Construction of College Students' Management Informatization Ecosystem Based on Data Analysis Technology

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Abstract—College students' management informatization ecosystem can help college students better manage information and resources, thus improving learning and life efficiency. It's important to introduce data technology into the college student management informatization ecosystem, which can better realize the extraction of student behavior fluctuation information and achieve more targeted student management decisions. The current research lacks consideration of its future development trend, such as the impact of the application of technologies, including artificial intelligence, big data Fenix, and the Internet of Things. This paper studies the construction of college students' management informatization ecosystem based on data analysis technology. Firstly, the design of the data fusion scheme applied to the college students' management informatization ecosystem is carried out, and the idea of the scheme is given. Aiming at the big data of students' learning and living behaviors, this paper digs deep into the value of data information, and extract historical student behavior characteristics, providing a basis for short-term student behavior prediction and management decision-making planning and implementation for the college students' management informatization ecosystem. Based on historical student behavior data and its characteristic data, the XGboost algorithm is used to quantify and extract the importance of each influencing factor on student behavior fluctuations. Experimental results verify the effectiveness of the method proposed in this paper.

Keywords—data analysis, management of college students, information ecosystem, data fusion, characteristic analysis of student behaviors

1 Introduction

The college student management informatization ecosystem can be composed of multiple informatization applications and tools, which can be interconnected and support each other to form a complete informatization ecosystem, providing support and services for the study and life of college students [1–6]. The information ecosystem used for college student management includes learning management systems, task management tools, information collection and organization tools, social networks and online communities, and cloud storage services [7–14]. These tools can cooperate and support each other to help college students better manage information and resources, and improve learning and life efficiency [15–21]. It is helpful to introduce data technology into the college student management informatization ecosystem in better realizing the extraction of student behavior fluctuation information and achieving more targeted student management decisions.

Xiang et al. [22] constructs an indicator to facilitate the monitor of college students' thought dynamic, which is difficult to capture. A visual management information system based on big data is developed to monitor the thinking dynamics of college students. The system is based on B/S architecture and uses SQL Server database, which can realize functions such as index modification, document recording, word segmentation statistics, index association, keyword search, index analysis, and document analysis. Online reviews, research reports, and other material content can be visualized through the use of visualization tools. It can provide a better decision-making basis for strengthening the ideological education of college students. In view of the fact that the traditional student information management system cannot maintain a certain system response speed in the case of a large number of concurrent users, Jiang and Song [23] designs a hierarchical management system for college student information based on deep learning. The hardware module of student information collection is constructed by using RFID technology, and the software part of the management system is designed. Through the comparison with the traditional management system, it is proved that the management system based on deep learning can maintain a high response speed and superior system performance in the case of a large number of concurrent users. Syn et al. [24] investigates the personal information management behavior of college students in three situations from the perspective of information vision theory. The research results show that students show different information behavior density and activity in different situations. Of all activities, it is the most active in the academic environment and the least in healthy. Yang [25] analyzes the business requirements of college students' psychological intervention, and elaborated on the problems that the system needs to solve. Through the analysis of the business requirements of psychological intervention in colleges and universities, the overall design of the system's architecture, work flow and functions is carried out. The development and application of the system conforms to the current development direction of educational informationization, and improves the work efficiency and management level of psychological intervention.

Through the analysis and summary, it can be seen that there are still some deficiencies in the existing research on the management informationization ecosystem of college students. Relevant studies mostly achieve single-point breakthroughs, but lack of overall system analysis and research on the structure, function, and operating mechanism of the ecosystem. And it is absent in forward-looking research on relevant future development trend, such as the impact of the application of artificial intelligence, big data Fenix, the Internet of Things and other technologies. Moreover, the current evaluation of college students' management informatization ecosystem is mostly qualitative analysis, lacking quantitative evaluation methods and index systems. Therefore, this paper conducts research on the construction of college students' management informatization ecosystem based on data analysis technology. First of all, in Chapter 2, this paper designs the data fusion scheme applied to the college students' management informatization ecosystem, and gives the scheme idea. In Chapter 3, this paper focuses on the big data of students' learning and living behaviors, digs deep into the value of data information, and extracts the characteristics of historical student behaviors, providing a basis for the realization of short-term student behavior prediction and management decision-making planning and implementation of the college students' management informatization ecosystem. In Chapter 4, based on historical student behavior data and its characteristic data, the *XGboost* algorithm is used to quantify and extract the importance of each influencing factor on student behavior fluctuations. Experimental results verify the effectiveness of the method proposed in this paper.

