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Construction of Personalized Teaching Strategies for College Students' English Learning Based on Learning Behavior Data Analysis

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Abstract This study takes college students' English learning behavior as an entry point and proposes a learning behavior analysis model based on multilayer perceptron (MLP). Through the synergy between the interactive feature capture module and the basic feature capture module, the accurate modeling of higher-order features such as learning concentration and initiative is realized. The English learning behavior data of 218 students were collected through the TULIP Smart Learning Platform, and a four-dimensional indicator system containing learners' basic information, operational behavior, collaborative behavior and problem solving behavior was constructed. In the teaching experiment, the designed MLP model realizes the accurate prediction of key behaviors such as learning concentration and initiative through the interactive feature capture module and the basic feature capture module. More than 90% of students chose to agree or strongly agree in the survey results of each test item of the model-assisted learning dimension. More than 90% of students believe that remedial learning is able to target their weak points, reduce their study load and improve their learning outcomes. More than 90% of the students said that the personalized teaching strategy is compatible with their own learning habits, and the average score of the personalized teaching strategy dimension is 4.63, which proves that using the proposed model to analyze learning behaviors and formulate targeted personalized teaching strategies can effectively improve learning effectiveness.

Index Terms multilayer perceptron, learning behavior analysis, English learning, interactive feature capture, basic feature capture

I. Introduction

Studying learners' online learning behavior is one of the important topics in open education, which is of special significance for individual learners, their schools and even localities. Learning is a relatively long-lasting process of individual change caused by experience, externally manifested as observable behavioral changes, and internally hidden as psycho-emotional conceptual changes [1]. Learning behavior is accompanied by learning and is an acquired activity of the subject [2]. With the arrival of the “Internet +” era, the development of network information technology has led to the gradual extension of teaching practice and learning activities from physical space to cyberspace, and students' online learning data have been effectively collected [3]-[5]. The core connotation of online learning is to supply learning content with the help of technology, enhance the learning environment, and promote the interaction between teachers and students distributed in different time and space [6], [7]. Based on the analysis of online learning behavior and knowledge discovery based on the data generated by learners' online learning, teachers or intelligent teaching systems can provide feedback on students' learning, effectively adjust the teaching plan, propose more targeted learning recommendations and guidance, help improve learning performance, and achieve the goals of education and teaching [8]-[11].

Nowadays, college students' English learning is no longer simply mastering basic language skills, but involves the cultivation of interdisciplinary knowledge, cross-cultural communication and comprehensive ability. Understanding and analyzing college students' English learning behavior pattern can provide reference for realizing personalized teaching and improving students' learning effect [12]-[14]. The data on college students' English learning time, the use of learning resources, and the choice of learning styles not only reflect the dynamics of students' learning, but also provide a strong basis for improving educational methods [15], [16]. The motivation and learning habits of college students are different, and it is necessary to analyze these learning behaviors in depth in order to develop more targeted educational programs [17], [18].

In this paper, we first introduce the smart learning platform selected for the experiment to capture the learning behavior data of the research object. Adopting the dual-channel parallel coding architecture, a multi-layer perceptron-based learning behavior analysis model is designed by collaboratively extracting higher-order behavioral features through the interactive feature capture module and the basic feature capture module. Based on the data from the smart learning platform, we analyze the spatial and temporal distribution characteristics of students' learning behaviors and resource preference patterns. The proposed model is used to analyze students' active and focused learning behaviors, and realize the analysis of multimodal learning behaviors. Design teaching experiments to explore the model's assistive effect in college English learning.

II. Experiments on Analyzing College Students' Online English Learning Behavior Based on Multilayer Perceptron Modeling

In the context of the deep integration of information technology and education, online learning platforms have gradually become an important carrier of higher education. However, the traditional teaching mode is difficult to adapt to the heterogeneous learning needs of students in the online environment, and there are problems such as homogenization of teaching strategies and coarse granularity of learning behavior analysis. It has been shown that learning behavior data contains key representations of individual cognitive states and learning effects, but existing analysis methods mostly rely on shallow statistical features (e.g., learning duration, task completion rate), and are limited in their ability to capture the complex interactions between behaviors and the dynamic evolution of laws. Multi-Layer Perceptron (MLP), with its advantages of non-linear mapping and automatic feature extraction, provides technical possibilities for mining deep learning behavior patterns.

