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Article

An Accurate Assessment Model of Big Data-Based Physical Education Programs in Colleges and Universities for Student Health Enhancement

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Abstract: In this paper, we design a research framework for college student health level data that integrates K-means clustering method and Apriori algorithm to establish an assessment model between physical education courses and student health. The maximum minimum distance and inter-sample density are used to improve the sample point categorization of K-means clustering and select more appropriate initial clustering centers. Apriori, a linkage linkage profiling class algorithm, is used to deeply mine frequent item sets at multiple levels to improve modeling efficiency and accuracy. It was found that five strong association rules were mined for each of male and female college students, with support and confidence ranges of 9.214%-10.925%, 57.071%-90.426% (male) and 11.351%-15.713%, 55.423%-67.153% (female), respectively. Male and female college students were clustered into 5 categories according to their physical fitness test scores respectively. Physical fitness level = 72.735 + 0.689*exercise intensity + 0.527*exercise time + 0.641*exercise frequency.

Keywords: k-means clustering; inter-sample density; Apriori algorithm; health assessment

1. Introduction

Since the promulgation and implementation of the National Physical Fitness Standard for Students by the Ministry of Education of China in 2014, the excellent rate of Chinese students' physical fitness attainment has been on an overall upward trend [1]. In recent years, with the emphasis on physical education and the promotion of related policies, some college students have improved their physical morphology and development indicators, with height, weight and other data to the good, lung capacity levels on the whole showing an upward trend, and cardiorespiratory fitness increasing [2-4]. However, there are still some problems that are not optimistic.

First of all, the growth of college students' excellent rate of physical fitness and health attainment is relatively slow, and there is a big gap compared with the improvement of primary and secondary school students. In terms of physical flexibility, strength, speed and endurance, college student groups have not shown significant improvement [5-6]. Secondly, some college students have poor living habits, such as lack of sufficient physical exercise due to academic pressure, social recreation, and other factors, and their physical function has declined [7]. China Youth Net 2023 surveyed 25125 college students on their physical activity, the results show that nearly 50% of college students exercise less than 3 times a week, while more than 70% hope to enhance their physical fitness through exercise, and 50% think that physical activity is very necessary [8]. This shows that although college students have the will to exercise, but the actual action is obviously insufficient.

Again, some college students have poor dietary habits. At present, some college students have problems such as picky eating, partiality, over-reliance on fast food and convenience food, resulting in malnutrition and affecting health [9]. In addition, some college students do not have enough sleep and stay up late, which not only affects their immunity, but also reduces their learning efficiency [10-12].

Some studies have pointed out that more than 60% of college students often stay up late, which leads to the decline of their body immunity and poor mental state, and then affects their physical health [13]. Finally, psychological stress is also an important factor affecting the physical fitness of college students, and the pressure from various aspects, such as academics, employment, and socialization, is prone to cause physical and psychological health problems [14-15]. Factors affecting students' physical health are multifaceted and need to be considered and intervened comprehensively at multiple levels [16]. Physical education programs in colleges and universities should be based on these factors, and design more scientific, reasonable, and diversified course content and teaching methods to promote the overall improvement of students' physical fitness [17].

In this paper, we improve the K-means clustering algorithm by combining the maximum-minimum distance, the density between samples and the sum of squares of clustering errors to improve the accuracy of cluster center and number selection and optimize the clustering effect of students' health level. Correlation analysis clusters the support and confidence of each item in the dataset, and constructs frequent item sets to improve the effect of rule mining. For the limitations of traditional association analysis to generate a large number of invalid linkage rules, the Apriori algorithm is introduced to scan the dataset several times, and the comprehensive threshold setting improves the screening standard of the itemset to improve the accuracy of association rule generation. Taking the actual students' health data in colleges and universities as the research object, we analyze the influence of physical education courses on the improvement of students' health level, and construct an assessment model.

