Influence Mechanism of Students' Learning Enthusiasm Based on Educational Big Data

https://doi.org/10.3991/ijet.v18i06.38717

Wei Liu, Shuyuan Bi(✉)
Department of Foreign Languages, Tangshan Normal University, Tangshan, China
bishuyuan@tstc.edu.cn

Abstract—Mining a large number of students' behavior data can analyze the differences of students' behavior characteristics. Mining based on students' behavior data can explore the influence mechanism of students' learning enthusiasm, and can provide reference opinions and suggestions for improving students' positive emotions in learning and helping students with poor grades to achieve academic success. The data collected and conclusions obtained by the existing research are not accurate and reliable, and other personality characteristics of students are not fully considered. Therefore, this article studies the influence mechanism of students' learning enthusiasm based on educational big data. It studies the performance of students with good learning enthusiasm in social relations, and mines students' social intercourse at school based on association rules. It analyzes the regularity of students' behavior and their diligence, and realizes the characterization of students' sustainability and enthusiasm in learning. Combining the differences of behavior characteristics between students with and without learning enthusiasm, this article constructs a learning enthusiasm recognition model and compares it by classification. Experimental results verify the effectiveness of the model.

Keywords—educational big data, learning enthusiasm, students' social intercourse at school, behavior regularity, behavioral diligence

1 Introduction

With the rapid development of informationization, the digitalization and informationization in the field of education are constantly promoted and improved, and the use of educational administration application system, access control system, all-in-one card data system and library lending system is gradually popularized [1–9]. It's possible to mine a large number of students' behavior data stored in the above systems, and analyze the differences in behavior characteristics among students [10–15]. Students' learning enthusiasm is an important indicators to measure their learning effectiveness and teaching quality, which can be characterized by students' time and energy for their studies [16–20]. Mining based on students' behavior data can explore the influence mechanism of students' learning enthusiasm, and can provide reference opinions and suggestions for improving students' positive emotions in learning and helping students with poor grades to achieve academic success.

Song and Sun [21] firstly expounds the basic theory of improving students' learning enthusiasm and defines the types of learning organizations in vocational schools; combining with the pertinent theory, it analyzes the current situation of vocational schools to improve students' learning enthusiasm and the problems existing in current management, and puts forward the corresponding specific strategies and measures to build vocational schools to improve students' learning enthusiasm. Wu and Dai [22] collected data through questionnaire survey, and processed 500 pieces of valid data by descriptive statistics, independent sample T test, correlation analysis, regression analysis and other methods. From the analysis results, it can be seen that the professional identity and learning enthusiasm of postgraduates are at the upper-middle level; there are significant differences between professional identity and learning enthusiasm in whether there are cross-majors and whether there are scientific research achievements; there is a significant positive correlation between graduate students' professional identity and learning enthusiasm, and professional identity has a positive predictive effect on learning enthusiasm. Colleges and universities strengthen students' professional identity, which will have an impact on learning enthusiasm and lay a foundation for students to achieve good academic results. Shi [23] conducted a questionnaire survey on 483 normal undergraduates in primary education to explore professional identity (cognitive identity, emotional identity, behavioral identity and appropriateness identity), academic self-efficacy (learning ability efficacy, learning behavior efficacy) and learning enthusiasm (vitality, dedication and professionalism). It is found that professional identity of undergraduate teachers in basic education can significantly positively predict their academic self-efficacy; professional identity and academic self-efficacy of normal undergraduates in primary education can significantly positively predict their learning input; the academic self-efficacy of normal undergraduates in basic education plays an intermediary role between professional identity and learning input. Fajri et al. [24] aims to determine the effectiveness of online learning, and use the Zoom cloud conference application as an alternative to solve the problem of students' learning activities in Universitas Nurul Jadid during the COVID-19. It uses descriptive qualitative research methods and investigation techniques. The tools used include observation, questionnaire survey and online interview. According to the results of the questionnaire survey, the effectiveness of using Zoom cloud conference application for online learning reaches 93.75%, followed by interviews and observation results, which can improve students' motivation and learning enthusiasm.

Through the statistics of the existing literature, it can be seen that there are some problems that are difficult to solve in previous studies, for example, the commonly used questionnaire survey and self-evaluation methods of college students' learning status are usually subjective, and the accuracy and reliability of the collected data and conclusions are lower. The academic achievement is usually set for the goal of mining students' behavior characteristics, but other personality characteristics of students are not fully considered. Therefore, this article studies the influence mechanism of students' learning enthusiasm based on educational big data. Firstly, in the second chapter, the article studies the performance of students with good learning enthusiasm in social relations, and mines students' social intercourse at school based on association rules. In the third chapter, the article analyzes the regularity of students' behavior and their diligence, and realizes the characterization of students' sustainability and enthusiasm in learning. In the fourth chapter, combining the differences of behavior characteristics between students at school with and without learning enthusiasm, the article constructs a learning enthusiasm recognition model and compares it by classification. Experimental results verify the effectiveness of the model.