II. A.Introduction of Smart Learning Platform and Construction of Indicator System

II. A. 1) Introduction to the Smart Learning Platform

TULIP Smart Learning Platform is designed to realize independent construction of knowledge and automatic assessment of related skills, creating a revolutionary online education model. The learning tasks are designed as a gateway mode, and the brand new knowledge required to complete each task is hidden in the resource library of the platform, supplemented by three step-by-step incremental “brochures” as hints, which learners need to find, explore, identify, and analyze on their own in order to unlock the tasks one by one.

In this paper, we select the university English course in the platform as the research object, and through the collation and analysis of the data generated by the learning platform, we explore the behavioral factors of learners' learning in the smart learning platform and their impact.

II. A. 2) Online learning behavior indicator system construction

The TULIP platform is capable of counting a variety of learning behavior data, referring to the three-dimensional S-F-T classification model of online learning behavior, extracting indicators with high relevance to learning behavior, and constructing an online learning behavior indicator system from four dimensions: learners' basic information, operational behavior, collaborative behavior and problem-solving behavior.

II. B.Learning behavior data collection

In this paper, the University English course offered by University A on the TULIP platform was selected as the source of data collection from March 1, 2024 to September 1, 2024, and the study population was determined to be the students of the Class of 2024, majoring in computer science, in the 3rd to 6th classes. The course structure was designed to include video learning, unit tests, discussion board interactions, and unit assignments, culminating in a comprehensive exam to summarize the study. The course grading mechanism consisted of four components: unit quiz (50% of the total), final test (30% of the total), interactive discussion (10% of the total), and unit assignment (10% of the total). The data involved in the study included viewing records of 42 instructional videos, such as viewing time, number of times, and total duration, totaling more than 3,850 records, and data from 20 tests, including completion time, number of times, and grades, totaling more than 800 records.

II. C.Design of Learning Behavior Analysis Model Based on Multilayer Perceptron

The existing learning behavior analysis models are not accurate enough. Many online teaching platforms predict learning effects based on simple performance data or a small number of learning behavior indicators, ignoring some complex influencing factors in the learning process, and insufficiently taking into account students' individual differences and learning scenarios. In addition, the prediction model lacks universality. Due to the large differences between different disciplines, different course contents and different student groups, the existing models are often much less effective when applied to other courses or student groups, and cannot be well adapted to diverse teaching scenarios. To solve the above problems, this paper designs a learning behavior analysis model based on multilayer perceptron.

II. C. 1) Interactive feature capture module

The interaction feature capture module of the model consists of an MLP and residual connections, where each MLP layer is separated by a BN layer, a Dropout and an activation function layer (the activation function used here is ReLU). The interaction feature capture module cascades the head node embedding vectors and the relation embedding vectors and then aggregates the information from both of them, and inputs the aggregated information into an MLP module, which can better capture the interaction features of the head nodes and relation nodes.

The head node embedding vector h and the relation embedding vector r are taken as inputs, and the output v_1 is obtained after feeding into the interactive feature capture module, which is denoted as $f(h,t)$. The specific definition is as in equation (1):

$$f(h,t) = BN\left([h \square t] + MLP\left([h \square t]\right)\right) \tag{1}$$

where the $\square$ notation denotes a cascade operation, i.e., connecting two tensors along the channel dimension; BN is batch normalization, which addresses the problem of difficult model training as the depth of the network is accelerated; and MLP is a multilayer perceptual machine, which is defined as in Eq. (2):

$$MLP^{(1)}(x) = \sigma\left(\left(Dropout\left(BN(W_1 x)\right)\right)\right) \tag{2}$$

where W_1 is the weight matrix and σ is the activation function (ReLU is used here).

The module combines the head node embedding vector h and the relation embedding vector r into a single vector after cascade operation, and then uses multiple multilayer perceptrons to capture the interaction features between the vectors, and finally obtains an output vector v_1.

