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Assessment of Smart Learning Environments in Higher Educational Institutions: A Study Using AHP-FCE and GA-BP Methods

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ABSTRACT The application of information and communications technology (ICT) in higher educational institutions has led to the transformation of the environment from digital to smart. The assessment of smart learning environments will highlight the advantages and disadvantages of its construction results and help establish a sustainable space for students' personalized study. However, the construction level and application effect are difficult to judge thoroughly, so a comprehensive evaluation method is needed. By rethinking the structure of a smart learning environment (the physical space, resource space and social space), this paper uses analytic hierarchy process–fuzzy comprehensive evaluation (AHP-FCE) and genetic algorithm–back propagation (GA-BP) neural network algorithm methods to assess the environment, with the aim of determining their scope of application and providing suggestions for updating the environment construction process. The questionnaire results of 300 students at Central China Normal University (CCNU) were analyzed with an evaluation index system that was collected by expert scoring. The results showed that the AHP-FCE model can simultaneously obtain multiple results but can be influenced by subjective factors, whereas the GA-BP-based model can make the evaluation process easier and improve fault tolerance. The results also indicated that the classrooms need to be modified in terms of the perception infrastructure and resource modules to provide students with a more suitable and comfortable learning space. We hope the study can provide a reference and inspiration for the construction and assessment of smart learning environments.

INDEX TERMS Smart learning environments, assessment, analytic hierarchy process, back propagation, higher education.

I. INTRODUCTION

Information and communication technology (ICT) has been widely employed in the field of higher education [1]. Providing a sustainable environment in which students have sufficient educational resources and opportunities has become a research focus. However, traditional classrooms have been unable to support the development of teaching models with information technology. To adapt to the changing demands of learning institutions and provide a dynamic learning atmosphere, the learning environment has begun to shift from digital to smart [2], [3]; thus, the smart learning environment emerged. Scholars worldwide have explored the smart learning environment [4]–[6].

From the perspective of learners, the smart learning environment should provide a satisfactory learning experience. The smart learning environment supports the training model in an information environment, breaks the constraints of the traditional learning environment, and fully considers the learners' experience in the learning process from both the physical perspective and the psychological perspective to create a physically and mentally comfortable environment for individuals or groups in learning activities. From the perspective of technology, the smart learning environment constructed via information technologies, such as artificial intelligence, virtual reality, and the Internet of Things (IoT) [7], is intelligent, interconnected, and convenient, which

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enables it to perceive, diagnose, and analyze the learning process. Information resources can be intelligently enhanced due to data collection and aggregation in the smart learning environment. The interconnected environmental terminal equipment makes classroom management and control intelligent, which intelligently influences learners' behaviors. From the perspective of classroom activities, the smart learning environment should be able to continuously cultivate and enhance learners' ''smartness.'' As classroom teaching becomes less restricted by time and space, the teaching model has gradually changed from teacher-centered to student-centered. Therefore, it is crucial to construct a diversified learning space for teachers and students to promote smart teaching innovations and achieve smart learning.

Presently, the construction of smart learning environments in primary and secondary schools in China is mostly based on improving the physical environment [8]. Due to restrictive factors, such as learners' age and learning abilities, the teaching mode is still dominated by teachers. However, learners in colleges and universities have higher-order thinking abilities, tend to learn independently and have an urgent need for resources and a sustainable, personalized learning space.

In higher educational institutions, the smart learning environment is an important foundation for students' personalized learning in the process of educational informatization. Evaluating the construction results of the smart learning environment has a positive effect on building a suitable environment for ability training. Since the emergence of the smart learning environment, the evaluation and research regarding its promotion of student learning effects and interaction conditions have been ongoing and are mainly carried out via classroom observations, questionnaire surveys, interviews and other methods. Related research on smart learning environments has focused on the reconstruction of learning spaces [9], [10], digital resource integration [11], [12], teaching mode applications [13]–[16] and subject teaching innovations [17]–[19], whereas evaluation research has focused on the adoption of scales or analysis of cases to evaluate the smart learning environment.

As a new type of interactive learning environment, the smart learning environment is different from traditional learning environments, but its purpose is still to support students' learning [20]. Therefore, the evaluation of the construction of a smart learning environment should not only consider the characteristics of the environment but also evaluate its impact on students' learning motivation. However, few comprehensive evaluations of smart learning environments that take into account all sustainable aspects. In this paper, we adopt two different evaluation models to attempt to maintain all the aspects of the environment in universities and colleges and identify the shortcomings of the present construction.

The contributions of this paper are listed as follows: First, we propose two evaluation systems based on the analytic hierarchy process–fuzzy comprehensive evaluation (AHP-FCE) method and the genetic algorithm–back propagation (GA-BP) method, whose index system is collected by a group of consulting experts from three different fields. This group consists of experts in the education technology industry, technical experts in education information enterprises, and experienced frontline teachers. Second, we apply the evaluation systems to an analysis of questionnaire survey data on the smart classrooms of Central China Normal University (CCNU) and then evaluate the environment. Furthermore, we draw some conclusions about how the construction should be updated based on the detailed results of the evaluation.

This paper is structured as follows: Section 2 provides a literature review and summarizes the results of previous studies; Section 3 introduces two environmental evaluation models for the research and their corresponding components; Section 4 describes the evaluation index system, research environment and data collection utilized in the research; Section 5 gives the data analysis and a discussion of the results of the two evaluation models, as well as improvement suggestions; Section 6 draws conclusions from the research and proposes the future development directions of the field.

II. LITERATURE REVIEW

Smart learning environments is difficult to be defined uniformly, because their meanings will change as a function of theoretical (e.g., cognitive psychology, computer sciences and AI) breakthroughs and technological (e.g., learning technology) advances. A wide variety of definitions of the smart learning environment has been given by previous scholars from different perspectives. For instance, from a technical perspective, smart learning environment integrates physical and virtual learning environments [21], which is usually promoted by information technology [22]–[24] and therefore contains a plenty of information devices (such as different kinds of supporting terminals and wireless devices) aiming to provide supports for both traditional and non-traditional [25], [26] learning. From a learning perspective, Gros [27] and Hoel and Mason [28] pointed out that the smart learning environment is not only a system that can be applied for learning anytime and anywhere, but also an adaptive support environment that can actively provide learning service according to the location, time and other requirements.

