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# Analysis of the change of teaching management mode and its implementation path in medical higher vocational colleges in the era of artificial intelligence

*Yan Liu*[1,2], *Tiegang Qiu*[1,*], *Zhangyuan Jin*[1], *Xianyu Yuan*[1], *Zhou Lu*[3] *and Yuan Ma*[4]

[1] Academic Affairs Office, Wuzhou Medical College, Wuzhou, Guangxi, 543000, China
[2] The First Clinical College of Changsha Medical University, Changsha, Hunan, 410219, China
[3] Wuzhou red cross hospital, WuZhou 543002, China
[4] Guangxi Chaoxing Information Technology Co., LtdNanNing 530000,China

**SUMMARY:** *The foundation of higher vocational education curriculum innovation and reform is how to produce highly competent professionals in accordance with societal needs, in response to the rapid modernization of vocational education. In this study, digital technology is used to support the school's comprehensive management service platform for information technology instruction. The enhanced k-means algorithm and Aprior algorithm are then used to analyze college students' behavioral data over the course of their education and identify the rules of correlation between students' behaviors and academic achievements. The article presents a unique ANN-CBL academic performance prediction model with an attention mechanism. The model's representation capability is strengthened by using an attention mechanism to assign weighted values to the outputs. The fully connected layer receives the weighted time-series information in order to estimate the students' academic achievement. The model suggested in this paper is able to identify the characteristics of the behaviors and grades in each semester and achieves better prediction accuracy with good interpretability. The experimental results indicate that by using the optimized k-means clustering algorithm to cluster the students in each index, the clustering outcomes will help the student management workers grasp the status of the students and offer decision support for enhancing the efficiency of educational management classification guidance for the students.*

***KEYWORDS:*** *association rules; attention mechanism; k-means algorithm; Aprior algorithm; learning prediction; teaching management platform*

## 1 Introduction

Medical schools must fully utilize artificial intelligence technology to improve their teaching management capacity in order to meet the demands of societal development. This is because the rapid advancements in artificial intelligence technology have brought about significant changes and challenges in the field of teaching management of higher education institutions [1-3]. Literature [4] discusses the use of artificial intelligence technology in teaching management through building an artificial intelligence ecosystem of higher education; thus, it innovates the method of application in the fields of students management, teacher team building, and teaching management.

*yyan621@126.com
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The continued development of AI technology has brought revolutionary changes in teaching management in medical institutions of higher education. The AI technology significantly increases the level of personalized teaching content customization [5]. Analyzing the needs and features of students, AI technology can offer individualized teaching content and methods for each student to improve students' results [6-8]. According to literature [9] , the trend in the development of AI technologies in personalized teaching at vocational schools suggests that AI technology can satisfy students' needs through personalized learning and customized recommendation of teaching resources, which can lead to improving students' results. Literature [10] notes that the application of AI is critical in higher education because of providing personalized learning recommendations and the optimization of students' learning paths based on their needs and learning level. AI technology can be helpful to teachers in teaching management [11]. Thanks to AI technology, teachers can control students' progress and analyze it in order to modify their teaching content and methods, which will improve students' results [12-14]. Literature [15] describes advantages of immersive learning supported by AI technology, such as increased motivation and engagement of learners, and calls for considering ethical issues while using AI technology. Literature [16] introduces the notion of AI, analyzes its development and application areas, and considers the influence of AI on teachers' professional development. The literature study is connected to the usage of intelligence and AI to improve professional growth of teachers. AI technology provides a wider range of learning materials and teaching methods that will be able to cover diverse needs of students [17, 18].

However, in the era of artificial intelligence, there are also some problems in the management of teaching in medical higher vocational colleges and universities. The current teaching management model of higher vocational education is relatively outdated, and it is difficult to meet the new requirements brought about by artificial intelligence technology [19, 20]. There is inadequate investment in artificial intelligence technology in the organization of teaching management in medical higher vocational education, which results in an insufficiency of personnel reserve and a lack of overall planning [21]. The professional ability and technical skills of teachers and managers must adapt to the development of artificial intelligence technology [22, 23]. In light of the development of artificial intelligence, medical higher educational institutions must actively respond to it and constantly improve their teaching management system to achieve good results and serve students' growth and development better [24-26]. Only in this way can they follow the trend of the times, conform to the development trend of artificial intelligence technology, and constantly improve the quality of the whole faculty team [27, 28].

Literature [29] reveals that the information age has seen the gathering of a huge database of information regarding education, learning, research, development of talents, and student management in universities, and discusses the need to analyze this information to manage learning and teaching at universities. Literature [30] presents the transformative power of AI in higher education, and analyzes the use of AI technology in higher education from the perspective of the "smart university" to reveal that using AI has transformed the model of teaching and learning management in higher education institutions, personalized learning processes, and improved efficiency. Literature [31] illustrates the opportunities and challenges presented by the emergence of AI in higher education, and creates a causal loop diagram of how AI transformation can influence a typical higher education institution. The findings in this research reveal that higher education can significantly enhance student learning, research, and management through the use of AI. The literature [32] provides a review of the use of AI technologies in education management, highlights innovative practices used by AI technologies, and discusses the drawbacks of using AI technologies in the field of education. The literature

[33] seeks to explore more deeply the implications of how education delivery processes have changed through the use of AI. The findings suggest that AI has made education management processes more efficient, personalized, and effective; however, AI faces such problems as the gap in resource allocation and data privacy. Literature [34] focuses on the application of AI technologies in vocational education and found that the positive contribution of AI in education is solving the problems associated with the diversity in learners' needs, low learner motivation, and poor learners' achievements. Literature [35] explores the application of AI technology in vocational education from four perspectives: personalized teaching, adaptive learning, intelligent tutoring, and teacher-assisted teaching. It acknowledges some problems faced by AI technologies in innovation in the area of teaching and learning in vocational education. This paper offers ways to address those challenges and promote transformational change. The abovementioned literature reviews focus on the application of AI in vocational education and higher education. It systematically identifies the impacts of AI technologies including both positive and negative influences. Positive impacts involve changes in teaching management, improvement in teaching effectiveness, and personalization in teaching, whereas negative impacts involve inequality in resource distribution, ethics, and data privacy.

The study builds a teaching management platform for medical higher education institutions based on data technology, and utilizes R language technology to perform data cleaning and data integration on the collected campus data. Then the optimized k-means algorithm and Aprior association rule algorithm are used to analyze the behavior of learning, mainly from the meal consumption level indicators, regularity indicators, diligence indicators using clustering algorithms to classify the students, and further mining the association rules between student behavior and academic performance. Then, a predictive model construction of student performance based on attention mechanism is proposed, and the model is verified by feature extraction and analysis of student behavior data using real data sets. In order to improve the learning motivation of informatization professionals in education and teaching at higher vocational schools and universities as well as the general quality of the teaching and teaching informatization management team in higher vocational schools and universities, the following implementation path is finally proposed based on the actual situation.

# 2 AI-based teaching management model for medical higher education institutions

## 2.1 Informatization Management Platform for Teaching in Higher Education Institutions

### 2.1.1 Platform architecture framework

In higher vocational schools, teaching informatization building is a challenging, methodical endeavor, hardware environment facilities is the foundation, platform architecture is the key, data acquisition and specification is the source, big data governance is the focus, business application is the core, student-centered, for teachers and students is the goal, so as to build a teaching informatization platform for higher vocational institutions and realize the informatization application of higher vocational institutions' various businesses. The system structure of teaching informatization platform for higher vocational institutions is shown in Figure 1.