2 Collected data fusion in the management informatization ecosystem of college students

Influenced and coupled by various factors, it is hard to maintain the smooth study and life of college students without the learning management system, including the school's learning management platform and various learning websites, which can provide functions such as course arrangement, test result query, learning resource download, and online learning, helping students better manage the learning process. It is necessary to use task management tools, including Evernote, Trello, Wunderlist and other apps, which can help students record to-dos and schedules, remind students of task completion, and improve efficiency. It is also need to use applications such as Feedly, Pocket, and OneNote to collect and organize information to facilitate learning and research. And it is important to use social networks and online communities including WeChat, QQ, Weibo, Zhihu and other platforms for students to communicate and learn with classmates, teachers, and experts. Students also need cloud storage services including Baidu Cloud, Google Drive, and Dropbox, which can assist students in storing and sharing various files and documents, and facilitate synchronization and backup between multiple devices.

Learning management systems, task management tools, information collection and organization tools, social networks and online communities, and cloud storage service systems constitute an informatization ecosystem for college students, which affect and act on the learning and living environment of college students from all aspects. Data fusion processes a large amount of multi-source and complex original data collected from the college student management informatization ecosystem with nonlinear mathematical calculation methods so as to obtain more effective student behavior fluctuation information and realize corresponding student management decisions. Next, this paper designs the data fusion scheme applied to the college students' management informatization ecosystem. Figure 1 shows the design idea of the data fusion scheme.

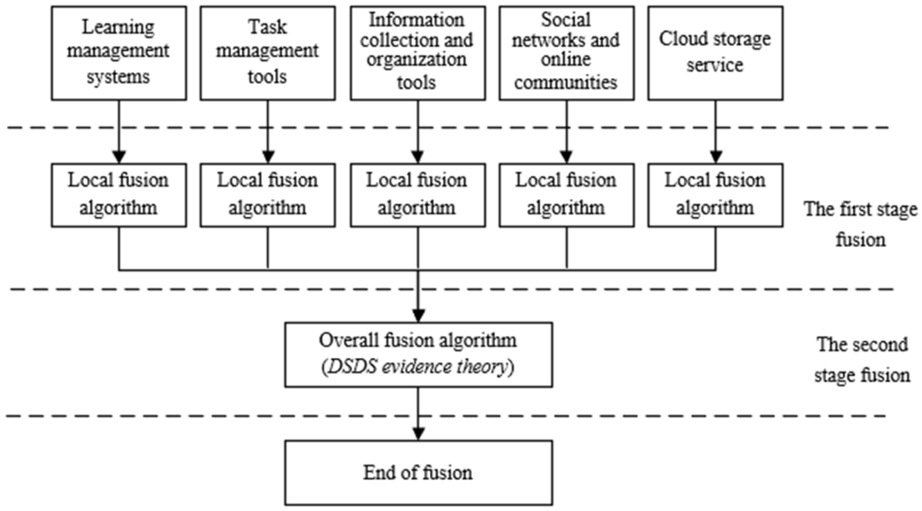


Fig. 1. Design ideas of data fusion scheme

The collected data with high reliability from each subsystem are filtered and put into the fusion set. It is assumed that at a certain moment *o,* the collected data supplied by each subsystem is $R_i(o)(i\in[1,m])$, then the absolute value of the observed data difference of each subsystem can be calculated by the following formula:

$$E_{ij}(o)=\left|R_i(o)-R_j(o)\right| \tag{1}$$

With the calculation results of the above formulas combined, the matrix $E_{ij}(o)$ of the absolute observed data difference at the corresponding time can be obtained, which is given by the following formula:

$$E_{ij}(o)=\begin{pmatrix} E_{11}(o) & E_{12}(o) & \cdots & E_{1m}(o) \\ E_{21}(o) & E_{22}(o) & \cdots & E_{2n}(o) \\ \vdots & \vdots & & \vdots \\ E_{m1}(o) & E_{m2}(o) & \cdots & E_{mm}(o) \end{pmatrix} \tag{2}$$

