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A Study of Human-Computer Interaction in Evaluating Students' Emotional Behavior and Educational Management under Big Data

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ABSTRACT
Students in adolescence are not mature in mind, thought, ability and other aspects, which are easily affected by various emotional behaviors. Positive emotional behavior contributes to students' mental health and academic progress. Negative emotional behavior would lead to psychological problems and academic frustration. If it is not paid attention to, students may act out of control under the control of negative emotions, thus resulting in serious mental illness, which is not conducive to the education and management of students. Due to the rapid development of social information network and science and technology, the analysis of students' emotional behavior and educational management by pure human intervention has fallen behind, and it is impossible to timely feedback, track and predict students' status. This paper introduced the general direction and achievements of human-computer interaction research, and discussed the combination of big data and human-computer interaction. The method of applying human-computer interaction technology to students' emotional behavior analysis and education management was studied. The pure human intervention method was compared with facial emotion recognition, voice emotion recognition, human-computer body feeling interaction and virtual scene education methods under human-computer interaction technology. Five experimental groups were designed to conduct research in three aspects of emotional behavior analysis, education and learning, and supervision and management. It was found that the average accuracy of facial emotion recognition for emotional behavior analysis was 88.0%; the average course learning efficiency of virtual scene education used for students' educational learning was 82.8%, and the total progress was up to 99.81%; the average success rate of human-computer somatosensory interaction for supervision and management was the highest, which was 68.1%.

Keywords: Student's Emotional Behavior, Educational Administration, Man-machine Interactive, Big Data

1. Introduction

With China's rapid social and economic development, many unavoidable social problems are becoming increasingly prominent. For example, accelerated urbanization, environmental pollution,

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large-scale population mobility, imperfect social and medical security system, increasing gap between the rich and the poor, changes in family structure, difficulties in student enrollment in school and nursery, regional cultural conflicts, and increasing pressure of study and life, etc., which have caused different degrees of negative impacts on the psychological and physiological development of students, and at the same time, the problem of students' mental health status is becoming more and more prominent [1-5]. In China, at least 30 million students and adolescents under the age of 17 suffer from emotional and behavioral problems. Therefore, it is necessary to evaluate students' emotional behavior, which can provide a more comprehensive understanding of the school's intervention strategies and provide a theoretical basis and relevant data support for schools to promote quality education and improve the quality of education management [6-8].

The innovation and development of big data has brought great changes and development opportunities to society. In the field of education, especially in the education and management of college students, the application of big data has become a hotspot of concern for schools [9-11]. The traditional education management mode of college students faces many challenges, which restricts the quality and efficiency of education management. However, big data technology provides new ideas and solutions for the optimization of student education management in colleges and universities [12-15]. Through the collection, analysis and mining of data, we can better understand the needs of students, provide personalized services, so as to optimize the teaching mode, improve the quality of teaching, and promote the overall development of students [16-17]. In the environment of “big data”, making full use of network technology and online platform resources, exploring human-computer interaction in the education and management of college students will be conducive to the innovation, integration and high-quality development of the education and management of college students, and will provide references and lessons for the education managers of colleges and universities [18-20].

Students’ emotional behavior is complex and changeable, and the process of education and management for students also needs to be carried out in an all-round and gradual manner. By combining human-computer interaction equipment and technology with big data and applying it to students’ emotional behavior analysis and education management, this paper compared the data before and after the use of human-computer interaction technology, and determined that human-computer interaction played a better role and effect in students’ emotional behavior analysis, education and learning, supervision and management than the traditional education model. It was undoubtedly more efficient and convenient to apply human-computer interaction to students’ emotional behavior analysis and education management.

2. Method of Human-computer Interaction for Students’ Emotional Behavior Evaluation and Education Management under Big Data

2.1. Human-computer Interaction under Big Data

Human-computer interaction refers to the interaction between people and computers in a specific language to complete the information exchange between the two parties. Since the 19th century, human-computer interaction has developed from the first generation of interaction based on keyboard and display, and the second generation of interaction based on mouse and graphic display, as well as the third generation of interaction based on multimedia technology, to the fourth generation of human-computer multimode information natural interaction, and gradually realized the development and progress of human-computer interaction technology. Big data can also be called massive data. It has the characteristics of large capacity, diversification, high value, and high-speed access. It uses distributed architecture to conduct data mining on huge databases, and uses cloud computing related technologies to obtain the required data. The human-computer interaction under big data is to be able to conduct real-time interactive data query and analysis after specialized data processing. The application of big data technology in human-computer interaction can improve the efficiency of data collection, analysis and application in human-computer interaction. For example, data visualization can greatly reduce the cumbersome process of human-computer interaction to obtain data, and visually see the data changes, so as to carry out classification summary and statistics.

Table 1 is the way to convert data from Excel tables, Gephi analysis tools and other general interactive visualization data to Tableau, ggplot2, Prufuse, Python and other programming visualization data. From Table 1, it can be seen that there are a variety of data visualization tools, and the visualized data in human-computer interaction can quickly transform information and data. In the analysis of students' emotional behavior and education management, the introduction of students' emotional behavior data and education management data into human-computer interaction technology and equipment is more conducive to the research. In addition, the data that has been concluded and collected can also be presented visually through data visualization.