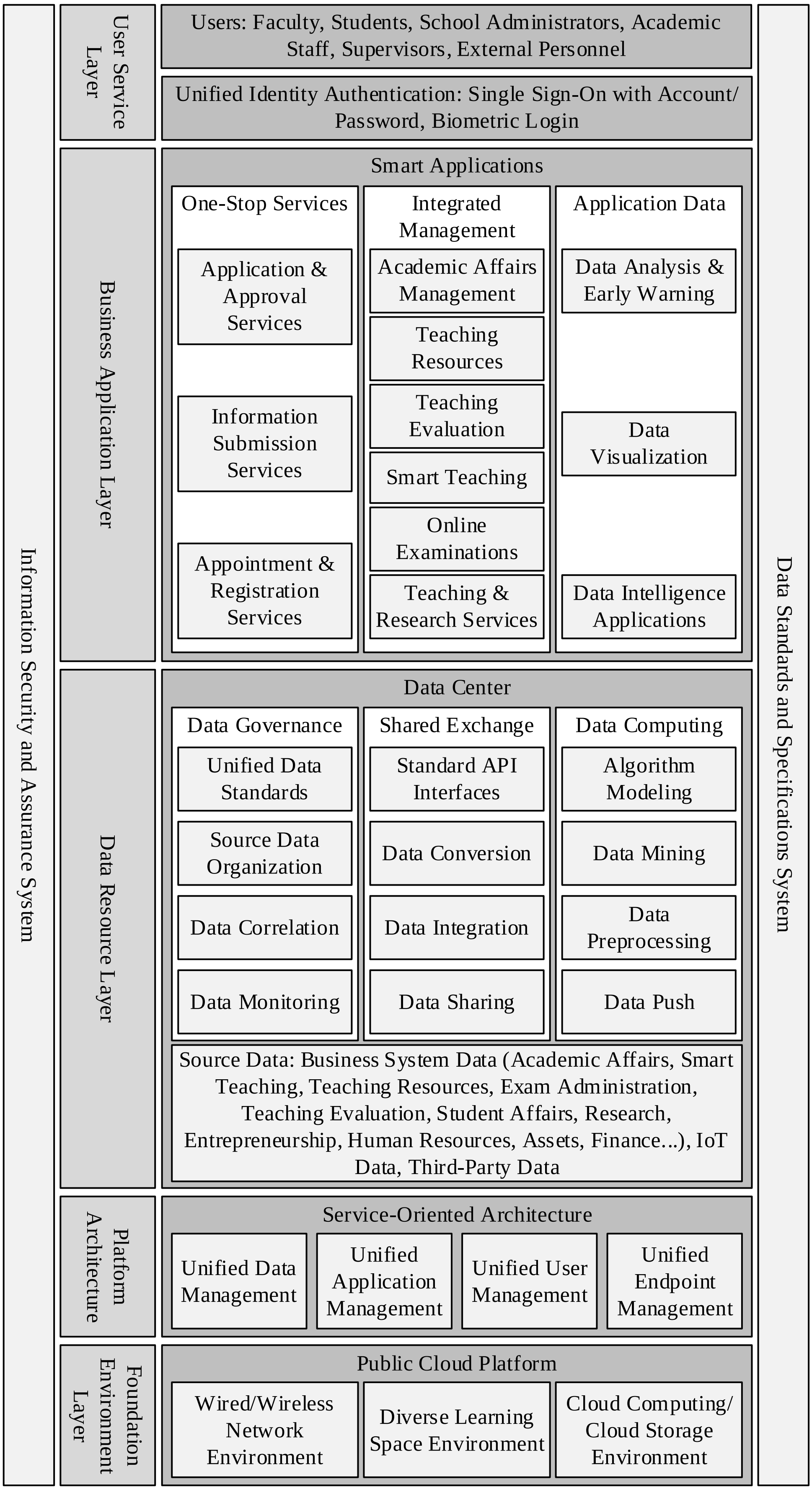



*Figure 1: Architecture diagram of teaching information platform in higher vocational colleges*

Upgrades to the informationization infrastructure and the integration of new technologies like cloud computing and wireless networks are undertaken on the basic environment layer, and build a high-performance wired/wireless network environment, a diversified learning space environment, and a cloud computing/cloud storage environment. The platform architecture adopts service-oriented architecture, and focuses on building unified data management, unified application management, unified user management and unified terminal management. In the data resource layer, it focuses on building a full-volume data center through the formulated data standards and specification system, and realizes data governance, sharing and exchange, and data computation to form teaching data assets and provide data support for the business application layer. In the business application layer, efforts are made to build intelligent applications and construct one-stop service, integrated management and data application. Teachers, students, teaching administrators and other relevant personnel in the user service layer verify their identities by logging into the Unified Identity Authentication and automatically enter the application services provided by the teaching platform.

### 2.1.2 Introduction to key technologies

(1) Big Data and Data Mining

The core value of big data and data mining technology is to collect, store, analyze and utilize massive data. Through a variety of intelligent terminal equipment and information management systems to obtain the basic state data and the process data of activity operation, and the organization and modeling of these massive data, not only through statistical data to prove the prejudgement point of view, but also more importantly, the use of data mining technology, to find out unforeseen laws and conclusions, to provide data support for accurate governance.

(2) Microservice Architecture

Based on Springcloud's microservice architecture, the business system is divided according to functional boundaries and decomposed into many loosely coupled and independent microservices to realize various business functions, each microservice corresponds to a component, and the relationship between components is relatively independent, so different components can be independently compiled, independently deployed, and independently run, which makes it flexible to build and easy to horizontally expand. Since microservices have independent running processes, if a service fails, it will only isolate the single service and will not affect the operation of the entire platform services, ensuring stable, reliable and efficient operation of the platform.

(3) Cloud Computing

Teaching information technology management service platform is an extremely complex system, must use open and compatible, mutual synergy, flexible expansion of the information technology framework and timely, efficient and convenient on-demand dynamic adjustment of the distribution of resources, that is, on-demand service cloud computing new model for the basic environmental facilities required for the provision of resource services to provide support and protection.

## 2.2 Clustering-Based Student Behavior Data Analysis Module

### 2.2.1 K-means clustering algorithm

The core idea of the $k$-means clustering algorithm is as follows: randomly obtain $k$ data samples based on the dataset $p$, and based on this specifically identified as the center of the initial clusters [36]. The similarity of the samples is calculated, generally by Euclidean distance, dividing each sample in $p$ into its nearest cluster. Combined with the convergence of the clustering criterion function to update the clustering center point, so as to form different classes have differences, while the same class is more compact data.

The clustering data set is $n$ student data samples $P=\{x_1,\ldots,x_j,\ldots,x_n \mid x_j \in R_t\}$, where $x_j$ is used to denote the $j$ th student data sample, which is a $t$-dimensional feature vector. Combined with the principle of the algorithm it can be seen that the algorithm aims to determine the set of $k$ points $M=\{m_1,m_2,\ldots,m_k\}$.

The specific steps are as follows:

(1) The initial clustering center point, i.e., $k$ points, needs to be rationally determined first. It can be randomly formed by the computer or let experienced people take appropriate methods to obtain, and then calculate the distance between each object and each center point, in line with the following function:

$$G=\sum_{i=1}^{k}\sum_{x_j \in P_i} d(x_j,m_i) \tag{1}$$

where $P_i$ denotes the sample set of the $i$ th class cluster and $m_i$ is used to denote the centroid of the $i$ th class cluster. $d(x_j,m_i)$ is used to denote the distance between the two, and the data samples are $t$ -dimensional feature vectors, so $x_j=\{x_{j1},\ldots,x_{js},\ldots,x_{jt}\}$ and $m_i=\{m_{i1},\ldots,m_{is},\ldots,m_{it}\}$, which can be defined in conjunction with Equation (2) for definition:

$$d(x_j,m_i)=\left\|x_j-m_i\right\|=\sqrt{\sum_{s=1}^{t}\left|x_{js}-m_{is}\right|^2} \tag{2}$$

(2) For each of the $k$ iterations, for each sample, calculate its value to the $k$ centroids, and then place that sample in the class where the centroid with the shortest distance from it is located, satisfying equation (3):

$$n_i=\{x_j : \| x_j-m_i\| \le \| x_j-m_j\| \ \forall j, 1\le j\le k\} \tag{3}$$

Similarly the number of samples $N_i$ in $n_i$ is obtained.

(3) The mean value of each point in the class is calculated, and then the purpose of updating the center point of each class is achieved. Equation (4) is satisfied:

$$m_i=\frac{1}{N_i}\sum_{x_j \in m_i} x_j \tag{4}$$

$N_i$ denotes the number of sample points in the $i$ th class cluster, and $x_j$ is the sample point belonging to the $i$ th class cluster.

(4) Repeatedly calculate $k$ cluster centroids using the two steps (1) and (2) iteratively and obtain the value of the centroids from the related data. With the update, if the value of the center point value remains unchanged after the update, the iteration is ended. If not, i.e., the values are still changing, continue the related work.

### 2.2.2 Criteria for evaluating clustering effectiveness

There are many shortcomings in the traditional $k-means$ algorithm, which evaluates the clustering only on the basis of the distance between this point and the center point of the class cluster, emphasizes only the similarity of the elements within the cluster, and does not fully consider the problem of the inadequacy of the clustering results between the class clusters. Based on this, the author believes that it is very necessary to introduce more effective evaluation criteria to accurately evaluate the clustering results. In short, that is, to take a method that can simultaneously realize the clustering of clusters and separation of categories. As shown in equation (5) the distance between the samples of each class and the center point of the class to which they belong is added up and its average value is calculated to calculate the similarity within the class.

$$V = \frac{B_1 - B_2}{B_1 + B_2} \tag{5}$$

### 2.2.3 Optimized k-means methods

By analyzing the evaluation criterion function, it can be seen that its value range is usually between $[-1,1]$, assuming that $V$ tends to be close to 1, then it indicates that the sample similarity is high, comparing the interclass dissimilarity, the similarity can be ignored, which corresponds to the statement that the clustering effect is good; on the contrary, if the value is close to -1, then it corresponds to indicate that the data object of all kinds of there is no significant difference, which can be ignored in the intraclass samples. similarity, its clustering effect is poor.

$$B_2 = \frac{1}{n}\sum_{i=1}^{k}\sum_{j=1}^{m} d(u_j, E_i) \tag{6}$$

where $d(u_j, E_i)$ denotes the distance from $u_j$ to $E_i$.

The separation of the clusters of each class can be judged by the inter-class dissimilarity and illustrated based on the average distance from the center of the clusters, as expressed in equation (7).

$$B_1 = \frac{1}{k}\sum_{i,j=1}^{k} d(E_i, E_j) \tag{7}$$

From this analysis, it can be clearly concluded that the classic $k-means$ algorithm is not without flaws, and indeed, there are quite a few issues with the objective of the algorithm itself. As such, an optimization of the algorithm needs to take place. The focus for optimization of the $k-means$ lgorithm can be taken from two different angles: one of those angles being the initial choice of the clustering center, and the other – the distance measure. Both the initial clustering center selection and the distance computation are optimized with the introduction of the improved design of the k-means algorithm. Because of this optimization, the algorithm can automatically adjust the number of clusters based on density, combining some classes into a single large cluster, lessening the impact of outliers on the clustering results, and speeding up calculations by eliminating some distance calculations.

