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Article

Research on Intelligent Optimization of Teacher Education Teaching Strategies Driven by Big Data in the Perspective of Basic Theory of Education

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Abstract: To clarify the teaching strategies and effects of teachers in educating students from the perspective of big data, this paper proposes a K-means algorithm based on density optimization. The behavioral data generated by different students are classified into classes for students with similar types. Then, the FP-growth algorithm is used to mine the correlation between students' learning effects and their learning behaviors. Provide students with a more targeted educational management model and better services. The results show that there is a positive correlation between joint entropy time and space and students' frequency of campus activities and grades, and there is a strong correlation between the total number of times students go to the library, the number of times they consume in the cafeteria, and students' grades; 54% of the students in the campus have a regular time and space behaviors, and 55.08% of the students show low intensity in their study behavioral inputs. In this paper, four class clusters of students were obtained by clustering students' consumption behavior, library borrowing behavior and students' sports behavior respectively. In the process of teaching, teachers should guide students in the first category to strengthen sports and participate in activities in moderation; let students in the second category take more important roles in the team to show and develop their leadership skills; for students in the third and fourth categories, they can cultivate their ability to socialize with others by recommending them to read books and works that are rich in philosophical and interpersonal behaviors.

Keywords: K-means algorithm; FP-growth algorithm; association rule mining; student behavior; teacher education and teaching

1. Introduction

The scientific level of teachers' educational and teaching strategies is a key element that affects the quality of education and teaching. Scientific teaching strategies often rely on a comprehensive grasp of the objective teaching situation, and access to the objective teaching situation often requires the use of advanced information technology means [1-3]. In recent years, with the application and development of cloud computing, mobile Internet and Internet of Things in the field of education, the amount of educational data has been growing explosively, and the era of educational big data has arrived [4-5]. Educational big data has injected new vitality into informatization teaching, and under the perspective of the basic theory of education, the scientific and reasonable application of big data to optimize teachers' teaching strategies and enhance the effect of education and teaching is an important part of the reform and innovation of informatization teaching [6-8].

In the classroom under the traditional teaching environment, the teaching roles are relatively simple, the teacher is the only subject of teaching strategies, and all the teaching strategy behaviors basically depend on the teacher's individual factors such as the teacher's knowledge and ability, experience and intuition [9-12]. Although these factors are not without their roles, they are often unstable and difficult to guarantee the consistency of strategic behaviors, and sometimes they even tend to lead to stubbornness and prejudice, which is not conducive to tailoring teaching to students' needs [13-14]. Driven by big data, teachers are able to obtain all kinds of data in the whole process of teaching, and these data are dynamically updated and infinitely related to the outside, through the deep mining and systematic analysis of these data, they can comprehensively grasp the teaching situation in real time, discover every detail in all aspects of teaching in a timely manner, and use data modeling to quickly make predictions, adjust and optimize the teaching strategy, and respond to various changes in the teaching scene at any time and any place. Various types of changes [15-19]. Big data makes the teaching strategy process from "passive feedback" to "active prediction" transformation. That is, teachers do not need to wait until the end of teaching to make adjustments to teaching strategies and optimize teaching programs [20-22]. Instead, they can establish a teaching early warning system through forecasting, directly identify current and future teaching trends, accurately control students' learning problems and potential needs in real time, and actively make corresponding strategies to improve teaching programs and enhance teaching effectiveness [23-26].

Teaching is the process of transferring knowledge and developing students' abilities, and teachers' teaching strategies are an important foundation of this process, and excellent teachers' teaching strategies are the key to realizing effective teaching. Literature [27] examined the impact of effective teaching strategies on good learning outcomes, pointed out through a questionnaire survey that effective teaching strategies have a positive impact on producing good and rapid learning outcomes, and suggested that teachers realize effective teaching methods by continuously improving their teaching strategies. Literature [28] analyzed the link between teachers' professional development and the effective application of newly acquired teaching strategies, based on analyzing teachers' questionnaires and interview data indicated that there is a significant positive correlation between teachers' professional development, teaching strategies and students' learning outcomes. Literature [29] examined the impact of interactive teaching strategies on students' learning outcomes and emphasized that the teaching strategy played an important role in improving students' critical thinking skills and collaborative skills. Literature [30] discussed the impact of different teaching strategies on students' academic achievement, and the findings concluded that traditional teaching methods positively impacted students' mathematical abilities, while more innovative active learning strategies negatively impacted students' academic achievement. Literature [31] articulates that scholars who attempt to translate the NLF into teaching practice face a daunting task that requires them to look beyond even their own disciplines to find instructional strategies that will meet the prescribed learning outcomes. Literature [32] analyzed the impact of active learning and student-led instructional strategies on student success and cognition, and the results showed that these instructional strategies had a positive impact on student learning outcomes and teaching evaluation. Literature [33] examined the overall impact of flipped classroom instructional strategies on student learning outcomes, and the literature review found that flipped classroom instructional strategies had statistically significant effect sizes. Literature [34] explored the relationship between students' classroom engagement and teachers' teaching strategies, highlighting the fact that teachers' teaching strategies are crucial for improving students' classroom engagement, and that in order to improve students' classroom engagement, teachers need to continuously optimize their teaching strategies.

Traditional teachers' teaching strategies mostly rely on teachers' personal experience, and the implementation of teaching strategies does not comprehensively consider the overall needs of students, while the application of big data has transformed the teaching methods of teachers and provided a scientific basis for optimizing teaching strategies. Literature [35] verifies the effectiveness of the big data-driven teaching strategy optimization and learning resource allocation model, and describes the application of big data in promoting educational equity and improving the quality of education. Literature [36] proposed an innovative method for analyzing and predicting attention and learning emotions in adaptive teacher-student interactions in intelligent teaching environments, and verified that the method has a very high accuracy rate, providing optimization strategies and theoretical support for personalized intelligent teaching. Literature [37] examined the analysis of students' learning behaviors and accurate teaching based on big data, and constructed various learning behavior analysis models to understand students' individualized needs and provide teachers with a strong basis for teaching reform. Literature [38] outlines the common application models of big data precision teaching, describes its implementation procedures, and verifies them through case studies, and analyzes the challenges faced in integrating big data into the process of precision teaching. Literature [39] proposes an accurate teaching model based on educational big data, and accurately analyzes each student's knowledge mastery based on the student's test performance, thus realizing personalized learning, emphasizing that the use of big data for accurate teaching in education can meet the learning needs of students at different levels. Literature [40] aims to investigate a framework model as a way for teachers to adapt to big data to help improve teaching effectiveness in the expectation of enhancing teaching effectiveness and exploring personalized teaching capabilities in the era of big data. Literature [41] analyzes a framework for the application of big data in the assessment of teaching quality in higher education, especially in the areas of data collection and integration, personalized learning path design, and innovation of teaching content and strategies. Literature [42] discusses the application of big data in education, exploring the development of complex models and their application to the allocation of teaching resources, and emphasizing personalized teaching strategies aimed at using big data to create rich and tailored learning environments that improve student engagement, satisfaction, and learning outcomes.

Due to the shortcomings of the traditional K-means algorithm in selecting the center of mass, determining the number of clusters, and dealing with non-convex datasets, this paper optimizes the algorithm in scientifically selecting the initial center of mass as well as reducing the number of distance calculations, and uses the algorithm to cluster student populations under different behavioral characteristic indicators. In order to clarify the correlation between teachers' education and teaching effects and behavioral habits, Apriori algorithm was introduced. However, because this algorithm needs to traverse the dataset several times, which leads to low efficiency and time-consuming data mining, this paper improves the Apriori algorithm by constructing an FP-tree and extracting the frequent item set directly from it, so as to obtain effective association rules. Finally, the correlation between students' activity patterns, students' behaviors and students' behaviors and teachers' education and teaching effects are analyzed, and corresponding optimization strategies are proposed for different types of students in the process of teachers' education and teaching.

