Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org

Volume 25, Issues 1, pp. 435–449, DOI 10.12694/scpe.v25i1.2310

BLENDED COLLEGE ENGLISH TEACHING MODEL AND EVALUATION BASED ON MOOC

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Abstract. MOOC teaching has been developing rapidly in the context of COVID-19, and its teaching quality has become the focus of social attention. Therefore, this study analyzes the blended college English teaching model based on MOOC by constructing a teaching evaluation model. The co-occurrence rate index is used to improve the K-modes algorithm, and then the important index in the teaching mode is extracted. The neural network is used to construct the prediction model of student learning effect, which reflects the advantages and disadvantages of the teaching mode. Through experimental analysis, the accuracy of the improved K-modes algorithm in the model reaches 0.985. The recall rate reached 0.982; The average error of the prediction model is less than 1 in the error analysis. Therefore, the model accurately reflects the problems existing in the teaching model, and has a high prediction accuracy, indicating that the teaching evaluation model has a good evaluation effect.

Key words: MOOC; Blended Teaching; Teaching Evaluation; Neural Network; Co-Occurrence Rate; K-Modes

1. Introduction. In recent years, due to the problem of the novel coronavirus pneumonia, most schools have been faced with the state of suspension of classes, Massive open online courses (MOOCs) have developed rapidly under the policy of continuous suspension of classes and become the focus of the society [1]. The main reasons for this are changes in educational needs, concerns about teaching quality, and support from technology and data. The epidemic has led to the suspension or restriction of traditional face-to-face teaching, and many students and educational institutions have turned to online learning and distance education. MOOC, as a large-scale online open course, has attracted widespread attention as it can meet the educational needs of a large number of students in a short period of time. With the rapid development of MOOC, people have begun to attach importance to the teaching quality of online education. Due to the characteristics of large-scale, remote, and heterogeneous student participation in MOOC courses, ensuring the effectiveness and quality of teaching has become an important issue. Ensuring the quality of MOOC teaching is not only related to students' learning outcomes, but also to educational equity and social development. In the context of the COVID-19 epidemic, the support of technology and data provides more possibilities for evaluating and improving the quality of MOOC teaching. Technologies such as data mining and machine learning can be used to analyze students' learning behavior and outcomes, thereby improving teaching methods and personalized learning. Therefore, the focus on the quality of MOOC teaching also involves the application of data mining and technology.

In college English teaching, the blended learning model based on MOOC has been widely explored and applied to address some specific challenges and problems. This includes a lack of motivation for students to learn; Insufficient interactivity and feedback; Technical application and facility conditions; Evaluation and certification. By designing motivational learning tasks, providing real-time interaction and personalized feedback, improving technical conditions, and diversifying evaluation methods, this model can improve teaching quality, promote students' active learning and participation. To ensure the quality of college students' English learning in MOOC, it is extremely important to evaluate the teaching of MOOC [2]. The reason is that MOOC based teaching evaluation can provide feedback and improvement opportunities, ensure learning quality and effectiveness, improve teaching design and resource allocation, and promote student participation and learning motivation. Through teaching evaluation, we can comprehensively focus on and improve the quality of learning, providing a better English learning experience and learning outcomes.

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Teaching evaluation can provide diagnostic functions for teaching models, including examining students' learning progress and mastery level, identifying problems and challenges in the teaching process, collecting student feedback and opinions. Through this diagnostic information, targeted improvements can be made to improve the effectiveness and quality of teaching models. Teaching evaluation has a feedback function, which can promote the further development of students and teachers and improve the quality of teaching by providing feedback on students' learning outcomes, teaching effectiveness, providing suggestions for teaching improvement, and promoting students' self-reflection. Teaching evaluation can stimulate teachers' enthusiasm and help them improve teaching quality by providing positive incentives, providing opportunities for improvement, promoting professional development, and utilizing student feedback. Through continuous self reflection and improvement, teachers can continuously enhance their teaching abilities and professional qualities, providing students with better educational experiences and learning outcomes. Teaching evaluation has the guiding function, establish the notarized teaching evaluation system, help teachers to find the direction of struggle, guide teachers to shift the focus of work to the teaching task; Teaching evaluation has management function and is an important basis for teacher promotion and evaluation [3, 4]. Establishing a comprehensive teaching evaluation system can provide accurate evaluation criteria, emphasize the importance of data and evidence, supervise the improvement of teaching quality, promote innovation and research in teaching methods, and promote the sharing and exchange of teaching experience. It can promote the scientification of teaching models, improve the quality and effectiveness of teaching. Therefore, the research carried out in-depth research on the teaching evaluation system, improved the teaching evaluation model by using improved K-modes algorithm and neural network, and realized student clustering analysis mainly through this method to identify student groups with similar characteristics and Learning styles. These characteristics may include students' interests, learning styles, learning tendencies, etc. By grouping students into different clusters, teachers can better understand their needs and differences, thereby providing personalized teaching support for each student. The improved K-modes algorithm can be used to mine and analyze student feedback data. By clustering students' feedback information, it can be discovered what similarities students in different clusters have in their evaluations and needs for teaching modes. Based on these common points, key points and directions for improving teaching models can be extracted, thereby further improving teaching quality.

2. Related Work. The MOOC teaching mode has developed rapidly in the environment of the COVID-19. Facing the situation of full offline suspension, the MOOC teaching mode has become the focus of many scholars due to its openness, flexibility, cross regional and cross-cultural, diverse learning methods and resources, social and Cooperative learning, data analysis and teaching improvement. Duan T scholars used ISM and MICMAC models to analyze the factors that affect ideological and political courses. Firstly, they selected 10 main factors that affect the teaching effectiveness of MOOC courses. Secondly, we establish a Adjacency matrix to clarify the basic Binary relation between these factors, find the reachability matrix through exponential operation, and obtain a 5-level interpretive structure model. Thirdly, based on MICMAC analysis, new ideas are provided for teaching optimization based on MOOC. Finally, through a detailed discussion of the survey results, we have proposed some suggestions for optimizing the effectiveness of ideological and political education MOOCs teaching [5]. Researchers such as Min Y D conducted a survey on the influencing factors of MOOC teachers' work engagement, and analyzed teachers' openness and teaching self-efficacy through online surveys. The results show that through learning and growth opportunities, innovation and teaching improvement, professional identity and social support, and interaction with students, Openness to experience can enhance teachers' self-confidence and professional ability, improve their commitment to teaching, and continuously improve teaching quality. Therefore, this characteristic has a direct impact on the self-efficacy and work engagement of MOOC teachers, while teaching self-efficacy has an indirect impact on work engagement [6].