The calculation formula of the average value of the absolute observed data difference between the i_{th} subsystem and other subsystems at the certain moment *o* is given as follows:

$$\bar{e}_i(o)=\frac{E_{i1}(o)+E_{i2}(o)+\ldots+E_{im}(o)}{m} \tag{3}$$

The absolute average observed data difference of the college students' management informatization ecosystem as a whole can be calculated by the following formula:

$$\overline{e}(o) = \frac{\overline{e}_1(o) + \overline{e}_2(o) + ... + \overline{e}_m(o)}{m} \tag{4}$$

If compared with the overall average value of the college student management informatization ecosystem, the ration difference absolute average observed data difference of the i_{th} subsystem is larger, then the data is discarded. If the ratio difference is smaller, it is judged that the collected data has higher credibility, which is put into the fusion set. The following formula gives the definition of the best fusion set Ψ generated:

$$\Psi = \{R_i(o) \mid \overline{e}_i(o) < \overline{e}(o)\} \tag{5}$$

If the data in the fusion set are represented by B_1, B_2,..., B_M, the minimum variance ε^2_{min} of ε_1, ε_2,..., ε_M, the observed data variances of the subsystems corresponding to each collected data, is calculated, and based on ε^2_{min}, the optimal weighting factor and the final fusion estimated value B^* are further calculated.

Through the above local fusion algorithm, the fusion results of the data collected by different subsystems can be obtained, which in this paper is assigned with the basic probability assignment function based on the fuzzy subordination degree to form the initial evidence source that is fused based on the *DS* evidence theory method.

If the numbers of target types and subsystems are denoted by M and N, the correlation coefficient of the i_{th} subsystem to the target type T_j is denoted by $Z_i(T_j)$, and the weight coefficient of the i_{th} subsystem is denoted by μ_i, then:

$$\begin{cases} \beta_i = \max\{Z_i(T_j) \mid j = 1, 2, \ldots, M\} \\ \delta_i = \dfrac{M\mu_i}{\sum\limits_{j=1}^{M} Z_i(T_j)}, i = 1, 2, \ldots, N \\ \gamma_i = \dfrac{\delta_i - 1}{N - 1}, N \geq 2; = 1, 2, \ldots, N \\ S_i = \dfrac{\mu_i \beta_i \gamma_i}{\sum\limits_{i=1}^{N} \mu_i \beta_i \gamma_i}, i = 1, 2, \ldots, N \end{cases} \tag{6}$$

Then the assignment of the basic probability assignment function of the i_{th} subsystem to the target type T_j can be expressed by the following formula:

$$n_i(T_j) = \frac{Z_i(T_j)}{\sum\limits_{i=1}^{N} Z_i(T_j) + M(1 - S_i)(1 - \mu_i \beta_i \gamma_i)} \tag{7}$$

The assignment of basic probability assignment function of the i_{th} subsystem to the "uncertain" can be expressed by the following formula:

$$n_i(\Theta) = \frac{M(1-S_i)(1-\mu_i\beta_i\gamma_i)}{\sum_{i=1}^{N} Z_i(T_j) + M(1-S_i)(1-\mu_i\beta_i\gamma_i)} \tag{8}$$

According to Equation 7 and Equation 8, except that μ_i is obtained from experience, and M and N are fixed values, it is necessary to focus on how to obtain accurate $Z_i(T_j)$. Because both the subordination function λ_{ij} and $Z_i(T_j)$ can be used to estimate the degree of contribution of the measured target pattern to a certain type of subsystem observation data, this paper uses the subordination function λ_{ij} to $Z_i(Tj_j)$ for equivalent. It is assumed that the fuzzy subordination function is represented by $X(a)$, which can represent the degree of subordination to X in the interval [0,1]. When the collected value of the i_{th} subsystem is represented by R_{ia}, the characteristic value of the subsystem attribute parameter is represented by ω, and the maximum deviation value of a collection item's characteristic in the i_{th} subsystem is represented by ε_{ia}, then the definition formula is as follows:

$$\lambda_{ij} = d^{-\left(\frac{R_{ia}-\omega}{\varepsilon_{ia}}\right)^2} \tag{9}$$

When the above formula is combined with formula 7:

$$n_i(T_j) = \frac{\lambda_{ij}}{\sum_{i=1}^{N} \lambda_{ij} + M(1-S_i)(1-\mu_i\beta_i\gamma_i)} \tag{10}$$

After the assignment of the basic probability assignment function based on the above steps is determined, the correlation between evidences can be calculated based on the *DS* evidence theory, and then the correlation matrix of all evidences can be generated, and the global credibility and weighted evidence of any evidence can be obtained. Finally, based on the different weight coefficients of each evidence, the basic probability assignment function is reassigned, and the fusion calculation is completed based on the combination rules.