2. Data-driven Intelligent Optimization of Teachers' Education and Teaching Strategies

2.1. Application strategy of teaching model based on big data algorithm analysis

2.1.1. Teacher education teaching model

To build a blended teaching model based on big data algorithm analysis, first of all, it is necessary to label all teaching resources and knowledge points involved in the whole process of the blended teaching model online and offline, and then effectively sort out and pre-process them, select appropriate data resources, so that it can accurately locate the knowledge point chapters corresponding to the teaching resources, so as to facilitate the teachers in the teaching of the students. Accurate teaching resources are pushed and targeted guidance is provided to meet the requirements of teaching students according to their aptitude.

In the blended teaching mode, students' online learning data information mainly includes online learning time, teaching resources viewing, online forum browsing and posting, online homework completion and online test scores, etc. Students' online learning data information is shown in Figure 1. In the blended teaching mode, students' offline learning data information mainly contains class attendance, class performance, group discussion speeches, offline activities and offline grades, etc., and students' offline learning data information is shown in Figure 2.

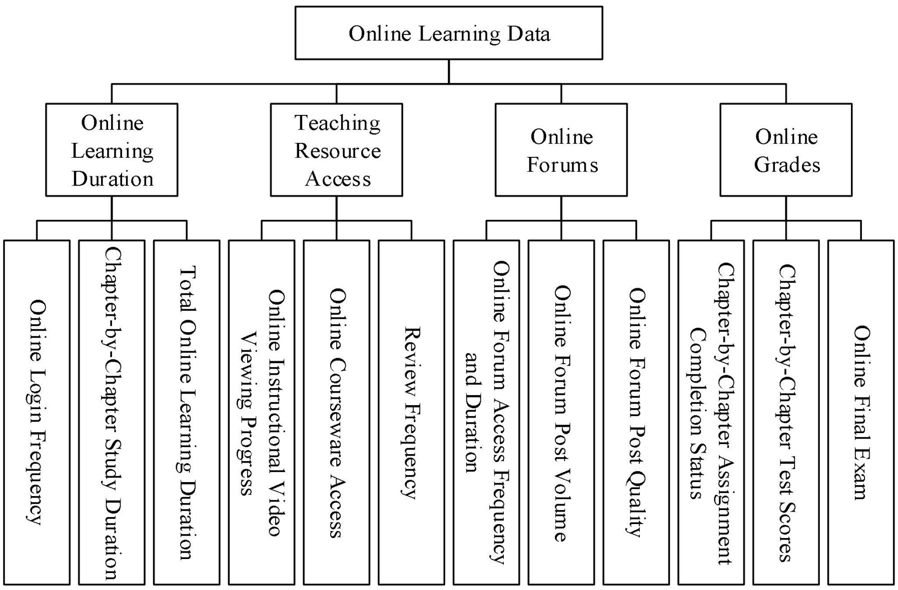

Figure 1. Student online learning data.

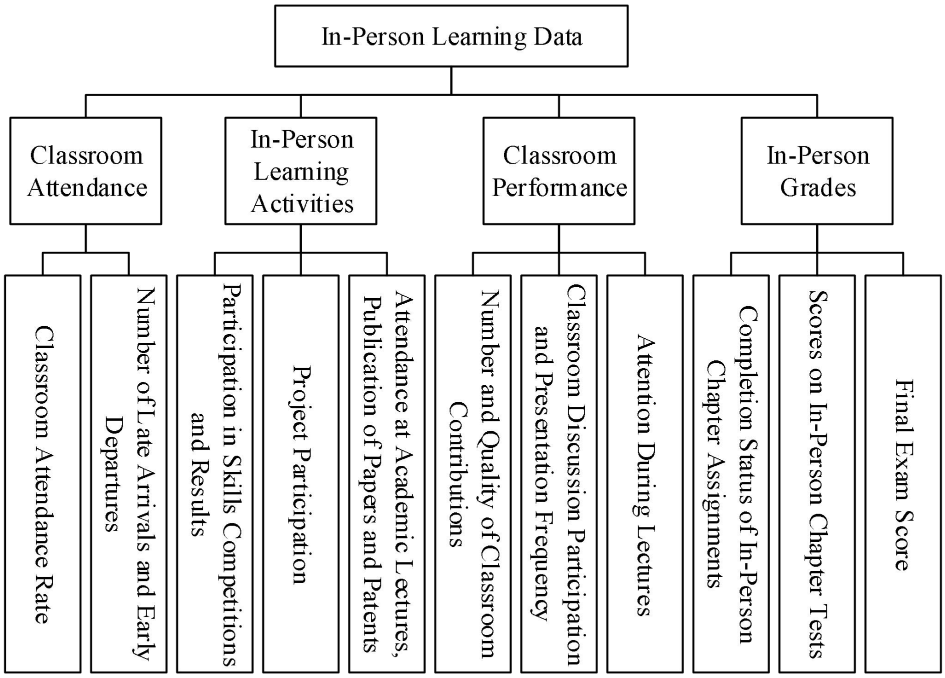

Figure 2. Offline learning data for students.

2.1.2. Utilizing big data algorithms

(1) Assessment of students' learning status

In the teaching process, association rule big data algorithms are used in phases to mine the data information of students' online and offline learning, to find out the interdependence and dependence rules between the data items hidden in the data set, with special focus on mining out the strong association rules between the data items in the online learning data set and the data items in the offline data set.

(2) Personalized Teaching

In the teaching process, clustering algorithm is used to cluster and analyze the data information of students' online and offline learning, cluster the students with close learning level into one class, divide the class into several classes, classify the teaching of students, arrange different independent learning contents to meet the needs of students' personalized learning, and dynamically adjust the clustering situation of the students and the teaching contents during the teaching process to adapt to the students' constantly changing learning needs. And in the process of teaching, students' clustering and teaching content are dynamically adjusted to meet students' changing learning needs.

(3) Online and offline hybrid course learning evaluation

Neural network big data algorithms can be used in the construction of course learning evaluation. Since neural networks can approximate a given continuous function with arbitrary accuracy, they are very suitable for the big data algorithms of online-offline hybrid course learning evaluation. Firstly, multiple learning data information of students is used as input layer neurons in stages, then a neural network is used, the hidden layer can be set dynamically according to the actual situation, and the course learning evaluation value is set as the output layer, and an optimal neural network is trained and fitted through the back-propagation algorithm, which is ultimately used as an online-offline hybrid course learning evaluation model.

2.1.3. Instructional interventions based on analysis of data outcomes

In the blended teaching mode, it is necessary to increase online teaching interventions, which should rely on the current network intelligence platform for students' online learning, and use the results of data analysis such as students' learning status assessment and personalized teaching to carry out teaching interventions on students' online learning status and content in multiple periods of time. Through these online teaching interventions and the combination of traditional offline teaching interventions, it can effectively improve the teaching effectiveness of teachers in the blended teaching mode. Through these online teaching interventions and the combination of traditional offline teaching interventions, teachers can effectively improve the teaching effect in the blended teaching mode.

2.2. Pre-processing of data

The data in this paper comes from the data stored in the campus card consumption data management system, library management system, and student sports data management system of a university in Northwest China for the academic year 2023~2024. It includes 42,591 enrolled students, with a total of 25,132,041 pieces of daily consumption behavior (42,591) running data; a total of 114,312 pieces of library book borrowing behavior (10,527 people) data; and a total of 35,979 pieces of student sports (7,954 people) behavior data. After these data are cleaned, integrated, converted and selected through data preprocessing techniques, the data of these three types of student behavioral indicators are clustered and analyzed separately using the clustering algorithm of this paper.

(1) Data cleaning

Data cleaning is the process of amending the disorganized, erroneous, repetitive, and non-conforming "dirty data" into "clean data" that can be directly brought into the model. Data preprocessing is mainly to remove missing values, deal with outliers, simple processing of text strings and so on.