2. Mining the Association between Physical Education Curriculum and Health Level Based on Big Data

2.1. Improvement of K-Means Clustering Algorithm

2.1.1. Optimization of Initial Clustering Centers

K-means clustering algorithm belongs to a class of algorithms with iterative nature, which is highly sensitive to the choice of initial conditions. Due to the difference of the initial clustering center, it will make a big difference in the whole clustering results. For K-means clustering algorithm, an excellent initial clustering center is the key to achieve better clustering results, especially when dealing with large-scale datasets, if the selected initial clustering center is similar to the final real clustering center, then the algorithm is able to significantly reduce the number of iterations during the operation.

In order to solve the problems of K-means clustering algorithms in the selection of initial clustering centers, a large number of K-means algorithms have been proposed to achieve better clustering results, in most cases, these algorithms tend to select the average or the data object closest to the average as the first initial clustering center, however, this method sometimes leads to a significant deviation between the initial clustering center and the actual clustering center. In the process of initializing the maximum and minimum distances, the boundary data points or anomalous data points are usually selected as the initial clustering centers, and most of the clustering centers are concentrated in the densely populated places of the data points in terms of the real geographic locations of the data points, and seldom appear in the edge regions. Therefore, simply selecting the initial clustering center on the boundary does not truly reveal the true distribution of the data set.

In order to overcome the random generation of initial clustering centers in the K-means algorithm resulting in unsatisfactory clustering results, the paper uses the principle of the combination of the maximum minimum distance and the density between each sample object to select the initial clustering centers.

Let there be M sample data in the dataset and each sample has N attributes, then any data can be represented as $X=\left(x_1,x_2,\ldots,x_m\right)$. The definitions used in the clustering process are as follows:

Definition 1. The distance between data points x_1 and x_2 is the Euclidean distance

$$d\left(x_i,x_j\right)=\sqrt{\sum_{n}^{m}\left(x_i-x_j\right)^2} \tag{1}$$

Definition 2. Sample Density: $N_\lambda\left(x_m,c_i\right)$ denotes all data objects whose distance from the object c_i is not greater than λ.

$$N_\lambda(x_m, c_i) = \{x_m \mid dis(x_m - c_i) \le \lambda\} \tag{2}$$

$$\lambda = \frac{1}{2} dis(c_i, \overline{x}) \tag{3}$$

The steps of the improved initialization method are as follows:

Step 1: Create a dataset X , calculate the average value $\overline{x}$ of the whole data, and calculate the farthest point from the average value as c_1 ;

Step 2: Let $\lambda = \frac{1}{2} dis(c_i, \overline{x})$, and let all the data points whose distance from c_1 is less than λ , as object $N_\lambda(x_m, c_1)$.

Step 3: Find the average value of $N_\lambda(x_m, c_1)$, and select the sample point closest to $\overline{x}$ as the cluster center for temporary update. If c_1 is less than a certain threshold, then c_1 is used as the first initial clustering center, otherwise return to Step 2;

Step 4: Group the remaining sample points into their nearest classes, calculate the distance between all sample points in each data set and the clustering center of this class, compare the size of the distance value, and select the farthest point as the next temporary clustering center c_i ;

Step 5: Make ε half of the distance between the sample points of the selected object and the center of the category to which it belongs. Search for the distance c_i less than ε for all data objects $N_\lambda(x_m, c_i)$;

Step 6: Calculate the mean value of $N_\varepsilon(x_m, c_1)$ and select the sample point closest to the mean value as the clustering center for temporary update. If c_i does not change, then c_i is used as the next initial clustering center, otherwise return to Step 5;

Step 7: Repeat Step 4-Step 6 until k clustering centers are found.

2.1.2. Selection of the Number of Clusters

The selection of the number of clusters has a great impact on the performance of the K-means clustering algorithm. If the number of clusters is too small, the clustering results may not be able to fully reflect the characteristics of the data and have a lower accuracy; if the number of clusters is too large, the algorithm may need to run more iterations and a longer runtime.

In practice, some methods can be used to determine the appropriate number of clusters, such as the elbow rule, contour coefficient and other methods. Also, the performance of clustering algorithms can be evaluated to obtain the optimal number of clusters.

