Exploring the English Teaching Model Based on College Students' Participation in Natural Environment Integration

Dan Zhao, Xinxiang Vocational and Technical College, China

Ji Li, Jinzhou Medical University, China

Yanping Wang, Jinzhou Medical University, China*

ABSTRACT

In ELT, how to assess and evaluate students' natural factors by labeling and classifying them has become a key issue. Based on this, this paper makes an in-depth study on the application of natural environment incorporation algorithm based on deep learning in English teaching. First, this paper briefly explains the background and development direction of the current applications in ELT, and categorizes, summarizes, and analyzes them, focusing on the characteristics, problems, and issues of each study itself, and dissecting their limitations. Secondly, the environmental integration technologies in English teaching are categorized, and an intelligent and smart teaching assessment scheme is proposed, combined with the assessment of English teaching mode. Finally, the paper also conducts an experimental validation. The results of the study show that applying English assessment methods to learners of different English levels to their categorized English teaching can improve the quality of English teaching.

KEYWORDS

Deep Learning, English Language Teaching, Natural Environment Integration, Teaching Evaluation

INTRODUCTION

The reform of college English teaching has increasingly emphasized all-around development and lifelong education. In the context of China's "Internet Plus" plan, students' learning channels and resources are more diversified. College English teaching inside and outside the classroom is undergoing new changes. Multi-modal teaching, flipping the classroom, and creating a "golden class" and "ideological and political curriculum" all emphasize the importance of classroom construction. However, some educational imbalances remain, such as the physical distance between teachers and students, the imbalance between professional learning and language learning, the imbalance between in-class teaching and extracurricular learning, and the disparity between training objectives and teaching effects. In the current reality of reduced college English class hours, it is increasingly important to enhance the efficiency of classroom teaching. Classroom teaching

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*Corresponding Author

is the primary form of educational work and the key to improving teaching quality. Innovative classroom teaching entails creating classroom situations, effectively managing the core elements and significance of the classroom, and endowing classroom teaching with real significance and educational value. However, the current “listening, speaking and writing” method has become the “weakness” of the English classroom (Rai et al., 2021). This critical issue must be addressed to improve the quality of English teaching (Duan et al., 2021). However, although many English teaching models have emerged, most education systems are not tailored to the characteristics of each student and their specific situation, thus limiting their creative and hands-on development and preventing them from fully utilizing their potential to learn English (Yu et al., 2023). In this context, this paper proposes a new English teaching system based on a natural environment integration algorithm to encourage college students’ participation.

The paper consists of four parts. Part 1 briefly describes several types of deep learning algorithms widely used in current English language teaching (ELT) models and briefly introduces recent developments in the field. Part 2 briefly discusses the similarities and differences between English language education at home and abroad, pointing out that the contextualization approach can be applied to the English classroom but cannot be replicated precisely. Part 3 proposes a new integrated learning approach through an in-depth analysis of English and combines natural integration techniques and multiple educational elements to form a new learning system. Part 4 uses an experimental study to practice and evaluate the constructed English classroom and teaching system. The paper’s contribution involves using an environment-based integration algorithm to analyze the relevant characteristics of the selected major teaching factors combined with the natural environment fusion technique to summarize the characteristics of different environmental factors and reclassify them using the attention mechanism to eliminate interference and obtain more helpful information. On this basis, the characteristics of various ELT factors in conjunction with relevant environmental theories are summarized into corresponding algorithms, improving classroom teaching and allowing students to grasp the key points more effectively.

