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Research Article

Study on the Distance Learners' Academic Emotions Using Online Learning Behavior Data

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In recent years, computer vision, artificial intelligence, machine learning, and other high-tech technologies have advanced rapidly. These strategies lay a new technical foundation for online learning and intelligent education by making it easier to promote the scientific, intelligent, and data-driven growth of learners' academic emotions. However, at present, online learning can better make up for the shortcomings of traditional learning and enable people to realize distance learning. However, as an important indicator, learners' learning emotion has a direct impact on learners' learning quality and effect. Therefore, this paper analyzes distance learners' academic emotions based on online learning behavior data. It extracts online learning behavior data by using a deep learning algorithm and multimodal weighted feature fusion based on DS (Dempster-Shafer) evidence theory, establishing distance learners' academic cognition motivation model, and constructs an online learning emotion measurement framework. Finally, it is determined through a correlation study of distance learners' academic emotions and learning impacts those learners' academic emotions in class. It will have a beneficial influence on learning since learners' academic emotion is favorably connected with instructors' emotion, and learners' addition, deletion, and modification behavior is positively correlated with learners' academic emotion.

1. Introduction

With the continuous reform of the educational concept, the problems of traditional classroom education have become increasingly prominent. In traditional classroom teaching, teachers and students communicate with each other in a variety of ways, such as students' facial expressions, body language, and answering questions in class. The online learning behavior of distance education learners needs to use technical means to capture sound, text, images, and other information, to realize indirect emotional communication with learners, thus increasing the difficulty of distance learners' academic emotion analysis [1]. Academic emotion is a major factor influencing the effect of online learning. Emotion permeates all aspects of people's life and works, showing the effects of perception and motivation, which can promote or inhibit people's learning motivation [2].

Chinese academic institutions have changed the education of big classes and in-person training in classrooms with insufficient ventilation to comply with the National Epidemic Control Center's requirements on social distance. These innovations have included teachers transitioning from traditional classrooms to online schools using computerized learning management systems, as well as providing synchronous instruction via distant courses. Yet, synchronous education has been criticized for its instructor-centric models, which prioritize educators above pupils [3]. As a result, several learners who were quarantined or unable to visit China during the COVID-19 epidemic preferred the small private courses online and massive online class's initially public and private colleges as means of distance learning. The MOE has established a statewide online learning framework that covers all educational sectors, especially higher education, to address the COVID-19 epidemic without interrupting lectures. This platform supports a collection of online educational programs and materials available throughout all systems for usage by all institutions [4]. The abovementioned system collaborates with telecommunication companies to provide special offers on online services, including free 4 G SIM cards and some other pupil discounted rates, to financially deprived students or students for whom the school systems have been stopped and are now attending courses online at home.

The idea of behavioral psychology states that analysis of behavioral data can provide information about students' psychodynamics and observable behaviors [5]. LMSs provide the ability to record a child's online operating habits, which are saved as part of a student record. To monitor a learner's learning behaviors, teachers might mine the student's biography for data. The operating actions of learners when participating in online learning are termed learning behaviors [6] and can indicate either explorative learning behavior or learning involvement behaviors. Various LMSs offer multiple data gathering limitations; therefore online operational behaviors vary. Investigators can collect recordings of various online operational activities to extrapolate information that is not readily visible in raw data. When a student clicks on a certain function in the LMS, the record and timing of that activity are saved in the database as part of the student biography. When appropriately evaluated, such online operational behaviors might mirror students' online learning practices. The majority of online learning activities are estimated using frequency and duration. These include the total frequency with which a class was accessible, the total time with which an instructional video was accessed, and the total amount of posts generated in online conversation [7, 8]. After researchers collect these online learning behaviors, data cleaning must be performed to avoid bias caused by aberrant outcomes, and the efficiency of the behavioral data collecting must be evaluated. This is done to mitigate the impact of determined online operational actions induced by user competition. This means that researchers must gather data about online learning behaviors properly to avoid things for which pupils are prone to be affected by the score, i.e., items from which students might gain higher scores by selecting more regularly or spending more time.

Based on the above, this research work focuses on the emotional problems of distance learners under the online learning behavior data. By collecting, identifying, and analyzing various emotional data formed by online learners, we can master the emotions of distance learners and mine the resources and values in educational data. In addition, we can establish an online learner emotion measurement model, which is conducive to better grasping the academic emotions of distance learners [9].

The main innovations in the research process of this paper are as follows: (1) this paper uses a deep learning algorithm to build a perception model and uses multimodal weighted feature fusion based on DS evidence theory to collect and analyze students' academic emotions [10]. (2) Summarize the connotation and different classifications of academic emotion, establish the academic cognition motivation model of distance learners, strengthen the learning effect and influence, and build the online learning emotion measurement framework [11].

The following sections are organized in the research process of this paper: Section 2 discusses the contributions of national and international researchers. Section 3 explains the material and approach for online learning behavior based on deep learning. Section 4 will give an analysis of the academic emotions of distant learners. Section 5 discusses in depth the results and simulation of distant learners' academic emotion analysis. Finally, this study is completed in areas such as Section 6.

2. Related Work

At present, scholars at home and abroad focus on the academic emotion analysis of distance learners and have achieved remarkable research results [12]. The work of [13] studied the influence of screen time on emotion regulation and student performance, studied the use of smartphones and tablets by more than 400 children in a four-year cycle, analyzed the relationship between these behaviors and emotion and academic performance, and evaluated students' ability and academic performance. Similar to the above scholar, the work of [14] studied the influence of early childhood emotion on academic preparation and social-emotional problems. Emotion regulation is the process of regulating emotional arousal and expression, which directly affects whether children can better adapt to the school environment. In this connection, the researcher of [15] introduced the connectionist learning theory to establish a new learning model of distance education and proposed the teaching content based on the emotional education objectives. They used the Mu class teaching mode to build a distance learning community, humanized network courses, and other new teaching modes for the problem of emotional deficiency in the stage of distance education. For effectiveness, the scholar of [16] builds a hybrid reality virtual intelligent classroom system. The system makes full use of television broadcasting technology and interactive space technology to form a network teaching environment. Teachers employ video, audio, text, and other techniques to realize contact between teachers and students and to increase communication between teachers and students in the network teaching stage.