The sum of squared clustering errors is a metric used to assess the performance of clustering, the smaller the value, the better the clustering is In selecting the number of clusters, SSE is one of the important metrics, this is because the clustering is best when SSE takes the minimum value.Minimization of SSE can be obtained by running the K-means algorithm at all possible numbers of clusters and calculating the SSE for each algorithm. The number of clusters corresponding to the minimum SSE is the optimal number of clusters.

It should be noted that the sum of squared clustering errors (SSE) decreases as the number of clusters increases, but when the number of clusters is too large, the decreasing trend of SSE becomes flat. Therefore, by plotting the curve of the clustering error sum of squares criterion function under the number of clusters, the k value of the number of clusters that makes the decreasing trend of SSE become slower can be selected as the optimal number of clusters.

The formula for the clustering error sum of squares criterion function is defined as follows:

$$J = \sum_{i=1}^{k} \sum_{j=1}^{n_i} \left\| x_{ij} - m_i \right\|^2 \tag{4}$$

2.2. Concepts Related to Correlation Analysis

1) Item and item set

Item, is an object we analyze and study, there are more than one object is a multinomial set, and an item set is a collection of combinations of more than one item, e.g., k item set is a collection of combinations of k items.

For example, in a physical fitness test, {normal weight} is one item, and {passing lung capacity} is also one item. And the set consisting of two and more scoring grades of physical test items is an item set, e.g., {excellent in 100-meter run, fail in pull-ups} is a 2-item set.

2) Support

The degree of support is the frequency of an item set in the data set. The degree of support reflects the frequency of an item set, only when the support of an item set reaches a set value, it is necessary to study the item set. Minimum support (min_sup), which refers to the association rule with the lowest importance, is the value set for the minimum support of an itemset. $\{A \to B\}$ is an association rule where A and B are two itemsets and do not intersect. The mathematical expression is as follows:

$$S(A \to B) = \frac{\delta(A \cap B)}{N} \tag{5}$$

where the numerator represents the number of times A and B appear together, and the denominator represents the total number, i.e. the number of rows.

3) Confidence level

Confidence reflects the degree of credibility of the rule, $\{A \to B\}$ is an association rule, if the confidence level of the association rule $\{A \to B\}$ is high, it means that when A occurs, there is a high probability of B occurring, which makes the study meaningful. Minimum confidence (min_conf), which refers to the association rule with the lowest confidence, is the value of the minimum confidence setting for the itemset. The mathematical expression is as follows:

$$C(A \to B) = \frac{\delta(A \cap B)}{\delta(A)} \tag{6}$$

where the numerator represents the number of times both A and B occur, and the denominator represents the number of times A occurs.

4) Frequent item set

Those itemsets whose support is greater than the minimum support become frequent itemsets. Usually, we only need to learn frequent itemsets. The meaning of frequent k itemset is that there are k elements in the frequent itemset.

2.3. Analysis of Apriori Algorithm

The direct application of simple association rule analysis methods for data mining may lead to the generation of a large number of invalid linkage rules, which will affect the efficiency of modeling. In this field, Apriori algorithm is considered as a standard linkage connection profiling algorithm. It is a practice that has significantly influenced common itemset mining algorithms and is the basis for most breadth-first search common itemset mining algorithms.The Apriori algorithm utilizes a deeper and iterative search methodology, which is simple and easy to implement without the need for a tedious reasoning process.

In order to create join rules, it is necessary to first find the common itemsets and then generalize the join rules from these common itemsets that satisfy the minimum trust requirement.The actual execution steps of Apriori algorithm are as follows:

Step 1: Generate candidate itemsets (C1):

1) Scan the whole dataset and count the support degree of each item.

2) According to the set minimum support threshold, filter out the items with support less than the threshold.

3) Use the remaining items as frequent 1-item set (L1).

Step 2: Generate frequent 2-item set (L2):

1) Based on the frequent 1-item set, generate all possible candidate 2-item sets.