The learning environment needs assessment as it is related to students' well-being and learning performance [29]. However, it is a complex problem to study the influence of learning environment on students, which is one of the possible reasons why both the connections between the design and use of learning environment in higher educational institutions and the production of teaching, learning and research are not well understood [30]. In recent years, many scholars have carried out evaluations of the learning environment, which mainly focuses on the following four issues separately, (i) environmental comfort [31]–[33], (ii) energy efficiency of classroom buildings [34], [35], (iii) digital learning tools [36], [37], and (iv) technology-enabled classroom [38]–[40]. There is a lack of comprehensive study that considers all the above four

issues, i.e. evaluates the entire construction of smart learning environments.

From a methodological perspective, in most of the studies reviewed the following two general steps are involved in environmental evaluation. First, user responses are collected by assessment questionnaires, which usually have certain assessment scales defined by researchers or experts [41] [42] in advance. Second, the collected data is analyzed by various statistical methods, such as, descriptive statistics, correlation analysis, analysis of variance, regression analysis, hypothesis testing, and so on [29]–[33]. It should be noted that, in the case of comprehensive evaluation, which is actually similar as this study, the most common used methods include grey evaluation method [43], AHP [44], FCE [45], and AHP-FCE. Grey evaluation method [46] is an effective and subjective method, in spite of the potential advantages of simplicity and convenience in calculation, the disadvantages also exist including for example that it is relatively difficult to get optimal evaluate indexes. Particularly, in the field of learning environment assessment, AHP and FCE methods have been used to evaluate acoustical environment [47], indoor lighting quality [48], and classroom course website quality [49]. Although AHP-FCE has not been applied in the field of learning environment assessment, as a combination of the two methods, it has been applied extensively in other kinds of environmental evaluation, such as suitability evaluations of urban construction land [50], risk evaluations in power transmission construction [51], and risk assessment models for hazard installations in lake basins [52]. However, as demonstrated in [53] that the results obtained by AHP-FCE are also considered subjective, because they are highly susceptible to experts' scoring. Therefore, to gain a suitable method for learning environment assessment, AHP-FCE needs to be further compared and supplemented with an objective evaluation method.

Under such background, BP neural network [54] come into our sight. With the rapid development of artificial intelligent, BP neural network has been widely used in evaluation research [55]–[57], due to its outstanding advantages, including strong nonlinear mapping ability, strong fault tolerance and strong dynamic adaptive ability. Regarding the field of learning environment assessment in particular, BP neural network could help gain a new insight, because it has rarely been used in this field. Therefore, a combination of AHP-FCE and GA-BP is employed in this study. On the one hand, the traditional AHP-FCE method is used to evaluate the learning environment initially; On the other hand, the GA-BP method is further used to make up for the disadvantage caused by the traditional method.

III. EVALUATION MODELS AND PRINCIPLES

In this section, we present the detailed data processing steps and principles for the adopted methods (AHP-FCE and GA-BP). Important components, such as the formula and matrix for the indexes calculation step and the flowchart, are also presented and explained. The main contribution of this section is that a novel evaluation approach is proposed based on a combination of AHP-FCE and GA-BP, to gain a holistic and systematic evaluation of the smart learning environment. To the best of our knowledge, this is for the first time that (i) such combination is used for evaluation in this field and (ii) a novel index evaluation system is constructed by integrating their respective characteristics. To be specific, with regards to the traditional AHP-FCE, AHP and FCE are used to set the weights of evaluation indexes and construct the evaluation matrix respectively. With regards to GA-BP, BP and GA are used to construct the advanced evaluation model and optimize the hyperparameters respectively.

A. EVALUATION MODEL BASED ON AHP-FCE

The evaluation model of the smart learning environment based on AHP-FCE is based on the FCE for quantitative scoring, combined with the AHP to determine the weights of the evaluation indicators.

1) CONFIRMING THE INDEX WEIGHTS IN THE AHP

The AHP is a decision analysis method that combines qualitative and quantitative methods. The detailed steps are described as follows:

Step 1: Constructing the judgement matrix

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{1}$$

The judgement matrix A is an n × n matrix; its main diagonal entries are all 1, which satisfies $a_{ij} = \frac{1}{a_{ji}}$, i ≠ j and $a_{ij} > 0$, I, j = 1, 2…, n. For example, in the judgement matrix of the indices at the first level, a_{ij} indicates the ratio of the relative importance of row index B_i and column index B_j. This paper uses the 1−9 scale method to assign the degree of importance; the specific meaning is shown in Table 1.

STEP 2: Weight Calculation. The weights of the indices in the smart learning environment are calculated according to the following steps:

Normalize the elements in every column of the judgement matrix, as shown in equation (2):

$$\bar{a}_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}}, \quad i, j = 1, 2, \cdots, n \tag{2}$$

Sum the normalized judgement matrix line by line, as shown in equation (3):

$$\bar{w}_i = \sum_{j=1}^{n} \bar{a}_{ij}, \quad i = 1, 2, \cdots, n \tag{3}$$

Normalize $\bar{w}_i$, as shown in equation (4):

$$w_i = \frac{\bar{w}_i}{\sum_{i=1}^{n} \bar{w}_i}, \quad i = 1, 2, \cdots, n \tag{4}$$

Next,w_i is the weighted result of every index in the judgement matrix.

STEP 3: Consistency Test. to examine whether the weights of the indices is plausible, the relative weights are input

TABLE 1. Meaning of the scale.

Scale	Meaning
1	Comparing the two factors, both are equally important
3	Comparing the two factors, the former is slightly more important than the latter
5	Comparing the two factors, the former is more important than the latter
7	Comparing the two factors, the former is certainly more important than the latter
9	Comparing the two factors, the former is much more important than the latter
2,4,6,8	The judgement is between the two adjacent judgements
reciprocal	If the ratio of element i's importance to element j's importance is a_{ij}, then the ratio of element j 's importance to element i's importance is $a_{ji} = 1/a_{ij}$

into the following formulas. The consistency index (CI) and consistency ratio (CR) are two important values in the consistency test of the AHP.

Calculate the largest characteristic root λ_{max}, where n is the number of indices, as shown in equation (5):

$$\lambda_{max} = \frac{1}{n}\sum_{i=1}^{n}\frac{(AW)_i}{w_i} \tag{5}$$

A is the judgement matrix, $W = [w_1, w_2, \cdots, w_n]^T$, $(AW)_i$ is the i-th element after the matrix operation between A and W, and w_i represents the weights of the indices.