Charo R team analyzed self-regulated learning strategies and MOOC related variables, understood students' self-regulated learning ability through questionnaires, and analyzed the data through Logistic regression model. The results showed that students who completed their studies were more capable of learning self-regulation than those who did not finish their studies. At the same time, it shows higher perception rate and participation in MOOC content [7]. The mixed teaching mode combines the advantages of traditional teaching and network teaching in the "Internet plus" era, and has become one of the important trends in the development of higher education teaching. In order to comply with this development trend, Yan R and other researchers proposed a hybrid teaching model based on MOOC resources and digital experimental teaching platforms. This teaching method combines the advantages of online teaching with the advantages of offline teaching, so that both teachers and students have a positive attitude in the teaching classroom. It is suggested to continue to increase the construction of MOOC courses and create a high-level hybrid teaching model [8].

Yu Y et al. introduced the platform design of MOOC using a software based virtual experience, combining virtual experiments with MOOC to achieve the concept of open sharing, effectively integrating teaching resources, and visually displaying the teaching content of MOOC courses. The software virtual experience provides practical opportunities and advantages such as immersive learning, non-linear learning and personalized paths, collaboration and communication, feedback and evaluation, as well as cross regional and cross-cultural learning, thereby improving the teaching effectiveness of the MOOC platform and making the relationship between teaching theory and practice closer [9]. Cross cultural teaching of college English has shifted from offline to online. Driven by the MOOC teaching model, online cross-cultural teaching of college English has exposed problems such as insufficient intelligence and poor online teaching effectiveness. In order to improve the efficiency of cross-cultural teaching in college English, scholars such as Xie H have improved traditional algorithms based on the teaching needs of MOOC and established relevant functional modules, which have been verified through control experiments. The experimental results indicate that the improved new model is more attractive for students' online learning, effectively improving the efficiency of cross-cultural teaching of college English, and addressing the shortcomings of traditional online teaching [10].

With the development of society, various teaching methods emerge. To guarantee the effect of teaching methods, the research of teaching evaluation system has become the focus of social attention. Caldwell K and other researchers developed the Chief Resident Teaching Evaluation and Assessment System to rate physician skill and teaching standardization through classroom observers and to analyze the physician's teaching experience. The developed teaching evaluation system effectively evaluated the teaching performance of teaching assistants as reflected by the results of teaching assistant assignments [11]. To explore the impact of teaching leadership on effective teacher teaching practices and learning outcomes, Kazi M scholars analyzed the value of teaching evaluation and used structural equation models to analyze teaching data. The data shows that students' performance has been improved in the perfect teaching evaluation, and teaching practice has also been improved in the perfect teaching evaluation [12].

The Tarraga Menguez R team established a theoretical framework through literature review, analyzed teaching evaluation data, and evaluated teachers' teaching abilities. The results show that the problems existing in the current teaching of teachers are accurately reflected in the framework, including teaching methods and teaching ability [13]. Fans et al. believe that evaluation must consider the aspects of teaching, learning, and educational background that are missing from digital data. Therefore, they advocate for the participation of different types of data outside of teaching in the teaching evaluation system, avoiding the transformation of teaching evaluation systems constructed using digital data into narrow instrumental education methods. Through the evaluation and judgment of the quality of educational practice, the proposed teaching evaluation system can better reflect the educational technology and educational purpose [14].

Researchers such as Yz A utilized inter relationships, evaluation texts, and existing "user project" format rating matrices to form a multi-source and multimodal data structure, and proposed a hybrid recommendation model that integrates network structural features, graphical neural networks, user interaction activities, and tensor decomposition. Firstly, a teaching evaluation network based on a graph structure is proposed, which analyzes teaching scores and comments. The extracted personalized features are used as the third dimension of the rating tensor. Finally, Bayesian probability tensor decomposition is used to predict course evaluation. Through experiments with real teaching data, the results show that this method has smaller prediction errors [15]. Antoci team analyzed the influence of social factors on the teaching evaluation system, and found that teaching evaluation and teachers' performance in subsequent courses had a direct impact on teacher rating, which could easily lead to the polarization of social results [16].

To sum up, the MOOC teaching method has been vigorously developed in the current environment, which has a significant impact on student learning. However, few of the current MOOC teaching methods have perfect teaching evaluation results. Therefore, this study combines traditional teaching with MOOC classroom to achieve blended college English teaching, and constructs a teaching evaluation system through K-modes and

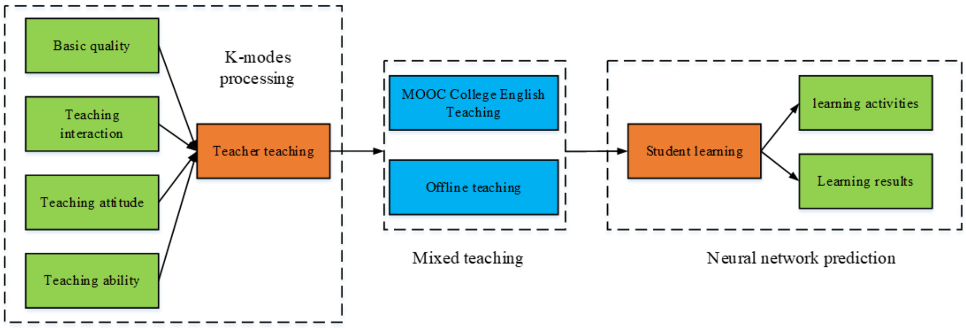


Fig. 3.1: MOOC based Mixed Teaching Evaluation Model for College English

neural networks to evaluate the proposed blended teaching, aiming to make the MOOC-based blended teaching model more perfect and scientific.

3. College English Blended teaching model and evaluation model construction based on MOOC.

3.1. Data selection of hybrid teaching model and evaluation model. At present, MOOC teaching methods lack a perfect teaching quality evaluation system, so it is impossible to make accurate and scientific judgment on the teaching quality of MOOC. Therefore, this study evaluates blended teaching by constructing a teaching evaluation model. The blended teaching model and teaching evaluation model are shown in Figure 3.1.

In Figure 3.1, the data generated by the hybrid teaching method are processed and analyzed by K-modes algorithm to obtain relevant evaluation indicators. The processed data will be sent to the neural network structure for learning and prediction, and the prediction effect will be compared with the actual situation to reflect the overall effect of the hybrid teaching method. In data selection and analysis, teaching behavior will produce more data information, and the information processing is difficult, so the model uses K-modes algorithm to process the data. The research adopts the MOOC teaching data of Y school for analysis, and sets four teaching evaluation indicators based on the evaluation of online teaching. The indicators include MOOC teachers' quality, MOOC teachers' teaching attitude, teachers' teaching methods and classroom interaction effects. Each evaluation index is divided into five grades, of which grade 0 is the lowest grade, and this grade indicates that the corresponding index fails; Level 4 is the highest level, which means that the corresponding indicators are excellent. The teaching data is mapped by setting evaluation indicators, but there are often abnormal data in the data. The elimination of abnormal data is an important link to ensure the accuracy of the evaluation model. The process of exception data elimination is shown in Figure 3.2.