II. C. 2) Basic Feature Capture Module

The basic feature capture model consists of an attention layer and an MLP. The head node embedding vector h and the relation embedding vector r are input into this module separately, and its specific structure is shown in Fig. 1. In order to better capture the respective basic features of the head node and the relation node, so the head node embedding vector and the relation node embedding vector are inputted into the MLP module to get the outputs respectively, and finally all the outputs are cascaded and aggregated to get the final output.

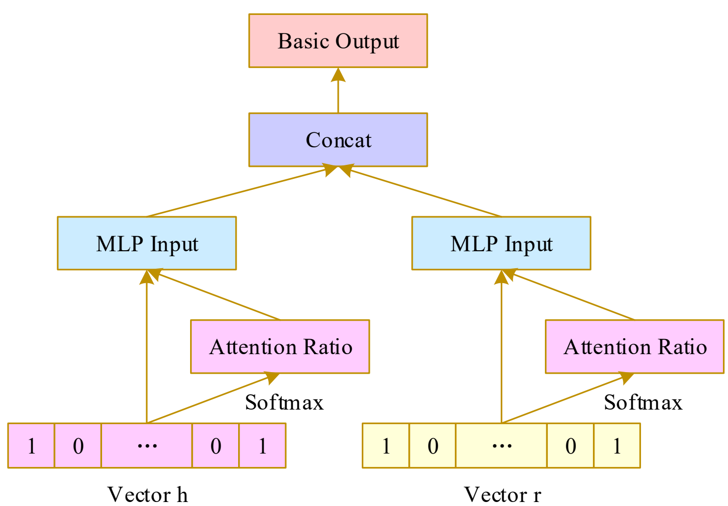

Figure 1: Basic feature capture module structure

First, the head vector h and the relation vector r are passed through the attention layer to obtain their attention weights α_h and α_r, respectively, as in Eqs. (3) and (4):

$$\alpha_h = Attention(h) \tag{3}$$

$$\alpha_r = Attention(r) \tag{4}$$

In this, the attention layer uses an attention function (Softmax is used here) to get the attention weights. After obtaining the attention weights of h and r, the attention weights and the initial inputs h and r are input into a merge function, where the merge function chooses the cascade operation and the product of elements, which is used according to the experimental results to choose which one to use, to obtain the final inputs h_1 and r_1, with the specific formulas as in Eqs. (5) and (6):

$$h_1 = concat(h, \alpha_h) \; or \; mul(h, \alpha_h) \tag{5}$$

$$r_1 = concat(r, \alpha_r) \; or \; mul(r, \alpha_r) \tag{6}$$

Then the final inputs h_1 and r_1 are fed into the MLP layer to get their respective outputs. The basic feature capture model is slightly different from the MLP structure of the interactive feature capture model, which only adds Dropout, BN, and activation functions to the last linear layer, as shown in Equation (7):

$$MLP^{(2)}(x) = Dropout\left(BN\left(\sigma\left(W_n\left(...W_1 x\right)\right)\right)\right) \tag{7}$$

Finally, the final output is obtained by cascading the outputs obtained from h and r, which is denoted as $g(h,t)$ and is defined as in Equation (8):

$$g(h,t) = MLP\left(Attention(h) \| Attention(r)\right) \tag{8}$$

The basic feature capture module uses a structure consisting of an attention layer plus a multilayer perceptron layer to capture the basic features of the head node embedding vector h and the relation embedding vector r, respectively, and finally uses a cascade operation to merge the two outputs to obtain the final output.