Table 1. Data generation tools for interactive visualization and programming visualization

Category	Programming tools	Introduction
Interactive	Excel	Entry-level data visualization tool
	Gephi	Network analysis visualization software package
	Polaris	Database analysis, visualization system
	Tableau Public	Algebraic framework data visualization software
	VisFlow	Table subset data flow model visualization framework
	DataVis	Self-service data visualization tool
	Google Refine	Data processing and analysis visualization tool
	NodeXL	Social network analysis visualization software
Visualization	D3.js	Data-driven JavaScript library
	Prefuse	Extensible software framework based on Java language
	Echarts	Open source visualization library using JavaScript
	Vega	Computer language for creating, saving visual design
	GGplot2	Visual package of R language
	Processing	Language and environment for creating data visualization projects based on Java language
	HighCharts	Visual chart library written in JavaScript
	Matplolib	Python's data visualization package
	Leaflet	Open source and mobile interactive map JavaScript library
	Dygraphs	Flexible open source JavaScript chart function library

2.2. Application Methods of Human-computer Interaction in Emotional Behavior Evaluation and Education Management

2.2.1. Human-computer Emotional Interaction. Emotional behavior belongs to the category of human emotional expression, which is fuzzy and complex. Although the improvement of human-computer interaction technology has reached a certain level, it is difficult to simulate and analyze human emotional behavior. The traditional human-computer interaction mode mainly relies on mouse, button command and other methods, which cannot accurately convey human emotions. In order to link human-computer interaction with students' emotional behavior expression, emotion must be calculated and expressed on the basis of massive relevant data through classification feature analysis and other methods.

Emotional computing is a new development direction in the field of human-computer interaction. Emotional computing extracts features such as facial expression, voice language, somatosensory action, physiological signals. It calculates the performance of various features, selects corresponding features, and then carries out emotional recognition, so as to analyze, understand and calculate the meaning of human emotional behavior.

1) Facial emotion recognition. Students' emotions are mainly expressed in their facial expressions, which are generally divided into six basic emotions in psychology: joy, sadness, anger, fear, surprise and disgust. Each emotion has its own expression characteristics, and facial expression recognition in emotion computing is to encode human facial movement after summarizing these facial expression change characteristics through massive data, and compare dynamic and static expression changes, so as to use algorithms to generate or simulate data.

Figure 1 is a basic face recognition step. One or more sequences of images are detected. Facial features are extracted after preprocessing, and facial expressions are recognized, calculated and classified by classifier. Before facial expression recognition, it is also necessary to preprocess the image to remove the interference scenes and information outside the face in the image.

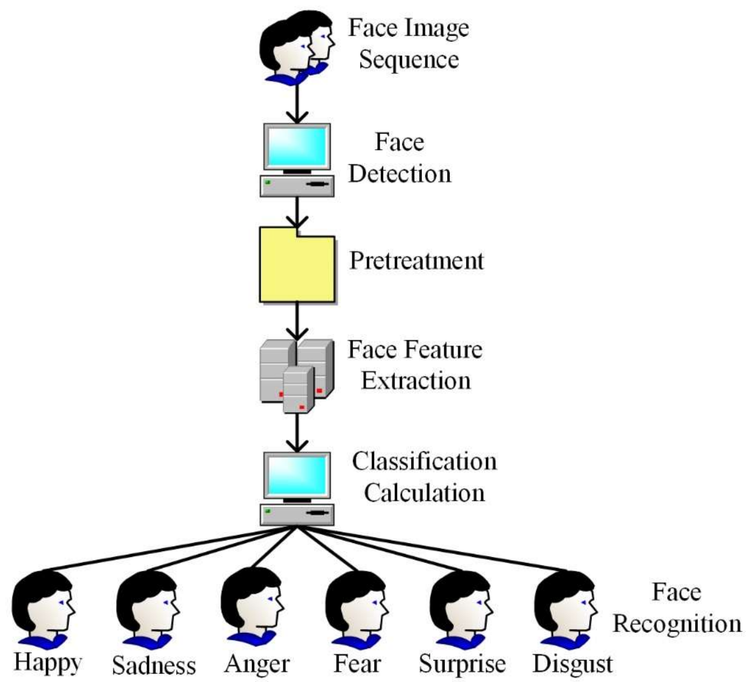

Fig. 1. Face recognition step diagram

The following is the formula for processing interference and grayscale operation with the mean variance normalization method:

$$K\_gray = \frac{1}{X}\sum R(a,b) \tag{1}$$

In Formula (1), $R(a,b)$ is the input image gray level, and the total number of image pixels is X. The standard deviation of pixel points is as follows:

$$\beta = \sqrt{\frac{1}{X}\sum R(a,b) - K\_gray^2} \tag{2}$$

After the standard deviation is obtained, the image gray level is $T(a,b)$, and the formula is as follows:

$$T(a,b) = \left(R(a,b) - K\_gray\right) / \beta \tag{3}$$

After the image is processed by gray scale, gray scale stretching is also required. The processed pixel value is written as $S(a,b)$. The minimum pixel value of the image is c, and the maximum pixel value is d. The whole gray normalization formula is as follows:

$$S(a,b) = \left(R(a,b) - c\right) * 255 / \left(d - c\right) \tag{4}$$

After preprocessing the expression image, the extraction of expression features can be carried out, and the algorithm model is built by using the data. With the development of science and technology, face recognition algorithms based on geometric feature analysis, template matching, OpenCV (Open Source Computer Vision Library), deep learning and so on have begun to be widely used.

