OPEN ACCESS Freely available online

ISSN 2737-5315
Volume 3, Issue 4
https://www.iikii.com.sg/journal/EIET
Educational Innovations and Emerging Technologies

Article

A Comprehensive Evaluation Scheme of Students' Classroom Learning Status Based on Analytic Hierarchy Process

Yuyang Sun

Beijing Yuying School, Beijing 100036, China, yyuyy99@163.com

Received: Sep 22, 2023; **Revised:** Oct 22, 2023; **Accepted:** Nov 7, 2023; **Published:** Dec 30, 2023

Abstract: The state of students' classroom learning refers to whether students are concentrating and listening in the class, whether they are interested in the content of the lecture, and whether they understand and master the content of the teacher's psychological state. The research on the state of students' classroom learning is of great significance in teaching activities. Usually, measuring students' classroom learning status is a subjective evaluation, and it is difficult to have a quantitative description. With the development of artificial intelligence (AI)technology, a large number of modern information technologies have been applied in education and teaching. People use video images, eye tracking technology, orfacial expression recognition technology in deep learning to describe students' attention and interest in classroom learning. However, with the complexity of students' learning process, no single information technology can accurately describe students' learning status and learning performance. Therefore, when evaluating students' learning status, it is necessary to consider the students' learning status, learning process, and learning performance. To this end, we used the Analytic Hierarchy Process (AHP)to establish a mathematical model in the four dimensions of interest, pleasure, concentration, and classroom performance and homomorphically adjusted the corresponding weights of the four dimensions in evaluating students' learning status. The proposed evaluation scheme of students' classroom learning status evaluated students' classroom learning status in real-time, providing modern information technology support for improving classroom learning efficiency and the quality of education and teaching.

Keywords: AHP, Multimodal fusion, Classroom learning status

1. Introduction

At present, school classroom (offline and online) learning is still the main way for students to acquire knowledge and receive education. The state of students in classroom learning directly reflects the success or failure of classroom teaching. A successful teaching class depends on how high the teacher's teaching level is, how strong the teaching ability is, and more importantly, how the students are in the classroom. It also depends on whether they are attentive in the class, they are enthusiastic about the teaching content, they are interested, and they understand and master the knowledge taught. With the development of information technology, the integration of information technology and education has become important to improve the quality of education. However, there is still a lack of intelligent and personalized information interaction technology in classroom teaching, which makes itdifficult to meet the needs of modern education. How artificial intelligence (AI), big data, and cloud computing technology provide more advanced information technology for class education and improve the quality of class education has important exploration significance.

At present, many AI technologies and big data technologies have been applied in education and teaching. AI is used to analyze the learning status of students and quantify the indicators, and the key points of students' faces are detected by deep learning algorithm to classify the expressions of students(Jia, 2019). Based on the online learning operation data of learners on the "cloud platform", a data-driven learning state analysis model is constructed, and the behavioral characteristics of four learning states of engagement, frustration, confusion and distraction are analyzed(Wang, 2019). Based on student data and learning environment data, students' learning status is evaluated to predict and analyze students' learning development based on historical learning data. Evaluation and prediction results are taken as guidance to implement teaching intervention on time and optimize the teaching process(Liu, 2017).

We have worked on the use of AI technology in education and teaching. We proposed a new eye-tracking technique (Sun, 2018b) and applied it to mathematics education technology. We usedHaar features and Adaboost learning algorithm to detect face images and locate eyes, and can get eye movement tracking data (initial attention position, process attention position, attention duration, attention frequency). Through the analysis of students' eye movement data, teachers couldunderstand students' learning attention in real time. We collectedfacial expression recognition data (drowsiness, concentration , pleasure, disgust) and proposed a convolutional neural network (CNN)-based facial expression recognition algorithm and an evaluation scheme for students' learning difficulties and concentration (Sun, 2018a). Using the max pooling method, the computational complexity of the upper layer was reduced by eliminating non-maximum values to design a new convolutional neural network and expand the expression database. Experimental results showed higher accuracy and efficiency than traditional facial expression methods. On this basis, a neural network-based recognition method for students' learning difficulties and concentrated expressions was proposed to provide information technology for teachers to understand students' learning status in real time. In classroom teaching, teachers need to know promptly the learning fatigue status of students for the improvement of teaching quality. The fatigue status of learners in classroom learning reflects students' interest in learning to some extent. We described the fatigue status of students in learning through face segmentation technology and eye area positioning technology in image processing. We built an optical and infrared image fusion system in which students' facial images were taken by a color lens and an infrared lens installed about 50 cm in front of the desk, marking the marks on the face and segmenting the eye area. Fatigue status was detected by calculating eye aspect ratio, eye closure time, blink rate, and color and infrared percentages (Sun, 2023).