Definition 1: The average distance $\bar{B}$ for the set of student data samples $S = \{u_1, \ldots, u_j, \ldots, u_n \mid u_i \in R_t\}$, calculating the distance of the data sample points in it from each other, and then get the average distance between the sample points. The formula is shown in equation (8).

$$\bar{B} = \frac{2}{n(n-1)} \cdot \sum_{i \neq j\, i,j=1}^{n} d(u_i, u_j) \tag{8}$$

$n$ denotes the total number of student data samples and $d(u_i, u_j)$ denotes the size of the distance from student sample $u_i$ to $u_j$.

Definition 2: $Z$-interior domain $Z$-interior domain means the range of $t$-dimensional hypersphere with radius $Z$, this range contains some student samples $u$.

$$N_Z = \left\{u_j \in S \mid 0 \le d(u_i, u_j) \le Z, j = 1, 2, \dots, n\right\} \tag{9}$$

where $d(u_i, u_j)$ represents the case of two sample distances in $S$. Specifically based on the formula (5) for the calculation:

Definition 3: The density of a known set of samples $S = \left\{u_1, \dots, u_i, \dots, u_n \mid u_i \in R_t \in R_t\right\}$, defines the density of $u_i$ to be the number of samples in the inner domain of $Z$ obtained by centering the sphere at $u_i$. , the density reflects the density of sample points in this range.

Definition 4: Density Sample Points The meaning of density sample points is to divide the density range of core and isolated points set by human or computer.

Combined with the above analysis of the algorithm, it can be seen that the algorithm is still insufficient, and it needs to be scientifically optimized by adopting relevant methods. Based on this, this paper mainly optimizes the method of selecting the initial clustering center, whose set point is $M$.

The initial center point optimization of the $k-means$ algorithm is completed in the following steps:

(1) The first step is to select the initial clustering center point (the specific method has been clearly explained above, and will not be repeated here), and establish the corresponding set $M$.

(2) Iterate over all the points $u_i$ in $M$, and aggregate this point with the nearby sample points, i.e., form a new class $H_i$. Iterate over all central points $m_i$ in $M$ and aggregate that point and the samples in its neighborhood into a class $H_i$.

(3) Find the distance $d_{\max}$ (i.e., the distance between the two $H_i$, $u_i$).

(4) Find the two classes $i$ and $j$ in the set of classes $H$, compare $2 \cdot \max(d_{\max i}, d_{\max j})$, and merge the two by assuming that the distances between the centroids $u_i$ and $u_j$ are small, where one also needs to compute $d_{\max k}$ (i.e., the distance between the new class centroid $u_i$ and the sample with the largest distance).

(5) Add $F_i$ (the remaining point in $S$) to the class based on the following rule.

Calculate the average distance $F_i$ to the centroid of all classes $\bar{B}$ and $B_{\min}$, assuming that the latter is less than half of the former, the point is added to the nearest class, if not then $F$ is used as the centroid, so that a new class is formed, based on which the data points need to be updated to get the centroid of the newest representation of the class. Repeat the above steps until all the data is processed.

## 2.3 Student Achievement Association Rule Mining Module

### 2.3.1 Association rules

Cluster analysis of data is just a process rather than an end for us to discover new knowledge and useful information. How to discover knowledge from unlabeled data that has been processed by clustering, association rules are used. Association rule is the process of discovering a hidden relationship between two different things that do not seem to have any connection, it is an important part of data mining techniques. A few concepts in association rules are given below.

Frequent itemset: If a given data sample contains a subset $U=\{u_1,u_2,\ldots,u_n\}$ and $U$ contains at least 1 data element, and if the support of the subset satisfies $Support(U)\geq MinSup$, it is a frequent item set.

Support: indicates the number of times data elements $X$ and $Y$ appear together as a proportion of all transactions.

$$Support(X,Y)=P(XY)=\frac{number(XY)}{num(AllSamples)} \tag{10}$$

Confidence: indicates the probability that when a data element occurs, the data element also occurs at the same time.

$$Confidence(X\Leftarrow Y)=P(X\mid Y)=P(XY)/P(Y) \tag{11}$$

### 2.3.2 Apriori algorithm

One common association rules mining algorithm is the apriori algorithm. All subsets of an item set are regarded as frequent item sets if the subset is present in a frequent item set; on the other hand, all supersets of an item set cannot be frequent item sets if it is not a part of a frequent item set [37].

Apriori algorithm steps:

Step1.Iterate through the entire set of data to be processed and take all the data elements as candidate frequent 1-item sets. If $k=1$, the frequent 0-term set is empty.

Step2.Mining frequent $K$ itemsets in the data set

a.Traverse the entire data set and calculate the support of the candidate frequent $K$ itemset;

b.If the support of the candidate item does not meet the set minimum support threshold, remove the candidate item and finally obtain the frequent $K$ itemset. If the frequent $K$ itemset is the empty set, the frequent $K-1$ itemset is output as the result of the algorithm execution, and the algorithm execution stops; if there is only one item in the last obtained frequent $K$ itemset, the algorithm does not continue to execute downward, and directly outputs the unique frequent $K$ itemset, and the algorithm execution stops.

c. On the basis of the frequent $K$ itemset, continue to generate candidate frequent $K+1$ itemsets.

Step3. make $K=K+1$, jump to Step2.

## 2.4 ANN-CBL based learning performance prediction module

### 2.4.1 Problem definition

For any student, how to predict the student's final grade level from the student's behavioral characteristics and historical grades. Assuming a set of student behavioral features $X$, where $X$ is a sequence $\{x_1, x_2, \ldots, x_n\}$ composed of the student's behavioral features over a period of time, and $x_i$ denotes the student's behavioral record at the $i$ th point in time, and each $x_i$ corresponds to the value of a specific behavioral feature such as the student's study hours, number of clicks, etc., and $n$ is the number of features, the predicted student achievement grade is $y_i (i \le 4)$, $y = \{y_1, y_2, \ldots, y_n\}$. The goal of the student performance prediction task is to construct a classification model based on a sequence of student behavioral features $X$ that maps student behavioral features to corresponding performance levels. The task of predicting student performance based on student behavioral features is defined as follows:

Inputs: number of individual student behavioral features $n$, student behaviors $x_i$, sequences of student behaviors generated by students each week: $\{x_{i1}, x_{i2}, \ldots, x_{in}\}$.

OUTPUT: The sequence of student behavioral features is input into the prediction model and results in a grade outcome $y_i (i \le 4)$, $y = \{y_1, y_2, y_3, y_4\}$.

### 2.4.2 Modeling framework

After taking the attention mechanism into account, the overall design of the ANN-CBL learning performance prediction model proposed in this research [38] is shown in Fig. 2. This model consists of CNN layer, BiLSTM layer, attention mechanism and fully connected layer.

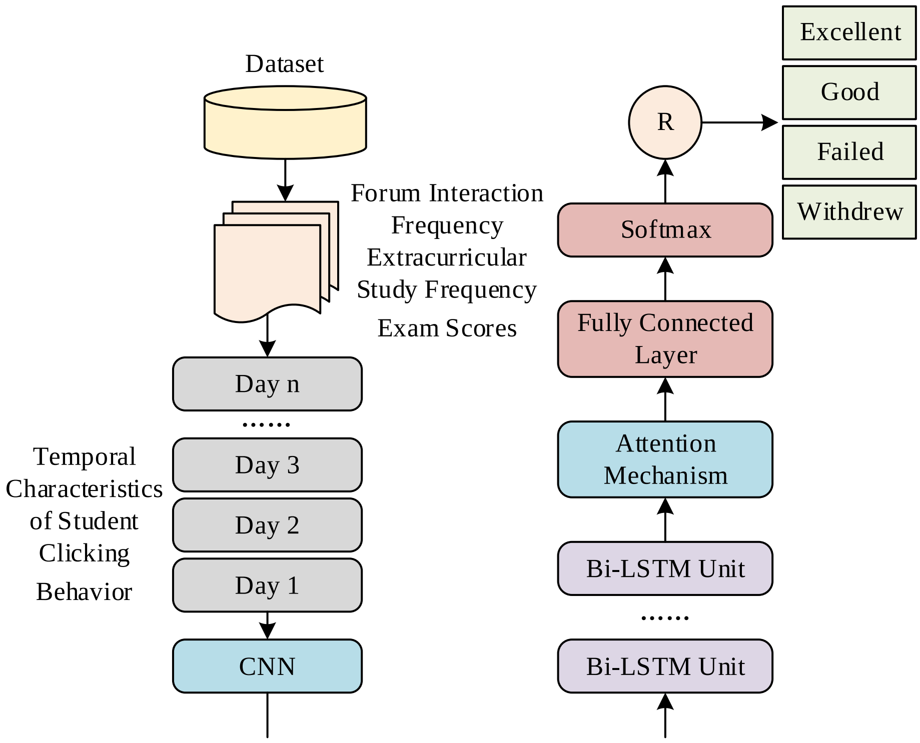



*Figure 2: Overall framework of ANN-CBL prediction model*

### 2.4.3 Algorithm design

The input layer, convolutional layer, pooling layer, and output layer make up the CNN., and the input layer receives the student behavioral features $X = \{x_{i1}, x_{i2}, \ldots, x_{in}\}$ and uses the convolutional layer to perform convolutional operations to extract features from a local time window or a local region. The convolutional layer output formula is shown in (12):

$$h_t^{(f)} = \sigma\left(\sum_{i=0}^{k-1}\sum_{j=0}^{d-1} W_{i,j}^{(f)} x_{t+i,j} + b^{(f)}\right) \tag{12}$$

where: $h_t^{(f)}$ is the output feature of the convolutional layer at time $t$, $W_{i,j}^{(f)}$ is the weight of the $f$ th convolutional kernel, $i$ denotes the index within the window, $j$ denotes the index of the input feature dimensionality, $x_{t+i,j}$ is the $j$ th dimensional feature of the input time series at time step $t+i$, $b^{(f)}$ is the bias term.