2 Mining students' social relations

Students' social relations are closely related to their psychological status, which seriously affects students' study and life. Moreover, students' attitudes towards learning will influence each other. Therefore, this article first studies the performance of students with good learning enthusiasm in social relations. Quantifying students' behavior characteristics is a very important link in excavating the influence mechanism of students' learning enthusiasm. On campus, if two students are friends, there will be more common behaviors. This article extracts and quantifies the behavior characteristics of students on the basis of a large number of original data such as the consumption records of students in the all-in-one card and the access control records of libraries and dormitories, in order to understand students' learning behaviors in school more intuitively. This article firstly mines students' social relations based on the adaptive threshold method of association analysis, then quantifies the data of students' behavior characteristics in school, such as regularity and diligence, and introduces the quantification methods in detail. Figure 1 shows the research route of students' behavior characteristics.

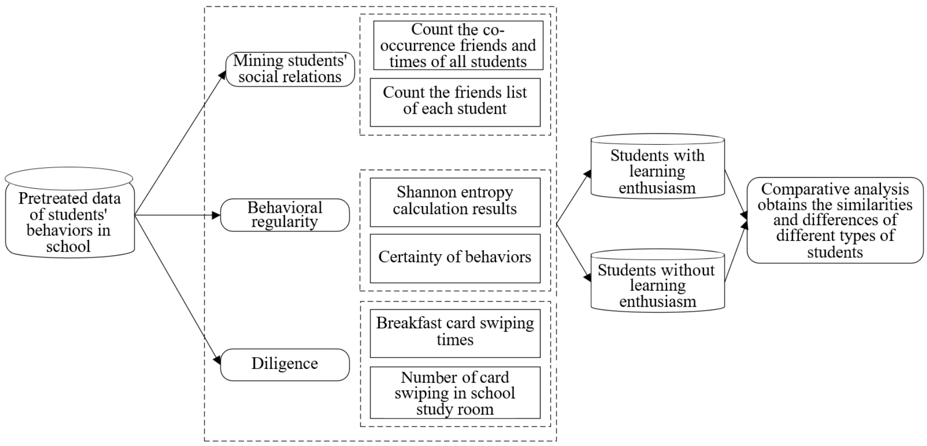


Fig. 1. Research route of students' behavior characteristics

In order to better express students' friend relationship in school, this article mines the co-occurrence data set between students. Assuming that the student *ID* is represented by v_i, the places including the dining room, library and dormitory are represented by k, the timestamp is represented by p, and the number of simultaneous occurrences of students i and j is represented by $\varphi(i \cup j)$, then:

$$V = \left\{ \left(i, j, \phi(i \cup j) \mid i, j \in v_{1,2,\ldots,M} \right) \right\} \tag{1}$$

To eliminate contingency, students i and j whose default number of co-occurrences is greater than the threshold P set for each location are friends. Assuming that the threshold of co-occurrence friends of student i at location k is represented by P_j^i, the total number of occurrences of student i at location k is represented by TN_j^i, and the ratio coefficient at location k is represented by η^k, the following formula gives the definition of location threshold as follows:

$$P_i^k = \frac{TN_i^k}{\eta^k} \tag{2}$$

It can be seen from the above formula that when $\varphi(i \cup j) > P_i$, student j is a friend of student i at location k, which is represented by $H(i \rightarrow j)$.

After the co-occurrence data pairs of all students are constructed, this article determines η^k based on association rules, that is, by default, if there is an association rule of $i \rightarrow j$ between students, students i and j are judged as friends. Support and confidence are important indicators in the correlation analysis of students' social relations at school. Support represents the frequency of students' simultaneous occurrence in the co-occurrence data set, while confidence represents the degree of association between students, which is expressed by $DO(i \rightarrow j)$ and $FG(i \rightarrow j)$, respectively. Assuming that the total number of credit card records in the student co-occurrence data set is represented by C, the co-occurrence times of students i and j are represented by $c\ (i \rightarrow j)$, and the card swiping record entries of student i are represented by $\varphi(i)$, the following formula gives the relevant definition formula:

$$DO(i \rightarrow j) = \frac{\phi(i \cup j)}{C}, i \neq j \tag{3}$$

$$FG(i \rightarrow j) = \frac{\phi(i \cup j)}{\phi(i)}, i \neq j \tag{4}$$

Usually, the thresholds of $DO(i \rightarrow j)$ and $FG(i \rightarrow j)$ are set by traditional statistical methods. However, the research goal of this article is to mine students' social relations in school. There is a great difference in the number of card swiping by different students in different places. If the same threshold is set for $DO(i \rightarrow j)$ and $FG(i \rightarrow j)$ in this scenario, it will lead to greater errors. This article sets adaptive thresholds for $DO(i \rightarrow j)$ and $FG(i \rightarrow j)$ based on correlation analysis.

