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A Study on the Intelligent Analysis Model of Diversified Facilities in Smart Classroom for English Learners' Learning Effectiveness

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Abstract Smart classrooms have attracted much attention as a new type of educational environment, and it is of great significance to study the diversified facilities in smart classrooms to improve the comfort and learning effect during the use of the classroom. In this paper, the TGAM module is used to collect and pre-process the EEG signals of English learners when they are studying in the smart classroom, and wavelet analysis and support vector machine are used to extract and identify the EEG signals, and the EEG signals are used to reflect the effect of English learning, so as to realize the intelligent analysis of the learning effect. Finally, based on the important elements in the space design of the smart classroom, the lighting facilities and thermal environment regulation facilities are selected to analyze their impact on the learning effect. It is found that the EEG signal α and β levels of English learners in the smart classroom are relatively highest when the illumination value is 700lx, and the English learning effect is more ideal at this time. When the PMV value of the thermal environment is -0.29, the R-value of the EEG signals δ + θ of the English learners decreases to 0.063, which indicates that the lighting and the thermal environment facilities in the smart classroom have a greater impact on the English learning effect. This study provides ideas for the development of future programs for the scientific and effective implementation of diverse facilities in smart classrooms.

Index Terms tgam module, electroencephalographic signals, learning effects, diverse facilities, smart classroom, spatial design

I. Introduction

With the continuous development of the education industry, classroom equipment continues to improve, a variety of new information technology gradually debut in the classroom, the smart classroom has become an inevitable product of the education industry in the context of the times, and with its unique charm to promote the development and reform of the education industry [1], [2]. English is an important subject, and high English literacy is of great significance to students. Smart classroom has great advantages in English teaching, which can make the English classroom become more efficient, therefore, in the actual English teaching, teachers should actively utilize the smart classroom environment to gradually improve the quality of English teaching and students' English proficiency [3]-[5].

In the process of promoting the reform of university English teaching, it is necessary to follow the laws of foreign language teaching, and at the same time, endeavor to create a smart classroom environment for students, to enhance students' participation in learning through effective classroom interactions, as well as to strengthen their sense of learning experience [6], [7]. The so-called smart classroom can be defined as the high-end form of multimedia and network classroom. It is a new type of classroom constructed with the help of Internet of Things (IoT) technology, cloud computing technology and intelligent technology [8], [9].

Smart classroom is a fusion of traditional classroom and emerging technology, in which smart classrooms are generally equipped with intelligent devices, terminal computers and other facilities [10]. In the classroom, teachers can use a variety of technologies to continuously enrich and improve the teaching methods, to achieve the effect of rich teaching content, fast access to resources, real-time interaction, timely feedback, giving full play to teacher-student interaction, human-computer interaction, intelligent analysis of the new classroom. The ecosystem of smart classroom contains three major systems: hardware equipment, software resources and training [11], [12]. The hardware equipment as the basic support, software resources as the carrier, and training as the elements of the three segments constitute a complete smart classroom, and the three elements complement each other and are indispensable to help students truly move towards intelligent learning and promote the great changes in the education industry [13], [14].

Effective design of college English classroom interaction in a smart classroom environment needs to pay attention to the following two points. The first is that in terms of educational technology, it should be controlled within the capacity of university English teachers. It is not difficult to understand that if the utilization of the functions of the smart classroom is beyond the capacity of teachers, the phenomenon of putting the cart before the horse will occur in college English teaching [15], [16]. Secondly, in the design of classroom interaction, we need to pay attention to the psychological characteristics of college students in English learning, as well as the current learning difficulties they encounter, so as to make it the starting point and landing point of classroom interaction design [17], [18].

With the development of digital information technology and artificial intelligence technology, education informatization and intelligence is an inevitable result, of which the more typical is the construction of smart classrooms, many studies around the smart classroom features, structural design, technology integration, there are many scholars focusing on the teacher, the student's point of view to analyze the effectiveness of the practice of the smart classroom as well as optimize the channels, which have made a contribution to the construction of education informatization and intelligence. Literature [19] combines the literature review method and expert theory analysis method to examine the association and practical effects of smart classrooms and ESD methods, pointing out the characteristics superior to smart classrooms, so smart classrooms combined with ESD methods show a high degree of adequacy. Literature [20] introduces an instrument with forty item indicator assessment for measuring students' preference for smart classroom learning and confirms the reliability of the instrument through a practical test, and points out that students' gender does not significantly affect smart classroom preference. Based on the structural equation modeling analysis method, literature [21] explored the key factors that influence students' learning effectiveness in the smart classroom environment, and the analysis results showed that peer interaction and learning motivation directly affect students' development of higher-order thinking skills, and learning strategies have an indirect impact, and put forward targeted recommendations for improvement to promote the development of students' higher-order thinking skills. Literature [22] proposes an intelligent classroom framework with real-time sensors and intelligent machines as the underlying architecture, which can be used to recognize students' nonverbal behaviors and guide them to improve the quality and memorability of students' speeches in the classroom, and points out the difficulties in the construction of this intelligent classroom, including technology integration, algorithm design, and quantitative methods. Literature [23] describes the integration and design of a smart classroom infrastructure, including the role of large displays, the significance of student-to-student communication, intelligent software agents, and other multi-dimensional aspects, and establishes a set of guidelines for smart classroom design. Literature [24] examined the performance of the introduction of IoT technology into the cloud education system, and based on the study, it was learned that the cloud computing technology with IoT as the core promotes the informatization and intelligent construction of classroom teaching and teaching management, facilitates students' sustainable learning, and realizes remote online learning, cloud payment, and cloud security management. Literature [25] attempts to dissect the effects and attributes of smart classrooms from a teacher's point of view and identifies that smart classrooms involve managerial procedures, educational policies, and administrative practices that design, enable, and enhance these attributes. It also points out that strategically oriented planning and other factors drive the transformation these influence the quality of smart classroom based teaching and learning.

