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Retraction

Retracted: Macro Education Approach to Improve Learning Interest under the Background of Artificial Intelligence

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] J. Hou, Z. Li, and G. Liu, "Macro Education Approach to Improve Learning Interest under the Background of Artificial Intelligence," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 4295887, 10 pages, 2022.

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Research Article

Macro Education Approach to Improve Learning Interest under the Background of Artificial Intelligence

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With the advent of the "Internet+" era, with the rapid development of emerging technologies such as the Internet of Things, cloud computing, big data, and artificial intelligence, the era of the technological change in education has arrived, with diversification of resources and large-scale data. And the intelligence of computing provides an opportunity for the research and practice of personalized support services. Personalized learning is the future learning method under the demands of smart education, and the learner's interest feature model is the core of personalized learning services. Although the research on smarter classrooms has achieved certain results, there are still shortcomings that cannot be ignored, that is, how to use smarter classrooms to meet the "personalized needs" of learners and give students "personalized feedback" is still an urgent problem to be solved. Therefore, building a student interest model in a smart learning environment will help teachers better capture students' learning interests and personalized needs, so as to provide them with personalized learning services.

1. Introduction

As an internal motivation of learners, interest is very important to their study, life, work, and even success [1]. From the perspective of pedagogy, interest is an element that directly affects the mastery of knowledge and academic performance, is the key to the development of intelligence and ability, is a good opportunity for ideological and political and moral education, and is also the basis for hard learning, in-depth learning, innovative learning, and even lifelong learning. From the perspective of psychology, interest is the internal driving force of knowledge, the source of happy learning, and the guarantee of maintaining attention. Psychological research shows that the learning process is a process in which the learners' cognitive and noncognitive psychological factors participate and influence each other [2]. The success of learning depends on the cooperative activities and close cooperation of the main processing system of cognitive factors and the main control system of noncognitive factors [3].

Psychologists believe that the cognitive operating system itself is not motivated, and its positivity comes from the noncognitive dynamic system, the core of which is "interest." As the main learning place of students, schools play an irreplaceable leading role in the interests of students [4].

Suhomlinsky said: "All intellectual work depends on interest, and the maintenance and development of intelligence and ability without interest is unimaginable." Confucius, a great educator in my country, pointed out that learning should be from "knowing" to "Good" to "happy" [5]. It can be seen that, as an educational concept, "interest education" brings together the quintessence of ancient and modern Chinese and foreign educational theories and modern advanced educational ideas and has a simple inheritance and a strong epoch [6]. There are many factors and conditions for the generation and formation of interest, one of which is that teachers are the implementers and leaders of school education and interest teaching, and are responsible for the discovery, guidance, and cultivation of students' learning interest. In this regard, Suhomlinsky said: "the first source of nurturing children's love for knowledge is teachers," "let students regard the subject you teach as the subject they are most interested in, and let as many teenagers as possible dream of creating in the field of the subject you teach like longing for happiness. You should be proud of this.". Dewey believes that interest is of great significance in classroom teaching. On the one hand, interest can meet the needs of students' intellectual and personal development. On the other hand, interest can be naturally cultivated by providing students with various materials and challenging educational opportunities [7].

With the advent of the "Internet+" era, with the rapid development of emerging technologies such as the Internet of Things, cloud computing, big data, and artificial intelligence, the era of technological change in education has come [8]. It is intelligent and provides a data source for mining the individual needs of students (as shown in Figure 1). Personalized learning can meet the current situation of children, help them strengthen their advantages, and make them better understand their abilities. Personalized learning can also find everyone's interests, make them accept various challenges in the cultivation of interests, and finally promote their personal growth. Personalized learning is a kind of teaching driven by students' interests. Personalized learning is one of the demands of future education, and identifying learner characteristics is an important prerequisite for promoting personalized learning [9].

To this end, Rahman et al. proposed an accurate learner model (ABP learner model) based on the preconcept theory [10].

The elements include three aspects of cognition, ability, and experience, which are used to identify students' cognitive level and analyze them in depth to provide students with adaptive learning resources and paths [11]. The student model constructed by the SS network identifies learner characteristics from three aspects of cognition, emotion, and skills and is used for self-directed learning [12]. It is mainly constructed from three aspects: resource recommendation, process monitoring, and community guidance [13].

Personalized learning is to put students' needs first, customize individualized learning plans, support students' potential release, provide comprehensive and flexible support for students, support parents' participation in students' learning process, and encourage students, parents, teachers, schools, and communities to develop relationships, cultivate lifelong learning ability, and support students to adopt learning methods related to their life, interests, and career goals [14]. At the 2010 American Society for Supervision and Curriculum Development seminar on personalized learning, participants reached a consensus on five basic elements of personalized learning, namely, flexible learning time and space, reshaping teacher roles, and task-based inquiry learning, custom learning path, and custom learning pace [15]. The Bill & Melinda Gates Foundation and other organizations believe that the implementation of personalized learning should rely on electronic school bags, customized paths, free environment, and the support of competitiveness [16].