After performing the convolution operation on the student behavioral features, they are fed into the pooling layer to achieve data dimension compression, a process that helps reduce the risk of overfitting. In the choice of pooling method, this paper selects the maximum pooling strategy, which can accurately screen out the key features that have the most influence on the prediction of students' performance from the student behavioral features that have been processed by convolution. The pooling method formula is shown in (13):

$$h_t^{pool} = \max\left(h_t^{(f)}, h_{t+1}^{(f)}, \ldots, h_{t+p-1}^{(f)}\right) \tag{13}$$

where: $h_t^{pool}$ is the feature value at time $t$ after the pooling operation and $p$ is the pooling window size.

After the CNN extracts the sequence of important feature vectors, it is inputted to the BiLSTM layer.BiLSTM consists of two directional LSTM units, and compared with the unidirectional LSTM, BiLSTM is able to deal with both forward and reverse temporal information of the data. The two LSTM units in the forward and reverse directions control the flow of information within the unit through forgetting gates, input gates, and output gates, and are able to fully explore the deep features in the time series data.

The forward computation process of BiLSTM is similar to that of traditional LSTM, and the computation process of the forward LSTM unit is as follows:

The forgetting gate $f$ is used to decide which information should be retained and which information should be forgotten in the output $h_{t-1}$ of the LSTM unit at the previous moment, whose formula is shown in (14):

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{14}$$

The input gate $i$ is used to update the cell state and decide which information from the input $x_t$ at the current time step $t$ can be added to the LSTM cell, which is calculated as shown in (15):

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{15}$$

The cell state $C_t$ is jointly determined by a combination of forgetting gates and input gates, and is updated by forgetting a portion of the old state and adding new input information. Unlike $h_t$, the cell state is not directly outputted by the activation function and therefore retains the important information in the time series for a longer period of time, as shown in (16):

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tanh\left(W_c \cdot [h_{t-1}, x_t] + b_c\right) \tag{16}$$

The output gate $o$ is used to determine the information to be output to the next LSTM cell, thus effectively avoiding gradient explosion and gradient vanishing, which is calculated as shown in (17):

$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right) \tag{17}$$

The BiLSTM layer is followed by a Dropout layer to reduce the likelihood of the model overfitting. Because it randomly removes certain neurons, this helps reduce the neural network's over-reliance on any one property. The Fully Connected layer, the model's last layer, mainly aids in converting characteristics produced in the previous layer into categorization labels. Each neuron is weighted and summed by the output of the previous layer with a bias term, where $W_i^{(out)}$ is the weight vector of the output layer corresponding to the $i$ th category, $h^{(L)}$ is the higher-order features of the output of the previous layer, $b_i^{(out)}$ is the bias term of the $i$ th category of the output layer to help the model to adjust the output result, and $z_i$ is the input sample score for the $i$ th category. After the Softmax activation function generates the classification probabilities, $z_i$ is the score for each category. The model will select the category with the highest probability as the final prediction result after the Softmax function outputs each category's probability distribution, where $y_i$ indicates the probability that the input sample belongs to the $i$ th category, and $\hat{y}$ is the final prediction result of the model.The Softmax activation function and prediction formulas are shown in (18) to (20).

$$z_i = W_i^{(out)} \cdot h^{(L)} + b_i^{(out)} \tag{18}$$

$$y_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \tag{19}$$

$$\hat{y} = \arg\max_i y_i \tag{20}$$

# 3 Testing and analyzing the teaching management model of medical higher vocational colleges and universities

## 3.1 Data sources

### 3.1.1 Campus behavioral data

The one-card consumption and grade data of students enrolled in the university's 2023 cohort during their four years of college studies, as well as the one-card consumption data (dining, shopping, showering, and water usage) and book borrowing data and grade data of students enrolled in the 2024 cohort for one semester, totaling 402,158 observations, are the main student behavioral data used for this article. The online learning data used was the Open University of the United Kingdom open dataset, which contains student online course-taking data for the university's seven online learning programs over two academic years, 2021 and 2022. It contains seven data tables with a data log of 11,986,329 rows.

### 3.1.2 Data cleansing

The campus behavior data used in this paper come from the Academic Affairs Office, the Modern Education Technology Center and the library of a university, respectively. Since campus cards have been used as the identity documents of students in campus and they have taken many functions such as shopping, meals, showering, access control, borrowing books and others, there have been numerous datasets related to campus activities of college students after years of running. Because the departments in charge of the systems differ from one another, the data has been stored in many databases. The offline learning datasets of the students on campus would be comprised of the following data: information about the purchases made by students using their campus cards would be kept in the database run by the campus card system; information about their grades would be kept in the database of the academic affairs management system; information about library access control and book borrowing would also be kept in the corresponding databases. The grade information includes: student number, name, course, credit, grade, semester, class, and major.

### 3.1.3 Data integration

Three distinct departments provided the data used in this paper's data mining technique. The Academic Affairs Office provided the grades data, while the Modern Education Technology Center provided the one-card consumption statistics. However, the data on the books that were borrowed came from the library. The data that emerged from the statistical examination of data tables was referred to as integrated data in the context of data analysis.

### 3.1.4 Data conversion

Following the completion of the aforementioned procedures, the data set was scaled using R's scale function in accordance with the specifications of the ensuing cluster analysis tests. Data discretization was done before association rules were created. The process of turning continuous line data into discrete point data by classifying it is known as discretization of data. The data conversion lays the data foundation for the subsequent cluster analysis and association analysis experiments.

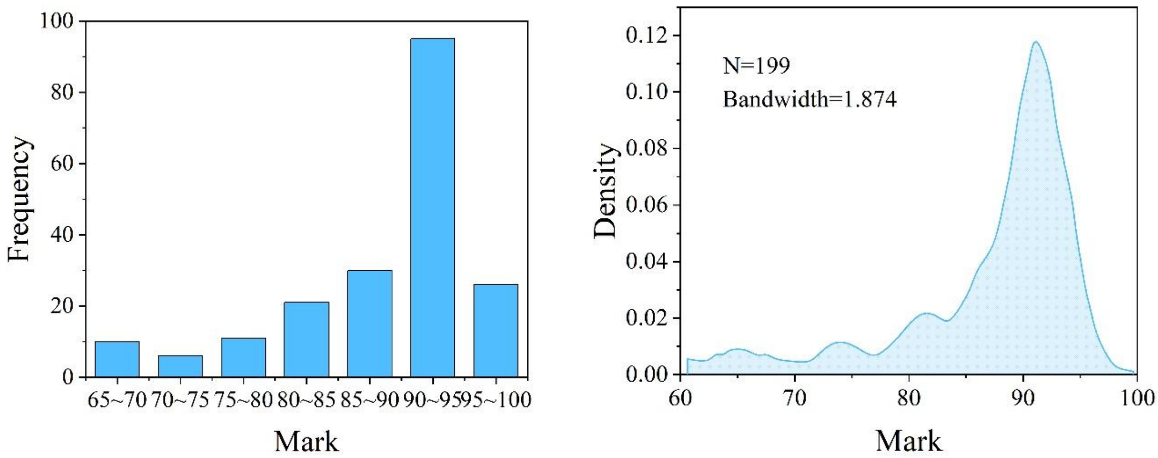
## 3.2 Examples of Learning Achievement Analysis

### 3.2.1 Application of histograms in performance analysis

A histogram can reliably show the distribution properties of the data set that require analysis, as well as the regularity of the changes in the data set. Histograms are frequently used to show the distribution frequency of continuous forms of data and to examine changes in the data collection. The distribution of the continuous variable p can be shown using the kernel density plot.

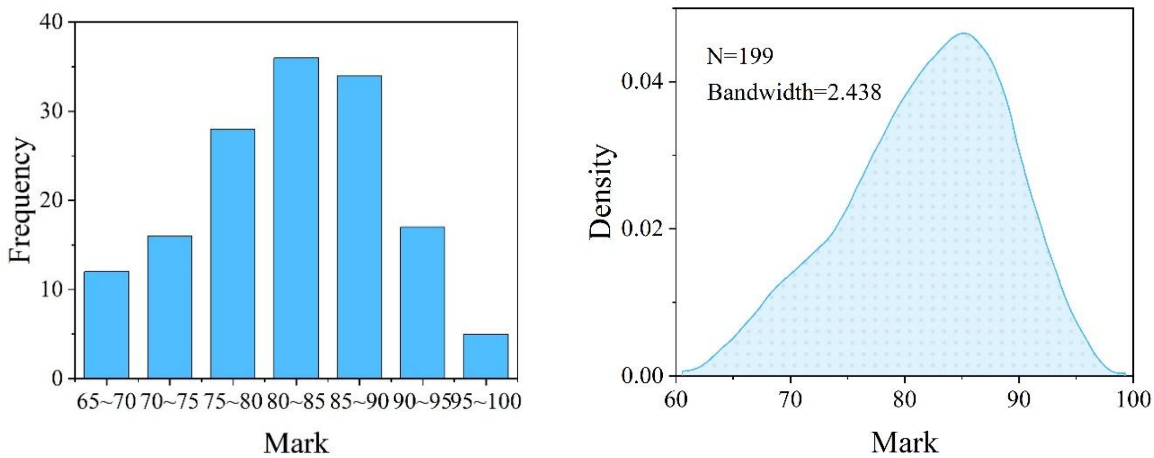
In the example, the score value will be used as the continuous type variable described, as shown in Fig. 3-Fig. 5, which are the histogram and kernel density plot of the three subjects' scores, respectively. Firstly, the different forms of distribution of the three subjects' scores can be observed in the whole, while the kernel density plot can observe more precisely whether it is normally distributed. It can be seen that the instructional system design histogram as a small mountain shape, high and low ups and downs, the mountain shape is oddly steep, 90 to 95 of the most prominent results; while the university English mountain shape is more gentle, to 90 of the most prominent results, the number of high and low scores are gradually decreasing, the kernel density curve is also smoother; in the figure of higher mathematics can be found in the histogram and the density graph of the high and low distribution of uneven, and there are two obvious prominent vertices, which are more randomly distributed in the graph.