3 Analysis of the time fluctuation characteristics of student behaviors in the college student management informatization ecosystem

Student behavior characteristics are the basis and premise of studying student behavior management. Reasonable and accurate analysis of student behavior characteristics can provide a reliable basis for subsequent short-term student behavior prediction, management decision-making planning and implementation research, which is the basic link of student behavior management by the college student management departments. At the same time, with the continuous improvement of the college students' management informatization ecosystem, subsystems such as learning management systems, task management tools, information collection and organization tools, social networks and online communities, and cloud storage service systems have accumulated a large number of different types of behavioral information data of college students. Therefore, this paper mainly focuses on the big data of students' learning and living behaviors, digs deep into the value of data information, and extracts the characteristics of historical student behaviors, so as to provide a basis for the realization of short-term student behavior prediction and management decision-making planning and implementation of the college students' management informatization ecosystem. Figure 2 shows the analysis process of the time fluctuation characteristics of student behaviors.

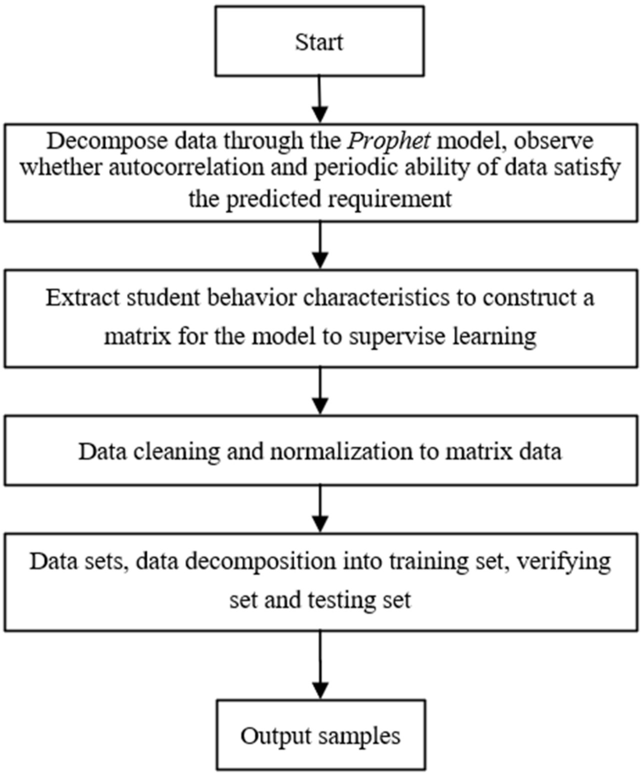


Fig. 2. Analysis process of time fluctuation characteristics of students' behavior

This paper chooses the *Prophet* model, which is the additive model-based decomposition model of college students' behavior sequence, to analyze the characteristics of college students' behavior time fluctuations. Based on the *Prophet* model, four items are disassembled in the behavior sequence of college students, namely the trend item $h(o)$, the cycle item $r(o)$, the holiday item $f(o)$ and the error item ρ^t, namely:

$$b(o) = h(o) + r(o) + f(o) + \rho^t \tag{11}$$

where, the non-periodic and periodic changes in the behavior sequence data of college students are modeled with the trend item $g(t)$ and the period item $s(t)$ respectively, the abnormal mutation of the data during holidays were quantified with the holiday item $h(t)$, and the error term εt represents any idiosyncratic changes that did not fit the model.