The research on cutting-edge English teaching is mainly related to the application of information intelligence technology, the optimization of English teaching strategies and the design of English teaching methods and contents. Literature [26], in order to improve the quality of English teaching in colleges and universities, proposes to take interactive teaching as the core, adopt intelligent classroom technology, and build an intelligent teaching system of English in colleges and universities with the Internet of Things and cloud computing as the infrastructure, which effectively enhances the students' personal learning experience, and significantly promotes the improvement of the students' learning performance. Literature [27] empirically explored the differences in English learning strategies and learning beliefs among students of different genders and ages, and found that students' gender was not significantly associated with students' learning beliefs but was strongly correlated with learning strategies, whereas students' age was associated with students' learning beliefs as well as learning strategies. Literature [28] examined the design of the ICAI system on an online course platform commonly used to assist students' English literacy improvement, including the system structure, design ideas, etc., focusing on the basic principles of its BP algorithm, the specific steps of training, the heuristic rules of evaluation and applications. And a prediction model based on particle swarm algorithm-backpropagation is proposed to realize the prediction of students' performance, which is conducive to improving the quality of English teaching. Literature [29] discusses the practice of English micro-lecture with the basic logic of hybrid wisdom education, points out its unique advantages and can provide a good contextual environment for teachers' teaching, and proposes ideas and directions to improve English micro-lecture.

This paper reflects the learning effect of English learners through EEG signals, and explores the relationship between the lighting and thermal environment regulation facilities and the learning effect in the smart classroom to provide a basis for the effective improvement of the learning effect. The TGAM module is first utilized as the EEG acquisition device for English learners in the smart classroom, and a filter is applied to pre-process the EEG signals. Wavelet analysis is used to localize and analyze the linear features in the EEG signals, the sample entropy algorithm is used to extract the nonlinear features in the EEG signals, and then the support vector machine method is used to classify and identify the features of the EEG signals. Finally, the EEG signals are transferred to the MongoDB database to display the changes of EEG signals related to learning effects in real time, realizing the intelligent analysis of English learning effects. This study combines the specific architecture of smart classroom space design, selects lighting facilities and thermal environment regulation facilities for research, and analyzes the two facility setting schemes and the learning effect of English learners.

II. Smart classroom space design

The construction of the smart classroom model includes the design of diverse technological facilities and spatial facilities, both of which can support the realization of pedagogy. The overall architecture of the smart classroom is shown in Figure 1. The common part between technical design and spatial design is a series of IoT hardware devices in the smart classroom, in which desks and chairs mainly affect the spatial layout of the classroom, while audio/video and intelligent loop control devices affect other environmental elements of the space. These IOT devices are connected to the cloud platform through the indoor ubiquitous network, and different subjects can access the cloud platform through the client to obtain network resources and software application services.

(1) Spatial environment

The desk and chair itself is part of the physical environment of the classroom, the physical environment includes the classroom layout, basic teaching facilities, and the classroom light lighting, color, sound, temperature and humidity, air quality and other physical factors, the physical environment can directly affect the students' emotional experience in the classroom. The spatial design of the classroom should be simple, bright and airy. The classroom infrastructure system includes sub-systems such as school equipment, power supply and distribution, ventilation and air conditioning, and lighting. Reasonable facility layout, safe and reliable power supply and distribution, healthy and energy-saving ventilation and air-conditioning, and lighting are the necessary facility conditions for smart classrooms.

(2) Blocked Space Layout

In addition to the basic spatial layout, there is also blocked classroom spatial layout. This layout divides the classroom space into several functional blocks, which generally include teaching display areas, group cooperative learning areas, and game (experiential) learning areas. Through a variety of diversified facilities and partitioning methods such as movable screens, combination cabinets, screens, etc., people are dispersed to communicate in the cooperative space. Group discussions, brainstorming, multi-person experiments, etc. can be conducted in this kind of hybrid teaching space, which supports both teacher-centered didactic teaching and group-based collaborative learning and independent learning, and students and teachers can easily learn and share with each other.

III. Intelligent analysis model of learning effect based on EEG signals

III. A. EEG signal acquisition and processing

III. A. 1) Dynamic EEG brainwave acquisition methods

TGAM module [30] is a programmable semiconductor chip based on Think Gear Asic module, which is a highly integrated monolithic EEG sensor. Through the integration of brainwave signal acquisition, filtering, amplification, A/D conversion and computation, the sampling frequency is 512 Hz, and its built-in filtering and noise reduction circuit can automatically filter out all kinds of noise interferences in the environment during use, with low power consumption.

The TGAM sensor has three contact points, EEG (EEG acquisition point), REF (reference point) and GND (grounding point).The ear clip 1 and ear clip 2 of the REF reference point are usually clipped on both ears of the subject, and are usually clipped on the earlobes of the testers.The EEG acquisition point should be placed on the forehead of the testers, and care should be taken to clean up the skin before using the device, as the hair also interferes with the signal. With the Bluetooth module, the subject can be free from the constraints of wired communication in the traditional acquisition mode, and the tester can move freely with the device, which facilitates the monitoring of EEG signals of English language learners in the smart classroom.