(2) Data Integration

After pre-processing the data in order to facilitate data mining we need to integrate a variety of different types of data. Because in the actual storage process will face the problem of inconsistent data types, so we need to integrate different data according to the specific circumstances to make the final input data meet the requirements.

(3) Data transformation

Data transformation is mainly for different forms of data into a unified form. In this paper, we mainly study the consumption of students, and the transformed data with consistency are aggregated, generalized and other operations are discretized. The discretized data has the characteristics of strong stability, which can make the fitting risk reduced.

(4) Data Statute

The mining of large amounts of data is not conducive to the improvement of efficiency, so we need to compress the data. The statute of the data is to ensure that the original appearance of the data through the transformation of the data compression process, common dimension statute, the number of statutes and data compression and other ways. Since the data in storage and this paper are not directly related, we can use the data statute to reduce the amount of data to be processed.

2.3. Clustering Algorithm for Behavioral Characteristics of High School Students

2.3.1. Segmentation of student behavioral characteristics

(1) Student consumption behavior indicators

Based on the data collected in the campus card, two indicators are constructed: the average monthly consumption amount of college students and the average monthly consumption frequency of college students. Through clustering of the average monthly consumption amount and the average monthly consumption frequency, the economic level and consumption habits of an undergraduate student can be presented.

(2) Indicators of students' life pattern

In this study, through the diet consumption data and bath consumption data recorded on the campus one-card platform, the campus log data, network subscription data, and morning running punch card data in the business system, the life behavior habits of undergraduates in colleges and universities are clustered and analyzed. According to the indicators of dietary routine, work and rest habits, physical exercise, bathing routine and Internet access routine, students' self-control ability can be examined to a certain extent.

(3) Indicators of students' learning behavior

As a college student, learning knowledge occupies a crucial position, in order to clearly show the students' efforts in learning life, this paper analyzes the school's library management platform and teaching management platform, and constructs four indicators, namely, "library access indicator, study room access indicator, book borrowing and class attendance rate" to reflect the students' learning behavior. "This paper analyzes the school library management platform and the teaching management platform, and constructs four indicators to reflect students' learning behavior.

2.3.2. Density-based optimization K-means algorithm

(1) K-means algorithm

The K-means algorithm [43], as a classical unsupervised clustering algorithm, is characterized by its ease of operation, ability to handle large-scale data sets, and fast convergence.

The K-means algorithm generally chooses the sum of squared errors (SSE) as an evaluation metric to measure the clustering effect. D_i is the i th cluster, x is the sample point in D_i, d is the distance between two objects, and k is the number of clustering categories. Namely:

$$SSE = \sum_{i=1}^{k} \sum_{x \in D_i} d(D_i, x)^2 \tag{1}$$

When k is certain, the smaller the SSE the better the clustering effect. As the value of k increases, the sample classification becomes finer, the degree of aggregation is higher, and the sum of squared errors becomes smaller.

(2) Improved K-means algorithm

The initial center of mass selection of the traditional K-means algorithm is often random, making it difficult to obtain a globally optimal solution. In this paper, we utilize a density-based method to select the initial center of mass, assuming the dataset $X = \{x_1, x_2, \ldots, x_n\}$, x_i is one of the sample points, k is the number of clusters, n is the number of samples, and N is the number of numbers. The density of the sample points in the dataset, $D(x_i)$, and the density threshold of the dataset, Density threshold, are compared, and then the sample points are assigned to either a high-density dataset, H, or a low-density dataset, L, and the samples with densities greater than the threshold are classified into the H dataset, while those with densities less than the threshold are determined to be outlier points, and are grouped into the L dataset. In this paper, the sample point with the largest density value in the sample set H is chosen as the first initial center of mass μ_1, and then it is removed from the sample set H; Select the second initial center of mass μ_2, so that it satisfies the distance $d(\mu_1, \mu_2)$ between μ_2 and μ_1 is greater than the threshold r, and μ_2 should have the maximum density at this time, and so on, until the selection of the k initial center of mass.

Arbitrarily select two samples x_i, x_j, using the Euclidean distance to calculate the distance between the two get:

$$d(x_i, x_j) = \sqrt{(x_i - x_j)^2}, i = 1, 2, \ldots, n, j = 1, 2, \ldots, n \tag{2}$$

The density of any sample point x_i in the data set X is denoted as:

$$D(x_i) = N\{x \mid d(x, x_i) < r, x \in X\} \tag{3}$$

Calculating the average density of the dataset yields:

$$avgD(x_i) = \frac{\sum_{i=1}^{n} D(x_i)}{n} \tag{4}$$

Calculating the dataset density threshold, where c is a constant, yields:

$$Density\ threshold = c \times avgD(x_i) = c \times \frac{\sum_{i=1}^{n} D(x_i)}{n} \tag{5}$$

For the problem of distance calculation, the traditional K-means algorithm has a tedious calculation process, and this paper optimizes the algorithm by reducing the number of distance calculations. Firstly, the Euclidean distance $d(x_i, \mu_1)$ from all sample points to the first initial center of mass μ_1 selected after optimization, and the distance $d(\mu_1, \mu_2)$ between μ_1 and μ_2 are calculated, according to the nature of space cubic geometry, if $2d(x_i, \mu_1) \le d(\mu_1, mu_2)$, then $d(x_i, \mu_1) \le d(x_i, \mu_2)$, i.e., the sample point x_i is closer to the center of mass μ_1, then there is no need to compute $d(x_i, \mu_2)$, the sample point does not belong to the cluster where μ_2 is located; and so on, to select which center of mass point x_i is closer to, will be further away from the sample point The initial center of mass that is farther away from the sample point is sifted out, and only the initial center of mass that is closer to the sample point is considered until the k th initial center of mass.

The specific flow of the improved K-means algorithm is shown below:

Input: dataset $X = \{x_1, x_2, \ldots, x_n\}$, number of clusters k, density threshold Density threshold.

Output: cluster division and initial center of mass.

I. Calculate the density $D(x_i) = N\{x \mid d(x, x_i) < r, x \in X\}$ of the sample points x_i in the dataset X, as well as the sample density threshold $Density\ threshold = c \times \frac{\sum_{i=1}^{n} D(x_i)}{n}$;

II. Compare the sample density $D(x_i)$ with the density threshold Density threshold, if $D(x_i)$ is less than the Density threshold, the sample is determined as an outlier and classified into the low-density sample set L, and vice versa, the sample is classified into the high-density sample set H;

III. Select the sample point with the highest density in the sample set H as the first initial center of mass μ_1 and move it out of the sample set H;

IV. Select the second initial center of mass μ_2, where $d(\mu_1, \mu_2) \geq r$ and $D(\mu_2) = \max\{D(x) \mid x \in (X - \mu_1)\}$;

V. Repeat step IV until k initial centers of mass are selected;

VI. Calculate the distance between the k initial centers of mass and the distance from all sample points to μ_1;

VII. Compare the sizes of $2d(x_i, \mu_1)$ and $d(\mu_1, \mu_2)$. If $2d(x_i, \mu_1) \leq d(\mu_1, \mu_2)$, then $d(x_i, \mu_1) \leq d(x_i, \mu_2)$, and x_i are closer to μ_1, then x_i does not belong to the clustering category where μ_2 is located;

VIII. Calculate again the distance between the sample and the next initial center of mass to which no comparison has been made, pick out which center of mass the sample point is closer to, and eliminate the initial center of mass that is further away from the sample point after the comparison;

IX. Repeat step VIII until the k th initial center of mass, and so on, until all samples are classified into the closest cluster.