Literature Review

Compared with the traditional approach to English education in China, new English education methods proposed by foreign researchers have better educational effects (Shen et al., 2021). Based on the basic motor characteristics of college students’ brains, scholars Agarwal and Alam (2020) divided the English language learning process into several basic brain movements, which should be repeated continuously for rapid proficiency (Agarwal & Alam, 2020). Lobo et al also argued that current ELT methods do not bring out learners’ full potential and are not conducive to accurately grasping the basic requirements of learning English, which defeats the purpose of teaching English (Lobo et al., 2021). A step-by-step approach can be used to gradually improve students’ English learning habits according to their exercise habits, thus improving their English language proficiency and learning efficiency. Kloos et al. (2020) have argued that in terms of English knowledge, students’ learning autonomy and concentration can be stimulated by adjusting the class’s teaching atmosphere. Liu et al. (2021) improved the learning methods for Chinese and Korean students by borrowing from the past and introducing a bionic teaching apparatus that uses simulated native voices to make students aware of English pronunciation problems, thus improving their English literacy. Onan et al. (2020) used a collector to capture information on the teacher’s EEG activity in the English classroom and a modified collection device to gather information on students’ brain activity during English teaching and learning. They used deep learning methods to build a corresponding transmission and reception model. Kim et al.’s (2021) experimental results showed that smart classrooms based on deep learning are more conducive to students grasping new information, expanding their thinking about English, breaking the barriers of traditional English thinking, and facilitating learning than traditional English smart classrooms. Malinee et al. (2020) compared teaching methods using deep learning assistance and traditional teaching methods and found that an outcomes-based education model contributes significantly to students' learning, proving that environmental factors affect students' development in English. Ying et al. (2022) developed a miniature EEG signal analyzer, which uses a novel machine learning algorithm to instruct students on the speed and rhythm of their English speaking in real time, considering their physical characteristics and environmental factors. Fansury et al. (2020) used chaotic neural networks to simulate the physiological conditions of various stages of learning English, such as heart rate and muscle tension, to develop a corresponding teaching plan for each individual. Through empirical studies of English education at home and abroad, Hu (2020) has argued that compared with foreign teaching models, English education in China is relatively rigid and cannot adapt to rapidly developing trends. However, incorporating contemporary big data technologies may change the current status quo. Guo et al. (2021) proposed a new hyper-chaotic mapping-based English learning smart classroom approach, which addresses the interrelationships between English classes and learners' preferences.

According to the findings, few in-depth discussions on integrating the natural environment into English teaching algorithms are available, and it is rare to introduce environmental factors into English teaching models (Zhu et al., 2020). On the other hand, differences exist in the intrinsic relevance of various aspects of intelligent classroom design (Su et al., 2021). Therefore, studies also differ significantly in terms of artificial intelligence, and few consider the use of deep learning in natural environment integration algorithms (Wang et al., 2021). In this context, exploring English teaching models based on the participation of university students and the integration of the natural environment is critical (Jin & Yang, 2021).

METHODS

Fundamental Ideas of Natural Environment Integration Algorithm in ELT Intelligent Classroom Design Model

Natural fusion is a improved and new approach based on deep learning (Masten et al., 2021). This algorithm aims to perform data mining and processing based on the relevance of various information to ensure high intrinsic relevance and the ability to categorize information based on uncertain information categories. Compared with traditional machine learning algorithms, the algorithm proposed in this paper can solve the problems of nonlinearity, small samples, and overfitting (Xu et al., 2020). Its primary approach involves downscaling multidimensional external environmental information and collecting data on the impact of environmental factors on teaching quality, thus effectively reducing the number of operations and improving the effectiveness of data use and analysis (Butko, 2020). Also, the natural environment incorporation algorithm is a common data mining and information training algorithm (Niu, 2021). To develop ELT smart classrooms, it is necessary to extract environmental factors, data mining, and dimensionality reduction operations using this algorithm, transform the data from the ELT environment into binary data, and perform data computation and analysis. This method can increase the classroom interaction rate, improve teaching efficiency, make it easier to grasp students' learning status based on the data, and quickly adjust the teaching approach (Deng & Yu, 2014). In practice, programmers usually organize and store various ELT data using the vector space model and then bring environmental factors into the ELT data model. The feedback is used to improve the ELT model continuously. In addition, the natural environment fusion algorithm combines virtual reality technology with the real environment. In English teaching, this algorithm can provide a more authentic, vivid, and exciting learning experience by simulating real-life scenes. It can provide more intelligent learning support through speech recognition technology and machine translation technology. For example, students can use speech recognition technology to detect their pronunciation and intonation in real time to correct pronunciation errors. Machine translation technology can help students better understand new words, difficulties, and language expressions in English, thus improving their English reading and language comprehension abilities.

