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Article

Hybrid Teaching Feedback Mechanism and Efficiency Improvement Paths for Students' Engagement in College English Learning in Guangdong Based on Learning Analytics

Xiao Jin [1,2], Syamsul Nor Azlan Mohamad [1,*], Norhayati Mohd Yusof [1] and Xian Liu [1]

1 Universiti Teknologi MARA(UiTM), Selangor Branch Puncak Alam Campus BANDAR PUNCAK ALAM, 42300 Kuala Selangor, Selangor, Malaysia
2 Zhuhai College of Science and Technology (ZCST), Zhuhai, Guangdong, 519000, China
* Correspondence author: syams9211@uitm.edu.my

Abstract: Blended teaching mode has become the mainstream English teaching mode in Guangdong colleges and universities, how to make the communication between teachers and students more timely and in place is an important part of whether the blended teaching mode can give full play to its advantages. This paper generates a personalized knowledge point collection based on the knowledge point organizing strategy, then uses a neurocognitive diagnostic model to obtain students' English cognitive level, and establishes a feedback mechanism for blended teaching of English in colleges and universities based on students' level with the help of the DKVMN model. On this basis, in order to reveal the path of student engagement enhancement under the blended teaching feedback mechanism, the structural equation theory and scale testing method were chosen to construct the student engagement model. After the calculation of DKVMN model, we get that English topic 1914 has high correlation with knowledge points 10, 11, 13, 14 and 4, while English knowledge point 18 has almost no correlation, which accurately detects the English knowledge points that students have not mastered, and then provides students with targeted review methods, which verifies the effectiveness of the feedback mechanism. In addition, the path coefficient of self-efficacy and engagement is 0.206, and the other potential variables are similar, which comprehensively visualizes the quantitative relationship between the paths of students' engagement augmentation under the feedback mechanism.

Keywords: dkvmn model; neurocognitive diagnostic model; structural equations; feedback mechanism; blended learning

1. Introduction

In the context of the information age, information technology has been widely used in various fields, changing people's lifestyles and habits to a great extent [1]. With the continuous promotion of higher education reform, English teaching in Guangdong universities is also exploring new teaching methods. The online-offline hybrid teaching mode has gradually become an inevitable trend of modern teaching reform [2-3]. In traditional classroom teaching, most college English teachers use an indoctrination approach to impart knowledge, neglecting to pay attention to the learning process of students, and there is a disconnect between teacher teaching and student learning, which is also a common deficiency in offline teaching. This is also a common deficiency of offline teaching. Online teaching is student-oriented and teacher-led, which can effectively make up for the deficiencies of offline teaching. At the same time, this teaching mode puts forward higher requirements for students' sense of autonomy and independent learning ability. By applying the blended teaching mode in teaching and actively applying the language learning practice strategy, English teachers in colleges and universities are able to emphasize the students' subjective status and improve the students' independent learning ability [4].

In recent years, blended teaching, as a new teaching mode, has become the focus of attention of educators and researchers around the world, leading another round of teaching reform. Its biggest feature is not the innovation of a certain teaching method, but the “subversive” reconstruction of the whole teaching structure. Literature [5] points out that the effect of blended learning is not natural, and its design needs to be differentiated and matched to the multidimensionality of participation - the choice of technology and activities should serve the depth of cognitive input, the frequency and continuity of behavioral input, the incentive mechanism of emotional input, and the target alignment of academic input. Literature [6] suggests that the effectiveness of blended learning is nationally or regionally context-dependent and cannot be generalized, and that the lack of significant increases in engagement may be related to variability in course design, technology integration, students' self-directed learning abilities, and assessment methods. Literature [7] suggests that the core of blended learning is student-centeredness with maximized active participation, and that its success is not the result of a technological overlay, but rather a synergistic evolution of technology, pedagogy, equity, and teacher support systems. Reference [8] states that the transition of blended learning from an experimental stage to a widespread practice lies in moving from "project-driven" to "system-integrated" - that is, driven by strategic collaboration at the institutional level, supportive structures, and professional communities rather than relying on individual teachers' isolated innovations. Literature [9] found that the effectiveness of blended learning is not universal or linear, but has a linkage effect with the individual psychological characteristics of learners, forming an interaction model of “pedagogy × learner characteristics”, suggesting that the design of blended learning needs to consider personalized emotional support and cognitive matching strategies. Literature [10] points out that successful learning in blended learning environments not only relies on external instructional design, but also relies on learners' internal self-regulation ability and its synergy with external support systems.

Regarding the research on blended instruction in English language learning, literature [11] states that the effectiveness of blended instruction in English language teaching depends on the interactive integration of design, technology, assessment and learner characteristics. Reference [12] examined the application of blended teaching in English as a Second Language education, and summarized four main themes: collaborative learning, learning management systems, social media applications, and technology-based learning. These four themes respectively represent different technological-teaching integration paths of blended teaching in English language learning, reflecting the evolution from "technology as a content carrier" to "technology as a collaborative ecosystem". Literature [13] found that there are still significant barriers and drawbacks to the application of blended learning in university English teaching, including the lack of infrastructure and technology, insufficient institutional policies and support, the lack of knowledge and experience in using blended learning, and the shortage of technological competence and information skills. Literature [14] constructed a blended learning model based on SPOC using a university English course as a case study, and the results of the study showed that the optimized blended learning model can stimulate foreign language learners' motivation and cultivate their self-directed learning ability, thus further constructing and improving self-directed learning behaviors. Literature [15] points out that the effectiveness of blended learning in foreign language learning is not driven by a single tool or platform, but a systematic coupling of pedagogy, strategy, assessment implementation and teacher role adjustment. Literature [16] explored the use of vocabulary m-learning apps in blended learning of English and their effectiveness, using the Angličtina Today app as a case study, which has content tailored to the language needs of the target student population. Literature [17] points out that blended learning not only enhances language skills, but also promotes the construction of global literacy through authentic intercultural communication, opens a window to the world for students using English as a foreign language, enables them to construct, use and share new knowledge with global literacy, and promotes the synergistic development of learner autonomy and English language proficiency.