Integrating emerging technical means to create an intelligent learning environment that is conducive to communication, cooperation, and sharing and conducive to students' independent exploration and learning is an inevitable choice for colleges and universities to implement the integration of information technology and education and improve the quality of student training [17]. Academic circles have reached a basic consensus on the concept of "smart classroom." This consensus believes that "smart classroom" is a teaching environment that uses artificial intelligence, human-computer interaction, and other technologies to enhance the presentation of teaching content and the perception of the whole teaching environment and uses communication technologies such as the Internet of things and the Internet to optimize the communication between teachers and students, so as to promote the development of personalized teaching activities. Smart classroom is a physical classroom, which is a physical space that reflects smart education in the building entity of school. It is a revolutionary upgrade on the basis of traditional classroom. The smart classroom uses modern means to cut into the whole teaching process, making the classroom simple, effective, and intelligent, which helps to develop students' independent thinking and learning ability. With the introduction of the concept of smart classroom, it has become an inevitable trend to make full use of sensing technology, Internet of Things technology, cloud computing technology, etc. to equip the physical classroom environment and promote the construction of smart classrooms [18]. In a smart learning environment, the learner becomes the center of the entire learning activity. Through effective self-management and a positive learning attitude, knowledge is actively constructed and internalized; the teacher becomes the guide of the entire learning activity, focusing on the individualization of the learners' services to help them complete the internalization of knowledge [19]. In recent years, a series of active explorations have been carried out in the construction of smart classrooms at home and abroad, and many professional subject tools have emerged as the times require, such as teaching assistants, electronic school bags, and virtual simulation experiment platforms. A large amount of learning process data can be saved, and various learning process data can be quantified, which also provides a basic guarantee for obtaining students' learning process data and learning feature information. The development and intelligence of smarter classrooms support the demands of providing students with personalized learning services [20]. The premise of personalized services is to understand students' individualized needs. Therefore, building a student interest model in smarter classrooms helps to promote students' individuality through personalized "learning" and teachers' personalized "teaching."

2. Theoretical Basis and Technology

2.1. Artificial Intelligence. Artificial intelligence has the English abbreviation AI. Although it contains the word intelligence, it does not have flesh and blood. It is mainly an artificial intelligence that simulates a series of complex activities related to human intelligence such as perception, learning, reasoning, and communication through computers. The founder of artificial intelligence, Marvin Lee Minsky, believes that artificial intelligence is to let machines do things that humans need to do with intelligence.

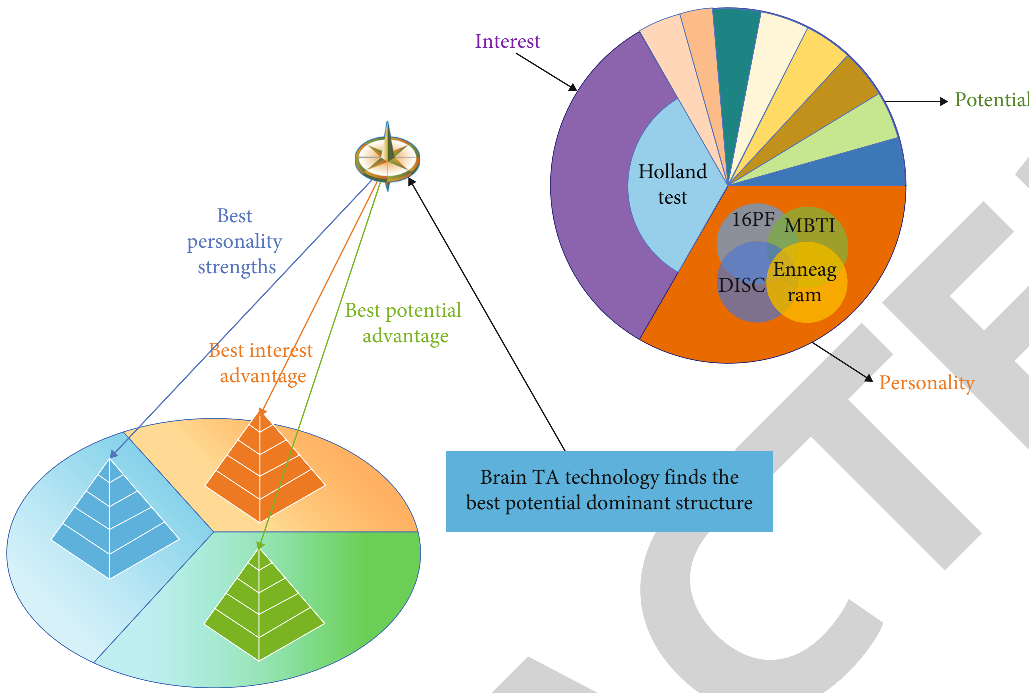

Figure 1: Testing techniques for learning interest in the context of artificial intelligence.

