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Design of a model for the instructional application of data from a physical fitness monitoring system in promoting student athletic performance enhancement in higher education institutions

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SUMMARY: *The traditional physical education teaching mode of generalization gradually creates invisible limitations on the development of students as their physical fitness levels diversify. In this paper, association rule mining technology is selected to mine the association and hierarchical relationship between physical fitness data and sports performance data, which provides technical support for physical education teaching of students in higher vocational colleges and universities. The association rule mining algorithm framework is formed by deleting unnecessary data transaction items and improving the execution efficiency of Apriori algorithm. In addition, the idea of stratification is introduced to design a stratified training program and teaching planning with the backing of the data support of the physical fitness monitoring system. After the experimental class students were stratified and set up, all of them had the best improvement effect with the low level students ($P<0.01$), the middle level students ($P<0.05$), and the high level students ($P<0.1$). And both male and female groups showed different degrees of significant improvement in exercise level compared with the preexperiment ($P<0.1$). The combination of physical fitness monitoring and stratified training is a scientific and effective new sports teaching mode, which is guided by the real-time changes of students' physical fitness data, and gives the most suitable sports training with full consideration of students' individual differences, and assists in the improvement of students' physical fitness level and sports performance.*

KEYWORDS: *association rules; Apriori algorithm; physical fitness data monitoring; sports performance; physical education stratified teaching*

1 Introduction

With the in-depth promotion of the strategy of Healthy China, higher vocational colleges and universities, as an important base for cultivating high-quality skilled talents, are facing new requirements and challenges in the teaching of their physical education classes [1, 2]. In the face of the urgent demand for comprehensive improvement of the comprehensive quality of talents in the society, the limitations of the traditional physical education teaching mode are becoming more and more prominent, and it is difficult to fully meet the requirements of the times [3, 4]. Therefore, actively exploring and practicing new teaching modes to improve the teaching quality of physical education courses has become the core issue of the current reform of physical education teaching in higher vocational colleges and universities. In recent years, China has successively issued relevant documents on school physical education teaching, continuously strengthened the nurturing function of school physical education teaching,

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emphasized the monitoring and assessment of students' physical fitness, and promoted the healthy development of school physical education [5-7]. Under the support of these policies, the application of physical fitness monitoring system in physical education is gradually becoming common, while more and more higher vocational colleges and universities have developed the design of teaching mode based on the data of physical fitness monitoring system, and have successfully applied it to the work of physical education teaching to enhance students' sports performance [8-10]. The development and application of physical fitness monitoring system in higher vocational colleges and universities is closely related to the development of educational intelligence, which is a comprehensive information system with data collection, analysis, evaluation and feedback based on intelligent technology, sensor technology and other constructions [11-13]. In physical education teaching practice, feedback on students' overall physical quality is provided to physical education teachers by collecting and analyzing students' sports history data, status data, body data, sports performance data, etc [14-16]. Teachers, in turn, can use these data to design targeted teaching models that not only meet the differentiated needs of students, but also adjust teaching strategies in real time to promote the improvement of students' athletic performance [17, 18].

In this paper, Apriori algorithm is used as mining algorithm and its transaction database is adjusted to build an association rule mining algorithm framework applicable to physical fitness data in higher vocational colleges. Then, the physical fitness indicators and sports performance indicators are subdivided, and the association rules are extracted based on the improved Apriori algorithm to construct a physical fitness monitoring system for higher vocational colleges. We select experimental samples and set up teaching experiments to improve students' sports performance under the guidance of the idea of hierarchical teaching, and verify the feasibility of combining the monitoring of physical fitness data with the hierarchical teaching method by analyzing the sports performance data of students at different stages and levels during the experimental process.

2 Framework of association rule mining algorithms

2.1 Description of the basic problem

2.1.1 Frequent data item sets

In the transaction database D, it is assumed that it contains n transactions (i.e., n records) and each transaction has a unique transaction ID number, called TID (i.e., primary key). Each transaction, denoted as T, is a collection of some commodities, each of which is called a data item. Let $I=\{i_1,i_2,\cdots,i_m\}$ be the set of all data items, defining a data item set to be a non-empty set of data items, and the number of data items in the set of data items to be called the length of that data item set. If the data item set X contains m data items, then X is said to be a m data item set or a m length data item set. Obviously each transaction T in D corresponds to a data item set, and for the sake of discussing the problem, it is assumed here that the data items in T are not duplicated and are ordered.

The support and frequent data item sets of data item X are defined as follows:

Definition 1: In database D, a transaction T is said to support X if it contains all subsets of data item set X, and the set of all transactions supporting X is described as $T(X)$. The support of the data item set X is abbreviated as $Supp(X)$, which is the ratio of the number of transactions (records) in D that support X to the number of all transactions.

That is, equation (1):

$$Supp(X) = \left|\{T : X \subseteq T, T \in D\}\right| / |D| \tag{1}$$

Definition 2: For a given minimum support minsup, a data item set X is said to be frequent if its support $Supp(X) > minsup$ and is called a frequent data item set or a large data item set.

Basic association mining is only interested in data itemsets that occur frequently in database records. Data itemsets have the following very useful properties that are the basis for the design of association rule mining algorithms.

Property 1: For a data itemset A, B, if $A \subseteq B$, then $Supp(A) \geq Supp(B)$.