2.4. Association Rule Mining Algorithm

2.4.1. Basic concepts of association rules

Association rule mining is one of the most important data mining tasks, which is capable of mining hidden association relationships from a dataset. An association rule is an implication of the form $X \rightarrow Y$, where X and Y are disjoint sets of terms, i.e., $X \cap Y = \varnothing$. Its strength can be measured in terms of support and confidence. The support $s(X \rightarrow Y)$ of an association rule $X \rightarrow Y$ denotes the probability that an event X and an event Y occur at the same time, whereas a confidence level of $c(X \rightarrow Y)$ denotes the probability that an event Y occurs in the presence of an event X. The definitions of support and confidence, respectively, are as follows:

$$s(X \rightarrow Y) = \frac{\sigma(X \cup Y)}{N} \tag{6}$$

$$c(X \rightarrow Y) = \frac{\sigma(X \cup Y)}{\sigma(X)} \tag{7}$$

A rule that satisfies both minimum support and minimum confidence thresholds is called a strong association rule.

If event X contains k elements, then this event X is a k-item set. If event X satisfies both minimum support threshold, then event X is called frequent k-item set.

2.4.2. Apriori algorithm

Apriori algorithm [44] is the classical association rule and frequent itemset mining algorithm. It uses the a priori knowledge that all infrequent $k-1$ -itemsets are not subsets of frequent k -itemsets to compress the data space, and uses a layer-by-layer iterative search approach, i.e., using k -itemsets to explore $(k+1)$ -itemsets.

First, the set of frequent 1-itemsets, denoted as S1, is found by scanning the dataset, counting the frequency of occurrence of each itemset, and eliminating the ones that do not satisfy the minimum support threshold; then, S2, which is a frequent 2-itemset, and S3, which is a frequent 2-itemset, are found using S1, and S2, which is found using S2, until no more frequent k -itemsets can be found. Finally, find the strong association rules that satisfy the confidence threshold in all the frequent itemsets, i.e., they are valid association rules.The disadvantage of Apriori algorithm is that a complete database scan is required for each frequent itemset Sk found.

There are several key strategies in Apriori algorithm as follows:

Connection step: the Apriori algorithm assumes that the itemsets are sorted in a certain order. If the first $k-2$ items in two $k-1$ itemsets are the same and the last item is different, they are connectable to generate k itemsets. For example, the 3-item set $\{a,b,c\}$ and $\{a,b,d\}$ can be connected to generate a 4-item set $\{a,b,c,d\}$.

Pruning strategy: Apriori algorithm satisfies that all infrequent $k-1$ itemsets are not subsets of frequent k itemsets. That is, if there is a candidate k itemset with infrequent $k-1$ itemsets, the candidate set is also infrequent and can be deleted, thus compressing the search space.

Deletion strategy: based on the compressed k itemsets, scan all transactions, count each itemset and discard the items that do not reach the minimum support, thus obtaining frequent k itemsets.

Apriori algorithm execution steps:

Step 1: Set the support threshold α.

Step 2: Each item is a member of the set C1 of 1-item sets, scan the whole database to get all the candidate 1-item sets.

Step 3: Mining frequent k itemsets. Scan the database and count for each k itemset. Discard the set of k items below the support threshold α to obtain the set of frequent k items. If the frequent k -itemset is empty, the $k-1$ -itemset is returned and the algorithm ends. If there is only one item in the k -itemset, the k -itemset is returned and the algorithm ends. The $k+1$ itemsets are generated by a concatenation step.

Step 4: $k=k+1$, go to step 3.

There are many advantages of Apriori algorithm: a) it is suitable for sparse datasets; b) the principle of the algorithm is simple and easy to implement; c) it is suitable for association rule mining in transactional databases. However, it has many disadvantages that cannot be ignored: the algorithm may produce a huge candidate set, which requires traversing the dataset many times, is inefficient and time-consuming.

2.4.3. Introduction to the FP-growth algorithm

FP-growth algorithm [45] improves on Apriori algorithm, unlike Apriori algorithm's strategy of generating candidate itemsets first and then filtering the frequent itemsets, FP-growth algorithm discovers frequent itemsets by constructing FP-tree and extracting frequent itemsets directly from FP-tree.The process of discovering frequent itemsets in FP-growth algorithm is as follows:

(1) Construct FP-tree

Scan the dataset for the first time, count the number of occurrences of each element, i.e., the frequency of 1 itemset, delete the itemsets smaller than the minimum support and sort them in descending order according to the frequency.

The second scanning dataset, participating in the scanning of the filtered data, if a data item is encountered for the first time, then create the corresponding contact, and add a pointer to the node in the header Table, otherwise find the node corresponding to the item in accordance with the path and update the node information.

(2) Discovering frequent itemsets

Extract conditional pattern base. First start from a single frequent itemset in the header Table, for each itemset, obtain its corresponding conditional pattern base, i.e., obtain the set of all prefix paths ending with that element item.

(3) Create conditional FP tree

For each itemset, using its corresponding conditional pattern base, delete the nodes in the prefix paths that are smaller than the minimum support to construct a conditional FP tree. From the conditional FP tree, frequent itemsets can be easily obtained, and further strong association rules can be obtained based on the confidence level.

3. Results and analysis of the correlation between teachers' educational and teaching effectiveness and behavioral habits

3.1. Analysis of student activity patterns

3.1.1. Joint temporal and spatial entropy activity patterns

(1) Definition of temporal entropy, spatial entropy, and joint temporal entropy

This paper borrows the properties of entropy and uses two methods of temporal entropy and spatial entropy to realize the quantitative evaluation of the degree of regularity of student activities. Campus activity is an activity with o as the main body and g as the purpose at t moment, s place. In this section, we use $\alpha_i(t,s)$ to denote the activity that takes place with student i, at t moment and s location, where the set of locations $S=\{s_1,...,s_m\}$ and the time set $T=\{t_1,...,t_{24}\}$. The randomness of moment t and location s is obtained by simplified one-card swipe record and calculating temporal entropy and spatial entropy respectively.

Temporal entropy: for any student, its temporal entropy is used to describe the degree of temporal regularity of the student's activities. It is defined as:

$$E^T = -\sum p(t)\log_2 p(t) \tag{8}$$

where E^T is the temporal entropy and $p(t)$ denotes the probability of the student's card-swiping behavior occurring during the t th hour. With reference to the information entropy, the physical meaning is that the student's activity time is concentrated in 2^{E^T} hours.

Spatial entropy: for any student, its spatial entropy is used to describe the degree of spatial regularity of student activity. Defined as:

$$E^S = -\sum p(s)\log_2 p(s) \tag{9}$$

where $p(s)$ denotes the number of occurrences on s locations. Where $p(s)$ is the number of swipes divided by the total number of swipes for locations with swipes. For locations that do not require card swipes, such as school buildings, $p(s)$ is the ratio of the time spent at a location to the total time spent there. With reference to the information entropy, the physical meaning is that the student activity space is concentrated in 2^{E^S} locations.

Joint spatio-temporal entropy: Joint spatio-temporal entropy is used to characterize the degree of joint regularity in both the temporal and spatial dimensions of student activity. It is defined as:

$$E^{T,S} = -p(t_i,s_j)\sum_{t\in T}\sum_{j\in S}\log_2 p(t_i,s_j) \tag{10}$$

where $p(t_i,s_j)$ is the joint probability at location s_j and hour t_i. T, S represent the set of times and the set of locations, respectively.

(2) Distribution characteristics of time entropy and place entropy

In schools, dormitories, teaching buildings and dining halls are places that students must pass through. According to the definition of temporal entropy and spatial entropy, the distribution of temporal and spatial entropy of the teaching building and dining hall in the data set is calculated. The space of the dining hall and the teaching building that students go to are distributed centrally in four locations and three locations, respectively. The time range of students going to the dining hall is centrally distributed within 8 hours, and the time range of students going to the teaching building is centrally distributed within 10 hours.