In Figure 3.2, the classification of teaching evaluation is the first step of data cleaning. Its classification method can be classified according to student year, semester time, course selection number and teacher number. There are 1548 data samples of School Y used in the study. After the sample data is classified, the cosine distance similarity formula is used to calculate the samples to eliminate the wrong results caused by abnormal data. By indicator grade classification, the sample data has five dimensions, and the average dimension of the sample is . In the similar cosine distance formula, if the denominator is 0, it will lead to errors in the similarity calculation. To ensure the accuracy of the calculation, increase the value of 0.001 in the evaluation value to solve the problem of zero denominator. The dissimilarity formula after improving the denominator is shown in Equation 3.1.

$$Sim(X,Y) = \frac{\sum_{i=1}^{q}((x_i - p_x)\cdot(y_i - p_y))}{\sqrt{0.001^2}\cdot\sqrt{\sum_{i=1}^{q}(y_i - p_y)^2}} = \frac{X\cdot Y}{\|X\|\cdot\|Y\|} \tag{3.1}$$

In Equation 3.1, $Sim(X,Y)$ represents the difference between sample X and Y . The dimension of sample data is represented by q. The comparison of cosine distance similarity requires two samples, one of which is taken

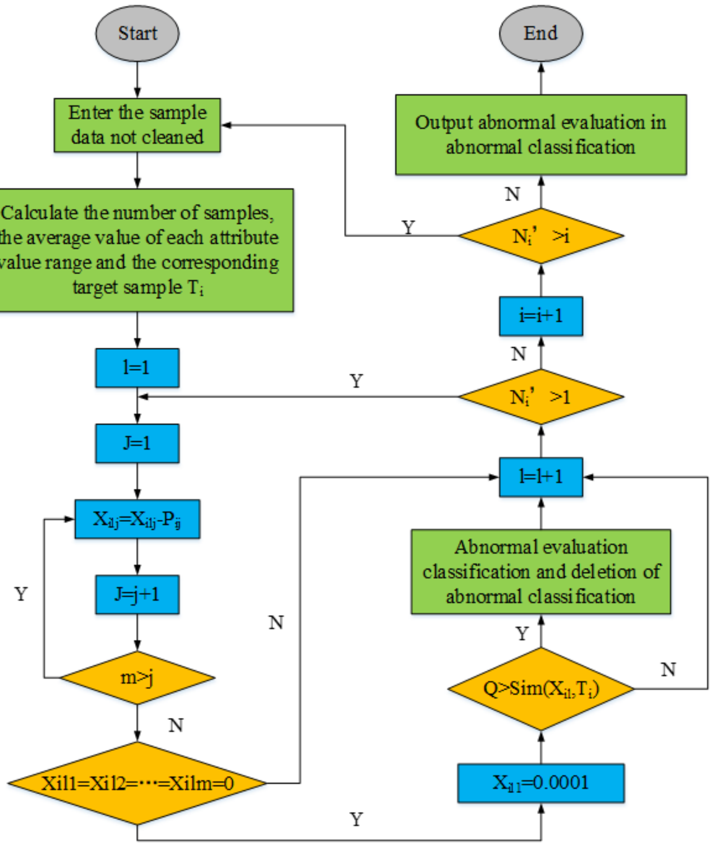


Fig. 3.2: Processing flow of abnormal data

as the target sample and the other is used as the sample of multidimensional data for comparison. According to the principle of center distance, the average value of the target sample in each dimension can be calculated. The calculation formula is shown in Equation 3.2.

$$T = \left(\frac{1}{N} \sum_{i=1}^{N} (x_{i1} - p_1), \frac{1}{N} \sum_{i=1}^{N} (x_{i2} - p_2), \ldots, \frac{1}{N} \sum_{i=1}^{N} (x_{iq} - p_q) \right) \tag{3.2}$$

In Equation 3.2, T represents the dimensional average of the target sample; N indicates the type of sample classification. The abnormal data can be eliminated by Equation 3.1 and Equation 3.2. After the data is processed abnormally, it needs to be standardized. Data standardization can be processed by min-max standardization method, which can shrink the data into the interval of [0,1]. The standardized data can be compared directly, so the min-max standardization is shown in Equation 3.3.

$$x_{ij} = (x_{ij} - min\ x_{ij} / max\ x_{ij} - min\ xij) \tag{3.3}$$

In Equation 3.3, $maxx_{ij}$ and $minx_{ij}$ represent extreme values; x_{ij} represents unstandardized raw data; x_{ij} represents the normalized data. After the data is standardized, the data in the same column need to be averaged and finally merged. The K-modes algorithm can be used to calculate the similarity of the merged data, as shown in Equation 3.4.

$$AVF(x_i) = \frac{1}{q} \sum_{j=1}^{q} f(x_{ij}) \tag{3.4}$$

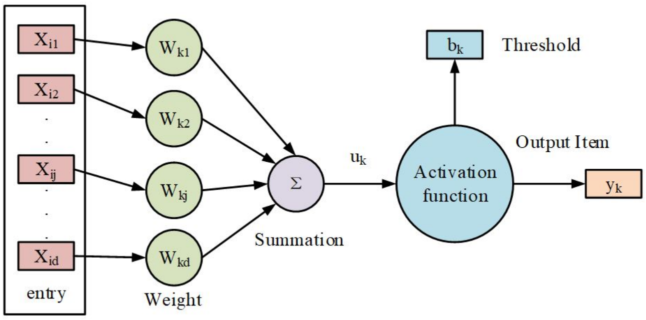


Fig. 3.3: Example of neuronal structure

In Equation 3.4, $AVF(x_i)$ represents the similarity based on frequency; $f(x_{ij}$ represents occurrences of the j attribute in the sample. When using K-modes algorithm to select the initial clustering center, problems such as unstable clustering results and influence of outlier data points on the availability of clustering results are likely to occur. Sum of Squared Error (SSE) can avoid such problems. The SSE expression is shown in Equation 3.5.

$$SSE = \sum_{l=1}^{k} \sum_{x \in L_l} \mathrm{Dist}(x, Z_l)^2 \tag{3.5}$$

In Equation 3.5, SSE is used to determine the initial cluster center stably, where k represents cluster families. Z_l represents the clustering center of the item; $\mathrm{Dist}(x, Z_l)$ represents the similarity between the data and the cluster center. In the same data, the value changes and value relationships of the same attributes and different attributes can affect the clustering effect, but this is not considered in the traditional K-modes algorithm. Therefore, the co-occurrence rate is used to improve the algorithm, and the distance measurement based on the co-occurrence rate is calculated as shown in Equation 3.6.

$$d(x, y) = \sum_{i=1}^{m} \sum_{j=1,\ldots,m, j \neq i} d_{ij}(x_{Ai}, y_{Ai}) \tag{3.6}$$

Co-occurrence rate is the probability that one thing will happen if another thing is certain to happen. In Equation 3.6, $d_{ij}(x_{Ai}, y_{Ai})$ represents the distance between an attribute in the sample data and another attribute. The smaller the distance, the greater the co-occurrence rate, indicating the higher the similarity of the samples. After the above analysis, the specific way to enhance K-modes through co-occurrence rate is as follows: firstly, the co-occurrence rate index is used to represent the degree of correlation between different discrete variables. Based on the characteristics and objectives of the data, an appropriate co-occurrence rate index is selected to measure the correlation between variables; Then, distance measurement is usually used to calculate sample similarity, thereby improving classification results.

