The Attitudes of Students' Parents Towards Their Children's Information-Based Learning Under the Background of the Combination of Large-Scale Online Learning and Multimedia Technology

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ABSTRACT

As a stakeholder group in the promotion of basic education informatization, parents' attitudes towards children's informatization learning is an important factor affecting the smooth development of school informatization teaching. Based on the classic convolutional neural network and CK+ dataset, this paper proposes a convolutional neural network model to evaluate the attitude of parents to children's information-based learning in the context of large-scale online learning and multimedia technology. It aims to provide an important reference for promoting the informatization teaching reform in the basic education stage in the post-pandemic era. The experiment shows that the convolution neural network model proposed in this paper can accurately identify the facial information of learners in the live classroom. Based on learners' emotional changes, teachers can adjust teaching strategies in time to improve the teaching process.

KEYWORDS

Information-Based Learning, Multimedia Technology, Online Learning, Parents' Attitudes, Students' Attitudes

INTRODUCTION

Realizing the organic combination of scale and personalization is the main task in the implementation of China's Education Modernization 2035. In the post-pandemic era, online courses have become an effective supplementary form of large-scale education and teaching. However, online courses have not solved the "temperature" problem between teachers and students. That is, teachers cannot analyse and accurately intervene in learners' emotions in real time. Thus, students' learning emotions are not addressed in a timely, effective manner. This, therefore, negatively impacts learning performance, learning perception, and high-level thinking ability (Zhu et al., 2022).

It is also a challenge to understand effective personalized emotional analysis in online education. The ministry of education, along with six other departments, stressed that the construction of online

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learning spaces and platforms should be supported by artificial intelligence (AI) to build a high-quality education system. Future large-scale education initiatives must identify ways to implement intelligent technologies to promote the teaching of online courses. For both theoretical and practical reasons, we must optimize existing emotion-computing technologies, carry out effective emotion recognition, and adapt to online education with new needs.

Due to their low information literacy and poor self-discipline, primary school students often need the assistance of their parents in an e-learning (home) environment. Both students and parents must, therefore, commit to e-learning resources (Drossel et al., 2020). As a stakeholder group in the promotion of basic education informatization, parents' attitudes toward their children's informatization learning is a factor that affects the smooth development of school informatization teaching (Su, 2021). During the COVID-19 pandemic, primary school students attended at-home schools, providing extensive characteristics and participation for review (Zheng et al., 2021). Researchers were then able to explore and understand parents' attitudes toward e-learning (Cahyadi et al., 2021).

This article combines emotion recognition and the live classroom, taking the online live classroom as the research carrier to map the relationship between expression and emotion, the relationship between emotion and learning state, and the individual learning state and overall learning state in online live classroom learning (Cheng et al., 2020; Lim & Jung, 2019). This information provides relevant theoretical and technical support for improving the teaching effect of the online live classroom (Tian & Tang, 2022).

This article uses the live information learning system model with feedback function to analyse students' emotions (attitudes) under the background of accepting large-scale online learning and multimedia technology. In addition, 3,793 parents of primary school students were given questionnaires and in-depth interviews. First, it aimed to find out whether large-scale online learning during the pandemic impacted parents' attitudes toward their children's e-learning. Second, it studied whether parents' gender, age, educational background, and e-learning experience affected their attitudes toward their children's e-learning.

MATERIALS

Research Status of Students' Learning Emotions in Information-Based Learning

Learners show many expressions to teaching content within the teaching process (Murzina, 2020). When the learner can accept and clarify the learning content and it is of interest, the learner will demonstrate high emotions with happy or excited expressions (Putjorn et al., 2018). On the contrary, the learner may find it difficult to understand the learning content or that it does not match their interest. In turn, they will frown, their eyes will appear dull, and their mood may seem low.

Learners' expressions provide important teaching feedback data for educational platforms and educators (Lv, 2022). Learning emotion is an important factor that impacts learning cognition, learning effectiveness, and mental health in online education (Garcia et al., 2021). First, learning emotion affects learning cognition. In a study of learners' online participation in learning tasks, researchers found that learning emotion affects learning cognitive style (Hu & Hu, 2021). Second, learning emotion affects learning effectiveness. Positive learning emotion can improve learners' learning emotion, reduce learners' difficulty in understanding learning content, and improve learning effect (Hermino & Arifin, 2020). Negative learning emotions can impact learners' mastery of knowledge and ability, as well as their final academic achievements (Zhu & Ren, 2022). Finally, learning emotions affect learners' mental health. At-home isolation during the pandemic caused greater psychological pressure on learners. Long-term online learning caused emotional problems related to learning time, space, and media use, which affected the psychological health of learners. Regarding media use, switching between online learning platforms and personal learning space may lead to anxiety and discomfort (Bai et al., 2021).