Property 2: The superset of an infrequent data itemset is still an infrequent data itemset.

Property 3: A subset of a frequent data item set is necessarily a frequent data item set, but a data item set in which all subsets are frequent is not necessarily a frequent data item set.

2.1.2 Association rules

The definition of association rules is derived from "shopping basket analysis", where the mining objective is to discover interesting connections between sets of data items in a massive dataset. Typical applications are the discovery of associations between different items in a transaction database, and the discovery of rules that identify patterns in customer purchasing behavior, such as the effect of purchasing one item on the purchase of other items. Discovering such rules can be applied to merchandise shelf design, inventory arrangement, and categorizing users based on purchase patterns. The basic association rules are defined as follows:

Definition 3: Let X,Y be disjoint sets of data items in database D, $X,Y \subseteq I$, $X \cap Y = \Phi$, then the association rule is an implication as in Equation (2):

$$R : X \to Y \tag{2}$$

In the above definition, the condition $X \cap Y = \Phi$, although not absolutely necessary, the lack of which produces redundant rules. For example, the rule $X \to Y$ is obvious and the rule $X \to X \cup Y$ has the same meaning as $X \to Y$ in the process of data mining.

As discussed earlier, association rules must have a certain level of support and confidence in order to be meaningful, and the following gives specific definitions of these two metrics of interest and strong rules.

Definition 4: The confidence of a rule R is referred to as $Conf(R)$ for c, which means that c% of the transactions that support X in the database D also support Y, based on the conditional probability of the definition of equation (3):

$$Conf(R) = p(Y|X) = \frac{p(Y \subseteq T \cap X \subseteq T)}{p(X \subseteq T)} = \frac{Supp(X \cup Y)}{Supp(X)} \tag{3}$$

Definition 5: A support of s for rule R means that s% of the transactions in database D contain $X \cup Y$.

Definition 6: A rule R is said to be strong if it is given a minimum support threshold minsup and a minimum confidence threshold minconf, if $Supp(R) = \min\sup$ and $Conf(R) = \min conf$.

Confidence denotes the strength of the rule and support denotes the frequency of the rule. In the definition of a strong rule, R must satisfy both the conditions of minimum support and minimum confidence to be meaningful. The association rules defined above do not satisfy the transferability and organization in the rule-based reasoning process. In most cases, whether a rule is valid or not cannot be derived from the confidence level of other rules.

2.2 Apriori Algorithm

2.2.1 Fundamentals of Apriori Algorithm

The association rule is defined as follows: $\{T_1, T_2, \cdots, T_n\}$ is the set of n events, $I = \{i_1, i_2, \cdots, i_m\}$ is the set of the set of all items, each transaction $T_j\left(1 \le j \le n\right)$ in database D represents an associated item $\left(T_j \odot I\right)$. An item set is defined as a non-empty subset of I. The association rule can be described as $X \to Y, c, s$, where $X \odot I$, $Y \odot I$, and $X \cap Y = \varnothing$. In this association rule, s is considered as the support of the association rule and c is considered as the confidence of the association rule. Support denotes the proportion of events in which X and Y occur in the same set of events, while confidence denotes the proportion of the total number of occurrences of Y in the set of events in which X occurs in D.

(1) Steps of Apriori algorithm

1) Formulate the minimum support and minimum confidence.

2) Apriori algorithm uses the concept of candidate item set, first produce the set of items, called the candidate item set, if the support degree of the candidate item set is greater than or equal to the minimum support degree, then the candidate item set is called the frequent item set.

3) In the process of Apriori algorithm, all the transactions are first read in by the database to derive the support of the candidate 1-item set C_1, then the frequent 1-item set L_1 is found and the combination of these frequent 1-item sets is utilized to produce the candidate 2-item set C_2.

4) Scan the database again to find the support of the candidate 2-item set C_2, then find the frequent 2-item set L_2, and use the combination of these frequent 2-item sets L_2 to generate the candidate 3-item set C_3.

5) Repeat scanning the database, comparing with the minimum support, generating a higher level of frequent itemsets, and then combining to generate the next level of candidate itemsets, until no longer combined to generate a new candidate itemset.

6) Once the frequent item set is found, strong association rules can be generated. The confidence level is calculated using equation (4):

$$c\left(A \Rightarrow B\right) = P\left(B \middle| A\right) = \frac{count\left(A \cup B\right)}{count\left(A\right)} \tag{4}$$

where the conditional probability is expressed by counting the support of the itemset in terms of $count(A \cup B)$ denotes the number of transactions containing the itemset $A \cup B$ and $count(A)$ denotes the number of transactions containing the itemset A.

According to equation (4), the association rule generation step is as follows:

For each frequent itemset l, generate all non-empty subsets of l;

For each non-empty subset s of l, output rule $s \Rightarrow (l-s)$ if $\frac{count(l)}{count(s)} \geq \min\_conf$.
where $\min\_conf$ is the minimum confidence threshold.

(2) Joining and Pruning

In this algorithm two steps, connection and pruning, are repeated over and over again.