CI, which measures the divergence of judgment matrix away from the consistency, is defined as follows, where n is the number of indices:

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{6}$$

CR is introduced, which is to determine the ratio of CI to the average random consistency index of the judgement matrix (RI). CR is expressed as:

$$CR = \frac{CI}{RI} \tag{7}$$

RI is the random consistency index of the judgement matrix. When CR is less than 0.1, the consistency of the judgement matrix is acceptable; otherwise, the judgement matrix needs to be adjusted until the consistency is satisfactory.

2) FCE METHOD

The fuzzy comprehensive evaluation method is an application of fuzzy mathematics, which is suitable for solving various non-deterministic problems. Hence, we adapted this method for the smart learning environment.

STEP 1: Establishing the Evaluation Factor Set. Assuming that the evaluation object has m evaluation indices, we record it as $U = \{u_1, u_2, \cdots, u_m\}$. For a multi-level evaluation index system, the evaluation factors can be divided into first-level evaluation factors according to their properties, the first-level evaluation factors can be divided into the corresponding second-level evaluation factors, etc. This process is written as $U = U_1 \cup U_2 \cdots \cup U_t$, where

$$U_i = \{u_{i1}, u_{i2}, \cdots, u_{im}\}, U_i \cap U_j = \emptyset, \quad i \neq j; i, \ j = 1, 2, \cdots, t \tag{8}$$

STEP 2: Establishing the Evaluation Set V. In this paper, we consider $V = \{v_1, v_2, v_3, v_4, v_5\}$ as {excellent, good, medium, poor, and very poor}.

STEP 3: Establishing the Fuzzy Relation Matrix R.

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix} \tag{9}$$

STEP 4: Determining the Weight Vector W. The overall weight vector of the smart learning environment is W, and the weight vectors of the first-level indices are W_1, W_2, W_3.

STEP 5: Calculating the Synthetic Result Vector B. The evaluation result vector B_1 of the evaluation factor U_1 is

$$B_1 = W_1 \circ R_1 = \begin{bmatrix} a_1, & a_{2,\cdots}, & a_n \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix} = \begin{bmatrix} b_1, & b_{2,\cdots}, & b_m \end{bmatrix} \tag{10}$$

where $\circ$ represents the fuzzy operation symbol and $b_j = \sum_{i=1}^{n}(a_i r_{ij}), j = 1, 2, \cdots, m$, B_2 and B_3 can be calculated in the same way. Therefore, the comprehensive evaluation matrix of the smart learning environment is $R = [B_1, B_2, B_3]^T$. The comprehensive evaluation result vector of the smart learning environment is $B = W \circ R$.

STEP 6: Calculating the Evaluation Result Score. To obtain the exact score value, the evaluation set is quantified, as shown in Table 3.

The evaluation set is defined as $N = [0.95, 0.825, 0.675, 0.55, 0.25]$; the overall evaluation result of the smart learning environment is $B \cdot N = B \times N^T$; and each first-level index can be obtained in the same way.

TABLE 2. Random consistency index.

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.46	1.49

B. EVALUATION MODEL BASED ON GA-BP

In the GA-BP method, factor analysis was adopted to reduce the indicators, and the evaluation model was established

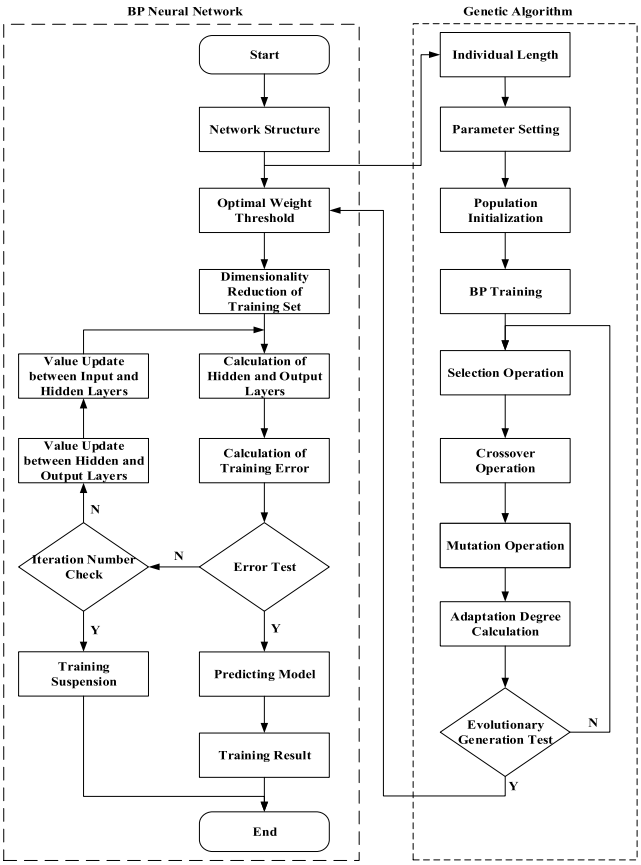

FIGURE 1. BP neural network flow chart after parameter optimization.

in conjunction with the BP neural network algorithm. The parameters of the BP neural network were optimized using genetic algorithms.

1) PRINCIPLES OF BP AND PARAMETER OPTIMIZATION WITH THE GA

BP network is trained according to the error BP algorithm. Error BP means that when the output layer cannot obtain the expected output, the error between the actual output and the expected output must be back propagated, and the weights and thresholds of each layer must be adjusted. After repeated training and learning, the training is terminated when the pre-set requirements are reached. The BP neural network performs local optimization well, so the initial settings of the network are especially important. Having different initial values will cause the BP neural network to converge to different local minimums. In order to solve the problem, this paper uses GA which is an optimization algorithm widely employed in combinatorial optimization problems [58]. The process of using a GA to optimize the parameters of the BP neural network is shown in Figure 1.

2) FACTOR ANALYSIS PROCESS

Additionally, the number of neurons in the hidden layer of the BP neural network affects the learning rate and generalization ability of the network. By incorporating factor analysis (FA) to reduce the dimension of the secondary indicators, multiple indicators are converted to a few comprehensive indicators. We can reduce the input variables of the BP neural network.