Due to the complexity of the students' learning process, no information technology can accurately describe the students' learning status and academic performance. For example, although a student is not looking at the blackboard or the projection screen, he may be listening; if a student is looking at the desktop with his chin resting, the AI algorithm may judge that the student's memory is not concentrated enough in class, but he may be thinking about the problem following the teacher's instruction. Therefore, when evaluating a student's learning status, it is necessary to comprehensively consider the student's learning status, learning process and academic performance.

In this study, we assessed the state of the student's learning process (learning concentration, interest, and joy) obtained using eye-tracking technology, fatigue detection technology, and facial expression recognition technology, and then through the in-class test scores of students studying in the classroom. Similar to the method used by Ren (2020), we proposed a method to establish a mathematical model for the evaluation of students' classroom learning status by using the analytic hierarchy process (AHP). A questionnaire survey was conducted on a large number of teachers through the WeChat applet. Using the analytic hierarchy process, starting from the four dimensions of students' interest, joy, concentration and classroom performance, the student's classroom learning status was assessed by determining the corresponding weights. The result provides a basis to choose appropriate technical support for teachers to improve teaching methods, adjust teaching methods, comprehensively and accurately evaluate students' classroom learning status and implement personalized intelligent education.

2. Design of Learning Status Evaluation Scheme

Eye movement tracking data (initial attention position, process attention position, attention duration, attention frequency), human eye fatigue data (eye opening time, eye closing time, flicker frequency) and facial expression recognition data (drowsiness, concentration, Pleasure, Disgust), and classroom test paper performance data (excellent, medium and poor) were summarized into four dimensions: concentration, interest, joy, and classroom assessment results. Research on these four dimensions reflected students' learning status to facilitate teachers to judge students' learning status, thereby adjusting teaching methods, stimulating students' learning interest, and improving classroom learning efficiency. We preprocessed the teaching video, in the first 35 minutes of the class and collected the corresponding eye movement, eye fatigue, and facial expression data of students using optical and infrared lenses synchronously. In the next 10 minutes, the on-site test was carried out, and the test scores were graded into four grades: excellent, good, medium and poor. After all the data was acquired, the AHP was used comprehensively to evaluate the learning status of each student in real time, providing an objective and more accurate evaluation method for teachers to grasp the overall learning status of students and obtain an intelligent comprehensive evaluation plan for students' classroom learning status. The results help teachers adjust teaching modes, change teaching strategies, and provide theoretical support for students' individualized training.

3. AHP

AHP is based on a comparison level obtained by experts after comparing each index with others according to the weight meaning standard table (Wang, 2018). We used AHP in weight analysis. The basic flowchart of the AHP is shown as follows (Fig. 1).

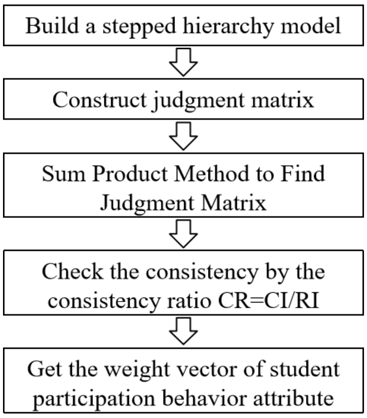

Fig. 1. Analytic Hierarchy Process Flowchart.