This paper completes the work of personalized knowledge point collection generation based on the knowledge point organizing strategy, followed by the use of neurocognitive diagnostic model to obtain the cognitive level of students under the blended teaching of English language learning in colleges and universities, and after that identifies the correlation relationship between the test questions and the knowledge points through the DKVMN model, to complete the work of designing the feedback mechanism for the blended teaching of English language learning in colleges and universities. On this basis, a questionnaire scale is designed and a student engagement model is jointly established with structural equations, with a view to revealing the mechanism's path of student engagement enhancement and providing theoretical references for the intelligent development of blended teaching of English Language Learning in colleges and universities in Guangdong.

2. Feedback Mechanisms for Blended Instruction in a Learning Analytics Perspective

In this paper, we first obtain a collection of personalized knowledge points, on the basis of which we use a neurocognitive diagnostic model to identify the cognitive level acquisition, followed by the use of identifying the correlation relationship between the test questions and the knowledge points through the DKVMN model, from which we design a hybrid teaching feedback mechanism based on the DKVMN model.

2.1. Personalized Knowledge Collection

The purpose of personality mining is to identify students' personalities, and knowledge points are the link between educational resources and students. Since students learn from test resources, which contain related knowledge points, students' answers on test resources are determined by their mastery of related knowledge points. Analyzing and utilizing the correlation relationship among the three can effectively personalize the analysis of students and achieve the purpose of optimizing the recommendation service. The student-knowledge association model constructed in this section can more accurately discover the knowledge points that students are weak, have not yet learned, have learned and will learn. Combined with the students' learning objectives, the number of knowledge points to be mastered by the students in the learning process and the degree of mastery required according to the cognitive level of the students in each knowledge point are clarified. Finally, a personalized collection of knowledge points is generated according to the knowledge point organization strategy in preparation for the following neurocognitive diagnostic model.

2.2. Cognitive level acquisition based on neurocognitive diagnostic models

The neurocognitive diagnostic model is implemented as shown in Fig. 1, and the interaction between the student and the test questions is modeled, and the following is the implementation of using the neurocognitive diagnostic model to obtain the cognitive level of the student.

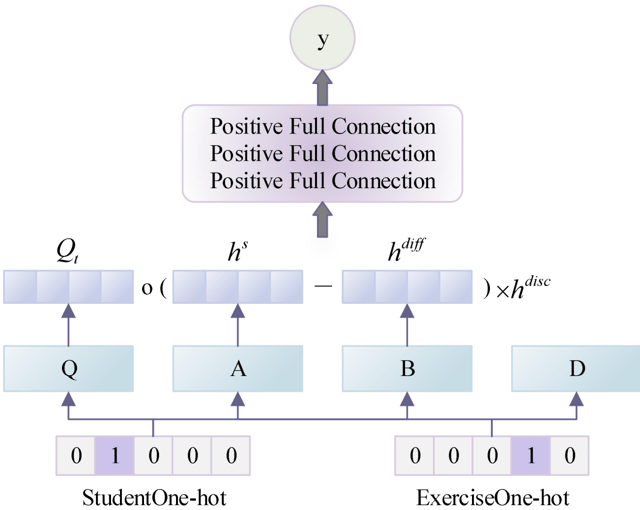

Figure 1. Neurocognitive diagnostic model

The number of students N, the number of test questions M, and the number of knowledge points K are known, so the set of students can be written as $S=\{s_1,s_2,...,s_N\}$, and the set of test questions can be written as $E=\{e_1,e_2,...,e_M\}$, and the set of related knowledge points is denoted as $K_n=\{k_1,k_2,...,k_K\}$. The set $R=\{r_{ij}\}_{N\times M}$ of triples (s,e,r) denotes the records of students' responses on the test questions. In addition, $Q=\{q_{ij}\}_{M\times K}$ denotes the correlation matrix of test questions and knowledge points. When the matrices of students' response records R and Q on the test questions are known, the students' mastery on each knowledge point can be inferred.

The one-hot vectors associated with the student and the test question are used as inputs to NeuralCDM, the predicted probability of the student answering the test question correctly is used as the output of the model, and the output y of the NeuralCDM framework is represented by Equation (1):

$$y = \varphi_n\left(\cdots\varphi_1\left(F^s, F^{kn}, F^{other}, \theta_f\right)\right) \tag{1}$$

The φ_i denotes the mapping function on the i th MLP layer, F^{other} denotes factors other than F^s and F^{kn}, and the model parameter for the interaction layer is θ_f. In the input layer $F^s \circ F^{kn}$ denotes that the computation is done by multiplying by elements, and its purpose is to make each dimension of the knowledge proficiency vector correspond to the test question knowledge point relevance measure.

With the basis of the above model framework we implement the model and perform cognitive diagnosis of students on the basis of the model. According to the above description, the student's knowledge point proficiency vector F^s, x^s is the student's one-hot vector, and the answer proficiency matrix of all students is A. It is specified here as equation (2). That is:

$$\begin{aligned} &h^s = sigmoid(x^s \times A) \\ &h^s \in (0,1]^{1\times K} \\ &x^s \in \{0,1\}^{1\times N} \\ &A \in R^{N\times K} \end{aligned} \tag{2}$$

F^{kn} is the trial-knowledge-point correlation metric and Q matrix correlation, and x^e is the one-hot vector of trial questions, as specified in equation (3):

$$\begin{aligned} &Q_e = x^e \times Q \\ &Q_e \in \{0,1\}^{1\times K} \\ &x^e \in \{0,1\}^{1\times M} \end{aligned} \tag{3}$$