(3) Joint temporal and spatial entropy distribution and validation

Time and space are both very important parts of campus activity research. Students with similar time patterns may have very different spatial distributions. To verify the spatial validity of joint spatio-temporal entropy, the relevant parameters represented by low (0.1), medium (0.5), and high (0.85) joint spatio-temporal entropy are listed, and a comparison of joint spatio-temporal entropy-related features is shown in Table 1. Students with medium and high joint spatio-temporal entropy have their dining hall temporal entropy and spatial entropy increase in order. It shows that the larger the value of joint spatial and temporal entropy, the more irregular the distribution of activities in time and space. It is noteworthy that their card swipes and grades were also elevated. Thus, it is conjectured that the entropy value not only represents the degree of disorganization also reflects the degree of activity to some extent. In order to test this hypothesis, the following correlation analysis was conducted to correlate the card spending, library access, teaching area hours and and grades with the joint spatio-temporal entropy in the student campus.

Table 1. Student representative features of joint temporal-entropic space.

Joint Time-Space Entropy Category	Low entropy	Entropy	High entropy
Spacetime entropy (normalized)	0.087	0.5419	0.8446
Restaurant space entropy	0.3797	1.5668	1.6169
Restaurant Time Entropy	2.7932	2.8816	3.4324
Card swipes	34.9571	275.9869	340.9953
GPA	60.3112	80.8005	87.017

The results of the correlation coefficients between joint spatio-temporal entropy and campus activities and grades are shown in Table 2. It is found that the joint entropy space-time is positively correlated with the frequency of campus activities and grades, and has a strong correlation with the total number of trips to the library, the number of times spent in the cafeteria, and the grades, which is manifested in the fact that the larger the entropy value is, the greater the frequency of activities. It is inferred that college students' life is more free and rich in activities within the campus, and the spatial and temporal activities are affected by various aspects (club activities, sports, and course schedules), which makes it difficult to ensure the regularity of the activities. Generally speaking, students with better grades are less likely to stay in the dormitory for a long period of time, and have a higher degree of on-campus activity (frequency of activities, reflecting positive attitudes towards study and life), and their joint spatio-temporal entropy will also be higher. Therefore, the joint spatio-temporal entropy also reflects the activity activity of students on campus side by side.

Table 2. Correlation coefficient results of joint space entropy.

Relevant feature	r	P	Importance degree
GPA mark	0.2491	0.0017	**
Total restaurant visits	0.4992	0.0000	***
Total library visits	0.2641	0.0012	**
Book Borrowing	0.1167	0.0247	*
Time spent in the learning area	0.0784	0.0413	*

(4) Clustering analysis of joint spatio-temporal entropy

The clustering results of joint spatio-temporal entropy and spatial entropy of the teaching building are shown in Fig. 3. The results show that Cluster 1 accounts for 9.24%; Cluster 2 accounts for 46.57%, Cluster 3 accounts for 44.19%, Cluster 1 and Cluster 2 joint spatio-temporal entropy belongs to the middle and low levels, and their joint spatio-temporal entropy clustering center values are 0.0.23647 and 0.31509, respectively, and the number of people accounts for 54%, which indicates that most of the people in the campus have their spatio-temporal behaviors in a regular manner with a high degree of predictability.

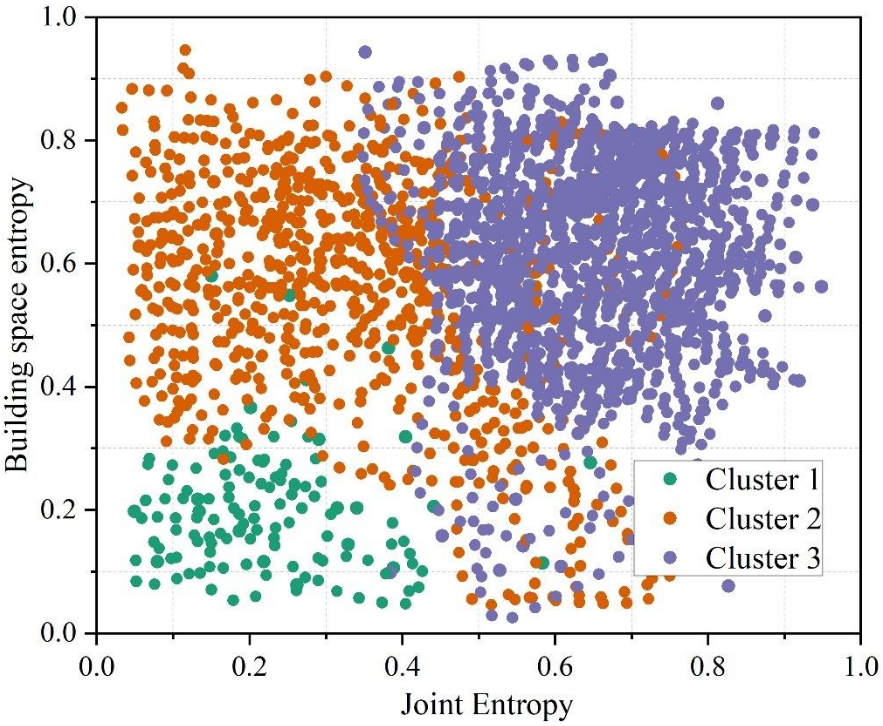

Figure 3. Cluster spatial entropy and teaching building spatial entropy.

3.1.2 House degree analysis

Internet time and number of breakfast meals in dormitory were used as K-Means clustering conditions for discovering groups of students' homeliness. After the attempt, the number of clusters is selected as 3 and the clustering effect is better. The results of clustering of dormitory internet time and breakfast meal times are shown in Figure 4. The results show that the percentage of low nerdiness is 17.14%, and this group of students is characterized by short time of internet access in dormitory and high frequency of breakfast; the percentage of medium and high nerdiness is 46.47% and 36.39% respectively, and this group of students is characterized by longer/longer time of internet access in dormitory and low frequency of breakfast.

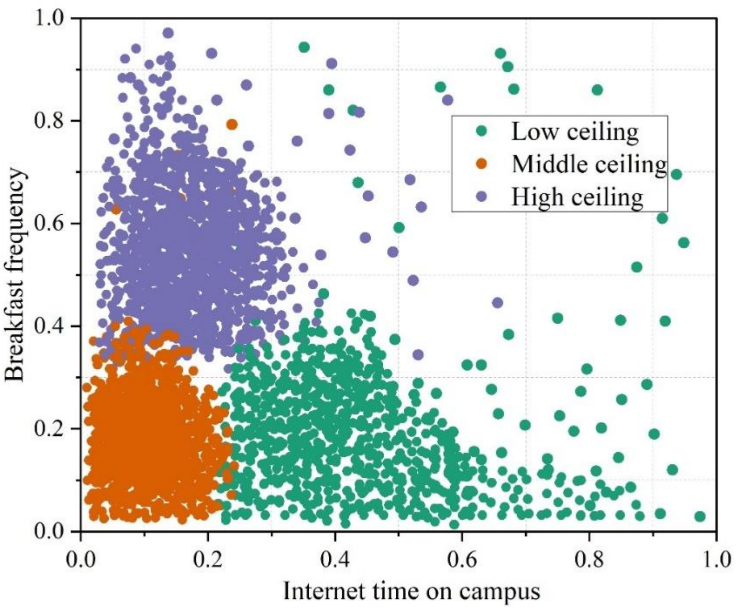

Figure 4. Cluster of dormitory Internet time and breakfast frequency.

3.1.3. Learning Behavior Engagement Analysis

Behavioral engagement in learning is reflected both in active learning behaviors and engagement in the classroom and in time spent studying outside of class. In the offline environment of university campuses, the main way for students to study outside the classroom is to go to the teaching building for self-study, and their behavioral trajectory is generally that students get up early to eat and go to the teaching building for self-study. Therefore, the frequency of students' early meals and the length of time spent in the teaching building are used as clustering conditions to discover the group characteristics of learning behavior investment. The clustering results of learning behaviors are shown in Figure 5. Among them, the proportion of students with low intensity of study behavior input is 55.08%, the proportion of students with medium and high study behavior input is 21.16% and 23.76% respectively, and the proportion of students with medium and high intensity of study behavior input is below 50%.