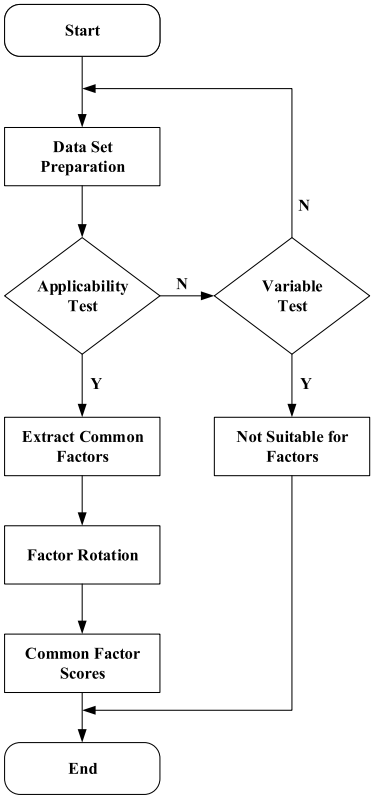

FIGURE 2. FA flowchart.

TABLE 3. Evaluation set quantification table.

Grade	excellent	good	medium	poor	very poor
Interval	[0.9-1]	[0.75-0.9)	[0.6-0.75)	[0.5-0.6)	[0-0.5)
Value	0.95	0.825	0.675	0.55	0.25

FA is an extension of principal component analysis. With the idea of dimensionality reduction, several new variables (common factors) that contain the original variable information are extracted from multiple variables. This multivariate statistical analysis method classifies the original variables by studying the internal correlations among them; the strongly correlated variables belong to the same common factor. The statistical analysis software SPSS 24.0 is adopted in this paper to perform FA of the index data. A general flow chart of FA is shown in Figure 2.

IV. EMPIRICAL APPLICATION OF THE EVALUATION MODEL

A. EVALUATION INDEX SYSTEM

To construct a smart learning environment evaluation index system, it is necessary to not only take into account the integrity and complexity but also comprehensively consider the actual operational complexity of the evaluation indices.

A set of basic evaluation index systems is proposed in this paper to conduct analysis experiments. Based on the understanding of the smart learning environment model, we consider only the constituent elements of the model as the evaluation dimension and incorporate them into the smart learning environment evaluation index system as first-level indices.

1) PRELIMINARY INDEX SYSTEM

To better illustrate the details of the smart learning environment, this paper divides the environment into three dimensions (physical space, resource space and social space). Physical space, as a setting for formal learning, is mainly composed of the teaching infrastructure and learning equipment in a network environment. The second-level indices in the physical space are constructed with reference to the relevant research results obtained by applying the smart learning environment. The resource space is an important tool for achieving the virtual and real integration of the smart learning environment. This space consists of a large number of resources and a supporting platform whose construction is similar to that of a website. The evaluation index can refer to related literature on website evaluation, and the information resource evaluation index can extract key indices from the resource construction literature. The social space conducts interactive exchanges between students and teachers via computers. With the premise of fully considering the learning experience of learners, the second-level indices in the social space dimension are sorted. A preliminary evaluation index system of 3 first-level indices and 28 second-level indices is formed.

2) EXPERTS CONSULTATION

The Delphi method [59] is adopted to further screen the indices as follows. First, this study selected personnel with extensive experience in the construction of smart classrooms to form an advisory group of 20 experts. In terms of number, university teachers accounted for 40% and technical personnel accounted for 60%; in terms of positions, 40% were professors, 40% were professional and technical personnel, and 20% were graduate students (technical support). Second, the questionnaire was sent anonymously to the selected experts to score each indicator. Third, statistical analysis of the returned questionnaires was performed to check whether the requirements of the Delphi method were met. Since in our study the Delphi method were not met in the 1st round consulting, the second round was launched soon after necessary modifications were made in the evaluation indicators accordingly. Finally, when the Delphi method were met, the multi-space integrated smart learning environment evaluation indicators were determined. To clarify,

According to the results of the first round of expert consultation, the coefficient of variation of three indicators (Practicality, Technology Architecture, and Plurality) is greater than 0.30, which indicates that experts have different opinions of these five indicators. The coordination coefficient of all indicators is less than 0.50, so a second round of expert consultation is required. For example, some experts pointed out that Practicality is not representative of the construction of the physical space, and some experts believe that learners cannot accurately grasp the profound meaning of the Technology Architecture. When judging indicators, experts may not be able to give a reasonable score due to ambiguity. Some experts pointed out the problem of overlapping content between Magnanimity and Plurality, so we exchange Plurality with Layout.

After summarizing the opinions of the experts in the first round, a fixed questionnaire was sent to the experts in the second round of consultation. As a result, the coefficient of variation of all indicators is below 0.25, and the coordination coefficient is higher than 0.50, which indicates that the expert opinions in the second round of consultation tend to be consistent; there is a high degree of agreement with the designed secondary indicators and the third round of expert consultation is not required.

After two rounds of expert consultation, an evaluation index system for a smart learning environment with 3 first-level indices and 26 second-level indices is established, as shown in Table 4.

Each indicator of the final version of the evaluation system is shown as follows:

- **Design C_1:** the physical space is designed in favor of teaching and learning.
- **Structure C_2:** the overall layout of the physical space is reasonable and adaptable to different teaching activities.
- **Comprehensiveness C_3:** the whole infrastructure of the physical space is complete.
- **Humanization C_4:** the facilities and equipment in the physical space are designed in a humanitarian way.
- **Diversity C_5:** the physical space is equipped with a variety of equipment for teaching and learning.
- **Intelligence C_6:** a range of intelligent functions can be implemented in the physical space.
- **Perception C_7:** the physical space is capable of environmental perception.
- **Accessibility C_8:** the physical space provides easy access to the equipment that supports learners during teaching activities.
- **Compatibility C_9:** the supporting platform is compatible with different resolutions, systems and browsers and can support access from a variety of mobile terminals.
- **Functionality C_{10}:** the supporting platform can meet different learning needs and respond quickly to users.
- **Safety C_{11}:** the supporting platform has a defense system that ensures whether critical resource data are backed up.
- **Operability C_{12}:** the supporting platform can be easily operated consistent with the cognitive rules of most users.

TABLE 4. Smart learning environment evaluation index system.

First level	Second level
Physical space B_1	Design C_1, Structural C_2, Comprehensive C_3, Humanization C_4, Diversity C_5, Intelligence C_6, Perception C_7, Accessibility C_8,
Resource space B_2	Compatibility C_9, Functionality C_{10}, Safety C_{11}, Operability C_{12}, Stability C_{13}, Connectivity C_{14}, Magnanimity C_{15}, Scientificity C_{16}, Openness C_{17}, Layout C_{18},
Social space B_3	Application awareness C_{19}, Teaching methods C_{20}, Information integration C_{21}, Technical mastery C_{22}, Interaction ability C_{23}, Willingness to learn C_{24}, Classroom performance C_{25}, Cognitive load C_{26},

*In the preliminary index system, there were 28 indices. C_9 is Practicality, C_{19} is Plurality and C_{20} is Technology Architecture.