The graph below illustrates how people are distributed differently according to their results, indicating an achievement gap if there is a significant variation in the number of persons who received a certain score. This might also be influenced by how challenging the subject is and how many persons received a score higher than 90. Comparison, pathology results are more ideal results of the study, the proportion of the number of high and low score groups is small, the results are basically gradient, 85 points about the number of other score groups compared to the proportion of the largest, in the number of people occupying a quarter of the proportion of the whole; 85 and above the score groups and decreasing step by step, to achieve a better teaching effect.



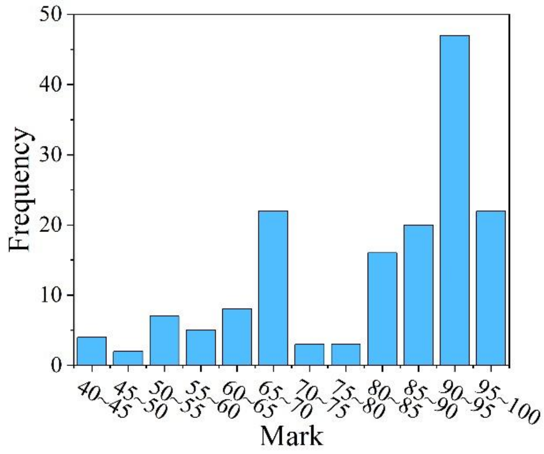

(a) Histogram of physiological scores (b)Density curve of physiological scores

*Figure 3: Overall trend chart of physiological scores*

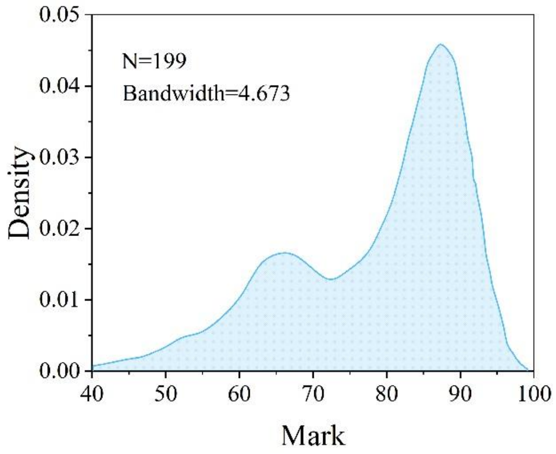



(a) Pathological score histogram (b)Pathological nuclear density curve

*Figure 4: Overall trend chart of pathological scores*




(a) Pharmacological score histogram

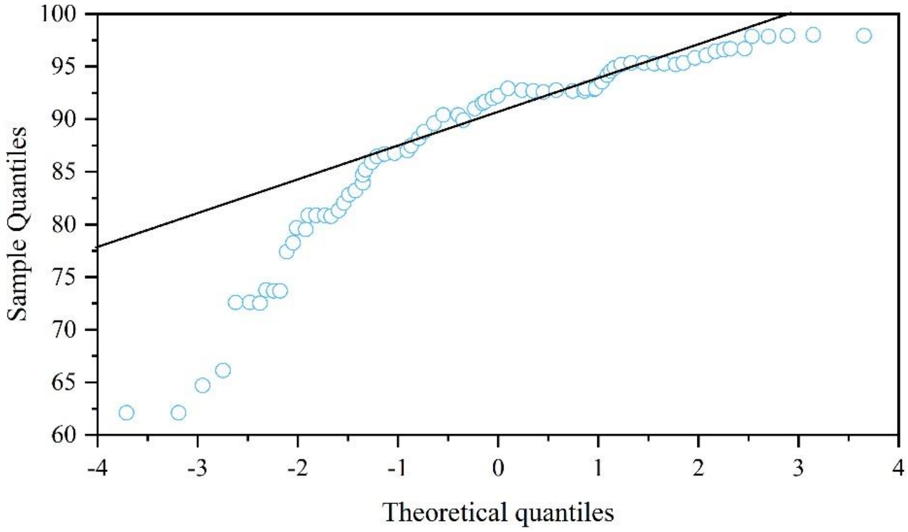



(b)Pharmacological kernel density curve

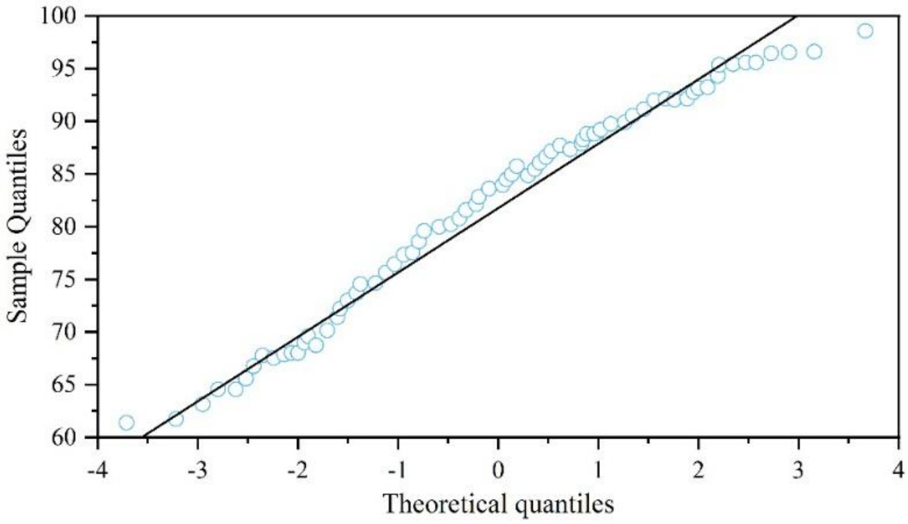
*Figure 5: The overall performance of pharmacology tended to be poor*

### 3.2.2 Application of QQ charts in performance analysis

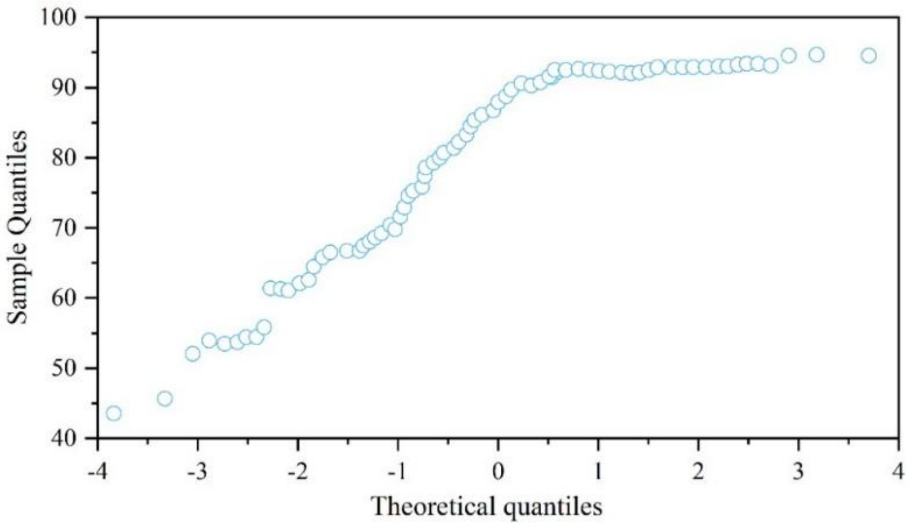
When the points on the QQ plot are arranged near the line $y = \sigma x + \mu$ . It means that the data are close to normal distribution. At this point, $\sigma$ and $\mu$ represent the standard deviation of the slope of the straight line and the mean of the intercept, respectively. Whether the data conforms to the normal distribution is seen from whether the points around the straight line are close to the straight line, and the closer they are indicates that the normal distribution is better.For this research example, the following QQ graph is generated by making the student data into an executable script that can be run in the R language as shown in Figure 6. The QQ graph can be used to check whether the grades conform to normality, and from the results of the analysis, it can be seen that Pathology is the course that conforms most to the normal distribution, since the grades of Pathology are the closest to the straight line fit.




