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Temporal Association Rule Mining of College Students' Extracurricular Exercise Behavior with Physical Fitness and Athletic Performance Based on Apriori Algorithm

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Abstract As the relationship between college students' extracurricular exercise behaviors and physical health is getting more and more attention, how to improve college students' physical health through effective exercise behaviors has become a hot research topic. In this paper, the temporal association rules between college students' extracurricular exercise behavior and physical health and sports performance are mined by applying Apriori algorithm. The study firstly collected the physical examination data and body side performance data of college students in a university, which included height, weight, body mass index, flexibility, cardiorespiratory function and other health indicators, and pre-processed the data with the athletic behavior performance of college students. The results of the study show that male college students have poor flexibility, medium reaction time and poor cardiorespiratory fitness in the “anticipation stage”, which directly affect their physical fitness level. Through data mining, we obtained 10 rules with decision-making significance. Among female college students, those with superior flexibility, poor cardiorespiratory fitness, and higher body mass index need to pay more attention to strength and endurance training. With the improved Apriori algorithm, the study not only improved the efficiency of data mining, but also expanded the mining scope of association rules and found more valuable associations between exercise behavior and health status. These findings provide a scientific basis for the development of sports interventions for college students.

Index Terms Apriori algorithm, college students, physical health, exercise behavior, association rules, data mining

I. Introduction

With the development of society and people's attention to healthy life, more and more college students realize the importance of physical exercise [1]. Extracurricular physical activity behavior can not only promote college students' physical health and athletic performance, but also improve their learning efficiency and quality of life [2], [3].

Modern college students generally have the problem of sedentary behavior, and prolonged classroom learning and electronic product use puts their bodies in a low-load state, leading to problems such as decreased physical performance, muscle relaxation, and slowed metabolism, which can be effectively improved through extracurricular sports [4]-[7]. Appropriate extracurricular sports can enhance the cardiorespiratory function, muscle strength and endurance of college students, improve the metabolic level of the body, promote the body's metabolism, and enhance immunity, thus reducing diseases and enhancing athletic performance [8]-[10].

At the same time, current college students generally have psychological problems such as high academic pressure, emotional fluctuations, anxiety and depression, and moderate extracurricular sports can effectively alleviate these conditions [11]-[13]. Exercise can allow college students to release tension and pressure, so that they can get physical and mental relaxation and pleasure in exercise [14], [15]. Through extracurricular sports, college students can regulate their emotional state, enhance self-discipline and stress resistance, which is conducive to improving mental health and improving the efficiency of work and study [16]-[18]. Through exercise, the brains of college students will release pleasure hormones such as dopamine, improve their moods, increase their sense of well-being, and thus obtain a better psychological state [19], [20].

This study aims to apply the Apriori algorithm to mine the temporal association rules between extracurricular exercise behaviors of college students and their physical health and sports performance. The study explored the relationship between exercise behavior and physical health by analyzing the physical examination data and physical test scores of college students in a university, and put forward scientific suggestions for exercise intervention in combination with exercise performance at different stages.

II. Mining the time-series association between physical fitness and sports performance of college students

II. A. Data mining of personal health information of college students

II. A. 1) Data sources

The study collected the physical examination data of college students in a university as a dataset for mining the temporal association rules of college students' extracurricular exercise behaviors and physical health. The goal of the study is to derive certain rules implied by analyzing the relationship between the exercise behavior of college students and the data of various physical examination indicators. Among them, the college students' physical examination data include desensitized basic information (including name, age, hukou type, ethnicity, and whether they are only child, etc.), height, weight, body mass index, flexibility index, and neurological reaction time, and other indexes.

The athletic performance data were derived from the results of the school's student body profiles, which mainly included students' basic information after desensitization, but also included students' scores in each of the indicators, such as standing long jump (A1), long-distance running (A2), pull-ups (A3), rope skipping (A4), lung capacity (A5), 50m (A6), sit-ups (A7), and so on.

II. A. 2) Data pre-processing

The data used in this paper has some incomplete, invalid noise data, the direct use of the data for experiments will have a certain impact on the experimental results, and complex data will also have an impact on the implementation of the algorithm efficiency to a certain extent. In order to ensure that the ideal experimental results, this paper carries out the following pre-processing operations on the data.

(1) Data screening: determine the goal of data mining, and keep only the data related to physical health and sports performance.

(2) Data cleaning: including missing filling, error detection, duplicate filtering, consistency check, etc.