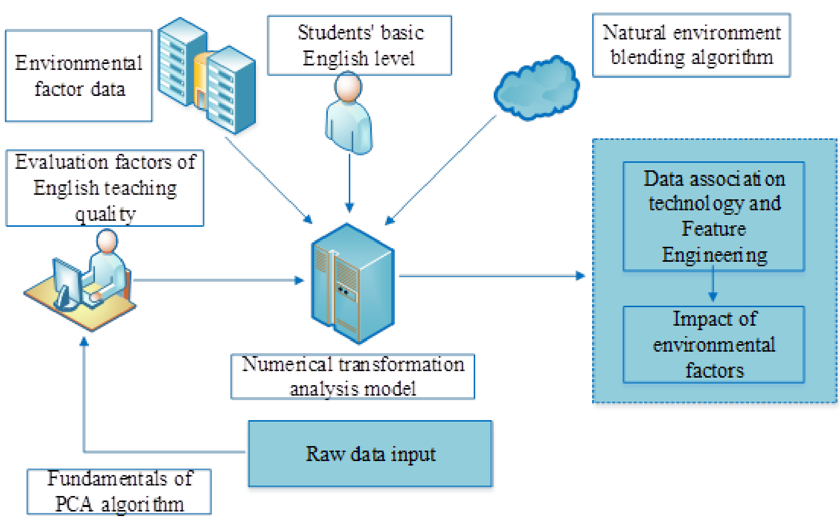
This paper introduces and evaluates an ELT natural integration algorithm. The principal component analysis (PCA)-based natural environment integration algorithm requires establishing an environmental learning assessment network. Establishing the network is a complex learning process. When a slight change occurs in the structure of the network in the previous stage, the error it causes in the environmental teaching effect will enter into the subsequent comprehensive analysis of the environmental factors performed, thus causing a significant error in the irrelevant data within the model. In this paper, when the PCA algorithm is operated and the allocation and order of the input data changes, it significantly impacts the system's performance, especially the dimensionality of the data. In addition, if the training data is constantly changed during the learning period, it negatively affects the learning efficiency of the network. The ELT assessment system built with natural fusion technology can be constantly updated according to the continuous upgrading of the PCA network. Each training and randomly generated small sample of the network has been tested repeatedly by PCA, and each training has been tested repeatedly. Based on this, this study can evaluate English teaching quality by continuously updating the environmental factors affecting teaching quality.

The Process of Building an ELT Classroom Design and Quality Evaluation Model Based on the Natural Environment Fusion Algorithm

This paper presents a scientific analysis of the role of various natural factors in English language learning by introducing "control factors." These factors include multiple teaching styles to provide different learners with teaching methods and textbooks suited to their personal characteristics and learning styles. By introducing these control factors, this paper more scientifically evaluates the role of natural factors in English learning. The study used a questionnaire to assess the effectiveness of ELT and learning using the contextualized algorithm.

The construction of the algorithm includes the following aspects. In the first step, relevant systems extract data based on students' current English learning situation in various subjects and classes (with English teaching performance as the primary concern). These data are converted into binary numbers through computerized language processing. Then, students' environmental factors are extracted at different levels; these environmental factors are associated with students' brain waves after the analysis. The model construction process is shown in Figure 1.

Figure 1. Data analysis and teaching model establishment process of natural environment integration algorithm



The second step involves data acquisition, using the existing students' learning results and entering the relevant data into the learning system to create an initial data warehouse, which is then entered into the computer for learning and analysis. The learning algorithm introduces additional knowledge, or knowledge of permissions, during the training process. After entering the data, the database is computed in multiple iterations using natural fusion methods and multidimensional operation rules. After the computation, the data is recovered and categorized according to the computer database and the preset, pre-determined decision procedure. A multivariate factor analysis is performed using various data group information to complete the reprocessing and recurring cycle of the first and second data information. The data analysis process is shown in Figure 2.