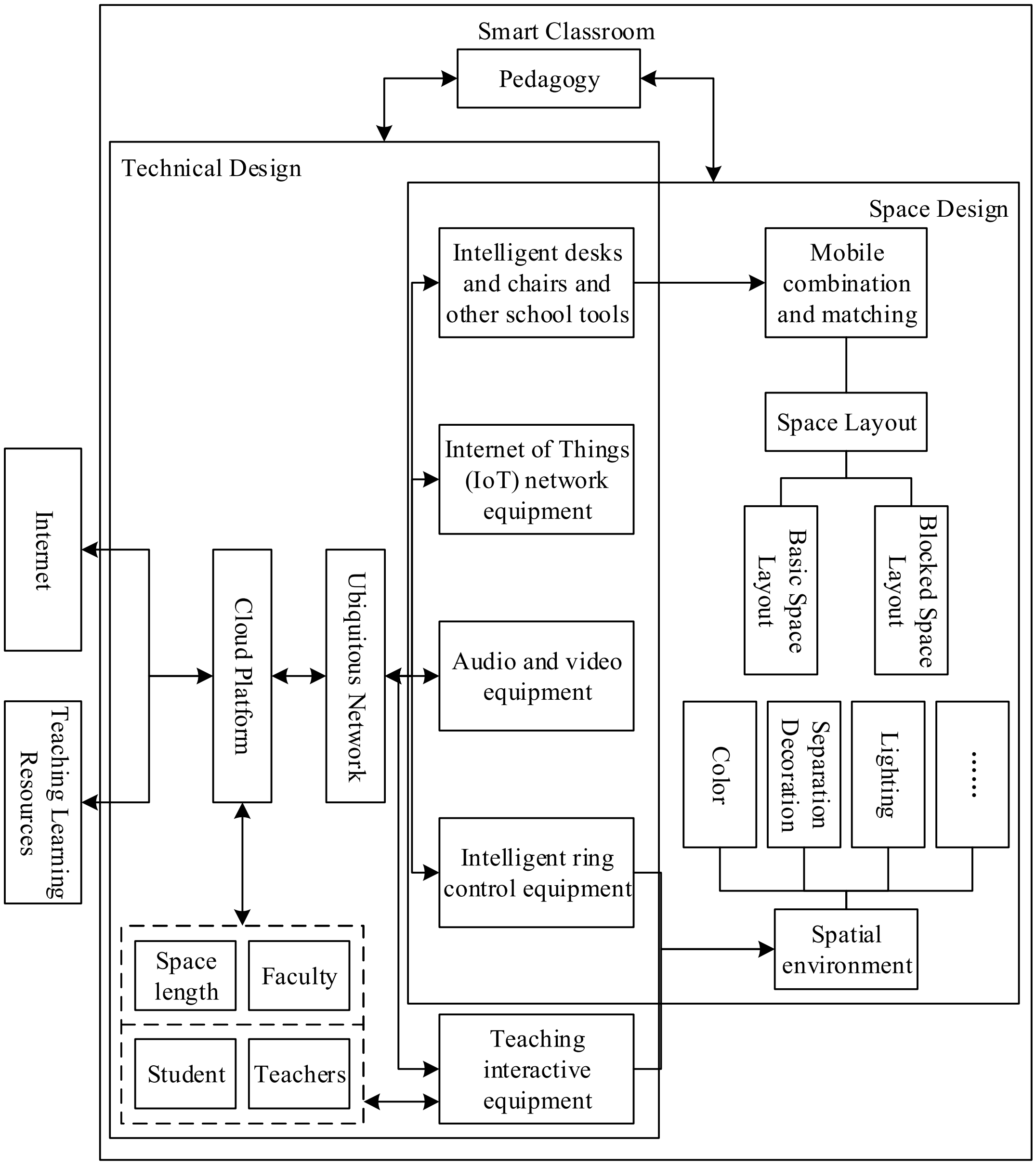


Figure 1: Intelligent classroom model architecture

The TGAM module sends about 513 packets per second, and there are two kinds of packets sent: the format of the small packet is $AAAA\ 04\ 80\ 02\ xxHig\ hxxLow\ xxCheckSum$ the $AAAA\ 04\ 80\ 02$ in front of it is unchanged, and the last three bytes are changing all the time, $xxHigh$ and $xxLow$ make up the original data $Rawdata$, and $xxCheckSum$ is the checksum. Through filtering, noise reduction and feature extraction, the processed signals are transmitted to the computer in the form of packets.The EEG EEG analysis software system realizes the data analysis through the following procedure. The formulas are as follows:

$$sum = \left(\left(0x80 + 0x02 + High + Low\right) \wedge 0xFFFFFFFF\right) \& 0xFF \tag{1}$$

And the packets are checksummed to calculate the packet loss rate, which is below 10% will not affect the final result. Then parse out the EEG raw data by the following program:

$$Rawdata = \left(xxHigh << 8\right) | xxLow \tag{2}$$

$$If\left(Rawdata\right) > 327680\left\{Rawdata = 65536;\right\} \tag{3}$$

Shifting the high byte left by 16 bits, the middle byte left by 8 bits, and leaving the low byte unchanged, and then summing them or arithmetic gives the result of 8 Brainwave Signal values, along with Attention and Relaxation values. These values are unitless and are meaningful only when compared with other Beta, Gamma, etc. values with each other.

In this study, the EEG signals are collected based on the TGAM module, the collected EEG signals are preprocessed by digital filters as well as band-pass filters, and then the relevant built-in algorithms are used to realize the output of the signals, and finally, through the Bluetooth device, the data are transmitted to the terminal device for appropriate processing and intelligent analysis.

III. A. 2) EEG Signal Extraction

Currently, the more commonly used time-frequency domain analysis method in the field of EEG feature extraction is wavelet analysis, whose features such as multi-resolution and multiwavelet bases play a very crucial role in the accurate analysis of EEG signals. Of course, these methods extract only the linear features of EEG signals, which is not enough to completely portray the essence of EEG signals, and their structural complexity promotes the application of Approximate Entropy (ApEn), Sample Entropy (SampEn), Fuzzy Entropy (FuzzEn) and other methods in the analysis of EEG signals.

In this paper, based on the existing research, wavelet analysis is used to analyze EEG signals in time-frequency domain, and linear features of EEG signals are extracted based on the analysis results, and sample entropy method is also used to extract nonlinear features of EEG signals, and the final features of EEG signals are obtained by combining the two.

(1) Wavelet analysis

Wavelet analysis [31], which is the localization of a signal in the time-frequency domain, is able to refine the signal at multiple scales through operations such as telescoping and panning, and thus derive the characteristics of the signal in the time and frequency domains. It is known that the experimentally acquired discrete EEG signal is S, and the discrete wavelet transform (DWT) of S is:

$$WT_S(a,b)=\frac{1}{\sqrt{|a|}}\int S(t)\Psi\left(\frac{t-b}{a}\right)dt \tag{4}$$

where, t is the time variable, $a(a\neq 0)$ is the scale factor, b is the shift factor and $\Psi(t)$ is the wavelet basis function.

And according to the Mallat algorithm, the EEG signal is decomposed into the sum of the approximation signal and the detail signal of each layer, i.e.:

$$S(n)=A_L+\sum_{i=1}^{L}D_i \tag{5}$$

where, L is the number of decomposition layers, A_L is the approximated signal, and D_i is the detailed signal of each layer. The original EEG signal is decomposed at five levels using orthogonal 4th order Daubechies wavelets (db4), taken as $a=2$, $b=0$.

(2) Sample entropy

Sample entropy [32] is a statistical index to measure the complexity of time series based on approximate entropy, compared with approximate entropy, sample entropy is more efficient in the calculation of physiological signals such as EEG signals, and at the same time, sample entropy is more effective in classifying as a feature under the condition of small samples. Therefore, this paper extracts the sample entropy of the EEG signal corresponding to each event as its nonlinear feature. The specific algorithm idea of sample entropy is as follows.

(a) The EEG signal sampled at a fixed frequency is known to be S, and its sampling sequence is specifically denoted as $s(1),s(2),\dots,s(n)$.

(b) The sequence S is reconstructed into a m-dimensional vector sequence X in the manner:

$$X_m(i)=\left[s(i),s(i+1),\dots,s(i+m-1)\right] \tag{6}$$

where $1\le i\le n-m+1$.

