



# Monitoring Method of Ideological and Political Class Learning Status Based on Mobile Learning Behavior Data

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**Abstract.** In order to improve the quality of ideological and political education, a method for monitoring the learning status of ideological and political courses based on mobile learning behavior data is proposed. Combined with mobile technology to collect ideological and political learning behavior characteristic data. According to the feature recognition results of the data, an accurate stu classification algorithm is designed, and an evaluation system for the learning status of ideological and political courses is constructed. Six characteristic actions in human poses are selected to study learning state classification. Realize the monitoring of the students' learning status in political courses. Finally, it is proved by experiments that the monitoring method of learning state of ideological and political courses based on mobile learning behavior data has high practicability and meets the research requirements.

**Keywords:** Mobile terminal · Learning behavior · Ideological and political lesson · State monitoring

## 1 Introduction

With the rapid development of information technology and the advent of knowledge explosion era, the demand for compound talents is increasing, continuing education and lifelong learning become the trend. In order to meet people's ideological and political course learning needs and provide technology and resources support for lifelong learning, we need to expand the scale of distance education. In order to improve the effect of ideological and political education, it is necessary to study the monitoring methods of ideological and political learning state [1]. Based on this, this paper aims to develop a distance learning process monitoring system based on mobile learning technology, and use mobile learning technology to collect part of the learning behavior of learners in real time. Learning process monitoring is a key link in distance education [2]. The distance learning process monitoring based on mobile learning can classify the learning behavior of different learners according to their learning behavior characteristics, and establish a learning behavior classification database; on the other hand, the mobile

learning behavior of the dynamically collected learners is entered into the learning terminal through Bluetooth and other wireless transmission methods, and then entered into the distance learning management center through the Internet, and the collected mobile learning behavior is compared with the mobile learning behavior classification database of the learners through the analysis software, so as to obtain the real-time learning status of the learners and provide timely and targeted support services for teachers to intervene and the learning of the learners. Experiments based on mobile learning behavior data show that mobile learning technology can monitor the distance learning process and help managers to master the learning state of learners, and provide personalized learning process and learning resources.

## 2 Monitoring Learning Status of Ideological and Political Class Based on Mobile Learning Behavior Data

The method of monitoring the learning situation based on mobile learning behavior data is shown in Fig. 1.

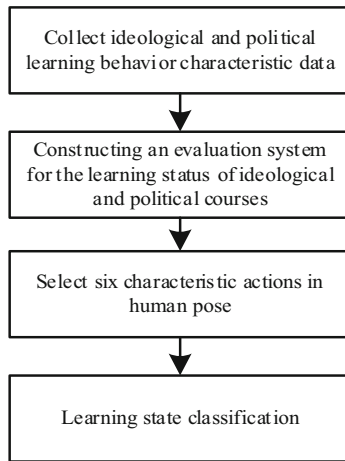
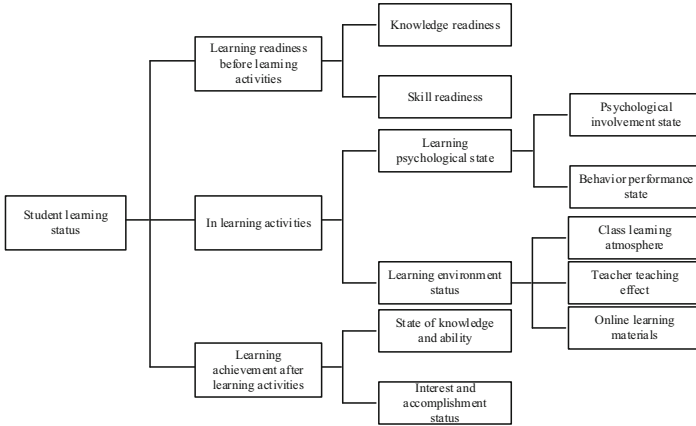


Fig. 1. Identification diagram of student learning behavior

### 2.1 Feature Recognition Based on Mobile Learning Behavior Data

For learning these two words, people have a lot of views, everyone’s understanding is that learning is the process of students to build knowledge system. On the definition of learning state, according to the previous research, several prominent viewpoints have been summarized: learning state is the comprehensive reflection of various functions of the body in the process of learning, specifically including body movements and attention, and learning state is the performance of the body stability of the learners in learning activities [3]. The state of learning refers to the degree to which the learner is grasping

the knowledge. The learner's learning state includes three aspects: the state of study preparation before learning activities, the state of study activities and the state reached after learning activities. The specific structure is shown as follows (Fig. 2):