In the traditional classroom, teachers and students communicate face-to-face within the same classroom setting. Experts and scholars from across the globe have carried out in-depth research in this field. Indian scholars like Orchek (2022) combined other physiological signals (i.e., heart rate, blood pressure, skin conductance) to obtain learners' emotional changes. They explored ways to make use of learners' emotional feedback to improve the learning experience (Wen et al., 2022). Rojas (2022) proposed the FILTWAM learning framework, combining facial expression recognition with speech expression. During the learning process, hardware devices like cameras and microphones were used to observe learners' facial expressions and voice information. Lian and Chang Pan (2022) studied the application of the FACS facial expression coding system. They built a SLE-FER learning emotion analysis framework based on facial expression recognition methods. Yi et al. (2021) proposed an intelligent agent-based emotional and cognitive recognition model for distance learners. The model simultaneously used eye tracking technology and emotion recognition technology. Wang, J. et al. (2021) used emotion recognition to identify learner fatigue in the learning process and implement corresponding interventions.

Compared with other physiological signals that reflect learners' emotions, facial expressions can naturally express learning emotions and objectively reflect the learners' emotional state (Garg & Cui, 2022). Expression recognition has received widespread attention from researchers across the globe. However, most of the research on facial expression recognition in the field of education focuses on the loss of emotion in online learning rather than feedback for teaching (Cheng et al., 2022). In the field of education, early research on facial expression recognition adopted traditional machine learning methods like face recognition, feature extraction, and classifier construction. In recent years, research on deep learning methods like convolutional neural networks have become an important direction (Zarrabi, 2018).

Parents' Attitudes Toward Information-Based Teaching or Information-Based Learning

Studies have shown that parents' cognition, attitude, and emotion toward information-based teaching or children's information-based learning show complexity and contradictions. Through a questionnaire survey, Zhu, W. et al (2022) found that parents worry that "E-book bag" will have a negative impact on their child's body, vision, cognitive ability, writing ability, interpersonal communication, attention, and online habits. Parents, as compared to their children, are more worried about the negative effects of tablets. "E-book bag" refers to electronic devices such as computers, netbooks, and dedicated readers. It is to digitize all the textbooks, homework books, in-class and out-of-class readings, and dictionaries in the student's book bag and integrate them into a portable mobile terminal. These studies show that parents have a negative attitude toward their children's informatization learning.

There are also studies that reveal parental ambivalence (Wei et al., 2020). Parents' feelings about reading on screen are usually three contradictory themes: (1) trust and distrust; (2) Agency and dependency; (3) Nostalgia and reality. Parents are very nervous about their children's use of mobile technology. They worry that students will miss out on educational benefits. They also question the negative impact on thinking and imagination. Some mothers are concerned about their children's use of mobile devices, while others consider it a useful educational tool.

Existing studies focus on parents' attitudes toward information-based learning devices like tablets or mobile phones. Overall, the research conclusions are inconsistent. In these studies, the use of information-based learning equipment is not the "normal" learning format for children. It is, however, a form of assisted learning (Wang, S. et al., 2021).

The online learning that took place during the pandemic was the first large-scale, long-term basic education informatization teaching practice in the history of education in China. It was also an informatization learning practice in which parents were deeply involved (Qin et al., 2021). Their experiences, feelings, and satisfaction will differ from prior educational studies.

The current study uses a questionnaire survey and in-depth interview to find out whether the large-scale online learning during the pandemic affected learning experience. It also looked at parents' gender, age, education background, and informatization learning experience to determine whether they will influence their attitudes toward their children's informatization learning.

