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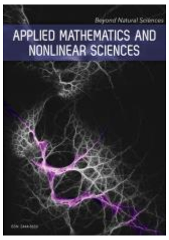

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Digital Technology Boosts the Construction of English Smart Classroom in Colleges and Universities

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Abstract

The application of digital technology in English smart classrooms in colleges and universities explores its impact on teaching effectiveness and students' academic performance. Based on digital technology, this study examines the construction of English smart classrooms in colleges and universities and its impact on teaching effectiveness. The study collects and analyzes 590,000 teaching behavior data, uses a clustering model to explore teachers' teaching behaviors, and constructs a set of algorithmic overlay methods for evaluating students' performance. Through the six-month competent classroom teaching practice, the experimental group showed significant improvement in thinking ability, learning effect and achievement. Specifically, the experimental group's mean values of verbal thinking, creativity, and critical thinking dimensions were higher than those of the control group by 0.663, 0.572, and 0.581, respectively, and the synergistic ability and problem solving ability were higher by 8.96% and 15.59%, respectively. In addition, the experimental group's learning attitude, process participation and knowledge mastery were significantly improved, and their academic performance improved by 5.941 points during the experiment. These data confirm the effectiveness of the intelligent classroom in improving learning effect and achievement.

Keywords: Digital technology; Smart classroom; Clustering model; Algorithm overlay; Teaching practice.
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1 Introduction

With the advent of the digital era, new media are commonly used in people's lives and learning, which are characterized by immediacy and convenience [1-3]. In English teaching in colleges and universities, making full use of new media with the help of digital technology can realize the effective dissemination of information. English teachers in colleges and universities should use digital technology to build an informatization education platform to assist classroom teaching effectively so that students' English knowledge learning methods are diversified. In actual classroom teaching, English teachers have a comprehensive understanding and mastery of English knowledge based on microblogging, WeChat, and other ways to carry out classroom teaching activities, create a good network teaching platform, and expand the educational space [4-6].

At the same time, the effective use of modern information technology in the cultivation of people in colleges and universities greatly improves the effectiveness of education in colleges and universities. The ecological construction of English classrooms in colleges and universities should also take advantage of modern information technology, do a good job in the design, of course, teaching content, fully around the effective use of modern information technology to achieve a high level of English course teaching in colleges and universities to meet the diversified needs of the ecological construction of English classroom in colleges and universities, to achieve the ecological construction of English classroom in colleges and universities of the multi-integrated and steadily advancing [7-9].

With the rapid development of the social economy, information technology is commonly used in various industries, and at the same time, it has had a great influence on the cause of college education. Under the background of digitalization, college education, and teaching and research personnel are constantly exploring and seeking new classroom teaching concepts and teaching techniques to realize the effective reform of classroom teaching, improve the quality of classroom teaching, and cultivate high-quality, professional, and comprehensive talents for society. Therefore, in the digital environment, English teachers in colleges and universities should innovate classroom teaching methods and realize the optimization reform of English classroom teaching mode [10]. Literature [11] studied the English teaching system and, summarized the defects of the network teaching system based on modern education theory and policy, and optimized the learning method and platform of the intelligent teaching system. Literature [12] constructed the English intelligent classroom teaching model based on the Internet of Things media communication technology and used a fuzzy hierarchical evaluation algorithm to assess the teaching effect of the model, pointing out that the student's satisfaction with the model is very high. Literature [13] explored the process of digital storytelling (DST) in the flipped classroom by prospective English education teachers (PEETs), which was found to be inspiring and challenging while entertaining at the same time. Literature [14] proposes a method for assessing the flipped classroom teaching model based on data mining techniques to deal with the problem of low levels of sharing due to too many teaching resources and the model's poor categorization ability. Literature [15] verified that students' participation in formal digital English language learning (IDLE) practices positively affects the perception of English as an International Language (EIL) based on structural equation modeling. Literature [16] examined how discussion groups in informal online language learning communities help members improve their English writing, pointing out that a shared distributed pedagogical presence in the forums and a social presence work together to support members' forum learning. Literature [17] conducted systematic research and analysis on the big data problem of MOOC based on data mining and designed to examine the flipped classroom of university English courses in MOOC and found that the teaching mode has a positive impact in promoting the improvement of teaching quality. Literature [18] evaluated the improved flipped classroom model and found that students' performance was significantly improved, and students showed recognition of the optimized flipped classroom teaching model. Literature [19] proposes a cloud classroom online teaching system under a personalized recommendation system, which can tap the potential preferences of users and carry out effective and personalized recommendations of teaching resources to meet the needs of smart teaching.