Professor Wang Zhuli believes that the main role of artificial intelligence is to make machines think like human beings, or even surpass human thinking ability, and can replace human beings to perform mental work and intellectual work when needed. Shi Chunyi believes that artificial intelligence is a discipline that studies the task of allowing computers to perform the task of expressing human intelligence (see Figure 2). To sum up, artificial intelligence research is to use computers to simulate human intelligence activities and replace some of human brain power. Regardless of the above explanations, artificial intelligence is regarded as a technological artifact and the use of machines to simulate and replace certain human brain activities, rather than an intelligent person who is superior to human beings. Intelligence is not a discipline, but a variety of intelligent devices and intelligent applications derived from the simulation of human intelligence.

There are many definitions of teaching mode at home and abroad, but the independent definition of teaching mode starts from the research of Bruce Joyce and others. They defined it as a plan or paradigm for selecting teaching materials and directing teaching activities in classrooms and other settings. Kekang et al. pointed out in “Teaching System Design” that the teaching mode belongs to the category of teaching methods and teaching strategies, that is, in the interaction between teaching and learning, in order to achieve the established teaching purpose, two or more teaching methods are used in teacher-student interaction activities based on methods or strategies. The teaching mode referred to in this study is mainly based on the academic viewpoints of Kekang et al. It is believed that the teaching mode refers to the use of two or more teaching methods or teaching strategies in the teaching process to create a suitable teaching environment for students to learn through the actual teaching environment. It is a concrete manifestation of the practical application of teaching theory, which can achieve a virtuous circle of guiding theory through practice and enriching practice through theory.

2.2. Definition and Classification of Interest Concepts. Interest itself is a very complex concept with rich meanings and is associated with many psychological phenomena, but it cannot be simply equated with a certain psychological phenomenon. As a psychological phenomenon, the complexity of interest itself makes it difficult for us to define it clearly. Interest has a long history in the field of psychology, dating back to the work of Herbart, who believed that interest is initiative. Dewey believes that interest is various, and he believes that the word interest has three meanings, namely, interest is the whole state of activity development; interest is the predictable and expected objective result; and interest is the individual’s emotional tendency, and interest is to maintain alertness, concern, and attention. Krapp et al. said that interest is both a mental state and an individual’s tendency, including cognitive and affective components. Interest is a cognitive tendency with emotional color. It is based on the need to know and explore something. It is an important motivation to promote a person to know and explore things. It is the most active factor in a person’s study and life. In short, interest is a starting point to promote people to continue to understand and explore things. For the concept of interest, Figure 3 defines it from different perspectives. For example, Renninger defines the concept of situational interest; Bergin defines the concept of individual interest. There are different descriptions of the meaning of interest in the field of psychology, but there is a consensus that

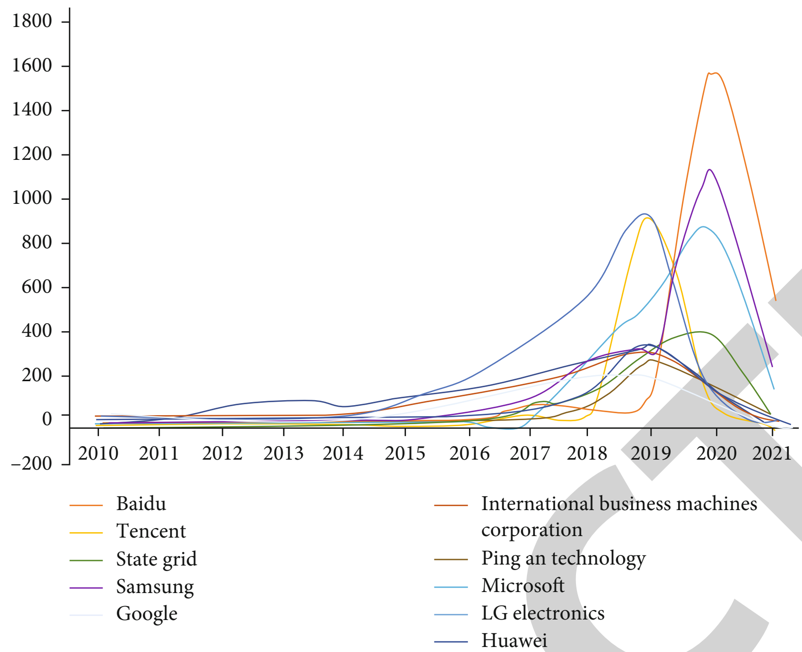

Figure 2: Application trends of the global artificial intelligence industry.

