anxiety about game preparation, the extent to which game preparation anxiety affects athletic performance is rather not particularly significant.

Table 5. Regression coefficient

Model	Non-standardized regression coefficient		Normalized regression coefficient	T
	B	Std.Error	B	
Constant	-560.486	54.691	-	-10.245
X1	-7.457	0.775	-2.987	-9.632
X2	-18.885	1.423	-4.483	-13.301
X3	-1.473	0.168	0.416	-8.893
X4	6.695	0.415	2.007	16.035
X5	34.764	3.000	6.914	11.587
X6	-13.442	1.155	-4.265	-11.604
X7	12.234	1.034	3.123	11.796

3.4. Gray correlation analysis of psychological indicators and athletic performance

According to the gray system theory, the six competition results (sports performance) can be regarded as a gray system project, through the analysis of the correlation degree, the psychological indicators and their status and role in sports performance can be analyzed to understand the interrelationship between them. Gray correlation analysis consists of three specific steps: initialization, determining the information space of gray correlation differences, and finding the gray correlation coefficient.

The original data are processed (unified scale), and the first value of each original column is removed from the other data in the column to obtain the initialized series. Table 6 shows the initialized series after processing the raw data. According to the initialized series to determine the gray correlation difference information space. Table 7 shows the absolute value difference series between the subsequence and the parent sequence at the same moment. After that, further gray correlation coefficients and correlation degree are solved. Table 8 shows the correlation coefficients of psychological indicators and sports performance. The gray correlation between each correlation coefficient and sports performance can be obtained by adding and averaging the correlation coefficients of each moment of each sequence. The calculation results of the gray correlation coefficients between psychological indicators and sports performance show that the gray correlation coefficients between psychological indicators and sports performance are in the order of X5>X4>X7>X2>X1>X3>X6. The principle of the correlation analysis and the results of the comprehensive evaluation show that cognitive state anxiety (X5), injury anxiety (X4), state self-confidence (X7) have the closest relationship with the final sports performance. The results of the gray correlation analysis were consistent with the results of the principal component analysis, which determined that changes in 2 psychological indicators, cognitive state anxiety and injury anxiety, had the greatest impact on the final athletic performance of student athletes. Therefore, teachers can target to alleviate students' anxiety in these two aspects according to the results of this numerical calculation in daily physical education teaching to enhance students' sports performance.

Table 6. Initialize the sequence after processing the original data

Grade	X1	X2	X3	X4	X5	X6	X7
1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.9899	1.0000	1.0000	1.0000	1.0000	0.9727	0.7824	1.0145
0.9792	1.1536	1.1537	1.1395	1.0664	0.9753	1.0000	0.9405
0.9768	1.0768	1.0765	1.0827	0.9615	1.0046	0.8697	0.9550
0.9736	1.0005	1.0000	1.1954	0.9563	0.9613	0.7828	0.9556
0.9715	1.2306	1.2303	1.1647	0.9687	0.9617	0.8263	1.0070
0.9534	1.0000	1.0000	1.0152	0.8873	0.9718	1.0437	0.9034
0.9525	0.9230	0.9231	0.9020	0.9425	0.9763	0.7821	1.0828

Table 7. Difference values of child and parent sequences at the same time

X1	X2	X3	X4	X5	X6	X7
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.0101	0.0526	0.0104	0.0103	0.0166	0.2071	0.0250
0.1746	0.0207	0.1600	0.0875	0.0037	0.0206	0.0386
0.1003	0.0398	0.1055	0.0158	0.0274	0.1074	0.0214
0.2576	0.0364	0.2227	0.0263	0.0120	0.1906	0.0186
0.2598	0.0969	0.1932	0.0030	0.0105	0.1456	0.0353
0.0464	0.1086	0.0615	0.0664	0.0175	0.0894	0.0506
0.0297	0.0150	0.0506	0.0091	0.0235	0.1701	0.1291

Table 8. Correlation coefficient of psychological index and sports performance

X1	X2	X3	X4	X5	X6	X7
1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.9271	0.7125	0.9271	0.9271	0.8843	0.3842	0.8374
0.4256	0.8611	0.4470	0.5972	0.9706	0.8611	0.7690
0.5645	0.7665	0.5506	0.8916	0.8234	0.5467	0.8562
0.3341	0.7824	0.3681	0.8300	0.9125	0.4044	0.8760
0.3336	0.5720	0.4012	0.9756	0.9235	0.4705	0.7837
0.7370	0.5435	0.6775	0.6600	0.8783	0.5907	0.7181
0.8144	0.8954	0.7191	0.9291	0.8446	0.4323	0.5001

4. Conclusion

This paper explores the association mechanism between psychological changes and athletic performance of student athletes in physical education through 2 types of numerical computation methods, principal component analysis and gray correlation analysis. It was found that the 9 indicators of psychological change dimensions selected in this paper are differentiated and can well participate in correlation analysis as psychological change research data. In both principal component analysis and gray correlation analysis, it was calculated that three psychological change indicators, namely, cognitive state anxiety, state self-confidence, and injury anxiety, have a greater impact on students' athletic performance. Students will affect their athletic performance in subsequent competitions due to psychological-emotional problems such as lack of cognition and confidence in themselves and fear of injury. It is recommended that relevant physical education educators should strengthen psychological interventions for students during the teaching process. Set up simulation training to reduce students' cognitive anxiety, while using positive incentives to enhance students' self-confidence in their own athletic status. The introduction of sports loss protection guidance, educate students scientific sports, relieve injury anxiety. Through these targeted measures, students' anxiety in sports is comprehensively alleviated, resulting in more outstanding sports performance.

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