The classification of common face recognition algorithm and machine learning algorithm can be seen from Figure 2. In this paper, the depth algorithm of machine learning was adopted, which was more efficient at present. The more widely used convolution neural network algorithm is used to analyze and recognize the large amount of facial images and judge the emotional state of students. The structure of convolution neural network is mainly divided into five data hierarchical modules: input, convolution, pooling, full connection and output. The image data to be input and processed is huge and complex. The function expression for multi-layer convolution is as follows:

$$x_k^a = f\left(\sum_{n=1}^{z^{a-1}} x_n^{a-1} \times y_{nk}^a + c_k^a\right) \tag{5}$$

In Formula (5), x_k^a represents the kth characteristic layer of this layer; a represents this layer; $a-1$ represents the upper level; x_n^{a-1} refers to the nth feature layer of the previous layer input to the current layer; y_{nk}^a in the formula is the convolution kernel of the nth feature layer of the previous layer and the kth feature layer of this layer; c_k^a represents the kth neuron input of this layer; z^{a-1} is the total number of neurons in the upper layer; $f()$ and $\times$ represent the function startup and convolution operation processes, respectively.

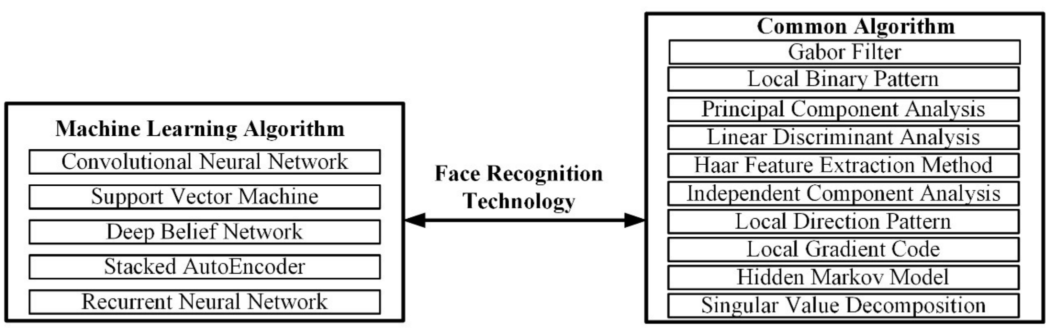

Fig. 2. Technical diagram of facial expression recognition algorithm

After the convolution layer is processed, there is also the processing of the lower sampling layer, that is, treatment of pooling layer. The expression formula is as follows:

$$x_k^a = f\left(\gamma_k^a \downarrow (x_n^{a-1}) + c_k^a\right) \tag{6}$$

In Formula (6), γ_k^a represents the kth feature layer weight coefficient of this layer a, and $\downarrow()$ represents the pooling function, which generally refers to pooling operations such as average pooling or maximum pooling. The main purpose of pooling is to solve the problem of excessive output information of the convolution layer and reduce the dimension of the output vector.

The full connection layer is equivalent to the classification processor in the whole convolutional neural network, and outputs the classification results. The prediction output value of the full connection layer is compared and calculated with the error value of the image feature sample to obtain a good parameter. The common function used for classification tasks is the cross entropy loss function, and the formula is as follows:

$$A_{loss} = \frac{1}{Z}\sum_{n=1}^{Z}\log\left(\frac{e^{h_{xn}}}{\sum_{n=1}^{d} e^{h_k}}\right) \tag{7}$$

After function calculation and sorting, it reaches the final output layer. The convolution neural network is used for facial expression recognition. In the process of emotion analysis, the parameters of the samples need to be trained until all the feature samples are trained, and an effective convolution neural network for analyzing human facial emotion expression is obtained.

The expression data needed to build the algorithm model of facial emotion recognition based on convolutional neural network are mainly obtained from databases such as RAF, CK+ (The Extended Cohn-Kanade Dataset), GENKI, FABO (Bimodal Face and Body Gesture Database), FERET, CMU Multi-PIE, etc.

2) Speech emotion recognition. Human voice is the sound wave generated by the vibration of lips, teeth, larynx and tongue. In order to facilitate the computer expression and recognition during human-computer interaction, it would be converted into binary digital signals that can be understood by the computer through voice sampling, hierarchical quantization, signal coding, etc., as shown in Figure 3.