Besides the above scholars, the early work of [17] proposed a sift emotion recognition algorithm based on facial expression scale invariant feature transformation. Based on emotion theory, this algorithm captures the facial expression of distance learners according to facial expression to realize SIFT feature extraction, recognize the expression of distance learners, and better compensate for the lack of emotion in the learning stage of distance learners, while the researcher of [18] established a learner emotion prediction model for an intelligent learning environment based on the fuzzy cognitive map. They used the model to extract and predict the learning emotion of distance learners, which is convenient for the teaching system to adjust the teaching scheme in real time according to the predicted emotion. The work of [19] developed the distance learner emotion self-assessment scale, which can define the basic emotion variables of distance learners and complete the design and establishment of the distance learner emotion early warning model. Finally, based on the regression model, the work of [20] analyzed the online academic emotion of adults, analyzed various factors affecting it, and studied the environmental factor model of online learning community related to academic emotion tendency in an online learning community. Inspired by the contributions and findings of the aforementioned scholars, we attempt to study distance learners' academic emotions using online learning behavior data and obtain significant results.

3. Material and Methodology for Online Learning Behavior Based on Deep Learning

3.1. Online Learning Behaviors and Its Features. Online learning behavior refers to learning behaviors that occur in a network setting. We concentrate on extracting learner features from online learning behavior following analysis to comprehend the quality of teaching and learning. The functioning of online learning behaviors lies at the heart of learning behavior [21]. The features of online learning behavior can be explained in Figure 1.

3.1.1. Style of Learning. Style of learning is the characteristic of a person of learners when studying and trying to solve their academic tasks, which influences learners' cognitive load. As per the Felder-Silvermande study habit concept, we may examine learners' learning styles using the 4 aspects of information process, information interpretation, information intake, and information comprehending [22].

(1) Processing of Information. Students studying the processing of information are quite interested in the material on the online learning system, and they are responsive to the opinions made by the other online learners and the comments from professors in the course materials instructional video on the learning system. Motivated students obtain information by constantly doing much to share or explain concepts to others, and they like cooperation, whereas reflective learners prefer learning via deep concentration, either alone or with a daily study partner.

(2) Awareness of Information. Learners of information are supported and are habituated to comprehending information by individual interpretation, and they choose conceptual and fascinating learning content. They are particularly interested in video learning on the learning system, extensive learning materials, and student communication. Insightful students enjoy studying information and great attention to detail. However, they frequently avoid complicated topics, whereas perceptive students enjoy studying theoretical knowledge and have the guts to learn complex subjects but they are careless in their gaining.

(3) Input of Information. Learners of this system of learning are clever or responsive and are used to learning from the contributions of others. This sort of learner is more interested in reading or watching videos. Visual students, for example, are exceptional at recalling what they see, such as video pictures, but on either side, auditory learners have a strong memory for what they listen to or read.

(4) Understanding of Information. This type of learner often analyzes and comprehends knowledge on their own, which is expressed in studying to meet their requirements. Stepwise learning and knowledge acquisition in predetermined logical order are characteristics of orderly learners. While comprehensive learners want to think globally, their thought is more varied and leaping.

3.1.2. References of Learning. Various types of students have different learning preferences, which influence students' success in the online learning system. The preferences of students reflect their requirements. Main input learning preferences, including audiovisual and verbal learning, are reasonably straightforward to accommodate, and existing online training systems may be incorporated. Intermediate preference is mostly for communication activities between persons and others, such as student inquiries, instructor responses, and contact between online learners. Enhanced preference is the process of autonomous creativity that occurs after pupils integrate knowledge, such as spreading information individually.

3.1.3. Interactive Learning. Human-computer interaction and human-human interaction are the two types of interactions that take place throughout the online learning procedure. Registration, browsing, downloads, and other actions that proactively obtain platform resources are the most common human-computer interface behaviors. Person-to-person interaction mostly refers to learner publishing and answering data in BBS, which can construct a learning interaction network graph. The geographic closeness in the network may be computed based on the size of learner nodes to determine the interaction scenario and learning law of the learner, as well as the connection with other learners [23]. Learners' engagement and engagement depth can be utilized as markers to measure interactive behavior.

3.2. Data Acquisition of Online Learning Behavior Data. The data created by the interaction among students and the platforms throughout the process of learning is primarily recorded in real time by the system database and other technologies. Learning partners may gain a more complete understanding of the study processes and realize empirical forecasting, assessment, and management of the learning experience by evaluating online learning behavior data. On the other hand, the foundation of learning evaluation is the collecting of behavioral data. It may be split into server-side and client-side methods based on variations in data capture targets and rules, whereas sources of data can be classified into wireless connections, PC connectors, and client connectors based on terminal viewpoints. Multiterminal and all-aspect data collecting approaches can help in understanding learners' learning features. Figure 2 depicts the online learning behavioral data gathering architecture [24].