This study involves the co-occurrence interval threshold Δp, the support thresholds P_{r1} and P_{r2}, and the confidence threshold. Usually, the interval in card swiping together between students is less than 1 minute, so this article sets the time interval threshold Δp to 1 minute.

Because it is difficult to mine the social relationships of students with less card swiping records, this article sets the support threshold P_{r1} to screen. Assuming that the average number of times students swiping their cards in a certain plocation is represented by $\hat{C}_i^k$, then:

$$P_{r1} = 0.01 \times \hat{C}_i^k \quad (5)$$

In order to confirm that there is no friend relationship between two students, this article sets the threshold P_{r2}, that is, if the number of students appears less than P_{r2}, the pair of students will be deleted. Because there is a great difference in the number of friend co-occurrences among different students in different locations, this article sets an adaptive threshold. Assuming that the average value of the total number of student co-occurrences is expressed by $\sum_{j=1}\varphi^*(i \bigcup j)$, then:

$$P_{r2} = 0.01 \times \sum_{j=1} \phi^*(i \cup j) \quad (6)$$

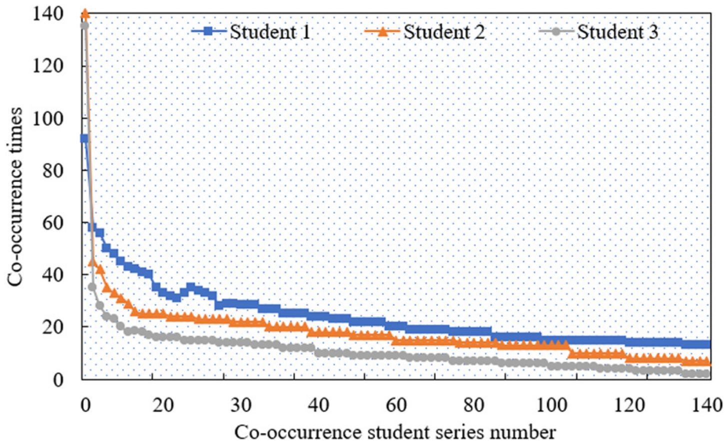


Fig. 2. Visual change curve of student series number under different co-occurrence times

In order to extract the high confidence rules of students' social relations, this article sets the confidence threshold P_d, that is, only when $FG\ (i \rightarrow j)$ is greater than P_d, it is judged that there is a strong rule association between students i and j, that is, there is a friend relationship between students i and j. Set the sequencing result between student i and all other students $\varphi(i \bigcup j)_{j=1}^{M}$ is represented by $\{\varphi'_{il}\}_{l=1}^{M-1}$. Based on $\{\varphi'_{il}\}_{l=1}^{M-1}$, it's possible to draw the curve of co-occurrence student series number changing with co-occurrence times, as shown in Figure 2. If the co-occurrence frequency between students is above the point l which tends to be balanced on the curve, it is judged that there is a friend relationship between students. The following formula gives the definition formula of P_d:

$$P_d = \frac{\phi'_{i,k}}{\phi(i)} \quad (7)$$

Assuming that the threshold parameter is represented by μ, φ'_{il} satisfies the following formula:

$$\phi'_{i,k} - \phi'_{i,(k+1)} \geq \frac{\phi(i)}{\mu}, \phi'_{i,(k-1)} - \phi'_{i,k} \leq \frac{\phi(i)}{\mu} \tag{8}$$

In this article, the most authentic social network of students' friends in school is generated by constantly adjusting μ. The expected value $SQ(A)$ of the number of students' friends in school can be calculated based on μ. Assuming that the total number of students is represented by M, the actual number of friends of the i-th student is represented by G_i, the number of friends identified by confidence rules is represented by g_i, and the number of friends identified incorrectly is represented by g'_i, the corresponding calculation formula is as follows:

$$SQ(A) = \begin{cases} \sum_{i=1}^{M} \frac{1}{M} \times \left(\frac{g_i - g'_i}{G_i} \right), g_i \neq 0 \\ 0, g_i = 0 \end{cases} \tag{9}$$

Finally, the number of students' friends in school can be obtained by removing the repeatedly calculated friends and then accumulating their friends in all locations. The following formula gives the corresponding calculation formula:

$$G_i = \sum_l H(i \to S^k) \tag{10}$$

To sum up, the specific steps of mining students' social friends in school based on association rules are as follows:

1) Define all the student list as $V_{1, 2, \ldots, v}$ and the card swiping record as CC_i^k, $i \in V$ generated at different locations. Count the total number of card swiping records of student i $\sum_{i=1}^{C'} i$. If the number of card swiping records of student i meets $\sum_{i=1}^{C'} i \leq P_{rk}$, ($P_{rk} = 0.01\hat{C}^k$), delete the student *ID*.
2) Count the co-occurrence friends and co-occurrence times of all students. If students appear together in Δp, they are recorded in set S.
3) For all the obtained co-occurrence pairs, the student pairs with low co-occurrence frequency are eliminated based on P_{r2}.
4) Calculate the P_d, and determine that the co-occurrence pair whose co-occurrence times satisfy $\varphi(i \cup j) > P_d$ has a friend relationship.
5) Count the friends list of each student.

3 Mining of students' behavior regularity and diligence

The regularity of students' behavior can represent their self-control ability and organization to a certain extent. Students with stronger behavior regularity have more resilience, better sustainability and enthusiasm of learning. Based on Shannon entropy, this article quantifies the regularity of students' behavior in school. Assuming that the probability of students' activities in the *i*-th time period is expressed by *GU*(*i*), then the calculation formula is as follows:

$$F = -\sum_{i} GU(i) \log GU(i) \tag{11}$$

In this article, 24 hours is defined as a research period unit, and students' behavior data are divided into 48 time series with 30 minutes intervals. If {2021-12-01,18:05; 2021-12-02,18:09; 2021-12-03,18:11; 2021-12-04,17:58; 2021-12-05,18:02} is a time series of behavior data of a student in a certain time period, the corresponding information entropy is {21,23,24,23,22} and the calculated result of behavior regularity is 1.495. The regular habits of students' behaviors can be described by high-frequency behaviors. The smaller the entropy value of students' behavior in a certain period of time is, the higher the certainty of behavior is and the higher the regularity of behavior is.

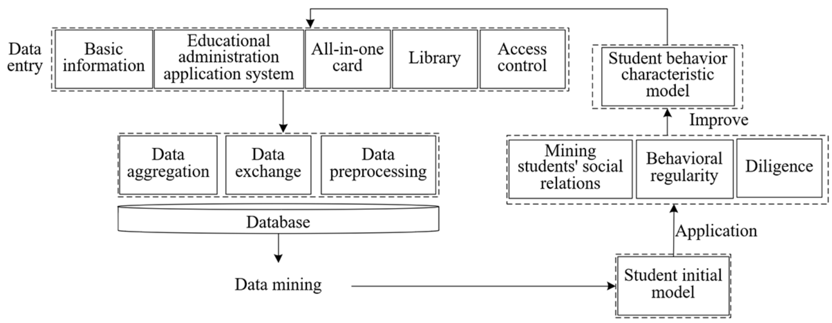


Fig. 3. Modeling process of students' behavior characteristics

Students' study diligence reflects students' desire and pursuit for excellent academic achievements. This article quantifies this indicators based on the time spent by students in learning. Due to the limited data collection conditions of students' study time, this article chooses to use the number of students appearing in the school study room to approximate quantify students' study diligence. In this article, the school study room is defined as a library with access control or a classroom without teaching activities. In addition, this article defines the number of times students swipe their cards for breakfast in the school restaurant as another quantitative indicator of diligence. To sum up, this article quantifies students' diligence based on the number of students' breakfast and entering the school study room, and separates students' behavior on holidays and weekends from that on weekdays. Based on the quantitative results of students' social relations, behavior regularity and diligence, the model of students' behavior characteristics can be constructed. Figure 3 shows the modeling process.

4 Recognition of students' learning enthusiasm

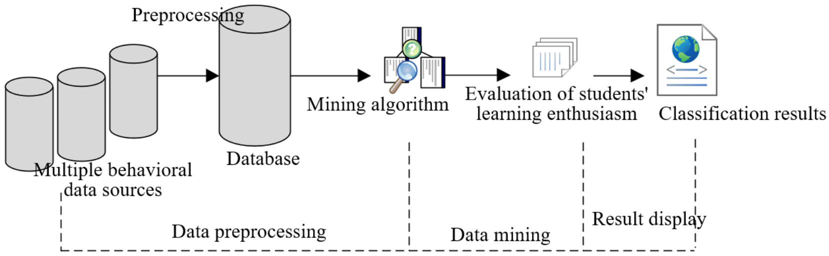


Fig. 4. Identification process of students' learning enthusiasm

Finally, the mining model is evaluated to measure whether the model completes the expected tasks and goals, and analyze and filter the results of data mining through a certain visualization technology so as to filter useful results and show them. Figure 4 shows the process of identifying students' learning enthusiasm.