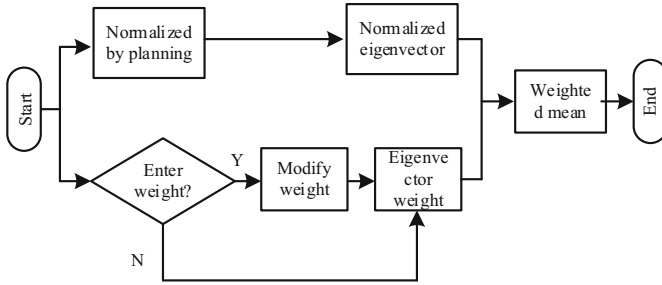
**Fig. 2.** Identification diagram of student learning behavior

According to the definition of learning state, learning state is the comprehensive performance of physiological and psychological characteristics of learners in learning activities. According to the monitoring requirements of students' classroom performance, learning state is defined as three states of concentration, general and non-concentration, so as to classify the classroom learning state of different students. The recognition of learning state is the recognition of local human motion [4]. In a certain aspect, the local motion state directly reflects the learner's learning state. Therefore, this paper studies the local motion of human body. It is found that local posture can be measured, local motion is relatively limited, and the state of local expression is relatively unlimited. Different people have different local motion characteristics. That is, a series of local posture into local actions, human learning actions constitute the learning state of the evaluation idea, and the use of the corresponding recognition algorithm recognition [5]. The method of multi-level hierarchical learning state pattern recognition is mainly divided into three levels, each level is classified according to the characteristics of the attitude itself. The recognition output data of the former level algorithm is used as the input data of the latter level algorithm. The structure of the designed attitude recognition is shown in Fig. 3:

After several discussions with many educators and experts, the study integrates and analyzes the related materials, and chooses the learning posture features in six classrooms as the basis to identify the learning state (Table 1).

In the technology of motion pattern recognition based on the mobile terminal, the common methods of feature information extraction for the attitude data collected by the mobile terminal are as follows.

From the Table 2, we can see that these three kinds of feature information extraction methods have their own characteristics, different perspectives, the choice of feature extraction methods are different. Based on the experimental results of this paper, it is



**Fig. 3.** Learning behavioral posture recognition architecture

**Table 1.** Learning state feature space model table

State	Eye	Mouth	Visual angle	Head	Body
Absorbed	The upper eyelid is lifted, the eyes do not turn their eyes, the blinking frequency is uniform, and the eye angle becomes larger	Open or close naturally	Static	Towards the teacher, which changes with the position of the teacher	Keep the distance between the front and rear tables
Commonly	Keep your eyes fixed or blink at a uniform frequency, with uniform eye angle and lower blinking frequency	Lips open slightly	Static	Keep the head in the same position for at least 5 s	Keep the distance between the front and rear tables
Inattention	The eyes keep staring at one place, and the angle of the eyes becomes smaller	Yawn and open your mouth	Shake	Nod slowly and often	Close to the front or back table

necessary to recognize the motion patterns of left turn head, right turn head, lower head, raise head, left deviation head, right deviation head and horizontal vision. Considering that the main difference of the motion patterns lies in the direction and angle, the mean of the 32-dimensional attitude angle in the time domain is selected as the feature information of the attitude recognition.

**Table 2.** Common feature information extraction methods

Feature extraction method	Characteristic parameter
Time domain method	Mean, standard deviation, variance, information entropy and correlation coefficient, etc.
Frequency domain method	Fast Fourier transform coefficients, discrete cosine transform coefficients, frequency domain entropy, energy spectral density, etc.
Time frequency method	Wavelet transform, Fourier transform, etc.