A hierarchical structure model was used to divide the decision-making target into the target, criterion, and program layers according to rules and draw a hierarchical structure diagram. When determining the weight of each dimension, if it was a fixed constant, this method was not rigorous. We proposed a method of mutual comparison with relative scales to improve the accuracy of the method. The $n \times n$ order judgment matrix was constructed according to the relative scale as follows.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{11} & x_{12} & \cdots & x_{1n} \\ \vdots & \vdots & \cdots & \vdots \\ x_{11} & x_{12} & \cdots & x_{1n} \end{bmatrix} \tag{1}$$

The value of each element in this $n \times n$ order matrix is obtained according to the scaling method in Table 1.

Table 1. Significance scale meaning table.

Scaling	Specification
1	Represents elements a and b for comparison, a and b are equally important
3	Represents the comparison between element a and b, a is slightly more important than b
5	Represents the comparison between element a and b, a is obviously more important than b
7	Represents element a in contrast to b, where a is more important than b
9	Represents the comparison between element a and b, a is extremely important than b
2，4，6，8	Represents the comparison between elements a and b, and the importance is the median value of adjacent judgments
Reciprocal	If a compares to b with a scale of x, then b compares with a with a scale of 1/x

The properties that make up the judgment matrix X are as follows.

$$\begin{cases} x_{ij} > 0 \\ x_{ij} = \dfrac{1}{x_{ij}} \qquad i, j = 1, 2, \cdots, n \\ x_{ii} = 1 \end{cases} \tag{2}$$

Next, the maximum eigenvalue and eigenvector of the judgment matrix were calculated by the sum-product method, and the eigenvector was normalized. The specific steps were as follows.

Each column of the judgment matrix was normalized.

$$y_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \qquad i = 1, 2, \cdots, n \tag{3}$$

The matrix obtained after normalizing each column was summed row by row.

$$\overline{W_i} = \sum_{j=1}^{n} y_{ij} \qquad i = 1, 2, \cdots, n \tag{4}$$

Then, the total vector $\overline{W}$ was obtained.

$$\overline{W} = \begin{bmatrix} \overline{W_1} \\ \overline{W_2} \\ \vdots \\ \overline{W_n} \end{bmatrix} \tag{5}$$

After normalizing the vector $\overline{W}$, we obtained

$$W_i = \frac{\overline{W_i}}{\sum_{i=1}^{n} \overline{W_i}} \qquad i = 1, 2, \cdots, n \tag{6}$$

Next, the feature vector W was obtained as follows.

$$W = \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_n \end{bmatrix} \tag{7}$$

The more critical step in the AHP is the consistency test. In this step, we defined the consistency ratio as

$$CR = \frac{CI}{RI} \tag{8}$$

where CI is the consistency index and RI is the random consistency index.

The specific steps to define the consistency ratio CR included the calculation of the largest eigenvalue $\lambda_{\max}$ of the judgment matrix.

$$\lambda_{\max} = \sum_{i=1}^{n} \frac{(XW)_i}{nW_i} \tag{9}$$

The consistency index $CI = \frac{\lambda_{\max} - n}{n-1}$ (where n represents the order of the matrix) was then calculated, and RI was chosen according to Table 2.

Table 2. Random consistency index RI value(Wang, 2019).

n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51

If $CR < 0.1$, the inconsistency of the matrix X was within the allowable range. At this time, the normalized feature vector W was used as a weight vector. Invited experts reviewed the created questionnaire. The expert group comprised teachers from primary, middle schools, and universities. The results of the questionnaires obtained by each expert based on their experienceswereinconsistent so it was necessary to use group decision-making to carry out the final analysis. Arithmetic mean, here the weight of the k-th expert was determined as follows (Yang, 2018).

$$P_k = \frac{1}{1 + a * CR} \quad (a > 0, k = 1, 2, \cdots, m) \tag{10}$$

In Eq. (10), the adjustment parameter $a = 10$.