After extracting students' social relations, regularity of school behavior, diligence and other behavior data characteristics based on educational big data, the article combines the differences of school behavior characteristics between students with learning enthusiasm and students without learning enthusiasm, pretreats the sample data of students' behaviors, and constructs a learning enthusiasm recognition model to classify and compare them.

For student behavior samples A_1, A_2, …, A_m, assuming that the maximum value of the sample is $max(A_i)$ and the minimum value is $min(A_i)$, the normalization formula is as follows:

$$a^* = \frac{A_i - \min(A_i)}{\max(A_i) - \min(A_i)} \tag{12}$$

By comparing the classification performance of different models, this article chooses the logistic regression algorithm with the best performance. In order to make the recognition accuracy and recall of the learning enthusiasm recognition model based on one-year data and three-year data reach more than 80%, this article adjusts and optimizes the parameters of the learning enthusiasm recognition model according to the characteristics of educational big data. Assuming that the parameter variable is represented by ω and the eigenvalue vector is represented by a, the following formula gives the hypothetical function expression transformed by *sigmoid* function:

$$f_\omega(a) = \frac{1}{1 + o^{-\omega^T a}} \tag{13}$$

In logistic regression model, the accuracy of learning enthusiasm recognition results is characterized by loss function. For a given student behavior sample $\{(a_1, b_1)\ldots(a_i, b_i)\}$, the recognition result of learning enthusiasm of predicted samples is represented by $\bar{b}_i$, and the recognition result of learning enthusiasm of actual samples is represented by b_i. The loss function can measure the deviation degree between $\dot{b}_i$ and b_i. The following formula gives the expression of logistic regression loss function:

$$J = -\frac{1}{n}\sum_{i=1}^{n} ER(\dot{b}_i, b_i) = -\frac{1}{n}\sum_{i=1}^{n}\left[b_i \log(\dot{b}_i) + (1-b_i)\log(\dot{b}_i)\right] \tag{14}$$

In order to avoid over-fitting of the learning enthusiasm recognition model, this article introduces the regularization term into the above formula, assuming that the regularization parameter is represented by μ, then:

$$J = -\frac{1}{n}\sum_{i=1}^{n}\left[b_i \log(\dot{b}_i) + (1-b_i)\log(\dot{b}_i)\right] + \frac{\mu}{2n}\sum_{j=1}^{\mu}\omega_j^2 \tag{15}$$

The parameter ω is solved by gradient descent method, and the step size of gradient descent is adjusted by learning rate β. The following formula gives the update formula of ω:

$$\omega_0 = \omega_0 - \frac{\beta}{n}\sum_{i=1}^{n}\left(f_0(a_i) - b_i\right)a_{0_{(i)}} \tag{16}$$

$$\omega_j = \omega_j\left(1 - \frac{\mu x}{n}\right) - \frac{\beta}{n}\sum_{i=1}^{n}\left(f_\omega(a_i) - b_i\right)a_i^{(j)}, j = 1, 2, \ldots, m \tag{17}$$

The students' behavior characteristics in school are input into the constructed model, and the related variables are input into the constructor as follows:

$$f_\omega(a) = \frac{1}{1 + o^{-(\omega_0 + \omega_1 a_1 + \omega_2 a_2 + \omega_3 a_3 + \omega_4 a_4)}} \tag{18}$$

When the gradient value is calculated, the solution ω = [–2.356, 4.157, –0.057, 2.541, 3.542]^T can be obtained. The student enthusiasm recognition model after parameter optimization is given by the following formula:

$$f_\omega(a) = \frac{1}{1 + o^{-(-2.356 + 4.157a_1 - 0.057a_2 + 2.541a_3 + 3.542a_4)}} \tag{19}$$

5 Experimental results and analysis

This article carries out the relevant experiments with the college English course learning of non-English majors as an example. Figure 5 shows the visualization results of students' friends and their number. As can be seen from Figure 5, the average number of friends of students with learning enthusiasm is about 2, which means that most students with learning enthusiasm have one or two friends at school. However, the average number of friends of students without learning enthusiasm is less than 1. Under the condition of 0.01 confidence level, Wilcoxon S rank sum test result is significant, and there is an obvious difference in friends distribution between students with learning enthusiasm and students without learning enthusiasm.