(c) Define the distance between vectors $X_m(i)$ and $X_m(j)$ as d_{ij}, calculated as:

$$d_{ij}=\max\left\{\left|s(i+k)-s(j+k)\right|\right\} \tag{7}$$

where $0\le k\le m-1$, $1\le i,j\le n-m+1$, and $i\neq j$.

(d) Set the similarity tolerance value $r(r>0)$ and for each vector $X_m(i)$, count the ratio of the number of $d_{ij}<r$ to the total number $n-m$, denoted as $B_i^m(r)$, i.e:

$$B_i^m(r)=\frac{1}{n-m}number\left\{d_{ij}<r\right\} \tag{8}$$

where $1\le i,j\le n-m+1$, $i\neq j$.

(e) Find the average of $B_i^m(r)$ for all values of i, denoted as $B^m(r)$, i.e.:

$$B^m(r) = \frac{1}{n-m+1} \sum_{i=1}^{n-m+1} B_i^m ® \tag{9}$$

(f) Let $m = m+1$, repeat the above process (b)~(e) to obtain $A^h(r)$, $h = m+1$.
(g) The sample entropy of the EEG signal sequence is defined as:

$$SampEn(m,r) = \lim_{n \to 0} \left\{ -\ln\left[\frac{A^h(r)}{B^m(r)} \right] \right\} \tag{10}$$

When n is a finite value, the estimate of the sample entropy is:

$$SampEn(m,r) = -\ln\left[\frac{A^h(r)}{B^m(r)} \right] \tag{11}$$

Similarly, the sample entropy calculation is performed in terms of events, and the parameter settings are taken as $m = 2$, $r = 0.2 \cdot std$, where, std denotes the standard deviation of the sequence of event EEG signals S.

III. A. 3) Classification and Recognition Algorithm

The two most commonly used algorithms for EEG classification and recognition are Artificial Neural Networks and Support Vector Machines, both of which have their own advantages and disadvantages depending on the specific application scenarios, in this paper, we choose the Support Vector Machine method for EEG signal classification and recognition.

Support Vector Machine (SVM) [33] is a generalized classifier based on supervised learning, and its goal is to find a hyperplane that can divide the samples belonging to different categories in a dimension space that is higher than the original data, so as to realize the classification of the sample data.

For the linear problem, let the equation of the classification hyperplane be $\omega^T x + b = 0$, then among the n-dimensional space, such that each sample in the sample set D containing m samples satisfies $y_i(\omega^T x + b) \geq 1 - \sigma_i$, while such that $\min_{\omega,b,\sigma_i} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{m}\sigma_i$, where, $\sigma_i(\sigma_i \geq 0)$ is the slack variable, $i = 1,2,\ldots,m$, C is the error penalty factor, and using the Lagrange multiplier method to solve its dyadic problem, the optimal decision function can be obtained as:

$$f(x) = \sum_{i=1}^{m} \alpha_i y_i x_i^T x + b \tag{12}$$

where α_i is the Lagrange multiplier.

When σ_i are 0, it is a linearly differentiable problem, otherwise it is a linearly indivisible problem, while for the nonlinear problem, it is necessary to map the original sample space to a higher dimensional space for linear division by upscaling, because the dimension of the feature space after mapping may be infinite dimensional, so the kernel function is introduced to calculate the inner product between two samples, and its optimal decision function can be expressed as:

$$f(x) = \sum_{i=1}^{m} \alpha_i y_i k(x, x_i) + b \tag{13}$$

where $k(x, x_i)$ is the kernel function. To obtain a model with better performance, in addition to the need for a large amount of training data, mainly rely on the choice of kernel function parameters and penalty factor, this paper uses different kernel function, penalty factor and gamma value to train the experimental data respectively, and then find the optimal model parameters.

III. B. Intelligent analysis model construction

After amplifying and processing the original signal, the TGAM EEG sensing device can output parameter values, including eight EEG values: delta, theta, lowAlpha, highAlpha, lowBeta, highBeat, lowGamma, highGamma, and poorSignalLevel, attention, and meditation [34]. delta represents the value of brain wave band δ, and the frequency is 1~3Hz. theta represents the value of brain wave θ band, and the frequency is 4~7Hz. lowAlpha indicates the value of the low α band of brain waves, and the frequency is 8~9Hz. highAlpha represents the value of the high α band of brain waves, and the frequency is 10~12Hz. lowBeta indicates the value of the low β band of brain waves, and the frequency is 13~17Hz. highBeta indicates the value of the brain wave in the β band high, and the frequency is 18~30Hz. lowGamma indicates the value of the brainwave in the lower γ-band and the frequency is 31~40Hz. highGamma indicates the value of the high γ band of brain waves, and the frequency is 41~50Hz. The value of these 8 brain waves is a floating-point number greater than 0 and has no units, which only makes sense when compared to each other. Attention represents the degree of attention, the range of this value is 1~100, and its value indicates the strength of the user's "concentration". Meditation means relaxation, the range of this value is 1~100, and its value indicates the strength of the user's "relaxation". After the EEG device works normally, the EEG data obtained by the EEG feature extraction and recognition method designed in this paper can be saved to the MongoDB database. Figure 2 shows the intelligent analysis model of English learners' learning effect in the smart classroom. First, start the MQTT proxy server on the remote server and work normally, and the client at the storage layer subscribes to the proxy server with the topic name and waits to receive the messages under the topic name. Then start the gateway program of the perception layer, add the EEG device number, English learner student number and other information to connect the EEG device. The third step is to establish an MQTT connection by using the CONNECT packet that carries the identity information in the message body and returns the CONNACK packet after the verification is successful. Then, the gateway program uses the PUBLISH packet to carry the EEG data in the form of JSON in the message body, and the MQTT control packet can be as small as 2 bytes and up in size as 256 MB. After receiving the EEG data from the client in the restorage layer, it can be converted into an object using the JSON toolkit. Finally, the database is inserted, and the EEG device data is saved to the MongoDB database document, so that the learning effect of English learners can be viewed in real time.