Connection: in order to find L_k, a collection of candidate $k-$ itemsets is generated by connecting L_{k-1} with itself. This set of candidate terms is denoted as C_k. Let l_1 and l_2 be the sets of terms in L_{k-1}. The notation $l\left[i\right]$ denotes the j th item of l_1. Perform the connection $L_{k-1} \infty L_{k-1}$, where the elements l_1 and l_2 of L_{k-1} are connectable if there is a relation (5):

$$(l_1[1]=l_2[1]) \cap (l_1[2]=l_2[2]) \cap \cdots (l_1[k-2]=l_2[k-2]) \cap (l_1[k-1]<l_2[k-1]) \tag{5}$$

The set of resultant items produced by the join is: $l_1[1]l_1[2]\cdots l_1[k-1]l_2[k-1]$

Pruning: the members of C_k may or may not be frequent, but all frequent $k-$ itemsets are contained in C_k. Scan the database to determine each candidate set count in C_k (set a flag bit Flag). From there, determine L_k.

2.2.2 Improvement of Apriori algorithm

From the above analysis, it can be seen that there must be a constant loop to produce the set of candidate $k-$ itemsets C_k, and that each itemset in C_k is produced by doing a $\left(k-2\right)-$ join of two frequent itemsets belonging to L_{k-1} that differ in only one item. The itemsets in C_k are the candidate sets used to generate the frequent sets, and the final frequent set L_k must be a subset of C_k. Each element in C_k needs to be validated in the transaction database to decide whether it is to be added to L_k or not, and the validation process here is a bottleneck in this algorithm. This method requires scanning a potentially large transaction database many times, i.e., if the frequent set contains at most 10 items, then the transaction database needs to be scanned 10 times, which requires a large I/O load. Thus, the main drawbacks of the Apriori algorithm can be seen: firstly, the number of candidate frequent $k-$ itemsets generated by self-joining of frequent $(k-1)-$ itemsets is huge, with a large amount of redundancy, which requires a large amount of auxiliary storage space; and secondly, the entire database needs to be scanned while validating the candidate frequent $k-$ itemsets, which is very time-consuming.

Based on the above analysis, this paper proposes an improvement idea: in the process of scanning the database, some transactions that can be judged not to need to be scanned again are directly deleted from the temporary transaction database, so as to improve the efficiency of Apriori algorithm. The improvement idea is based on the property that the necessary condition for a $k-$term set to be a frequent term set is that all its $(k-1)-$term subsets are frequent term sets, in other words, if a transaction t does not contain any frequent $(k-1)-$term set, then transaction t must not contain any frequent $k-$term set.

The above improvement of Apriori algorithm shows that when transaction t does not contain any frequent $k-$ itemsets, it will be deleted from the temporary database, therefore, the number of transactions in the transaction database will gradually decrease as k increases, especially when k is larger, the number of transactions reduced in the database is larger. In this way, the time for scanning the database is reduced to a certain extent, and the execution efficiency of the algorithm is significantly improved compared with the original algorithm.

3 Association rule-based monitoring system for physical fitness data

3.1 Data acquisition

A total of 8,534 students in their freshman year within Higher Education Institution B were used as the experimental sample, and their raw student data were scrutinized in order to remove the missing value data, and 8,279 student data were retained. According to the need of data mining, physical databases were created by gender, height, weight, and lung capacity. Raw data were consistently processed according to national student health standards. There are 11 colleges in this higher education institution, including College of Liberal Arts, College of Life Sciences, College of Mathematics and Information, College of Animal Science, College of Agriculture, College of Economics and Management, College of Engineering, College of Food, College of Foreign Languages, College of Horticulture, and College of Resources, and the college attributions of the 8279 students are shown in Table 1.The college attributions of the first-year students in this higher education institution are more uniformly distributed, and each college contains students in the range of 500~1000.

Table 1: The affiliation of the college

College	Number	College	Number
Humanities	922	Life Sciences	781
Mathematics and Information	853	Animal Science	834
Agriculture	712	Economics and Management	682
Engineering	698	Food Science	873
Foreign Languages	764	Horticulture	590
Resources	570		

Further combing and extracting the data indicators related to the physical fitness program in the database, there are 12 attributes: (A1) school registration number, (A2) gender, (A3) height (cm), (A4) body weight (kg), (A5) lung capacity (ml), (A6) 50m(s), (A7) standing long jump (cm), (A8) seated body forward bend (cm), (A9) 800m (female) (s), (A10) 1000m (male) (s), (A11) sit-ups (female), (A12) pull-ups (male). Among them, the items tested by different genders are different, i.e., the corresponding data attributes are different, then the physical test data of male and female students were extracted and analyzed respectively, and the physical test scores of some students were listed in Table 2.

Table 2: The physical fitness test results of some students

A1	**** 002	**** 916	**** 850	**** 438	**** 317	…	**** 357
A2	Female	Female	Male	Female	Male	…	Female
A3	165.1	158.6	178.4	163.9	175.9	…	172.3
A4	52.6	43.8	72.8	49.3	68.4	…	55.8
A5	4319	6606	2525	5384	3735	…	2844
A6	9.03	8.99	8.45	9.26	8.11	…	9.73
A7	170.48	165.79	208.37	178.62	229.02	…	210.56
A8	22.6	24.1	16.8	13.1	11.2	…	16.9
A9	210.48	228.74		252.33		…	255.7
A10			218.19		203.63	…	
A11	32	35		29		…	25
A12			3		2	…	
Total score	80	85	79	77	76	…	68

3.2 Establishment and analysis of association rules

Two indicators, (A3) height (cm) and (A4) weight (kg), were combined and expressed as (A34) BMI. So far, there were three indicators of physical fitness: (A2) gender, (A34) BMI index, (A5) lung capacity (m1), and seven indicators of athletic performance: (A6) 50m(s), (A7) standing long jump (cm), (A8) seated forward body flexion (cm), (A9) 800m(s), (A10) 1000m(s), (A11) sit-ups, (A12) pull-ups.