(a) Physiological normal distribution




(b) Normal distribution diagram of pathology



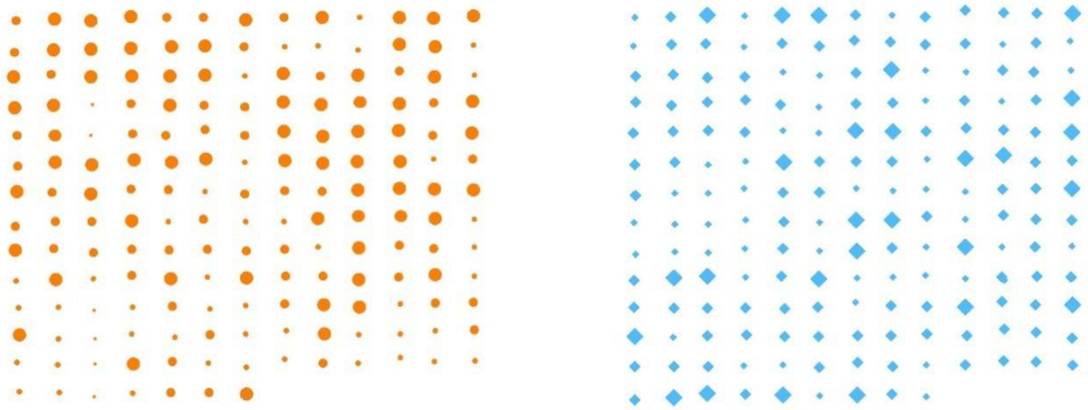

(c) Pharmacological normal distribution diagram

*Figure 6: Normal distribution of grades*

### 3.2.3 Application of star charts in performance analysis

After obtaining the obtained report card data of all students, with each learner as a unit of study, a visualized graph of the overall distribution of student achievement can be generated, which can be used by teachers to analyze teaching and learning situation variables. Star charts, also known as radar charts or spider charts, each graph represents a value, in this paper, each graphic unit represents each student's academic performance in each subject, where each corner of the graph represents a variable, the example part of this paper can be seen by the 360-degree angle of the Pingping three courses, each course subject are respectively accounted for 120 degrees. Figure 7 are the use of the statement stars () generated by the "angular star graph and circular star graph. In the figure, the larger the graphic area means that the better the results of the subject, if the graphic corners of the length of the more similar means that the door of the course results are similar, the results of the subjects are not obvious millimeters.

From the following two photos of the graph can be seen in the eleventh row of the fifth student of all courses scores are all very low, the first row of the first with the pathology of the poor performance, the last first row of the first student in addition to the physiology course, other than the other two courses, the performance of the other two courses are poor, while the first four students in the first column of the overall performance is better. Teachers can use star charts to quickly capture learners' course grades and can identify students with large deviations in grades at a glance.



(a) Orange irregular star map (b) Blue Hubble image

*Figure 7: Star map*

## 3.3 Big Data Correlation Analysis

First of all, the original data will be normalized and extracted to get the basic data that can be processed, and then the data table will be correlated and analyzed using the Apriori algorithm, and the breakdown of related variables is shown in Table 1.

*Table 1: Detailed list of discrete correlation analysis variables*

| Class | Variable name | Description | Variable discretization |
|---|---|---|---|
| Consumption variables | Use_exp | Number of cards used | much, middle, little |
| | Sc_exp | Food consumption | much, middle, little |
| | Sm_exp | Supermarket spending | much, middle, little |
| | Ib_exp | Hot water consumption | much, middle, little |
| | Bus_exp | Public transport spending | much, middle, little |
| Student work variables | S_type | Category of consumer groups | one, two, three, four |
| | S_section | Library access control data department | much, middle, litle |
| | S_major | Professional code | one, two, three |
| | S_mark | Examination performance | good, medium, poor |
| | S_register | Whether to take the postgraduate entrance examination | one, zero |
| | S_admit | Whether to take the postgraduate entrance examination | one, zero |
| | S_scholarship | Scholarship | one, zero |
| | S_grant | Stipend | one, zero |
| Library variables | I_book | Number of books borrowed | much, middle, litle |
| | I_time | Number of library visits | much, middle, litle |

The frequent item sets whose posterior items are academic achievement variables are shown in Table 2. It can be seen that the attributes of low food consumption, major code 1, attending graduate school, and moderate number of card usage are the strong association sets with outstanding academic performance. In terms of lift and confidence, the lift of all 10 itemsets is greater than 1 and the confidence level is greater than 0.6, indicating a good degree of association.

*Table 2: The posterior orientation is a partial frequent item set of the academic performance variable*

| ID | Priorities | Postscripts | Level of support | Confidence | Improvement | Count |
|---|---|---|---|---|---|---|
| 1 | (use_exp=middle, sc_exp=midle, s, major=one, s_register=one) | (s_mark=good) | 0.22745 | 0.68132 | 1.67284 | 51 |
| 2 | (use_exp-middle, s_major=one, s_register=one) | (s_mark=good) | 0.24095 | 0.67341 | 1.65184 | 55 |
| 3 | (use_exp-middle, sc_exp=midle, s_major=one) | (s_mark=good) | 0.23175 | 0.66842 | 1.63752 | 52 |
| 4 | (use_exp=middle, s_magjor=one, s_register=one, s_admite=zero} | (s_mark=good) | 0.22356 | 0.66435 | 1.63581 | 50 |
| 5 | (us_exp=middle, s_mgjor=one) | (s_mark=good) | 0.24584 | 0.66105 | 1.67208 | 57 |
| 6 | (sc_exp=middle, s_major-one, s_registerone, s_admit=zero) | (s_mark=good) | 0.22218 | 0.65149 | 1.61157 | 50 |
| 7 | (sc_exp=middle, s_major=one, s_register-one) | (s_mark=good) | 0.24425 | 0.65662 | 1.60072 | 55 |
| 8 | (use_exp=middle, s_major-one, s_admit=zero) | (s_mark=good) | 0.22567 | 0.65474 | 1.60284 | 51 |
| 9 | (sc_exp=middle, s_major=one, s_admit=zero) | (s_mark=good) | 0.22567 | 0.63743 | 1.56368 | 51 |
| 10 | (se_exp=middle, s_major=one) | (s_mark=good) | 0.24782 | 0.64638 | 1.56184 | 57 |

The combined short matrix of 13,274 association rules for student consumption behavior and grades is shown in Figure 8, which gives an overall view of the closeness of the association rules between the various variables.

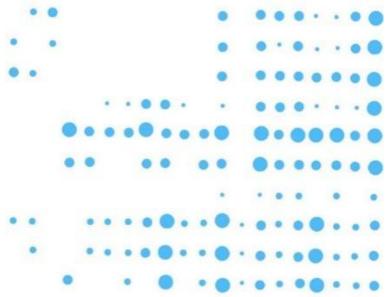


*Figure 8: Combination of association rules*

## 3.4 Cluster Analysis of Student Behavior

### 3.4.1 Clustering of Meal Consumption Levels

In this experiment, first, we will extract the data on the food consumption level of college students on campus based on the on-campus one-card dataset collected by organization for conducting the clustering analysis experiment. Then, the clustering analysis experiment will be conducted based on the K-means algorithm in the R language software on the collected data, where the sum of squared error within the cluster will be used as an index to obtain the optimum number of clusters, which is illustrated in Figure 9.

In comparison to the other two categories, the number of times students from category I have swiped their cards for eating inside the campus is higher and the amount spent by them per transaction is the lowest.

Students in Category 2 had a medium level of on-campus meal spending frequency and the highest average single purchase amount, which corresponded to the overall spending level of the majority of students in the program.

Students in Category 3 had a lower level of card frequency for on-campus dining, a medium average amount spent per transaction, and a relatively small percentage of students in the major.

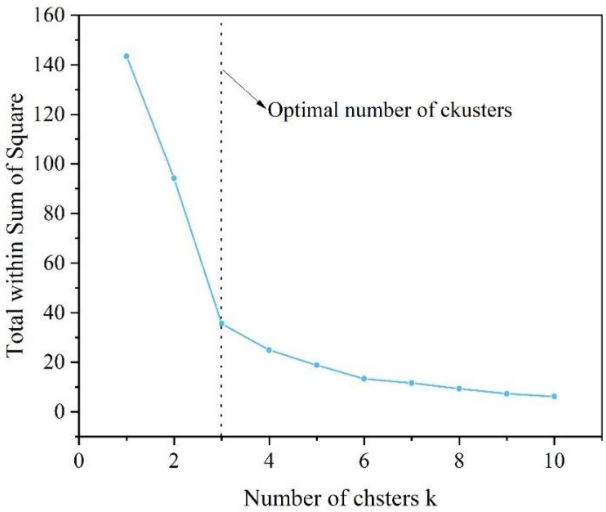



*Figure 9: Best clustering number diagram*

From the graph of the optimum cluster number generated through the above experimentation process, the optimum cluster number was found to be K = 3 due to its minimal change in slope, and finally, the results of the cluster analysis for dining consumptions were produced through the experiment, which are displayed in Table 3.

*Table 3: Cluster results of meal consumption*

| class | Number of meals consumed | Meal consumption amount | Student category label | Percentage of students |
|---|---|---|---|---|
| 1 | 464 | 2381 | Regular, frequent and stable consumption on campus | 50.28% |
| 2 | 272 | 1475 | High single consumption and small amount of off-campus consumption | 33.15% |
| 3 | 118 | 628 | Low consumption, off-campus consumption is the majority | 16.57% |

### 3.4.2 Regularity clustering

Secondly, the cluster analysis was done on the regularity information like food intake level and shower use water turn-on information from the students' behavior information. The best number of clusters was determined through the use of sum of squares of errors within clusters as a criterion in evaluating the best number of clusters through K-means method using R language software in performing clustering experiment as shown in figure 10.