In the third step, the data correction and error operations are performed on the existing database, the change of the data volume fitness dimension is performed on the corrected database, and the data recording is performed by vector unification so that the variable data in the database are stored as vectors and iterative values. The algorithm uses a criterion based on the space and angle of multiple data sets, which is used to determine the degree of similarity of multiple data sets. In the solution of temporal delay, the temporal sequence can be divided into multiple segments, and the similarity comparison method is used to determine the lag between moments. The research results show a significant correlation between the theoretical foundation of English education and the practical ability of English education, and its judgment simulation process is shown in Figure 3.

It can be seen from Figure 3 that due to the differences in the essential characteristics of data, their corresponding judgment factor indexes have changed significantly. The relationship between data groups has a similar trend due to the differences between data groups. In the correlation analysis, the trend of the correlation judgment index obtained from their data is basically the same, regardless of the space or time series, and their judgment criteria have not changed. The similarity measure between different data groups in this process $q(x)$ is:

$$q(x) = \sum_{k=0}^{p} (x_{ij} + \bar{x}_i)^{i+p} \left(\frac{x_{jk} - \sqrt{\bar{x}_j}}{2j * 4(k-i)} \right) \tag{1}$$

The formula for determining the correlation between data groups $r(x)$ and the formula for determining the coupling $t(x)$ are:

Figure 2. Data analysis process of the natural environment fusion algorithm

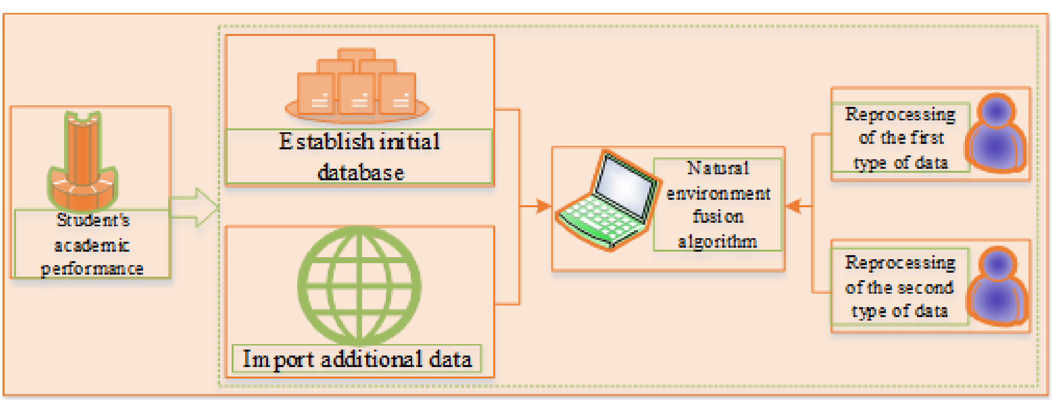
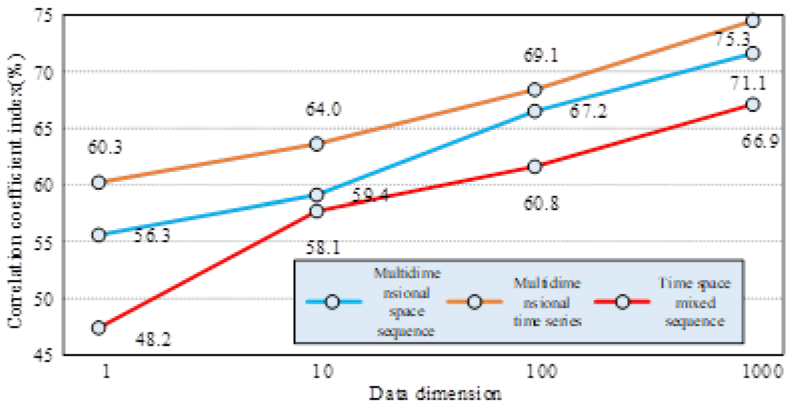