$$P_k^{\Phi} = \frac{P_k}{\sum_{k=1}^{m} P_k} \tag{11}$$

Finally, the weight of the kth expert was multiplied by the weight of the corresponding indicator.

$$L_k = W^k \cdot P_k^{\Phi} \qquad l = 1, 2, \cdots, m \tag{12}$$

The weight value of the i-th attribute of the student's participation behavior, that is, the sum of L_k was calculated as the final weight.

$$W_i = \sum_{k=1}^{m} W_i^k \cdot P_k^{\Phi} \tag{13}$$

4. Evaluation Scheme for Students' Classroom Learning Status

When evaluating students' learning status, the students' eye-tracking, eye fatigue, and facial expression data were collected with optical and infrared lenses. Secondly, the previously taught knowledge was tested in the last 10 minutes of the class. The test scores were graded into excellent, good, medium and poor. Starting from the data and test scores, hierarchical analysis and decision-making fusion were carried out to evaluate students' learning status, adjust teaching modes, and change teaching methods.

4.1. Fusion Structure of Test Paper Score

The information fusion model for the four levels of test scores was established as follows (Fig.2).

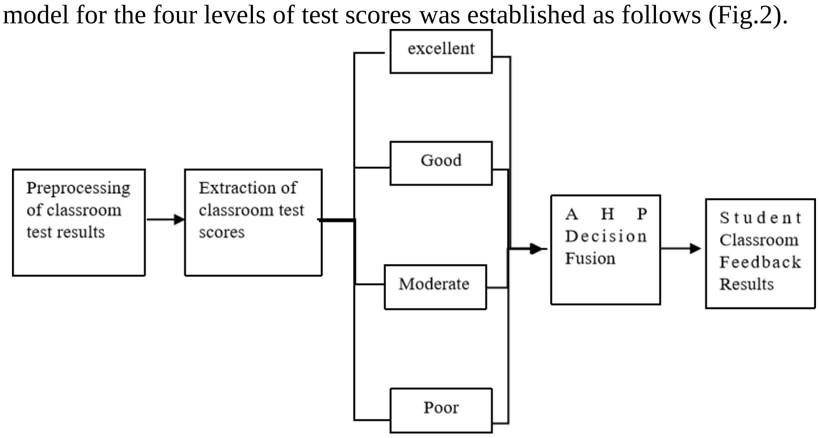

Fig. 2. Multimodal information fusion based on test scores.

At the same time, the following was defined based on the idea of information fusion of different dimensions of the above test scores. The scores of m students who were excellent, good, medium, and poor (m_1,m_2, m_3, m_4)were normalized to obtain a required dataset.

$$A = \frac{m_1}{m}, B = \frac{m_2}{m}, C = \frac{m_3}{m}, D = \frac{m_4}{m} \tag{14}$$

$$(m = m_1 + m_2 + m_3 + m_4)$$

Here, the corresponding A, B, C, and D were used to replace the four evaluation grades. When $N = \{x_1, x_2, \ldots, x_n\}$ was a data set containing n examples, each example was expressed as

$$x_i = \begin{bmatrix} A_i \\ B_i \\ C_i \\ D_i \end{bmatrix}, \quad i = 1, 2, \ldots, \quad n \tag{15}$$

where A_i represents the percentage of the i-th example x on attribute A. According to the analytic hierarchy process, the corresponding vectors of the four test-level weights was obtained as follows.

$$W = [W_A, W_B, W_C, W_D] \tag{16}$$

where W_A, W_B, W_C, W_D corresponds to the weights of the four test levels of excellent, good, medium and poor respectively.

The test score $Score_M$ wasobtained based on the fusion of multiple dimensions of classroom test scores.

$$Score_M = W \cdot M = [W_A, W_B, W_C, W_D] \cdot \begin{bmatrix} A_1 & A_2 & \cdots & A_n \\ B_1 & B_2 & \cdots & B_n \\ C_1 & C_2 & \cdots & C_n \\ D_1 & D_2 & \cdots & D_n \end{bmatrix} \tag{17}$$

The n matrix factors were calculated as $1 \times n$ matrix representing the test-level results.