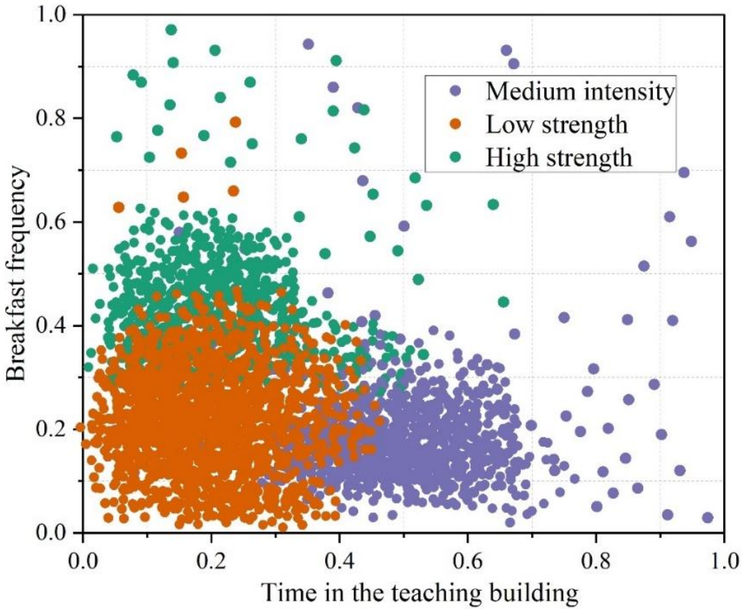

Figure 5. Learning behavior clustering results.

3.2. Cluster Analysis of Student Behavior

In this paper, the data are clustered multiple times on the basis of determining the number of class clusters, and the evaluation metrics of both clustering algorithms are defined as the average of the evaluation metrics obtained from multiple experiments, i.e:

$$\overline{V} = \frac{1}{T}\sum_{t=1}^{T} eval_i \tag{11}$$

Where $\overline{V}$ is the clustering effect evaluation index of K-Means and K-Means++ clustering algorithms; T is the number of runs of these two clustering algorithms; and $eval_i$ is the value of the effect evaluation index of the i th clustering.

3.2.1. Cluster analysis of student consumption behavior

The clustering results of students' consumption behavior data are shown in Figure 6. It can be seen that the students in the first cluster belong to the group of students with exceptionally low consumption, and it can be found by observing the cluster heart of this type of cluster that all the indicators of the cluster heart are far below the average value. In addition, the average daily consumption amount, the average consumption amount and the peak consumption value of a single month are all much lower than the other clusters. Students in this cluster not only spend a very low amount of money on campus, but are also very likely to spend a lot of money off-campus.

Students in the second cluster are moderate spenders and, with the exception of the sub-averaged spend amount indicator, are slightly higher than the overall student average for all indicators. Observing the average number of times of consumption per month and the average amount of consumption per month, it can be seen that the students in this cluster consume steadily and frequently, and the consumption level of students in this cluster is average.

Compared with the average value of each indicator of the overall students, although the average monthly consumption level of the students in the third cluster is lower, the average monthly consumption times of the students in this cluster are higher, which can be inferred that the students in this cluster consume more at school, and the sub-average consumption amount is lower, which reflects that the students in this cluster are thrifty in their life from the side. Therefore, this cluster belongs to the student group with low consumption and more stable consumption.

The consumption amount indicators of the students in the fourth cluster are much higher than the average value of the indicators of the overall students. Therefore, the consumption level of students in this cluster is much higher than the average consumption level of the overall students, and their living conditions are superior, belonging to the group of high-consumption students with stable and frequent consumption.

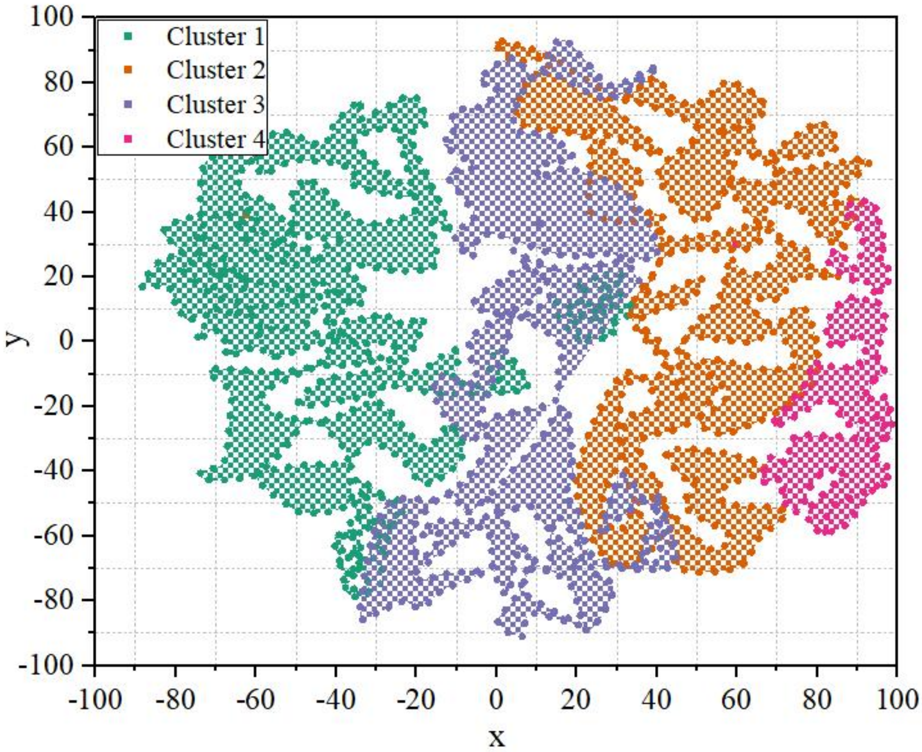

Figure 6. Cluster results of consumer behavior data.

Comparison of evaluation metrics between K-Means algorithm and this paper's algorithm is shown in Table 3. The evaluation index value of the improved K-Means clustering algorithm of this paper is the lowest when the density threshold is 3309 and the number of class clusters K is 3. At this time, the inter-cluster dissimilarity is small and the intra-cluster cohesion is poor. The evaluation index eval of K-Means clustering algorithm (72.15%) is lower than the improved K-Means clustering algorithm (88.94%) in this paper under the same conditions. In summary, the improved K-Means algorithm of this paper is more advantageous for clustering student consumption behavior data under the same conditions, and the method improves the applicability of K-Means algorithm for clustering student consumption behavior data.

Table 3. Comparison of evaluation indicators of the two algorithms.

Algorithm name	*eval* metric value (%)
K-Means	72.15
Improved K-Means (Ours)	88.94

3.2.2 Cluster Analysis of Students' Book Borrowing Behavior

The clustering results of student book borrowing behavior data are shown in Figure 7. It can be seen that the improved K-Means clustering algorithm in this paper divides the 10527 student readers into four classes, of which the largest proportion of readers is class cluster 1, accounting for 46.36% of the total number of readers, and all the indicators of this class cluster heart are lower than the average value, and readers' book borrowing in this class cluster is on the low side, and the borrowing habits are more regular. The smallest proportion of readers is class cluster 4, accounting for 5.07% of the total number of readers, the average number of single borrowing days of readers in this cluster is as high as 145 days, but the total number of books borrowed and the total number of times of book borrowing are the lowest among all class clusters. Thus, the readers of this cluster have the least amount of borrowing and the cycle of borrowing is unstable. Class Cluster 3 accounts for 40.74% of the total number of readers and the readers of this cluster have low borrowing volume and high single borrowing period. Class Cluster 2 accounts for 7.83% of the total number of readers, the cluster cluster heart in the total number of books borrowed, the total number of books borrowed, the total number of books borrowed peak value of the indicators is much higher than the other clusters, and the average single borrowing days for 41.06 days. The readers in this cluster often borrow books and their borrowing habits are more regular.