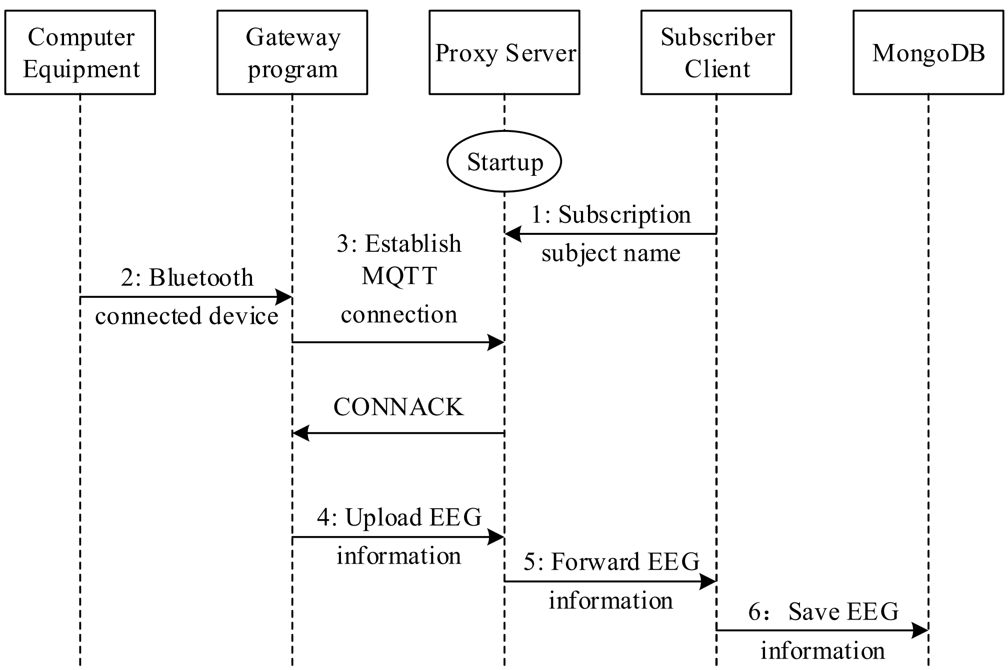


Figure 2: Brain intelligence analysis model

IV. Analysis of the Relationship between Diverse Smart Classroom Facilities and Learning Effectiveness

IV. A. Screening of Subjects for English Language Learners

In this paper, we chose School A, which has a mature smart classroom, as the research site, and conducted a pre-experiment by recruiting volunteers from middle school students in the school. In order to simulate the actual smart classroom students' classroom situation, certain conditions were set for the selection of subjects, including good health, no bad work and rest habits, normal corrected visual acuity, and certain knowledge and evaluation of the light environment, etc. A total of 20 subjects were finally selected. The subjects were informed of all the experimental procedures and safety matters and signed an informed consent form, and were required to be well rested and emotionally stable the day before the experiment, and to avoid consuming videos that stimulate the body, such as coffee or energy drinks.

IV. B. Analysis of the impact of different lighting facilities on learning outcomes

Through the previous design of the smart classroom space, it can be found that the importance of the lighting facilities in the smart classroom is high, so the purpose of this section of the experiment is to study the effects of different indoor lighting in the smart classroom on the EEG signals and fatigue of English learners, and then reflect its relationship with the learning effect.

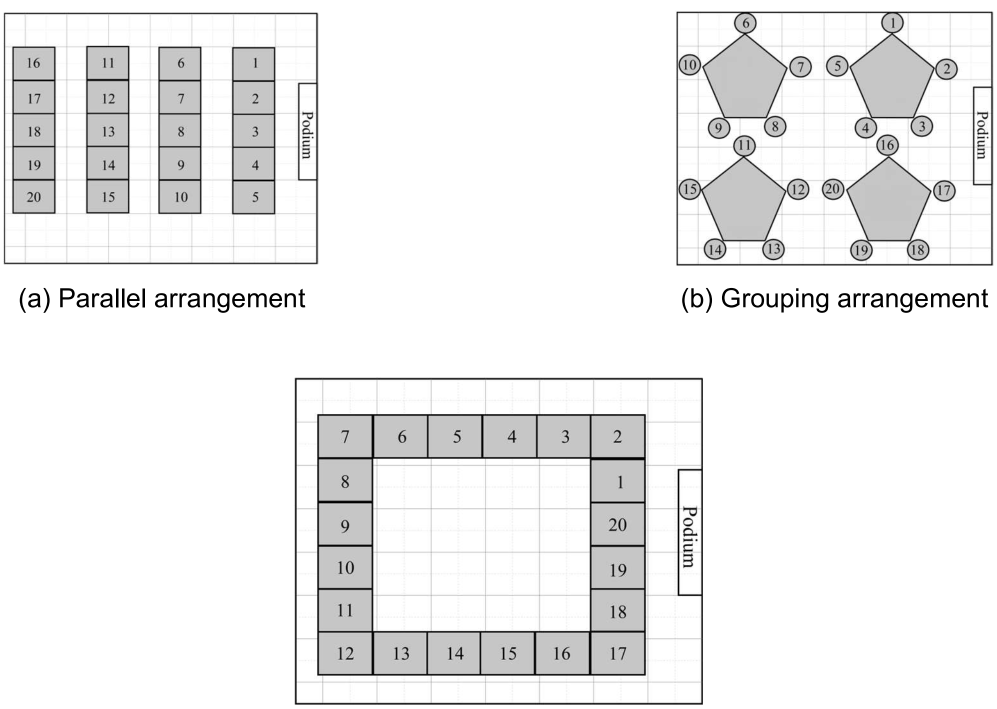
IV. B. 1) Light source selection and arrangement scheme

According to the experimental design in the previous research on intelligent classroom lighting, 150lx is generally taken as an incremental amount, and the minimum illuminance value of 300lx required by the national standard is gradually increased, and the research shows that the luminance of more than 1,100lx will trigger discomfort and glare incapacitation. Therefore, the average illuminance value range generated by the light source arrangement selected for this experiment should be maintained at 300lx-1100lx, and the incremental amount of each time is 200lx±50lx, simulating the laboratory space and light source arrangement through DIALux software, selecting lamps in accordance with the indicators of classroom-specific lamps and lanterns, and ultimately selecting the light source and determining the arrangement through repeated simulation calculations.