III. Analysis of learning behavior pattern based on multi-layer perceptron model and application effect research

III. A. Analysis of Students' Online Learning Behavior

III. A. 1) Analysis of the number of studies and course length settings

The number of study times is an important measure of students' learning status and an important reference for determining the duration of course hours and time. The data show that the more intensive data on the number of study times in the university English course began in March 2024 and peaked in April 2024, with the highest being class 4, where the number of study times reached 5,239 frequencies. In May 2024, the number of times students took the course was still informative, proving that students were still in a critical period of course work during that month. Starting from June 2024, the number of times students study plummeted, and in July and August 2024, a small number of students still click on the course to start studying, so there are still some clicks, which confirms the importance of the online learning platform. For students, they can start learning at any time according to their needs, which is not affected by the teacher's time or the time when the course is offered, and the specific statistics on the change of the total learning frequency of the course are shown in Figure 2. The data show that the main duration of the university course is the best within 3 months, students are very interested in the knowledge of the stage, they will frequently log in the learning platform to start learning, the duration of the course is too short, can not achieve the learning effect of the students, the duration of the course is too long, the interest of the students is weakened, but is not conducive to the mastery of course knowledge.

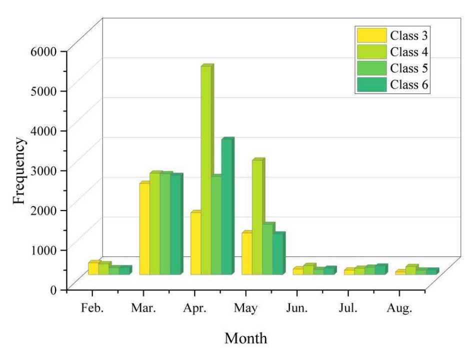

Figure 2: Statistics of changes in the total learning frequency of the course

III. A. 2) Analysis of daily study time and frequency

By counting the learning click-through rates of the four classes at different times of the day to observe the students' learning habits so that teachers can choose the right time when releasing notices, activities, resources, etc., the statistics of the daily learning frequency changes of the course are shown in Figure 3. The peak of students' learning frequency is mainly concentrated between 8-12 p.m., 12-16 p.m., and 20-24 p.m. Although 8-12 p.m. and 12-16 p.m. may have the influence of clicks during class, the highest daily learning frequency is 20-24 p.m. in the evening, with a total learning frequency of up to 6,639 clicks, at which time students have generally finished the day's lessons and have more time for independent learning. The learning frequency in this time period also reflects that students have a certain sense of independent learning and ability.

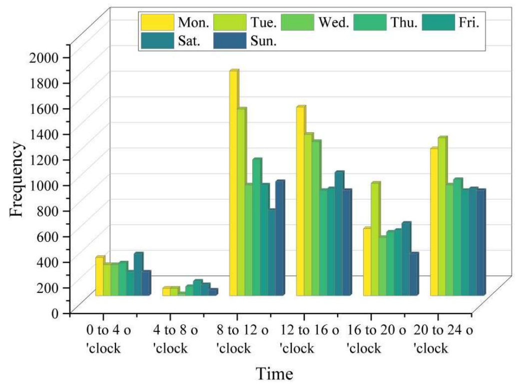

Figure 3: Statistics on the daily learning frequency changes of the course

III. A. 3) Analysis of mission point completion versus resource allocation

In the course construction, task points such as course introduction, literature reading, video viewing, check-in, homework, etc. are added, and after students complete the task points, the smart learning platform will make records accordingly. The platform will record in detail the number of times students watch, the length of video viewing and the regurgitation ratio, which is calculated as the proportion of video viewing time to the actual length of the video. By counting the task points of university courses into three types of resources: documents, videos and chapter tests, analyzing the completion degree of the task points, further observing the students' learning frequency, summarizing the students' interest in learning, in order to select the resources that are acceptable to the students to provide them with, and ultimately to achieve a better learning effect. The analyzed statistics of the course task point completion are shown in Figure 4. As can be seen from Figure 4, the task point completion of students in Class 3, Class 4, Class 5 and Class 6 have reached more than 60% of the standard, and the completion of video resources is higher than that of other resources, therefore, students are more inclined to learn from video resources, and in the process of preparation and setting of the resources, the proportion of video resources can be strengthened, and the document resources and test resources can be existed as auxiliary resources.