Define the difficulty of a test question as formula (4), which indicates how difficult it is to examine each knowledge point on a test question, and the differentiation of a test question as formula (5), which indicates that the test question is able to differentiate between students of different cognitive levels:

$$\begin{aligned} &h^{diff} = sigmoid(x^e \times B) \\ &B \in R^{M\times K} \end{aligned} \tag{4}$$

$$\begin{aligned} &h^{disc} = sigmoid(x^e \times D) \\ &D \in R^{M\times 1} \end{aligned} \tag{5}$$

The input layer is Eq. (6), and A, B, and D can be obtained by data training:

$$x = Q_e \circ \left(h^s - h^{diff}\right) \times h^{disc} \tag{6}$$

The $\frac{\partial y}{\partial h_i^s} \geq 0$ is set to satisfy the monotonicity assumption, where the direction of adjustment of h_i^s is aligned with the change in the output y, and Eqn. (7) represents the cross-entropy of the predicted value with the true score:

$$loss_{CDM} = -\sum\left(r_i \log y_i + (1-r_i)\log(1-y_i)\right) \tag{7}$$

The diagnostic results of the students are obtained by model training, h^s denotes the degree of mastery of the students on the knowledge points in the range of $(0,1)$.

2.3. Dynamic Key-Value Pair Memory Network (DKVMN)

Observe the sequence $X = \{x_1, x_2, ..., x_t\}$, a prediction is made about the student's performance on the next answer, i.e., $p_t\left(r_t = 1 \middle| i_{t+1}; X\right)$. where the input is $x_t = \{i_t, r_t\}$, where the test question answered by the student at moment t is denoted by the number i_t, and r_t is the label of the test question, i.e., the binary response of the student's answer correctly or incorrectly (0 is an incorrect answer, 1 is a correct answer). M^k in the model is the static matrix that stores the representation of the knowledge points, which will be named key. M^v in the model is the dynamic matrix that stores and updates the student's mastery on the knowledge points, which will be named value. e.g., there are c knowledge points stored in the matrix $M^k(C \times d_k)$, and the state of the student's mastery of each knowledge point $\{s_1, s_2, ..., s_t^C\}$ is stored in the value matrix $M^v(C \times d_v)$, and the student's mastery state on each knowledge point is updated as the learning process progresses. As shown in Equation (8), p_t as the output of the model represents the probability of a student answering the relevant test question correctly in the next moment, and the model is trained using the standard cross-entropy loss between the true values r_t and p_t. i.e:

$$L = -\sum_t \left(r_t \log p_t + (1 - r_t) \log(1 - p_t) \right) \tag{8}$$

2.4. Mathematical modeling

The DKVMN model can be utilized to automatically discover the correlation relationship between test questions and knowledge points, and then assess the cognitive level of students. In constructing the DKVMN model, the MXNet framework is used.The DKVMN model can realize dynamic end-to-end annotation between test questions and knowledge points, and get the mapping matrix between test questions and knowledge points.The process of the feedback mechanism is shown in Figure 2. After the test question number is input, it goes through an embedding layer to get a vector of relevant dimensions, and then this vector is input into the “reading process”. At the same time, the vector and the M^k matrix for the inner product operation, the use of softmax activation function to calculate the relevant weights. Since the knowledge points of the test questions are stored in the M^k matrix, after the softmax activation function, the correlation weight w_t between the test questions and the knowledge points is obtained and represents the test question-knowledge point mapping relationship. In the next calculation, the students' answers to the unknown questions are predicted based on the mastery status of the knowledge points stored in the M^v matrix, and the M^v matrix is updated with the labels of the questions, and the mastery status of the students on each knowledge point is also updated. In the “writing process”, the test number and the test label are inputted, and the M^v knowledge point mastery matrix is inner-producted with the vector obtained after the embedding layer, and it is known that the M^v matrix represents the matrix storing the mastery level of the knowledge points in the model, and the student's performance in the test is labeled by the labeling of the answer. Answer performance of students on the test questions is input through labeling, so the knowledge mastery level in the M^v matrix is also updated after the inner product operation from the M^v knowledge mastery level matrix and the related vectors, and the test-knowledge matrix is constructed by using the w_t weights. The calculation process of w_t is shown in Equation (9), for the stored and updated test question numbers are represented by a vector as $\hat{l}$, T is the set of test questions, and the knowledge point matrix is represented as M^k. i.e:

$$w_t = soft\max\left(\hat{l} M^{k(T)} \right) \tag{9}$$

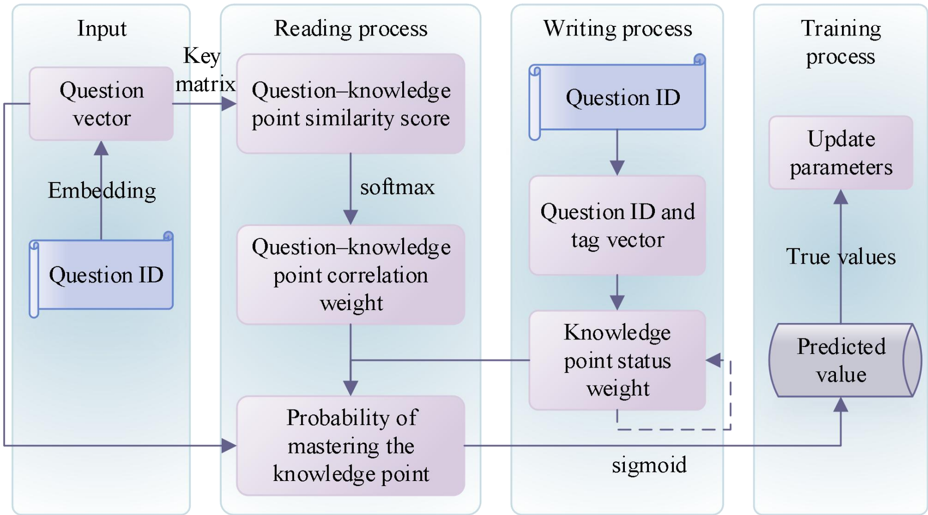

Figure 2. The process of constructing a feedback mechanism

Based on the personalized knowledge point set D, appropriate test questions are selected from the test bank, and a list of test question recommendations is generated by combining students' personalized information. Specific steps:

(1) According to the personalized knowledge point set D, randomly generate a set of test question sets under the knowledge set.