The *Prophet* model provides a saturated growth model and a linear segment model based on logistic regression for the modeling of the non-periodic changing part of college students' behavior sequence data. If the maximum amount of behaviors in a certain interval on day *o is* represented by $Z(o)$, the growth rate of the behavior sequence data curve of college students is represented by l, the offset of the curve is represented by n, the corresponding point when the growth rate changes is represented by R_j, the column vector composed of $x_j(o)$ is represented by $x(o)$, whether a certain change point R_j has occurred on day o is represented by $x_j(o)$, the column vector composed of growth rate change is represented by ξ, and the column vector composed of correction factors is denoted by α, then the model expression is as follows:

$$h(o) = \frac{Z(o)}{1 + \exp(-(l + x(o)^T \xi)(o - (n + x(o)^T \alpha)))} \tag{12}$$

$$h(o) = (l + x(o)^T \xi) o + (n + x(o)^T \alpha) \tag{13}$$

$$x(i) = \begin{pmatrix} x_1(i) \\ x_2(i) \end{pmatrix} \tag{14}$$

$$x_j(o) = \begin{cases} 1, o \ge R_j \\ 0, o \le R_j \end{cases} \tag{15}$$

The *Prophet* model provides a simulation method of Fourier series for the modeling of the periodically changing part of the behavior sequence data of college students. If the total number of days that the sequence lasts is represented by M, the smoothing parameters are represented by x_m and y_m, and the cycle days are represented by C, then the expression is as follows:

$$r(o) = \sum_{m=1}^{M} \left(x_m \cos\left(\frac{2\pi mo}{c}\right) + y_m \sin\left(\frac{2\pi mo}{c}\right) \right) \tag{16}$$

Based on the *Prophet* model, the abnormal mutation of college students' behavior sequence data during the holiday period can be quantified based on the holiday list preset by the user. If the position vector of day o in the holiday set is denoted by $C(o)$, the column vector composed of the corresponding influence parameters of each day in the holiday set is denoted by l, and the influence of different types of holidays is fixed, then:

$$f(o) = C(o)l \tag{17}$$

Through the construction of the *Prophet* model, it is possible to model and quantify the behavioral characteristics of yearly, monthly, weekend, and holiday behaviors of students' daily learning and life in a big data environment, which is helpful for college student management departments to extract and analyze the behavioral characteristics of college students in different grades and different study periods with massive historical data, thus facilitating the identification and extraction of abnormal behaviors, and also providing the original basis for the planning and implementation of student management-oriented management decisions.

4 Analysis of factors affecting student behavior fluctuations in the college student management informatization ecosystem

It is important for the short-term student behavior prediction feature engineering of the college student management informatization ecosystem to accurately quantify and extract various factors that affect student behavior fluctuations. The accuracy of feature extraction directly affects the prediction accuracy of short-term student behavior prediction by the college student management informatization ecosystem. Therefore, this paper uses the *XGboost* algorithm to quantify and extract the importance of each influencing factor on student behavior fluctuations based on historical student behavior data and its characteristic data. Figure 3 shows the analysis process of factors affecting student behavior fluctuations.