2) Scan the dataset again and count the support of each candidate 2-item set.

3) Filter out the candidate 2-item sets whose support is less than a threshold to obtain frequent 2-item sets.

Step 3: Generate frequent $k-$ itemsets (Lk):

1) Generate candidate $k-$ itemsets based on frequent $(k-1)-$ itemsets by iterative way.

2) Scan the dataset again and count the support of each candidate $k-$ itemset.

3) Filter out the candidate $k-$ itemsets whose support is less than the threshold to get the frequent $k-$ itemsets.

4) If the frequent $k-$ itemset is empty, stop the iteration.

Step 4: Merge frequent itemsets:

Merge all frequent itemsets to get the set of all frequent itemsets.

Step 5: Generate association rules:

1) For each frequent itemset, generate all its non-empty subsets as antecedents of the rule.

2) Calculate the confidence level of the rule and filter out the rules whose confidence level is less than the set threshold.

3) Obtain all the association rules that fulfill the requirements.

The key to the whole process is to calculate the support by scanning the dataset at each step and filter out the sets of items that do not satisfy the conditions by setting the threshold. The iterative process ensures that the algorithm can gradually generate higher order frequent itemsets. Eventually, by generating association rules, interesting association relationships can be mined from the frequent itemsets.

3. Study on Physical Education Curriculum and Health Level Based on Big Data

3.1. Knowledge Discovery and Decision Support for College Students' Physical Fitness and Health Based on Association Rules

3.1.1. Knowledge Discovery of Association Rules among Male College Students with Different Physical Activity Behaviors

Different physical activity behavior settings in college physical education courses affect students' physical fitness level. Setting min_Sup=9%, Confidence=55%, physical activity behavior stage as output, the maximum number of entries of rule results is 4, and a total of 20 pieces of knowledge are found. After screening, a total of 5 knowledge with decision-making significance was found. Table 1 shows the knowledge of association rules for male college students with different physical exercise behaviors. There are 2 meaningful knowledge for the 3 stages of anticipation, preparation, and action of male college students' physical education course exercise behaviors.The support of the 5 rules ranged from 9.214% to 10.925%, and the confidence level ranged from 57.071% to 90.426%, which were over the preset level. From the 6 associated knowledge, it can be found that the main manifestation of the anticipation stage that affects the physical fitness level of male college students is low cardiorespiratory fitness; in the preparation stage, male college students have poor reaction time, poor strength qualities, and poor cardiorespiratory fitness; and in the action stage, it indicates that exercising in the physical education program positively and effectively enhances the flexibility of the nervous system of male college students.

Table 1. Rule knowledge discovery in different exercise behaviors of male.

Serial number	Rule		Support (%)	Confidence (%)
	Consequent	Antecedent		
1	Expectation	Left back hook = excellent, body fat percentage = normal, reaction time = medium, VO2max= poor	10.872	57.071
2	Expectation	VOzmax phase = poor, left back hook = excellent, reaction time = medium, VOzmax= poor	10.925	57.104
3	Get ready	Reaction time = pass, grip strength = poor	9.214	68.352
4	Get ready	Reaction time = pass, VOzmax= poor	9.836	68.850
5	Action	Reaction time = excellent	9.683	90.426