(2) Use the neurocognitive diagnostic model to obtain the student's initial cognitive level.

(3) On the basis of the students' initial cognitive level, use the DKVMN model to construct a blended teaching feedback mechanism under the learning analytics perspective, and update the students' cognitive level through the mechanism.

(4) Extracting test questions that match students' cognitive level according to the antecedent (subsequent) relationship between knowledge points, and generating a list of test question recommendations, aiming to improve the quality of blended teaching of English in Guangdong universities.

3. Modeling Student Engagement

As can be seen from the above research content, a blended teaching feedback mechanism under the learning analytics perspective was constructed, and in order to visualize the mechanism's path of student engagement enhancement, it is proposed to use the structural equation theory together with the scale test method to establish a student engagement model.

3.1. Theory of structural equations

Structural equation modeling is generally divided into two parts: measurement modeling and structural equations. Where measurement equations are used to describe the relationship between latent variables and indicators, while structural equations describe the relationship between latent variables.

(1) Measurement modeling

For the relationship between indicators and latent variables, the measurement equation is usually written as follows:

$$x = \Lambda_x \xi + \delta \tag{10}$$

$$y = \Lambda_y \eta + \varepsilon \tag{11}$$

where x represents the vector consisting of exogenous indicators; y represents the vector consisting of endogenous indicators; Λ_x denotes the relationship between exogenous indicators and exogenous latent variable ξ, which is the factor loading matrix of exogenous indicators on exogenous latent variables; Λ_y refers to the relationship between endogenous indicators and endogenous latent variable η, which is the factor loading matrix of endogenous indicators on endogenous latent variable; δ is the error term of exogenous indicator x; and ε is the error term of endogenous indicator y.

(2) Structural modeling

For the relationship between latent variables, it is usually written as the following structural equation:

$$\eta = B_x\eta + \Gamma\xi + \zeta \tag{12}$$

where η refers to the endogenous latent variable; ξ is the exogenous latent variable; B represents the relationship between the endogenous latent variables; Γ reflects the effect of the exogenous latent variable on the endogenous latent variable; and ζ is the residual term of the structural equation, which reflects the part of the equation that is not explained by η.

The model should be established with the following assumptions:

a) The measurement equation error term ε with mean δ is zero.

b) The residual term ζ of the structural equation has a mean value of zero.

c) The error term ε, δ is uncorrelated with the factors η,ξ and ε is uncorrelated with δ.

d) The error term ζ is uncorrelated with the factors ξ, the error term ε, and δ.

A complete structural equation model contains the following eight parameter matrices: Λ_x, Λ_y, B, Γ, Φ, Ψ, Θ_ε, Θ_δ. The first four matrices are already present in the measurement or structural equations. Φ is the covariance matrix of the latent variable ξ, Ψ is the covariance matrix of the residual vector ζ, and Θ_ε and Θ_δ are the covariance matrices of ε and δ respectively.

In order to find the covariance matrix of the $p+q$ -dimensional vector $\left(y'+x'\right)'$ composed of all the indicators, the covariance matrices of each of Y, X, as well as the covariance matrices between them can be found first. The covariance can be obtained by finding the covariance on both sides of equation (13):

$$\begin{aligned} E\left(\Lambda_x\xi+\delta\right)\left(\xi'\Lambda_x'+\delta'\right) &= \Lambda_x E\left(\xi\xi'\right)\Lambda_x' + E\left(\delta\delta'\right) \\ &= \Lambda_x\Phi\Lambda_x' + \Theta_\delta \end{aligned} \tag{13}$$

So the covariance matrix of x is:

$$\Sigma_{xx}(\theta) = \Lambda_x\Phi\Lambda_x' + \Theta_\delta \tag{14}$$

Similarly the covariance matrix of y is:

$$\Sigma_{yy}(\theta) = \Lambda_y E(\eta\eta')\Lambda_y' + \Theta_\varepsilon \tag{15}$$

From equation (10)

$$\eta = (I-B)^{-1}(\Gamma\xi+\zeta) = A(\Gamma\xi+\zeta) \tag{16}$$

where $(I-B)^{-1} = A$, and the implicit assumption here is that $I-B$ is an invertible matrix. It can be derived from Eq. (15):

$$E(\eta\eta') = A(\Gamma\Phi\Gamma'+\Psi)A' \tag{17}$$

Substituting (17) into (15) gives:

$$\Sigma_{yy}(\theta) = \Lambda_y A(\Gamma\Phi\Gamma'+\Psi)A'\Lambda_y' + \Theta_\varepsilon \tag{18}$$

The covariance matrix between y and x is:

$$\Sigma_{yx}(\theta) = E\left[(\Lambda_y\eta+\varepsilon)(\xi'\Lambda_x'+\delta')\right] = \Lambda_y E(\eta\xi')\Lambda_x' = \Lambda_y A\Gamma\Phi\Lambda_x' \tag{19}$$

So the covariance matrix of $\left(y'+x'\right)'$ can be expressed as a function of the 8-parameter matrix:

$$\Sigma(\theta) = \begin{pmatrix} \Sigma_{yy}(\theta) & \Sigma_{yx}(\theta) \\ \Sigma_{xy}(\theta) & \Sigma_{xx}(\theta) \end{pmatrix} = \begin{pmatrix} \Lambda_y A(\Gamma\Phi\Gamma'+\Psi)A'\Lambda_y' + \Theta_\varepsilon & \Lambda_y A\Gamma\Phi\Lambda_x' \\ \Lambda_y E(\eta\eta')\Lambda_y' + \Theta_\varepsilon & \Lambda_x\Phi\Lambda_x' + \Theta_\delta \end{pmatrix} \tag{20}$$

3.2. Scale design

Based on the "Influencing Factors of Online Learning Participation of College Students" questionnaire, the "Student Participation Measurement Scale" and the "Learning Effect Survey" questionnaire, a six-dimensional student participation survey scale, a student participation influencing factor survey questionnaire and a student learning gain questionnaire suitable for the feedback mechanism of blended teaching were designed. Table 1 shows the student participation survey scale.