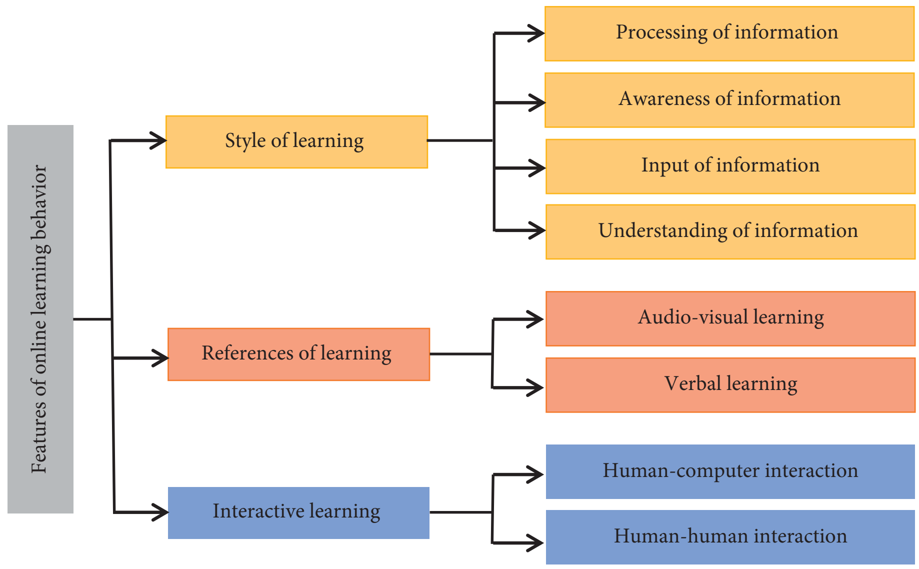

Figure 1: Features of online learning behavior.

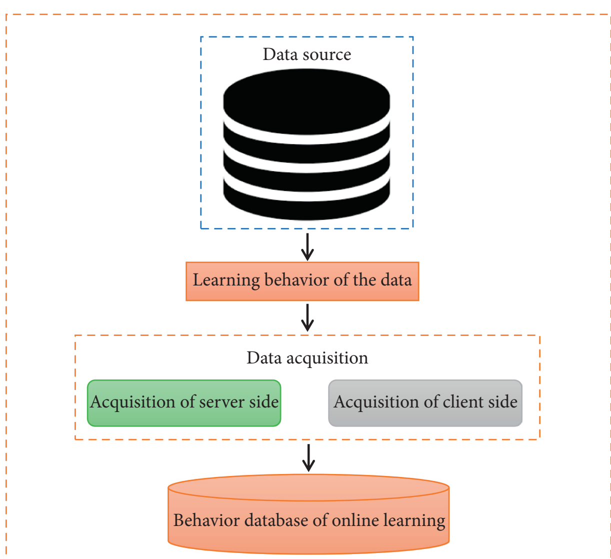

Figure 2: Architecture of online learning behavioral data gathering.

As per the above figure, Web services and Web-logging are two examples of server-side data collecting. A weblog is being used to record data from the learner's real-time operation, such as the user's demand moment, demand type, demand contents, request progress, the client's accessible location, the time of procedure completion, and the browser version used by the clients, among other things. A web application is a method of implementing data collecting using backend programming. Investigators may create the platform component database module based on the kind of learning behavior so that the target material can be gathered based on the demands, and learner behavior collected data could be more complete and adaptable, with a wide variety of services.

Furthermore, client-based collected data involves the collection of data created by learners when they are using the browser to study directly, which mostly employs the Java script Cookies to gather data to conveniently obtain information about the learner's browsing activity. This approach stores learner behavior data in a specified area and gets the data from the information stored as required, allowing for even more adaptable data collecting and recording of caching proxy server usage, as well as more precise tracking of visitor activity.

3.3. Deep Learning. Machine learning is to build statistical models based on data and use models to predict and analyze data. As the main branch of machine learning, deep learning is called "depth," which is a machine learning model compared with the traditional shallow feature learning. The essence of deep learning is to imitate the brain neurons of the human brain. The use of a multilayer neural network structure to simulate the way the human brain processes information is a deep-seated feature learning method. Deep learning can imitate many different data types such as images, texts, sounds, and videos analyzed by the human brain and build an analysis model that imitates the human brain. Its analysis ability is strong.

The learning method adopted by deep learning is similar to the neuron structure of the human brain. Its components include a hidden layer, input layer, and output layer. The nodes of the input layer are used on input data, and the nodes of the output layer are used on model output. The input layer is similar to neurons, the output layer is similar to decision-making neurons, and the weight coefficient is similar to the strength of connecting each neuron. The perceptron model is a basic artificial neural network. The architecture of the perceptron model is seen in Figure 3. To imitate the stimulation process of the human brain, the perceptron model employs the $f(x)$ activation function.

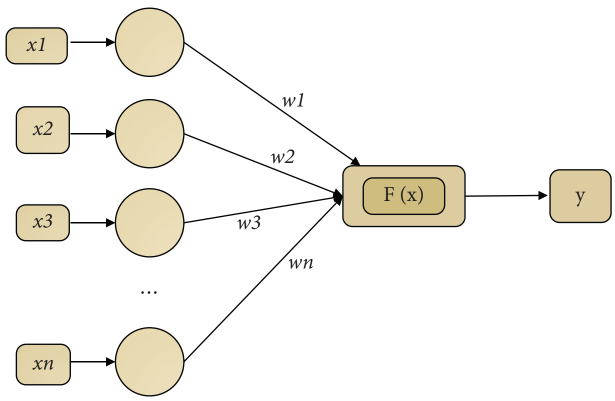

Figure 3: Perceptron model structure diagram.

According to the above, each perceptron is a function whose input is represented by x and which may be obtained by creating a function. Similarly, the output is represented by y as the function is processed. Equation (1) represents the function.

$$x = w_1 x_1 + w_2 x_2 + \cdots + w_n x_n + b \longrightarrow y = f(x). \tag{1}$$

Deep learning can generate a complex function and automatically learn the input features, so the model accuracy is higher than other learning methods. In Chinese text classification, the deep learning method can realize the automatic extraction of text features, reduce manual intervention problems, significantly improve the accuracy of the learning model, and greatly improve the classification degree. Therefore, using deep learning algorithm in emotion classification is feasible and more efficient [25].