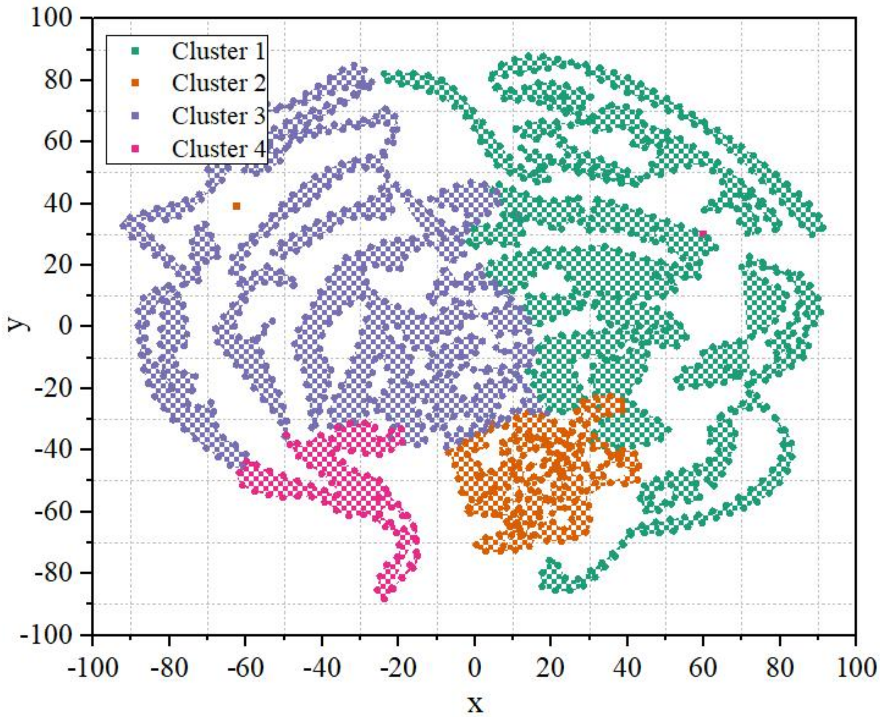

Figure 7. Student book borrowing behavior data clustering results.

The comparison results of the evaluation indexes of the two algorithms are shown in Table 4. It can be found that the eval index value of this paper's algorithm under the same conditions is 20.94% higher than the traditional K-Means clustering algorithm. It can be seen that the improved K-Means algorithm in this paper has more advantages over the K-Means algorithm for clustering student book borrowing behavior data under the same conditions, and the method improves the applicability of the K-Means algorithm for clustering student book borrowing behavior data.

Table 4. Comparison results of two algorithm evaluation indicators.

Algorithm name	*eval* metric value (%)
K-Means	72.65
Improved K-Means (Ours)	93.59

3.2.3. Cluster Analysis of Student Exercise Behavior

The clustering results of students' sports data are shown in Figure 8. It can be seen that the improved K-Means clustering algorithm in this paper divides the sports data of 7954 school students into four classes, of which the largest proportion of students is class cluster 4 (45.69%), the cluster heart of this class is larger than the average of the overall students' sports behavior indexes in the three indicators, and the students in this class cluster belong to the group of students who often exercise and often take attendance, and have better sports habits.

The smallest percentage of students is class cluster 2 (11.05%), whose cluster heart of the number of attendance, running kilometers, and overall performance indicators can be found that all three indicators are the lowest among all class clusters. Therefore, it can be inferred that very few students of this cluster are in the habit of exercising. Class Cluster 3 accounted for 23.41% of the total number of athletic students, and this cluster is in the middle of all the class clusters in terms of running kilometers and general performance indicators, but its attendance number is low. Therefore, this cluster belongs to the group of moderately athletic students, and student administrators also need to urge students in this cluster to participate in attendance on a regular basis. Class Cluster 4 accounts for 19.85% of the total number of athletic students, and the value of the attendance count indicator for this cluster center is the highest on all class cluster centers. Therefore, it can be inferred that this cluster belongs to the group of students who exercise occasionally, and there may be cases of participation in attendance but not in exercise, and student administrators should pay attention to the exercise of students in this cluster.

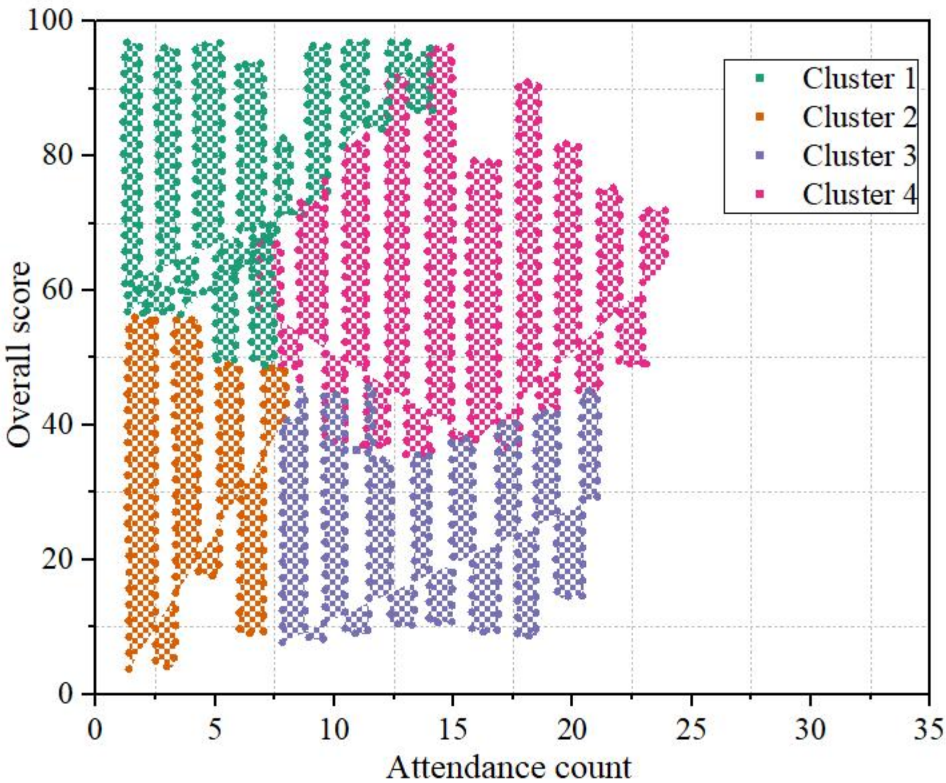

Figure 8. Student movement data clustering results.

The comparison results of the evaluation metrics of different algorithms are shown in Table 5. It can be found that under the same conditions, the value of the *eval* index of this paper's algorithm increases by 25.85% compared with the K-Means clustering algorithm. It can be seen that the improved K-Means algorithm in this paper is more advantageous for clustering students' sports behavior data, and the method improves the applicability of K-Means algorithm for clustering students' sports behavior data.

Table 5. Comparison of evaluation metrics for different algorithms.

Algorithm name	*eval* metric value (%)
K-Means	64.63

Improved K-Means (Ours)	90.48

3.3 Correlation and Analysis of Teaching Effectiveness and Behavioral Habits

In the various types of student groups performance and behavioral habits association rule mining, the Apriori model support and confidence level is set, this control experiment set the minimum support is set to 10%, the minimum confidence level is set to 70%, the Apriori algorithm model to generate 23 rules, this paper has chosen to have a reference value of 11 strong rules. In the table, a, b, c, and d represent the first to the fourth category of students, respectively.