## 2.2 Evaluation Algorithm for Learning State of Politics Course

In the traditional classroom teaching activities, how to realize the classification of students' learning status in the classroom is an important issue under the background of quality-oriented education. The most direct and efficient place for students to acquire knowledge is the classroom, so the overall learning efficiency of students has a close relationship with their learning state in the classroom. Lack of attention and poor learning condition will directly affect students' mastery of knowledge. Inattentive learning condition will not only result in low learning efficiency, but also cause students' learning enthusiasm to drop [6]. If the students pay attention in the course and pay attention to the lecture in a good study state, they will not only learn the most knowledge in the limited class time, but also make the students more confident in the study. Because of the traditional classroom a teacher facing the situation of dozens of students, teachers simply can not pay attention to every student. Therefore, in order to make each student's learning state known by the teacher accurately, it is very important to design an accurate classification algorithm of student's learning state. The state of learning is closely related to the state of local movement of human body. Therefore, the local motion information of learners is used as the basis to detect and analyze the learning state of learners. In order to realize the detection of local motion information, accurate local position coordinates should be obtained firstly [7]. Because the local motion of human body has the characteristics of large range and low motion frequency, the traditional attitude algorithm can not be completely applied to calculate the local attitude angle. Therefore, based on the traditional attitude description method, the mobile learning behavior and the extended Kalman filtering algorithm are studied respectively. A local attitude solution method is proposed. In the process of attitude description, the angle can be chosen to represent the attitude information, namely Euler angle. Euler Point was first proposed by Euler. The Euler angle consists of roll angle  $\gamma$ , pitch angle  $\theta$  and heading angle  $\phi$ . The Euler angle has a range, the roll angle  $A$  has a range of  $(-x, x)$  radians, and the pitch angle  $B$  has a range of  $(-x/2, x/2)$  radians turning angle  $C$  has a range of  $(1 - x, 1 x)$  radians converting the data from the carrier coordinate system into the coordinate system. The Euler angle is used to represent this conversion process. It is assumed that the sum of the head steering angle, pitch angle and roll angle is represented by the moment of inertia alpha. Such as:

$$\omega = A\dot{\phi} + B\dot{\theta} + C\dot{\gamma} \quad (1)$$

Let the angular velocities in the head coordinate system be expressed as  $m$ ,  $n$ , respectively, and the angular values are differentiated to get the formula.

$$\varpi = \prod \omega(M - N) \quad (2)$$

The differential expressions of the attitude angles  $\gamma$ ,  $O$ ,  $q$  are shown by the simplification of the expression.

$$\begin{bmatrix} \dot{\gamma} \\ \dot{\theta} \\ \dot{\phi} \end{bmatrix} = \frac{1}{\cos \theta} \begin{cases} \omega_x - \sin \gamma \cos \theta \\ \omega_y + \sin \gamma \sin \theta \\ \omega_z - \cos \gamma \sin \theta \end{cases} \quad (3)$$

Learning behavior feature point recognition is to automatically mark the key points from the input image data, including eye contour, nose, mouth, eyebrows, face contour and so on. The key point of feature recognition is the accuracy and speed of recognition. A method of feature point recognition using regression tree structure is proposed. In this paper, we use the mobile learning behavior recognition method to design the loss function and modify the error of data marker, the training effect is better, and improve the precision of sparse subset. According to the definition of learning posture, this paper mainly chooses six kinds of feature actions in human posture to study the classification of learning state. They are eye closing feature action, yawn feature action, mouth closing feature action, nodding and dozing feature action, angle of view moving feature action and body leaning feature action. First of all, the above six movements can be relatively easily captured by the camera, there is no undetected problem. Then, according to the angle range of local rotation, we can divide the local learning posture of a certain moment into 17 kinds of learning postures, and define the head-up state as  $(-5, 5)$ . Because of the selected "front and bottom right" coordinate system, we can divide it into three equal parts, corresponding to the local state of small, medium and large left-turn head. Then the heading angle range of the small left turn head is  $(-12, 15)$ ; the heading angle range of the medium left turn head is  $(24, -12)$  the heading angle of the large left turn head is greater than  $-24.2$ . Based on this, seven local learning postures are divided in different degrees as shown in Table 3.

The fatigue detection based on weighted average is to fuse the information by summing up the fatigue features according to their weights and calculate the fatigue value  $f$ , the calculation formula is as follows:

$$\begin{aligned} f &= \sum_{i=1}^n w_i x_i = w_1 x_1 + w_2 x_2 + \dots + w_n x_n, \\ i &= 1, 2, \dots, n \\ \sum_{i=1}^n w_i &= 1 \end{aligned} \quad (4)$$

Variable descriptions are shown in Table 4.