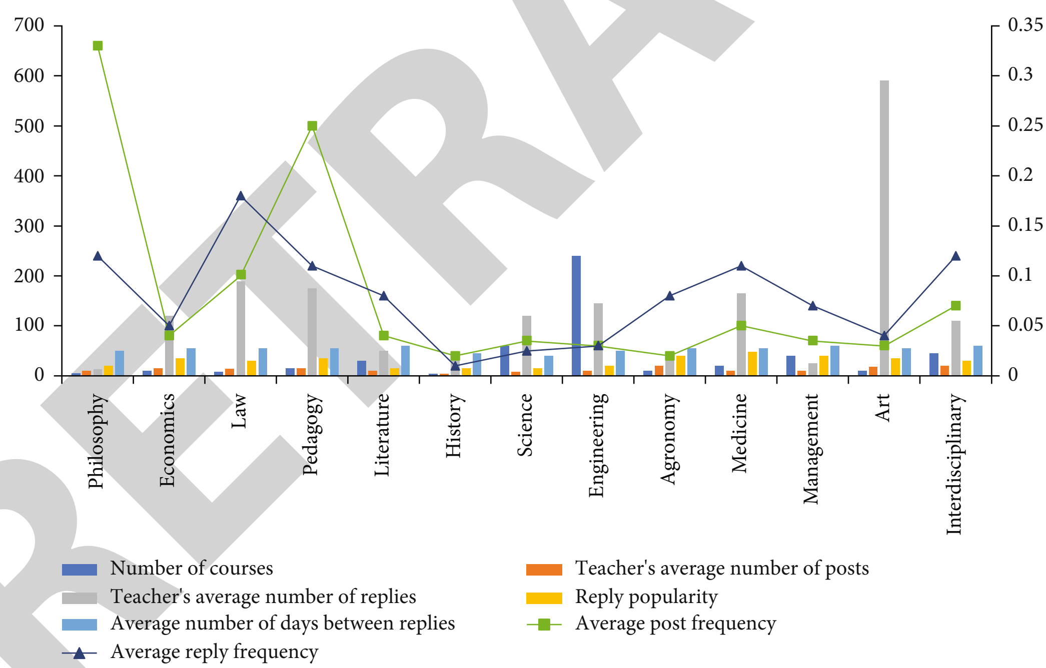

Figure 3: Influence indicators on students' learning status under big data analysis.

interest is a psychological phenomenon that arises from the interaction of an individual with his environment.

Interest is generated in the process of the interaction between the active subject and the object. The object here can be a real object, a concept, a person, or an activity. Figure 2 shows that the student's learning experience data is an important basis for us to construct the student's interest model, so we need to mine the information that can truly reflect the student's learning interest from the massive data information. There are two ways to obtain students' interest information, namely, explicit and implicit ways.

The representation method of learning interest refers to how to describe its learning preference and extract corresponding features. The representation method of interest information determines the diversification of interest model construction. By browsing the relevant literature, this paper summarizes the representation methods of the user interest model. Among them, the representation methods of the