Table 1. Student Engagement Survey

Dimension	No.	Item
Offline behavioral participation	Q1	I will complete the task list carefully
	Q2	I often discuss problems with my classmates in class
	Q3	In class, I will pay close attention to the teacher's lecture and the answers of other classmates
	Q4	In class, I will take the initiative to raise my questions to the subject teacher
	Q5	I will take the initiative to answer questions in class
	Q6	I will actively participate in the situational performances
Offline emotional engagement	Q7	The way the teacher teaches never makes me feel bored
	Q8	I feel very happy discussing with my classmates in class
	Q9	I like all the teaching activities designed by the subject teachers. They are very interesting
	Q10	The classroom teaching content is very interesting
Offline cognitive engagement	Q11	I can understand the knowledge taught by the teacher in class as well as that discussed with my peers
	Q12	I can summarize the knowledge discussed in class
	Q13	I will express my own opinions on the discussed content in class
	Q14	I often reflect on my learning methods
Online behavioral engagement	Q15	Search for learning materials related to the course online
	Q16	Choose to minor in online courses related to the curriculum
	Q17	I will look at the teacher's evaluation of my preview results
	Q18	I will finish the preview content in the Rain Classroom before class
Online emotional engagement	Q19	I like communicating with teachers online via QQ
	Q20	There is a sense of achievement when solving problems in online previewing
	Q21	Participating in classes through bullet comments using online learning tools makes me feel happy
	Q22	I like the online learning tool called Rain Classroom
	Q23	I think previewing with online learning tools can better motivate me to study
	Q24	The way of online submission and anonymous answering questions makes me feel very at ease
Online cognitive engagement	Q25	I can arrange my own preview plan
	Q26	I can and will actively summarize the knowledge I have previewed
	Q27	After previewing, I will correct my wrong understanding of the knowledge online based on the teacher's evaluation
	Q28	I can understand the subject knowledge in the preview PPT
	Q29	When previewing, I can discuss the content in the PPT with the teacher and express my own opinions

This study will analyze the impact on student engagement and student learning gains in terms of learning environment and student self-efficacy, where the learning environment is assessed in terms of five dimensions: school support, instructor, group peers, instructional tools, and instructional resources, and the influencing factors survey scale is presented in Table 2.

Table 2. Questionnaire of influencing factors

Dimension	No.	Item
Self-efficacy	P1	I have made a detailed study plan
	P2	I have a good ability for self-study
	P3	I have a good ability of self-reflection
	P4	I have a strong sense of self-discipline
	P5	I have a strong interest in learning
Instructor	P6	Teachers can provide timely feedback and interaction
	P7	The teacher's novel teaching methods
	P8	When teaching, the instructor highlights key points and provides a large amount of information, reflecting the cutting-edge of the discipline
	P9	Teaching interaction is evaluated by teachers
	P10	The subject teachers often share resources and information with us through Rain Classroom and Cloud Disk, which can help me with my studies
	P11	Teachers can offer guidance and assistance
Group companions	P12	Members of the group will collaborate and help each other
	P13	Often communicate and discuss with peers
	P14	There is a reasonable division of labor among the groups
	P15	Peer evaluation among each other
	P16	My companions are knowledgeable and willing to share
Teaching resources	P17	The learning resources are very dull and boring
	P18	Learning resources will guide my future practice
	P19	The learning resources are extremely abundant
	P20	The quality of learning resources is high
Teaching tools	P21	The interface of Rain Classroom is very clear and straightforward, eliminating the need to explore hidden functions
	P22	Rain Classroom makes learning easy, allowing you to view preview and review materials anytime and anywhere
	P23	The preview materials pushed by Rain Classroom are conducive to urging me to preview before class
	P24	Through Rain Classroom, I can promptly view the statistics of voting options, which I find very convenient
	P25	The answer distribution map displayed in the Rain Classroom is conducive to the discussion of questions among students
School support	P26	The school Internet fee is too expensive
	P27	The school's policy on recognizing the academic performance of this course
	P28	The talent cultivation goals of the school
	P29	The extent to which schools have made efforts in the construction of learning resources
	P30	The school provides students with a good learning environment

The same methodology described above was taken to construct the Learning Gains Survey Scale, which is a five-point Likert scale that gives a score of 5-1 in the order of Strongly Agree, Agree, Don't Know, Basically Agree, and Strongly Disagree, and Table 3 shows the Learning Gains Survey Scale.

Table 3. Survey scale of learning achievements

Dimension	No.	Item
Learning gains	O1	The knowledge of this discipline has been increased and consolidated
	O2	To further one's studies and acquire profound professional knowledge
	O3	Get a series of information about your career
	O4	It has increased my understanding and interest in knowledge outside my discipline
	O5	I have acquired excellent professional teaching skills and enhanced my practical abilities
	O6	The ability of teamwork has been enhanced
	O7	The ability to express one's own opinions to others more effectively
	O8	The ability to apply modern information technology and information literacy have been enhanced
	O9	The ability of effective autonomous learning has been enhanced
	O10	This course has enabled me to acquire a new way of learning, not only through textbooks but also through 10The information technology and network resources assist me in my study

3.3. Model construction

Combining the theoretical knowledge mentioned above, a model of student engagement under the feedback mechanism of blended teaching of English in Guangdong colleges and universities is constructed, which is a structural model of the influence relationship between the five components of the learning environment, student self-efficacy, offline student engagement, online student engagement, and learning gains, and the structure of the model is shown in Figure 3. Among them, the campus environment contains five potential variables of lecturer, group peers, teaching resources, teaching tools and school support, student engagement is divided into two dimensions of online and offline potential variables, each dimension of student engagement contains three dimensions of behavioral, affective and cognitive connotative explanations, and students' learning gains include cognitive gains and ability gains. The five variables around the three influences, student engagement and learning gains components.