For each indicator, there are five levels of evaluation from excellent to poor: very good, good, fair, poor, and very poor, using a 1-5 scale. For example, “A34-1” would indicate that the student had an excellent BMI, and “T-1” would indicate that the student had an excellent overall physical performance. The minimum confidence level was set at 0.7 and the minimum support level at 0.05. Using Apriori algorithm to mine the association rules between physical fitness indexes and physical fitness of students of different genders, the contents of 20 association rules with confidence level above 0.7 for male students are listed in Table 3.Taking rules 1-3 as an example, it can be seen that the BMI index has a higher degree of influence on the basic physical fitness indexes, such as lung capacity, and if a male student's BMI is above the general grade level, the probability of his physical fitness performance has a probability of achieving a rating above the general grade level of 0.700.

Table 3: Association rules with a confidence level greater than 0.7 (male)

Serial number	s	c	L	Rule
1	0.756	0.108	20.107	A34-1⇒A5-2⇒T-2
2	0.731	0.105	1.0123	A34-2⇒A5-3⇒T-2
3	0.919	0.193	9.917	A34-3⇒A6-3⇒T-3
4	0.906	0.148	24.408	A5-1⇒A6-2⇒T-2
5	0.972	0.086	2.042	A5-5⇒A10-5⇒T-4
6	0.79	0.136	17.972	A5-4⇒A6-5⇒T-4
7	0.802	0.107	19.697	A6-2⇒A10-3⇒A5-2
8	0.936	0.202	6.641	A6-5⇒A5-5⇒A4-4
9	0.99	0.173	14.415	A6-3⇒A8-3⇒T-3
10	0.858	0.143	16.226	A7-2⇒A8-1⇒T-2
11	0.83	0.188	10.844	A7-1⇒A9-1⇒T-1
12	0.967	0.219	7.321	A7-5⇒A10-4⇒A4-4
13	0.766	0.228	24.738	A8-4⇒A9-3⇒T-4
14	0.741	0.087	9.6524	A8-3⇒A6-2⇒T-3
15	0.843	0.114	13.964	A10-2⇒A5-1⇒A2
16	0.916	0.236	23.435	A10-2⇒A6-2⇒T-2
17	0.787	0.136	5.151	A10-3⇒A12-3⇒A2-2
18	0.775	0.201	15.829	A12-1⇒A8-2⇒T-2
19	0.811	0.105	10.048	A12-4⇒A10-5⇒T-4
20	0.975	0.111	18.889	A12-3⇒A8-3⇒T-3

In addition, 20 association rules for female students with a confidence level of 0.7 or higher are listed in Table 4. Taking rules 1-3 as an example, if a female student's BMI can be maintained at or above the average level, her overall physical performance has a probability of 0.7000 or higher to be “very good”, the same as male students, reflecting the cornerstone role of physical fitness in physical performance. This reflects the role of physical fitness as a cornerstone of physical performance.

Table 4: Association rules with a confidence level greater than 0.7 (female)

Serial number	s	c	L	Rule
1	0.737	0.249	0.229	A34-2⇒A5-2⇒T-1
2	0.719	0.089	20.443	A34-4⇒A9-3⇒T-3
3	0.783	0.142	14.908	A34-1⇒A11-2⇒T-1
4	0.817	0.171	11.526	A5-3⇒A6-3⇒T-2
5	0.745	0.157	12.043	A5-5⇒A9-4⇒T-4
6	0.739	0.084	15.541	A5-4⇒A11-3⇒A3
7	0.768	0.139	2.779	A6-2⇒A9-2⇒T-2
8	0.944	0.177	2.302	A6-1⇒A9-1⇒T-1
9	0.914	0.196	9.103	A6-2⇒A5-2⇒T-1
10	0.84	0.094	24.195	A7-3⇒A6-2⇒A2
11	0.827	0.196	3.19	A7-2⇒A6-3⇒T-3
12	0.745	0.135	9.433	A7-3⇒A8-3⇒T-3
13	0.875	0.14	17.99	A8-2⇒A6-3⇒A2
14	0.897	0.151	21.629	A8-1⇒A9-1⇒A1
15	0.872	0.208	7.833	A8-4⇒A11-5⇒T-4
16	0.932	0.199	22.558	A9-5⇒A4-4⇒T-4
17	0.851	0.124	1.037	A9-5⇒A3-3⇒T-4
18	0.869	0.248	21.37	A9-2⇒A11-2⇒T-2
19	0.894	0.238	21.84	A11-3⇒A9-2⇒T-3
20	0.853	0.189	1.809	A11-3⇒A6-3⇒T-2