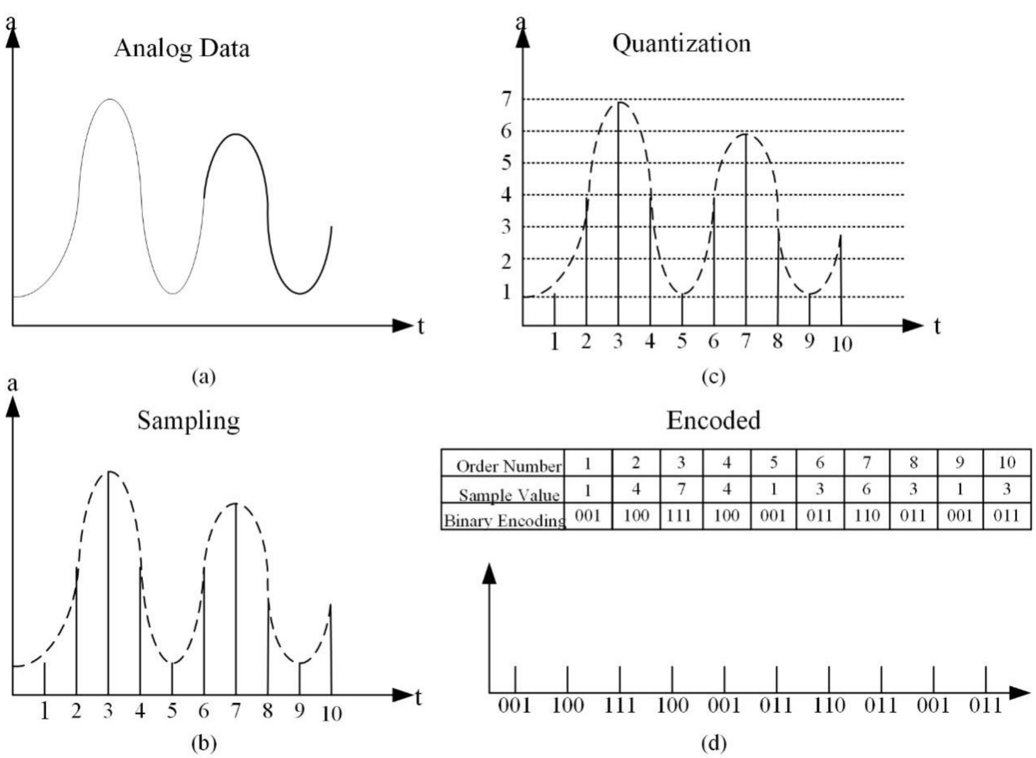

Fig. 3. Speech signal conversion diagram

The feature selection of speech signal is the key point of speech processing. Due to the different tone, pitch and sentence of emotion expression in different languages, it is necessary to study a large number of speech data for sorting and summarizing.

Big data is used to obtain relevant data from various voice emotion databases such as CASIA Chinese database, ACCorpus series of Chinese emotion language database, Belfast English emotion voice, Maribor database, VAM, FAU AIBO, etc. It can use common machine learning algorithms for voice emotion recognition, such as Gaussian mixture model, hidden Markov model, deep learning algorithm, etc. The convolutional neural network of deep learning algorithm is also suitable for speech feature extraction and speech emotion recognition, so this paper used convolutional neural network with spectrogram to build a speech emotion recognition model.

2.2.2. Human-machine Somatosensory Interaction. Human-machine somatosensory interaction technology allows people to interact directly with nearby devices or devices through body movements without using remote control, keyboard, mouse and other control devices. Compared with the traditional mouse and keyboard and touch-based interaction, body-sensitive interaction transcends some limitations of the device itself and makes the human-computer interaction process more profound and direct. Somatosensory interaction is used to judge students' actions and behaviors, involving motion tracking, gesture recognition, posture recognition, expression recognition, speech recognition and other technical means. Now there are many somatosensory interaction devices, such as Leap motion, Wii Remote, Psmove, CyWee, Kinect, MYO wristband, etc., which can provide device reference and support for studying students' emotional behavior and educational management.

The application of somatosensory interaction technology in the field of education includes the use of somatosensory games to help students soothe their emotions, and guide students to learn, so as to correct their learning posture and simulate the manipulation of objects and the content of courses, which can greatly improve the ability of students to control and express their emotional behaviors, and is more conducive to the education and management of students.

Figure 4 shows the process of capturing and collecting human motion information by body sensor. Different sensors have their own advantages and disadvantages. At present, the sensors on the market are mainly divided into gyroscope sensor, accelerometer sensor, infrared sensor, gravity sensor and magnetometer sensor. Due to the functional characteristics of different sensors, the types and accuracy of data obtained are different. In the process of somatosensory interaction, the use of multiple devices can obtain more comprehensive data for analysis, and correct and manage students' behavior through somatosensory devices.