3.1.2. Knowledge Discovery of Association Rules for Female College Students with

Different Physical Activity Behaviors

Setting min_Sup=9%, Confidence=55%, Physical Activity Behavior Stage as the output, and the maximum number of entries in the rule result as 4, a total of 30 pieces of knowledge were found. After screening, a total of 5 knowledge with decision-making significance was found. Table 2 shows the knowledge of association rules for female college students with different physical exercise behaviors. The 3 stages of exercise behavior in physical education courses for female college students are pre-expectation, anticipation, and action, in which there is 1 association knowledge for pre-expectation, and 2 association knowledge for anticipation and action each.The support of the 5 association knowledge ranges from 11.351%-15.713%, and the confidence range is from 55.423%-67.153%, which is more than the pre-determined range. Analyzing the five associated knowledge, knowledge 1 is the only knowledge found in the pre-expectation stage of female college students' physical activity behavior, poor strength and good flexibility are their physical characteristics, and their lack of physical activity may be due to their "softness", which can be seen that female college students are more focused on flexibility and ignore the characteristics of strength qualities. In the anticipation stage, female college students' grip strength is passable, back hook is excellent, reaction time is medium, and relative VO2max is medium. Physical education teachers should actively encourage female college students to participate in physical education courses to comprehensively develop their strength and cardiorespiratory endurance qualities. The physical quality of female college students in the action stage is characterized by poor strength, medium reaction time, and excellent flexibility, and female college students in this stage have already understood the relevant knowledge of physical fitness and expect to improve their physical fitness and health status through physical exercise. Decision support can continue to encourage their participation in physical exercise, form sports habits, and enhance confidence in physical exercise through regular physical fitness tests.

Table 2. Rule knowledge discovery in different exercise behaviors of female.

Serial number	Rule		Support (%)	Confidence (%)
	Consequent	Antecedent		
1	Previous expectation	Grip strength = poor, right back hook = excellent	11.351	55.423
2	Expectation	Grip strength = pass, reaction time = medium, right back hook = excellentVOzmax= poor	11.910	56.718
3	Expectation	Body fat percentage = overweight, grip strength = passing, BMI= normal	12.156	60.163
4	Action	Grip strength = poor, reaction time = medium, right back hook = excellent	15.713	67.153
5	Action	Grip strength = poor, body fat percentage = overweight, BMI= normal	12.855	61.269

3.2. Analysis of K-Means Clustering Results of Physical Fitness Test

3.2.1. Analysis of K-Means Clustering Results of Male Physical Fitness Test Scores

In accordance with the preliminary analysis of the knowledge of association rules in the previous section, the number of clusters was determined to be 5, and K-means clustering was carried out on the physical fitness level of male and female students (as reflected by the physical fitness test scores) according to their gender, to analyze the specific impact of the various types of sports set up in the physical education curriculum of colleges and universities on the health level of students.

Table 3 shows the clustering results of physical fitness test scores of male college students. Figure 1 shows the changes in the mean values of the clustering variables for male college students. The largest number of male students was found in category A with 5213 students.The test results of total score score, body mass index, lung capacity, long jump, forward body flexion, and endurance running were moderate in category A, but the results were extremely poor in sprinting. The results of total score, lung capacity, body mass index, standing long jump, forward body flexion were extremely poor in category B boys. But performed extremely well in sprinting and endurance running events.There were fewer boys in category

B with only 2357.Boys in category C had the lowest values of body mass index and high performance in sprinting. There were 3066 boys in this category.Boys in category D had poor performance in endurance running and sprinting, poor sprinting qualities, endurance qualities and good performance in long jump, forward bends and lunges.There were 4111 boys in category D. Boys in category E were the least in number (2065) but scored high in total scores, had the highest performance in long jump, forward bends and the highest lunges and body mass index, but performed extremely low in endurance running. Although the category with the highest total score, it is not physically well rounded and lacks more in endurance.

Table 3. Clustering results of the physical health test scores of male students.

Clustering	A	B	C	D	E
Total score	79.688	69.954	76.271	80.607	82.025
BMI	24.751	24.236	25.057	25.549	26.426
Vital capacity	3548.505	2386.182	3050.554	4047.892	4712.904
Sprinting	9.917	8.589	8.751	8.924	8.726
Long jump	228.517	225.232	226.954	230.613	231.575
Forward bend	16.135	14.668	15.671	16.729	17.979
Endurance running	262.674	260.613	264.756	263.781	260.602
Power	5.628	5.432	5.667	5.385	5.272
Number of people	5213	2357	3066	4111	2065