3.4. Multimodal Weighted Feature Fusion Based on DS Evidence Theory. The core of learning emotion is to explain the differences in various model features. For example, human posture features describe the position of human joints from a global perspective, and facial expression features explain the apparent structure of local areas of the image, which are quite beneficial. Following a large number of trials, the accuracy of diverse emotion recognition on different particular characteristics differs, indicating that various aspects differ significantly in the recognition sensitivity of an emotion type [26]. The Dempster-Shafer probability concept, abbreviated as DS theory, is a popular method in the field of multisensor data fusion. It is an imprecise derivative of probability and statistics, and Bayesian thinking may work without previous information and random selection. As a result, this work provides a weighted feature fusion approach based on DS evidence theory that computes the weight vectors of all feature types based on the verification set samples determined by DS evidence theory.

DS evidence theory is mainly used to deal with the problem of multimodal information fusion represented by Θ. The identification framework and the concept of m trust assignment function explain uncertain information. To identify the framework, setting the mapping to [0, 1] represents the trust allocation function of M; if $AA \subseteq \Theta$, then it expresses any subset of the following equation:

$$\begin{cases} m(\varphi) = 0, \\ \sum_{A \subseteq \Theta} m(A) = 1. \end{cases} \tag{2}$$

In the above equation, $m(\varphi) = 0$ indicates that the empty proposition has no trust, and $m(A)$ indicates the trust allocation function of event a. In the light of Θ subset a must meet the requirement of $m(A) > 0$, which is called evidence focal element. The evidence body is represented by $(A, m(A))$ binary body composed of evidence focal elements and basic trust. The combination of multiple evidence bodies is called evidence. If $m_1, m_2, \ldots, m_n$ are the same multiple basic trust allocation functions in Θ, then A_i, $i = 1, 2, \ldots, N$, is the corresponding focal element, and equations (3) and (4) are DS evidence synthesis rules.

$$m(A) = (m_1 \oplus \ldots \oplus m_n) = \frac{1}{1-K} \sum_{\cap Ai = A} \prod_{1 \le i \le n} m_i(A_i), \; A \neq \varphi. \tag{3}$$

$$K = \sum_{\cap Ai = \varphi} \prod_{1 \le i \le n} m_i(A_i). \tag{4}$$

In the above equations, $E1$ and $E2$ represent the evidence under different recognition frameworks in the two synthesized pieces of evidence, while $m1$ and $m2$ are the corresponding mass functions. Similarly, the corresponding focal elements are represented by A_j and B_j, respectively. From simplification of equations (3) and (4), we obtained the following equation:

$$\begin{cases} m(A) = \dfrac{1}{1-K} \sum_{\cap Ai = A} m_1(A_i) m_2(B_j), \; A \neq \varphi, \\ K = \sum_{Ai \cap Bj = \varphi} m_1(A_i) m_2(B_j). \end{cases} \tag{5}$$

In the above equation, $1/1-K$ is the regularization factor. K represents the conflict coefficient between different evidence pieces. If K is larger than or equal to 1, the evidence cannot be synthesized since there is no orthogonal sum between $m1$ and $m2$.

4. Analysis of Distance Learners' Academic Emotion

4.1. Connotation and Classification of Academic Emotion. Academic emotion refers to various emotional responses associated with academic tasks such as learning or teaching. Academic emotion is often classified into two types: negative emotion and positive emotion. It has been determined via extensive study that both negative and positive academic emotions pay little regard to the arousal dimension and that the arousal value also has a direct impact on the complicated behavior of students' learning. Therefore, some scholars add arousal factors to the classification of academic emotions and further divide academic emotions into arousal emotions with higher positivity than low positivity and arousal emotions with lower negativity and higher negativity.

The emotional types involved in the above four academic emotions are listed in Table 1. The first kind of arousal emotion with high enthusiasm is reflected in hope, happiness, pride, etc., which is formed after positive events, such as teacher encouragement, support, reward, etc. The second kind of arousal emotion with low enthusiasm is reflected by calm, relaxation, satisfaction, and other emotions because the learners' learning environment is stable, and their performance remains stable. The third kind of negative arousal emotion is anxiety, anger, and guilt. The fourth is the low negative arousal emotion, which is manifested as boredom, disappointment, depression, and so on.

4.2. Distance Learners' Academic Cognition Motivation Model. The cognitive effect of academic emotion is reflected in the extraction, preservation, processing, and attention to resources of academic emotion. This paper analyzes the effect of academic emotional motivation from two different perspectives: internal motivation and external motivation. Internal motivation is the motivation of task generation and completion influenced by personal factors. Positive emotions will form positive internal motivation; negative emotions will reduce internal positive motivation and even generate negative internal motivation. Usually, external motivation refers to the motivation that students take to implement a task. Therefore, the emotion related to the results will interfere with the external task motivation, including retrospective emotion and anticipatory emotion. Happiness and hope will form positive external motivation, while personal anxiety will lead to negative motivation. Strong disappointment will enhance learning helplessness and reduce external motivation. Academic emotion will also interfere with the motivation effect and cognitive effect, which will be enhanced by adding this effect. Figure 4 shows the impact model of academic emotion on learning achievement.

4.3. Online Learning Emotion Measurement Framework. Figure 5 shows the proposed system's architecture, which defines the technical, application, and data visualization layers of the developed framework that describe the academic feelings of distant learners. The layers communicate via an interface that allows for the replacement and upgrade of their components as needed. Big data is employed for processing in this case. Data collecting, data processing, and data set analysis application services are the major components of the process. A model for measuring emotions in online learning is developed based on this and other aspects of emotion assessment.

This section can be used to discuss each layer's specifics of the recommended model.

4.3.1. Data Layer. A data layer may transform the data on our model so that it can be used by many tools. It guarantees that a homepage and a label management system communicate. This layer is also used to process, read, and store data. Its primary role is to preprocess data supplied by learners during online learning, such as posture, voice, physiology, and text. The index function is preserved and created into the database during automated clustering based on the appropriate system results, and retrieval and query activities are accomplished using the index.