Because the range of fatigue value is different in turn, blink frequency, yawn frequency and nod frequency, it is necessary to quantify these fatigue characteristics as fatigue values from 0 to 1.  $X_k$  is the fatigue value of the  $k$  component in the fatigue eigenvector, and  $k$  is the weight corresponding to the  $k$  component  $x_k$ , and the sum of

**Table 3.** Attitude classification table

Category		Label	Pitch angle/(°)	Heading angle/(°)	Roll angle/(°)
Turn left	Small range	A	(-5, +5)	(-12.2, -5)	(-5, +5)
	Medium amplitude	B	(-5, +5)	(-25.2, -12.2)	(-5, +5)
	Substantially	C	(-5, +5)	<(-25.2)	(-5, +5)
Turn right	Small range	a	(-5, +5)	(+5, +15.3)	(-5, +5)
	Medium amplitude	b	(-5, +5)	(+15.3, +28.2)	(-5, +5)
	Substantially	c	(-5, +5)	>(28.2)	(-5, +5)
Bow your head	Small range	D	(+5, +23.3)	(-5, +5)	(-5, +5)
	Medium amplitude	E	(+23.3, 46.5)	(-5, +5)	(-5, +5)
	Substantially	F	>(45.5)	(-5, +5)	(-5, +5)
rise	Small range	d	(-20.2, -5)	(-5, +5)	(-5, +5)
	Medium amplitude	e	(-41.2, -20.2)	(-5, +5)	(-5, +5)
	Substantially	f	<(-41.3)	(-5, +5)	(-5, +5)
Left leaning head	Small range	G	(-5, +5)	(-5, +5)	(-25.2, -5)
	Medium amplitude	H	(-5, +5)	(-5, +5)	(-51.2, -25.2)
	Substantially	I	(-5, +5)	(-5, +5)	<(-51.2)
Right slanting head	Small range	g	(-5, +5)	(-5, +5)	(+5, 27.6)
	Medium amplitude	h	(-5, +5)	(-5, +5)	(+27.6, +55.2)
	Substantially	i	(-5, +5)	(-5, +5)	>(55.2)

all weights is 1. The tool supports the user to set weights corresponding to each feature component according to the needs, and the threshold value for judging fatigue can be determined by the user himself or by using the results of several experiments in this case as the default threshold value. When the fatigue value is higher than this threshold value, the fatigue state is determined.

### 2.3 Realization of Monitoring the Learning State of Politics Curriculum

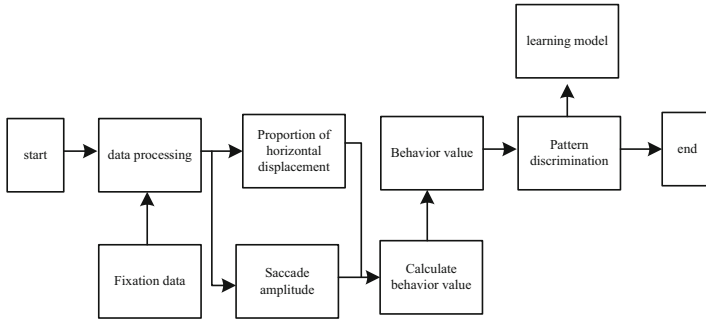
Since the time of closing eyes increases and the frequency of blinking decreases with the occurrence of yawning and nodding, the detection of fatigue based on behavioral features is mainly based on the recognition of these behaviors. Therefore, we choose PERCLOS,

**Table 4.** Variable descriptions

Variable	Explain	Variable	Explain	Variable	Explain
Q	PERCLOS value	Z1	Fatigue value corresponding to PERCLOS	M1	Weight corresponding to Z1
W	Blink frequency	Z2	Fatigue value corresponding to blink frequency	M2	Weight corresponding to Z2
E	Yawn frequency	Z3	Fatigue value corresponding to yawn frequency	M3	Weight corresponding to Z3
R	Nodding frequency	Z4	Fatigue value corresponding to nodding frequency	M4	Weight corresponding to Z4