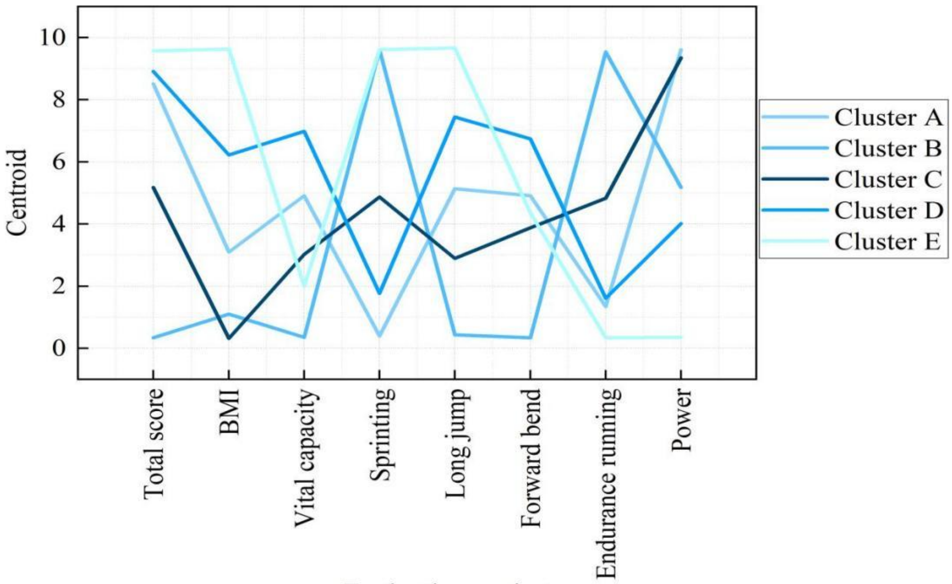

Figure 1. The mean change of clustering variables for male college students.

3.2.2. Analysis of K-Means Clustering Results of Girls' Physical Fitness Test Scores

Table 4 shows the clustered results of physical fitness test scores of female college students. Figure 2 shows the changes in the mean values of the clustered variables for female college students. Female students in category A have the lowest total score of 76.105. Female students in category A perform better only in the tests of sprinting and endurance running, while they perform extremely poorly in the performance tests of lung capacity, sprinting, standing long jump, and forward bending of the body. There were 1595 girls in this category. Girls in category C are somewhat similar to girls in category A, but the overall performance of girls in category C is higher than the performance of all girls in category A. The number of girls in this category is 3,021. The number of girls in this category C is 3021. Category D has the highest number of girls belonging to it with 3598 girls, and the girls in category D have only a slight advantage in sprinting and endurance running.Category E has the highest overall score (89.059) and the lowest number of girls belonging to it with only 1084 girls, and the girls in category E have extremely poor performance in sprinting and endurance running, however, they have better performance in other areas such as forward bending and standing long jump.

Table 4. Clustering results of the physical health test scores of female students.

Clustering	A	B	C	D	E
Total score	76.105	86.117	83.252	85.006	89.059
BMI	22.683	24.314	23.142	23.565	24.771
Vital capacity	1859.907	2981.161	2274.116	2609.077	3548.611
Sprinting	9.016	9.974	10.072	9.823	11.908
Long jump	175.194	180.082	177.123	178.196	182.951
Forward bend	19.432	21.569	20.391	20.972	22.596
Endurance running	249.861	250.972	253.118	250.562	260.056
Power	37.113	38.328	37.522	37.854	39.035
Number of people	1595	2284	3021	3598	1084