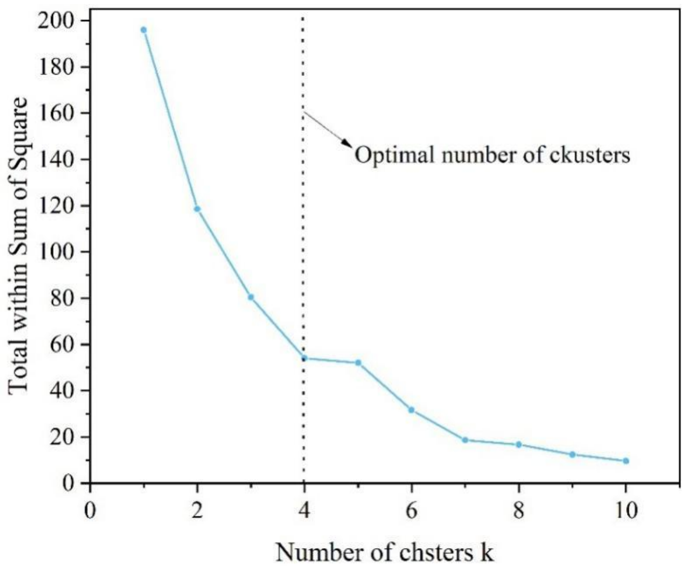



*Figure 10: Best clustering number diagram*

After interpreting the graph representing the optimal number of clusters derived from the experiment mentioned above, the point K=4 with an insignificant variation in slope was chosen as the optimal number of clusters, and finally, the regularity clustering results are presented in Table 4 below.

For the students in category I, the frequency of card use in order to have on-campus meals is very low, whereas the frequency of bathing is the highest, as well as using the water.

As for students belonging to the second category, the frequency of card use for having on-campus meals is the highest, while bathing and turning on the water are done at a medium level.

For students who belong to the third category, their card usage for purchasing on-campus meals was found to be low, while their frequency of bathing and turning on the water was medium.

The fourth category of students is characterized by a high frequency of using their card for purchasing on-campus meals, while at the same time they have the lowest frequency in terms of bathing and turning on the water.

*Table 4: Regular clustering*

| Class | Number of meals consumed | Number of baths | Number of water openings | Percentage of students |
|---|---|---|---|---|
| 1 | 85 | 28 | 149 | 22% |
| 2 | 453 | 16 | 126 | 20% |
| 3 | 127 | 16 | 112 | 44% |
| 4 | 283 | 11 | 56 | 25% |

### 3.4.3 Diligence Clustering

Since the majority of the drinking equipment is situated in the teaching building, we categorize the periods when the water is turned on according to how often they visit the building to read as well as the quantity of books they check out, which shows how diligent they are. As shown in Figure 11, we utilize the sum of squares of error inside each cluster as a criterion to calculate the ideal number of clusters for the optimum grouping.

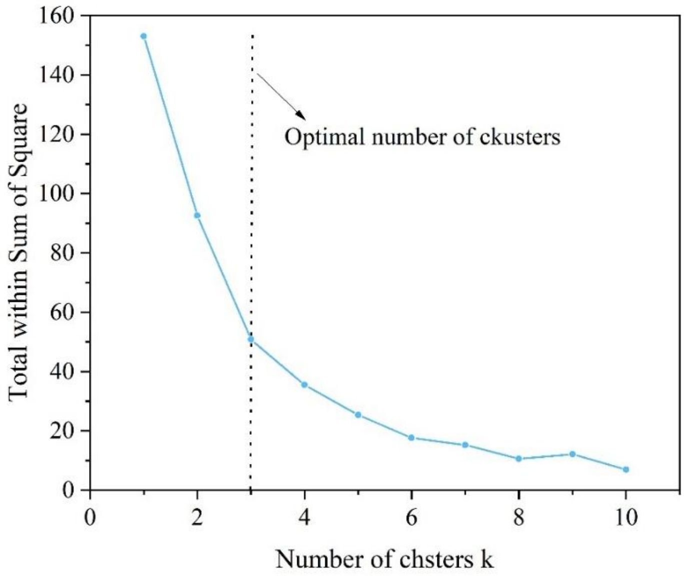



*Figure 11: Best clustering number diagram*

By interpreting the graph for the optimal number of clusters based on the above experiments, it was found that the optimal cluster is 3 since the slope does not change significantly at this point, and the results of the diligence clusters are shown in Table 5.

In the group I students, the frequency of turning on the water and using their card to swipe in the teaching building is of average frequency, while the frequency of borrowing books in this semester is of maximum frequency among the students of this department.

The frequency of turning on the water and swiping their card among students belonging to group II in the academic building is of highest frequency, while the frequency of borrowing books in this semester is of moderate frequency.

The group III students had the lowest frequency of turning on water in the building and borrowing books in this semester.

*Table 5: Results of the diligence clustering*

| Class | Number of water openings | Number of books borrowed | Percentage of students |
|---|---|---|---|
| 1 | 85 | 14 | 38% |
| 2 | 109 | 11 | 36% |
| 3 | 58 | 5 | 32% |

## 3.5 Results and Analysis of Predictions of Learning Achievement

### 3.5.1 Experimental environment and metrics

The entire model is trained in the PyTorch environment, on a single NVIDIA GeForce GTX 2060 GPU, using the Adam optimizer with a learning rate of 0.001, a Batch-size of 16, and an epoch of 500. The number of behavioral categories in the experiments is 24, i.e., $n$ is 24, and the dimensionality of the parameter matrices in the vectorized representation is 64 dimensions, with $k$ is set to 64.

The convolutional attention module has two completely connected layers of 32 and 1, respectively, while the two attention modules in the attention layer have three fully connected layers of 128, 64, and 1, respectively. The inputs of the two attention modules are 128-dimensional. The features are converted into dimensions of 129, 256, 64, and 3 in the Classification Prediction module's Feature Fusion layer. All fully linked layers and internal activation algorithms are Relus.

To evaluate the performance of the proposed method quantitatively, we split the obtained dataset into two parts where the first 80% part serves as the training set and the other 20% part serves as the testing set. We will utilize mainstream measurement indices to assess our experiment results, including accuracy, precision, recall, and f1 values, in which accuracy is expressed as follows:

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} \tag{21}$$

Precision rate is the ratio of the number of positive samples to the total number of predicted positives from the model, expressed in the form of a mathematical expression as:

$$\mathrm{Pr}\,ecision = \frac{TP}{TP + FP} \tag{22}$$

The recall metric is measured as the ratio of positively classified instances out of the total number of actual positives within the sample using the formula below:

$$\mathrm{Re}\,call = \frac{TP}{TP + FN} \tag{23}$$

The F1 score is a reconciled mean between precision and recall and can be calculated using the following formula:

$$F1 = \frac{2 * \mathrm{Pr}\,ecision * \mathrm{Re}\,call}{\mathrm{Pr}\,ecision + \mathrm{Re}\,call} \tag{24}$$

where TP represents instances that are positively classified and correctly predicted, FN represents instances that are positively classified but predicted to be negatively classified, FP represents instances that are negatively classified but predicted to be positively classified, and TN represents instances that are negatively classified and correctly predicted.

### 3.5.2 Experimental results and analysis

The performances of the models from this paper for real datasets will be compared with other conventional machine learning algorithms including Logistic Regression (LR), Decision Tree (DT), Support Vector Machine (SVM), and Random Forest (RF). All these algorithms will be used in the data mining process for predicting the performance of the students and the performance of these algorithms on the real dataset will be analyzed by determining the best parameters for each model.

The experimental results are presented in Table 6. The proposed algorithm for grade prediction in this paper performs better than the other conventional algorithms since the accuracy rate obtained was 85.29% while that of random forest was only 69.88%, thus an improvement of 15.41%. All other indexes were also significantly improved.

*Table 6: Results of different methods on data sets*

| Method | Accuracy(%) | Precision(%) | Recall(%) | F1(%) |
|---|---|---|---|---|
| LR | 65.38 | 66.09 | 64.76 | 60.74 |
| DT | 65.6 | 65.25 | 63.82 | 64.67 |
| SVM | 67.65 | 67.63 | 63.74 | 64.74 |
| RF | 69.88 | 70.5 | 68.28 | 68.44 |
| ANN-CBL | 85.29 | 84.53 | 82.85 | 83.51 |

To further intuitively analyze the difference in influence degrees among various behavioral features on performance, we have drawn the attention scores of various behavioral features, and the results are displayed in Fig. 12. The abscissa in the figure is the serial number of the behavioral features, and the ordinate represents the weight values. From the figure, it can be observed that the weight values of various behavioral features included in the learning behavior of this kind are comparatively larger, whereas the weight values of the behavioral features related to the consumption behavior are comparatively smaller. Among these, the frequency of entering the library per month has the largest weight value, showing that the introduction of attention mechanisms in the model improves the ability of the model to extract key features and treats different behavioral features differently.