Setting up a control experiment to mine the correlation between students' performance and behavioral habits for all students can only mine the rule information of some types of students, and the effective rules mined are not comprehensive, which can't reflect the correlation between the performance and behavioral habits of all types of students in a comprehensive way. Therefore, this paper takes four different types of student groups after clustering as the research object. The correlation rules between academic performance and behavioral habits of each type of student group are mined, and the following are the correlation rules between academic performance and behavioral habits of different types of student groups.

3.3.1. Category I students

The first type of students' performance and behavioral rules are shown in Table 6. It can be seen that the students in this category are able to eat breakfast regularly as well as ensure that their breakfast diet is of high nutritional quality. There is a good habit of reviewing before homework and after class as well as a positive attitude towards pre-study before class, but are less involved in outdoor activities. In terms of learning styles the students in this category are associated with four learning styles: sequential, perceptual, visual, and contemplative, and have learning characteristics such as strong logical thinking, patience, good knowledge acquisition from graphs and pictures, good memorization, and calmness in thinking.

Table 6. Rules for the first category of students' grades and behavior.

Rule	Antecedent	Support	Confidence
1	Breakfast quality =a	0.2532	0.9722
2	Breakfast quality =a and after-class review method =a	0.1541	0.9576
3	Breakfast quality =a and breakfast situation =a	0.2265	0.9437
4	Number of activities =c	0.2478	0.9402
5	Number of activities =c and breakfast status =a	0.2093	0.9229
6	Number of activities = c and the sequence type and comprehensive type =a	0.1698	0.9159
7	Number of activities =c and insight-based and intuition-based =a	0.1783	0.9102
8	Activity count =c and preview attitude =a	0.1799	0.9025
9	Pre-class review time =a and post-class review method =a	0.1054	0.8561
10	Pre-job review time =a and visual-verbal type =a	0.1477	0.8346
11	Active vs. Reflective =b and Pre-reading Attitude =a	0.2518	0.8248
12	Midday rest = c and night sleep =a	0.1649	0.8167

3.3.2. Category II students

The second category of students' performance and behavioral habits correlation rules are shown in Table 7. It can be seen that students in this category do not care about the quality of breakfast choices, and the number of outings is high, and they also devote their efforts to pre-study and review, but they are slightly less than students in the first category. Students in the second category have an intuitive and contemplative learning style, which is characterized by calm thinking and good understanding of abstract concepts.

Table 7. The second category of student performance and behavior rules.

Rule	Antecedent	Support	Confidence
1	Post-class review method = b and activity frequency = a	0.1336	0.8874
2	Breakfast quality = c and activity time = b	0.1544	0.8167
3	Midday rest = a and activity frequency = a	0.1693	0.8032
4	Preview time = c and review time before homework = b	0.0697	0.7748
5	Night sleep = b and activity frequency = a	0.2129	0.7506
6	Pre-reading attitude = b and activity frequency = a	0.2348	0.7253
7	Breakfast quality = c and insight-based versus intuition-based = b	0.1178	0.7144
8	Pre-work review time = b and activity frequency = a	0.1895	0.7175
9	Breakfast quality = c and preview time = b	0.2066	0.7061
10	Post-class review method =b and active type versus reflective type =b	0.1659	0.7047

3.3.3. Category III students

The third type of students' performance and behavioral habits association rules are shown in Table 8. It can be seen that this type of students are mostly associated with the habit of not reviewing before assignments and the habit of not doing preclass pre-study. In the attitude of pre-study before class is not helpful for learning in class held. Solely able to maintain the habit of eating breakfast regularly and having enough time for lunch breaks. This type of student is also associated with the learning styles of intuitive, sequential, and active learning styles. Students with this style have learning characteristics such as being able to do something well and actively, being good at grasping new knowledge, and being able to solve problems according to linear logic.

Table 8. Third category of student performance and behavior rules.

Rule	Antecedent	Support	Confidence
1	Preview time = d and review time before homework = d	0.3462	0.9445
2	Breakfast = a and study time before homework = d	0.2996	0.9367
3	Breakfast situation = a and preview time = d	0.1543	0.9012
4	Lunch break = a and preview time = d	0.2045	0.9003
5	Pre-reading attitude = d and the sequence type and comprehensive type = a	0.1909	0.8913
6	Post-class review method = c and pre-class review time = d	0.2717	0.8833
7	Preview time = d and insight-based versus intuition-based = b	0.2687	0.8753
8	Preview time = d and sequence type and comprehensive type = a	0.3158	0.8682
9	Midday rest = a and review time before homework = d	0.2796	0.8501
10	Preview time = d and active type versus contemplative type = a	0.3384	0.8239
11	Preparation attitude = d and preparation time = d	0.1657	0.8099

3.3.4. Category IV students

The fourth type of students' performance and behavioral rules are shown in Table 9. We find that students of this type do not pay much attention to the habit of breakfast and do not have the habit of eating breakfast. Passionate about sports, the number and duration of activities are more. This type of students mostly belong to the integrated and active visual learning style, with learning characteristics such as good active activities, good memorization of pictorial information, and the ability to solve complex problems quickly.

Table 9. Category 4 student performance and behavior rules.

Rule	Antecedent	Support	Confidence
1	Breakfast situation = d and breakfast quality = d	0.2044	0.9156
2	Breakfast scenario = d and activity time = b	0.2033	0.9017
3	Breakfast quality = d and sequence-type versus comprehensive-type = b	0.1976	0.9005
4	Pre-work review time = b and breakfast quality = d	0.1721	0.8867
5	Breakfast quality = d and activity time = b	0.3323	0.8763
6	Breakfast quality = d and active type versus contemplative type = a	0.3284	0.8658
7	Breakfast quality = d and visual and verbal types = a	0.2391	0.8502
8	Breakfast quality = d and activity frequency = a	0.2307	0.8324
9	Number of activities = b and activity time = b	0.1973	0.8201

4. Conclusion

In this paper, in order to clarify the correlation between students' behaviors and teaching effectiveness, the K-means algorithm based on density optimization is used to cluster students according to their behaviors, and then the FP-growth algorithm is used to mine the correlation between each type of teaching effectiveness and behavioral habits, and summarize the characteristics of different types of students. The results show that:

(1) There is a significant correlation between students' activity patterns such as "card spending, number of times borrowing from the library, and length of time in the teaching area" and students' grades. For example, the higher the students' grades are, the less time they spend on the Internet in the dormitory, and the higher the frequency of eating breakfast and going to the teaching building for self-study.

(2) In this paper, students are clustered by the improved K-means algorithm from the students' behaviors of "consumption, library borrowing and sports", and the characteristics of students in different categories are summarized.

(3) This paper analyzes the correlation between students' performance and students' behaviors, and obtains four types of students with the following characteristics:

Type 1: Learning characteristics such as strong logical thinking, patience, good at acquiring knowledge from graphs and pictures, good at memorizing and calm thinking. This type of student is very good at learning and can become an all-around good student with just the right amount of increased exercise and participation in more engaging activities.

Type 2: Learning characteristics such as calm thinking and good understanding of abstract concepts. Teachers should guide these students to participate in group activities and allow them to take on more important roles in the team to help them integrate into the larger group and to demonstrate their leadership skills.

Category 3: Students who are good at doing something actively, good at grasping new knowledge, and able to solve problems according to linear logic and other learning characteristics. This kind of students' character is jumpy and often unsatisfactory when dealing with things that require patience. During the teaching process, teachers should focus on guiding them to be calm and cultivate their habit of quiet thinking.

Category 4: Learning characteristics such as good at active activities, good at memorizing pictorial information, and the ability to solve complex problems quickly. These students are extremely adaptable and have strong independent thinking ability, but they do not perform well in maintaining teacher-student relationships and other aspects. Teachers should share some thought-provoking short dramas or books to guide them to realize the tricks of the trade.

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