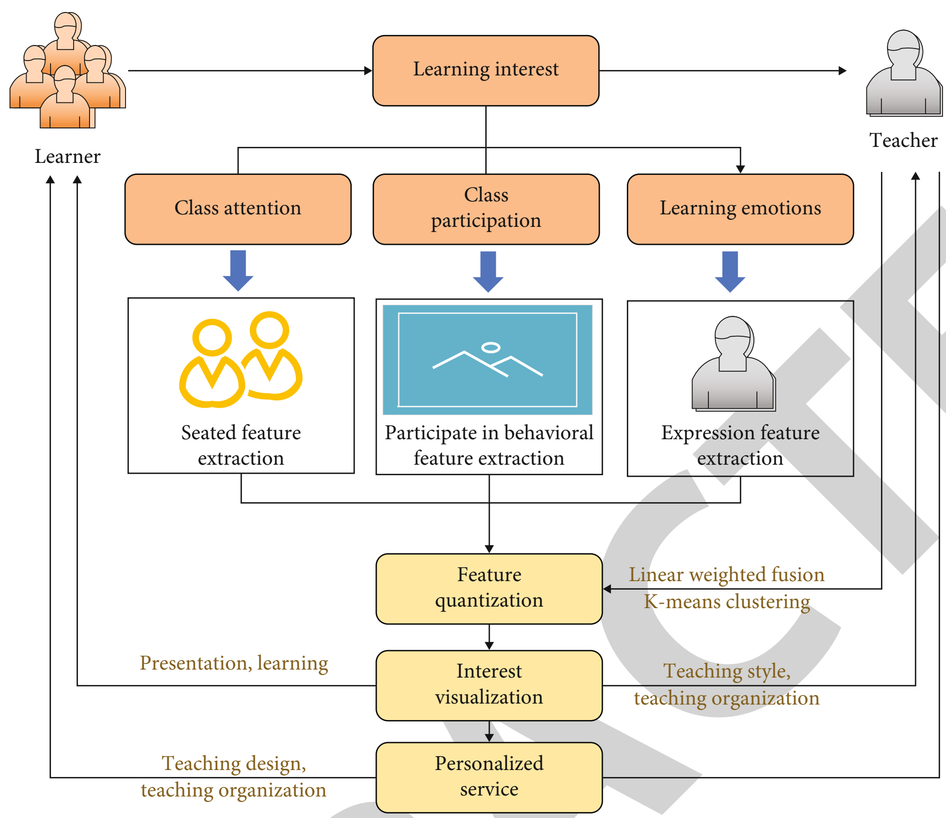

Figure 4: The conceptual model framework of the student interest model.

interest model mainly include the representation method based on the vector space model and the construction method based on the ontology, etc. This paper only describes several typical representation methods.

2.3. Conceptual Framework of Student Interest Model. Interest is a psychological tendency to seek to explore something or engage in a certain activity, usually described as an interaction between an individual and an aspect of the environment. Dewey emphasized that interest is related to positive emotions and that interest can produce a pleasant experience. He believes that interest is an individual's emotional tendency, and interest is keeping alert, caring, and paying attention. When a student is interested in a learning activity or learning object, he will consciously participate in the activity and concentrate on learning and research. In addition, a pleasant emotional experience is a guarantee of interest maintenance. It can be seen that if students are very interested in a certain learning activity, they will take the initiative to pay attention to the learning activity, actively participate in the classroom learning activities, and maintain a high sense of pleasure. According to the analysis of the students' explicit behavioral characteristics of interest in the previous section, combined with the characteristics of the smarter classroom environment and the research purpose of this study, a conceptual model of students' interest in classroom learning is constructed, as shown in Figure 4.

As mentioned in the previous literature review, one of the more commonly used representation methods for user interest modeling is the representation method based on the vector space model. By browsing the relevant literature, it is found that this method is mostly used in the construction of text-based interest models. By analyzing the use characteristics of various methods, combined with the characteristics of students' learning behavior in smarter classrooms, this study selects spatial vectors to represent students' interest characteristic information. Each vector represents a quantitative dimension of interest, including quantitative indicators of interest and their corresponding weight values, such as a student interest model of an n -dimensional feature vector can be expressed as

$$S = \{v_1, v_2, \cdots v_i\} = \{(l_1, w_1), (l_2, w_2), \cdots, (l_i, w_i)\} 1 \le i \le n. \tag{1}$$

Among them, S represents the student's interest, and v_i represents a quantitative dimension of the student's interest, which is composed of the quantitative interest index l_i and its corresponding weight.

This study constructs a vector space model from three dimensions of explicit interest behavior, namely classroom attention (attention), classroom participation (engagement), and learning emotion (emotion). The time vector (time) is used as a variable to represent students' interest in classroom learning, and the model can be expressed as

$$S_t = \{G_t, B_t, E_t\} = \{(G_t, w_1), (B_t, w_2), (E_t, w_3)\}. \tag{2}$$

Table 1: Sitting posture-attention level mapping rule base.

Sitting position name	Sitting position description	Attention level	Attention score
Sitting & leaning forward	Taking the body facing as the forward and reverse direction, the angle between the student and the sitting surface should not exceed 110°	Most concentrated	10 points
Lean forward	Lean to the left while leaning forward	More focused	8 points

Among them, S_t represents students' interest in classroom learning at time t, G_t represents students' class attention level at time t, B_t represents students' classroom participation at time t, and E_t represents students' emotional state of learning at time t.

The specific steps of K-means clustering are divided into two steps.

The first step is to minimize the total cluster variance with respect to the cluster mean for a given encoder C, i.e. to do the following minimization:

$$\min \left\{\widehat{\mu}_j\right\}_{j=i}^{K} \sum_{j=i}^{K} \sum_{C(i)=j} \left\|x(i)\widehat{\mu}_j\right\|^2 \quad (3)$$

The second step is to minimize the encoder, which is to do the following minimization:

$$C(i) = \arg \min_{1\leq J\leq K} \left\|x(i) - \widehat{\mu}_j\right\|^2 \quad (4)$$

According to the three-dimensional space vector model proposed in the previous section, with time as a variable, the spatial vector set of students' interests is constructed from the three-dimensional interest information of the explicit behavior of interest, and an initial cluster center is selected and initialized randomly for many times. At the center point, the vector with the best running result is selected as the student's learning interest level in a class.