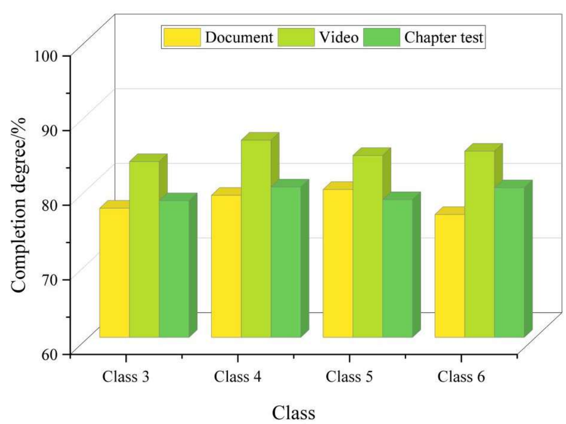

Figure 4: Completion status of course task points

III. B. Multimodal Learning Behavior Frequency Analysis

III. B. 1) Active Learning Behavior

Active learning behaviors are mostly reflected in language-based teaching activities, which are the behavioral manifestation of students' learning “attitude”, i.e. multimodal sound data. Based on the multilayer perceptron, we obtained a total of 85 sound data of students' active learning behaviors (active response, active questioning, discussion and communication, sharing, evaluation and feedback) in three semesters, including 19 at the beginning of the semester, 25 in the middle of the semester, and 41 at the end of the semester. The five sets of data were subjected to frequency analysis to obtain the ratio of the number of active learning behaviors actually produced by students in a class to the total number of active behaviors that should have been produced in that class. The closer the ratio is to 1, the higher the frequency of students' active learning behaviors. The active response, active questioning, discussion and communication, results sharing, evaluation and feedback are numbered as A1~A5, and the beginning of the semester, the middle of the semester and the end of the semester are numbered as D1~D3, and the multimodal data frequency situation of the active learning behaviors is shown in Fig. 5, and the ratio of the five groups of data in Fig. 5 shows an upward trend with the development of the semester and is constantly close to 1. It can be seen through the analysis of the frequency of the students' active learning behaviors, the frequency of active learning behaviors is higher when students in the smart classroom at the beginning of the semester, the number of active learning behaviors that occurred less frequently gradually increased with the development of time, and the students' learning attitude was effectively improved. For example, students' active learning behaviors of raising their hands, posting results and evaluations online and answering questions and communicating and discussing offline using learning tablets have increased.

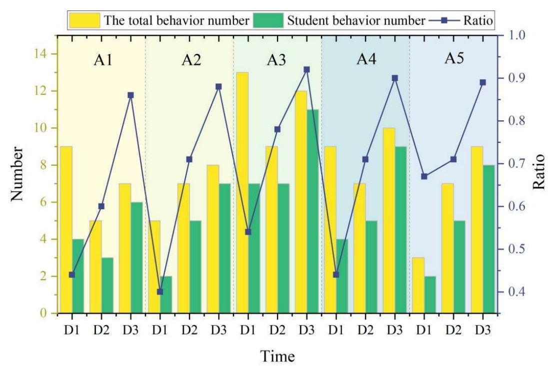

Figure 5: Frequency of multi-modal data of active learning behavior

III. B. 2) Focused learning behavior

Concentration learning behavior is mainly reflected in the physical action behavior in the image data. According to the definition and dimensions of concentration, learning concentration refers to a psychological state in which the learner focuses on the learning process and learning activities, emphasizing the durability of the time period and the stability of attention, which is the behavioral manifestation of the learner's learning “ability”. The observer counted the ratio of the duration of students' focused behavior in each learning activity to the total duration of learning activities in the classroom in seconds to determine the degree of students' focused behavior. The closer the ratio is to 1, it means that students have high concentration and improved learning ability.

Based on the multimodal data of focused learning behavior obtained from the multilayer perceptron, students' gaze at the interactive whiteboard, gaze at the teacher, gaze at classmates, gaze at learning aids, and gaze at books are numbered as B1~B5, and their frequency is shown in Fig. 6. As the semester develops, students' focus on the learning content aspect is reduced in the number of times the teacher reminds the students to focus on the interactive whiteboard in a timely manner, and the students' concentration on the interactive whiteboard, students' attentiveness to listening to the teacher, their classmates' speeches, and viewing of the The concentration on book content is gradually improving, and the concentration ratio is gradually converging to 1. It is found that at the beginning of the semester, the ratio of the students' gaze on learning aids behavior is more than 1, which indicates that the students are overusing the learning aids, and the attention of learning is shifted to the learning aids themselves As the semester develops, the frequency of this behavior is shrinking and converging to 1, which indicates that the irrelevant learning behavior of using learning aids is gradually decreasing, and the concentration of students on the classroom is gradually improving.