- **Stability C_{13}:** the supporting platform can process a large user volume and will not cause an unexpected delay or abnormal incident during operation.
- **Connectivity C_{14}:** the source nodes are dynamically linked to form a knowledge network.
- **Magnanimity C_{15}:** a large amount of online and offline data resources can be provided to meet the learning needs of different learning communities.
- **Scientificity C_{16}:** the knowledge points of the teaching resources are organized in a scientific or logical way and the content has high authority.
- **Openness C_{17}:** the resources are shared and accessible to all users.
- **Layout C_{18}:** the presentation styles of the resources match the content, whether the layout is aesthetic and reasonable, and whether the content is expressed in a straightforward and comprehensible way.
- **Application awareness C_{19}:** the teachers have accepted a new learning environment, and they still use the smart classroom as a multimedia classroom.
- **Teaching methods C_{20}:** the teachers can conduct diverse teaching activities that are not bound by the time and place of learning.
- **Information integration C_{21}:** the teachers can enrich the teaching content by integrating necessary informational resources based on the course requirements.
- **Technical mastery C_{22}:** the teachers are proficient in operating various teaching equipment in practice.
- **Interaction ability C_{23}:** the students have increased interactions with their teachers and classmates to replace the traditional spoon-feeding method.
- **Willingness to learn C_{24}:** students are learning with more motivation, interest and investment in class.
- **Classroom performance C_{25}:** students look at the teachers more frequently and decide whether they have an active part in thinking, discussing and answering questions.
- **Cognitive load C_{26}:** the learning effectiveness of students is impacted because they spend too much time processing superabundant information or information presented in an improper way.

B. ENVIRONMENT INTRODUCTION

As the main application of the learning environment, many universities have explored the construction and application of smart classrooms. In recent years, CCNU has actively promoted the integration of information technology with education and teaching, reformed the learning environment, and built dozens of smart classrooms. With optimized infrastructure and high-quality teaching resources, this kind of smart classroom focuses on teacher-student interaction and student-student interaction and can also be connected to external classrooms to achieve remote synchronous teaching. In this paper, the smart learning environment in a university that is evaluated is the smart classroom of CCNU. The actual scene is shown in Figure 3.

FIGURE 3. Smart classroom scene.

C. DATA PREPARATION

In this paper, the secondary indices in the evaluation index system were translated into corresponding questionnaire items. (Refer to Appendix A) The actual value of each index was obtained based on the learners' learning experience in the smart classroom. The questionnaire contained three main parts: the description of the questionnaire, personal information, and index score. The personal information included the

grade, major and gender of each student; the index scoring options were divided into "strongly disagree," "disagree," "not sure" "agree," and "strongly agree" according to a Likert scale, in which these options corresponded to 1-5 points.

Reliability test: The reliability test refers to the reliability of a questionnaire, which is measured by Cronbach's alpha. The coefficients of the three dimensions are 0.829, 0.871 and 0.811, and the overall Kronbach's coefficient is 0.910, which indicates that the questionnaire has high reliability.

Validity test: The validity test refers to the validity of the questionnaire, which is measured by the Kaiser-Meyer-Olkin (KMO) value, the significance level of the Bartlett sphere test, and the factor cumulative variance contribution rate. The three dimensions and the overall KMO value are greater than 0.80; the significance level is less than 0.05; and the factor cumulative variance contribution rate is higher than 60%., Thus, the questionnaire is recognized as valid.

The formal questionnaires included paper and electronic versions, which were distributed to students who had attended classes in the smart classroom in the CCNU. A total of 210 paper questionnaires were issued, and 204 questionnaires were recovered. Electronic questionnaires were distributed by the questionnaire star platform, and 132 questionnaires were recovered. The return rate of this questionnaire was therefore 93.3%. Invalid questionnaires with missing answers and mostly consistent scores were eliminated, and 300 valid questionnaires were retained. The questionnaires revealed that the following proportions of students in different grades: freshman—36.00%, sophomore—33.67%, junior—24.33%, and senior—6.00%. Among them, 54.67% of the students majored in science and engineering, while the remaining 45.33% of students majored in the liberal arts. For the gender distribution, 68.67% of the students who participated in the questionnaire were female. The results of the questionnaire are counted and employed as a data set for further evaluation and analysis.

V. RESULTS ANALYSIS

In this section, first, the evaluation results obtained by AHP-FCE and GA-BP models are presented respectively. Subsequently, a comparison between these two models is made, and the improvement suggestions for the classroom of CCNU is proposed, on this basis and limitations of this study are discussed.

A. EVALUATION MODEL BASED ON AHP-FCE

1) INDEX WEIGHTS

The CR values of the four judgement matrices constructed in this paper were all less than 0.1, which passed the consistency test. The calculation results are summarized in Table 5

2) CALCULATING THE EVALUATION RESULTS

Summarizing the evaluation of the second-level indices, the fuzzy relationship matrix of the first-level indices is obtained as follows:

$$R_1 = \begin{bmatrix} 0.307 & 0.610 & 0.056 & 0.017 & 0.010 \\ 0.287 & 0.600 & 0.077 & 0.033 & 0.003 \\ 0.280 & 0.563 & 0.114 & 0.043 & 0.000 \\ 0.367 & 0.493 & 0.097 & 0.040 & 0.003 \\ 0.267 & 0.503 & 0.183 & 0.047 & 0.000 \\ 0.157 & 0.387 & 0.373 & 0.080 & 0.003 \\ 0.180 & 0.303 & 0.414 & 0.103 & 0.000 \\ 0.233 & 0.457 & 0.247 & 0.063 & 0.000 \end{bmatrix}$$