Figure 3. Judgment simulation process of different data groups



$$r(x) = \sum_{k=1}^{n} \left((ik - j) * \sqrt{\frac{x_{ij}}{jk - i}} + (jk - i) * \int \frac{x_{kj}}{ik - j} \right) \quad (2)$$

$$t(x) = c(x) * \left(2x_{ij} + 8x_{ki} \right) * \frac{x_{ki}}{k + i} \quad (3)$$

The error degree coefficients between data sets $R(x)$ and correction factors $P(x)$ are:

$$R(x) = \frac{(q(x) - c(x))^2}{c^2(x) * t(x) + 2\sqrt{c(x)} + 1} \quad (4)$$

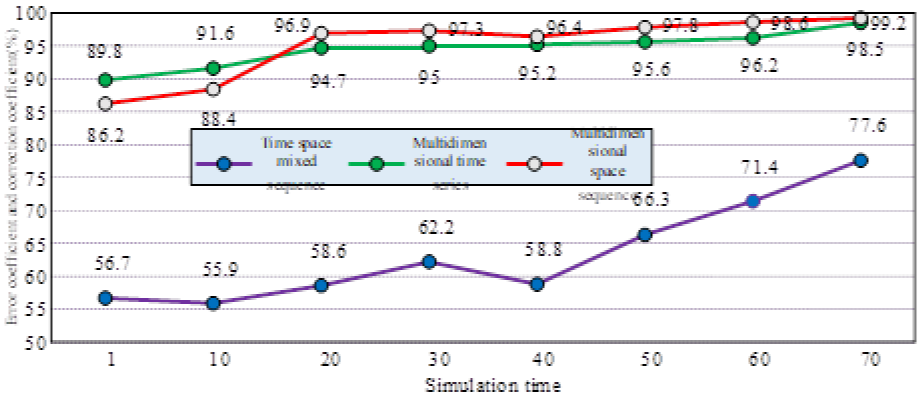
$$M(x) = \frac{c(x) * R(x)}{9t(x) - 3t(x)^2 + c(x_0)} \quad (5)$$

The results of the simulation analysis of the corresponding data set at this point are shown in Figure 4.

The simulation results in Figure 4 show that each array's error and correction factor show variability in the simulation, but there is a generally similar trend. Compared with the other two types of information, the error and correction factors of the spatiotemporal mixing sequence are much smaller. This is due to differences in the internal correlation and confidence of information. Therefore, it will not produce excessive similarity. The sum of squares $e^2(x)$ and the coefficient of squared differences $s^2(x)$ are:

$$e^2(x) = \frac{1}{n} \sum_{k=1}^{n} \left[\frac{p(x) * c(x) - t(x) * p(x)}{k^2 + c(x)} \right]^2 \quad (6)$$

Figure 4. Simulation analysis results of the data set in terms of error and correction coefficient



$$s^2(x) = \frac{1}{n}\sum_{k=1}^{n}\left[\frac{t(x) * c(x) - p(x)c(\bar{x})}{\sqrt{p(x)} * r(x)}\right]^2 \tag{7}$$

The average coefficients k under the level cycle $k(x)$ and the values of the operations between different clusters $h(x)$ are:

$$k\left(x\right) = \frac{1}{n}\sum_{k=1}^{n}\frac{\int [c(x)^2 + p\left(x\right)]dx}{n * (n-1)} \tag{8}$$

$$h\left(x\right) = \frac{1}{n}\sum_{k=1}^{n}\frac{r(x) - x * p^2(x) + c^2\left(x\right)}{k * n} \tag{9}$$