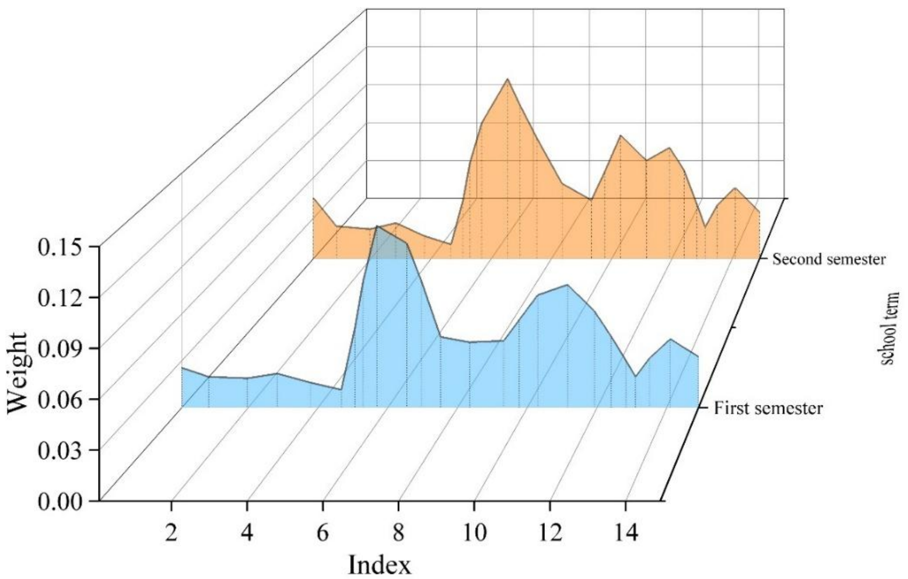



*Figure 12: The weight of each behavioral feature*

Balanced scores have also been illustrated, and this has been done by plotting the results in Fig. 13, where x-axis is student samples and y-axis is balanced scores values. The two horizontal lines have been plotted to understand the impact of balanced scores on final grades, and it can be seen that there is difference in balanced scores distributions for similar categories of students, e.g., A grade students have more balanced scores compared to students having grade C, whose balanced scores are below 0. Thus, it can be said that balanced scores indicate the grades, and hence, improve the accuracy of predictions.

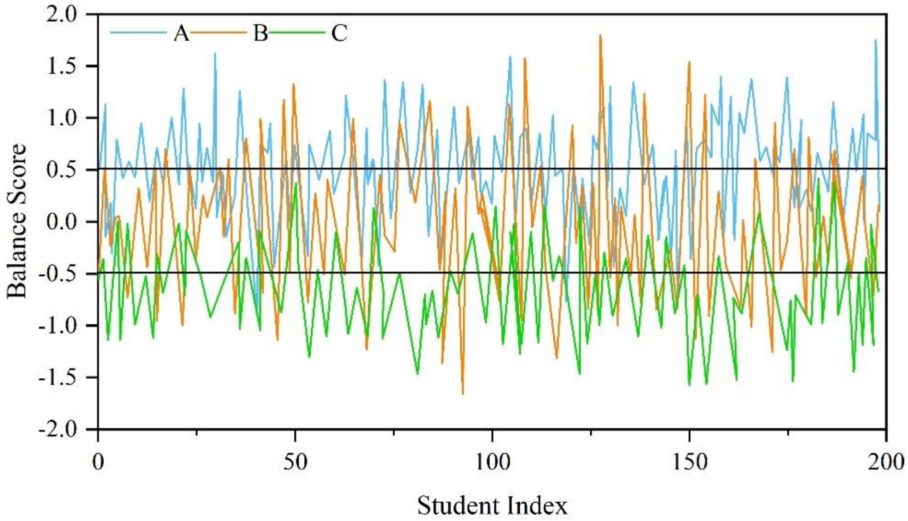



*Figure 13: Balanced scores for different categories of students*

# 4 Path of implementation of teaching management mode in medical higher vocational colleges and universities

## 4.1 Build a vertical and horizontal data exchange and sharing platform

At present, the data sources of the business departments of higher education institutions are different, some of which are data from the relevant system platforms and some are derived from statistics, which are stored in various forms in the business departments in a decentralized manner, which hinders information sharing and leads to inconsistencies in the storage of data among the departments and hinders collaboration among the departments. Inconsistency in storage standards also hinders data fusion. Moreover, many higher vocational schools are short-sighted, and the sharing of operational data between business departments is not timely, which not only wastes storage space, but also perpetuates the phenomenon of information silos. In the context of big data, teaching management can realize the sharing of resource data through the establishment of a unified network platform, which runs vertically through the students, teachers, teaching department and secondary colleges, and horizontally through the business departments within the school, and through the sharing of data to achieve data exchange and collaboration.

## 4.2 Expanding the coverage of the application of the Academic Affairs Management System (AAMS)

Many vocational institutions use the teaching affair management system through the purchase of a teaching affair management system from a software house. The purchased teaching affair management system is convenient for use; however, it may differ slightly from the management system of the institution. Therefore, there is need to pay close attention to individualized treatment of this management system with reference to the nature of the institution. Regarding the teaching management system itself, it is clear that at the moment, the teaching management system has few application modules, and its application is not as wide-ranging as expected, either within or beyond the scope of the teaching management. There is need to conduct demand analysis on the basis of its performance and carry out research and development or improvements to make it functional.

### 4.3 Developing a new system for teaching management and standardizing the process of teaching management

The current management system and management process can no longer adapt to the current new situation. On the one hand, under the premise of adapting to the current big data background, a unified data management standard is established, which is conducive to the integration of data from various platforms, thus facilitating the elimination of information silos, so that the data can achieve higher utilization value through sharing or correlation analysis. On the other hand, considering the lack of clarity in the management system and the lack of clarity in the management process in relation to big data, it is important for the teaching management system to be further developed, while the teaching management process needs to be clearly defined.

### 4.4 Early warning analysis to improve scientific decision-making capacity

The mining of resources requires the use of information technology to collect and organize through professional data collection techniques. A big data management system for higher vocational institutions can be built, and data analysis techniques can be utilized to integrate and process research and in-depth exploration of the information kept in the system. Through the comparison and analysis of similar or related data and information, experience is summarized, which is conducive to guiding practice, improving the effectiveness of management, and facilitating the leadership to make a good prediction for the development of other programs to do a good job of reasonable planning.

### 4.5 Enhancing data literacy for instructional administrators

It is necessary for teaching managers to have a strong level of data literacy. Historical data should be organized, and relevant data should be continually collected. Big data should be used to make up for the drawbacks of traditional management in education, emphasizing the relationship between these pieces of information to enhance the quality of the collection and analysis of data, thus maximizing its use. The professionalism of educational management workers should be improved.

### 4.6 Strengthen campus network security management

In the context of big data, relying on convenient network sharing platforms, access to information has become easy and convenient, which also carries the risk of information resources being leaked or stolen. How to avoid this risk is particularly important. On the one hand, network security measures can be taken through technical support. On the other hand, it is necessary to improve the comprehensive quality of network security personnel and improve network security awareness. In the usual management work, monitoring and management should be strengthened.

## 5 Conclusion

This research project adopts digital technology to establish a teaching management platform for vocational institutions of higher education. An optimized k-means clustering algorithm and association rule mining technology are adopted to mine the behaviors of college students within their educational period in order to implement the accurate classification and the accurate analysis of the learning status of the students. After that, an ANN-CBL performance prediction model with the introduction of attention mechanism is established, and its findings are presented as follows:

(1) R language data analysis technology is used to collect and extract the basic data for analysis, and the indicators of meal consumption level, regularity, and diligence are classified, and the results show that the students in this major can be classified into 3 to 4 categories according to their behavioral performance, and the analysis is carried out by using the Apriori association rule algorithm to get the association rules between behavior and achievement, and the results show that breakfast is often on time and regularity of life, bathing and turning on the water frequency are in the middle level of the students in this specialty have better grades.

(2) Lastly, all the traits are integrated to forecast the students' results. The experiment shows that the model works well when applied to real-world data; its accuracy reaches 85.29% with good interpretability, making it capable of solving the problem of forecasting students' academic achievement.

According to the above analysis, the following are suggested for the teaching management informatization improvement measures: develop a platform for data sharing for teaching purposes, increase the use of the teaching system, improve the teaching management system, regulate the process of teaching management, anomaly analysis, do a good job of early warning, improve the decision-making capabilities scientifically, enhance the competence of data literacy among managers, and improve campus network security management.

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## About the Author

Yan Liu was born in Shaoyang, Hunan, China, in 1978. I obtained a master's degree from China University of Geosciences. I am now working at Wuzhou Medical College, and my main research direction is internal and medical higher education management.

Tiegang Qiu was born in Yueyang, Hunan, China in 1983. I obtained a Bachelor's degree from Changsha Medical University. I currently working at Wuzhou Medical College, and my main research direction is medical college management.

Zhangyuan Jin was born in Gaoyou, Jiangsu, China in 1989. He obtained a Bachelor's degree from Changsha Medical University. I currently working at Wuzhou Medical College, and my main research direction is the management of medical practice teaching.

Xianyu Yuan was born in Ningxiang, Hunan, China in 1975. I obtained a master's degree from South University. I am a member of the Hunan Provincial Biochemistry Association and the Hunan Provincial Language and Writing Workers Association, and my main research direction is the protein structure and function, teacher development and management research.

Zhou Lu was born in wu zhou guangxi china in 1981.He obtained a bachelor’s degree from Hua zhong University of Science and Technology.He is working at wu zhou red cross hospital.His main research direction is Medical education management.

Yuan Ma was born in chong qing china in 1991. she is dedicated to providing clients with smart education solutions and resource services. Equipped with rich experience in market development and team management, she excels at integrating resources to drive project implementation, and commits herself to boosting regional education digital transformation with innovative services.

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