$$R_2 = \begin{bmatrix} 0.187 & 0.393 & 0.337 & 0.070 & 0.013 \\ 0.103 & 0.380 & 0.340 & 0.167 & 0.010 \\ 0.103 & 0.373 & 0.454 & 0.060 & 0.010 \\ 0.103 & 0.480 & 0.250 & 0.150 & 0.017 \\ 0.073 & 0.260 & 0.420 & 0.220 & 0.027 \\ 0.107 & 0.580 & 0.267 & 0.043 & 0.003 \\ 0.123 & 0.603 & 0.224 & 0.047 & 0.003 \\ 0.117 & 0.543 & 0.267 & 0.070 & 0.003 \\ 0.100 & 0.324 & 0.470 & 0.093 & 0.013 \\ 0.147 & 0.657 & 0.160 & 0.033 & 0.003 \end{bmatrix}$$

$$R_3 = \begin{bmatrix} 0.073 & 0.437 & 0.220 & 0.257 & 0.013 \\ 0.200 & 0.543 & 0.203 & 0.050 & 0.003 \\ 0.133 & 0.540 & 0.247 & 0.077 & 0.003 \\ 0.114 & 0.490 & 0.240 & 0.143 & 0.013 \\ 0.087 & 0.453 & 0.320 & 0.123 & 0.017 \\ 0.093 & 0.517 & 0.266 & 0.107 & 0.017 \\ 0.103 & 0.493 & 0.290 & 0.107 & 0.007 \\ 0.070 & 0.464 & 0.280 & 0.183 & 0.003 \end{bmatrix}$$

From the matrix, the first-level indices and the overall weight vectors of the smart learning environment are obtained as follows:

$$W_1 = [0.098 \quad 0.193 \quad 0.039 \quad 0.145 \quad 0.036 \quad 0.177 \quad 0.284 \quad 0.028]$$
$$W_2 = [0.065 \quad 0.131 \quad 0.215 \quad 0.032 \quad 0.048 \quad 0.123 \quad 0.230 \quad 0.111 \quad 0.029 \quad 0.016]$$
$$W_3 = [0.047 \quad 0.195 \quad 0.062 \quad 0.109 \quad 0.269 \quad 0.097 \quad 0.187 \quad 0.034]$$

We perform fuzzy calculations on the weight vectors and the fuzzy relationship matrix to obtain the fuzzy comprehensive evaluation result vector:

$$B_1 = [0.245 \quad 0.454 \quad 0.240 \quad 0.062 \quad 0.003]$$
$$B_2 = [0.114 \quad 0.474 \quad 0.320 \quad 0.082 \quad 0.008]$$
$$B_3 = [0.117 \quad 0.493 \quad 0.270 \quad 0.112 \quad 0.010]$$
$$B = [0.169 \quad 0.472 \quad 0.268 \quad 0.084 \quad 0.007]$$

After calculating the fuzzy comprehensive evaluation result vector B and the quantified evaluation set N, the evaluation results of three dimensions are listed as follows: physical space—0.801, resource space—0.764, and social space—0.762. The overall evaluation result of the smart learning environment is 0.779.

TABLE 5. Index weights.

First-level indices	Weights	Second-level indices	Weights
Physical SpaceB_1	0.413	Design C_1	0.098
		Structure C_2	0.193
		Comprehensiveness C_3	0.039
		Humanity C_4	0.145
		Diversity C_5	0.036
		Intelligence C_6	0.177
		Perception C_7	0.284
Resource SpaceB_2	0.260	Accessibility C_8	0.028
		Compatibility C_9	0.065
		Functionality C_{10}	0.131
		Safety C_{11}	0.215
		Operability C_{12}	0.032
		Stability C_{13}	0.048
		Connectivity C_{14}	0.123
		Magnanimity C_{15}	0.230
		Scientificity C_{16}	0.111
Social SpaceB_3	0.327	Openness C_{17}	0.029
		Layout C_{18}	0.016
		Application awareness C_{19}	0.047
		Teaching methods C_{20}	0.195
		Information Integration C_{21}	0.062
		Technical mastery C_{22}	0.109
		Interaction ability C_{23}	0.269
		Willingness to learn C_{24}	0.097
		Classroom performance C_{25}	0.187
		Cognitive load C_{26}	0.034

B. EVALUATION MODEL BASED ON GA-BP

1) INPUT VARIABLE EXTRACTION

The three dimensions of KMO measurement and Bartlett's sphere test meet the requirements, which indicates that the data in the questionnaire are suitable for FA. SPSS 24.0 is adopted to extract the common factors. The optimal oblique method is used to rotate and name each common factor and calculate the scores. Two common factors are extracted for each dimension. The six common factors of infrastructure, teaching equipment, information resources, support platforms, learners, and educators are employed as the input variables of the GA-BP evaluation model, and the factor scores are applied as the values of the input variables.

2) CALCULATING THE EXPECTED VALUES

The training samples of supervised learning require inputs and expected outputs so that an optimal model can be obtained via training. However, there is no expectation value that can be directly utilized in the smart learning environment. This paper uses the catastrophe progression method to determine the expectation value. The relative importance in this paper refers to the cumulative variance contribution rate of FA to make the target value solution more scientific and reasonable.

3) MODEL TRAINING AND TESTING

Figure 4 shows the training results of the BP neural network. It can be seen that the fit between the predicted value and the true value is improved. Figure 5 shows that the fitting degree of the BP neural network training set after GA optimization is 98.137%; the fitting degree of the test set is 97.643%; and the fitting degree of all samples is 96.67%. The trained network needs to test the performance of the model with the test set.

As shown in Figure 5, during the simulation prediction process of the network, a small number of samples fluctuate

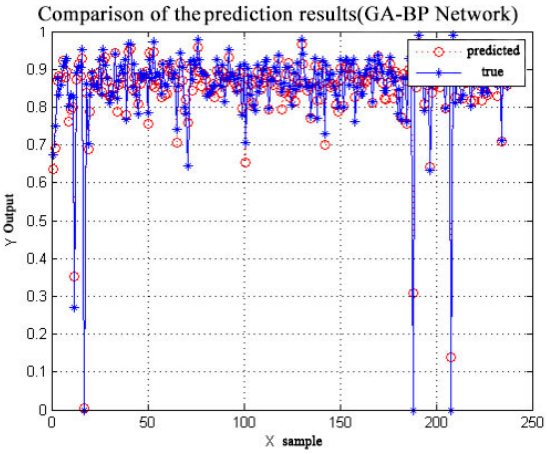

FIGURE 4. BP neural network training effect.

TABLE 6. Evaluation results of the two evaluation models.