3. Quantitative Technology of Student Learning Interest Index

3.1. Calculation of Attention Level. In this study, the student's sitting posture-attention mapping rule base was developed, as shown in Table 1. The sitting posture-attention mapping rule base designed in this research is divided into 10 sitting posture types, corresponding to 5 attention levels, namely, the most concentrated, with a score of 10; the more concentrated, with a score of 8; less focused, scored 6 points; more distracted, scored 4 points; and least focused, scored 2 points. According to the angle between the collected sitting posture and the sitting posture schematic diagram in the rule base, the sitting posture type is matched to obtain the corresponding attention level.

On this basis, formula (5) is used to calculate the student's class attention level, where G represents the student's class attention level score in a unit time (30 seconds as a time unit has been mentioned in the previous section), n represents the total number of sitting posture feature images per unit time, s_i represents the attention level score corresponding to the ith sitting posture of the student, and W_i represents the weight of the ith sitting posture of the student.

$$G = \sum_{i=1}^{n} s_i * w_i. \quad (5)$$

The calculation method of the weight is shown in formula (6), where N represents the frequency of a certain type of sitting posture in a specified unit time and N_A represents the total number of sitting postures that appear in a specified unit time.

$$w_i = \frac{N}{N_A}. \quad (6)$$

After collecting students' classroom participation behaviors, the degree of classroom participation is calculated according to the linear weighting method. The specific calculation method is shown in formula (7). Among them, n is the student's classroom participation score, n is the number of dimensions of students' participation behavior, X_i is the participation score corresponding to the ith index and w_i is the weight of the i index.

$$\prod = \sum_{i=1}^{n} x_i w_i. \quad (7)$$

In this paper, there are two levels of student participation behavior, one is dimension classification, and the other is index classification of a single dimension, so do it twice with linear weighted summation to arrive at the final student class engagement score. The specific calculation method is shown in formula (8). Among them, B is the student's classroom participation score and n is the number of dimensions of students' classroom participation behavior; in this paper, n is 4, m is the total number of indicators under the ith dimension, and X_{ij} is the student's ith dimension in the ith dimension. For the class participation score of j indicators, W_{ij} is the weight of the jth indicator in the ith dimension of students' classroom participation behavior.

$$B = \sum_{i=1}^{n} \left(\sum_{j=1}^{m} x_{ij} w_{ij} \right) * w_i. \quad (8)$$

Among them, there are two layers of index weight calculation. The first layer of weight is the weight calculation of the internal indicators of each dimension in teacher-

Table 2: Facial expression recognition rule base.

Emotion	Combination
Happy	5 + 12/5 + 26
Surprise	4 + 24/4 + 25
Bored	9 + 10/15/16/17/19/23
Puzzled	3 + 10/3 + 17/4 + 10/4 + 17
Fatigue	6 + 25/7 + 25
Focus	4 + 14/4 + 22
Confidence	6 + 14/6 + 26

student interaction, student-student interaction, and student-resource interaction, as shown in

$$W_1 = \frac{n_{ij}}{N}. \tag{9}$$

In the formula, W_1 represents the weight of the internal indicators of each dimension,n_{ij}refers to the frequency of occurrence of the ith indicator of the jth dimension, and N refers to the total frequency of the jth dimension.

The second layer of weight refers to the calculation of the weight W_2 of the three dimensions of teacher-student interaction, student-student interaction, and student-resource interaction, as shown in

$$W_2 = \frac{T_j}{T_A}. \tag{10}$$

In the formula, W_2 represents the weight of the three dimensions, T_j refers to the total interaction time of the j th dimension, and T_A refers to the total duration of classroom interaction and participation.

On the basis of the designed facial activity unit coding system, this study designed a facial expression recognition rule base, as shown in Table 2. The facial feature codes are combined to form seven expression types, namely, happy, surprised, bored, confused, fatigued, focused, and confident.

The quantification method of learning emotion is shown in Equation (11). Among them, E represents the student's learning emotion score in a unit time, n represents the total number of facial expression images in a unit time, l_i represents the student's ith expression feature score, and W_i represents the student's ith expression the weight.

$$E = \sum_{i=1}^{n} l_i * w_i. \tag{11}$$

The calculation method of the weight is shown in formula (12), where n represents the frequency of a certain expression type in a specified unit time and N represents the total number of expression images that appear in a specified unit time.

$$w_i = \frac{n}{N}. \tag{12}$$

Because the explicit behavior data of students' interests collected in the smart classroom are of different structural types and cannot be linearly integrated, this paper chooses to use the three-dimensional space vector method to express students' learning interests. The expression of students' interest is shown in formula (13), where S_i refers to the student's classroom learning interest vector at time i, G_i refers to the student's class attention level score at time i, and B_i refers to the student's class at time i. For participation score, E_i refers to the student's learning emotion score at moment i .