(3) Data conversion: Convert the cleaned data into a data format that is convenient for data analysis and mining. Time formats such as assessment time and time spent on assessment are converted to a unified format, and all Chinese characters in the assessment database are converted with English acronyms to reduce data storage space.

After the above data processing, it is found that the data acquired in this paper are of high quality, and the number of data samples still has 8619 data after processing. Secondly, in this paper, the training data and the test data are divided according to the ratio of 8:2, so the training data set has 6,895 sample data and the test data set has 1,724 sample data.

II. B. Apriori Algorithm

Association rules [21] is one of the popular topics of current research in data mining technology, and its significance is to mine the connections that each data item in the transactional database has, which has a great influence. In this paper, Apriori algorithm [22] is applied to realize the temporal association rule mining of college students' extracurricular sports behavior with physical health and sports performance.

II. B. 1) Properties of Apriori algorithm

Suppose the user is given a transaction database DataBase of $\{T_1, T_2, T_3, \ldots, T_n\}$, and a set of all individual itemsets in the transaction database Item of $\{I_1, I_2, I_3, \ldots, I_m\}$, where $T \subseteq Item$. An association rule is an implication such as $x => y$, where x is called the predecessor, y is called the successor and x, y are true subsets of Item, and the intersection of x and y must be the empty set.

Transaction support and confidence are two key concepts in association rule mining algorithms, and are also two evaluation indexes to determine whether an association rule is effective or not. Transaction support indicates the likelihood of an item set appearing in all transactions of a database, and the confidence level of $x => y$ indicates the likelihood of the existence of an item set y in a transaction assuming that the item set x appears in the transaction. Association rule mining searches the database for frequent itemsets that do not fall below the minimum transaction support threshold by using a minimum support threshold set by the user, and then finds rules with strong associations by maximizing the frequent itemsets.

Definition 1: The transactional support of an itemset x is denoted as $sup(x)$:

$$\sup(x) = \frac{|x|}{|D|} \tag{1}$$

Here, $|x|$ denotes the number of times the itemset x occurs in all transactions of the database, and $|D|$ denotes the total number of transactions.

Definition 2: The confidence of $x => y$ is denoted as $conf(x => y)$:

$$conf\left(x \Rightarrow y\right) = \frac{|x \cup y|}{|x|} \tag{2}$$

Here, $|x \cup y|$ is the number of transactions that contain both the x itemset and the y itemset, and $|x|$ is the number of transactions that contain only the itemset x.

Property 1: All non-empty subsets of a frequent itemset are frequent itemsets.

Property 2: All supersets of an infrequent itemset are infrequent itemsets.

Theorem 1: If a single item in the set of frequent $k-$itemsets has less than k repetitions, then that item is not an element of a frequent $(k+1)$-itemset.

Theorem 2: If the number of frequent itemsets in the set of frequent $k-$itemsets is not less than $k+1$, the algorithm continues to iterate, otherwise the algorithm ends.

II. B. 2) Flow of Apriori algorithm

(1) Scan the initial database and consider all individual data items that have appeared in the database as candidate 1-item sets, and the set where the candidate 1-item sets are located is denoted as C_1.

(2) Consider the candidate 1-item sets whose transaction support is higher than the minimum support threshold as frequent 1-item sets, and the set where all frequent 1-item sets are located is denoted as L_1.

(3) Repeat steps 4, 5, and 6 for $k > 1$.

(4) Generate candidate $(k+1)-$ itemsets from the frequent itemsets in L_k by self-joining, and the set where the candidate $(k+1)-$ itemsets are located is labeled as C_{k+1}.

(5) Save the candidate $(k+1)-$ itemsets whose transaction support is higher than the user-specified minimum support threshold to obtain the frequent $(k+1)-$ itemsets, and the set where the frequent $(k+1)-$ itemsets are located is labeled as L_{k+1}.

(6) If the number of itemsets in L is not 0, then $k = k+1$ and step skip 4, otherwise the algorithm iteration ends.

II. B. 3) Disadvantages of Apriori algorithm

The advantage of Apriori algorithm is that the idea is simple, the operation is not complicated, the realization is also easier, but the algorithm at the same time there are many shortcomings. Specifically, there are the following shortcomings:

(1) In the process of generating candidate itemsets by frequent itemsets self-joining, it generates a lot of candidate (k+1)-itemsets when there are few frequent k-itemsets.