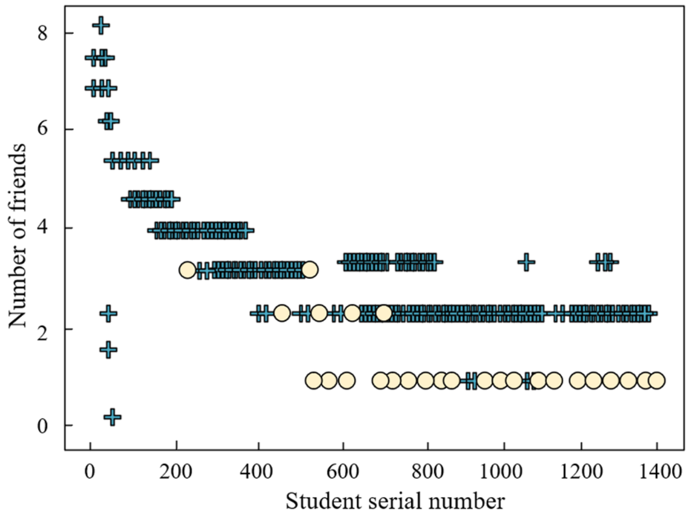


Fig. 5. Student friends

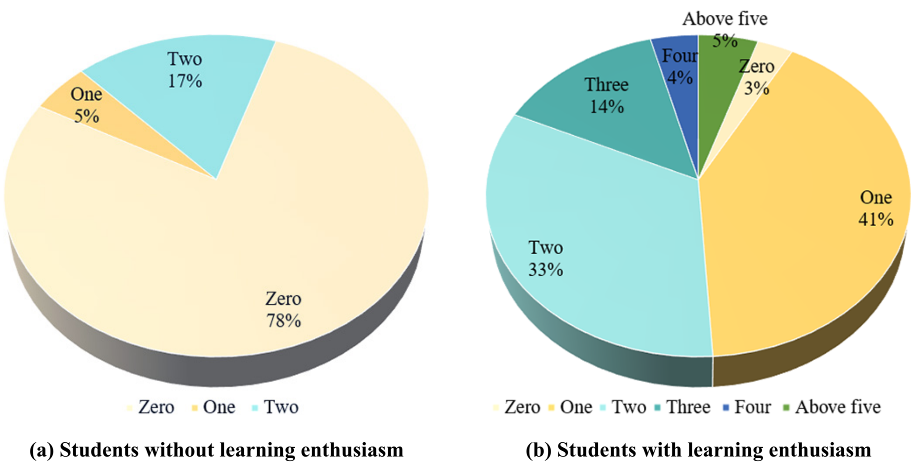
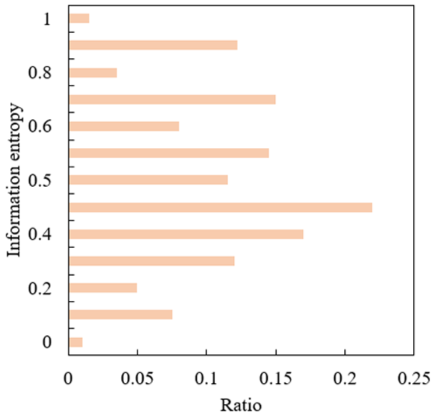
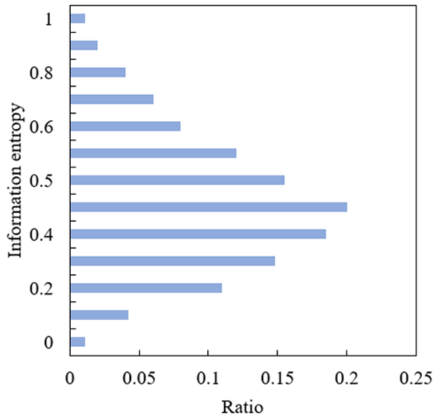


Fig. 6. Friends distribution of students of different types

Figure 6 shows the distribution of friends among students of different types. It can be seen from the figure that most students without learning enthusiasm have no friends at school, while most students with learning enthusiasm have more than one friend or even more than five friends. However, some students with learning enthusiasm are keen to be alone and have no friends at school, because they are not good at communicating with others, or think that being alone is more conducive to focusing on learning and thinking independently. Therefore, it is necessary to further identify the learning attitude of such students based on the quantitative results of behavior regularity and diligence.



(a) Students without learning enthusiasm



(b) Students with learning enthusiasm

Fig. 7. Comparison of Shannon entropy distribution of different types of students' behaviors in school

When the result of Shannon entropy is 0, it shows that the students' behavior in school is obvious; when the result of Shannon entropy is 1, it shows that students' behavior in school is irregular. In this article, the Shannon entropy distribution of campus activities of students with and without learning enthusiasm is represented by histogram, as shown in Figure 7. It can be seen from the figure that the Shannon entropy distribution of the two types of students is quite different, and the Shannon entropy of the students with learning enthusiasm is more concentrated. Through the double-sided test of Shannon entropy calculation results, the results show that under the confidence level of 0.05, there are significant differences in behavior regularity between students with learning enthusiasm and students without learning enthusiasm. Based on the quantitative results of social relations, behavior regularity and diligence, Table 1 summarizes the significance of students' characteristic behaviors.