This study analyzes large-scale teaching behavior data and uses clustering models to optimize the analysis of teacher behavior. It then proposes an algorithmic overlay method for evaluating students' performance, which effectively combines traditional teaching behavior and digital technology. The experimental design includes a six-month smart classroom teaching practice, where students are divided into experimental and control groups in order to compare the differences in thinking ability, learning effect, and achievement between the two groups. The research methodology integrates data analysis, machine learning, and empirical research, aiming to comprehensively assess the effectiveness of digital technology in English teaching in colleges and universities.

2 English Smart Classroom Model Construction

2.1 Teacher Teaching Behavior Cluster Centric Clustering

Teacher-side, student-side, group-side, and the Internet are the main components of the starC teaching platform, which provides platform support for learners to carry out personalized inquiry learning modes such as self-directed, collaborative, and group cooperation. Relying on the teaching platform's data recording of teaching behaviors and visual feedback of classroom teaching display, it perfectly shows the sequence of teaching behaviors in the teaching session, fully expands the teaching atmosphere context, attracts learners to actively integrate, and improves the classroom teaching effect. This study obtains about 590,000 record data from four semesters of start teaching platform and writes a data preprocessing program to clean, integrate, encode, and normalize the record data to get the record data of 1,000 effective classroom teaching behaviors.

2.1.1 Sequential Feature Vector of Teacher Teaching Behavior

Teachers' application patterns are influenced by only a few teaching behaviors. The sequence feature vectorization approach essentially maps the sequence of instructional behaviors into the same low-dimensional vector space, i.e., each instructional behavior is represented as a low-dimensional, dense vector called a feature vector. Each component of the vector measures the degree of correlation between the instructional behavior and the influences or potential factors. This serial feature vectorized representation can be connected with machine learning models such as logistic regression, K-means clustering, and other refinements to further model teacher teaching behaviors. In this paper, when modeling teachers' teaching behaviors, we also adopt this method of sequence feature vectorization of teaching behaviors. First, for the n -dimensional teaching behavior sequence $B=\begin{cases}(b_1,t_1)\\(b_2,t_2)\\\cdots\\(b_n,t_n)\end{cases}$ of the first class, the feature vector extraction is performed by Eq. (1) to obtain the feature vector $X=\{d_1,d_2,\ldots,d_k\}$ of the first class:

$$d_k=T_k*i_k(k\geq 2) \tag{1}$$

Where k indicates the k nd teaching tool, t_k indicates the k th teaching tool operation length, calculated as the $k+1$ th teaching tool operation moment minus the k th teaching tool operation moment, in unit of s, i_k indicates the operation step between the k th teaching tool and the $k+1$ th teaching tool, calculated as the number of operation behaviors from the k th teaching tool to the $k+1$ th teaching tool, with a range of $i=1,2,\cdots,n$. For example. Teaching Tool a and Teaching Tool b have 3 manipulation behaviors in between, when the manipulation step is $i=4$, and when $k=1$, the distance is $d=i$.

Using a dataset consisting of feature vectors of the teaching behaviors of teachers in each classroom, these vectors not only contain the entire interaction trajectory of teachers' teaching but also retain the sequential nature of the sequence data of the interaction behaviors; the behaviors are somewhat sequential in timing, and the length of the sequences is not necessarily the same for each classroom, in which the data of the teaching behaviors of each classroom are extracted as a series of feature vectors, and the length of the sequences is also not necessarily the same The sequence length and the sequential nature of the time sequence affect the clustering results, so that the sequential and interactive nature of the original teaching behavior sequence data is preserved.

2.1.2 DTW cumulative distance matrix

After extracting the feature vectors of the teacher's teaching behavior sequence, we obtain the feature vectors of all the data classrooms $X_c=\{d_1,d_2,\ldots,d_k\}$. Let the lengths of the first and second samples be the feature vectors of n and m, respectively, $X_p=\{d_{p1},d_{p2},\ldots,d_{pn}\}$ and $X_q=\{d_{q1},d_{q2},\ldots,d_{qm}\}$. In order to understand how the points in the teaching behavior sequence feature vectors X_p and X_q correspond to each other in the DTW, we usually first construct a $n\times m$ distance matrix $D_{base}=\left(d_{base}\left(X_{Pi},X_{qj}\right)\right)_{n\times m}$. The distance between point d_{pi} in the Instructional Behavior Sequence Feature Vector X_p and point d_{qj} in the Instructional Behavior Sequence Feature Vector X_q is referred to as the base distance of the (i,j) th element in the distance matrix and is denoted as $d_{base}\left(X_{Pi},X_{qj}\right)$. The base distance used in the original DTW can then be expressed as:

$$d_{base}(x,y)=(x-y)^2 \tag{2}$$

Meanwhile, point d_{pi} in the teaching behavior sequence feature vector X_p and point d_{qj} in the teaching behavior sequence feature vector X_q represent the (i,j) th element in the distance matrix matching each other correspondingly. One of the correspondences between the two teaching behavior sequences obtained is actually matching a series of consecutive elemental points in the distance matrix such that the cumulative sum of the elements in the distance matrix it passes through is minimized, and an optimal bending path is found.