(2) Each candidate itemset has to scan the database once when calculating its own transaction support, and the more candidate itemsets there are, the more database scans there are, making the whole algorithm run too long.

(3) The condition of the end of the algorithm iteration is that the number of items in the maximum frequent itemset collection is empty. If there is still an item set in the frequent item set collection, the algorithm will continue until the maximum frequent item set collection is empty, which also makes the algorithm execution time increase dramatically.

II. C.Improved association rule mining algorithm

II. C. 1) Ideas for Algorithm Improvement

Assuming that there are m transactions in the transaction database D and that the set of transactions $D = \{T_1, T_2, T_3, \ldots, T_m\}$. n matters, the set of items $I = \{I_1, I_2, I_3, \ldots, I_n\}$, and one can construct a 0-1 transfer matrix M with m rows and n columns:

$$M = \begin{bmatrix} a_{11} & a_{11} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \tag{3}$$

$$where: a_{ij} = \begin{cases} 1 & a_{ij} \in T_i \\ 0 & a_{ij} \in T_i \end{cases}, i = 1, 2, \ldots, m, j = 1, 2, \ldots, n \quad (4)$$

where the rows of the matrix M correspond to transactions and the columns to matters.

Based on the above transaction database, to illustrate the improvement idea of the algorithm in this chapter. The improvement of the algorithm consists of three aspects: time domain compression, matrix approximation, and candidate set optimization strategy.

Time domain compression: the Gap-Apriori algorithm targets the temporal data, superimposes the transaction items in the time range t_gap, further generalizes the data, and marks the matters with more than half of the frequency of occurrence as the positive trend in the time domain, so as to make the statistical situation more consistent with the reality, and covers the correlation situation in the unit of t_gap.

Matrix approximation: two vectors R and C corresponding to the row and column sums, respectively, are obtained by summing the columns of a Boolean matrix separately. The conditions are extracted according to the rules, and the unwanted transaction rows are removed by utilizing the sum vector R of the Boolean matrix rows, and the matter columns that will be less than the minimum support are removed by utilizing the sum vector C of the Boolean matrix columns.

Optimization strategy for candidate set: separate column j from matrix M and perform an add operation with the data to the right of column j in M to obtain matrix A_j. Accumulate the rows of A_j to obtain the vector a_i, then the vector a_i is the frequent 2-item set judgment condition. Perform the add operation on each column in turn, and combine the results to form an upper-right triangular matrix P, at which time the minimum support can be used to filter the frequent 2-item set, and carry out the search process of frequent 3-item set until there is no set that can satisfy the minimum support.

II. C. 2) Steps to improve the algorithm

The proposed Gap-Apriori algorithm, which combines the improvement ideas of time-domain compression, matrix approximation, and candidate set optimization strategies, improves the efficiency of the algorithm by reducing the number of times the algorithm accesses to the database, and eliminating the redundant candidate sets during the algorithm operation. At the same time, the improved algorithm expands the mining scope of association rules, and more effective analysis results can be obtained. The steps of algorithm realization are as follows:

Step 1, scans the entirety of the data in the target transaction database D and maps the contained transaction information in the database into a Boolean matrix M.

Step 2, merge the data transaction rows by accumulating the Boolean matrix obtained in step 1 along the time axis according to the time domain range t_gap input by the algorithm. During the merging process, if the value of the matrix element a_{ij} obtained from the merging is greater than $t\_gap/2$, the matrix element $a_{ij} = 1$ is set, otherwise the matrix element $a_{ij} = 0$ is set, and a new Boolean matrix M_t is obtained.

Step 3, calculates the cumulative sum col_sum of the element values of each column and the cumulative sum row_sum of the element values of each row in the Boolean matrix M_t, and rearranges the rows of the matrix in descending order according to the cumulative sum of the element values of each row and the columns of the matrix in ascending order according to the cumulative sum of the element values of each column and the cumulative sum of the element values of each column col_sum, respectively.

Step 4, from the Boolean matrix M_t, columns whose cumulative sum of element values per column col_sum is less than the minimum support are removed to obtain the frequent 1 itemset C_1. Subsequently, from the Boolean matrix M_t, the rows in which the cumulative sum of the element values of each row and row_sum is less than 2 are deleted, at which time the matrix M_t obtained after matrix approximation is denoted as matrix G.