4.2. Intelligent Evaluation Scheme of Classroom Learning State Based on AHP

The research plan for the evaluation of students' learning status in the four dimensions of eye-tracking data, human eye data, facial expression data, and classroom test scores was constructed as follows (Fig.3).

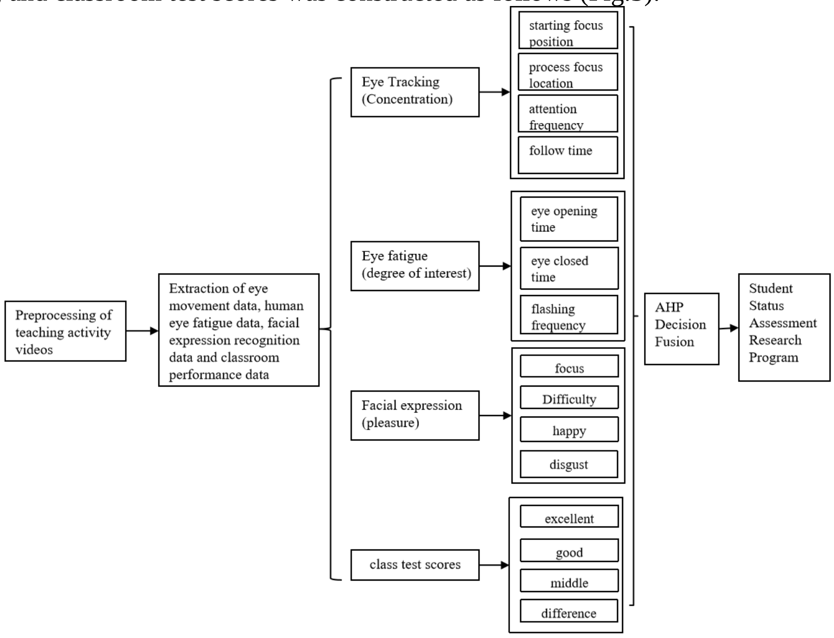

Fig. 3. Learning state fusion based on multi-dimensional.

The flowchart for inputting data and evaluating learning status is as follows (Fig.4):

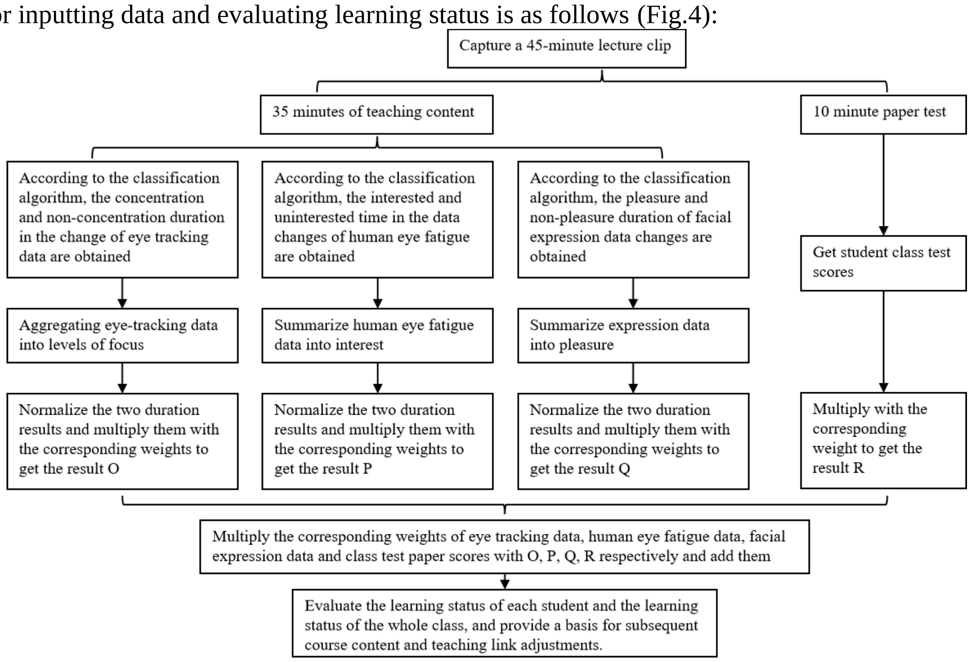

Fig. 4. Flow chart of student learning status evaluation.