4.3.2. Technical Layer. The technology layer is used to analyze emotions and collect data. The parts of this layer can be utilized to describe our model's technological architecture, detailing the structure and behavior of our model. The node is the major component of the active structure for this layer. In this layer, the component can be used to represent architectural objects. It precisely represents a system's factors in the form: its behavior is represented by an explicit link to the behavior component. A technical interface is a location where other nodes or software modules from the application layer can utilize the technological services provided by a node. Nodes come in a variety of configurations, incorporating device and system programs. A device represents a physical computing capacity on which objects can be executed. Various technologies are involved in data collection and analysis and diagnosis. Therefore, this system uses a variety of data acquisition technologies such as wearable devices, video surveillance, and web crawlers to record and save the data formed during learners' online learning and transmit it to the data layer. Then the system extracts the information from the data layer and uses text mining, emotion recognition, and other analysis and diagnosis techniques to identify students' academic emotions.

4.3.3. Application Layer. End-user applications such as internet browser programs employ the application layer. It offers protocols that enable software to communicate and collect information while also presenting useful data to consumers. The application layer in our proposed model is responsible for realizing mutual interaction with users, strengthening academic emotional interaction using visualization techniques to feedback data processing results to users, and developing reverse intervention or reinforcement adjustment schemes for learners in conjunction with their actual learning emotions.

5. Results and Simulation of Distance Learners' Academic Emotion Analysis

5.1. Correlation Analysis of Distance Learners' Academic Emotion and Learning Effect. When studying the correlation between distance learners' academic emotions and learning effect, this paper selects 50 students who have published posts on the course and have homework scores for analysis. The average emotional value of students' postings on the course during distance course learning is the learner's emotional value provided to the course, which is considered as the learner's ultimate learning outcome as its learning impact. After completion, Pearson correlation analysis is carried out [27]. Finally, the correlation analysis result

Table 1: Classification and performance of academic emotion.

Academic emotion	Emotional enumeration
Highly motivated arousal emotion	Joy, hope, pride
Low arousal emotion	Relaxed, calm, satisfied
Negative high arousal emotion	Anger, anxiety, guilt
Negative low arousal emotion	Disappointment, boredom, frustration

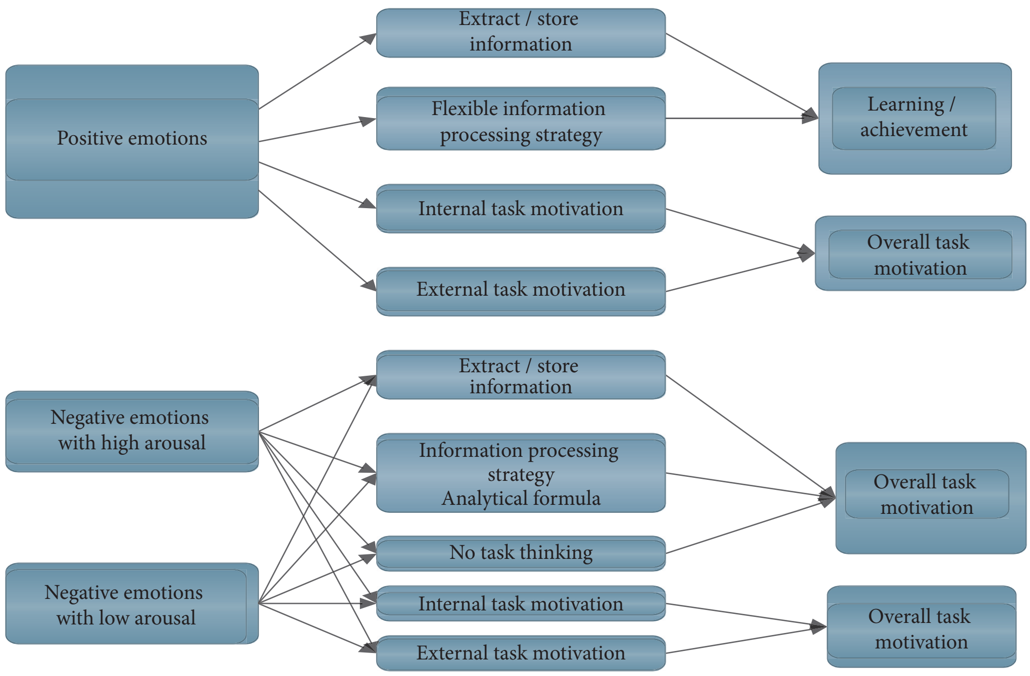

Figure 4: The influence model of emotion on learning achievement.

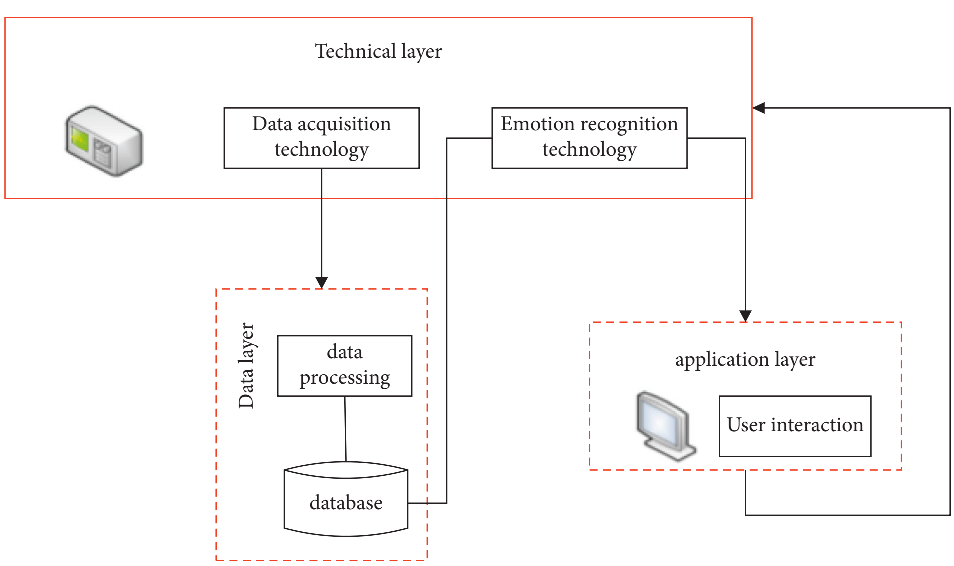

Figure 5: Online learning emotion measurement model.

obtained is $r = 0.537$, $p < 0.01$. Figure 6 shows the scattered distribution results between learners' academic emotions and achievements in class.