The dynamic time bending distance between the teaching behavior sequence feature vectors X_p and X_q is:

$$DTW\left(X_p, X_q\right) = \min_w \left[\sum_{k=1}^{k} d_{base}\left(w_k\right)\right] \tag{3}$$

Where $w_k = \left(i, j\right)$, $d_{base}\left(w_k\right) = d_{base}\left(X_{Pi}, X_{qj}\right)$.

It is usually found using dynamic programming as follows:

$$DTW(i,j) = d_{base}\left(X_{Pi}, X_{qj}\right) + \min\begin{cases} DTW(i, j-1) \\ DTW(i-1, j-1) \\ DTW(i-1, j) \end{cases} \tag{4}$$

Where $i \in \left(1, n\right]$, $j \in \left(1, m\right]$, and $DTW\left(1,1\right) = d_{base}\left(X_{P1}, X_{q1}\right)$. $DTW\left(i, j\right)$ denotes the current optimal bending distance, which is calculated $DTW\left(i, j\right)$ to obtain a $n \times m$ matrix that we call the DTW matrix is the dynamic time bending distance between these two teaching behavior sequence eigenvectors.

2.1.3 Cluster center group clustering

A cluster centroid group is a collection of several less-differentiated sample representations of objects in a similar instructional behavior data set such that the distance of the sample of represented objects from the sample of represented objects and is minimized. Formally, for all instructional behavior sequence datasets $D = \left[d_{ij}\right]$, the instructional behavior sequence dataset is partitioned into K subsets, $B = \left\{B_1, B_2, \ldots, B_k\right\}$, cluster centroid groups $C = \left[c_1, c_2, \ldots, c_k\right]$, such that $c_k = \operatorname{Re} p\left(B_k\right)$, where $B_i \in A, B_i \cap B_j = \varnothing$ and $\cup_{i=1}^{k} B_i = D$.

The cluster centroid group is a collection of characterization objects for the subset of teaching behavior sample data with small differences in similar teaching behavior datasets, which can better correspond to the data feature expressiveness of the actual interpretability of teaching and learning than the traditional unique characterization of teaching behavior data objects, and can greatly reduce the distance error between the characterization object and the characterized object, i.e.:

$$\sum_{k=1}^{K} \sum_{i=1}^{|B_k|} \left\| b_{ki} - C_k \right\|^2 \le \sum_{j=1}^{M} \left\| d_j - d_0 \right\|^2 \tag{5}$$

In order to select the cluster centroids of all the teaching behavior sequence datasets more accurately, this paper uses a method of centroids selection based on nearest neighbor propagation clustering (APCG). Its algorithmic process is as follows:

Near-neighbor propagation clustering (AP)-based cluster centroid clustering method for instructional behavioral sequence datasets $C = APCG\left(D\right)$.

Input all instructional behavior time-series behavior datasets $D = \left[d_{ij}\right]$, where d_{ij} represents one instructional behavior time-series behavior DTW cumulative distance.

Output, cluster centroid clusters $C=\left[c_1,c_2,\ldots,c_k\right]$, c_k denotes the k th centroid representation object sample data in the cluster.

1) The same cluster of instructional behavior dataset is divided into K instructional behavior data subcluster and the corresponding samples of objects characterizing instructional behavior data according to the algorithm of Approximate Neighbor Propagation (AP) clustering, i.e., $\left[B,C'\right]=AP(D)$, B, and C' denote the set of subclusters of the divided instructional behavior data and the set of samples of the objects characterizing instructional behaviors, respectively, i.e., $B=\left\{B_1,B_2,\ldots,B_k\right\}$, and $C'=\left[c_1',c_2',\ldots,c_k'\right]$, and c_k' denote the center of the k th subcluster of the samples of the objects characterizing data.
2) Using c_k' as the teaching behavior sequence as the starting center, calculate the central teaching behavior sequence corresponding to subcluster B_k, i.e., $C_k=DBA\left(B_k,c_k'\right)$, using the mean-centered teaching behavior sequence (DBA) algorithm.
3) Continue to repeat step (2) to calculate the mean-centered instructional behavior sequences for all the instructional behavior dataset subclusters B, and finally obtain the instructional behavior cluster center cluster $\mathrm{C}=\left[c_1,c_2,\ldots,c_k\right]$.