METHODS

Model of Live Broadcast Information Learning System With Feedback Function

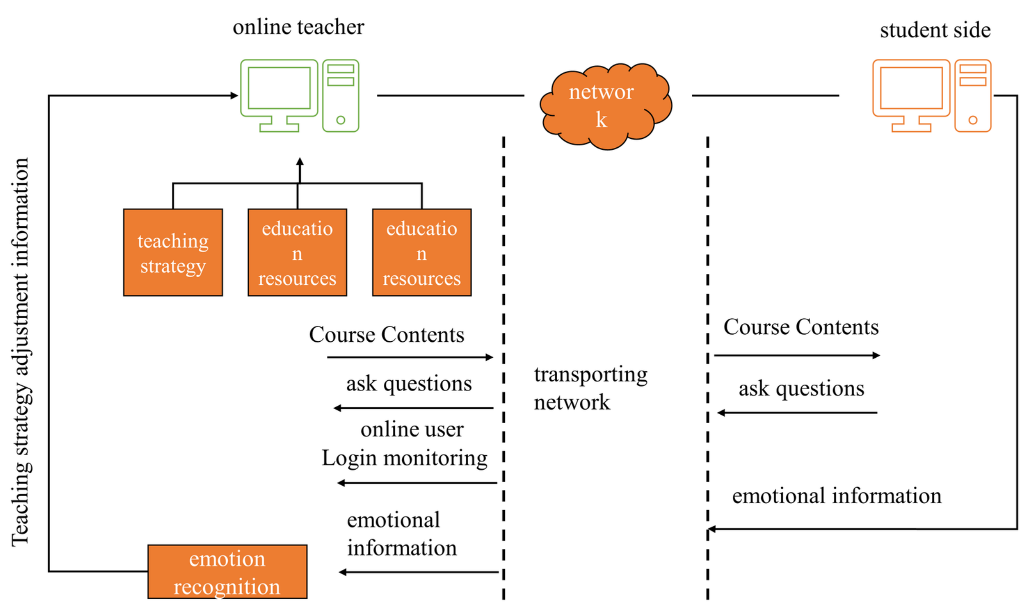
The online learning emotion computing system is equipped with a depth camera to obtain the emotional data of students' online learning in real time. It also analyses and processes the collected emotional data in real time before transmitting the data to the server in real time through the internet. The server recognizes the current emotional state of students according to the received data. This application system divides online learners' emotions into six types. It implements corresponding learning intervention strategies or pre-measures to improve online learning efficiency and achieve the personalized learning service goal of the new generation online learning platform.

The system captures learners' facial information via the live classroom teacher's class. It recognizes a learner's facial expression, obtains the current learning emotion, and judges the current learning state. The state change of the learner in overall learning can be obtained based on the emotional change of the learner. Use of learning status information and feedback to the platform and teachers help teachers adjust their strategies and improve the teaching process in real time.

Two feedback mechanisms within the system provide teaching assistance. The first, real-time feedback, aims to convey learners' current learning status to online teachers. This helps teachers adjust their teaching process and methods in real-time, make necessary prompts according to the situation, improve learners' interest, and adjust learners. The second is non-real-time feedback. It aims to help online teachers review changes in learning status during the class, change later teaching methods, and, to a certain extent, stabilize the learning status of learners (see Figure 1).

First, the learner logs into the online learning emotion computing system through a verification stage. Second, the camera automatically captures the original facial expression data. Third, via a specific interface, the facial expression data is transferred to an online background database for learning emotion. Finally, the system can use emotion-computing algorithms to process the data by extracting emotional features and classifying emotions.

Figure 1.
Live Course Model with Feedback Function



The system's core will monitor learners' expressions in real time. It uses the live online learning environment to judge learners' emotions through changes in their expressions. Its feedback on learning status is given to teachers in real time, helping teachers adjust their teaching methods and prompts. At the end of the course, a time sequence diagram is generated. It provides the learning state changes of all learners during the learning process. The information is divided into individual and class. It provides overall feedback for the teachers, helping them understand the learning difficulties encountered by all learners in this course. It also assists teachers in providing targeted tutoring and classroom teaching supplements. Finally, teachers can improve their teaching plans and teaching strategies.