By analyzing the correlation analysis results and scatter diagram in Figure 4 above, students' academic emotions and learning effects in this course are significantly positively

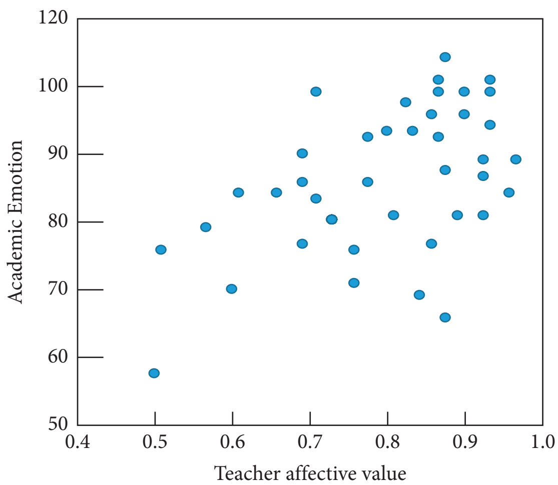

FIGURE 6: Scatter diagram of learners' academic emotion and achievement distribution.

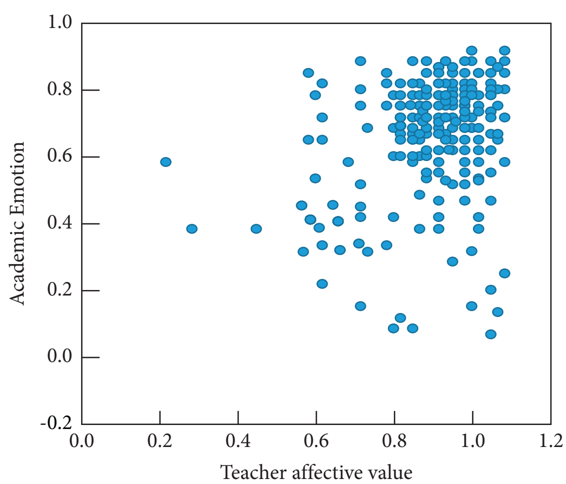

FIGURE 7: Scatter plot of learners' academic emotion and teachers' emotional value.

correlated at the level of 0.01, and the correlation coefficient result is 0.537. That is, learners' academic emotion in the classroom has a good impact on the learning effect, and the outcomes of learners' academic emotion in the classroom reveal that they are excited about students' learning. Furthermore, their impact and quality are higher, demonstrating the critical importance of analyzing distant learners' academic emotions [28].

5.2. Correlation Analysis between Distance Learners' Academic Emotion and Teachers' Emotional Tendency. This paper studies the positive correlation between distance learners' academic emotions and teachers' emotional tendencies based on the posting on student forums. By sorting out various topic posts under different course forums, it also conducts mining research on the evaluation results and data given by the courses in this topic post in one semester [29]. After analyzing the real content of the course post, it is concluded that most of the content of the course topic post is to arrange learning tasks, learning activities, etc., without significant emotional performance. Therefore, this paper only focuses on the course content of academic emotion analysis in the topic post replies. The selected research objects here are 100 teachers and learners of the residual course. The average value of teachers' post emotion in each topic post is calculated as teachers' emotion value, and the average value of learners' post emotion is calculated as learners' academic emotion. The correlation result of Pearson correlation analysis is 0.168, and $p < 0.01$. Figure 7 shows the scatter distribution results between teachers' emotional values and learners' academic emotional values.

By analyzing the learners' academic emotions on the topic post in Figure 5 above and the teachers' emotional values on this topic post, a significant correlation is shown. At the same time, the emotional distribution of students and teachers posted on the same topic in this course shows a triangular state, which is consistent with the above emotional calculation results. This demonstrates that there is a good association between students' academic emotions and instructors' emotions and those teachers have a favorable influence on students while teaching. The emotional tendencies of teachers have a direct influence on the academic inclinations of students.

5.3. Correlation Analysis between Real-Time Academic Emotion and Online Learning Behavior of Distance Learners. Based on the dynamic characteristics of distance learners' academic emotion, this paper proposes distance learners' learning emotion related to learning environment and learning tasks, and the emotion will not change in a certain period of time. The time period selected in the study is 2 days, 5 days, and 14 days. The online learning behavior indicators of learners before and 1 day, 2.5 days, and 7 days after posting are calculated according to the time point when learners post. Then Pearson correlation analysis is conducted between the online learning behavior indicators and the academic emotions of learners in corresponding posts [30]. The statistics ($^{*}p < 0.05$, $^{**}p < 0.01$) of the obtained results are shown in Table 2.

By analyzing the correlation results shown in Table 2 above, it is concluded that there are few online behaviors related to learners' real-time academic emotions, and some online behaviors have high significance and low correlation coefficients. In the above table, by analyzing the correlation analysis of the three groups in different time periods, only the addition, deletion, and modification behaviors of learners are significantly correlated with the real-time academic emotions of distance learners. The smaller the time period is, the higher the significance between academic emotions is, and the significance increases from 0.15 in 14 days to 0.004 in 2 days. Only the amount of forum and workshop participation and the addition, deletion, and

Table 2: Correlation between learners' academic emotion and real-time learning behavior.