2.2 Algorithmic Overlays for Evaluating Student Achievement

2.2.1 Basic ideas

Setting the number of students in a course T as n, and the total number of classes in course T as i, then the set of grades for student x is $\alpha_x=\left(Score_1,\cdots,Score_i\right)$, and the corresponding set of grades for students with a k th class is $\beta_k=\left(Score_1,\cdots,Score_n\right)$, then there is a matrix of T classroom student scores:

$$T=\left[\alpha_1 \quad \cdots \quad \alpha_n\right]=\begin{bmatrix}\beta_1\\ \vdots\\ \beta_i\end{bmatrix}=\begin{bmatrix}Score_{11} & \cdots & Score_{1n}\\ \vdots & \ddots & \vdots\\ Score_{i1} & \cdots & Score_{in}\end{bmatrix} \tag{6}$$

$Score_{jk}$ denotes the j nd student's grade for the k rd class.

Setting the K th class to have y interactive behaviors, each of which calculates a rubric value, the rubric value of the p th interactive behavior is denoted as Rankp. Then the j th student's grade $Score\_jk$ for the k th class is:

$$Score_{jk}=\frac{\sum_{p=1}^{y} Rank_p}{y} \tag{7}$$

Each behavioral value has a range of possible values. If there is k interactive behavior per class, the highest sum of evaluated values for that class is defined as $\sum_{p=1}^{k}\max Score_p$. If there are a total of i classes in a semester, the highest sum of evaluated values for that course is defined as $\sum_{u=1}^{i}\left(\sum_{r=1}^{k}\max Score_r\right)_u$.

The final assessed grade for course T for the xth student is defined as:

$$FinalScore_x = \frac{\sum_{q=1}^{i} Score_{qx}}{\sum_{u=1}^{i}\left(\sum_{r=1}^{k}\max Score_r\right)u*100} = \frac{\sum_{q=1}^{i}\frac{\sum_{p=1}^{y} Rank_p}{y}}{\sum_{u=1}^{i}\left(\sum_{r=1}^{k}\max Score_r\right)u_u*100} \tag{8}$$

$\sum_{u=1}^{i}\left(\sum_{r=1}^{k}\max Score_r\right)_u$ Is the queer value of the total cumulative score for each class and $\sum_{u=1}^{i}\left(\sum_{r=1}^{k}\max Score_r\right)_u*100$ is taken according to the percentage scale. Where $FinalScore_x$ represents the final score belonging to the xth student, i.e., the percentage grade of the sum of the student's grades for each class in this course in relation to the maximum class score.

2.2.2 Calculation of Behavioral Appraisal Values

This paper gives the calculation method of four different types of behavior; similar behavior can refer to the division, if it does not belong to these four categories, can be added. These four types of behavior are Rank_sign sign-in type data, carried out a time. rank_scene in the class type data carried out b times and, Rank_interact interactive type data carried out c times, Rank_paper homework content type data carried out d times. Then:

$$\begin{aligned}\sum_{p=1}^{y} Rank_p &= \sum_{p1=1}^{a} Rank_s ign_{p1} + \sum_{p2=1}^{b} Rank_s cene_{p2} \\ &+ \sum_{p3=1}^{c} Rank_i nteract_{p3} + \sum_{p4=1}^{d} Rank^2 paper_{p4}\end{aligned} \tag{9}$$

Here are the total number of interactions $y = a+b+c+d$.

1) Rank_sign sign-in type calculation method.

The classroom interactive system supports six types of sign-in forms: quick, gesture, positioning, face sweep, Bluetooth, Bluetooth face sweep, then there is set $C=\{c_1,c_2,c_3,c_4,c_5,c_6\}=$ {quick, gesture, positioning, face sweep, Bluetooth, Bluetooth face sweep}, and the student chooses to use one form of sign-in each time. The final sign-in scores calculated based on the data of different sign-in types are different. A student's classroom check-in score is defined as the value of the score and accuracy of the check-in form they use:

$$Rank_{sign} = Ci, i \in (1,2,3,4,5,6) \tag{10}$$

2) $Rank\_interact_k$ is how the k nd interaction score is computed.

The start time attribute is set as the set of samples S, S there is a set of 14 samples where $>5s<10s$ appeared 9 times in the start time column as positive examples P_1 and 5 did not appear as negative examples P_2 then according to the standard entropy formula for the metric of information gain:

$$Entropy(S) = \sum_{i=1}^{c} -P_i \log 2^{P_i} \tag{11}$$

$Entropy([9+,5-]) = -(9/14)\log 2(9/14) - (5/14)\log 2(5/14) = 0.940$ The information gain Gain (S, A) is defined as:

$$Gain(S,A) = Entropy(S) - \sum_{v \in \{A\}} \frac{|S_v|}{|S|} Entropy(S_v) \tag{12}$$

S_v is the set of samples in S that have values equal to v on attribute A, e.g., $>5s<10s$ occurs 9 out of 14 times in the start time column then $\frac{|S_v|}{|S|} = \frac{9}{14}$. The final calculation of the information gain rate Gain (S, A) is defined as:

$$GainRatio = Gain(S,A) / Entropy(S) \tag{13}$$

For the research of the decision tree method in student performance prediction, as Liu Zhi-flattery has been described. The final score of the interaction is composed of weights and factor scale grades:

$$Rank\_interact_k = \sum GainRatio(k,A) * grade \tag{14}$$

3) Calculation of Rank_scene presence score.