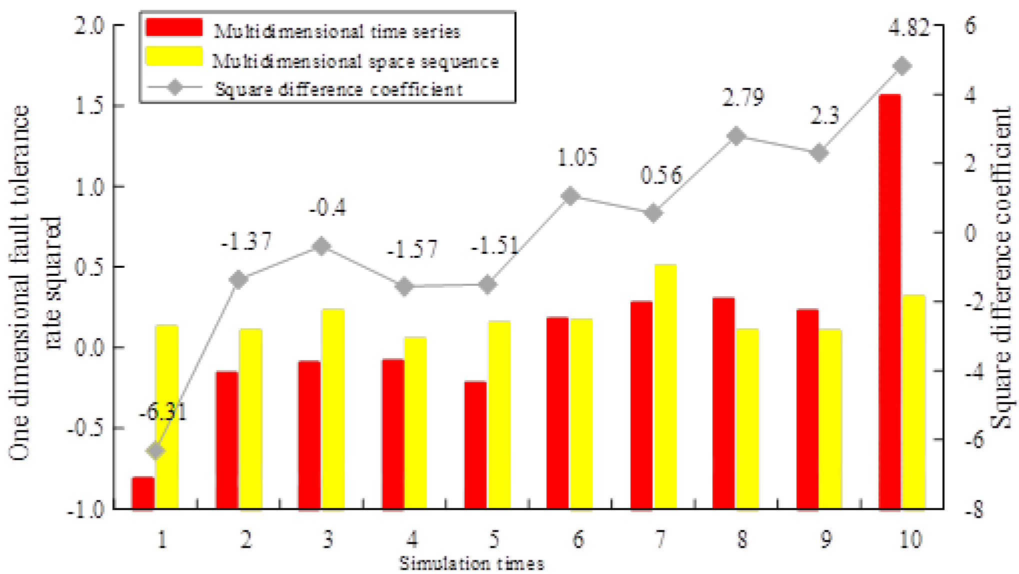
where $s^2(x)$ is the weighted sum of squared differences, x is the individual component of the data set, x_{kj} and x_{ki} are the vectors to be detected within the clusters, $k(x)$ is the value of the operations between the different clusters, and $h(x)$ is the value of the processing within each cluster. The results of the simulation analysis of the corresponding data set are shown in Figure 5.

Figure 5 shows that with the increased number of simulations, the error of the sum of squares of space and time series is basically unchanged. However, during the first and tenth simulations, the time series changed suddenly due to an excessive time series error. However, the square difference coefficients corresponding to the two sets of sequences subsequently increased. This is because the higher the number of simulations, the greater the correlation between more dimensions and the higher the resolution of the results.

An Intelligent Classroom Evaluation Model and Improvement Strategy for ELT Based on the Natural Environment Integration Algorithm

In evaluating and exploring the quality of teaching in intelligent English classrooms, this paper adopts a process and outcome-based approach as well as a qualitative approach to achieve a scientific and authentic outcome. The correlations between the scores for ELT theory classes and the English teaching types were classified and compared according to each grade and subject, and on this basis,

Figure 5. Variation curve of square difference coefficient of different types of sequences with simulation times



the two methods were combined. The corresponding perturbation adaptive degree function $W(x)$ and ranking function $Y(x)$ for this process are:

$$W(x) = \frac{e^2(x) * s^2(x) + t(x) * c(x) - 5h\left(x\right)}{\sum_{k=1}^{p}[r(k) + c(k)]} \tag{10}$$

$$Y(x) = \frac{(5s^2(x) - 2W(x) + e^2(x))^3}{\sqrt{r(x) + t(x) + c(x)}} \tag{11}$$

where x is a single constituent unit of the data set. The perturbation adaptivity function $R(x)$ and the ordering function $Y(x)$ satisfy the following relationship:

$$W^2(x) + Y^2(x) = \frac{c(x) * r(x) + W(x) \,/\, Y(x)}{\sqrt{t(x) - W(x)}} \tag{12}$$

To avoid misjudgments when solving and transforming vectors between multiple clusters, it is necessary to ensure the average connection between clusters and the average connection in clusters with the average connection function $w(x)$ as:

$$w(x) = \frac{2W^3(x) - 5Y^2(x)}{R(x) + W(x)} \tag{13}$$

Here, formula 13 is a single data set. After redetermining the fusion of each natural element with the sample point centers of the training phase of the algorithm, the similarity between the clusters is determined by comparing the minimum spacing between the types, thus constituting a logical cluster with a cluster group correction function $L(x)$ and a distance correction function $F(x)$ as:

$$L(x) = [c(x) + t(x)] * \frac{W(x) - Y(x)}{W(x) + Y(x)} \tag{14}$$

$$F(x) = \frac{9_x^5 - H(x) * x + R(x)}{H(x) + W(x) - 5x^2} \tag{15}$$

where x is a single component of the data set.