Behavioral indicators	Relevance			Significance		
	14 days	5 days	2 days	14 days	5 days	2 days
Workshop participation	0.015	0.006	0.004	0.571	0.794	0.919
Page view	0.025	0.005	−0.011	−0.326	0.845	0.670
Number of access users	−0.032	−0.044	−0.041	0.201	0.079	0.098
Forum participation	0.048*	0.047	0.060*	0.044	0.053	0.016
Courseware visits	0.011	0.027	0.016	0.670	0.283	0.536
Browse course volume	0.036	0.027	0.033	0.16	0.286	0.195
Number of browsing behaviors	0.044	0.040	0.049*	0.081	0.113	0.051
Number of additions, deletions and modifications	0.062*	0.062*	0.071*	0.014	0.013	0.005

Table 3: Record form of learner's behavior indicators of adding, deleting, and correcting errors.

Functional module	Behavior action	Behavioral indicators	Number of records
Workshop	Increase	Increase the number of workshop activities	827
	To update	Update the number of behaviors in the workshop	193
Forum	Increase	Increase the number of actions in the forum	1886
	To update	Update the number of behaviors in the forum	93
	Delete	Delete the number of actions in the forum	21

modification of learners correspond. The number of online learning behaviors of learners is shown in Table 3.

In this paper, Pearson correlation analysis is conducted on the learning behavior indicators of learners within 2 days and the real-time academic emotions of corresponding learners. The correlation analysis results are shown in Table 4 below.

According to the correlation analysis results listed in the above table, the learners' behaviors of entering the forum to create new posts and the learners' academic mood are significantly high at the level of 0.01. In terms of correlation coefficient and significance, the number of learners' addition, deletion, and modification activities has greatly increased [29].

To improve the analysis of learners' online learning behavior data, thoroughly mine the students who have posted in this study and examine the link between their academic emotion law and their online learning behavior and academic emotion. If a learner has posted, it is necessary to calculate the emotional value of posting on this day and select the average value as the academic emotion value of the learner. After that, calculate the number of learning behaviors in the log when the learner posts. Figure 8 below shows the scatter distribution results between the academic emotion value of distance learners and the total number of online learning behaviors.

Figure 9 compares our eight behavioral indicators: workshop attendance, number of access users, forum involvement, courseware visits, browse course volume, number of browsing activities, and number of additions, deletions, and alterations. This data clearly shows that the indication number of additions, deletions, and alterations is more relevant than other indicators.

Figure 10 compares our eight behavioral indicators: workshop attendance, number of access users, forum involvement, courseware visits, browse course volume, number of browsing activities, and number of additions, deletions, and alterations. This data clearly shows that the indication workshop participation is more significant than other indicators.

Table 4: Results of correlation between learners' academic emotion and addition, deletion, and modification behavior.

Behavioral indicators	Relevance	Significance
Add number of behaviors to workshop	0.013	0.619
Number of update actions in workshop	−0.015	0.575
Number of behaviors added to the forum	0.074*	0.004
Number of updated behaviors in the forum	0.002	0.932
Number of deleted behaviors in the forum	0.001	0.954

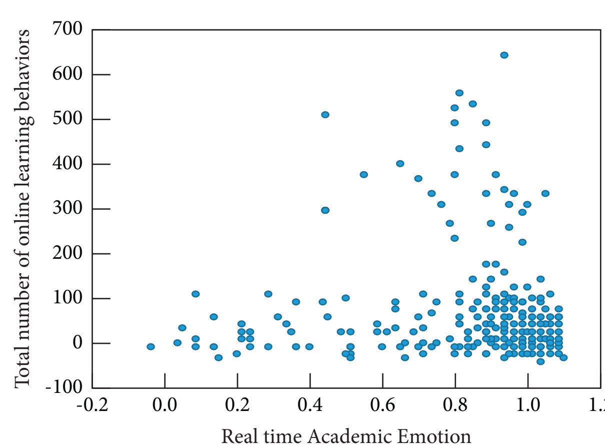

Figure 8: Scatter plot of learners' real-time academic emotion and total times of online learning behavior.

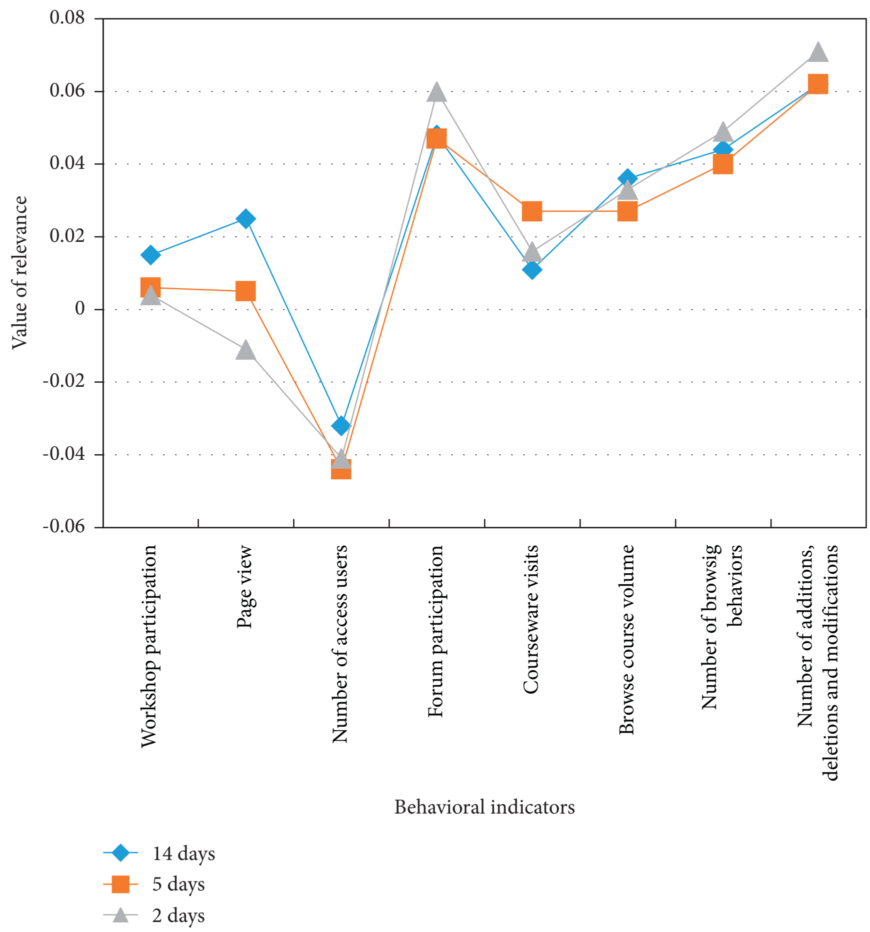

Figure 9: Comparison of relevancy.