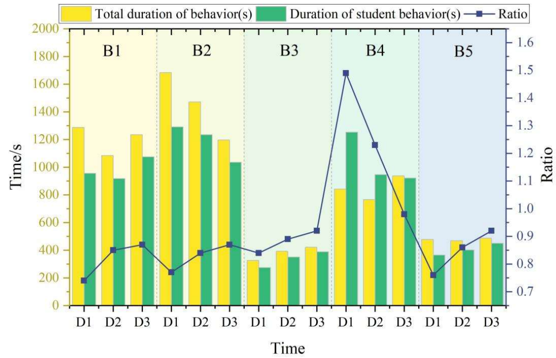

Figure 6: Frequency of multi-modal data of focused learning behavior

III. C. Analysis of model application satisfaction

In this paper, the designed learning behavior analysis model is put into auxiliary teaching to carry out a semester-long experiment, and the experimental subjects are also the students of 3~6 classes of computer science majors in the class of 2024. At the end of the experiment, students' satisfaction with the application of the model was collected through the questionnaire method to explore the effect of the actual application of the model.

In this study, questionnaires were distributed to 218 students who participated in the experiment, and 209 valid questionnaires were returned, with an effective rate of 95.87%. There are five options for each question, strongly disagree (1 point), relatively disagree (2 points), generally (3 points), relatively agree (4 points), strongly agree (5 points), and the lowest score for each test question is 1 point and the highest score is 5 points.

III. C. 1) Model-assisted learning friendliness

The multilayer perceptron-based learning behavior analysis model is used in practice throughout the pre-course, in-course and post-course sessions, and it is crucial that the model is used in a way that is friendly to the students; therefore, this paper investigates the satisfaction level of the model's friendliness, and the specific results of the survey are shown in Table 1.

As can be seen from Table 1, for the five test items of model friendliness, no students chose the two options of strongly disagree or disagree.97.61% of the students think that the model is simple to operate and easy to get started (Q1).97.13% of the students think that the model's functions are comprehensive and powerful, and it can satisfy their own learning needs (Q2).97.61% of the students think that the model's interaction design is reasonable and meet their own usage habits (Q3). 94.74% of the students thought it was convenient to use the model to analyze in the pre-class pre-study and post-class remediation sessions, and it would not cause any additional study burden (Q4). 96.17% of the students were willing to recommend the model to other students (Q5), which indicated that the model was recognized by most of the students. More than 90% of the students chose to agree or strongly agree with the findings of each test item and the mean score of each test item was more than 4, indicating that the students were satisfied with all aspects of the dimension, and the mean of the overall score of the dimension was 4.30, indicating that the students had a high level of satisfaction with the friendliness of the learning behavior analysis model.

Table 1: Findings on model friendliness

Question	Strongly disagree	Disagree	General	Agree	Quite agree	Mean value	Standard deviation
Q1	0	0	2.39%	49.76%	47.85%	4.39	0.386
Q2	0	0	2.87%	50.72%	48.41%	4.22	0.408
Q3	0	0	2.39%	63.64%	33.97%	4.07	0.395
Q4	0	0	5.26%	46.89%	47.85%	4.23	0.429
Q5	0	0	3.83%	40.67%	55.5%	4.61	0.457
Overall average value						4.30	0.593

III. C. 2) Remedial learning usefulness

The multilayer perceptron-based learning behavior analysis model for remediation of students includes common problem explanation and personalized remediation, and the learning analysis report provides a basis for teachers to solve students' common problems and recommend personalized learning resources. In order to understand whether the remedial learning resources selected according to the results of the model analysis are in line with the cognitive state of students, remediate students' knowledge weaknesses, meet students' learning needs, reduce the burden on students, and improve the learning effect, the study designed five tests for the usefulness of remedial learning to understand the students' satisfaction with the usefulness of remedial learning, and the specific results of the survey are shown in Table 2.