3.2. Construction of student learning prediction model based on neural network. After the K-modes algorithm is used to process the teaching evaluation data and teaching data, the processed data is used to predict student learning [17, 18]. Firstly, the input data and output data of the model are determined. The second is to construct the network structure, including the network depth, the distribution form of neurons and the selection of excitation function. Finally, the training times of the model were adjusted [19, 20]. The output layer study takes K neurons as an example to construct a neural network, and the structural diagram of the neurons is shown in Figure 3.3.

The neuron structure in Figure 3.3 can be represented by mathematical expressions, as shown in Equa-

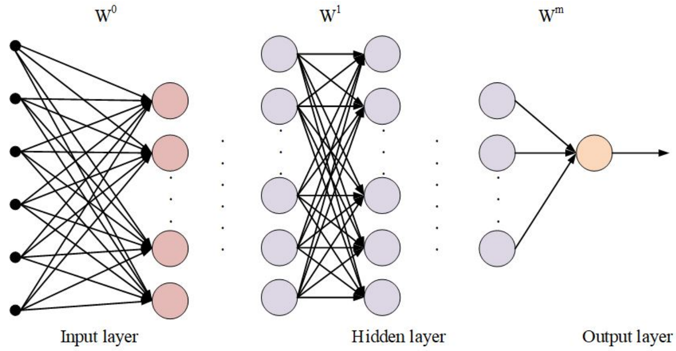


Fig. 3.4: Topological structure of neural network

tion 3.7.

$$\begin{cases} u_k = \sum_{i=1}^{n} w_{kj} a_{ij} \\ v_k = u_k + b_k \\ p_k = \varphi(v_k) \end{cases} \tag{3.7}$$

In Equation 3.7, a_{ij} represents the features extracted from the training sample, where i and j represent the number of the training sample and the sample features respectively. w_{kj} is the feature weight of the input data, k represents the input number; u_k indicates the weight relation between the input item and its corresponding weight. b_k represents the threshold in the structure; $\varphi(v_k)$ represents the excitation function of model selection; p_k is the output of the neuron. The topology structure of the constructed neural network is shown in Figure 3.4.

For feedforward neural network networks, there are only two types of neurons, one is the output unit, and the other is the calculation unit. For computing units, they can accept multiple different inputs, but due to the lack of feedback information, they can only have one output. However, this unique output can be coupled to any other unit as input, so for all layers other than the input room, the input is only related to the previous layer. The input and output layers are connected to peripherals, and the other layers in the middle are all hidden layers. When learning and training a network model, continuous testing can determine the appropriate number of layers, the number of neurons on each layer, the excitation function, and the number of training times. This model can then obtain the corresponding weights and ratings of each input item. In this way, we can input the learning behavior data of students' courses through this model to predict the students' Final examination scores, so as to predict their learning effects according to their daily learning behavior. Based on the above mathematical model, the network flow chart is shown in Figure 3.5.

In Figure 3.5, the input data is based on students' daily learning behavior and learning situation, such as class attendance, homework completion, online learning time and in-class test, etc. The input data is recorded as A_i . The final grade, which can best reflect the learning effect of students, is taken as the output data of the prediction model and denoted as B_i. The setting of network depth and the number of neurons has a direct influence on the model performance. The selection of excitation function can adjust the input weight of the model. The setting of training times can ensure that the weight value is adjusted to the best value and avoid over fitting. Assuming the network depth is m , the calculated values of each layer are shown in Equation 3.7.

If the output value of the first layer is H_k^1, the input value of the second layer is h_k^2, namely $h_k^2 = H_k^1$. The output calculation of the second layer is shown in Equation 3.8.

$$H_k^2 = \varphi(w_{kj}^2 h_k^2 + b_k^2) \tag{3.8}$$

It can be inferred that the input value of the m layer of the neural structure is the output value of the previous

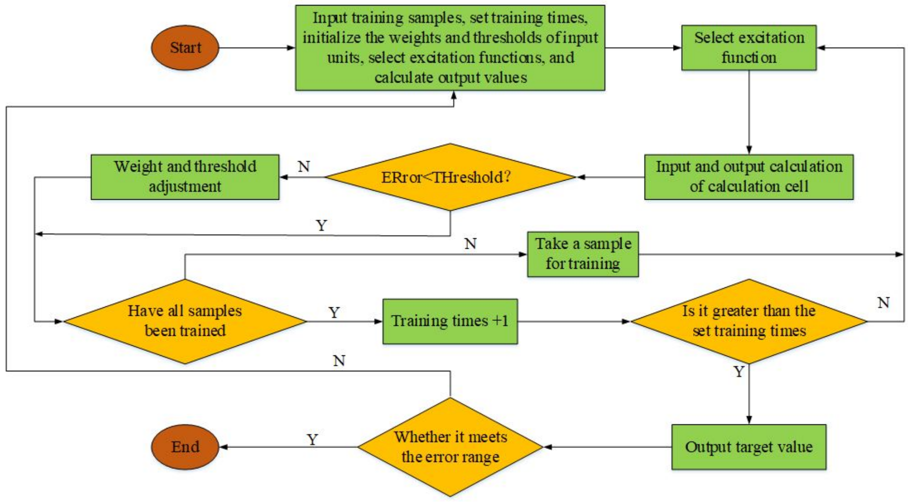


Fig. 3.5: The construction of neural network in student achievement prediction model

layer, namely $h_k^m 2 = H_k^m$, and the output expression of the m layer is shown in Equation 3.9.

$$H = \varphi\left(\sum_{j=1}^{N}(w_j^m h_j^m + b_j^m)\right) \tag{3.9}$$

During the training process, the prediction model can adjust the parameters of the network structure in real time to achieve the most appropriate value. Since the neural structure of the prediction model has only one output result and can accept multiple input information at the same time, the information is not the most useful feedback, so the model belongs to the feedforward neural network. As an important data in the teaching quality evaluation system, the smaller the error of the model in predicting students' performance, the better the system is. Now the excitation function is selected to optimize the constructed prediction model. Two kinds of functions are used as the excitation function of the model, in which the ReLu function is expressed as Equation 3.10.