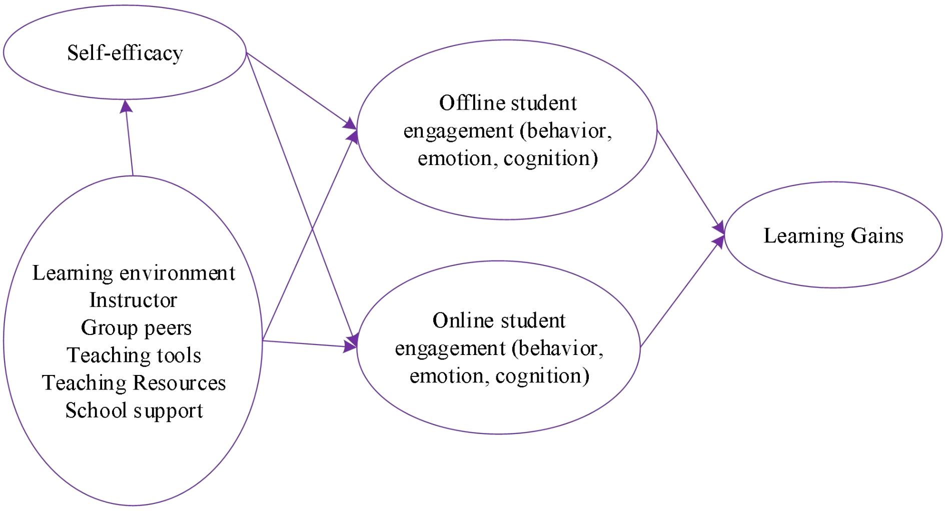

Figure 3. Model structure

4. Exploratory Analysis of Blended Teaching Feedback Mechanisms

4.1. Data set and parameters

In order to show the application value of the DKVMN model, we selected the EnglishArticle dataset as the main data source, which consists of the number of students, the number of questions, the number of correct answers, and the number of incorrect answers. The DKVMN model parameters were also determined to facilitate the subsequent research work, and the parameter settings are shown in Table 4.

Table 4. Parameter setting

Parameter	Value
batch_size	64
q_embed_dim	80
qa_embed_dim	100
memory_size	40
init_std	0.001
maxgradnorm	100
final_fc_dim	100

4.2. Degree to which English test questions are related to knowledge points

Our proposed DKVMN can be used to mine the degree of correlation between English teaching test questions and knowledge points, and a part of the exercises in the EnglishArtical dataset are extracted to find the correlation between them and the knowledge points, and to observe whether they are in line with the actual situation. When the number of English knowledge points is set to 19, the correlation degree between some test questions and knowledge points in the EnglishArtical dataset, and the results of the correlation degree between English test questions and knowledge points are shown in Figure 4. It can be seen that each English test question is more or less related to the set 19 English knowledge points, i.e., there are more English knowledge points involved in the process of English teaching and testing, and the knowledge components are more dispersed. For example, the question number 1914 can be seen to have a high correlation with English knowledge points 10, 11, 13, 14, and 4, and almost no correlation with English knowledge point 18. English writing involves a wide range of knowledge concepts, students who want to complete an English composition accurately and correctly usually need to consider a variety of factors, such as: whether the words are spelled correctly, whether the grammar is correct, and grammar involves a number of categories, which is more of a test for students to combine the details of the various knowledge points. Overall, the heat map with color shades of error types demonstrates the level of mastery of different English test topics, enabling students to quickly locate writing weaknesses and helping them to avoid common problems, while effectively reducing teachers' workload; The DKVMN model analyzes the degree of correlation between English test questions and knowledge points, provides students with targeted revision suggestions, and forms a feedback support system that runs through the whole cycle of blended English teaching in Guangdong universities.

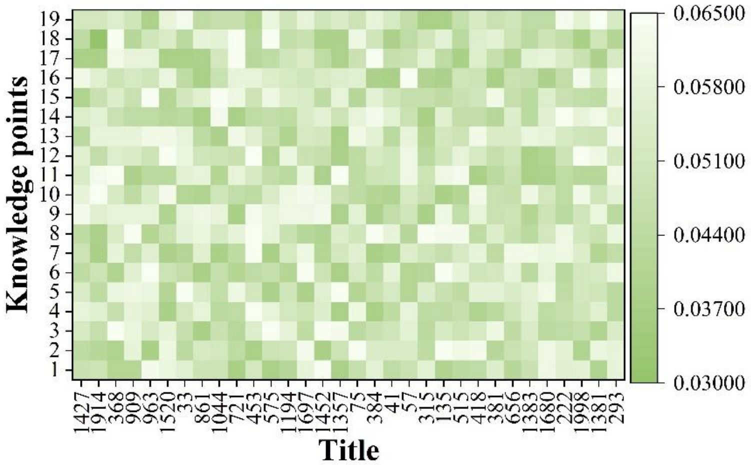

Figure 4. The degree of correlation between English test questions and knowledge points

4.3. Students' mastery of English language knowledge points

After obtaining the students' answers to the exercises and the degree to which the questions are related to the concepts, the students' mastery of these hidden knowledge concepts and their change processes can be easily obtained, and these change processes can provide help for personalized teaching and teaching feedback. Using the DKVMN model to carry out the analysis of students' mastery of English knowledge points, the students' mastery of English knowledge points is shown in Figure 5, the lighter the color means that students have a higher degree of mastery of the concept, and the darker the color means that the students have hardly mastered the concept. The horizontal coordinate is the question number and the student's answer, for example, “1427-1” means that the student gave a correct answer to the question number 1427, and “1452-0” means that the student gave an incorrect answer to the question number 1452. From the horizontal coordinates, it can be found that the student used almost every statement grammatically correct in his writing, except for the statements labeled 1452, 135, 315, and 418, which were written incorrectly. English writing involves many complex concepts, and when the student has completed the series of exercises, it can be assumed that he has basically mastered these concepts completely. Therefore, it is considered that the student did have a better mastery of many aspects of knowledge and completed an English composition, and it can also be introduced that the student has a high level of English proficiency.

