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Evaluation of the Ecological Sustainable Development Strategy of Students' English Autonomous Learning Ability under Mobile Learning Technology

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Abstract: Autonomous learning has always been a hot issue in the field of education. The development of mobile learning technology and the popularity of mobile devices provide a favorable material basis for current English teaching and students' autonomous learning. However, in practice, the ecological sustainable development factors that affect students' ability to learn English independently cannot be ignored. Based on the background of mobile learning technology, this paper analyzed the ecological sustainable development strategy of students' English autonomous learning ability. The research showed that students' satisfaction with autonomous English learning based on mobile learning technology increased by about 9.05%. It showed that the application of mobile learning technology in English teaching could be recognized and accepted by students, which promoted the improvement of students' English autonomous learning ability and enhanced their ecological and sustainable environmental development.

1. Introduction

Nowadays, with the rapid development of information technology, students' learning methods have changed a lot. Today's learners are no longer limited to traditional learning methods. They use more information technology to learn and make learning plans, so as to achieve planned learning objectives and improve students' learning effectiveness.

Autonomous learning has improved students' learning ability, and more and more scholars have studied it. Aminatun Dyah studied language learning applications to improve students' autonomous learning skills when learning English,The data showed that autonomous learning could help students learn English and especially improve their vocabulary [1]. Fazilet Karakus discussed the influence of flipped classroom model on students' autonomous learning preparation and their attitudes towards English courses[2]. Razali Abu Bakar believed that autonomous learning was very important in the field of second language education[3]. Hawkins Melissa Williamson mentioned that learner autonomy and self-regulated learning were equally important [4]. Luu Thi Mai Vy believed that it was necessary for educational institutions to transform traditional learning into online learning. Through investigation and research, it was found that one of the effective predictors of successful completion of online course assignments was students' online learning preparation [5]. Shaalan Iman El-Nabawi Abdel Wahed mentioned that autonomous learning was considered a key goal of higher education. He studied the impact of Emotionally Impaired (EI) on autonomous learning [6]. Talan Tarik investigated students' perceptions of using digital storytelling to improve learner autonomy. [7]. Although the research on autonomous learning is relatively rich, students still have weak self-control in autonomous learning.

The importance of mobile learning technology in the education process has attracted the attention of many researchers to this field and created important academic research institutions. Grant Michael M studied the impact of mobile learning on students' learning performance. [8]. Zhonggen Yu proposed a feature framework for mobile learning environment design to provide learners with opportunities for mobile learning in a foreign language learning environment [9]. Camilleri Mark Anthony determined whether the mobile learning platform could significantly improve the proficiency of English as a foreign language and generate learner satisfaction [10]. Howlett Graham discussed the application of collaborative learning of college English writing on the mobile learning WeChat platform[11]. Geng Shuang showed that there was a strong correlation between students' perception of the usefulness of mobile technology and their behavioral intentions to use mobile technology for learning [12]. Lasfeto Deddy investigated to what extent senior high school students believed that mobile devices improved learning and learner satisfaction in the classroom environment [13]. Although there are many theoretical researches on mobile learning technology, the theoretical research on mobile learning technology still lacks time validation.

Mobile learning technology has changed people's education, learning and thinking modes. By analyzing the advantages of mobile learning technology in English autonomous learning, mobile learning technology and students' autonomous learning are combined to improve students' autonomous learning ability and learning interest, so as to promote the ecological sustainable development of students' English autonomous learning ability.

2. Mobile Learning Technology and Learner Autonomy in English Learning

(1) Core advantages of mobile learning technology

1) Flexible and convenient learning style,2) Advanced and efficient learning concept,3) Refined reading+professional courses,4) Complete mastery of learning effect,5) Reduction of training equipment investment,6) Customization of end enterprise solutions

(2) Factors affecting the sustainable development of English autonomous learning ability

1) Teacher factor

In practice, many teachers do not follow the modern educational concept. They only attach importance to students' learning strategies and neglect the cultivation of metacognitive strategies. This is contrary to the role of "language teacher" advocated in modern foreign language teaching and the sustainable development requirements of students' self-development [14].

2) Student factor

The learning attitude of learners affects the effectiveness of learning, which involves learners' attitudes towards their role in learning and their views on their learning ability. Students in the traditional basic education system think that teachers should guide students and students should follow teachers' instructions [15].

3) Environmental factor

Environmental factors include family environment, school environment and social environment. Environmental factors affect students' interest and enthusiasm in independent learning. A good learning environment can enhance students' learning initiative.