$$S_i = (G_i, B_i, E_i). \tag{13}$$

In this paper, the Z-score normalization method is used to adjust the data unit capacity of the three dimensions of the interest model to be the same for vector fusion, as shown in formula (14), where Z_1 refers to the vector of the ith dimension after normalization, x_i refers to the original vector of the ith dimension, μ_i refers to the mean of the ith dimension, and σ_i refers to the standard deviation of the i th dimension.

$$Z_i = \frac{x_i - \mu_i}{\sigma_i}. \tag{14}$$

Assuming that the student's m learning interest vector data set in time t is D, the student's interest behavior set can be expressed as formula (15). The horizontal row represents the student's interest behavior vector set at time $T\,(t = l, 2, \cdots t)$, and the vertical row represents the student in the $M\,(M = l, 2, \cdots m)$th dimension. The set of interest explicit behavior vectors are as follows:

$$D = \begin{bmatrix} (a_{11}, b_{11}, c_{11}) & (a_{12}, b_{12}, c_{12}) & \cdots & (a_{1m}, b_{1m}, c_{1m}) \\ (a_{21}, b_{21}, c_{21}) & (a_{22}, b_{22}, c_{22}) & \cdots & (a_{2m}, b_{2m}, c_{2m}) \\ \cdots & \cdots & \cdots & \cdots \\ (a_{t1}, b_{t1}, c_{t1}) & (a_{t2}, b_{t2}, c_{t2}) & \cdots & (a_{tm}, b_{tm}, c_{tm}) \end{bmatrix}. \tag{15}$$

Therefore, for any two time t and time s, the distance between them is represented by $d(b_t, b_s)$, and its calculation method is shown in formula (15), where b_{tk} represents the vector of the kth dimension at time t and b_{sk} represents the vector of the kth dimension at time s.

Select a cluster center, select the initial center multiple times through the k-means clustering algorithm, and find the optimal solution, and the final cluster center obtained is the overall interest vector of the students.

4. Experiments and Analysis

According to the data collection rules designed in the previous chapter, the sitting behavior characteristics of all the students in this case were collected. First, from the acquired image sequence, the natural human body images that can represent the students' sitting posture are selected; secondly,

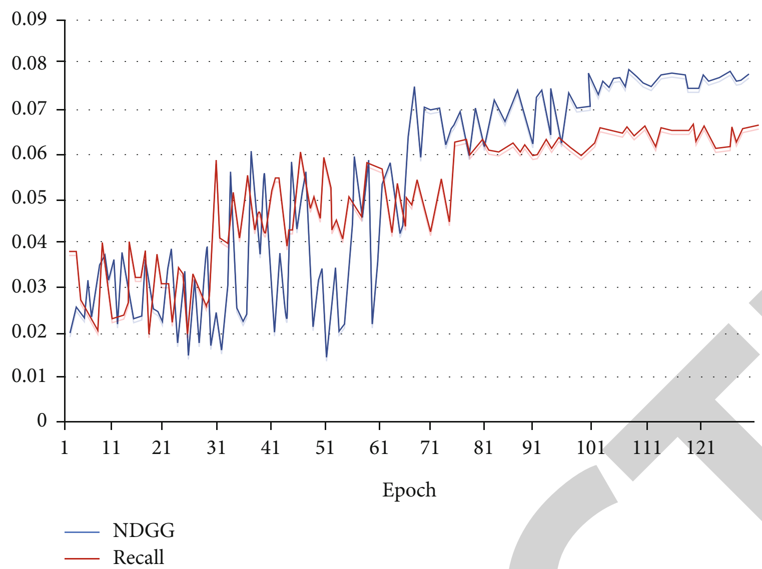

Figure 5: Performance of AKG-DNNRec in 128 epochs.

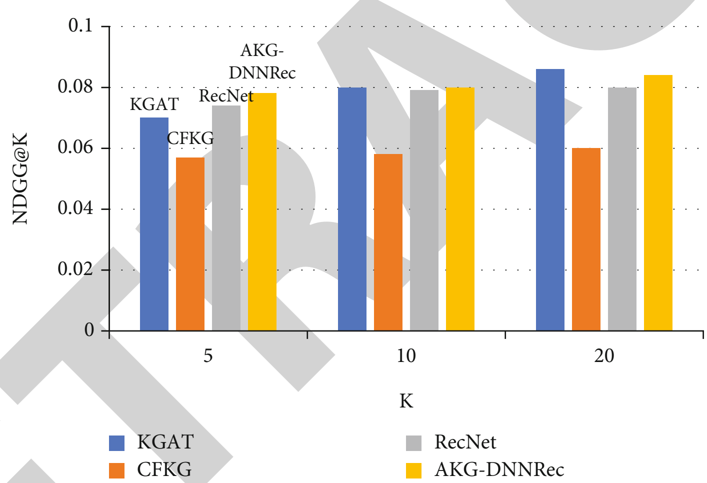

Figure 6: Comparison of various algorithms in NDCG@k.