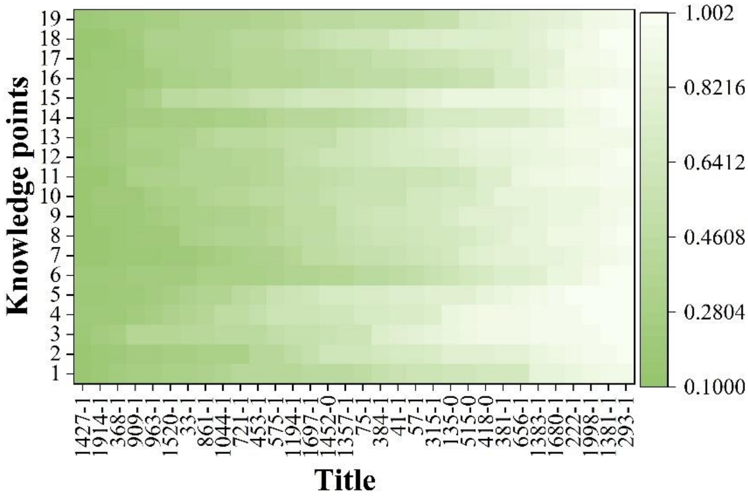

Figure 5. The degree to which students master English knowledge points

5. Exploratory Analysis of Student Engagement Models

The results of the previous investigation and analysis have verified the practical application value of the blended teaching feedback mechanism under the perspective of learning analytics, and then we use structural equation theory and scale testing methods to explore the path of student engagement enhancement of this mechanism from multiple dimensions.

5.1. Descriptive statistical analysis

Descriptive statistical analysis was carried out through the Learning Gains Questionnaire Scale, Influencing Factors Questionnaire, and Student Engagement Questionnaire in the questionnaire, and the results of the descriptive statistics of the latent variables are shown in Table 5. The mean, median, maximum, minimum, standard deviation, kurtosis, skewness, and the fit of the normal distribution of the findings of the questionnaire's latent variables were calculated with the aim of assessing the reasonableness of each latent variable. The mean values of all latent variables ranged from 3.622 to 4.375, and the median was all 4. The skewness was all negative, indicating that the results of this statistical survey were skewed to the left relative to the standard normal distribution. Secondly, the standard deviation of all the latent variables lies within the range of 0.915 to 1.048, a range that is reasonable for the data of this study, showing a degree of consistency and stability.

Table 5. Latent variables describe the statistical results

Project	Mean	Median	Min	Max	SD	Super kurtosis	Skewness	Cramer-von Mise p-value test
Offline behavioral participation	4.141	4	1	5	1.013	-0.42	-0.667	0.002
Offline emotional engagement	3.719	4	1	5	1.029	0.571	-0.666	0.004
Offline cognitive engagement	3.977	4	1	5	0.976	0.028	-1.097	0.003
Online behavioral engagement	3.934	4	1	5	0.947	0.783	-0.566	0.009
Online emotional engagement	4.375	4	1	5	1.001	-0.015	-0.714	0.008
Online cognitive engagement	4.251	4	1	5	0.971	-0.418	-0.648	0.006
Self-efficacy	4.245	4	1	5	1.044	0.66	-0.621	0.003
Instructor	4.203	4	1	5	1.048	0.802	-0.53	0.003
Group companions	4.186	4	1	5	0.986	0.3	-0.972	0.008
Teaching resources	3.671	4	1	5	1.016	-0.243	-0.462	0.003
Teaching tools	4.369	4	1	5	0.962	-0.158	-0.744	0.006
School support	3.622	4	1	5	0.915	-0.027	-0.549	0.005
Learning gains	4.116	4	1	5	1.042	0.634	-0.834	0.008

5.2. Analysis of model evaluation

The SmartPLS 4.0 software was then used to evaluate the student engagement model and the path results are shown in Figure 6. First, we examined the variance inflation factor (VIF) values of each predictor variable in the model, and these values ranged from 1.717 to 4.667, which were all less than 5 and below the suggested threshold, indicating that none of our predictors had a critical level of constructed relationships with each other, i.e., the factors were better independent of each other, proving the accuracy and reliability of our model. Second, we analyzed the fit indices of the model, including the standardized residual root mean square (SRMR) and the normative fit index (NFI). The SRMR value of 0.058 and the NFI value of 0.839 were obtained, both of which conformed to the corresponding norms (SRMR<0.084, NFI>0.821), indicating that the fitting effect of our model was acceptable. Finally, taking offline behavioral engagement as an example, the path coefficient of self-efficacy on offline behavioral engagement among the influencing factors is 0.206, that is, it indicates that for every one unit quantity of self-efficacy enhancement, the offline behavioral engagement also enhances by 0.206 unit quantities along with it, and the other potential variables are based on the values in the figure, and will not be repeated in the presentation, which visually demonstrates the quantitative relationship between the paths of student engagement enhancement, and provides an opportunity for learning The feedback mechanism of English language learning blended teaching in Guangdong colleges and universities under the perspective of analysis and the research on the path of increasing student engagement provide theoretical references.