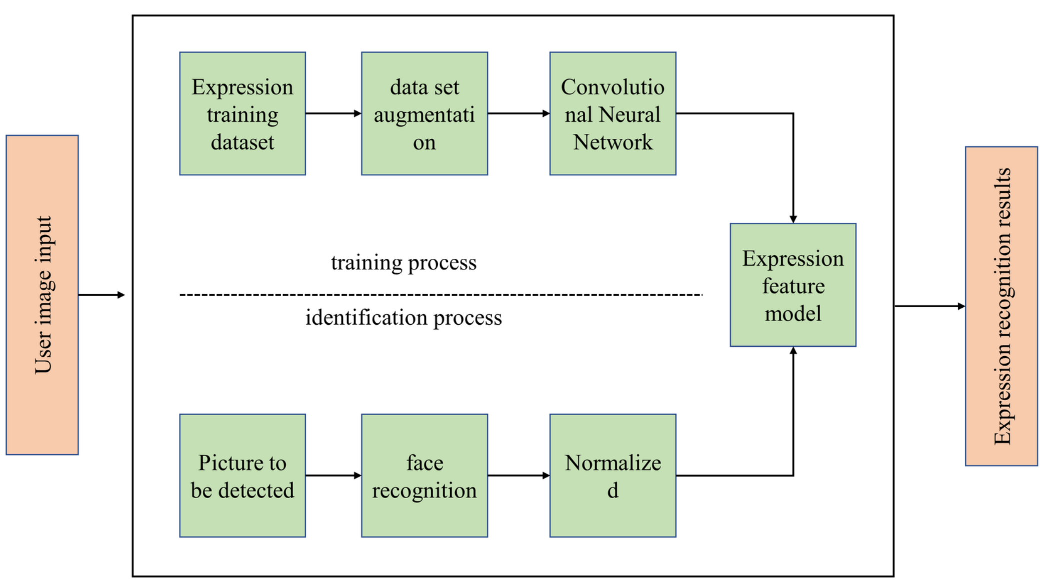
The system visualizes the emotional data to better understand the emotional state and emotional change track of online learners. Learners and online platform managers can then view the emotional state and emotional track in real time, identifying overall emotional responses of learners. Thus, the system can promote effective evaluations and interventions.

Emotion Recognition of Students' Information Learning Based on Convolutional Neural Networks

In the traditional classroom teaching, teachers judge learners' attention and understanding of current knowledge by asking questions and observing changes in learners' expressions. With the evolution of smart devices, online learning systems can now use a smart device camera to obtain images of learners' facial expressions. Systems can judge current learning status through expressions. Then, it provides traditional online learning systems or live classroom teachers with emotional feedback. The existing personalized recommendation system and teaching experience of live classroom teachers alleviates the "emotional lack" phenomenon in online learning. The structural framework of the emotion recognition module is shown in Figure 2. The emotion recognition module is divided into two parts. One part uses the existing expression data set to train the convolutional neural network and generate the expression feature model. The other part uses the trained facial expression feature model to recognize the user's facial images, and finally outputs the recognition results.

Facial expression recognition includes image recognition and dynamic image recognition. The first uses an expression from a single image. The dynamic image refers to continuous expression

Figure 2.
Schematic Diagram of Emotion Recognition Module



changes (image sequence). The image must be pre-processed once it is obtained through the camera or other equipment. Images will be affected by lighting, background, position, and contrast. Expression recognition requires the test image and training image to maintain the same conditions to eliminate the influence of irrelevant factors. The face information is obtained through a series of methods, including face detection and positioning, scale normalization, and grayscale normalization:

1. **Face Detection:** Crop the face image area and segment the face expression area.
2. **Scale Normalization:** Expression images are different sizes. The processed images will all be classified as standard sizes:

$$y = b + w_1 x_1 + w_2 x_2 \tag{1}$$

3. **Grayscale Normalization:** The facial expression images have many colours, light and shade, and contrast. The processed images will be normalized to standard grayscale:

$$N\left(i,j\right) = M_0 + \sqrt{V_0 * \frac{\left(I\left(i,j\right) - M\right)^2}{V}}, I\left(i,j\right) > M \tag{2}$$

$$N\left(i,j\right) = M_0 - \sqrt{V_0 * \frac{\left(I\left(i,j\right) - M\right)^2}{V}}, I\left(i,j\right) \le M \tag{3}$$

The convolution neural network, which originated in the 1980s, is one of the earliest deep learning methods. This method can achieve the goal of classifying pictures of different categories in a group of pictures without designing specific features of the classification method for a specific image set. Moreover, the convolutional neural network has excellent performance in classification tasks and regression tasks. It has significantly improved the effect of traditional image classification. Since 2006, with the rise of deep learning, the learning ability of convolutional neural network representation has been improved with updates to numerical computing equipment.