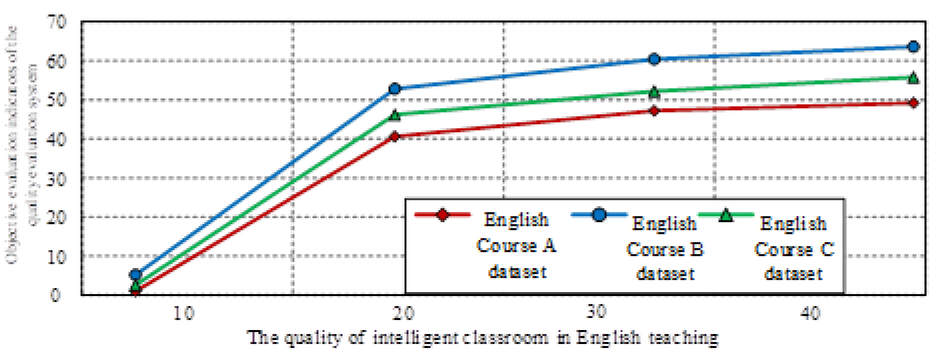
RESULTS AND DISCUSSION

Experimental Design Process for an Innovative Design Model for ELT Classroom Based on Natural Environment Integration Algorithm

This paper explores the relationship between teaching differences in different classes and students' learning effectiveness in ELT by addressing the issues related to curriculum and testing for an English major at a university. Based on this, an improved contextual integration method is introduced into the experiment first to establish a multinomial coupled threshold analysis model to analyze the teaching effectiveness of the teaching model constructed using the contextual integration algorithm and then compare the various covariates and transform the information into a multidimensional classroom model to ensure a high degree of similarity and pairing of data information among the clusters in the experiment. Figure 6 shows the preliminary results of the objective assessment criteria for the ELT intelligent classroom quality assessment system during the experiment.

As seen in Figure 6, the ELT Smart Classroom Assessment System has led to a gradual decrease in errors in the holistic approach due to increased student interpretation and practice of exercises. This is due to its ability to analyze and quantitatively describe various pieces of English knowledge at multiple levels from multiple perspectives, to compare correlations with each later external environmental factor, and then to compare and analyze errors with existing reference thresholds; then, based on the perspective and spacing of the data generated in the English course and comparison with the values set at the time of the experiment, the data represented by the model were derived from the similarity

Figure 6. Analysis and evaluation of teaching quality of English teaching model



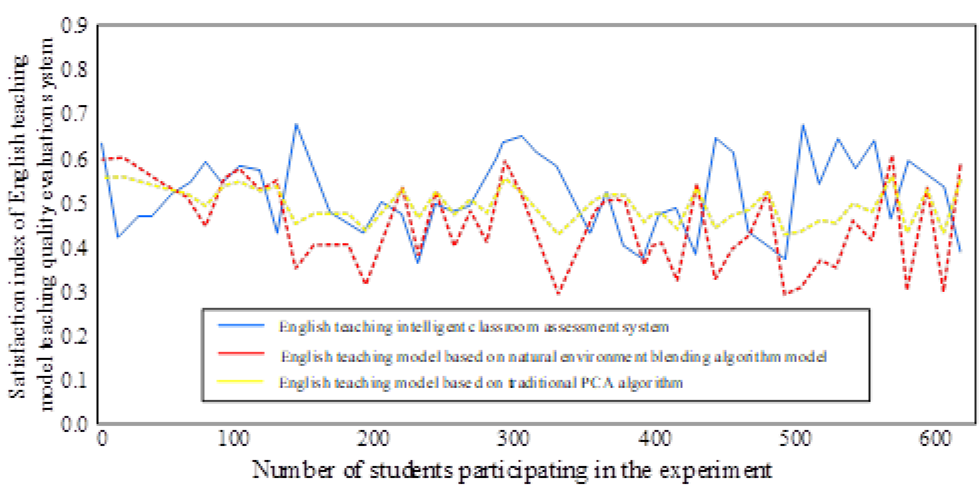
of the reference data, and thus the similarity of the model. At the same time, the sampling points for each cluster were redetermined to make it possible to efficiently provide the source of data needed for the evaluation of intellectual classrooms in college English education.