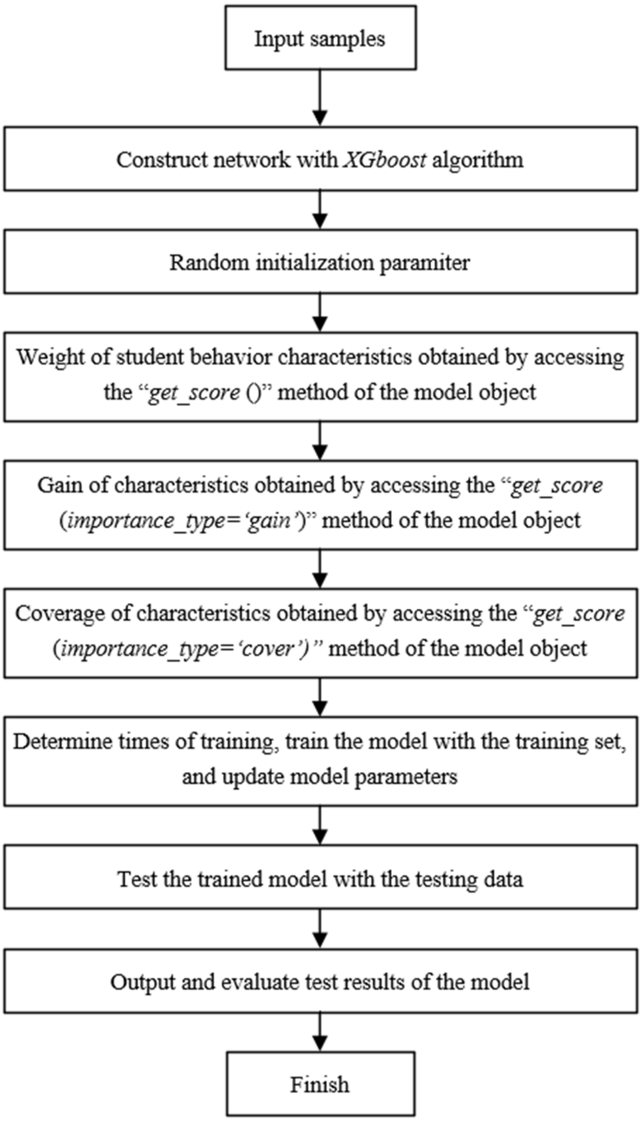


Fig. 3. Analysis process of influencing factors of student behavior fluctuation

For the regression problem of processing student behavior data, if the number of the decision tree is represented by s, and the leaf node score returned with feature a brought into s is represented by $g_s(a)$, the corresponding *XGboost* algorithm expression is given by the following formula:

$$b^* = \sum_{s=1}^{S} g_s(a) \tag{18}$$

Each decision tree of *XGboost* can be scored based on the input student behavior characteristics, and a new decision tree is continuously added through feature splitting. Each time a tree is added, the model learns a new function to approximate the error of the previous prediction. The model starts training with the goal of minimizing the total loss function value of the training set samples, that is, the difference between the total score of the first *S* trees and the actual value is the prediction target of the $S+1_{th}$ tree. If the feature matrix and actual value of the i_{th} sample are represented by a_i and b_i respectively, and the error between the predicted output of a single sample, the actual value is represented by the Γ () function, the amount of training samples in total is represented by *M*, the number of leaf nodes included in the S_{th} regression tree is represented by O_S, the score of *the* r_{th} leaf node is represented by θ_r, and the custom weight coefficient is represented by α and μ, then:

$$K_S = \sum_{i=1}^{M} \Gamma\left(b_i, \sum_{s=1}^{S} g_s(a_i)\right) + \left(\alpha O_S + \frac{1}{2}\mu \sum_{r=1}^{O_S} \theta_r^2\right) \tag{19}$$

After the training is completed, the *XGboost* algorithm provides three methods to calculate the importance of student behavior characteristics, and the weight refers to the number of times a certain student behavior characteristic is used in all tree nodes. When a feature is used for splitting decisions, the weight of the feature is increased, which can be obtained by accessing the "*get_score* ()" method of the model object. Gain refers to how much average information gain can be brought after splitting using the student's behavior characteristics, which can be obtained by accessing the "*get_score* (*importance_type='gain'*)" method of the model object. Coverage refers to the average number of samples affected by a certain student behavior characteristic segmentation, which can be obtained by accessing the "*get_score* (*importance_type='cover'*)" method of the model object.

5 Experimental results and analysis

Figure 4 shows the comparison results of algorithm fusion results under the condition of the number of targets collected by different subsystems, the number of which is 5, 10, 15, 20, and 25. It can be seen from Figure 4 that the algorithm in this paper can still maintain a good fusion effect when the number of targets collected by different subsystems, and the data fusion result is closer to the actual value.

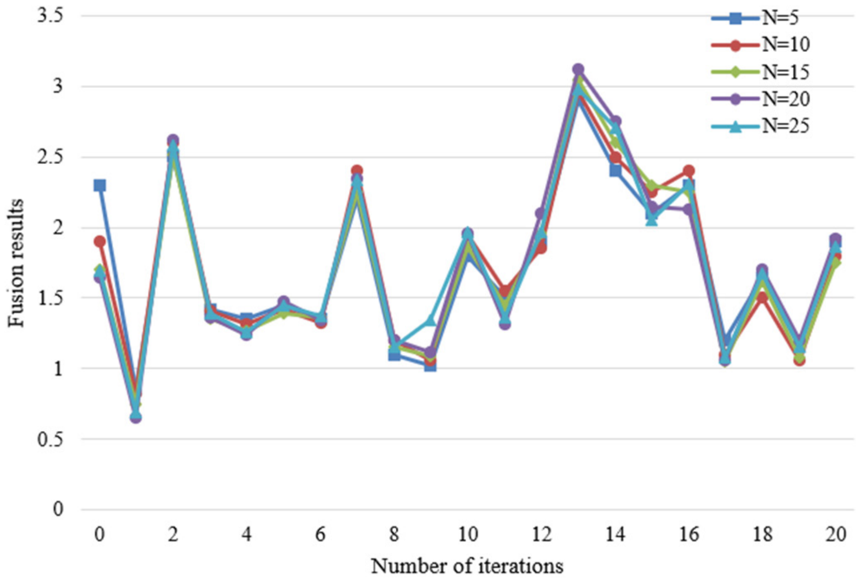


Fig. 4. Comparison of algorithm fusion results in the case of the number of targets collected by different subsystems