4 Practical Strategies of Physical Fitness Teaching in Higher Vocational Colleges Based on Stratification

4.1 Accurate assessment and stratification of students' physical fitness

Realizing accurate assessment and stratification of physical fitness based on big data requires the construction of an all-round evaluation system. From a theoretical perspective, it is necessary to combine multiple data collection channels such as wearable devices, intelligent venue sensors, and teaching management systems to collect relevant data such as students' exercise intensity, heart rate variability, movement completion status, and training attitude. Through the association rule mining algorithm framework in this paper, these data should be deeply mined and input into the physical fitness data monitoring system. Present students' physical fitness levels with specific values from different aspects such as cardiopulmonary function, muscle strength, flexibility, and motor coordination. At the same time, it is necessary to introduce a dynamic stratification approach to break through the traditional fixed stratification model, adjust the stratification results in real time according to the data generated by the students at different stages of training, to ensure that the stratification is scientific, reasonable and in line with the actual situation. In addition, the assessment process should emphasize the combination of qualitative and quantitative evaluation, incorporating teacher observation, student self-assessment and mutual evaluation into the scope of evaluation, to comprehensively demonstrate the development of students' physical fitness.

4.2 Development of Tiered Training Programs and Individualized Instructional Plans

In the development of stratified training programs and personalized teaching plans, teachers need to follow the guidelines of teaching students according to their abilities, and develop differentiated training programs based on students' physical condition and personal development needs. From a theoretical point of view, for students with excellent physical fitness, the focus should be on the enhancement of athletic ability and the cultivation of innovative thinking in sports, and the development of high-intensity and difficult special training content, such as combining the principles of sports biomechanics to carry out technical optimization training; for students with medium level of physical fitness, the focus should be on the strengthening of basic physical fitness and expansion of sports skills, and the comprehensive ability should be gradually improved through modularized training; for students with relatively weak fitness, restorative training and individualized training plan should be developed. For students with relatively weak physical fitness, recovery training and interest cultivation should be the main focus, and a gradual training plan should be formulated. At the same time, it is necessary to combine the students' career planning and interests to incorporate special teaching contents, such as adding teaching skills training modules for students majoring in physical education, and designing courses related to body shaping for students majoring in art. In addition, teachers can also use the goal-oriented design method to set short-, medium- and long-term training goals for different levels of students, and equipped with corresponding evaluation standards and incentive mechanisms.

5 Experiments in tiered instruction based on monitoring of fitness data

5.1 Preparation of the study

5.1.1 Objects of study

Considering the significant differences in physiological structure and physical fitness level of individuals by gender, this paper conducts two groups of teaching experiments in girls' classes and boys' classes according to gender. Four public elective classes of physical education in the first year of senior college B were selected as the experimental samples, with 30 students in each of the four classes, two of which were girls' classes and two of which were boys' classes. One of the male and female classes was set up as an experimental class, and the other male and female classes were set up as control classes.

5.1.2 Experimental methods

The layered teaching method under the monitoring of physical fitness data and the traditional teaching method were respectively used to conduct nearly one semester's teaching experiment for the experimental class and the control class, to explore the differences between the two teaching methods in achieving the teaching goals and tasks, so as to validate the superiority of physical education teaching using the layered teaching method.

The stratified teaching method used in the experimental class is mainly based on the principles of psychology and pedagogy, comprehensively analyzing the physical qualities of students before the experiment, determining the teaching content, tasks and objectives of each level, and setting up different teaching methods and learning strategies according to the teaching tasks and objectives of different levels by the teachers, in the process of teaching, the teachers obtain the performance of students' physical qualities in real time through the physical data monitoring system, and make timely and appropriate adjustments accordingly. Students' situation in time to make corresponding adjustments. Encourage students to interact with each other to learn, and adjust the stratification of students according to their learning status, consciously stimulate students' competitive consciousness, so that students always maintain a high degree of motivation and interest in learning, and ultimately make students of all levels reach or exceed the predetermined learning goals through their efforts, a teaching method. In addition, before stratification, according to the students' pre-laboratory test results and questionnaires, the students are divided into different levels and the number of students grouped at each level is determined. Teachers categorize students into three levels (high level, middle level, and low level) based on their physical fitness, learning attitudes, and other factors. During the teaching process, the students are not aware that they are experimental subjects, but are only stratified in real time by the teacher according to the learning situation of the students at different stages of the teaching process.

The control class, on the other hand, is mainly based on the teaching principle of “class lecture system”, which adopts uniform teaching content, tasks and objectives for students, and in the process of teaching, the teacher provides timely guidance on students' learning, encourages interactive learning among students, formulates teaching tasks and objectives based on the learning of most students, and adopts uniform assessment standards to assess students' performance. A teaching method that uses uniform assessment standards to assess students.