Step 5, according to the optimization strategy for calculating the frequency of the candidate set, a judgment matrix P for the frequent itemsets is generated based on the matrix G, and the frequent k itemsets obtained from each round of filtering are stored in the corresponding two-dimensional array map_k.

Step 6, repeat step 5 until no more frequent itemsets are generated.

Step 7, the algorithm ends and outputs all the frequent itemsets found in the algorithm run.

III. Association rule mining analysis based on Apriori algorithm

III. A. Optimized Apriori Algorithm Execution Efficiency Analysis

In order to verify the performance of the improved algorithm, data experiments were conducted to compare with the original Apriori algorithm. The test uses the dataset collected above to generate two sets of datasets with parameters set to T10, I4, D50K, N0.03 and T10, I4, D10K, N0.03, respectively. The significance of which is that the average length of the data items in the dataset is 10, the average length of the frequent items is 4, and the dataset has 50,000 and 10,000 records respectively, and the number of attributes of each record is 30.

Experimental hardware environment: Configuration is Pentium® Dual-Core CPU E6300 (2.80GHz) processor and 2G RAM.

Operating system environment: Windows XP SP3.

Development software: SQL2000+ Visual C++ 6.0.

In order to facilitate the comparison of results, this experiment sets two groups of experiments:

Experiment 1: The dataset parameters are T10, I4, D50K, N0.03, the perturbation parameter p=0.75, and the minimum support min_sup=8%.

Experiment 2: The data set parameters are T10, I4, D10K, N0.03, perturbation parameter p=0.75, and minimum support min_sup=8%.

Fig. 1 shows the results of runtime comparison between the optimized algorithm and the original algorithm on two experiments. As can be seen from the figure, the running time variation between the optimization algorithm and the original algorithm is basically the same in the two experiments, and the analysis is carried out on Experiment 1. When the n-term set n<=5, there is little difference in the running time of the 2 algorithms, while when n=6, the improved algorithm improves its execution efficiency by 1.7 to 2.2 times over the original Apriori algorithm. When n>=7, the execution efficiency of the original Apriori algorithm degrades sharply, while the improved algorithm still maintains good execution. When the order of n is raised to 9 and 10, the running time of the improved algorithm is only 28.21 seconds and 49.07 seconds, which is a 4-fold improvement in execution time efficiency compared to 121.75 seconds and 205.81 seconds of the original Apriori algorithm. Such experimental results show that the improved algorithm in this paper is significantly better than the original Apriori algorithm in terms of time performance.

Based on the results of the above two sets of experiments, it can be found that the execution time efficiency of the improved algorithm is significantly better than that of the original Apriori algorithm, and it is more obvious with the increase of the nth order. And the improved algorithm can show better time performance when dealing with large-scale data sets.