Table 1 shows the comparison of fusion errors of *KNN*, Bayesian network, BP neural network and the algorithm proposed in this paper under *AVRE*, *RMSE* and *R2*. Compared with *KNN,* Bayesian network, and BP neural network, the algorithm in this paper performs significantly better in the three evaluation indicators of *AVRE*, *RMSE*, and *R2*. Specifically, in terms of *AVRE* and *RMSE*, the algorithm in this paper has improved by 18.12% and 11.75% compared with the Bayesian network model, and by 32.35% and 34.61% compared with the BP neural network model. It shows that the algorithm in this paper performs better in terms of data fusion accuracy. In terms of goodness of fit *R2*, the algorithm in this paper is closer to 1, indicating that the performance of the algorithm is better. The main reason is that the basic probability assignment function based on fuzzy subordination is assigned in the algorithm to form the initial evidence source, which avoids the defect that the algorithm is sensitive to the initial value.

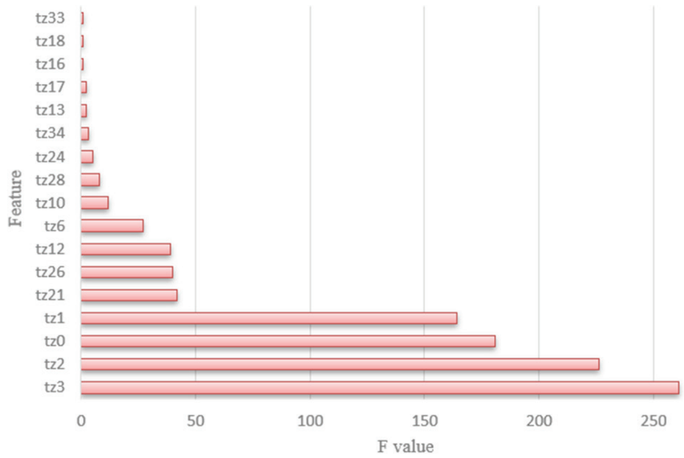
Table 1. Comparison of fusion errors of different algorithms

Index	KNN	Bayesian Network	BP Neural Network	Algorithm in this Paper
AVRE	0.5123	0.4921	0.4356	0.3519
RMSE	0.5679	0.5296	0.4297	0.3764
R^2	0.7751	0.8125	0.8834	0.9052

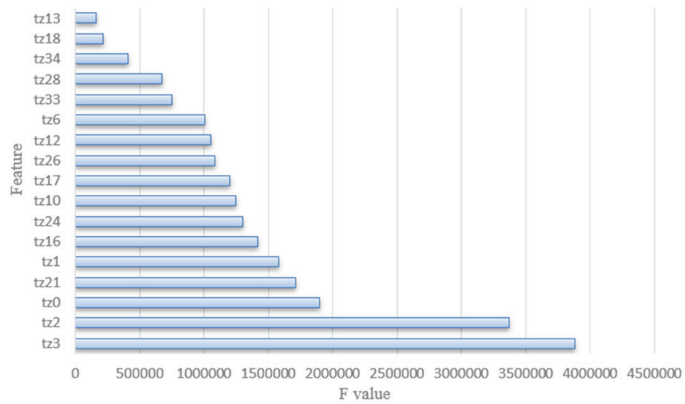
For the extracted 40 student behavior characteristics, this paper measures their importance based on "weight", "gain" and "coverage". The analysis results are given in Table 2 and Figure 5. Table 2 eliminates the factors that have a small impact on passenger flow changes, and sorts results in descending order according to the average importance of student behavior characteristics. The "weight", "gain" and "coverage" with * represent percentages of the corresponding values of the characteristics to the overall proportion.