(3) Ecological sustainable development strategy for promoting students' autonomous English

learning ability

1) Establish humanistic education concept and adhere to the education concept of sustainable development

The sustainable development of English requires teachers to meet the students' comprehensive, coordinated and sustainable development ability in teaching.

2) Use multimedia teaching environment and construct the teaching model of constructivism

In teaching, teachers should create teaching situational teaching and guide students to learn independently. They need to use mobile phones, networks and other ways to create real language situations [16].

3) Strengthen the cultivation of learning strategies and promote the development of students' autonomy

Teachers should teach students how to learn and fully mobilize their enthusiasm, so that students have time and space to learn and think independently to form good autonomous learning methods and cognitive strategies.

4) Change teachers' ideas and speed up role transformation

Mobile learning is a system of learning environment and learning process. In this environment, the role of teachers should be diversified.

5) School support and guarantee

Students should cultivate the habit of autonomous learning from the moment they enter the school. As the main body of educational activities, schools should strengthen environmental management to create a better learning environment for students.

3. Advantages of Mobile Learning Technology in English Autonomous Learning

(1) The role of mobile learning technology in student attendance assessment: Teachers can keep track of students' attendance and classroom conditions at any time.

(2) Mobile learning technology plays an advantage in the evaluation of students in and out of the classroom: In the exam, students can scan the quick response code to get the content they need to evaluate, get any information, and send their evaluation results back to the teacher in any form. In this way, there is no need to print the test paper and prepare the text for printing a lot of time in advance [17]. It reduces the workload of teachers and simplifies the participation process of students.

(3) Mobile technology plays an advantage in learning interaction and learning feedback: In the whole process of learning, students' progress is understood to timely evaluate students and help students solve difficulties encountered in learning. This requires constant interaction and timely feedback. Mobile learning technology plays a positive role in promoting the interaction between students and teachers and students in the learning process.

(4) Mobile learning technology plays an advantage in teaching effect analysis: Some courses and distance learning with a large number of students are not suitable for collecting and processing students' feedback in the traditional way. In the current environment driven by mobile learning technology, the overall learning situation of students has been evaluated and assessed, and the results are concise and accurate. At the same time, students can learn about other students' achievements and learning conditions in real time through mobile learning technology, thus forming a competitive relationship and improving learning efficiency.

4. Algorithm of Mobile Learning Technology in English Autonomous Learning Ability

(1) Selectivity based integration approach

The sample data set $G = (x_i, y_i)\Big|_{i=1}^{n}$ is given. Each sample is labeled by the feature vector X_i and its corresponding sample y_i. From the training sample set F, a model is learned. It is assumed that $l(x)$ is used to predict the new sample X to obtain the corresponding prediction value. The form is as follows:

$$F(x) = \arg\max \sum_{t=1}^{Q} K(l_t(x)), y \in Y \tag{1}$$

First, the base model with the best performance on the pruning dataset is integrated to form the initial sub integration model P_1. The sub integrated system P_u with the scale of u incorporates the classifier with the smallest integration error after combining with the classifier P_{u-1} into the sub integrated system P_{u-1} with the scale of $u-1$, which is formally expressed as follows:

$$P_u = \arg\max_k \sum_{(x,y)\in V_{set}} K\left(H_{P_{u-1}\cup l_k}(x) = y\right) \tag{2}$$

In the formula, P_u represents the label of the candidate model to be added to the pruning integration system in the original integration system

The $d^{(t)}$ th component of the vector is as follows:

$$d_i^t = (h_i(x) - y_i), (x_i, y_i) \in V_{set} \tag{3}$$

If the base model t can perfectly match the i th sample in V_{set}, the i th component d_i^t in its signature vector $d^{(t)}$ is equal to 0. The signature vector of the integrated system is defined as the sum of all the model signature vectors, so the signature vector of the integrated system is defined as follows:

$$\langle d \rangle = S^{-1} \sum_{t=1}^{S} d^{(t)} \tag{4}$$

The i th component of $\langle d \rangle$ is the boundary of the i th sample, which represents the classification result of the i th sample by the integrated system. Therefore, the smaller the i th component is, the better the instance is fitted by the integrated system.