$$Relu(x) = f(x) = \begin{cases} x & \text{if } x > 0 \\ 0 & \text{if } x \le 0 \end{cases} \tag{3.10}$$

As a unilateral inhibition function, the ReLu function is 0 when its independent variable is not greater than 0. When the independent variable is greater than 0, the function value does not change at all. Such unilateral inhibition function makes the neural structure have sparse activation property in the model, so that the network can better mine the data features and ensure the fitting effect of the data. Another excitation function is Sigmoid function, whose expression is shown in Equation 3.11.

$$Sigmoid(x) = f(x) = \frac{1}{1 + e^{-x}} \tag{3.11}$$

The range of the function can be any value, but the range is in the interval (0,1). The image generated by the excitation function is continuous, smooth and derivable. In addition, when the domain value of the function is 0.5, the function is in central symmetry. The Sigmoid function has two properties that can describe the uncertainty of the decision with a smaller granularity. In the range close to the threshold, the convergence speed can be improved and the training times of the model can be reduced. The training times of the model can be determined by superposition experiment. Therefore, the learning ability of the model can be reflected by Maximum Error (ME) and Cumulative Error (CE). The calculation of ME is shown in Equation 3.12.

$$ME = \begin{cases} \max(o_i' - o_i) \\ \min(o_i' - o_i) \end{cases} \tag{3.12}$$

The maximum errors of positive and negative values are respectively expressed in Equation 3.12. The calculation of CE is shown in Equation 3.13.

$$E = \begin{cases} \sum_{i=1}^{102}(o_i' - o_i) \\ \sum_{i=1}^{48}(o_i' - o_i) \end{cases} \tag{3.13}$$

Equation 3.13 respectively represents the cumulative errors of positive and negative values, and the corresponding average errors can be calculated through the cumulative errors. The error between the output value and the actual value is represented by . Predictability expressed by mean and variance. Then the average value is calculated as shown in Equation 3.14.

$$\text{Average error} = \begin{cases} \sum_{i=1}^{150} o_i^{'}/150 \\ \sum_{i=1}^{150} o_i/150 \end{cases} \tag{3.14}$$

Formula 3.14 respectively shows the average error of the actual value and the output value. By comparing the difference between the output and the actual situation, the effect of the prediction model can be judged. The variance calculation of the model is shown in Equation 3.15.

$$\text{Variance} = \begin{cases} \frac{\sum_{i=1}^{150}\left(o_i' - \left(\frac{\sum_{i=1}^{150} o_i'}{150}\right)\right)^2}{150}/150 \\ \frac{\sum_{i=1}^{150}\left(o_i - \left(\frac{\sum_{i=1}^{150} o_i}{150}\right)\right)^2}{150}/150 \end{cases} \tag{3.15}$$

The variance of the actual value and the output value is respectively expressed in Formula (15). If there is a small error between the variance of the output value and the variance of the actual value, it indicates that the prediction ability of the model is stronger. However, the variance of the actual value is less than the variance of the output value, which indicates that the training samples of the model are insufficient or the training times are too few.

4. Performance analysis of blended College English teaching Model and evaluation model based on MOOC.

4.1. Performance analysis of K-modes algorithm in Blended College English Teaching evaluation Model. After the construction of the overall model is completed, the performance of the model is analyzed, and then the advantages and disadvantages of MOOC-based blended college English teaching are judged. The datasets used in the experiment were all from the actual teaching evaluation information of A school. Through organizing the data from A school, 2000 pieces of data were obtained as the experimental dataset, with the training and testing sets verified in a 9:1 ratio. Through the analysis of teachers' teaching behavior data, the model can judge the accuracy of students' learning effect improvement and finally reflect the feasibility of the teaching method. The research first analyzes the teaching evaluation data, reflecting the distribution of teaching quality through proportion, and then judges the classification performance of the model through three indicators: classification accuracy, recall, and error. Finally, the experiment adds different teaching groups and different prediction models for comparative analysis to verify the progressiveness of the proposed model. The accuracy, recall, and error calculations are shown in Equation 4.1.

$$\begin{cases} \text{Precision} = \frac{TP+TN}{TP+TN+FP+FN} \\ \text{Recall} = \frac{TP}{TP+FN} \\ \text{SSE} = \sum(y_i - \bar{y})^2 \end{cases} \tag{4.1}$$

Table 4.1: Statistics of teaching evaluation data of students in Y University in a semester

Evaluation grade	Basic quality	Teaching attitude	Teaching ability	Extracurricular links	Total	Proportion
Excellent	335	328	54	7	724	0.2233
Good	293	296	377	78	1044	0.3200
Secondary	182	182	328	500	1192	0.3677
Pass	1	16	43	191	251	0.0774
Fail	0	1	2	28	31	0.0096

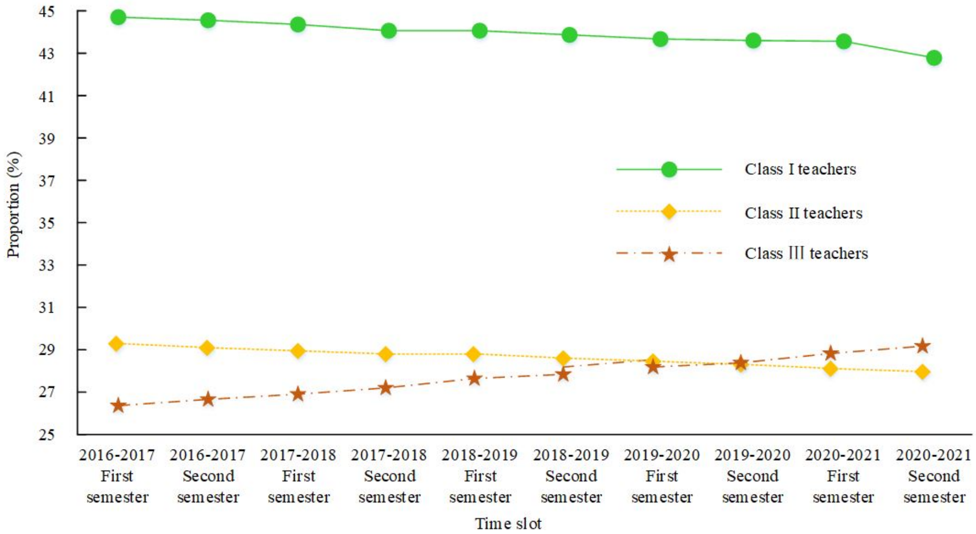
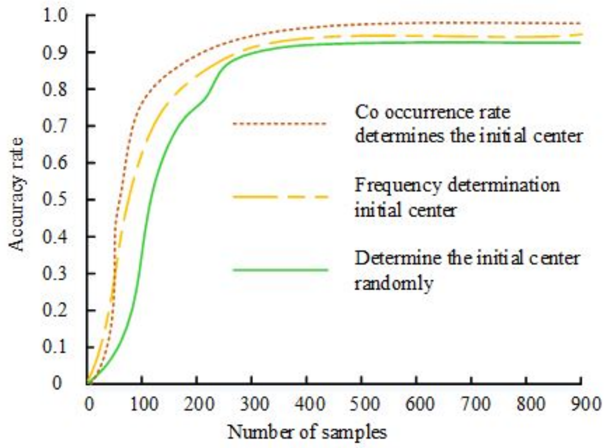