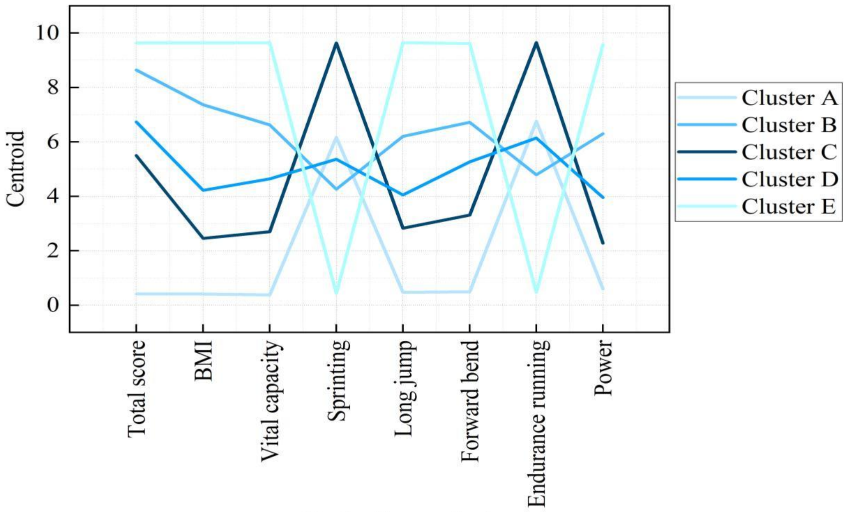

Figure 2. The mean change of clustering variables for female college students.

3.3. Linear Regression of Physical Activity and Physical Fitness of College Students

According to the clustering results of students' physical fitness level, in order to understand in which dimension the exercise arranged in college physical education courses predicts and influences students' physical fitness, the dimensions of college students' physical exercise were divided into independent variables, physical fitness level as the dependent variable, and gender as the control variable, and multiple regression analysis was used. Table 5 shows the results of regression analysis of college students' physical activity and physical fitness level.

The R^2 is 0.273, indicating that the total score of the physical fitness level test can be explained by 27.3% of the variation in the dimensions of physical exercise; the F-test of the model yields F=152.84, P=0.001<0.001, which reaches the level of significance; in addition, through the test of the linear regression model, it is concluded that the VIF value of the intensity of physical exercise, the time of exercise, and the frequency of exercise is 1.092, 1.117, and 1.261 are lower than 4.5, indicating that there is no covariance problem in this model. The B-value of exercise intensity was 0.689 (t=5.183, p=0.001<0.01), exercise time was 0.527 (t=4.267, p=0.002<0.01), and exercise frequency was 0.641 (t=4.145, p=0.002<0.01), and the B-values of all three were positive, indicating that all dimensions of physical activity have a significant positive effect on the Physical health has a significant positive impact relationship, the regression equation is: physical health level = 72.735 + 0.689*exercise intensity + 0.527*exercise time + 0.641*exercise frequency. College students' physical exercise has a positive predictive effect on physical health, and the exercise intensity, exercise time and exercise frequency of sprinting, standing long jump, seated forward bending and other sports should be reasonably arranged in different types of physical education curriculum activities to comprehensively improve college students' physical health level.

Table 5. Regression analysis of physical exercise and physical health level.

	Non-standardized coefficient		Standardized coefficient	T	P	VIF
	B	Standard error	Beta			
Constant	72.735	0.692	-	94.672	0.000***	-
Exercise intensity	0.689	0.203	0.067	5.183	0.001***	1.092
Exercise time	0.527	0.172	0.051	4.267	0.002**	1.117
Exercise frequency	0.641	0.213	0.054	4.145	0.002**	1.261
Control variable:	-					
Gender (Male)	-9.254	0.473	-0.528	-24.721	0.001***	1.125
Gender (Female)	0	-				
R^2	0.273					
F	152.84***					
Dependent variable: Physical health level						

4. Conclusion

This paper combines the K-means clustering method and Apriori algorithm to study the association between college physical education course scheduling and students' physical fitness level. A total of 10 association rules for different physical activity behaviors of male and female college students exceeded the minimum support level of 9% and the confidence level of 55%. According to the physical fitness test scores, college students with different fitness levels were each clustered into five categories by gender, and the health characteristics of students in each category varied greatly. Through linear regression modeling, the assessment model of college physical education courses and students' health level was constructed as follows: physical fitness and health level = 72.735 + 0.689*exercise intensity + 0.527*exercise time + 0.641*exercise frequency. In the future, colleges and universities should arrange the exercise intensity, time and frequency reasonably and effectively according to the characteristics of various types of physical exercise activities, and guide students to realize the improvement of physical fitness and health through physical education courses.

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