blinking frequency, yawning frequency and nodding frequency as characteristic vectors to measure the fatigue state. Through the mobile end and the SDK provided by Microsoft, we can capture the movement unit of human face, including the degree of eyes closing, mouth opening amplitude, local deflection angle and so on. When the degree of ocular closure is greater than 0.8, it is judged to be ocular closure. The ratio of ocular closure frames to total frames is calculated as PERCLOS parameter. Eyes from open to close to open again, as a blink, statistics within a certain period of time blink times, that is, blink frequency. When the mouth is closed, then opened and then closed, it is regarded as a yawn, and the number of yawns in a given period of time is calculated as the frequency of yawning. Nodding behavior depends on the angle of local downward deflection. When the deflection angle is greater than a certain threshold value, and then returns to the normal value, the nodding behavior is judged to occur once, and the nodding times in a certain time are counted, that is, the nodding frequencies are determined by using the weighted average method and the support vector machine model. Users can choose from the program interface to calculate the fatigue level of the method - weighted average method or support vector machine. If the weighted average method is selected, the user can input the corresponding weights of each fatigue parameter according to the needs, or choose the default combination of weights without filling in. If a support vector machine is selected, the provided trained model is used. In this way, it is very convenient for users to customize their fatigue rules and choose suitable fatigue detection methods for students. The specific flow of the weighted average method for calculating fatigue degree is shown in Fig. 4.

First of all, because the fatigue parameters are different in order of magnitude, it is necessary to map the fatigue parameters to 0–1 uniformly according to certain rules. Here, we do not plan the fatigue parameters according to their values, because the fatigue values do not necessarily increase linearly with the increase of fatigue parameters. For example, the normal range of blinking frequency is 10–15, and too large or too small



**Fig. 4.** Flow chart of fatigue value calculation by weighted average method

may be a sign of fatigue. If the user selects to set the weights of each fatigue parameter, modify the corresponding weights, otherwise, the default weights combination is adopted. Finally, the fatigue value can be obtained by summing the normalized fatigue parameters multiplied by the corresponding weights. Users can set their own threshold to judge fatigue can also adopt the default threshold, when the fatigue value is greater than the threshold, it is judged as fatigue. Because reading text is generally slow horizontal movement of the line of sight, until the line, then the next line of text to read. Therefore, in slow reading, the line of sight has a direction, the general level of movement in the majority. Therefore, when watching video, the saccade of the eyes is larger, and the line of sight is not directional, so the typing behavior is similar to slow reading. Therefore, the amplitude of typing mode is smaller than reading mode, and the line of sight is also directional. According to these objective laws and experimental observations, it is easy to distinguish two eye movement parameters of three learning modes, i. e. saccade amplitude and horizontal displacement ratio. Firstly, the ratio of horizontal displacement time in a period is calculated, the average saccade amplitude is calculated, the behavior value is calculated according to the formula, and the behavior mode is divided according to the range of behavior value.

### 3 Analysis of Experimental Results

The recognition of learning state mainly includes two aspects: fatigue state and inattention state. According to experience and a lot of experiments, a monitoring period of state identification is set to 100 s. In fatigue state, the threshold of nodding times in one cycle is 4, while in inattention state, the threshold of turning times in one cycle is 4. By recording and counting the results of the above 43.2 learning action recognition experiments in 100 s, i. e. the number of times that each action appeared, 5 experimenters were selected to do the experiment, and each experimenter did more than 4 nods in one monitoring cycle. First of all, six kinds of features captured were tested. The experiment selects 20 students to carry on the experiment according to the characteristic movement. The data obtained are shown in tables, and the experimental results are shown in Tables 5 and 6.

In this study, 20 students were selected to collect the video clips of their focused, general and non-focused learning states. A total of 87 groups of video clips were collected, each of which lasted 1 min and was decomposed into 10 frames per second. Then

**Table 5.** Sample of learning behavior features and actions

Characteristic motion	Positive sample	Negative sample
Eye closing feature action	50 frame eye opening video	50 frame closed eye video
Close your mouth	50 frames mouth closed video	50 frames mouth opening video
Lean forward	50 frames of body not leaning forward video	50 frame forward leaning video
Perspective movement	50 frame view not moving video	Moving video frame 50
Yawn	Video containing 100 yawns	
Nod and doze off	Contains a video of 100 nodding and dozing	

**Table 6.** Experimental results of characteristic actions

Characteristic action	Recognition accuracy
Eye closing feature action	80%
Close your mouth	85%
Lean forward	98%
Perspective movement	89%
Yawn	92%
Nod and doze off	96%

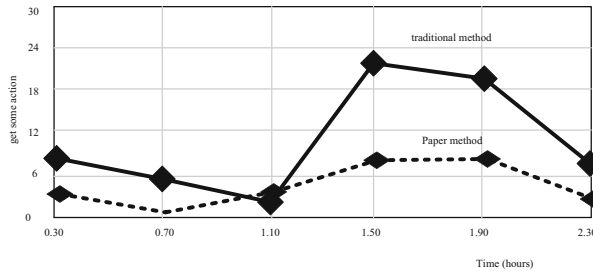
we use all kinds of feature methods to get the feature actions and record and randomly arrange them. 80% data are divided into training sets and 20% data are divided into testing sets. Used to train training support. The final result of behavioral recognition is shown below (Table 7).