Fig. 4.1: Proportion of English teachers in different categories

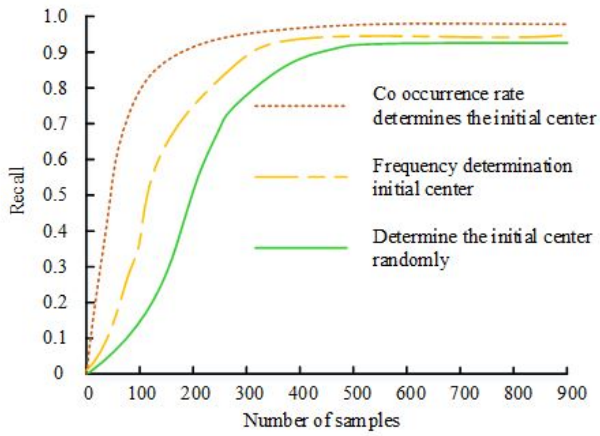
The study selected common teaching evaluation indicators in teaching quality evaluation through literature review, which are basic qualities, teaching attitude, teaching ability, and extracurricular activities [21]. At present, the data of teachers' teaching modes are collected and classified according to the indicators. The classified teachers are clustered by K-modes algorithm to analyze the existing problems in teaching. Finally, the performance of K-modes is compared.

In Table 4.1, teaching evaluation can be divided into four evaluation indicators. If three of the four evaluation indicators of teachers have good or above evaluation, they are regarded as first-class teachers, and the proportion of first-class English teachers is about 45%. If there is a medium evaluation, the teachers in this category are regarded as Class II teachers, and the proportion of Class II English teachers is about 28.5%. If the evaluation of the four indicators is below average, the teachers in this category are regarded as third-class teachers, and the third-class teachers account for about 26.5%.

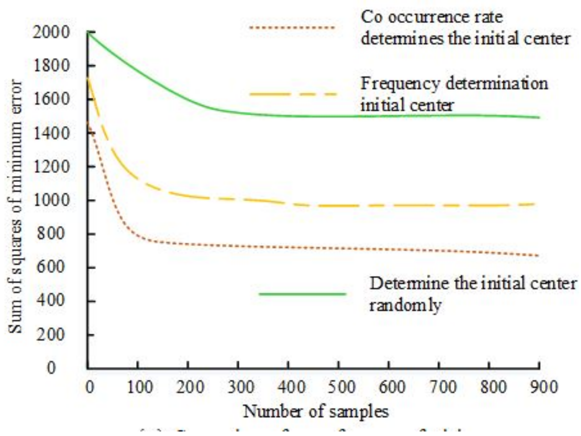
In recent years, the proportion of three types of English teachers in each semester through K-modes clustering algorithm is shown in Figure 4.1. Figure 4.1 and Table 4.1 are combined for analysis. Among the two evaluation indexes of teachers' basic quality and teaching attitude, about 76% are rated as excellent and good, and the remaining 24% are rated as medium, pass or fail. In the index of teachers' teaching ability, the number of teachers evaluated as excellent and good accounted for about 53%, and the total number of teachers evaluated as medium, pass and fail accounted for 47%. Among the indicators of teacher interaction, only about 10% are rated as excellent or good, 65% are rated as medium, and 25% are rated as pass or fail. Therefore, through the improved K-modes algorithm, shortcomings in blended teaching can be clearly found. Nearly half of the students feel inadequate about the teaching ability of MOOC teachers, and 90% of the students believe that MOOC teachers lack interactive links in teaching.



(a) Comparison of the accuracy of three algorithms



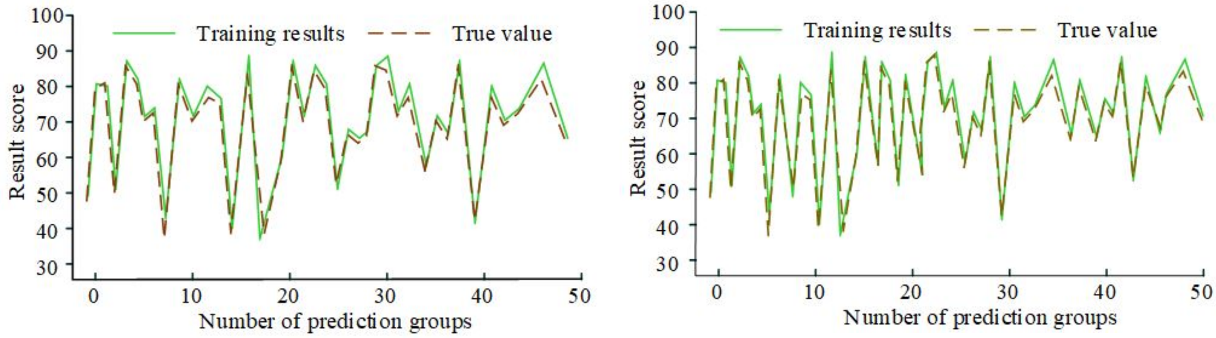
(b) Comparison of recall rate of three algorithms



(c) Comparison of sum of squares of minimum error of three algorithms

Fig. 4.2: Performance Results of Different Clustering Algorithms

In K-modes algorithm, three methods are used to test the initial clustering center. Figure 4.2 shows the comparison of the three methods. In Figure 4.2a, with the same number of samples, the clustering center was determined by the co-occurrence rate, and the classification exactitude of the model reached 0.985. The prediction accuracy of the model is 0.936 when the clustering center is determined randomly. In Figure 4.2b, the model of co-occurrence rate is adopted. When the number of samples is around 100, the maximum recall rate is reached, and the recall rate is 0.982. For the model whose clustering center is determined by frequency, its maximum recall rate is about 350 samples, and its recall rate is 0.925. The model of clustering center was determined by random method, and the maximum recall rate was reached only when the number of samples was 500. Its recall rate was 0.887. In Figure 4.2c, the minimum error sum of squares (MESS) of the improved K-modes algorithm is 725. The MESS is 1022 for the model whose clustering center is determined by frequency. The MESS is 1526 for the model that randomly determines the cluster center. Therefore, the improved K-modes algorithm adopted in this study has strong learning ability and good performance.