5.2 Preliminary results of the study

5.2.1 Physical and athletic performance of the experimental and control classes before the experiment

A total of 9 physical fitness quality indexes of the students in the two experimental classes and the control class before the experiment were combed by gender are shown in Table 5. In the experimental class and the control class of female students, (A34) the mean values of BMI index were 20.31, 20.05 (P>0.1), (A5) the mean values of lung capacity (m1) were 2903.25, 2913.14 (P>0.1), (A6) 50m(s) mean values were 9.02 and 9.00 (P>0.1), (A7) standing long jump mean values were 165.23 and 166.21 (P>0.1), (A8) seated body flexion (cm) mean values were 15.23 and 15.29 (P>0.1), (A9) 800m(s) mean values were 214.12, 214.57 (P>0.1), (A11) sit-ups mean 26.12, 27.26 (P>0.1), respectively, and no indicators showed significant differences. In the experimental and control classes of male students, (A34) the mean values of BMI were 22.35 and 22.51 (P>0.1), (A5) the mean values of lung capacity (m1) were 3206.14 and 3245.23 (P>0.1), (A6) the mean values of 50m(s) were 8.52 and 8.47 (P>0.1), and (A7) standing long jump mean values were 186.03, 187.52 (P>0.1), (A8) seat body forward flexion (cm) mean values were 7.42, 7.69 (P>0.1), (A10) 1000m(s) mean values were 206.28, 205.63 (P>0.1), (A12) pull-up mean values were 2.41, 2.58 (P>0.1), and no indicators showed significant differences. To summarize, there is no significant difference in physical fitness quality between students in the experimental group and the control group before the experiment, and the experimental class and the control class have a high degree of consistency and matching.

Table 5: Comparison of physical fitness performance before the experiment

Type	Female				Male			
	Experi mental	Control	T	P	Experi mental	Control	T	P
A34	20.31±0.89	20.05±0.82	0.534	>0.1	22.35±0.93	22.51±0.95	0.036	>0.1
A5	2903.25±98.58	2913.14±99.47	0.032	>0.1	3206.14±103.49	3245.23±103.56	0.168	>0.1
A6	9.02±0.57	9.00±0.53	0.019	>0.1	8.52±0.43	8.47±0.48	0.365	>0.1
A7	165.23±9.28	166.21±8.65	0.296	>0.1	186.03±12.03	187.52±11.11	0.749	>0.1
A8	15.23±0.67	15.29±0.70	0.201	>0.1	7.42±0.76	7.69±0.77	0.955	>0.1
A9	214.12±14.54	214.57±13.96	0.759	>0.1				
A10					206.28±18.88	205.63±19.02	0.585	>0.1
A11	26.12±3.78	27.26±3.06	0.376	>0.1				
A12					2.41±0.48	2.58±0.41	0.758	>0.1

5.2.2 Comparison of physical fitness and athletic performance of students in the control class after the experiment

Comparison of the post experimental physical fitness performance between the female control class and the male control class is shown in Table 6.It can be seen that after one semester of teaching and learning, the mean value of (A5) spirometry (m1) of the female control class was 2913.39, which did not show a significant difference from the pre experimental (2913.14) (P=0.294>0.1). (A6) The mean value of 50m(s) was 8.93, which did not show a significant difference from the pre-experimental (9.00) (P=0.153>0.1). (A7) The mean value of standing long jump was 169.45, which did not show a significant difference (P=0.282>0.1) from the preexperimental (166.21). (A8) The mean value of seated forward body flexion (cm) was 15.82, which did not show a significant difference from the pre-experimental (15.29) (P=0.373>0.1). The mean value of (A9) 800m(s) was 212.1, which did not show significant difference from the pre-experimental (214.57) (P=0.292>0.1), and the mean value of (A11) sit-ups was 29.37, which did not show significant difference from the pre-experimental (27.26) (P=0.183>0.1). The data of (A5) lung capacity (m1), (A6) 50m(s), (A7) standing long jump, (A8) seated body forward flexion (cm), (A10) 1000m(s), (A12) pull-ups of the male control class after the experiment were 3277.57, 8.36, 193.99, 8.23, 202.42, and 3.52 in that order, and compared with the data of the pre-experiment P values were 0.267, 0.286, 0.369, 0.166, 0.164, 0.267, respectively, all > 0.1, and again none of them showed statistically significant differences. It shows that traditional teaching methods in physical education courses do not have a high enhancement effect on students' physical fitness quality or even sports performance.

Table 6: Physical fitness analysis of the control class after the experiment

Type	Female				Male			
	Experimental stage		Sig(bilateral)	T	Experimental stage		Sig(bilateral)	T
	Before	After			Before	After		
A34	20.05±0.82	20.23±0.81	0.183	1.327	22.51±0.95	22.86±0.96	0.179	-1.247
A5	2913.14±99.47	2913.39±95.74	0.294	1.496	3245.23±103.56	3277.57±100.47	0.267	1.887
A6	9.00±0.53	8.93±0.55	0.153	-1.099	8.47±0.48	8.36±0.49	0.286	1.301
A7	166.21±8.65	169.45±8.74	0.282	-1.131	187.52±11.11	193.99±10.98	0.369	-1.606
A8	15.29±0.70	15.82±0.72	0.373	1.842	7.69±0.77	8.23±0.71	0.166	1.715
A9	214.57±13.96	212.1±13.58	0.292	1.185				
A10					205.63±19.02	202.42±18.76	0.164	-1.254
A11	27.26±3.06	29.37±2.97	0.183	-1.327				
A12					2.58±0.41	3.52±0.48	0.267	1.887