The base model with the maximum reduction in the distance between the average integrated signature vector $\langle d \rangle$ and the coordinate origin o is taken as the initial sub integration system P_1. The model marked with a number should be selected for the u th time:

$$P_u = \arg\max_k b\left(o, S^{-1}\left(d^{(k)} + \sum_{t=1}^{u-1} d^{(k)}\right)\right) \tag{5}$$

In the formula, P_u represents the label of the selected model in the original integrated system.

(2) Direct push learning

Direct learning is a special semi supervised learning method, which assumes that the unlabeled samples used in the training process are samples with predictions. m labeled samples $(x_1, y_1), \cdots, (x_m, y_m)$ and n unlabeled samples x_{m+1}, y_{m+1} are given, a real predictive value h_i is calculated first, and finally the label of unlabeled sample can be obtained from this real value:

$$y_i = sign(h_i) \tag{6}$$

The direct learning algorithm reorganizes the solution h_i into a quadratic optimization problem:

$$\min_{A \in R^n} A^T RA + (A-Y)^T B(A-Y) \tag{7}$$

Among them, $R \in R^{n \times n}$ is a regularized matrix; n is the number of samples; $A = [h_1, \ldots, h_n]^T$ is the real predictive value vector corresponding to each sample; B is a diagonal matrix.

The closed form solution of the optimization problem can be obtained by taking the derivative of Formula (7) and making the derivative 0, as shown in the Formula (6):

$$A = (R+B)^{-1} BA \tag{8}$$

In the direct deduction learning, the regularization matrix calculation is commonly used, which is recorded as G, and the formula for matrix G is as follows:

$$G = D - Q \tag{9}$$

If x_i and y_i are connected in the figure, q_{ij} is calculated as follows:

$$q_{ij} = \exp\left(-\frac{1}{\alpha} x_i - y_i\right)^2 \tag{10}$$

Among them, α is the scale parameter. If x_i and y_i are not connected in the figure, $q_{ij} = 0$.

It is assumed that $R = A$ and it is substituted into Formula (7), and the first regular term in the formula can be written as follows:

$$A^T GA = \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} q_{ij} (h_i - h_j)^2 \tag{11}$$

(3) Domain adaptation

Domain adaptation is a specific transfer learning method that transfers knowledge to different fields. Θ is recorded as a collection of models and an optimal classification model θ^* is found. $l(a,b, \ \theta)$ is the loss function. The optimal model is obtained by minimizing the objective function:

$$\theta^* = \underset{\theta \in \Theta}{\operatorname{argmin}} \sum_{(a,b) \in \kappa \times \lambda} V(a,b) h(a,b,\theta) \tag{12}$$

Since $V(a,b)$ is unknown, empirical distribution $\tilde{V}(a,b)$ is used to estimate $V(a,b)$. An estimated model is obtained by minimizing empirical risks θ^*:

$$\theta^* = \underset{\tilde{\theta} \in \Theta}{\operatorname{argmin}} \sum_{(a,b) \in \kappa \times \lambda} \tilde{V}(a,b) h(a,b,\theta) = \underset{\tilde{\theta} \in \Theta}{\operatorname{argmin}} \sum_{(a,b) \in \kappa \times \lambda} h(a,b,\theta) \tag{13}$$

By considering the domain adaptation, the optimal model $\theta^{*}{}_T$ of the target domain can be obtained by minimizing in an ideal case:

$$\theta^*{}_T = \underset{\tilde{\theta}\in\Theta}{\operatorname{argmin}} \sum_{(a,b)\in\kappa\times\lambda} V(a,b)h(a,b,\theta) \tag{14}$$

However, in fact, the training samples are randomly sampled from the source domain distribution $V_S(a,b)$. Therefore, the method to deal with domain adaptation is as follows:

$$\begin{aligned}\theta^*{}_T &= \underset{\tilde{\theta}\in\Theta}{\operatorname{argmin}} \sum_{(a,b)\in\kappa\times\lambda} \frac{V_T(a,b)}{V_S(a,b)} V_S(a,b)h(a,b,\theta) \\ &\approx \underset{\tilde{\theta}\in\Theta}{\operatorname{argmin}} \sum_{i=1}^{ns} \frac{V_T(a_i^S, b_i^S)}{V_S(a_i^S, b_i^S)} h(a_i^S, b_i^S, \theta)\end{aligned} \tag{15}$$

Another domain adaptation assumption is $V_T(a|b) = V_S(a|b)$, but $V_T(A) \neq V_S(B)$. It is generally believed that the difference is caused by category imbalance. Under such assumption, the weight can be rewritten as follows:

$$\frac{V_T(a,b)}{V_S(a,b)} = \frac{V_T(b)V_T(a|b)}{V_S(b)V_S(a|b)} = \frac{V_T(b)}{V_S(b)} \tag{16}$$

(4) Intensive learning

There are two main methods to deal with this kind of problem.