Assume that the duration of the eye movement in focusing (t_{11}) and that not focusing (t_{12}), and $T=t_{11}+t_{12}$, and the corresponding weights of t_{11} and t_{12} were 1 and 0 for, the duration of expression changes was calculated as

$$O=\frac{t_{11}}{T} \tag{18}$$

The duration of eye fatigue in watching the teaching video included t_{21} for eye fatigue status when focusing, t_{22} when not focusing, and $T=t_{21}+t_{22}$. The corresponding weights of t_{21} and t_{22}were 1 and 0. After normalizing the duration of the eye fatigue state, we obtained

$$P = \frac{t_{21}}{T} \tag{19}$$

The duration of facial expression changes included t_{31} of happy facial expressions, t_{32} of unpleasant facial expressions in watching the video, and $T = t_{31} + t_{32}$. The corresponding weights of t_{31} and t_{32} were 1 and 0. After normalizing the duration of eye fatigue state, we obtained

$$Q = \frac{t_{31}}{T} \tag{20}$$

In the last 10 minutes of the class, the knowledge point level test was conducted and scores were classified into four grades: excellent, good, medium, and poor. When m_1 students with excellent test scores, m_2 students with good test scores, m_3 students with medium test scores, m_4 students with poor test scores, and $m = m_1 + m_2 + m_3 + m_4$ the normalized results were obtained as follows.

$$R = W_A \cdot A_1 + W_B \cdot B_1 + W_C \cdot C_1 + W_D \cdot D_1 \tag{21}$$

When calculating the weights of the four dimensions later and $N = \{y_1, y_2, ..., y_n\}$ representing a data set containing *n* examples, the multimodal information fusion based on machine vision was formalized as

$$\mathrm{y_i} = \begin{bmatrix} O_i \\ P_i \\ Q_i \\ R_i \end{bmatrix}, \quad i = 1, 2, ..., \quad n \tag{22}$$

where O, P, Q, R respectively represent the four fusion dimensions eye tracking state, fatigue state and facial expression state of the fusion object i, and the percentage of the test paper test results.

5. Questionnare Data Analysis

We conducted questionnaire surveys to 101 authoritative experts in related fields from 11 provinces, municipalities and autonomous regions including Hebei, Henan, Guizhou, Jiangsu, Shandong, Shaanxi, Hubei, Guangdong and Xinjiang. The professional titles and qualifications of experts in this questionnaire survey are summarized in Table 3, among which primary school, middle school, and university teachers accounted for 18.81, 38.61, and 42.57%, respectively.

Table 3. Respodents of questionnaire surveys.

Title or qualification	University Teachers（43）			High school teacher（39）			PrimarySchool Teachers（19）		
	Advanced	Intermediate	Primary	Advanced	Intermediate	Primary	Advanced	Intermediate	Primary
quantity	15	14	14	2	25	12	3	8	8

We compared the importance of the four dimensions of concentration, interest, pleasure, and test scores, and the attention position, frequency, and duration. The opening time, closing time, and flicker frequency of the eye were also analyzed. The comparison of four typical expressions reflected the students' interests: concentration, distress, joy, and disgust. In the questionnaire survey, the five-point scale was used: equally important, slightly important, obviously important, strongly important, and extremely important, and the corresponding numbers were 1, 3, 5, 7, and 9. We also invitedstudentsto add items on eye movement, fatigue, and facial expression. For example, the external manifestations of learning status include language changes, students' learning postures, interaction between students and teachers, and the frequency and amplitude of shaking their heads. In addition to attention position, duration, attention, eye-opening, eye-closing, flicker frequency, sleepiness, concentration, joy, disgust, actions, and expressions, students' learning status also included the sitting posture, dazed and raised eyebrows,andpride. These can be used for further research on students' learning status.