As shown in Table 2, for the test item “Q6 The remedial learning resources recommended according to the results of the model analysis are consistent with my cognitive state”, all the students agreed or strongly agreed, of which 62.68% strongly agreed, which reflects the accuracy of the model's analysis of students' behaviors. For the test item “Q7 The learning resources recommended according to the model results can meet my learning needs”, 92.82% of the students agreed or strongly agreed, indicating that the remedial learning resources can meet the needs of the majority, and the remedial learning resources are basically in line with students' needs. More than 90% of the students think that remedial learning can target their weak knowledge points, reduce their learning burden and improve their learning effectiveness, which shows that most students think remedial learning is useful and necessary. All students want to continue to use this personalized remedial learning method, which indicates that this remedial learning method is very popular. The overall average score for this dimension is 4.57, indicating that remedial learning resources are in line with students' cognitive level and have a strong relevance, helping students to solve their learning difficulties and improve their learning effectiveness.

Table 2: Satisfaction with the Usefulness of Remedial learning

Question	Strongly disagree	Disagree	General	Agree	Quite agree	Mean value	Standard deviation
Q6	0	0	0	37.32%	62.68%	4.55	0.482
Q7	0	0	7.18%	42.58%	50.24%	4.36	0.501
Q8	0	0	3.83%	33.01%	63.16%	4.58	0.493
Q9	0	0	6.22%	36.36%	57.42%	4.65	0.488
Q10	0	0	0	26.79%	73.21%	4.71	0.472
Overall average value						4.57	0.583

III. C. 3) Rationalization of Personalized Instructional Strategies

In order to understand whether the application process of learning behavior analysis model based on multilayer perceptron in personalized teaching is in line with students' learning habits, fits students' learning progress, improves students' participation, and is recognized by students, this study conducts a satisfaction survey on personalized teaching strategies, and the specific findings are shown in Table 3.

As can be seen from Table 3, more than 90% of the students agreed or strongly agreed with the test item "Q11 This personalized teaching strategy is in line with my learning habits", indicating that most students think that this strategy is in line with their own learning habits. In response to the test items "Q12 teaching implementation progress can match my learning progress well", "Q13 teaching mode makes me more involved in the learning process", "Q14 compared with the traditional teaching mode, I prefer this personalized teaching mode", "Q15 I hope to continue to use this personalized teaching mode in future learning" all students agreed or strongly agreed, indicating that most students can adapt to and like this teaching mode. The average score of this dimension is 4.63 points, which is more than 4 points, indicating that most students think that this personalized teaching strategy is more reasonable.

Table 3: Satisfaction with the Personalized Teaching Application Process

Question	Strongly disagree	Disagree	General	Agree	Quite agree	Mean value	Standard deviation
Q11	0	0	4.31%	42.58%	53.11%	4.27	0.535
Q12	0	0	0	45.93%	54.07%	4.52	0.451
Q13	0	0	0	26.79%	73.21%	4.76	0.446
Q14	0	0	0	29.19%	70.81%	4.77	0.402
Q15	0	0	0	23.44%	76.56%	4.85	0.485
Overall average value						4.63	0.476

IV. Conclusion

In this paper, a learning behavior analysis model based on the multilayer perceptron model is designed and used in college students' English teaching to explore the effect of its practical application.

In the survey results of each test item of the model-assisted learning dimension, more than 90% of the students chose to agree or strongly agree, and the mean score of each test item was more than 4, and the overall average score of this dimension was 4.30. More than 90% of the students believed that remedial learning could target their weak knowledge points, reduce the burden of learning, and improve the effectiveness of learning, and all of them hoped to continue to use this personalized remedial learning method, and the overall average score of remedial learning effectiveness reached 4.30. Over 90% of students reported that they believed that remedial learning was able to target their weak points, reduce their learning load, and improve their learning effectiveness, and all of them would like to continue to use this personalized remedial learning approach. More than 90% of the students said that they thought the personalized teaching strategy was compatible with their own learning habits, and the average score of the personalized teaching strategy dimension was 4.63, which proved that the use of the proposed model-assisted teaching can significantly reduce the ineffective learning inputs and further improve the learning effect.