**Table 7.** Learning behavior recognition results

Learning state	Number of experiments	Correct times	Number of errors	Recognition rate
Fatigue state	510	455	55	90.8000%
Inattention	510	462	48	92.0000%
Population	1200	917	103	91.5000%

From the results of behavior recognition in the table, the recognition rate of fatigue state based on threshold method is obviously higher, which shows that the recognition method designed in this paper has higher recognition effect. After excluding the invalid data of 7 subjects and summarizing the distribution characteristics of blinking signals of 38 valid subjects, it is found that the action characteristics of the subjects mainly

focus on the following three conditions. The distribution of the number of actions of 20 subjects (52.6%) is shown in Fig. 5.



**Fig. 5.** Distribution of abnormal actions of 20 subjects

In order to compare the performance of the two algorithms, we calculate the mean square deviation of the EKF algorithm and the algorithm designed in this paper in static and dynamic conditions. The results are shown in Table 8.

**Table 8.** Comparison of mean square deviation of two detection methods

Test content	Static state			Dynamic		
	Roll angle/(°)	Pitch angle/(°)	Heading angle/(°)	Roll angle/(°)	Pitch angle/(°)	Heading angle/(°)
Extended Kalman filter algorithm	0.0521	0.0568	0.0525	0.6752	0.4256	0.7625
Algorithm in this paper	0.0215	0.0265	0.0325	0.3256	0.2236	0.1658

Compared with Table 8, the mean square deviation of the proposed method is smaller than that of Extended Kalman Filter, which shows that the proposed method can track and respond to local attitude changes more quickly and accurately. In the local motion attitude measurement experiment, the moving end can get the accurate local motion attitude. Because this paper combines mobile technology to collect ideological and political learning behavior characteristic data. According to the feature recognition results of the data, an evaluation system for the learning status of ideological and political courses is constructed. Six feature actions in human poses are selected to study learning state classification. In this way, a high-precision student's political course learning status is achieved.

## 4 Conclusion

To sum up, it is of great significance to monitor the learning process of distance learners by using the mobile learning technology. On the one hand, distance learning managers

and teachers can dynamically grasp the learners' learning situation, gradually understand the learners' learning characteristics, and provide personalized learning process support services. According to the abnormal changes of the learner's learning state, corresponding intelligent intervention or manual support services are provided for effective communication and interaction in real time. So that learners feel the teacher's attention and respect, and then stimulate enthusiasm for learning, to maintain a good state of learning. Through the analysis of monitoring data, we can evaluate students' learning behavior and provide reference for learning management to evaluate the learners' process. In addition, the assessment results can be fed back to learners to help them understand their own learning characteristics, progress and effects and to monitor and regulate themselves accordingly. On the other hand, distance learning management can design and push personalized learning resources for learners based on these data.

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## References

1. Xu, N., Fan, W.: Research on interactive augmented reality teaching system for numerical optimization teaching. *Comput. Simul.* **37**(11), 203–206+298 (2020)
2. Sun, Z., Anbarasan, M., Praveen Kumar, D.: Design of online intelligent English teaching platform based on artificial intelligence techniques. *Comput. Intell.* **37**(3), 1166–1180 (2021)
3. Martin, F., Ritzhaupt, A., Kumar, S., et al.: Award-winning faculty online teaching practices: course design, assessment and evaluation, and facilitation. *Internet High. Educ.* **42**, 34–43 (2019)
4. Luo, Y., Han, X.: Research on blended courses classification based on characteristics of students online learning behavior. *China Educ. Technol.* (06), 23–30+48 (2021)
5. Li, H., Wei, Y.: Research on the construction and application of learning behavior evaluation system in hybrid teaching. *China Educ. Technol.* **10**, 58–66 (2020)
6. Jing, Y., Li, X.: Characteristics analysis of teachers' online learning behavior supported by learning analytics. *China Educ. Technol.* **23**(02), 75–82 (2020)
7. Yuan, L., Yuan, Y., Du, X.-F., et al.: The influence of subjective norms on mathematical learning behavior: the mediating effect of mathematical interest. *J. Math. Educ.* **29**(05), 14–19 (2020)