In this article, students without learning enthusiasm are defined as negative examples, while students with learning enthusiasm are defined as positive examples. The student behavior data samples are divided into test set and training set according to equal proportion, that's, 60 students with learning enthusiasm are randomly separated and constructed into the test set together with 60 students without learning enthusiasm, and the remaining student behavior data samples are constructed into training set. Figure 8 shows the recognition results of the optimized recognition model. The models participating in the comparison include support vector machine and *K-Means* clustering algorithm. According to the experimental results, the recognition accuracy of the model is 87.51%, the recall rate and G-mean are 85.24% and 88.07%, respectively, which are higher than the classification results of other reference models.

Table 1. Summary of significance of students' characteristic behaviors

Characteristic	Significance	Significant Difference
Social relations	0.041	Weak
Regularity	0.074	Yes (Strong)
Diligence	0.069	Yes
Gender	0.619	Yes
Age	0.427	Yes (Strong)
Nationality	0.548	No

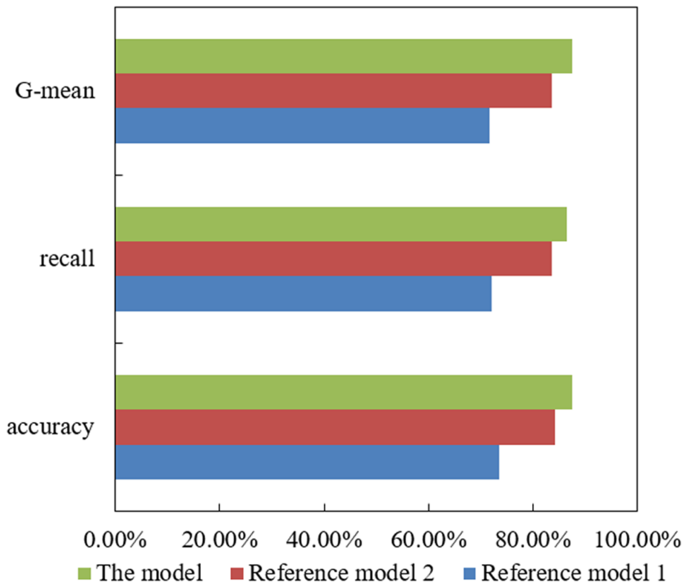


Fig. 8. Recognition results of the optimized recognition model

6 Conclusion

This article studies the influence mechanism of students' learning enthusiasm based on educational big data with the college English course learning of non-English majors as an example. It studies the performance of students with good learning enthusiasm in social relations, and mines the social intercourse of students in school based on association rules. It mines the regularity of students' behavior and their diligence, and realizes the characterization of students' sustainability and enthusiasm in learning. Combining the differences of behavior characteristics between students with and without learning enthusiasm, this article constructs a learning enthusiasm recognition model and compares it by classification. Experimental results verify the effectiveness of the model.

7 References

[1] Lei, K. (2021). Educational informatization in the reform of physical education teaching. In Application of Big Data, Blockchain, and Internet of Things for Education Informatization: First EAI International Conference, BigIoT-EDU 2021, Virtual Event, Proceedings, Part I 1, pp. 263–271. https://doi.org/10.1007/978-3-030-87900-6_32

[2] Wang, Z. (2022). Evaluation and analysis of the informatization degree of college english education based on big data technology. Security and Communication Networks, 2022: 2420071. https://doi.org/10.1155/2022/2420071

[3] Wang, D., Guo, X. (2022). Research on evaluation model of music education informatization system based on machine learning. Scientific Programming, 2022: 9658735. https://doi.org/10.1155/2022/9658735

[4] Yu, D. (2021). Application of cloud computing in education management informatization construction. In Journal of Physics: Conference Series, 1744: 032062. https://doi.org/10.1088/1742-6596/1744/3/032062

[5] Liu, S., Wang, J. (2021). Ice and snow talent training based on construction and analysis of artificial intelligence education informatization teaching model. Journal of Intelligent & Fuzzy Systems, 40(2): 3421–3431. https://doi.org/10.3233/JIFS-189380

[6] Zheng, L., Xu, C. (2021). Research on innovative scheme of mixed teaching mode in fine arts normal education based on intelligent informatization mode. In Journal of Physics: Conference Series, 1915: 032009. https://doi.org/10.1088/1742-6596/1915/3/032009

[7] Zhao, Y. (2022). The decentralized structure of the digital cultural network affects the research on education informatization. In 2022 International Conference on Edge Computing and Applications (ICECAA), Tamilnadu, India, pp. 359–362. https://doi.org/10.1109/ICECAA55415.2022.9936167

[8] Zhong, W. (2022). The integration of network application platform to promote the process of regional education informatization in the era of big data. In Frontier Computing: Proceedings of FC 2021, Seoul, Korea, pp. 680–687. https://doi.org/10.1007/978-981-16-8052-6_85