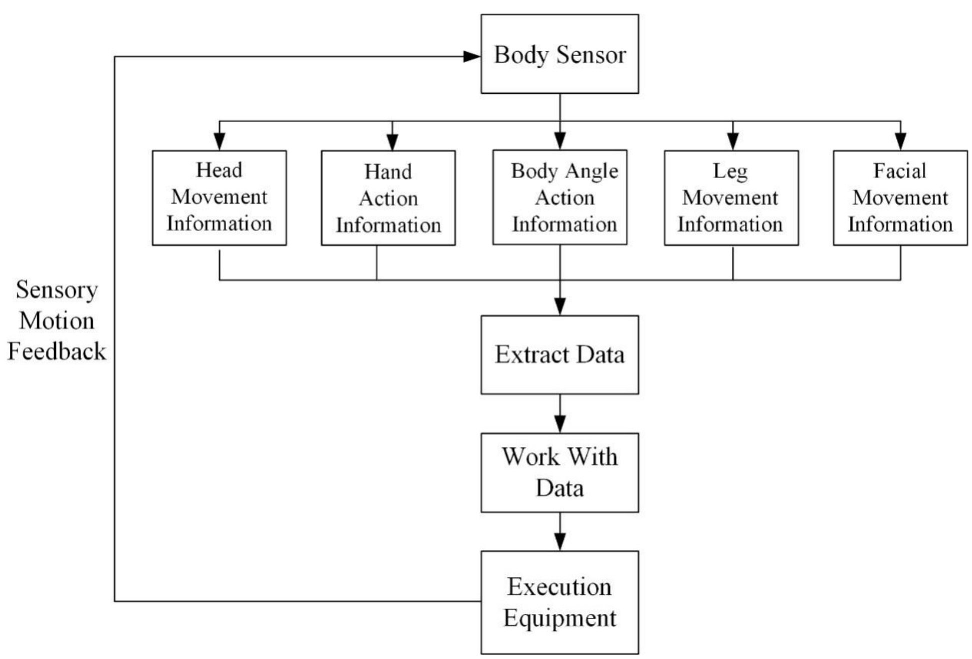

Fig. 4. Flow chart of somatosensory information reception

2.2.3. Virtual Scene of Human-computer Interaction and Online Education. Virtual scene is also a kind of Virtual Reality (VR), which is based on computer technology and combined with various scientific and technological methods to generate a digital scene that is highly similar to reality, including vision, hearing, touch and other senses. The overall concept of VR generally includes three aspects: VR, Augmented Reality (AR), and Mixed Reality (MR). It is characterized by interactivity, immersion, and imagination. Online education (E-Learning) refers to a human-computer interactive education method that spreads knowledge or learning through information technology and network technology.

The purpose of combining virtual scenes with online education is to attract students to devote themselves to situational learning, and solve students' anxiety, weariness, inattention, and irritability caused by negative emotions by enhancing learning experience, course training, interactive games, etc. This encourages students to control and manage their own emotional behavior, and actively learn to improve their knowledge and skills. Common development tools for VR include VR-Platform, OpenGL, Virtools, VRML (Virtual Reality Modeling Language), Cult3D, WTK (Sun J2ME Wireless Toolkit), Java3D, MultiGen, Rend386, etc. The specific process of the development of virtual scene online education module using Virtools and 3Dmax is shown in Figure 5:

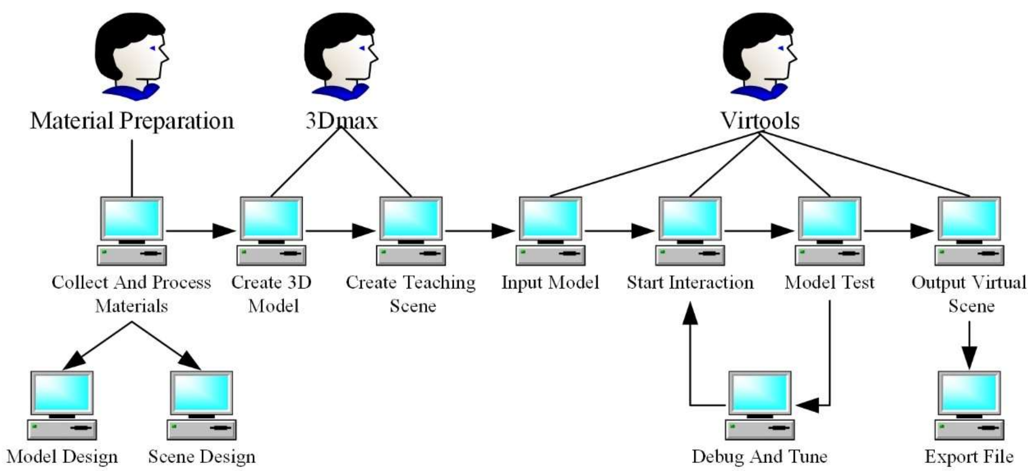

Fig. 5. Virtual teaching scenario development diagram

Online education through the generated virtual scene not only saves teaching materials, but also gets rid of the space and time constraints of reality. When human-computer interaction is conducted in image, video, voice, touch and other aspects, due to the different functional characteristics of different development tools and according to the needs of the scene and model, WTK, VR-Platform, OpenGL and other tools should also be used to build complex virtual scenes. After the successful construction of the virtual scene and model, in order to achieve the purpose of online education, it is also necessary to use big data to obtain more learning materials and course knowledge, including data on the performance of students' emotional behavior characteristics, so that the built virtual scene education system can observe and analyze students' emotional behavior and conduct education management for students, so as to collect relevant data to optimize and debug the entire virtual scene education model.