The presence score refers to the percentage of students who are present in the classroom, which counts whether students leave the classroom early after signing in or do not pay attention to the class. The calculation method is defined below:

$$Rank\_scene = Rank\_sign * \frac{\sum_{r=1}^{k} Rank\_interact_r}{\sum_{r=1}^{k} maxScore_r} \tag{15}$$

$Rank\_sign$ is the result of the check-in type mentioned earlier, $Rank\_interact_r$ is the r rd interaction score, and $\sum_{r=1}^{k} \max Score_r$ is the total score for a total of k interactions, which is the threshold for accumulating the total score for each class.

2.2.3 Flow of Performance Evaluation Methodology for Algorithmic Overlays

1) Structure of the evaluation indicator table

The more important indicators, such as common indicators, including time, type, and mode, are singled out to analyze the indicator weights. Simplify the Table into columns as follows:

$$\begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{14} & X_{15} & X_{16} \\ X_{21} & X_{22} & X_{23} & X_{24} & X_{25} & X_{26} \\ & & & \vdots & & \\ & & & \vdots & & \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{m1} & X_{m2} & X_{m3} & X_{m4} & X_{m5} & X_{m6} \end{pmatrix} \tag{16}$$

2) C4.5 algorithm to compute attribute columns

The C4.5 algorithm is first used to construct the decision tree classification model.

The training data set is preprocessed, and if there are continuous attributes in the data set, they need to be discretized first.

It is assumed that the data are categorized according to each attribute of the data set respectively, and for each classification result, the corresponding information gain rate is calculated. The measure of information gain value is to see how much information the feature can bring to the classification system, and the more information it brings, the more important the feature is. The measure of information gain is called entropy:

$$Entropy(S)=\sum_{i=1}^{c}-P_i\log 2^{P_i} \tag{17}$$

According to the attribute corresponding to the maximum information gain rate, the current dataset is divided into different subsets, and the corresponding branches of the decision tree are built to form new child nodes. The information gain Gain (S, A) is defined as:

$$Gain(S,A)=Entropy(S)-\sum_{v\in\{A\}}\frac{|S|}{|S|}Entropy\left(S_v\right) \tag{18}$$

S_v is the set of samples in S that have a value equal to v on attribute A, e.g., >5 seconds <10 seconds occurs 9 out of 14 times in the start time column then $\frac{|S_v|}{|S|}=\frac{9}{14}$. The final calculation of the information gain rate $Gain\left(S,A\right)$ is defined as:

$$GainRatio=Gain\left(S,A\right)/Entropy\left(S\right) \tag{19}$$

Through the above steps, the set of weights $\mathrm{w}_1=\left\{\mathrm{C}\omega_{11} \quad \ldots \quad \mathrm{C}\omega_{1n}\right\}$ corresponding to $\varphi_1=\left\{X_{11} \quad \ldots \quad X_{1n}\right\}$ can be derived.

3) AHP algorithm for calculating sub-attributes

In hierarchical analysis, it is difficult to quantitatively analyze all factors due to the influence of multiple factors. The steps of the algorithm are firstly, the evaluation matrix needs to be created as M :

$$M = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ 1/a_{ij} & 1 & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \dots & 1 \end{bmatrix} \tag{20}$$

When evaluating indicator $b_i b_j$ in pairs, the values in the matrix are provided by the importance table, and then the relative advantages and disadvantages of each evaluation indicator are ranked according to the ratio of the 9th percentile, and the judgment matrix M of the evaluation indicators is constructed sequentially.

When the order of judgment matrix M is $n > 2$, the relative importance of the indicators is prone to inconsistency, such as a is 2 times more important than b, b is 3 times more important than c, and then say c is 2 times more important than a. The consistency test is performed on judgment matrix M :

$$I_C = \frac{\lambda_{\max} - n}{n-1}, R_C = \frac{I_C}{I_R} \tag{21}$$

Where $\lambda_{\max}$ indicates the maximum eigenvalue of the judgment matrix, I_C is the consistency index of the judgment matrix, I_R is the average random consistency index of the judgment matrix, and R_C is called the random consistency ratio of the judgment matrix. When $R_C < 0.1$, the consistency of the judgment matrix is considered acceptable, otherwise the judgment matrix should be appropriately amended. When the judgment matrix M passes the consistency test, the weight of each evaluation index is calculated:

$$Aw = \lambda_{\max} w \tag{22}$$

Where w is the eigenvector belonging to the eigenvalue $\lambda_{\max}$ of the judgment matrix M, which is the weight vector of the evaluation indexes sought. From the above description, it can be seen that constructing a suitable judgment matrix is the key to the hierarchical analysis method. In this paper, the set $\varphi_p = \left\{ X_{p1} \quad \cdots \quad X_{pn} \right\} p > 1$ of sub-attributes $X_{mn}(m > 1)$ of Table $a1$ is split into 6 evaluation matrices, and the corresponding weight set $w_2 = \left\{ \omega_{21} \quad \cdots \quad \omega_{m1} \right\}$ is obtained through the above AHP calculation steps.