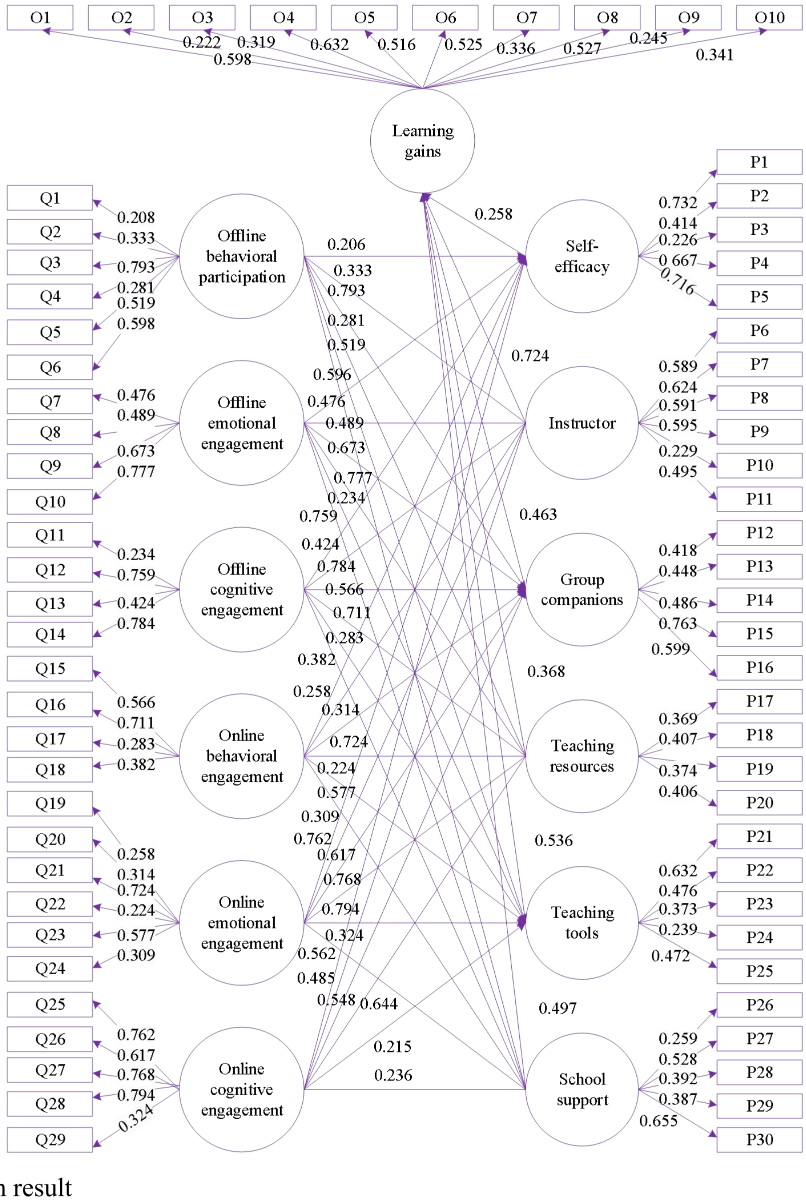

Figure 6. Path result

6. Conclusion

In this paper, under the perspective of learning analysis, the DKVMN model is first used to construct a feedback mechanism for blended teaching of English in colleges and universities, and then, in order to show the path of increasing student engagement under the conditions of this mechanism, the student engagement model is constructed with the help of scales and structural equation theory, and empirical analysis is carried out on it.

(1) English test topic 1914 has a high degree of correlation with theoretical knowledge points 10, 11, 13, 14, 4, and a low degree of correlation with theoretical knowledge point 18. The DKVMN model intuitively shows the degree of students' mastery of different English test topics, which helps to realize the intelligent diagnosis of the students' knowledge weaknesses, and then provides students with targeted feedback to promote the intelligent development of blended teaching of English in colleges and universities. Intelligent development of teaching.

(2) The path coefficient of self-efficacy and offline behavioral engagement is 0.206, which means that for every one unit increase in self-efficacy, the offline behavioral engagement increases by 0.206 units. The structural equation model demonstrates the quantitative relationship between the paths of students' engagement in order to provide theoretical references for the paths of students' engagement under the blended teaching feedback mechanism of English language learning.

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About the Author

Xiao Jin is a PhD candidate in Education at the Faculty of Education, Universiti Teknologi MARA. She holds a Master's degree in Education from Yanbian University, China. Her research focuses on the application of blended learning in higher education. She has published two papers in Chinese academic journals and participated in three university- and provincial-level research projects during her tenure as a university English teacher in China. Her research interests include innovative pedagogical approaches and the integration of technology in teaching and learning.

Syamsul Nor Azlan Mohamad, holding a Phd in Education and Master in Educational Technology. His areas of expertise in curriculum, e-Portfolio/alternative assessment, learning and predictive analysis. Now, he is a Director of Academic Assessment and Evaluation Division in Universiti Teknologi MARA. Leading the transformation of assessment at UiTM, and expending his interest into learning analytics by ensuring the quality, integrity and flexibility in measuring students performance. Therefore, he actively engaged with ministries, industries, public and private universities for research and consultation for digital maker talent and innovation initiatives. UiTM Academic Award Recipient Category Teaching - Social Sciences and Humanities in 2019 & UiTM Academic Award Recipient Category Best Speaker 2022.

Norhayati Mohd Yusof is a Senior Lecturer at the Faculty of Education, Universiti Teknologi MARA (UiTM), Malaysia. She holds a PhD in Education specialising in Instructional Technology. Her teaching and supervision focus on educational technology, digital pedagogy, qualitative research methodology, and technology-enhanced learning. Her research interests include digital learning environments, metaverse and avatar-based learning, e-personality development, netnography, and self-regulated digital engagement in education.

Xian Liu is currently an Associate Professor at Zhengzhou Institute of Technology, Henan, China, and a PhD candidate in the Faculty of Education at Universiti Teknologi MARA (UiTM), Malaysia. Her research primarily focuses on English teaching in higher vocational education, with special emphasis on innovative pedagogy and the integration of artificial intelligence in language instruction. She is particularly interested in the application of AI agents and intelligent tutoring systems to enhance vocational English learning outcomes, motivation, and autonomous learning abilities. Her current doctoral work explores the effectiveness of AI-driven tools in Chinese higher vocational English classrooms.