3. Evaluation and Education Management Experiment of Human-computer Interaction for Students' Emotional Behavior under Big Data

Human-computer interaction has always been a conceptual technology to achieve the communication and understanding between adults and computers. However, with the development of science and technology in the new era, there are more and more researches and attempts related to the natural interaction between human and computer. The analysis and management of students' emotional behavior belongs to the category of natural human-computer interaction. The software, hardware and network configuration of the computer, including the equipment and equipment connected to the computer, need to be adjusted and optimized according to the different psychological emotions and behavior states of people. After obtaining relevant data through big data, and building a series of relevant algorithm models, as well as installing and adjusting equipment and equipment, it also needs to combine with real experiments to test the effect.

In order to study the effect of human-computer interaction on students' emotional behavior analysis and education management under big data, the experiment randomly selected 50 students aged 10-15 years as experimental subjects, and conducted research from three aspects: emotional behavior analysis, education learning, and supervision and management. Five experimental groups were designed with 10 people in each group as a unit to carry out comparative experiments in the way of pure artificial intervention, facial emotion recognition, voice emotion recognition, human-machine body feeling interaction, and virtual scene education. The experiment allowed students to study the same course in groups. The course content included emotional text reading, physical chemistry experiment, math test solution, music and painting learning, sports training, etc. The learning cycle was three weeks and a total of 21 days. At the end of each day's course, the students' emotional behavior and education management related data in the class were analyzed and summarized, and finally the experimental data was obtained.

1) Emotional behavior analysis. Emotional behavior analysis focused on the observation and summary of human facial expressions, gestures and actions, voice and intonation, and physiological state. The experiment divided students' emotional behaviors into ten categories: joy, sadness, pain, anger, fear, surprise, disgust, irritability, calm and confusion. The accuracy of the five groups of experimental data was shown in Figure 6:

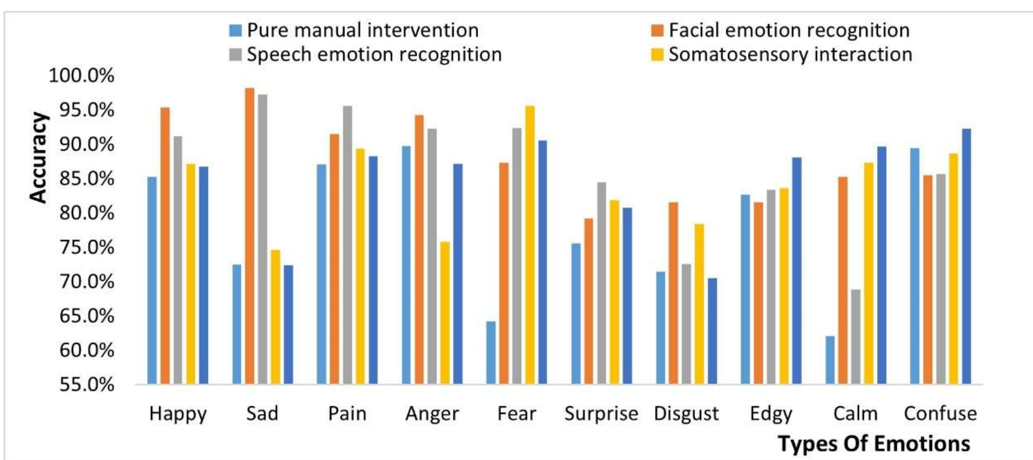

Fig. 6. Accuracy of emotional analysis

In Figure 6, the pure artificial intervention group had the highest analysis accuracy of anger behavior, which was 89.8%; the accuracy rate of calm emotion behavior analysis was the lowest, which was 62.1%; the average accuracy of emotional analysis was 78.0%. The facial emotion recognition group had the highest accuracy of sad emotion analysis, which was 98.2%; the accuracy rate of surprise emotion behavior analysis was the lowest, which was 79.2%; the average accuracy was 88.0%. The voice emotion recognition group had the highest accuracy rate of sad emotion behavior analysis, which was 97.3%; the accuracy rate of calm emotion behavior analysis was the lowest, which was 68.9%; the average accuracy was 86.4%. Human-computer somatosensory interaction group had the highest accuracy in analyzing fear behavior, which was 95.6%; the accuracy rate of sad emotion behavior analysis was the lowest, which was 74.6%; the average accuracy of emotional behavior analysis was 84.3%. The virtual situation education group had the highest accuracy rate of analysis of confused emotional behavior, which was 92.3%; the accuracy of the analysis of aversion behavior was the lowest, which was 70.5%; the average accuracy of emotional behavior analysis was 84.7%.

From the comparison results of the five experimental groups, the accuracy rate of emotional behavior analysis of facial emotion recognition was the highest, and the accuracy rate of pure artificial intervention was the lowest. The difference of average accuracy of emotional behavior analysis between human-computer somatosensory interaction and virtual scene education was the smallest. The accuracy rate of emotional behavior analysis of pure artificial intervention was significantly lower than that of facial emotion recognition, voice emotion recognition, human-machine body feeling interaction and virtual scene education.