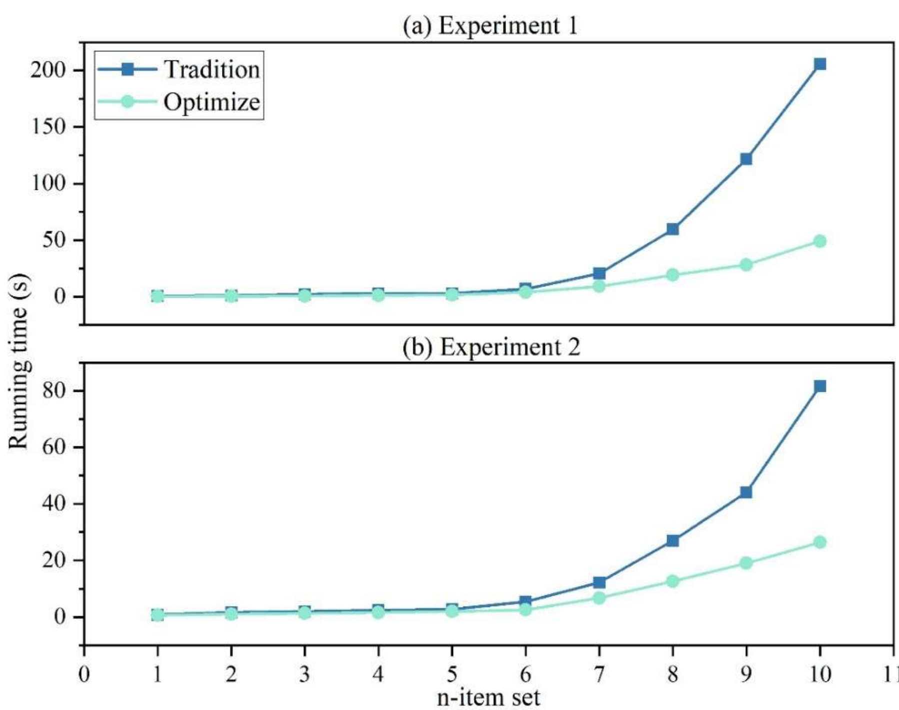

Figure 1: The operating time comparison results of the two experiments

III. B. Knowledge discovery of college students' physical fitness and health based on association rules

In this section, the temporal correlation rules between college students' extracurricular sports behavior and physical health are mined, and the min_Sup=9%, Confidence=60%, and the extracurricular sports behavior stage are the output. The maximum number of entries in the rule results for male college students is 4, and a total of 30 pieces of knowledge are found. After screening, a total of 10 association rules with decision-making significance were found. In order to facilitate the analysis, the physical health indicators of college students were divided into body mass index (BMI), cardiopulmonary index (VO2max), neural response time (RT) and flexibility, and the flexibility was divided into left dorsal hook (LBH) and right dorsal hook (RBH). According to the health status of each index, it is divided into "excellent", "good", "medium", "poor" and "extremely poor", and the score is 5~1 in turn. Table 1 shows the rules associated with the physical health of male college students with different extracurricular sports behaviors.

In the expected stage of extracurricular sports behavior of male college students, there are a total of 4 meaningful association rules. Summarizing the four strongly correlated knowledge, it was found that the flexibility of male college students in the expected stage was "poor", the response was "medium", and the cardiopulmonary function (VO2max) was "very poor". The support of the four rules is 9.84%~10.42%, and the confidence is 71.88%~78.67%. It can be seen that the main manifestation affecting the physical health of male college students in the expected stage is low cardiopulmonary function. There are 3 pieces of physical health knowledge that male college students have strongly associated with in the preparatory stage. In general, male college students in the preparation stage had poor reaction jet lag, poor flexibility, and poor cardiopulmonary function. For example, in serial number 5, male college students responded to "extremely poor" and VO2max "extremely poor", the support of the rule was 10.13%, and the confidence level was 71.14%. In the action stage, the association rules of male college students excavated three meaningful knowledge. The support level is 10.32%~10.61%, and the confidence level is 70.39%~77.46%. At this stage, college students have been exercising for more than a month, but their cardiopulmonary function has not improved, indicating that their exercise is not very targeted.

Table 1: The health association rules of male college students

Number	Consequent	Association rule	Support (%)	Confidence (%)
1	Anticipation	RBH=2, BMI=3, RT=3, VO_2max=1	9.95	74.42
2		LBH=2, RT=3, VO_2max=1	10.02	78.67
3		RBH=2, LBH=2, BMI=3, RT=3, VO_2max=1	10.42	73.74
4		LBH=2, BMI=3, RT=3, VO_2max=1	9.84	71.88
5	Preparation	RT=1, VO_2max=1	10.13	71.14
6		RT=1, LBH=1	10.29	73.18
7		RT=2	9.77	69.19
8	Action	RT=5	10.43	77.46
9		RT=4, VO_2max=1	10.61	70.39
10		RT=4, LBH=3, VO_2max=1	10.32	71.97

In addition, the association rules of physical fitness and health of female college students were mined, and the maximum number of entries of the rule results was 4, and a total of 18 pieces of knowledge were found. After screening, a total of 6 knowledge with decision-making significance was found, and the association rules of physical health of female college students with different extracurricular exercise behaviors are shown in Table 2.

In the expected stage, two related rules were found, and the "very poor" lung capacity and "excellent" flexibility of girls were their physical characteristics, and they did not have the idea of physical exercise. It can be seen that female college students pay more attention to flexibility and ignore the characteristics of strength quality. There are two meaningful association rules for female college students in the preparatory stage of physical exercise behavior, and the characteristics of physical fitness are "excellent" in the back check, "good" in response, and "poor" in VO2max. However, serial number 3 shows that the body mass index is overweight, and participation in physical activity should be actively encouraged. And develop strength, cardiorespiratory endurance qualities in an all-round way. There are two related rules for decision-making support for female college students in the action stage, and the physical fitness of female college students at this stage is characterized by "poor" lung capacity, "medium" reaction time, and "excellent" flexibility. Poor strength, moderate reflexes, overweight body mass index, and low cardiopulmonary function may be the reasons for female college students to participate in physical exercise.