Model	Result	Grade	Process	Strengths	Shortcomings
AHP-FCE	0.779	Good	Complex	Evaluation content is more detailed	Human influence factors are large
GA-BP	0.854	Good	Simple	Avoids subjective factors	Can only assess the overall goal

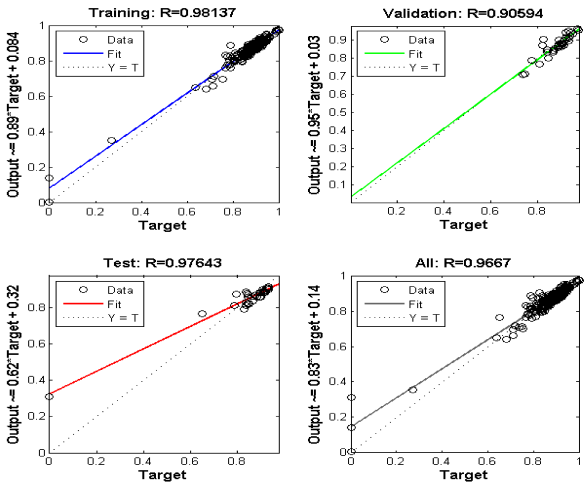

FIGURE 5. Fitting effect of the BP neural network.

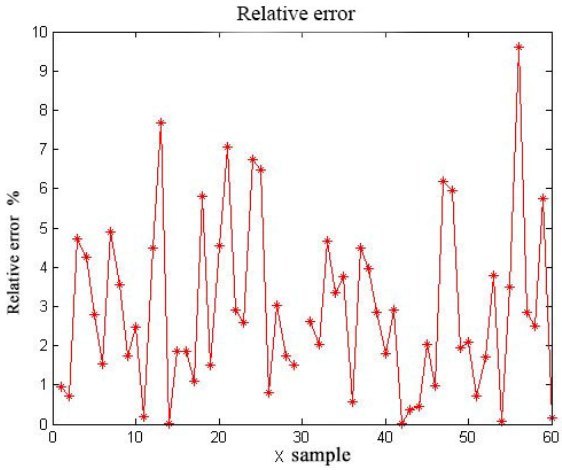

FIGURE 6. Relative error of the test set.

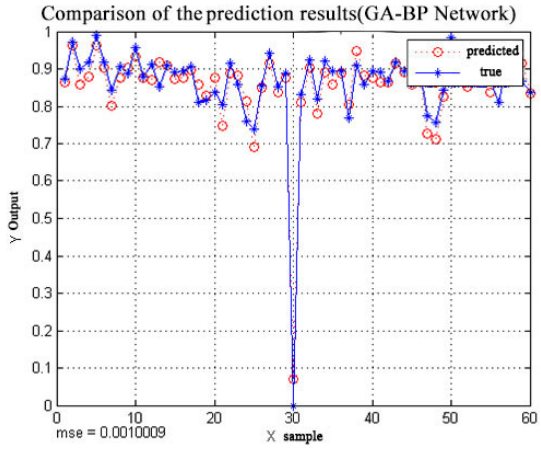

FIGURE 7. Network simulation prediction effect.

greatly, but the error between the predicted values of most samples and the true values is small. It can be seen from Figure 6 that the relative errors of the 60 test samples are within 10%, which reflects the excellent generalization ability of this model. Figure 7 shows the difference between the predicted value of the test set and the true value. The mean square error (MSE) is 0.0010009, which indicates that the prediction effect is ideal. The average value of 0.854 for the predicted output result of the test set is taken as the evaluation result of the smart learning environment.

C. COMPARISON AND ANALYSIS

1) COMPARISON BETWEEN AHP-FCE AND GA-BP MODELS

It can be seen from Table 6 that although there is a gap between the evaluation results of the two evaluation models (AHP-FCE: 0.779; GA-BP: 0.854), the evaluation levels are the same, which verifies the validity of the GA-BP evaluation model. The traditional evaluation model based on AHP-FCE can obtain the evaluation results of not only the smart learning environment but also the first-level indicators. The weights of the indicators obtained by the AHP can be used to analyze the degree of the impact of each indicator overall, and the target evaluation is more detailed. Although the BP neural network has shortcomings in this respect, the human subjective factors of the traditional evaluation model have a great influence on the evaluation results, and the solution process is cumbersome and time-consuming. The GA-BP-based evaluation model simplifies the evaluation process. The model has satisfactory complex problem handling capabilities and fault tolerance performance, as well as a fast calculation speed. Most importantly, the same evaluation level can be obtained without the interference of subjective factors, which is more consistent with the real needs of the smart learning environment.

2) IMPROVEMENT SUGGESTIONS

Based on the empirical analysis of the smart classroom of CCNU, the smart classroom needs to be further improved.

In the analysis of the sample questionnaire, the two indicators with the lowest satisfaction in the physical space are intelligence and perception, and the two indicators with the highest satisfaction belong to the design and structural categories, which indicates that students are relatively satisfied with the infrastructure construction. By optimizing the IoT system in the smart classroom, the problems of intelligence and perception can be addressed. For example, connecting the equipment in the smart classroom with a central control host enables the teachers to control various environmental conditions, including the intelligent adjustment of temperature and humidity, which ultimately increases the comfort of the classroom.

In the resource space, the lowest indicators of satisfaction are stability, openness, and functionality, and the highest indicators of satisfaction are magnanimity and layout, which indicates that the content construction of resources has met the learning needs of students, but the current sharing of resources is not universal. The limited access to information resources in certain areas needs to be addressed in the future. To solve the problem that the stability and functionality of the supporting platform cannot meet the requirements of students, developers must upgrade and maintain the platform by improving the performance of the supporting platform, optimizing the response efficiency, and adding new functions according to actual needs.

In the social space, students do not agree that smart classrooms clearly promote learning for them, and the interactivity has not improved significantly. Teachers mostly use simple technology, such as PowerPoint presentations, to teach. The purpose of constructing smart classrooms is to improve the learning environment and enhance teaching effectiveness, yet teachers'' unskilled use of equipment leads to the continued use of the multimedia classroom teaching mode in smart classrooms. This inability to develop diversified teaching modes causes poor classroom interaction. When building smart classrooms, we must strengthen and guide teachers to accept these new classrooms, become trained in using the equipment, and we encourage innovative teaching to improve teaching quality.