When the task model is known, it is easy to calculate this value. $Y^\pi(u)$ is recorded as the long-term reward value that can be brought by using strategy π in state u. It has the Markov property and the state value function can be expanded as follows:

$$Y^\pi(u) = \sum_{a\in A}(u,a) \sum_{u'\in U} P_{s\to s'}^{\pi(u)} \left(W_{s\to s'}^{\pi(u)} + \lambda Y^\pi(u')\right) \tag{17}$$

It is assumed that the value function V corresponding to the optimal strategy * of the reinforcement learning task is the optimal value function. In Formula (17), the sum is changed to the maximum value, and the formula is as follows:

$$Y^\pi(u) = \max \sum_{u'\in U} P_{s\to s'}^{\pi(u)} \left(W_{s\to s'}^{\pi(u)} + \lambda Y^\pi(u')\right) \tag{18}$$

With the optimal value function, the optimal policy can be written as follows:

$$\pi^*(u) = \arg\max\left(\sum_{u'\in U} P_{s\to s'}^{\pi(u)} \left(W_{s\to s'}^{\pi(u)} + \lambda Y^\pi(u')\right)\right) \tag{19}$$

5. Impact of Mobile Learning Technology on the Ecological Sustainability of English Self-study Ability

(1) Experiment purpose

Based on mobile learning technology, this paper analyzes the ecological and sustainable development strategies of students' English autonomous learning ability in recent years. Students from the school of foreign languages of school Y are selected as the research objects. Class A is the traditional autonomous English learning situation, and Class B is the autonomous English learning situation under mobile technology. The research is conducted from five aspects: satisfaction with autonomous learning, self-control of autonomous learning, implementation of students' plans, English learning achievements, and comparison chart of oral English achievements.

(2) Experimental data

1) Satisfaction

The students' satisfaction with autonomous learning reflects the application effect of mobile learning technology autonomous learning in English autonomous learning. The research on the students' satisfaction with English autonomous learning is shown in Table 1.

Table 1: Satisfaction with self-directed learning

Satisfaction	2016	2017	2018	2019
Satisfied	26.94%	30.87%	33.86%	35.99%
generally satisfied	30.38%	33.17%	35.67%	37.94%
dissatisfied	42.68%	35.96%	30.47%	26.07%

In Table 1, based on the background of mobile learning technology, students' satisfaction and general satisfaction with autonomous learning are increasing, while their dissatisfaction is decreasing. In 2016, students' satisfaction with autonomous learning is about 26.94%. In 2019, it would be about 35.99%, which is about 9.05% higher.

2) Self control of independent learning

The self-control of English autonomous learning of students in Class A and Class B is studied, and the results are shown in Figure 1.