In the DIALux software for laboratory space modeling, take the wisdom of the classroom special lamps and lanterns in the simulation space for the layout, from 3 × 3 (that is, three rows and three columns of a total of nine lamps and lanterns) to achieve the minimum illuminance value required by the national standard, the number of lamps and lanterns into rows or columns of sequential incremental, for example, 3 × 4, 4 × 4, 4 × 5, etc., and so on, and then select a different power of the classroom special lighting fixtures and lamps, respectively, for the above-mentioned Then select different power classroom lighting fixtures for the simulation of the above layout, select the lamps and lanterns that can meet the experimental set illuminance range of models and layout programs, and finally export the lamps and lanterns parameters. Selected lamps and lanterns for Philips office / classroom LED strip light pendant light all aluminum special lamps, is no strobe classroom LED lamps and lanterns, color temperature of 4000K, power of 30W, the size of the lamps and lanterns used in the simulation of the same. A total of 3 × 3 (300lx), 3 × 4 (500lx), 4 × 4 (700lx), 4 × 5 (900lx) and 5 × 5 (1100lx) five light source arrangement. Installation height is unified for 2.5m, all light source layout program does not exist staggered and panning design, for uniform layout.

IV. B. 2) Experimental groups

The lighting environment of the experimental environment is divided into five types according to the arrangement, and the three forms of the simulated smart classroom classroom are ordinary classroom, group discussion and collective meeting, and the plan layout is shown in Fig. 3, in which (a)-(c) represent the parallel arrangement, group arrangement and enclosure arrangement, respectively. The group experimental design is shown in Table 1. There were a total of 15 working conditions in the experiment to avoid the effect of cumulative visual fatigue on the experimental results that might result from the experimental barriers.



(a) Parallel arrangement

(b) Grouping arrangement

(c) Enclosure layout

Figure 3: Table and chair layout

Table 1: Experimental conditions

Experimental label	Classroom form	Table and chair layout	Fixture	Illumination value
1	General class	Parallel arrangement	3×3	300lx
2	Panel discussion	Grouping arrangement		
3	Collective meeting	Enclosure layout		
4	General class	Parallel arrangement	3×4	500lx
5	Panel discussion	Grouping arrangement		
6	Collective meeting	Enclosure layout		
7	General class	Parallel arrangement	4×4	700lx
8	Panel discussion	Grouping arrangement		
9	Collective meeting	Enclosure layout		
10	General class	Parallel arrangement	4×5	900lx
11	Panel discussion	Grouping arrangement		
12	Collective meeting	Enclosure layout		
13	General class	Parallel arrangement	5×5	1100lx
14	Panel discussion	Grouping arrangement		
15	Collective meeting	Enclosure layout		

IV. B. 3) Analysis of Smart Classroom Lighting Experimental Results

Using the EEG signal acquisition and intelligent analysis model proposed in this paper to analyze the brain waves of English learners under different lighting facilities in the smart classroom, the R-value averages of the brain waves of the five subjects were calculated separately. Since both δ and θ bands appear in a non-focused state such as fatigue or drowsiness, they are usually combined to indicate different degrees of fatigue when making evaluations, and are recorded as $R\delta + \theta$. The results of the analysis of the changes in the brain waves of the English learners with the lighting facilities in the smart classroom are shown in Fig. 4, and the results of the analysis under the parallel arrangement, group arrangement, and enclosing arrangement modes are shown in (a)-(c), respectively. In the process of increasing the illumination value level of lighting facilities in the smart classroom, the $R\delta + \theta$ value in the EEG signals of the subjects reflected a positive change followed by a negative change with it. Under the 5×5 light source arrangement scheme (1100lx), the $R\delta + \theta$ levels (0.783, 0.563, 0.513) are all the highest under different classroom arrangement schemes, and the $R\delta + \theta$ levels are all the lowest (0.221, 0.236, 0.162) when the illuminance value is 3×3 (300lx). This indicates that when the illumination setting level in the smart classroom is too high, it is more likely to lead to the occurrence of brain fatigue problem of English learners, and when it is in the middle moderate illumination level, the brain fatigue level will be reduced to some extent. From the results of the analysis of the changes in $R\alpha$ values with illumination values, the $R\alpha$ values of the English language learners of the subjects in each classroom facility arrangement showed a trend of a steady increase followed by a continuous decrease. 700lx and 300lx were the illumination values when the $R\alpha$ value levels were relatively the highest (0.485, 0.473, and 0.498) and the lowest (0.124, 0.145, and 0.169), respectively. The $R\beta$ values were also the same. In terms of the change trend, it also rises first and then decreases, and the parameter level of $R\beta$ reaches the highest and the lowest at 700lx and 300lx illumination respectively, which fully proves that when the illumination level of the lighting facilities in the smart classroom is 700lx, the overall state of the English learning of the subjects is relatively more relaxing, and at this time, their spirit also reaches the state of high excitement, and their brain fatigue value becomes smaller, and the effect of English learning is better. In addition, the results of the analysis also show that the subjects were more relaxed in their English learning. In addition, it can be found from the analysis results that when the lighting facilities in the smart classroom are at the optimal illuminance value of 700lx, the English learners in the form of centralized meeting classroom arrangement have the optimal learning effect, and the R-values of the EEG signals of α-wave, β-wave, and $\delta + \theta$-wave are 0.498, 0.284, and 0.397, respectively.

IV. C. Analysis of the relationship between thermal environment and learning outcomes

IV. C. 1) Thermal Environment Facility Data Collection and Calculation

This experiment adopts the human thermal comfort index PMV proposed by related research to describe the indoor thermal environment. The thermal comfort data of the facilities related to the thermal environment in the classroom are intelligently utilized with the corresponding instruments to measure the relevant physical quantities of the thermal environment under different working conditions, and then the PMV value of the working conditions is obtained through the calculation of the following formula:

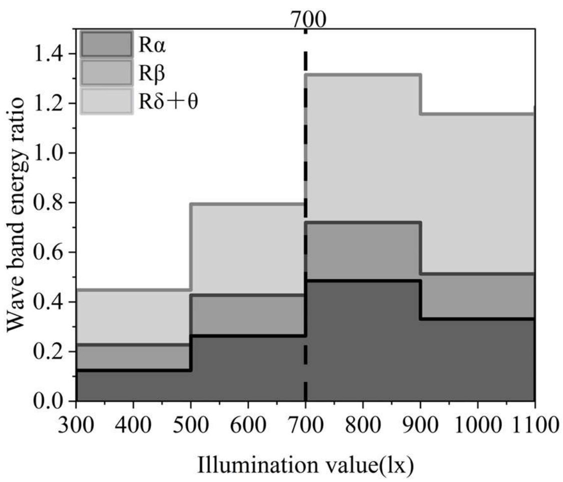
$$M - W - C - R - E = 0 \tag{14}$$

Where M, W, C, R and E represent the metabolic rate of the human body (W/m^2), the mechanical work done by the human body (W/m^2), the convective heat transfer between the surface of the clothed human body and the surrounding surfaces (W/m^2), the radiative heat transfer between the surface of the clothed human body and the surrounding surfaces (W/m^2), and the heat taken away by, sweat, respiration, and evaporation (W/m^2), respectively.