2) Educational learning. Human-computer interaction was used in the field of education to help students learn more efficiently. The five experimental groups used pure human intervention, facial emotion recognition, voice emotion recognition, human-computer body feeling interaction, and virtual scene education. According to the emotional behavior of students in the classroom, students were scientifically and reasonably soothed in time and answered questions and doubts They were instilled knowledge and assisted education. The following was the learning efficiency chart of five experimental groups in seven courses of language, mathematics, physics, chemistry, music, painting, and physical education and the daily learning progress chart of 21 days.

In Figure 7, the pure manual intervention education group had the highest learning efficiency in the painting course, which was 78.5%; the learning efficiency in physics course was the lowest, which was 71.4%; the average learning efficiency was 74.6%. The facial emotion recognition group had the highest learning efficiency in the painting course, which was 79.6%; the learning efficiency in physics course was the lowest, which was 71.8%; the average learning efficiency was 75.5%. The voice emotion recognition group had the highest learning efficiency in music course, which was 81.5%; the learning efficiency in physics course was the lowest, which was 72.3%; the average learning efficiency was 77.0%. Human-computer somatosensory interaction group had the highest learning efficiency in physical education, which was 88.6%; the learning efficiency in language courses was the lowest, which was 75.6%; the average learning efficiency was 79.9%. The virtual scene education group had the highest learning efficiency in physics course, which was 85.9%; the learning efficiency in music course was the lowest, which was 79.6%; the average learning efficiency was 82.8%.

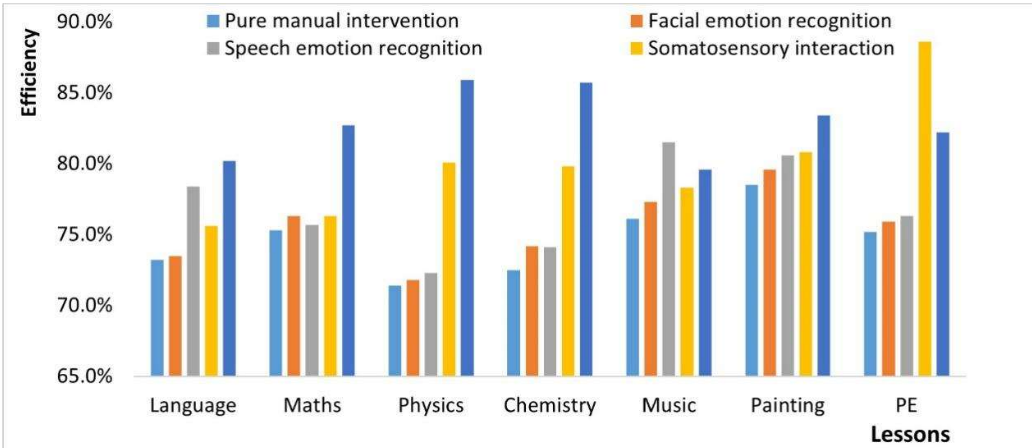

Fig. 7. Course learning efficiency

In Figure 8, the total learning progress of the pure manual intervention group was 89.28% in 21 days; the highest progress was on the 21st day, which was 5.84%; the lowest progress was on the first day, at 2.32%; the average progress was 4.25%. The total progress of facial emotion recognition group in 21 days was 92.64%; the maximum progress was on the 19th day, which was 5.12%; the lowest was 3.44% on the second day; the average progress was 4.41%. The total progress in 21 days of speech emotion recognition group was 91.35%; the learning progress was the highest at 6.24% on the 16th day and the lowest at 3.06% on the 1st day. The average progress was 4.35%. The total progress of human body sensory interaction in 21 days was 98.40%. The learning progress was the highest at 6.88% on the 9th day and the lowest at 2.66% on the 20th day; the average daily learning progress was 4.69%. The total progress of virtual scene education group in 21 days was 99.81%; the learning progress reached the highest on the fourth day, which was 8.08%; the lowest was 2.71% on the 17th day; the average daily learning progress was 4.75%.