6. Fusion Weight Determination Based on AHP

The judgment matrix obtained according to the survey results of an expert on the learning state was as follows.

$$X_k = \begin{bmatrix} 1 & 3 & 1/5 & 1 \\ 1/3 & 1 & 1/5 & 1 \\ 5 & 5 & 1 & 5 \\ 1 & 1 & 1/5 & 1 \end{bmatrix} \tag{23}$$

The normalized eigenvectors were

$$W_k = \begin{bmatrix} 0.1686 \\ 0.0956 \\ 0.6123 \\ 0.1226 \end{bmatrix} \tag{24}$$

The maximum eigenvalue $\lambda_{\max} = 4.1545$.

Taking $a = 10$, according to formula 10, the authority of the expert wascalculated as $P = 0.6360$, and the sum of the authority of all 101 experts was

$$\sum_{k=1}^{101} P_k = 61.1365 \tag{25}$$

The weight of the expert wasobtained after normalizing the weight of the expert.

$$L_k = W_k \cdot P_k^* = \begin{bmatrix} 0.1686 \\ 0.0956 \\ 0.6123 \\ 0.1226 \end{bmatrix} \cdot 0.0104 = \begin{bmatrix} 0.0018 \\ 0.0010 \\ 0.0064 \\ 0.0013 \end{bmatrix} \tag{26}$$

The above wasthe scoring result of one of the experts. The final evaluation results of 101 experts were as follows.

$$L = \sum_{k=1}^{101} L_k = \begin{bmatrix} 0.3010 \\ 0.2518 \\ 0.2806 \\ 0.1666 \end{bmatrix} \tag{27}$$

In the research on the performance of students' learning status, the weight vectors of these four behaviors werecalculated according to the AHP, and then the corresponding weights of interest, pleasure, concentration, and classroom grades were obtained according to the above steps. The calculation results showed that among the four performances, the most related to the student’s learning status was the degree of interest, followed by the degree of concentration, joy, and finally the grades in class. The experts assessed the students' concentration level in the classroom for eye focus, focus duration, and focus frequency, and the data was compared to the measured data. The weights of attention position, attention duration, and attention frequency were 0.3892, 0.3408, and 0.2701, respectively. For an eye-opening time, eye-closing time, and flickering frequency, the weights were 0.4596, 0.2492, and 0.2939, respectively. The weights of concentration, pleasure, and disgust were 0.2512, 0.3221, 0.2595, and 0.1672, respectively.

7. Multimodel Fusion Weight Table and Analysis

The final multimodal fusion weight is presented in Table 4. The degree of interest accounted for a large proportion of students' learning status, followed by the degree of concentration and pleasure. The proportion of classroom test scores was the smallest. It is necessary to improve students' interest in what they learn and to make the classroom vivid and full of vitality. In terms of concentration, the attention position reflected the student’s learning status better than other attributes. The concentration of the students in the class presents the attention position of the students. When students do not concentrate, teachers need to interact with them to improve students' attention. In terms of interest, the eye-opening time is important as it reflects the enthusiasm of students. By observing the students' eye-opening time, the interests of students can be assessed for teachers to grasp the individual differences of students and teach students according to their aptitude. In terms of happiness, we analyzed the relationship between four expressions. Concentrated expressions better reflected students' happiness in class, indicating that when students concentrated on class, students felt happier while they felt less pleasure. By observing the students' facial expressions, learning status can be assessed. In terms of classroom performance, since there was no specific evaluation data, we used the grades to understand theirmastery of knowledge.

Table 4. Multimodal data fusion weight table.