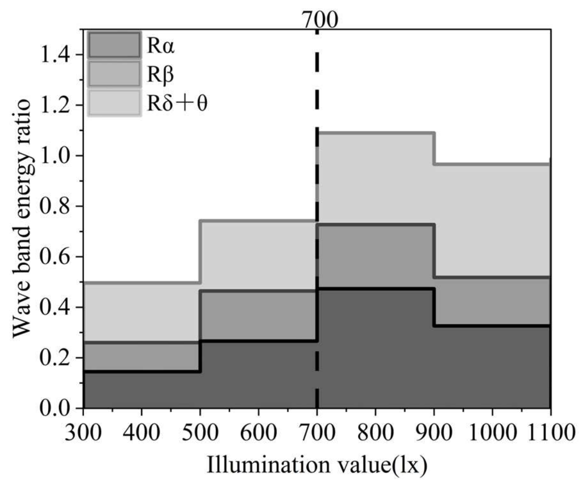
Based on the above theory, six factors affecting the PMV index are also considered comprehensively, so that the mathematical model of the PMV index is deduced as:

$$PMV = \left[0.303 \cdot \exp(-0.036 \cdot M) + 0.028\right] \cdot L \tag{15}$$

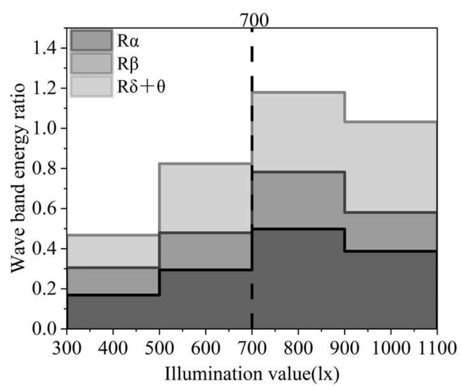
where L is the body load and the expression is:



(a) Parallel arrangement



(b) Grouping arrangement



(c) Enclosure layout

Figure 4: R δ+θ,R α And R β Change results with illumination

$$\begin{aligned} L = {} & \left(M - W\right) - 3.05 \cdot 10^{-3} \cdot \left[5733 - 6.99 \cdot \left(M - W\right) - P_a\right] \\ & -0.42 \cdot \left[\left(M - W\right) - 58.15\right] - 1.7 \cdot 10^{-5} \cdot \left(5867 - P_a\right) \\ & -0.0014 \cdot M\left(34 - t_a\right) \\ & -3.96 \cdot 10^{-8} \cdot f_{cl} \cdot \left[\left(t_{cl} + 273\right)^4 - \left(\overline{t_r} + 273\right)^4\right] \\ & -f_{cl} \cdot h_c \cdot \left(t_{cl} - t_a\right) \end{aligned} \tag{16}$$

The surface temperature of the garment can be obtained by an iterative method:

$$\begin{aligned} t_{cl} &= 35.7 - 0.028 \cdot (M - W) \\ &- I_{cl} \cdot 3.96 \cdot 10^{-8} \cdot f_{cl} \cdot \left[\left(t_{cl} + 273\right)^4 - \left(\overline{t_r} + 273\right)^4 \right] \\ &- I_{cl} \cdot f_{cl} \cdot h_c \cdot \left(t_{cl} - t_a\right) \end{aligned} \tag{17}$$

The surface convective heat transfer coefficient can be found in the same way:

$$h_c = \begin{cases} 2.38\left(t_{cl} - t_a\right)^{0.25} & 2.38\left(t_{cl} - t_a\right)^{0.25} > 12.1\sqrt{v_{ar}} \\ 12.1\sqrt{v_{ar}} & 2.38\left(t_{cl} - t_a\right)^{0.25} < 12.1\sqrt{v_{ar}} \end{cases} \tag{18}$$

Clothing surface area ratios are as follows:

$$f_{cl} = \begin{cases} 1 + 1.29 \cdot I_{cl} & I_{cl} \le 0.078 \\ 1.05 + 0.645 \cdot I_{cl} & I_{cl} > 0.078 \end{cases} \tag{19}$$

The water vapor pressure of air is expressed as:

$$P_a = \varphi_a \cdot \exp\left[\frac{(16.6536 - 4030.183)}{\left(t_a + 235\right)} \right] \tag{20}$$

Where P_a is the pressure of water molecules in the air around the human body (kPa), t_a, $\overline{t_r}$ and t_{cl} represent the temperature of the air around the human body (℃), the average radiation temperature in the room (℃), and the temperature of the outer surface of the clothes (℃). f_{cl} represents the ratio of the surface of the clothed human body to the surface area of the naked human body, h_c, v_{ar} and φ_a are the surface convective heat transfer coefficient (W/ m^2 . ℃), indoor wind speed (m/s) and relative humidity (%).

In this paper, the corresponding experimental environment was constructed, and six environmental parameters, such as air temperature, relative humidity, air flow rate, carbon dioxide concentration, noise and illumination, were measured by instruments. Among them, the first 3 items are controllable factors, which can be regulated by air conditioners, humidifiers, fans and other equipment. The last 3 items are uncontrollable factors, and their actual measurements were recorded in the experiment. In the experiment, by changing the air temperature, relative humidity and air flow rate of the facilities related to the thermal environment in the smart classroom, the working conditions with different thermal environments are built, the six environmental parameters mentioned above are collected, and the PMV value of the current thermal environment is calculated, and the experimental working conditions measured are shown in Table 2. The PMV values (-0.78~0.96) of different working conditions were calculated to be more evenly distributed in the range of (-1, 1) interval, which can summarize the thermal environment in the classroom under most natural conditions.