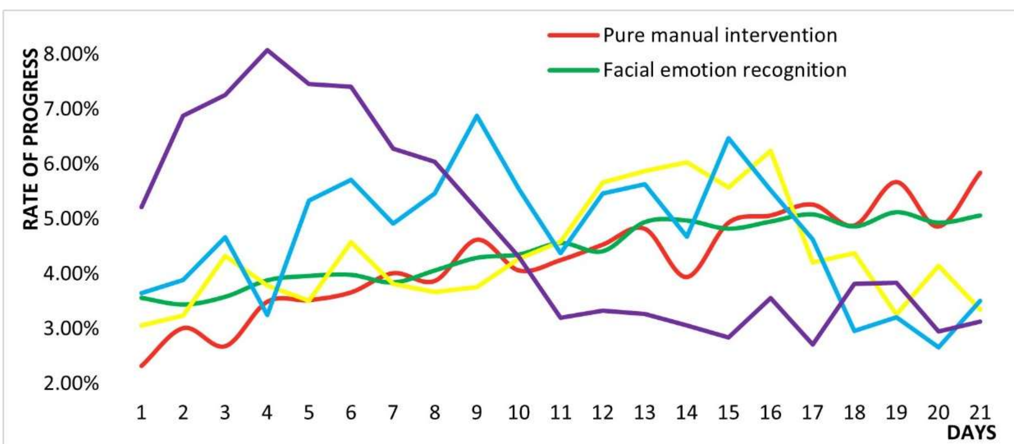

Fig. 8. Daily learning progress chart

It could be seen from Figure 7 and Figure 8 that the course learning efficiency of pure manual intervention in students' education and learning was the lowest, and the progress of learning progress was slow; the course learning efficiency and learning progress of virtual scene education for students' education and learning were faster and higher. The human-computer interaction methods of facial emotion recognition, voice emotion recognition, human-computer somatosensory interaction, and virtual scene education could improve the course efficiency and learning progress more than the pure human intervention methods in student education and learning.

3) Supervision and management. The supervision and management of students was mainly reflected in the timely awareness and correction of students' emotional behaviors, and the guidance of students according to the norms. The five experimental groups supervised and managed students by reminding, warning, guiding, correcting and other ways after analyzing their emotional behaviors. The success rate of supervision and management of students' non-standard behaviors in 21 days was shown in Figure 9:

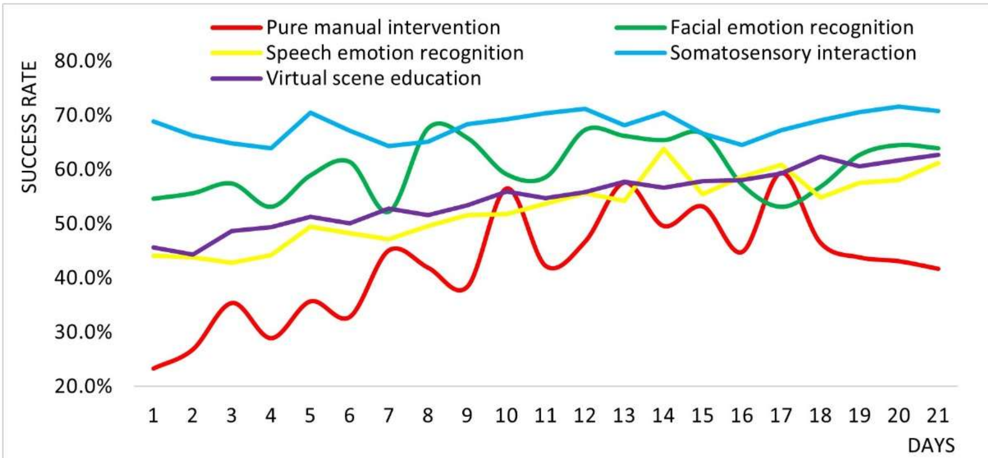

Fig. 9. Success rate of supervision and management

In Figure 9, the success rate of supervision and management in the pure artificial intervention group was the highest on the 17th day in 21 days, which was 59.4%; the success rate of supervision and management was the lowest on the first day, which was 23.3%; the average success rate was 42.5%. The success rate of 67.6% in the facial emotion recognition group was the highest on the 8th day; the lowest success rate was 52.2% on the 7th day; the average success rate was 60.4%. The success rate of speech emotion recognition group on the 14th day was 63.8%, which was the highest; the lowest success rate was 42.8% on the third day; the average success rate was 52.7%. The success rate of supervision and management in the human-computer somatosensory interaction group on the 20th day was 71.6%, which was the highest; the lowest success rate was 63.9% on the fourth day; the average success rate was 68.1%. The success rate of supervision and management in the virtual scene education group on the 21st day was the highest, which was 62.7%; the success rate of supervision and management was the lowest on the second day, which was 44.3%; the average success rate was 54.8%. The success rate of human-computer somatosensory interaction for the supervision and management of students was the highest, and the success rate of pure human intervention was the lowest.

4. Conclusions

In the big data environment, the application of human-computer interaction in students' emotional behavior analysis and education management has brought more innovation and development. In the process of students' emotional behavior analysis, the accuracy of facial emotion recognition and voice emotion recognition in human-computer interaction emotion calculation was higher. If the two could be combined, students' emotional behavior could be more accurately analyzed; in addition, virtual scene education and human-computer interaction were more suitable for students' education and learning, which could improve students' learning efficiency and promote students' progress in completing learning tasks than traditional education methods; facial emotion recognition and human-computer somatosensory interaction had a higher success rate than the other three ways of supervising and managing students. The application of human-computer interaction in the field of education became increasingly revolutionary. However, by considering that there were still some technical difficulties and limitations in human-computer interaction technology that were not broken through, the experimental period of this paper was relatively short and there was still room for optimization of experimental methods and grouping. In order to popularize human-computer interaction in the field of education, more market factors, social factors and cultural factors needed to be considered.

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