5.2.3 Comparison of physical fitness and athletic performance of students in the experimental class after the experiment

Comparison of physical fitness and athletic performance between the girls' and boys' experimental classes after the experiment is shown in Table 7.The girls' experimental class not only showed a significant improvement in physical fitness (A5) lung capacity (m1) compared with the preexperimental period (P=0.009<0.01), but also narrowed the gap between the classes in the stratified teaching mode. Similarly, in (A6) 50m(s), (A7) standing long jump, (A8) seated body flexion (cm), (A9) 800m(s), and (A11) sit-ups, all of them showed a statistically significant difference of P<0.05 compared with the pre-experimental performance. Similar to the performance of the girls' experimental class, the boys' experimental class showed statistically significant differences in both physical fitness and athletic performance indicators under the tiered teaching mode. Its physical fitness quality index (A5) lung capacity (m1) was improved by 226.14 on average compared to the preexperiment, while in the sports performance quality index, there were (A6) 50m(s) improved by 0.39 on average, (A7) standing long jump improved by 12.68 on average, (A8) seated body forward bending (cm) improved by 1.13 on average, (A10) 1000m(s) improved by 9.46, and (A12) pull-ups improved by 2.67 on average.

Table 7: Physical fitness analysis of the experimental class after the experiment

Type	Female				Male			
	Experimental stage		Sig(bilateral)	T	Experimental stage		Sig(bilateral)	T
	Before	After			Before	After		
A34	20.31±0.89	20.44±0.72	0.011	2.492	22.35±0.93	22.91±0.86	0.014	3.491
A5	2903.25±98.58	3026.7±80.34	0.009	-2.847	3206.14±103.49	3432.28±95.28	0.018	2.903
A6	9.02±0.57	8.71±0.33	0.002	2.054	8.52±0.43	8.13±0.39	0.021	-3.478
A7	165.23±9.28	174.81±7.43	0.003	-3.002	186.03±12.03	198.71±9.64	0.003	3.178
A8	15.23±0.67	16.12±0.49	0.008	2.012	7.42±0.76	8.55±0.58	0.026	-3.321
A9	214.12±14.54	205.59±10.28	0.002	3.188				
A10					206.28±18.88	196.82±15.24	0.028	2.571
A11	26.12±3.78	31.59±3.03	0.011	-2.492				
A12					2.41±0.48	5.08±0.41	0.018	2.903

5.2.4 Comparative analysis of students' performance between experimental and control classes after the experiment

Comparison of the physical quality and motor performance of the girls' experimental class with the control class and the boys' experimental class with the control class after the experiment, respectively, is shown in Table 8.Overall, both the girls' experimental class and the boys' experimental class showed superior physical quality and motor function compared with the control class after the experiment, and achieved a p-value of <0.05 for each index, respectively. Specifically, the girls' experimental class had (A5) lung capacity (m1) 113.31 more than the control class after the experiment, (A6) 50m(s) 0.22 ahead of the control class, (A7) standing long jump 5.36 more than the control class, (A8) seated body flexion (cm) 0.3 more than the control class, (A9) 800m(s) 6.51 ahead of the control class, (A11) sit-ups more than the control class by 2.22. The male experimental class, on the other hand, had 154.71 more lung capacity (m1) than the control class after the experiment in (A5), 0.23 ahead of the control class in (A6) 50m(s), 4.72 ahead of the control class in (A7) standing long jump, 0.32 ahead of the control class in (A8) seated body forward flexion (cm), 5.6 ahead of the control class in (A10) 1,000m(s), (A12) pull-ups 1.56. The facilitating effect of a tiered instructional approach on students' athletic performance enhancement, monitored by physical fitness data, was fully validated.

Table 8: A comparison of the performance of different classes after the experiment

Type	Female				Male			
	Experi mental	Control	Sig(bilateral)	T	Experi mental	Control	Sig(bilateral)	T
A34	20.44±0.72	20.23±0.81	0.023	3.441	22.91±0.86	22.86±0.96	0.013	3.422
A5	3026.7±80.34	2913.39±95.74	0.001	-3.245	3432.28±95.28	3277.57±100.47	0.031	3.118
A6	8.71±0.33	8.93±0.55	0.014	2.194	8.13±0.39	8.36±0.49	0.009	-3.135
A7	174.81±7.43	169.45±8.74	0.034	-2.417	198.71±9.64	193.99±10.98	0.019	-2.992
A8	16.12±0.49	15.82±0.72	0.037	2.816	8.55±0.58	8.23±0.71	0.0325	3.176
A9	205.59±10.28	212.1±13.58	0.030	2.037				
A10					196.82±15.24	202.42±18.76	0.003	-2.118
A11	31.59±3.03	29.37±2.97	0.023	3.441				
A12					5.08±0.41	3.52±0.48	0.031	3.118

5.3 Comparison of athletic performance enhancement of students at different levels of study

The LSD multiple comparisons of the athletic performance of the students in the experimental classes at different levels before and after the experiment were conducted, and the results of the LSD multiple comparisons of the students in the male class in five athletic performance indicators, namely, (A6) 50m(s), (A7) standing long jump, (A8) seated body flexion (cm), (A10) 1,000m(s), and (A12) pull-ups, are shown in Table 9. Thanks to the tiered teaching method and the monitoring of physical fitness data, teachers were able to formulate corresponding teaching plans based on the physical fitness and athletic performance of students at different levels, so as to achieve the optimal teaching effect according to the students' abilities, and thus the overall five athletic performance indexes of the three levels of male students were significantly improved after the experiment. In addition, the most obvious improvement in the five sports performance was found in the lower level students ($P<0.01$), followed by the middle level students ($P<0.05$), and the last improvement in the higher level students ($P<0.10$), because the students' sports performance level increased with the level of the students, and the room for improvement was reduced accordingly.