Dimension	Weights	Property	Weights
Concentration	0.2806	Focus on location	0.3892
		Attention frequency	0.2701
		Follow time	0.3408
Interest	0.3010	Eye-opening time	0.4569
		Eyes closed	0.2492
		Flashing frequency	0.2939
Pleasure	0.2518	Focus	0.3221
		Difficulty	0.2512
		Disgust	0.1672
		Happy	0.2595
Classroom test scores	0.1666	Excellent	0.1
		Good	0.4
		Middle	0.4
		Difference	0.1

8. Conclusions

The learning status of students in the classroom is related to a complex cognitive process. There are many factors involved in whether students are interested in the class and accurately understand the teacher's teaching content. Usually, measuring students' classroom learning status is a subjective evaluation that is difficult to describe quantitatively. With the development of AI technology, a large number of modern information technologies have been applied in education. People use video images, eye-tracking techniques, and facial expression recognition techniques of deep learning to describe students' attention and interest in learning. However, facing the complexity of students' learning process, there is no single technology that can accurately describe students' learning status and performance. Therefore, when evaluating students' learning status, it is necessary to consider their learning status, learning process, and academic performance. We used AHP to obtain corresponding weights for the four dimensions of interest, enjoyment, focus, and classroom performance in evaluating students' learning status through information technology. Each student's learning status was assessed in real-time which is a basis for teachers to adjust teaching modes, improve students' classroom learning efficiency, and provide educational technology support for personalized training of students. Due to various factors, the collected data may not be accurate, and changes in various weights affected the accuracy of the AHP model. In the future, it is necessary to increase the number of samples, continuously modify various parameters of the model, more accurately describe students' learning behavior in the classroom, and better enhance the quality of education and teaching to do a good job in information technology work.

Funding: This research was funded by the Research topic for the 2023 Education Science Plan of HaidianDistric of Beijing, Grant No. HDGH2023117-6.

Acknowledgments: The paper has received strong support from the leaders of Yuying School and teachers from the Information Science Department.

Conflicts of Interest: The author declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

References

1. Jia, P., Zhang, C., Zhao, X., &Yan, X. (2019). Analysis of Classroom Student Status Based on AI Video Processing. *Modern Educational Technology*, *29*(12), 82–88.
2. Liu, Q., Wang, Y., Lei, S., & Zhang, S. (2017). Research and Reflection on the Application of Learning Analysis from the Perspective of Education Big Data.*Journal of Distance Education*, *35(03)*, 71–77.
3. Ren J. (2020). Research on Comprehensive Evaluation of Student Concentration Based on Machine Vision. Master's Thesis, North China University of Technology, Chian, July 2020.
4. Sun, Y. & Li, Q. (2018). The application of deep learning in mathematical education. In Proceedinds of the 2018 1st IEEE International Conference on Knowledge Innovation and Invention (ICKII), Jeju Island, South Korea, 23–27 July, 2018; pp. 130–133.
5. Sun, Y., Li, Q., Zhang, H., & Zou, J. (2018b). The application of eye tracking in education. In Proceedinds of theAdvances in Intelligent Information Hiding and Multimedia Signal Processing—Proceedings of the 13th International Conference on Intelligent Information Hiding and Multimedia Signal Processing, Smart Innovation, Systems and Technologies, Matsue, Shimane, Japan, 12–15August, 2017; pp.27–33.

6. Sun, Y. (2023). A method for detecting student classroom learning fatigue based on optical and infrared images, Proceedings of the 2023 IEEE 6th International Conference on Knowledge Innovation and Inventiob, ICKII 2023, Sapporo, Hokkaido, Japan, 11–14 August, 2023; 474–478,
7. Hwang, S,H., Chang Y.F. (2018), The Adaptive Indicators and Weighting System for the reuse of industrial heritage, *Journal of the Science of Design*, *2*(2), 111–120.
8. Wang, L. (2019). Cost control of high-rise residential construction and installation based on standard cost method. Master's Thesis, Nanchang Universiy, China, July, 2019.
9. Wang, Y., Liu, Q. & Zhang, W. (2019). Research on data-driven online learning state analysis model and its application. *Journal of Distance Education*, *37*(2),74–80.
10. Yang, J.M., & Lee, S.G. (2018). A mathematical theory of the AHP (Analytic Hierarchy Process) and its application to assess research proposals. *Communications of Mathematical Education*, *22*(4), 459–469.