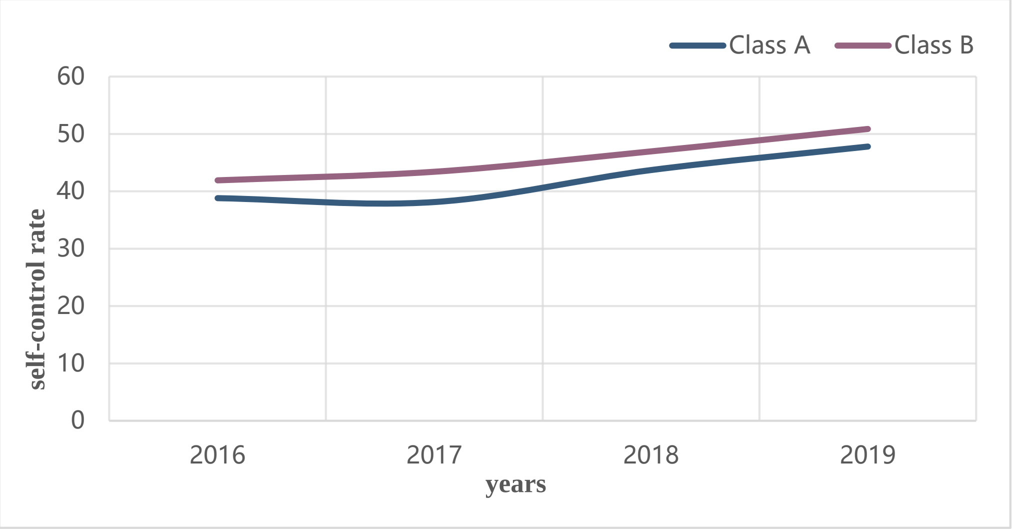

Figure 1: Comparison of self-control in self-directed learning

In the situation of self-regulated learning self-control, the self-regulated learning self-control of students in Class B based on mobile learning technology shows a steady upward trend, while the self-regulated learning self-control of students in Class A based on traditional technology shows a downward trend from 2016 to 2017. From 2017 to 2019, it began to increase gradually. Mobile learning technology can detect students' learning status and progress, which is conducive to improving students' self-control in English autonomous learning.

3) Implementation of plans made by students

According to the implementation of the learning plan made by students, the results are shown in Figure 2.

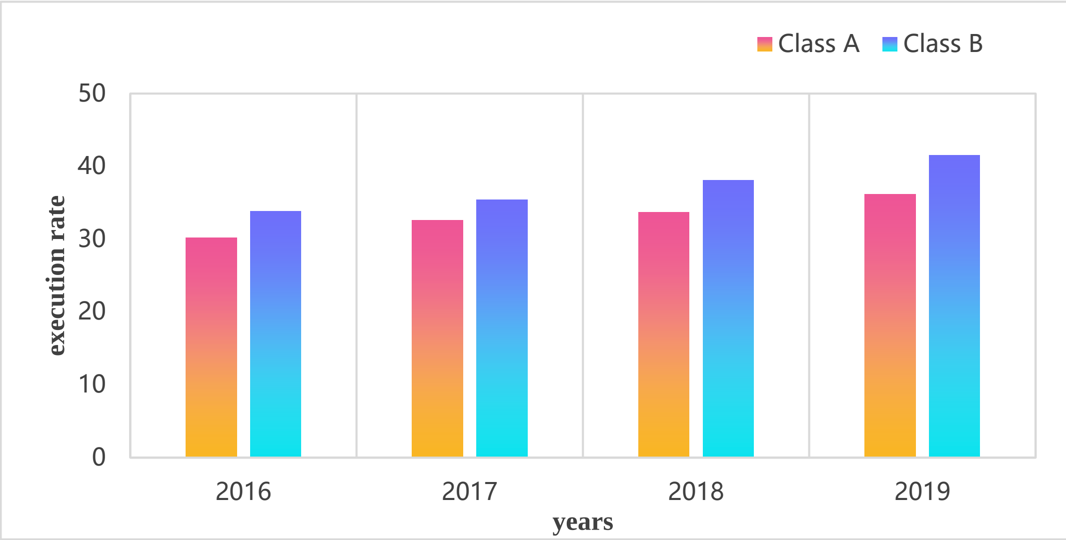

Figure 2: Comparison of the implementation of the plan developed by students

In the implementation of the plans made by students, the implementation rate of the plans made by students in Class A and Class B is constantly improving, and the growth rate of the implementation rate of the plans made by students in Class B is faster than that of the plans made by students in Class A. Based on mobile learning technology, it provides students with learning opportunities. Students can learn at home, and mobile learning technology can also play a supervisory role. It can regularly check the students' learning situation and enhance the students' consciousness of implementing and making plans.

4) English learning achievements

The English learning achievements of Class A and Class B are taken as the research subjects, and the analysis results are shown in Figure 3.