Convolutional neural networks contains multiple neurons. The full connection of the layers is easy to bring about the problem of the expansion of the number of parameters, and it will fall into the state of overfitting and local optimization. In addition, local features inherent in facial images, such as eyes, nose, mouth, etc., cannot be well represented. The hidden layer of a convolutional neural network consists of a convolutional layer, a pooling layer and a fully connected layer. The neurons in the upper and lower layers of the convolutional neural has the characteristics of local connection, shared weights and down sampling. Compared with the traditional neural network, it can mine local features in the image well. Image warping has high robustness. The convolutional layer of the entire network and completes feature extraction. After the convolution layer is convoluted, it will reduce the dimension of the upper layer results and reduce the network training parameters. The fully connected layer generally appears before the output, which reduces the previous multi-dimensional results into one-dimensional data.

Convolutional Layer

It is specified size (also called a filter) to slide the image from left to right and top to bottom according to the specified step size to complete the convolution process, and finally form the feature map. The output of the convolutional layer is shown in Equation (4):

$$feature_j^l = \varphi\left(\sum\nolimits_{i \in M_j} w_{ij}^l \otimes x_i^{l-1} + b_j^l\right) \tag{4}$$

Formula (4) $\otimes$ is the convolution operator, $feature_j^l$ represents the jth output feature map in the first layer, M_j represents the input feature map set, w_{ij}^l represents the convolution kernel of the jth feature map in the first layer and the ith input data, x_i^{l-1} represents the i-th feature map in the 1-1 layer, b_j^l represents the bias of the j-th feature map in the 1st layer, and $\varphi()$ represents the activation function. Commonly used activation functions are ReLU, sigmoid, and tanh.

Activation Function

Activation functions provide non-linear modelling capabilities for convolutional neural networks. Once the activation function is missing, the network is limited to representing linear maps, so that there is not much difference between what a multi-layered convolutional neural network can express and a single- or two-layered convolutional neural network. The commonly used activation functions are described below.

The expression of sigmoid Is show" in formula (5):

$$sigmoid\left(x\right) = \frac{1}{1 + e^{-x}} \tag{5}$$

The expression of the Tanh function is shown in formula (6):

$$\tan h(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{6}$$

The Tanh function is an odd function whose output ranges from -1 to 1, and has gradient saturation effects. Compared with the Sigmoid function, the output mean of the Tanh function is 0, and the convergence speed is faster in the actual training.

Such expression of the ReLU function is shown in public (7):

$$relu\left(x\right) = \max(x, 0) \tag{7}$$

Pooling Layer

The pooling layer ensures that most of the important information is not missing, and the pooling layer will appear periodically in the entire convolutional neural network under the condition of reducing the dimension of each feature map. Generally, the pooling layer mainly uses the Max pooling layer and the Average pooling layer.

Let the input image size be WxH, where W: (number of channels), the size of the convolution kernel is FxF, and S: step size. Output image size after pooling:

$$W = \frac{W - F}{S} + 1 \tag{8}$$

$$H = \frac{H - F}{S} + 1 \tag{9}$$

Fully Connected Layer

$$\begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} = \begin{bmatrix} W_{11} & W_{12} & W_{13} \\ W_{21} & W_{22} & W_{23} \\ W_{31} & W_{32} & W_{33} \end{bmatrix} * \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} \tag{10}$$

After comparing the classic convolutional neural network, this paper refers to the Inception network structure of GoogLeNet and uses the ReLU activation function.

Research on the Attitudes of Students' Parents Towards Their Children's Informatization Learning

This survey takes the attitude theory in social psychology as the theoretical basis for questionnaire design. Social psychology believes that attitude is a complex cognitive process, and it is people's evaluation of things and behavioral tendencies. Attitude is defined as an evaluative response to someone or something expressed in beliefs, emotions and behavioral tendencies, and it is divided into three components: cognition, emotion and behavioral intention. Among them, the cognitive component refers to the individual's description of the attitude object with evaluation significance, including the individual's knowledge and understanding of the attitude object; emotional component refers to the emotional experience of individuals towards attitude objects, such as liking or hating; behavioral intention refers to the reaction tendency or behavior preparation state of individuals towards attitude objects.