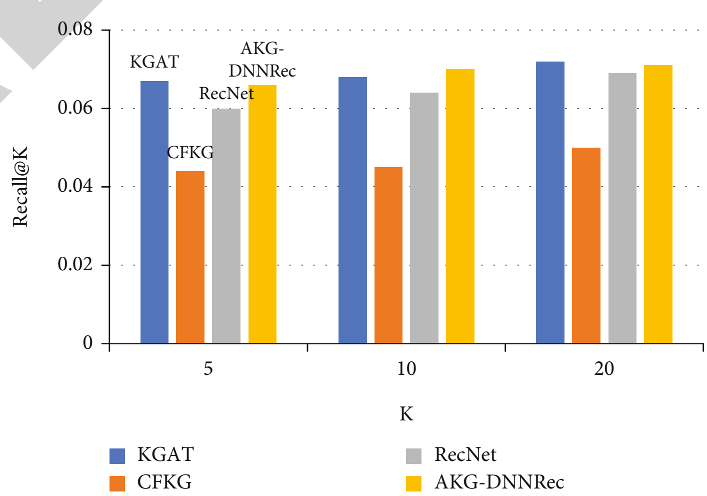

Figure 7: Comparison of various algorithms in Recall@k.

all image sequences are normalized, and the coordinates of the images containing the students' sitting posture are calibrated. An image containing the students' sitting posture features is used to calibrate the coordinate axis and the sitting posture angle; finally, measure the sitting posture angle of the students on each image and compare them with the sitting posture-attention level mapping library in turn to obtain the sitting posture type and the corresponding attention. The force level score is calculated, and the attention level score per unit time is calculated as the vector value of this dimension to facilitate the subsequent interest cluster analysis.

All experiments in this chapter are done on AMD R7 5800X processor, Nvidia 3080 graphics card, 64 G memory, and 256 GB SSD hardware. The experimental software environment is Ubuntu 20.04 system. The programming framework of the algorithm uses Pytorch for experiments.

The experimental parameters involved in the experiment include the dimension d of each entity and the dimension k of the relation space in embedding. The relational reasoning layer, the Gaussian distribution variance σ of each jump, and the progress δW. As well as the amount of data processed each time in the experiment, batch, the number of iterations of the experimental set data epoch, the learning rate lr, and the recommended number of interest points K.

During the experiment, the dimension d of the entity and the dimension k of the relation space are both set to 64. The learning rate lr is set to 0.001, the data volume batch is set to 32, and the number of iterations epoch of the experimental set data is set to 128.

During the experiment, when the recommended number of interest points is 5, the forward pace δW is adjusted. During the adjustment process, the δW is set to 1-7 for adjustment. The impact of parameters on performance is expressed in NDCG metrics. The experimental results are shown in Figure 5.

It can be seen from Figure 5 that the experimental results can all converge, which proves the effectiveness of the algorithm. To compare the performance of the 4 algorithms, plot Figures 6 and 7.

As can be seen from Figures 6 and 7, respectively, the algorithm proposed in this chapter is on par with the KGAT algorithm in terms of NDCG and recall, but the calculation of the attention mechanism through the egocentric network in the KGAT algorithm will be relative. The amount of calculation is increased. As shown in Figures 6 and 7, the algorithm proposed in this paper outperforms the algorithm using knowledge graph embedding and neural network alone on two indicators. Among the four algorithms, the CFKG algorithm has the worst effect, because it uses the TransE model to imply all the vectors in the same space, which is not applicable in a network with a large number of relationships such as LBSN.

Longitudinal comparison, the four algorithms on the two indicators, all increase with the increase of k. When $k = 20$, AKG-DNNRec improves NDCG and recall by 39% and 41%, respectively, compared to the CFKG algorithm. Compared with the RecNet algorithm, it is improved by 6% and 5.9%, respectively.

In this section, the vectors of users and points of interest are represented based on knowledge graph embedding and deep neural network based on attention mechanism, so as to calculate the predicted scores of users for points of interest based on the inner product of the two. In the method of this paper, users or points of interest only need one interaction to join the LBSN, and they can be better represented by vectors. Therefore, the method in this paper can well solve the cold start problem faced in the recommender system and also solve the data sparsity problem well. The experiments in this section show that the method in this paper can perform better than the simple neural network-based algorithm.

5. Conclusion

Based on the research on the current situation of user interest model at home and abroad, referring to the classroom observation method, combined with the characteristics of smart learning environment, from the perspective of affecting learners' learning interest, this paper analyzes various behaviors that affect students' learning interest in smart learning environment and proposes a method for constructing students' interest model in a smart learning environment. Then, for the students' learning behavior in the smart learning environment, the analysis techniques and quantification methods of the interest model are studied. Finally, the subject video cases in the smarter classroom are selected to verify the effectiveness of the interest model analysis indicators and quantitative methods.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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