Table 2. Analysis on the importance of characteristics of student behavior fluctuations

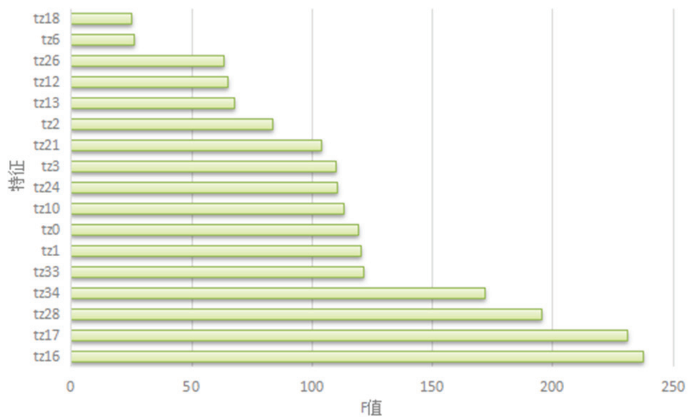
Feature Number	Weight	Gain	Coverage	Weight*	Gain*	Coverage*	Average	The Number of Occurrences
tz3	258	3883648	112.42	25.72%	16.87%	5.39%	15.99%	446
tz2	224	3368351	105.57	22.13%	15.31%	5.07%	14.17%	446
tz0	180	1898579	121.23	17.56%	8.29%	5.92%	10.59%	446
tz1	164	1578983	122.19	16.35%	6.89%	5.87%	9.70%	446
tz16	3	1420356	240.52	0.21%	6.21%	11.62%	6.01%	28
tz21	42	1712665	112.16	4.08%	7.53%	5.36%	5.66%	155
tz17	3	1196372	234.51	0.21%	5.23%	11.31%	5.58%	10
tz28	10	575914	198.25	0.87%	2.96%	9.56%	4.46%	30
tz10	12	1254623	117.11	1.12%	5.53%	5.62%	4.09%	22
tz26	40	1077113	66.95	3.88%	4.71%	3.23%	3.94%	172
tz24	7	1301898	114.23	0.62%	5.72%	5.46%	3.93%	23
tz12	38	1010485	66.35	3.65%	4.42%	3.19%	3.75%	197



a) Weight



b) Gain



c) Coverage

Fig. 5. Calculation results of student behavior fluctuations affecting feature importance

It can be seen from Figure 5 that course attributes and learning stage characteristics have the greatest impact on student behavior fluctuations, especially in the "weight". It is because course attributes contain more feature states, followed by learning stage characteristics, and more nodes are required for splitting in features of the two aspects. While other attributes only have two states of 0 and 1, no more nodes are needed for splitting. Some attributes with low weight may also lead to large fluctuations in student behavior because of the large number of samples involved in the impact. It can be seen from the "gain" that the frequency of students using social networks for communication and learning also has a greater impact on their behavioral fluctuations.

In order to ensure the optimization of the algorithm performance while maintaining its generalization characteristics, this paper constructs a training set and a verification set, performs fitting and prediction of the models under different parameter values, and compares their performance through errors. The performance of the algorithm under different parameter values is shown in Figure 5.

6 Conclusion

This paper conducts research on the construction of college students' management informatization ecosystem based on data analysis technology. Firstly, the design of the data fusion scheme applied to the college students' management informatization ecosystem is carried out, and the idea of the scheme is given. Aiming at the big data of students' learning and living behaviors, this paper digs deep into the value of data information, and extracts historical student behavior characteristics, so as to provide a basis for short-term student behavior prediction and management decision-making planning and implementation for the college students' management informatization ecosystem. Based on historical student behavior data and its characteristic data, the XGboost algorithm is used to quantify and extract the importance of each influencing factor on student behavior fluctuations. Combined with the experiment, the comparison results of the algorithm fusion results under the condition of the number of targets collected by different subsystems are given, which verifies that the algorithm in this paper can still maintain a good fusion effect under the conditions of the number of targets collected by different subsystems. The fusion error comparison of *KNN*, Bayesian network, BP neural network and the algorithm proposed in this paper under *AVRE, RMSE* and *R2* is carried out, and the performance of the algorithm proposed in this paper is verified to be better. The importance of the extracted 40 student behavior characteristics is measured based on "weight", "gain" and "coverage", and the corresponding analysis results are given. The training set and verifying set are constructed, and the models under different parameter values are fitted and predicted, thus comparing the performances by errors, and providing the algorithm performance under different parameter values.

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