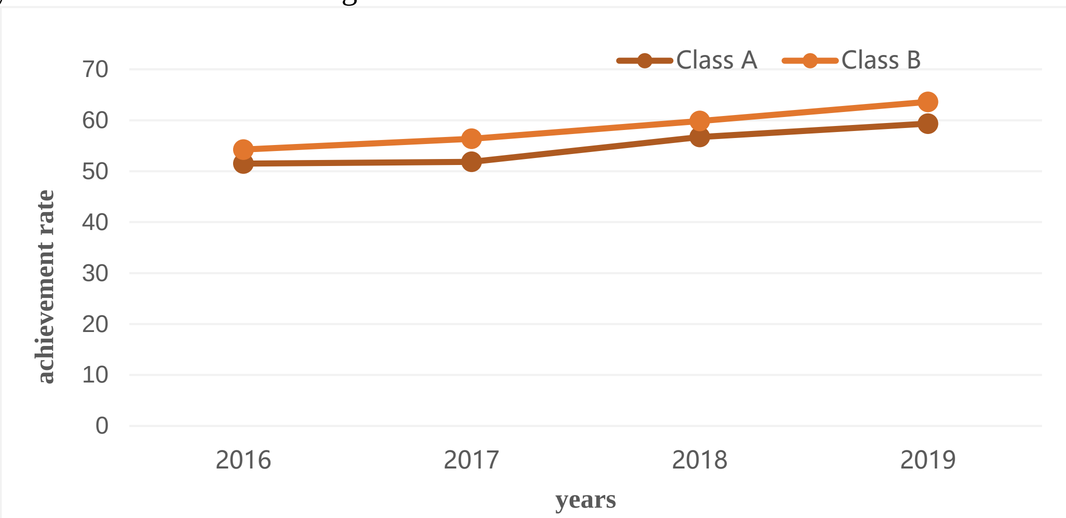

Figure 3: English learning performance comparison

Among the English learning achievements, the English learning achievements of Class B are significantly higher than those of Class A. Mobile learning technology provides students with more learning opportunities and learning resources. It transcends geographical restrictions and allows teachers and students to communicate with each other, which greatly improved the learning effect.

5) Comparison chart of oral performance

The comparison chart of oral English scores is shown in Figure 4.

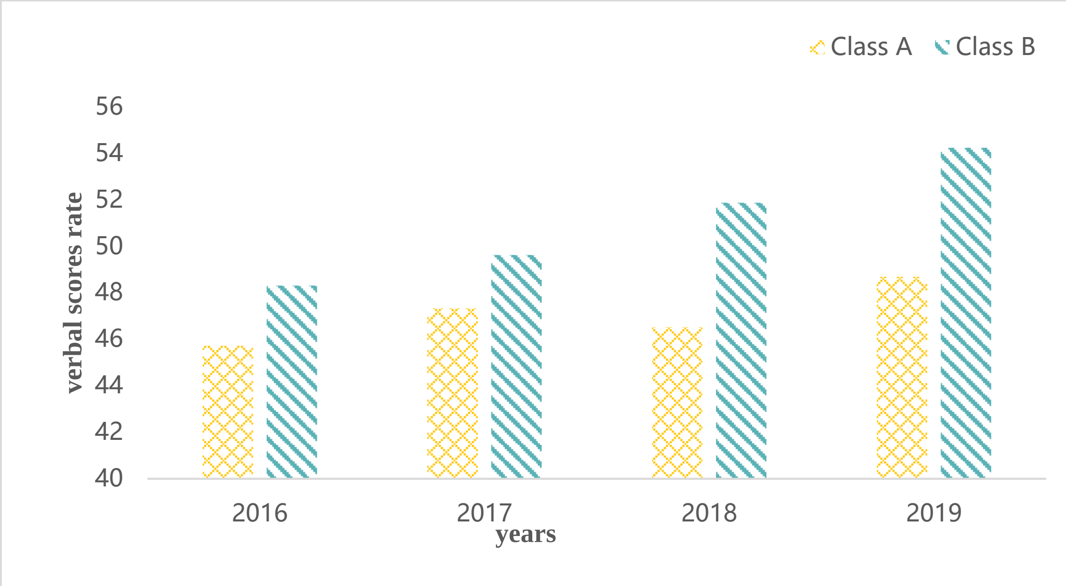

Figure 4: Comparison chart of oral language scores comparison chart of oral language scores

In the comparison chart of oral English scores, the oral English scores of Class A are unstable, and the oral English scores of Class B are rising steadily. Based on mobile learning technology, oral English can improve students' pronunciation in English practice. Through the audio of English pronunciation practice provided by mobile technology, students' oral English expression and communication ability can be improved.

6. Conclusions

Education is a long-term work, while learning is closely related to the whole growth of people. Contemporary educational thought increasingly emphasizes the cultivation and development of students' comprehensive abilities. In order to truly solve the problems in current English teaching, educational concepts must be changed. The teaching models must be updated, and students' autonomous learning ability must be improved. Mobile learning technology provides an external environment for independent learning. Based on mobile learning technology, it improves the quality of environmental management in students' autonomous learning. It enhances and enriches the existing learning resources and learning equipment, and supplements the learning methods. However, this cannot replace textbook and classroom learning. The cultivation of students' autonomous English learning ability and ecological sustainable development need the joint efforts and long-term cooperation of teachers and students.

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