Taken together, the support of the association rule between extracurricular exercise behavior and physical fitness of female college students ranged from 9.96% to 10.87%, while the confidence level ranged from 60.93% to 72.98%. Decision support can continue to encourage their participation in physical activity, form sports habits, and increase confidence in physical activity through regular physical fitness tests.

Table 2: The health association rules of female college students

Number	Consequent	Association rule	Support (%)	Confidence (%)
1	Anticipation	LBH=5, RBH=4, BMI=3, VO_2max=1	10.32	70.87
2		VO_2max=1, RT=3	10.58	71.07
3	Preparation	BMI=2, RT=4	10.74	72.98
4		VO_2max=2, LBH=5	10.04	67.76
5	Action	VO_2max=2, BMI=2, RT=3	9.96	69.71
6		LBH=5, VO_2max=2, RBH=5, RT=3	10.87	60.93

III. C. Association Rule Mining for Motor Behavior and Motor Performance

In order to find the correlation between the body-side items and explore whether the performance of other body-side items can be enhanced by exercising one or more body-side items, the rules of correlation between the body-side items and athletic performance were found from the athletic performance data. Since there are many body-side items for college students, only the standing long jump (A1), long-distance running (A2), pull-ups (A3), rope skipping (A4), lunges (A5), 50m (A6), and sit-ups (A7) are examined in this section.

The results of the association rule mining between motor behavior and body-side motor performance are shown in Table 3. Serial numbers 1~10 in the table show the association rules between exercise behaviors and body-side sport performance of male college students, from which it can be found that there is a strong correlation between standing long jump, long-distance running and 50m, with a confidence level of 0.782. It indicates that exercising standing long jump and long-distance running can indirectly improve the performance of 50m, which is especially applicable to male students. Similarly, serial numbers 11 to 20 are the association rules of female college students' exercise behavior and body-side exercise performance. Observing the association rules, it is found that the main sports that can indirectly improve the performance of sit-ups are long-distance running and 50m with a confidence level of 0.798, which is especially applicable to female students. The results show that using the optimized Apriori algorithm to obtain the frequent items in the physical measurement data can effectively mine the association rules between exercise behavior and the performance of each physical measurement item.

Table 3: The association rules of motion behavior and body side sports table

Male			Female		
Number	Association rule	Confidence	Number	Association rule	Confidence
1	[A1-A2] →A6	0.782	11	[A1-A2] →A7	0.745
2	[A1-A3] →A6	0.694	12	[A1-A4] →A7	0.699
3	[A1-A4] →A6	0.76	13	[A1-A5] →A7	0.725
4	[A1-A5] →A6	0.711	14	[A1-A6] →A7	0.798
5	[A2-A3] →A6	0.692	15	[A2-A4] →A7	0.721
6	[A2-A4] →A6	0.768	16	[A2-A5] →A7	0.693
7	[A2-A5] →A6	0.679	17	[A2-A6] →A7	0.775
8	[A3-A4] →A6	0.686	18	[A4-A5] →A7	0.714
9	[A3-A5] →A6	0.709	19	[A4-A6] →A7	0.756
10	[A4-A5] →A6	0.793	20	[A5-A6] →A7	0.697

IV. Conclusion

Through the experimental analysis in this paper, the correlation between the exercise behavior of college students and their physical health and sports performance was significantly revealed. Male college students have poorer cardiorespiratory fitness in the anticipation stage, indicating that physical exercise in this group needs to focus on enhancing cardiorespiratory endurance in the early stage. Female college students, on the other hand, were more prominent in flexibility but lacked sufficient strength training, showing poor lung capacity and high body mass index. Therefore, differentiated exercise interventions should be developed for college students of different genders.

In the association rule mining of athletic performance, male college students' standing long jump and long-distance running performance had a strong contribution to the improvement of 50m running performance, while female college students were able to indirectly improve the performance of sit-ups through long-distance running and 50m exercise. These results provide a theoretical basis for colleges and universities to develop extracurricular exercise programs, especially in different stages of exercise intervention, which should be personalized according to students' physical characteristics.

The application of the improved Apriori algorithm in time-series data mining not only improves the efficiency of data processing, but also provides data support and decision-making basis for the improvement of college students' physical fitness and health. Future research can further combine student data from different regions and schools to deeply analyze the multidimensional relationship between exercise behavior and health status.

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