3) LIMITATIONS

There are three following limitations in our study.

i) The sample size of this study is not large enough. The number of effective samples in this study is 300. For the BP neural network, such an insufficient amount of data will possibly render the model not fully trained, which will definitely affect the evaluation effect. Based on the outcomes obtained in this study, our future work will try to collect a larger number of questionnaires further from the real-word smart learning environment.

ii) There is lack of diversity in the current data set. This article only conducts an evaluation study of one university rather than multiple universities and only verifies the validity of the proposed evaluation model but cannot show its applicability. In addition, regardless of teachers' experience/option, in the current evaluation model only students' experience is taken into account. This is reasonable in this explorative study, due to that the smart learning environment is usually student-centered. However, teacher's option is also quite valuable work to gain a more comparative view, which will be considered in our future.

iii) The number of indicators is insufficient. It is quite challenging to assess the smart learning environment scientifically from a systematic view. To initially alleviate this problem, in this study an evaluation system is proposed from three dimensions (i.e. physical space, resource space, and social space). In each dimension the representative indicators are extracted respectively, however, all these indicators can only generally represent certain characteristics of one single dimension. In other words, the current indicators are not comprehensive enough, therefore the advanced indicators which can represent multi-dimension characteristics need to be proposed further in our future work.

In conclude, to overcome these limitations, more data from different environments and more elegant methods are expected to verify the evaluation of the smart learning environment.

VI. CONCLUSION

The aim of the smart learning environment is to provide a resource-rich and sustainable atmosphere for college students [60] and help teachers dynamically adjust their teaching modes and strategies according to the students' learning performance and acceptance degree. To explore the effect of constructing a smart learning environment, this paper starts with the existing data analysis methods and employs two models based on AHP-FCE and GA-BP as well as questionnaires to evaluate the smart classrooms of CCNU. The evaluation focuses on aspects of the learning environment, such as sustainability and stability [61].

The results show that the traditional evaluation model based on AHP-FCE can obtain the evaluation results of not only the smart learning environment but also the first-level indicators, which verify the effectiveness of the evaluation model. The GA-BP-based model can simplify the evaluation process and improve its fault tolerance. Furthermore, the detailed results of the two evaluations indicate that the smart classrooms in CCNU are accepted by the students and teachers, but they need to be further improved. The technologies employed in smart classrooms can strengthen the interaction between teachers and students via interacting devices and improve students' satisfaction with a certain class. Improvements in the areas of resource acquisition and the stability and convenience of the related supporting platforms are needed.

In practical application, the learning environment is the physical cornerstone with which college students conduct active learning. A well-designed smart learning environment will be in a state of constant adjustment to address the changing needs of students and teachers. Thus, for sustainable smart learning environment development, the evaluation of the environment is an indispensable and important part of the process of promoting students' active learning experience. With the further integration of various science and technology and teaching concepts with classroom teaching, obtaining a more accurate and intelligent evaluation model will become a primary direction for future environmental evaluation research.

APPENDIX A

Questionnaire of smart learning environment

Dear students:

Thank you very much for your participation in this research. The purpose of this questionnaire is to understand your valuable views on the smart classrooms of our school. Please fill in objectively according to the actual situation. There is no right or wrong answer, all answers are okay. We will keep this questionnaire strictly confidential and will not bring you adverse effect. Thank you very much for taking your precious time to complete this questionnaire! Have a good time.

Part 1: Personal information

1. My grade is:
   ◯ freshman ◯ sophomore ◯ junior ◯ senior
2. My major belongs to:
   ◯ liberal arts ◯ science ◯ engineering
3. My gender is:
   ◯ male ◯ female

Part 2: Smart Classroom

The options for all questions are the same (◯ strongly disagree ◯ disagree ◯ not sure ◯ agree ◯ strongly agree)

1. The sound insulation effect of the smart classroom is good, and the color matching of the classroom is beautiful, generous and comfortable.

2. The overall layout of the smart classroom is reasonable, which is conducive to carry out different teaching/learning activities.

3. The infrastructure in the smart classroom (such as desks and chairs, lighting, sound, air conditioning, curtains, display screen, camera, network equipment, central control host, etc.) is fully configured.

4. The desks and chairs in the smart classroom are light, comfortable, adjustable (in height), and can be freely combined according to the requirements of different teaching/learning activities.

5. The smart classroom is fully equipped with intelligent terminal equipment (including tablet, PC terminal, electronic class brand), multimedia teaching equipment (including teaching platform controller, LCD touchscreen, recording and broadcasting equipment, wireless microphone, etc.), and Internet of things equipment (including temperature, humidity, light sensors, etc.).

6. In the smart classrooms, students' smart sign-in, smart grouping, and smart push of information and resources can be realized.

7. In the smart classroom, the lights, curtains, air conditioning, and ventilation systems can be easily turned on and off through the wall buttons or the teacher's tablet.

8. In the smart classroom, it is pretty convenient for you to conduct interactive activities with teachers through your own mobile phone or tablet.

9. The e-learning platform (which is a SPOC platform equipped in each smart classroom) can support mobile phones and computers with different resolutions, systems and browsers.

10. The e-learning platform has the ability of fast search and rapid response in the process of operation.11. The e-learning platform is highly secure and will not be infected by viruses frequently.

12. The e-learning platform can provide smooth and convenient operation.

13. The e-learning platform can support high-concurrency access, and abnormalities will not occur during its operation.

14. A wide variety of information and resources in the e-learning platform are interconnected to form a knowledge network.

15. The e-learning platform can provide massive data resources to meet the needs of people with different learning targets.

16. The teaching resources presented in the e-learning platform are comprehensive and updated rapidly, and their contents are highly authoritative.

17. The information resources of the e-learning platform are open to everyone.

18. With regard to the information resources of the e-learning platform, its presentation form matches the contents, making the contents easy to understand.

19. Even in the smart classroom, slide is the most common used teaching tool.

20. I prefer teachers to carry out classroom teaching with different forms in the smart classrooms and to interact with us on the e-learning platform after class.

21. In the smart classroom, teachers can integrate the relevant information resources to enrich teaching contents according to their course requirements.

22. Teachers can skillfully operate the information technology equipment in the smart classroom, and well applied to teaching.

23. The interaction between teachers and students and the interaction among students have both increased significantly.

24. Thanks to the smart classroom, I can learn more actively, my interest in learning increases and my absenteeism rate decreases.

25. Thanks to the smart classroom, my head-up rate increases and my concentration improves. Meanwhile,

I actively participate in the discussion, thinking, and answering questions during class.

26. I think the teaching slides with over-abundant material resources (including images, videos, audios, flash animations, etc.) will reduce the efficiency of classroom learning and affect the learning effect.

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