4) Weight calculation method of Apriori-AHP-C4.5

To summarize the process of the above subsections.

First of all, create the performance evaluation index table and simplify the index table into a number column as follows:

$$\begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{14} & X_{15} & X_{16} \\ X_{21} & X_{22} & X_{23} & X_{24} & X_{25} & X_{26} \\ & & & \vdots & & \\ & & & \vdots & & \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{m1} & X_{m2} & X_{m3} & X_{m4} & X_{m5} & X_{m6} \end{pmatrix} \tag{23}$$

From the above equation, the set $\varphi_1 = \{X_{11} \ \ \dots \ \ X_{1n}\}$ is proposed to obtain the corresponding weight set $w_1 = \{C\omega_{11} \ \ \dots \ \ C\omega_{1n}\}$ according to (1), $\varphi_p = \{X_{p1} \ \ \dots \ \ X_{pn}\} \ p > 1$ is used as the data judgment reference set, $\delta_2 = \{X_{21} \ \ \dots \ \ X_{m1}\}$ is obtained according to (2) to obtain the corresponding weight set $w_2 = \{\omega_{21} \ \ \dots \ \ \omega_{m1}\}$, then there is a set $w_k = \{A\omega_{ki} \ \ \dots \ \ A\omega_{mi}\}$ of $\delta_k = \{X_{ki} \ \ \dots \ \ X_{mi}\}$, and the sub-attribute weights $\psi_{mn} = C\omega_{1m} + A\omega_{mn} / 2$, then there is a weight array:

$$\begin{pmatrix} \Psi_{21} & \Psi_{22} & \psi_{23} & \psi_{24} & \psi_{25} & \Psi_{26} \\ & & \vdots & & & \\ \psi_{m1} & \psi_{m2} & \psi_{m3} & \psi_{m4} & \psi_{m5} & \psi_{m6} \end{pmatrix} \tag{24}$$

Normalize the sum of the m-row supports:

$$Apriori_j = \sum_{i=1}^{k} \frac{Set_i}{Set_{\max}} \tag{25}$$

Where j denotes the set of attributes in row j, k denotes the number of included attributes, Set_i denotes the support of an attribute, and $Set_{\max}$ denotes the largest support in the list of attributes.

If the values in the interactive data value set $C_r = \{C_1 \ \ \dots \ \ C_6\}$ belong to the data judgment reference set φ_r then take the weight set $\Psi_r = \{\Psi_{r1} \dots \Psi_{r6}\} * Apriori_r$. Then the score of the q th interactive data under the evaluation criteria according to the judgment index table in Table $a1$ is $S_q = \sum_{i=1}^{6} \psi_{ri}$.

In summary, the following formula is obtained:

$$S = \sum_{i=1}^{m} \left(C\omega_{1m} + A\omega_{im}\right) / 2 * Apriori_i \tag{26}$$

3 Analysis of the Effect of English Smart Classroom in Colleges and Universities

In this chapter, we will set up an experimental group and a control group; the experimental group will carry out a six-month college English smart classroom teaching practice activities, the control group will continue to be taught in the traditional classroom teaching mode, and we will analyze the changes in the thinking ability, the learning effect and the academic performance of the experimental group compared with the control group after receiving college English classroom teaching.

3.1 Thinking skills

Thinking ability includes five dimensions: linguistic thinking, creativity, synergy, critical thinking, and problem-solving ability. After six months of college English smart classroom teaching, the experimental group and the control group are shown in Table 1. From the Table, it can be learned that after the experiment, the experimental group and the control group showed significant differences in the three dimensions of linguistic thinking, creativity, and critical thinking ($p<0.05$), and the dimension means of the experimental group were higher than those of the control group by 0.663, 0.572, and 0.581, respectively, whereas, in the case of synergistic ability and problem-solving ability, the dimension means of the experimental group and the control group showed highly significant differences ($p<0.01$), and the dimension means of the experimental group were higher than those of the control group by 0.581, 0.663, 0.572, and 0.581, respectively. 0.01), and the dimension means of the experimental group were 8.96% and 15.59% higher than those of the control group, respectively. Obviously, after the practice of English smart classroom teaching, the thinking ability of the experimental group was significantly improved compared with the control group.