[9] Zhang, F. (2022). The application of english vocabulary education informatization under 5G and cloud computing environment. Mathematical Problems in Engineering, 2022: 9717449. https://doi.org/10.1155/2022/9717449

[10] Neha, K., Sidiq, J., Zaman, M. (2021). Deep neural network model for identification of predictive variables and evaluation of student's academic performance. Revue d'Intelligence Artificielle, 35(5): 409–415. https://doi.org/10.18280/ria.350507

[11] Wan, N. (2022). Improving college English reading teaching efficiency based on student behavior data mining and mobile edge computing. Wireless Communications and Mobile Computing, 2022: 2959423. https://doi.org/10.1155/2022/2959423

[12] Wu, B., Wang, C.M., Huang, W., Huang, D., Peng, H. (2021). Recognition of student classroom behaviors based on moving target detection. Traitement du Signal, 38(1): 215–220. https://doi.org/10.18280/ts.380123

[13] Muhammed, L.A. (2021). Educational data mining: analyzing teacher behavior based student's performance. In 2021 4th International Conference of Computer and Informatics Engineering (IC2IE), Depok, Indonesia, pp. 181–185. https://doi.org/10.1109/IC2IE53219.2021.9649366

[14] He, J., Lin, K.Y., Dai, Y. (2022). A data-driven innovation model of big data digital learning and its empirical study. Information Dynamics and Applications, 1(1): 35–43. https://doi.org/10.56578/ida010105

[15] Gusnina, M., Wiharto, Salamah, U. (2022). Student performance prediction in Sebelas Maret University based on the random forest algorithm. Ingénierie des Systèmes d'Information, 27(3): 495–501. https://doi.org/10.18280/isi.270317

[16] Yang, B., Yao, Z., Lu, H., Zhou, Y., Xu, J. (2020). In-classroom learning analytics based on student behavior, topic and teaching characteristic mining. Pattern Recognition Letters, 129: 224–231. https://doi.org/10.1016/j.patrec.2019.11.023
[17] Athani, S.S., Kodli, S.A., Banavasi, M.N., Hiremath, P.S. (2017). Student academic performance and social behavior predictor using data mining techniques. In 2017 International Conference on Computing, Communication and Automation (ICCCA), Greater Noida, India, pp. 170–174. https://doi.org/10.1109/CCAA.2017.8229794
[18] Chen, L., Wang, L., Zhou, Y. (2022). Research on data mining combination model analysis and performance prediction based on students' behavior characteristics. Mathematical Problems in Engineering, 2022: 7403037. https://doi.org/10.1155/2022/7403037
[19] Wang, P., Li, P., Cuntapay, M.C. (2022). Recognition of student emotions in classroom learning based on image processing. Traitement du Signal, 39(4): 1331–1337. https://doi.org/10.18280/ts.390426
[20] Qu, D., Guan, Q. (2022). Predictive model and analysis of psychological depression based on college students' behavior data mining. Wireless Communications and Mobile Computing, 2022: 5352283. https://doi.org/10.1155/2022/5352283
[21] Song, Y., Sun, J. (2015). The study enthusiasm of the students' learning. Information, Computer and Application Engineering – Proceedings of the International Conference on Information Technology and Computer Application Engineering, Hong Kong, China, pp. 733–734.
[22] Wu, W., Dai, Y. (2021). The relationship between professional identity and learning input of master students. In 2021 5th International Conference on Education and E-Learning, Japan, pp. 244–248. https://doi.org/10.1145/3502434.3502474
[23] Shi, Z. (2021). The relationship between professional identity and learning input of primary school undergraduate normal students: The mediating role of academic self-efficacy. In 2021 5th International Conference on Education and E-Learning, Japan, pp. 270–275. https://doi.org/10.1145/3502434.3502473
[24] Fajri, Z., Baharun, H., Muali, C., Farida, L., Wahyuningtiyas, Y. (2021). Student's learning motivation and interest; The effectiveness of online learning during Covid-19 pandemic. In Journal of Physics: Conference Series, 1899: 012178. https://doi.org/10.1088/1742-6596/1899/1/012178

8 Authors

Wei Liu, graduated from Hebei Normal University with the Master's Degree of Arts in English Language and Literature, and now teaches English for non-English majors in Tangshan Normal University. The main focuses of research are on the academic teaching, teaching techniques and the studies of methodology. Email: liuwei@tstc.edu.cn

Shuyuan Bi, graduated from Hebei Normal University with the Master's Degree of Arts in English Language and Literature, and now teaches English for non-English majors in Tangshan Normal University. The main focuses of research are on the teaching of listening and reading and the studies of methodology. Email: bishuyuan@tstc.edu.cn

Article submitted 2023-01-09. Resubmitted 2023-02-12. Final acceptance 2023-02-13. Final version published as submitted by the authors.