Table 9: The multiple comparison results of LSD in the male experimental class

Level	Sport performance	Mean difference	Standard error	Significance	95% confidence interval	
					Lower limit	Upper limit
High	A6	0.49	0.2117	0.084	-0.0399	0.0064
	A7	12.81	0.1968	0.056	-0.1188	0.0055
	A8	1.17	0.4819	0.084	-0.1309	0.1375
	A10	9.55	0.3951	0.071	-0.1454	0.1252
	A12	2.72	0.1752	0.082	-0.0551	0.0134
Medium	A6	0.48	0.1619	0.007	-0.0916	0.1798
	A7	12.8	0.1378	0.021	-0.1632	0.0395
	A8	1.16	0.2105	0.024	-0.1825	0.0038
	A10	9.54	0.1042	0.007	-0.1126	0.0648
	A12	2.71	0.4883	0.045	-0.147	0.1884
Low	A6	0.56	0.0295	0.002	-0.0289	0.1756
	A7	12.91	0.2299	0.004	-0.1369	0.0431
	A8	1.18	0.2048	0.007	-0.0032	0.1983
	A10	9.61	0.0171	0.001	-0.0955	0.066
	A12	2.74	0.2017	0.006	-0.1933	0.0606

Similarly, the results of LSD multiple comparative analysis of pre- and post-experimental data of the students in the girls' class in (A6) 50m(s), (A7) standing long jump, (A8) seated body flexion (cm), (A9) 800m(s), and (A11) sit-ups are shown in Table 10.After one semester of the layered teaching method, the girls' experimental class performed similarly to the boys' class, both in terms of the overall athletic performance and the effect of improvement in each level. After one semester of layered teaching method, the girls' experimental class was consistent with the boys' class in terms of both overall exercise performance and the effect of enhancement at each level. The overall athletic performance of the girls' experimental class was significantly improved compared with that of the boys' class before the experiment ($p<0.1$), and the improvement effects, in descending order, were as follows: low level ($p<0.01$)>medium level ($p<0.05$)>high level ($p<0.1$), which verified the high feasibility of combining the monitoring of physical fitness data with the layered teaching method to promote the improvement of the students' athletic performance level.

Table 10: The multiple comparison results of LSD in the girls' experimental class

Level	Sport performance	Mean difference	Standard error	Signi ficance	95% confidence interval	
					Lower limit	Upper limit
High	A6	0.40	0.2832	0.056	-0.1828	0.0649
	A7	9.70	0.1737	0.05	-0.1559	0.0414
	A8	0.92	0.2382	0.078	-0.1194	0.0708
	A10	8.61	0.2913	0.051	-0.0025	0.0475
	A12	5.51	0.1458	0.095	-0.0903	0.1461
Medium	A6	0.41	0.1339	0.002	-0.0931	0.1633
	A7	9.71	0.0012	0.006	-0.1526	0.0499
	A8	0.93	0.2735	0.041	-0.1825	0.0778
	A10	8.62	0.0842	0.029	-0.0485	0.0583
	A12	5.52	0.0356	0.012	-0.0124	0.0855
Low	A6	0.48	0.2788	0.003	-0.0444	0.1078
	A7	9.81	0.2888	0.003	-0.1799	0.0588
	A8	0.94	0.1809	0.006	-0.1423	0.1429
	A10	8.68	0.2024	0.005	-0.1257	0.1338
	A12	5.54	0.1724	0.001	-0.0394	0.1612

6 Conclusion

This paper combines the overall physical fitness and sports performance data of the experimental sample of students in higher vocational colleges and universities, using gender, BMI and lung capacity (ml) as three physical fitness monitoring indicators, and 50m(s), standing long jump (cm), seated body forward flexion (cm), 800m(s), 1000m(s), sit-ups, and pull-ups as seven sports performance performance indicators. The minimum confidence level was set at 0.7 and the minimum support level at 0.05, and the relationship between students' physical fitness quality and their athletic performance was reflected through the association rule mining to realize the effective use of physical fitness data.

With the assistance of the physical fitness monitoring system, the teaching comparison experiment of stratified teaching method was launched. After one semester of teaching experiment, the female experimental class and the male experimental class achieved different degrees of significant improvement ($P<0.1$) in the values of their corresponding five sports performance indexes compared with the pre-experimental and control classes. At the same time, within their levels, due to the targeted teaching and training, both the girls' and boys' experimental classes have positively improved their athletic performance levels, and the improvement effect shows the pattern of low level ($p<0.01$)>medium level ($p<0.05$)>high level ($p<0.1$).

The physical fitness level of students was accurately assessed through the correlation of physical fitness indicators and sports performance indicators, which provided a reliable real-time adjustment direction for the teaching plan and training program during the teaching process, and it is a new type of physical fitness monitoring mode applied to sports training, which can satisfy the diversified needs of individual students for the contents and methods of sports teaching and is conducive to the effective enhancement and stable development of the students' overall sports performance and the core qualities of sports. It is conducive to the effective improvement and stable development of students' overall athletic performance and sports core literacy.

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