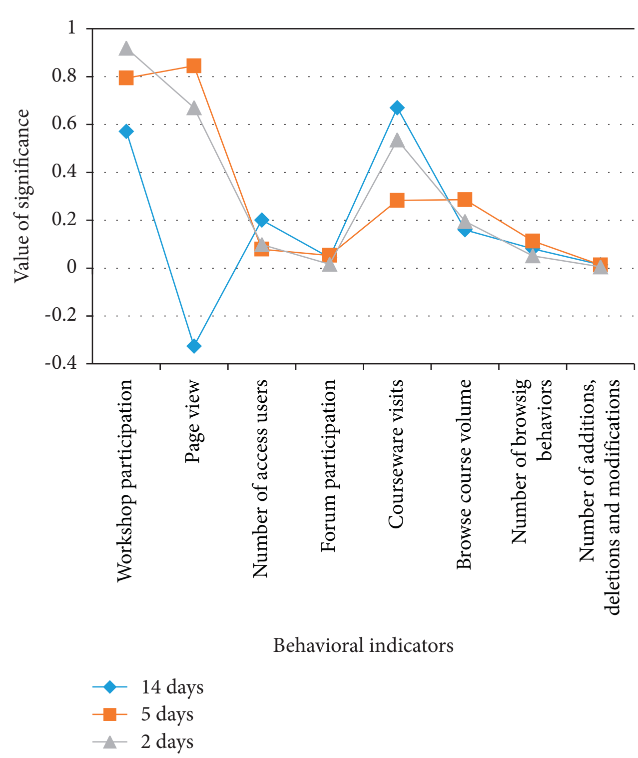

Figure 10: Comparison of significance.

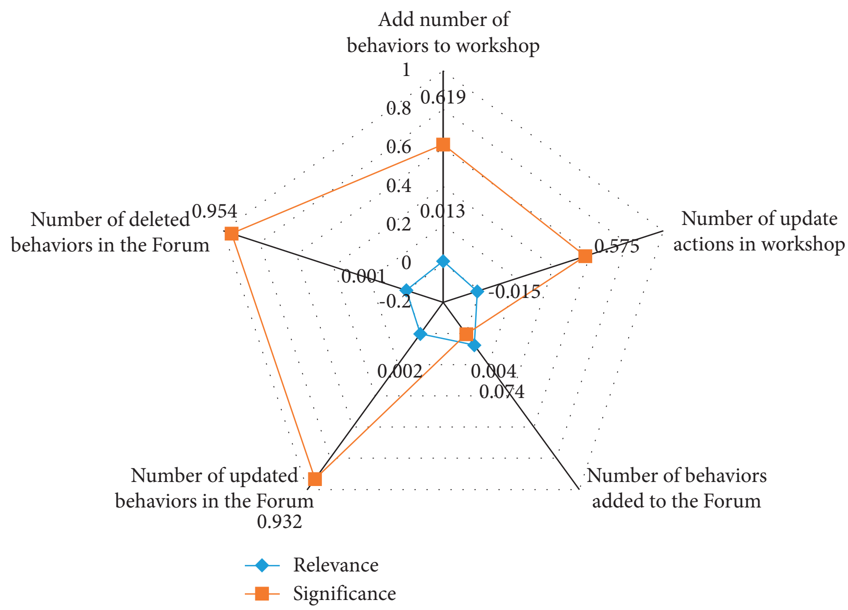

Figure 11: Comparison of relevancy and significance.

Figure 11 shows the comparison between relevancy and significance of our eight behavioral indicators: workshop attendance, number of access users, forum involvement, courseware visits, browse course volume, number of browsing activities, and number of additions, deletions, and alterations.

The distribution shape of dispersed points is a triangle, and the density in the lower right corner is high, indicating that this distribution state is associated with the strong intellectual emotion of some course participants. When more than 80% of learners' postings reflect the same emotional tendency, it suggests that the learners' academic emotions are heavily veiled and cannot be identified through an online learning activity.

6. Conclusions

With the fast growth of information technology, the online learning model is now extensively employed in the field of education and has evolved into a teaching mode with a broader range of applications. Online learning, which is based on information technology, disrupts traditional teaching techniques by connecting students, teachers, and online learning materials in a diverse interactive environment. Learners will experience a range of learning emotions throughout online learning, which will have a significant impact on the learning effect. Positive learning experiences can increase students' enjoyment and drive to study. When there are too many negative emotions, the learning effect suffers and the learning efficiency suffers. As a result, this article employs a deep learning system to assess distance learners' academic emotions based on data from online learning behavior. The multimodal weighted feature fusion algorithm based on DS evidence theory is used in this paper to extract online learning behavior data, and the academic cognition motivation model and online learning emotion measurement framework for distance learners are built. It is determined through a correlation study of distance learners' academic emotions and learning impacts that learners' academic emotions in class will have a favorable influence on learning, and there is a positive relationship between students' academic emotions and instructors' emotions. Furthermore, there is a favorable relationship between learners' addition, deletion, and modification activity with academic mood.

Data Availability

The data used to support the findings of the study can be obtained from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there are no conflicts of interest for publication of this paper.

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