Table 2: Experimental working conditions table

Operating condition	Temperature (℃)	Humidity (%)	Wind speed (m/s)	CO_2 (ppm)	Light (lux)	Noise (dB)	PMV
1	24.50	43.70	0.39	482.00	347.00	46.20	-0.78
2	22.20	49.00	0.34	461.00	328.00	42.80	-0.52
3	24.90	41.60	0.22	508.00	338.00	45.00	-0.29
4	23.30	44.70	0.22	506.00	322.00	49.20	-0.05
5	22.90	42.10	0.37	491.00	316.00	45.10	0.06
6	22.40	41.70	0.44	489.00	350.00	42.90	0.35
7	25.70	42.00	0.46	487.00	302.00	40.00	0.62
8	25.80	34.90	0.22	496.00	338.00	42.10	0.96

IV. C. 2) Analysis of the relationship between PMV and learning outcomes

The data collected by the EEG intelligent analysis model were organized to obtain the data on the learning effect of English learners under different working conditions as shown in Figure 5. When the indoor environment of the smart classroom is too cold (PMV = -0.78), the preheated environment is in a state of extreme cold discomfort. The subjects' English learners' physical functions decreased due to the cold, and their ability to think and react to external things slowed down, resulting in the learning effect being in a poor state (Rα = 0.319, Rβ = 0.266, Rδ + θ = 0.364). Subsequently, the thermal environment facilities in the smart classroom were modulated so that the PMV gradually increased (-0.78<PMV<-0.29) and was in a cooler state. At this time, the subjects' brains were awake, their minds were agile, and they were more enthusiastic about learning, so their English learning efficiency showed a gradual upward trend, and the R values of EEG signals α and β reached 0.531 and 0.481, respectively, and the Rδ + θ value was reduced to 0.063 when PMV was -0.29. However, with the increase of PMV (-0.29<PMV<0.06), the environment was gradually comforted, and some of them said that "the environment was cooler and cooler, and it was more comfortable". Some subjects said "I want to take a break because the environment is very comfortable", which can reflect that English learning in the current environment is not ideal. When the PMV increases above 0.06, the environment in the smart classroom becomes hot and stuffy, and the subjects are in a state of thermal discomfort and easily feel sleepy, which leads to a gradual decrease in the learning efficiency (the Rα and Rβ decrease rapidly, and the Rδ + θ increases rapidly). It can be seen that the facilities related to the thermal environment in the smart classroom have a great impact on the learning effectiveness of English learners.

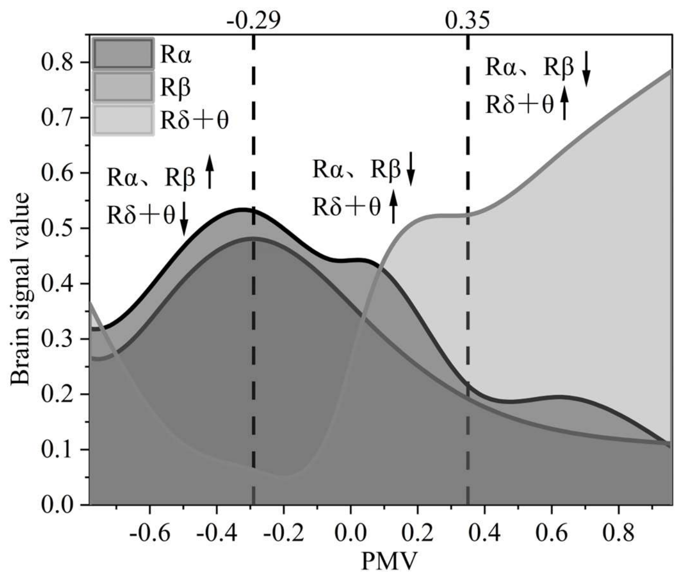


Figure 5: The results of the analysis of the results of different working conditions

IV. D. Correlation analysis between classroom facilities and learning outcomes

The results of the R-value calculation of all EEG signals were subjected to Pearson correlation analysis using SPSS, and the results of the correlation analysis are shown in Table 3. From the results of correlation analysis between lighting facilities and classroom format and English learning effect in the smart classroom, the correlation between Rβ value (r=0.624, P=0.001) and Rθ+δ value (r=0.649, P=0.004) and the light source arrangement of the lighting facilities is significant. The correlation between Rα value and the light source arrangement (r=0.326) and classroom format (r=0.295) were not significant (p=0.623, 0.085>0.05). In the correlation analysis between the thermal environment facilities of the smart classroom and the learning effect of English learners, it can be found that there are significant correlations between the thermal environment facilities and the Rα, Rβ and Rθ+δ values, and the correlation coefficients are in the range of 0.544-0.624, which indicates that there is a greater relationship between the thermal environment facilities and the learning effect.

Table 3: Correlation analysis results

Classroom facilities		Brain electrical signal		
		Rα	Rβ	Rθ+δ
Light source layout	Correlation coefficient	0.326	0.624	0.649
	P	0.623	0.001	0.004
Classroom form	Correlation coefficient	0.295	0.554	0.824
	P	0.085	0.042	0.012
Thermal environment	Correlation coefficient	0.624	0.593	0.544
	P	0.032	0.025	0.016

V. Conclusion

In this study, the brainwave signals of English learners are collected and processed for feature extraction and classification recognition, reflecting the effect of English learning according to the changes of specific EEG signals and realizing the intelligent analysis of English learning effect. The relationship between two diverse facilities, lighting and thermal environment regulation, and the learning effect in the smart classroom is analyzed, and the results show that:

(1) The R-value levels of students' EEG signals $\delta + \theta$ were all lowest at an illumination value of 300lx for the smart classroom lighting facilities, and the learning effect was poor. The EEG signals α and β levels are relatively highest when the illuminance value is 700lx, and the R-values in parallel rows, group discussion rows and centralized classroom facility rows are 0.485, 0.473, 0.498, and 0.235, 0.254, and 0.397, respectively.The R-values of EEG signals α and β of English language learners in the smart classroom with the value of the PMV of the thermal environment in the smart classroom being -0.29 are up to 0.531 and 0.481, and the value of $R\delta + \theta$ decreased to 0.063, when the English learning effect was the best.

(2) Significant correlations were found between $R\beta$ values ($r=0.624$, $P=0.001$) and $R\theta+\delta$ values ($r=0.649$, $P=0.004$) and the light source arrangement of the lighting facilities, in addition to a greater relationship between the thermal environmental facilities and the learning outcomes.

(3) Lighting facilities and thermal environment regulation facilities in smart classrooms, as an important part of classroom environment facilities, play an important role in improving the learning effect of English learners. Future research can start from improving the degree of standardization of facilities and other aspects to promote the further construction and development of diverse facilities in smart classrooms. This study also has some limitations, and similar studies can be conducted by enlarging the sample size, in addition, the period of the study can be longer and the measurement period can be longer.

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