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References

[1] Zhang, J. H., Zhang, Y. X., Zou, Q., & Huang, S. (2018). What learning analytics tells us: Group behavior analysis and individual learning diagnosis based on long-term and large-scale data. Journal of Educational Technology & Society, 21(2), 245-258.

[2] Bessadok, A., Abouzinadah, E., & Rabie, O. (2023). Exploring students digital activities and performances through their activities logged in learning management system using educational data mining approach. Interactive Technology and Smart Education, 20(1), 58-72.

[3] Hwang, G. J., Spikol, D., & Li, K. C. (2018). Guest editorial: Trends and research issues of learning analytics and educational big data. Journal of educational technology & society, 21(2), 134-136.

[4] Shayan, P., & van Zaanen, M. (2019). Predicting student performance from their behavior in learning management systems. International Journal of Information and Education Technology, 9(5), 337-341.

[5] Yan, N., & Au, O. T. S. (2019). Online learning behavior analysis based on machine learning. Asian association of open universities journal, 14(2), 97-106.

[6] Mehenaoui, Z., Lafifi, Y., & Zemmouri, L. (2022). Learning behavior analysis to identify learner’s learning style based on machine learning techniques. Journal of Universal Computer Science, 28(11), 1193.

[7] Kew, S. N., & Tasir, Z. (2022). Learning analytics in online learning environment: A systematic review on the focuses and the types of student-related analytics data. Technology, Knowledge and Learning, 27(2), 405-427.

[8] Minguillón, J., Conesa, J., Rodríguez, M. E., & Santanach, F. (2018). Learning analytics in practice: Providing E-learning researchers and practitioners with activity data. Frontiers of cyberlearning: emerging technologies for teaching and learning, 145-167.

[9] Joseph, B., & Abraham, S. (2023). Identifying Slow Learners in an e-Learning Environment Using K-Means Clustering Approach. Knowledge Management & E-Learning, 15(4), 539-553.

[10] Lee, L. K., Cheung, S. K., & Kwok, L. F. (2020). Learning analytics: Current trends and innovative practices. Journal of Computers in Education, 7, 1-6.

[11] Zhang, T., Taub, M., & Chen, Z. (2022, March). A multi-level trace clustering analysis scheme for measuring students’ self-regulated learning behavior in a mastery-based online learning environment. In Lak22: 12th international learning analytics and knowledge conference (pp. 197-207).

[12] Hussain, M. S., Salam, A., & Farid, A. (2020). Students' motivation in English language learning (ELL): An exploratory study of motivational factors for EFL and ESL adult learners. International Journal of Applied Linguistics and English Literature, 9(4), 15-28.

[13] Abe, M., & Kogo, C. (2021). Effects of instruction of English learning design focusing on individual learners’ needs. Information and Technology in Education and Learning, 1(1), Trans-p007.

[14] Poedjiastutie, D., & Oliver, R. (2017). English Learning Needs of ESP Learners: Exploring Stakeholder Perceptions at an Indonesian University. TEFLIN Journal: A Publication on the Teaching & Learning of English, 28(1).

[15] Yunita, W., Emzir, E., & Mayuni, I. (2018). NEEDS ANALYSIS FOR ENGLISH GRAMMAR LEARNING MODEL FROM STUDENTS’PERSPECTIVES. English Review: Journal of English Education, 6(2), 85-94.

[16] Huang, F., Hoi, C. K. W., & Teo, T. (2018). The influence of learning style on English learning achievement among undergraduates in Mainland China. Journal of Psycholinguistic Research, 47, 1069-1084.

[17] Yuanfei, Z. (2022). A personalized recommendation system for English Teaching resources based on learning behavior detection. Mobile Information Systems, 2022(1), 4531867.

[18] Yang, Q., & Zhang, J. (2025). Research on the Analysis of students’ English Learning Behavior and Personalized Recommendation Algorithm based on Machine learning. Scalable Computing: Practice and Experience, 26(1), 450-457.