(a) Same Course and Same Teacher

(b) Different Teachers for Different Courses

Fig. 4.3: Prediction effect of the model on two groups of different data

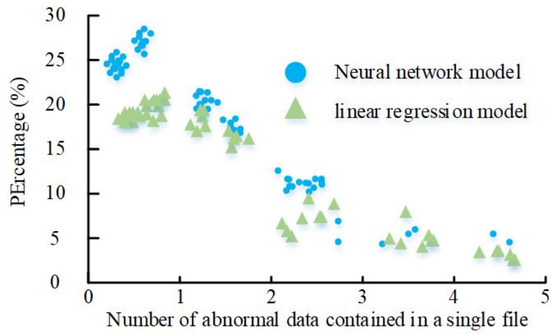


Fig. 4.4: Distribution of two groups of error prediction

4.2. Performance analysis of neural network in Blended College English teaching evaluation model. The improved K-modes algorithm has good data processing effect, which has been effectively verified in the experiment, and the predictive ability of the teaching evaluation model is analyzed. The effectiveness of the neural network model (NNM) was tested through two sets of different data, the performance of the NNM was reflected through the error distribution, and then the performance was compared with the linear regression model.

Two sets of data were used to analyze the performance of the NNM, and the specific results are shown in Figure 4.3. In Figure 4.3a, this set of data is tested under the condition of the same course and the same teacher, and the predicted result overlaps highly with the real value, indicating that the model has a high prediction accuracy. The maximum error and cumulative error can be calculated by combining Equation3.12 and Equation3.13, and the positive value of the maximum error is 6.04. The maximum negative error is -5.82; The cumulative positive error is 1.87; The cumulative negative error is -2.26. In Figure 4.3b, this set of data is tested without different courses and teachers, and its prediction effect is also highly overlapped with the real value. The maximum positive and negative errors obtained by the formula are 6.57 and -5.86. The cumulative error is 1.93 and -2.27.

The absolute error results of the two groups of data obtained by formula (14) are shown in Figure 4.4. In Figure 4.4, the absolute error of the two groups of data in the interval [0,2] accounts for the highest proportion, and the actual average of the first group is 72.15, the predicted average is 73.13, and its average error is 0.98. The actual mean of the second group was 73.06, the predicted mean was 73.77, and its mean error was 0.71.

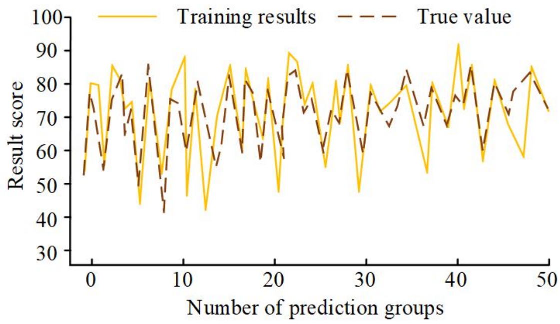


Fig. 4.5: Prediction results of linear regression model on data

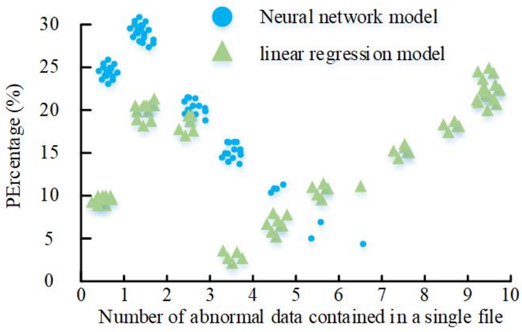


Fig. 4.6: Error distribution of linear regression model

There is a small difference in the calculated values of each index, and the prediction results of the model are more accurate under the teaching environment of different courses and different teachers. The results show that the prediction model has better prediction accuracy and stronger adaptability.

The traditional regression model is introduced to predict and analyze the learning effect of students, and the prediction effect is shown in Figure 4.5. In Figure 4.5, there is a large error between the predicted results of linear regression model and the real results, and the coincidence degree between the predicted linear and the real linear is low. Equation 3.12 and Equation 3.13 were also used to calculate the error values of the model, where the positive and negative error values were 22.46 and -13.19 respectively. The cumulative error is 6.84 and -3.54. Compared with the neural network prediction model, the prediction error of traditional linear regression model is larger.

The error distribution of the linear regression model is shown in Figure 4.6. In Figure 4.6, the linear regression model has a large error range, and the error value is relatively heavy in the interval [5,10]. The errors of the NNM are mainly distributed in the interval range of [0,3]. Therefore, neural network plays a huge role in the blended English teaching evaluation model based on MOOC classroom. The proposed evaluation model can accurately predict the learning effect of students. The experiment shows that the evaluation indexes selected by K-modes algorithm have an important influence on the teaching mode. Based on the above results, for teaching evaluation models, neural network models are usually able to more accurately predict students' learning outcomes and teaching quality. Compared to traditional linear regression models, neural network models can better capture nonlinear relationships and complex patterns, thereby improving the accuracy of prediction. Neural network models can perform end-to-end learning and representation learning on data, automatically extracting and learning features, thereby better reflecting the performance of evaluation models. By learning hidden patterns and association relationships in data, neural network models can comprehensively consider the complex relationships between multiple evaluation indicators, thereby improving the accuracy and robustness of the evaluation model. The neural network model also has strong generalization ability and can handle data with noise and incomplete information. For evaluation models in the field of education, neural network models can model and predict students' learning processes and outcomes, thereby more comprehensively evaluating teaching quality.

5. Conclusion. In the context of COVID-19, MOOCs have seen rapid growth. To explore the effect of the blended college English teaching model based on MOOC, this paper uses data mining technology and deep learning to build teaching evaluation model. The improved K-modes algorithm is used to analyze the teaching methods of MOOC teachers, and the main evaluation indexes of the mixed teaching mode are obtained. The evaluation model is verified by experiments. In the experiment, the correct rate of the improved K-modes model in the experiment is 0.985. The recall rate was 0.982; The minimum error sum of squares is 725, and its performance is significant due to other algorithm models. The maximum positive error of the prediction model constructed by the neural network is 6.04. The maximum negative error is -5.80; The average error of positive and negative values is 1.87 and -2.26 respectively, and the prediction accuracy is that the actual results have high coincidence. Compared with the traditional linear regression model, the neural network prediction model has higher prediction accuracy and can better reflect the performance of the evaluation model. This paper establishes a teaching evaluation model, extracts the evaluation indicators of the MOOC hybrid college English teaching model, and obtains the accurate evaluation effect through the prediction model.