Experimental Results and Analysis of the ELT Model Teaching Quality Assessment System

To further dissect the effectiveness of teaching English courses in depth and reduce the error rate, it is necessary to compare the teaching of English with traditional teaching. This study used an experimental comparison method (based on an intelligent teaching group and a traditional teaching group) to evaluate the intelligent teaching of English to university students using an offline one-to-one random survey method. The survey adopted stratified sampling and random sampling methods. A total of 600 questionnaires were distributed, and 576 were recovered, of which 504 were valid, with recovery rates of 96% and 84%, respectively. The sample was representative. The questionnaire was designed mainly regarding interest, time, and effectiveness. The questionnaire included 15 items, such as English thinking, English logical thinking, English reasoning and judgment, class participation, homework completion, and average class grade. The satisfaction results for different numbers of students from the quality assessment system for the English teaching model are shown in Figure 7.

As seen in Figure 7, the experiment found that the overall quality of instruction in the English classroom for students who participated in the experiment improved significantly compared to the English classroom constructed using the traditional PCA algorithm. The overall experimental results showed that 95.1% of the students, of which 30.0% were female and 65.1% were male, were satisfied with the English classroom teaching. In the usual English tests, 92.5% of the students, of which 62% were male and 30.5% were female, improved their scores significantly. The results showed that the students' independent learning ability and English learning performance improved significantly. Regarding specific ELT module knowledge, such as English exercises, comprehension of English principles, and English teaching interaction, 93.1% of the students had a clear understanding. Regarding online classroom participation, 96.5% of the students actively answered the teacher's questions. When asked whether the new ELT model based on the natural environment integration algorithm was effective, 93.2% of the surveyed students approved of the teaching quality of the model. The system provides students various English learning experiences by combining the natural environment fusion

Figure 7. Different numbers of students' satisfaction with the new English teaching model and the teaching quality evaluation system



algorithm. In addition, the system also provides a variety of learning resources and tools, including online courses, voice recognition technology, and virtual reality technology, to help students master English knowledge and skills.

CONCLUSION

With the continuous improvement of technology, the traditional mode of evaluating the quality of English classroom teaching in colleges and universities can no longer meet the objective needs. This paper evaluated the English teaching model based on integrating the natural environment with college students' participation. First, the paper briefly summarized the current development of English education in colleges and universities and the methods used in the classroom. Based on this, it studied five major external environmental factors of the college English classroom and applied these to English teaching to establish a more scientific English teaching model. The model's effectiveness was demonstrated using actual teaching at a university as an example. This experimental study found that using naturally integrated artificial intelligence technology for English teaching evaluation in a smart English classroom can evaluate teachers' English proficiency. However, the current research has focused on the design and evaluation model of establishing a smart classroom for teaching English in college while still have some drawbacks. Future assessments should focus on the practical application of students' knowledge, including oral expression, listening comprehension, reading comprehension, and writing abilities. At the same time, the assessment should adopt diversified methods, such as examination, homework, speaking, and practice, to comprehensively assess students' English language and application abilities.

DATA AVAILABILITY

The figures used to support the findings of this study are included in the article.

COMPETING INTERESTS

The authors of this publication declare that there are no competing interests.

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Dan Zhao graduated from the Foreign Language College of Northwest Agriculture & Forest University in 2010. She worked at Xinxiang Vocational and Technical College. Her research interests include foreign language teaching theory and research.

Ji Li is a professor at Jinzhou Medical University.

Yanping Wang is a professor at Jinzhou Medical University.