Table 1. Dimensions of thinking ability

Dimension	Group	Mean value	Standard deviation	P
Language thinking	Experimental group	15.584	1.914	0.037*
	Control group	14.921	1.5	
Creativity	Experimental group	15.443	1.483	0.026*
	Control group	14.871	1.024	
Collaborative ability	Experimental group	15.275	1.505	0.002**
	Control group	14.019	1.123	
Critical thinking	Experimental group	15.048	1.258	0.048*
	Control group	14.467	15.818	
Problem solving ability	Experimental group	21.456	4.562	0.005**
	Control group	18.563	3.548	

("*" indicates significant difference i.e. $p<0.05$ and "**" indicates highly significant difference i.e. $p<0.01$)

3.2 Learning outcomes

3.2.1 Changes in learning outcomes

After a 6-month teaching experiment utilizing the smart classroom teaching mode and the traditional classroom teaching mode for the experimental class and the control class, respectively, the effects of different teaching modes on the learning effects of the subject students were measured in terms of four indicators, namely, learning attitudes, participation in the learning process, knowledge mastery, and learning quality. The specifics of learning effects are shown in Figure 1, with the experimental group on the left and the control group on the right on each index. According to the analyzed data in the figure, it can be seen that the experimental group and the control group show significant differences ($p<0.05$) in the three indicators of learning attitude, learning process participation, and learning quality, and highly significant differences ($p<0.01$) in the indicator of knowledge mastery. After six months of English smart classroom teaching practice, the experimental group students' learning attitude, learning process participation, knowledge mastery, and learning quality have been effectively improved, and the learning effect is good.

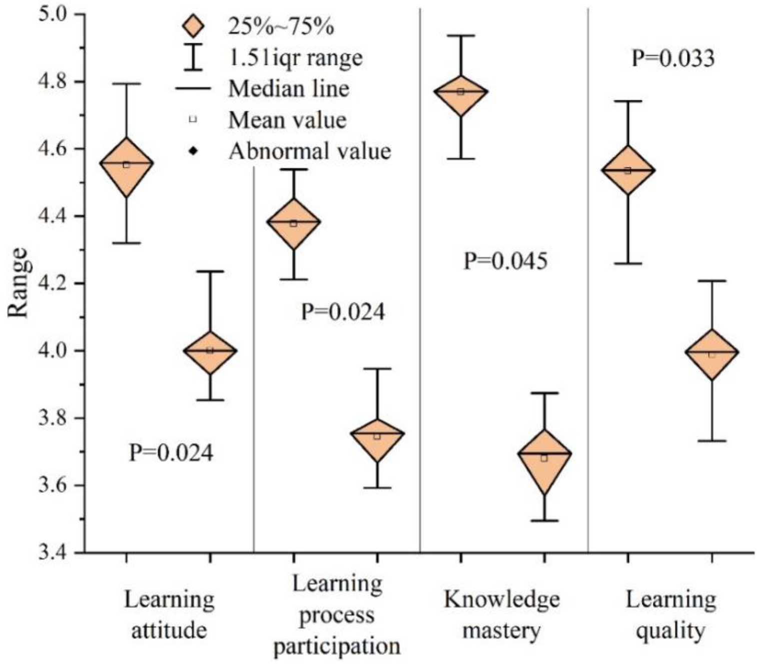

Figure 1. Changes in the learning effect of the experimental class and the control class

3.2.2 Analysis of the correlation between smart classroom and learning outcomes

The links in English smart classroom teaching include five links: scenario creation, task-driven, classroom monitoring, diversified evaluation, and personalized resource pushing. The correlation closeness between each link of the smart classroom teaching model and each dimension of students' learning effect is shown in Table 2.

The correlation test probabilities of learning attitude with classroom monitoring, diversified evaluation, and personalized resource pushing are 0.821, 0.256, and 0.542 in order, all of which are greater than 0.05, indicating that there is no significant relationship between classroom monitoring, diversified evaluation, and personalized resource pushing and learning attitude. The correlation test probabilities of learning attitude with context creation and task driving are 0.0017 and 0.0036, respectively, which are all less than 0.01, indicating that context creation and task driving are highly correlated with learning motivation.

The correlation test probabilities of learning process participation, context creation, and personalized resource pushing are 0.0489 and 0.0361, respectively, which are greater than 0.05, and there is a correlation, but the correlation level is relatively low. In the correlation test probability with task-driven, classroom monitoring, and diversified evaluation, they are all less than 0.01, with high correlation.

The correlation test probabilities of knowledge mastery with context creation, task-driven, and classroom monitoring are 0.621, 0.954, and 0.345 in that order, all of which are greater than 0.05 and do not have a significant relationship. In the correlation test probability with diversified evaluation and personalized resource pushing, it is 0.0076 and 0.0061, respectively, which are less than 0.01 and obviously have a significant relationship.