In the context of the COVID-19 and the rapid growth of MOOC, the results of this study have important significance and development contributions. First, it can adapt to the epidemic situation and future education development. The COVID-19 has had a great impact on the traditional face-to-face teaching method. The research results of the MOOC based blended teaching model indicate that this model can provide a way for the education field to respond to the epidemic and future education development. By combining online learning and face-to-face teaching, this model can continue to provide high-quality college English education and meet students' personalized learning needs. The second is to improve teaching quality and student engagement. The blended teaching model can provide more teaching resources, interactive opportunities, and learning support through online platforms. This helps to improve teaching quality and student engagement. Compared to traditional linear regression models, research results indicate that teaching quality evaluation and prediction models can more accurately reflect students' learning outcomes and teaching outcomes, thereby further improving teaching quality. The third is to promote the future development of online education, and the research on MOOC blended teaching mode has provided beneficial contributions to the future development of online education. By combining online education platforms with traditional teaching methods, the blended teaching model can balance its advantages, provide students with a more flexible and diverse learning experience, and meet personalized learning needs. In addition, the research results also provide a basis for evaluating and predicting the quality of teaching in online education, helping to develop strategies and measures to improve and optimize online education.

However, there are still shortcomings in the research. The teaching evaluation indicators used in the model are relatively broad and prone to incorrect evaluation methods. Therefore, more detailed classification of evaluation indicators can be carried out, which can be refined from multiple perspectives such as students' learning outcomes, coverage of course content, student evaluation and participation. More specific and quantifiable evaluation indicators can be determined through in-depth understanding of relevant research, disciplinary characteristics, and educational practices. Subsequent research can also further optimize the structure of the prediction model, considering the use of Transfer learning technology, through pre trained models in other fields or tasks, we can extract more abundant feature representations, and further improve the performance of the prediction model.

REFERENCES

[1] Lebedeva, M. Instructional Design of Skill-Balanced LMOOC: a Case of the Russian Language MOOC for Beginners. *Journal OF Universal Computer Science.* **27**, 485-497 (2021)

[2] Okoye, K., Arrona-Palacios, A., Camacho-Zuiga, C., Jag, A., Escamilla, J. & Hosseini, S. Towards teaching analytics: a contextual model for analysis of students' evaluation of teaching through text mining and machine learning classification. *Education And Information Technologies.* **27**, 3891-3933 (2022)

[3] Sun, Q. Evaluation model of classroom teaching quality based on improved RVM algorithm and knowledge recommendation. *Journal Of Intelligent And Fuzzy Systems.* **40**, 2457-2467 (2021)

[4] Luo, Y., Zhao, X. & Qiu, Y. Evaluation model of art internal auxiliary teaching quality based on artificial intelligence under the influence of COVID-19. *Journal Of Intelligent And Fuzzy Systems.* **39**, 8713-8721 (2020)

[5] Duan, T. A new idea for the optimization of MOOC-based teaching. *Education And Information Technologies.* **27**, 3623-3650 (2022)

[6] Min, Y., Zhu, M., Bonk, C. & Tang, Y. The effects of openness, altruism and instructional self-efficacy on work engagement of MOOC instructors. *British Journal Of Educational Technology.* **51**, 743-760 (2020)

[7] Charo, R., Maite, A. & Guillermo, M. Self-regulation of learning and MOOC retention. *Computers In Human Behavior.* **6423**, 1-10642 (2020)

[8] Yan, R., Wang, L., Liu, L., Li, X. & Liu, H. A preliminary study on the mixed teaching of human parasitology based on MOOC resources and the experimental teaching digital platform. *Chinese Journal Of Schistosomiasis Control.* **33**, 74-78 (2021)

[9] Yu, Y., Li, F., Zhao, S. & Liu, H. Virtual experiment method for MOOC to solve teaching practice skills and difficult points. *Mechatronic Systems And Control (formerly Control And Intelligent Systems).* **47**, 77-82 (2019)

[10] Xie, H. & Mai, Q. College English cross-cultural teaching based on cloud computing MOOC platform and artificial intelligence. *Journal Of Intelligent And Fuzzy Systems.* **40**, 1-11 (2020)

[11] Caldwell, K., Hess, A., Kramer, J., Wise, P., Awad, M. & Klingensmith, M. Evaluating chief resident readiness for the teaching assistant role: The Teaching Evaluation assessment of the chief resident (TEACh-R) instrument. *American Journal Of Surgery.* **222**, 1112-1119 (2021)

[12] Kazi, M. Instructional leadership: teaching evaluation as a key element for 6th grade student's achievement in mathematics. *International Journal Of Educational Management.* **35**, 1191-1204 (2021)

[13] Tarraga-Minguez, R., Suarez-Guerrero, C. & Sanz-Cervera, P. Digital Teaching Competence Evaluation of Pre-Service Teachers in Spain: A Review Study. *IEEE Revista Iberoamericana De Tecnologias Del Aprendizaje: IEEE-RITA.* **16**, 70-76 (2021)

[14] Fawns, T., Aitken, G. & Jones, D. Ecological Teaching Evaluation vs the Datafication of Quality: Understanding Education with, and Around, Data. *Postdigital Science And Education.* **3**, 65-82 (2021)

[15] Yz, A., Hao, L., Ping, Q., A, K., B, J. & Znac, D. Heterogeneous teaching evaluation network based offline course recommendation with graph learning and tensor factorization - ScienceDirect. *Neurocomputing.* **415** pp. 84-95 (2020)

[16] Antoci, A., Brunetti, I., Sacco, P. & Sodini, M. Student evaluation of teaching, social influence dynamics, and teachers' choices: An evolutionary model. *Journal Of Evolutionary Economics.* **31**, 325-348 (2021)

[17] Suryanarayana, G., Lnc, P., Mahesh, P. & Bhaskar, T. Novel dynamic k-modes clustering of categorical and non categorical dataset with optimized genetic algorithm based feature selection. *Multimedia Tools And Applications.* **81**, 24399-24418 (2022)

[18] Yuan, F., Yang, Y. & Yuan, T. A dissimilarity measure for mixed nominal and ordinal attribute data in k-modes algorithm. *Applied Intelligence.* **50**, 1498-1509 (2020)

[19] Abdulkarim, S. & Engelbrecht, A. Time series forecasting with feedforward neural networks trained using particle swarm optimizers for dynamic environments. *Neural Computing And Applications.* **33**, 2667-2683 (2021)

[20] Chen, Z. & Cao, F. Construction of feedforward neural networks with simple architectures and approximation abilities. *Mathematical Methods In The Applied Sciences.* **44**, 1788-1795 (2021)

Edited by: Mudasir Mohd
Special issue on: Scalable Computing in Online and Blended Learning Environments: Challenges and Solutions
Received: May 18, 2023
Accepted: Oct 9, 2023