In the dimension of learning quality, the correlation with context creation, diversified evaluation, and personalized resource-pushing session thinking is more significant, with correlation test probabilities of 0.015, 0.048, and 0.026, respectively, which are all less than 0.05. In the correlation test probabilities with task-driven and classroom monitoring, the correlation is highly correlated with 0.0045 and 0.0063, respectively, which are all less than 0.01.

Table 2. The correlation between intelligent classroom and learning effect

-	-	Scenario creation	Task-driven	Classroom monitoring	Diversified evaluation	Personalized resource push
Learning attitude	Pearson correlation	0.426	0.447	0.012	0.032	0.062
	Significance(bilateral)	0.0017**	0.0036**	0.821	0.256	0.542
Learning process participation	Pearson correlation	0.326	0.482	0.714	0.613	0.326
	Significance(bilateral)	0.0489*	0.0086**	0.0012**	0.0052**	0.0361*
Knowledge mastery	Pearson correlation	0.226	0.071	0.284	0.495	0.703
	Significance(bilateral)	0.621	0.954	0.345	0.0076**	0.0061**
Learning quality	Pearson correlation	0.241	0.626	0.517	0.326	0.016
	Significance(bilateral)	0.015*	0.0045**	0.0063**	0.048*	0.026*

(**. Significantly correlated at the 0.01 level (two-sided), *. Significantly correlated at the 0.05 level (two-sided))

3.3 Academic performance

Before the implementation of the experiment, English knowledge level tests were conducted on the experimental group and the control group to detect the initial level of the two groups on the teaching content of the teaching experiment to be implemented as pre-experimental achievement data. The experimental process stage test and experimental result check test were also conducted at two different stages during and after the experiment. After the data collection was completed, the student's performance was statistically analyzed using SPSS25, and the results of the data analysis are shown in Table 3.

According to the learning achievement data before the experiment in the Table, it can be found that the difference between the mean value of the test scores of the experimental group and the control group is 1.095 points, and it is the result of the control group is slightly higher than that of the experimental group, which shows a non-significant difference ($p>0.05$), and the two groups have a comparable level of starting point of the knowledge of English so that they can carry out the teaching experiment. In the stage test in the experimental process, the difference between the average value of the test scores of the experimental group and the control group is 3.296, and the test scores of the experimental group exceeded those of the control group, showing a significant difference ($p<0.05$), and the effect of the teaching of the English smart classroom has been seen.

In the post-test test after the practice of English smart classroom teaching, the difference between the mean scores of the experimental group and the control group is 5.941 points, showing a highly significant difference ($p<0.01$). As for the standard deviation, the standard deviation of the experimental group is 6.501, which is lower than that of the control group, indicating that the degree of dispersion of the English test scores of the students in the experimental group is lower than that of the control class. Accordingly, we conclude that the English smart classroom teaching model can significantly improve students' academic performance, and there is less variability in performance among students.

Table 3. The correlation between intelligent classroom and learning effect

Time phasing	Group	Mean value	Standard deviation	P
Before experiment	Experimental group	74.526	8.991	0.386
	Control group	75.621	6.356	
In experiment	Experimental group	79.81	7.647	0.0452*
	Control group	76.514	8.017	
After experiment	Experimental group	84.751	6.501	0.0076**
	Control group	78.81	9.275	

(“*” indicates significant difference i.e. p<0.05 and “**” indicates highly significant difference i.e. p<0.01)

4 Conclusion

This study confirms the effective application of digital technology in English smart classrooms in colleges and universities through empirical analysis. The teacher behavior clustering model constructed by analyzing 590,000 teaching behavior data effectively optimizes the teaching process. The experimental results show that students in the experimental group showed significant improvement in the dimensions of thinking ability, especially in linguistic thinking (0.663 points of improvement), creativity (0.572 points of improvement), and critical thinking (0.581 points of improvement). Meanwhile, in terms of synergistic ability and problem-solving ability, students in the experimental group were 8.96% and 15.59% higher than those in the control group, respectively.

In terms of learning effect, the learning attitude, process participation, and knowledge mastery of students in the experimental group were significantly improved, especially the knowledge mastery showed a highly significant difference after the experiment ($p<0.01$). The correlation analysis between different aspects of the smart classroom teaching model and students’ learning outcomes further confirmed its effectiveness, especially the high correlation between context creation, task-driven learning, and learning motivation. Eventually, the learning achievement of the students in the experimental group gradually improved during the experiment, and the average achievement at the end of the experiment was 5.941 points higher than that of the control group, and the standard deviation of the achievement distribution was smaller, indicating that the achievement improvement also reduced the achievement difference.

These results show that the smart classroom not only improves the learning process but also significantly improves students’ learning effect and performance, which provides an important reference for the future development of English education in colleges and universities. This study provides strong evidence for the in-depth application and research of digital technology in the field of education, demonstrating its great potential in improving teaching quality and students’ learning outcomes.

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