The preliminary questionnaire of this study contains 36 questions, including basic information and attitude. The basic information survey's 12 questions capture parents' gender, age, education background, e-learning frequency, working status during large-scale online learning, gender of their children, whether they are only children, grade, academic level and previous e-learning frequency. The attitude survey contains 24 questions. Twelve questions investigate parents' attitudes toward their children's e-learning before large-scale online learning. Twelve questions investigate parents' attitudes after large-scale online learning. The questionnaire used the cognition, emotion, and behaviour dimensions to investigate parents' attitudes toward the four basic elements of e-learning: (1) resources; (2) methods; (3) support; and (4) evaluation. SPSS22.0 was used to test the reliability and validity of the questionnaire. The clonal Bach alpha coefficient of the questionnaire is 0.901, indicating that the reliability of the questionnaire is good. The KMO coefficient was 0.918, and Bartlett sphericity test reached a significant level ($p < 0.01$).

Let the population mean be μ and the population variance be σ^2 (unknown):

Sample mean: $$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \tag{11}$$

Sample standard deviation: $$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2} \tag{12}$$

According to the above, there are:

$$\frac{\bar{X}-\mu}{\sigma / \sqrt{n}} = \frac{\sqrt{n}\left(\bar{X}-\mu\right)}{\sigma} \sim N\left(0,1\right) \tag{13}$$

From the chi-square variable, we obtain Eq. (14) for the t-test:

$$\frac{\frac{\sqrt{n}\left(\bar{X}-\mu\right)}{\sigma}}{\sqrt{\frac{\frac{\left(n-1\right)s^2}{\sigma^2}}{n-1}}} = \frac{\sqrt{n}\left(\bar{X}-\mu\right)}{s} \sim t\left(n-1\right) \tag{14}$$

The test conditions are shown in Eq. (15):

$$\begin{cases} \left|\frac{\sqrt{n}\left(\bar{X}-\mu\right)}{s}\right| > t_{\frac{\alpha}{2},n-1} \\ \frac{\sqrt{n}\left(\bar{X}-\mu\right)}{s} < t_{\frac{\alpha}{2},n-1} \\ \frac{\sqrt{n}\left(\bar{X}-\mu\right)}{s} > t_{\frac{\alpha}{2},n-1} \end{cases} \tag{15}$$

RESULT ANALYSIS AND DISCUSSION

Experiment of Emotion Recognition Algorithm in Student Information Learning

Data Set Production

This article uses the CK+ dataset during training. The CK+ dataset contains 123 subjects and 593 image sequences. Of this, 327 image sequences contain emotional labels with seven expressions: (1) anger; (2) contempt; (3) disgust; (4) fear; (5) happiness; (6) sadness; and (7) surprise. According to the relevant face algorithm, the data set in Figure 3 is identified.

Training Process

After image processing, the dataset normalizes the image to 3*48*48. (Regarding C*H*W, C is the number of image channels within the network. The Pytorch TenCrop method is used to enhance the training data set. The data set is enlarged through image rotation, scaling, and random cropping. The enlarged dataset as shown in Figure 4.

Online Experiment

The learning state sequence diagram of the learner is shown in Figure 5.

Figure 3.
Data Set Display

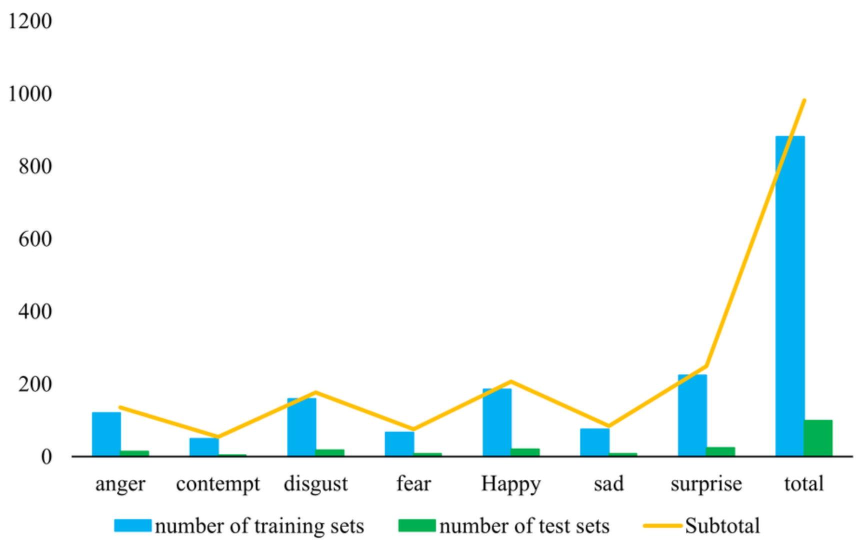


Figure 4.
Training Results

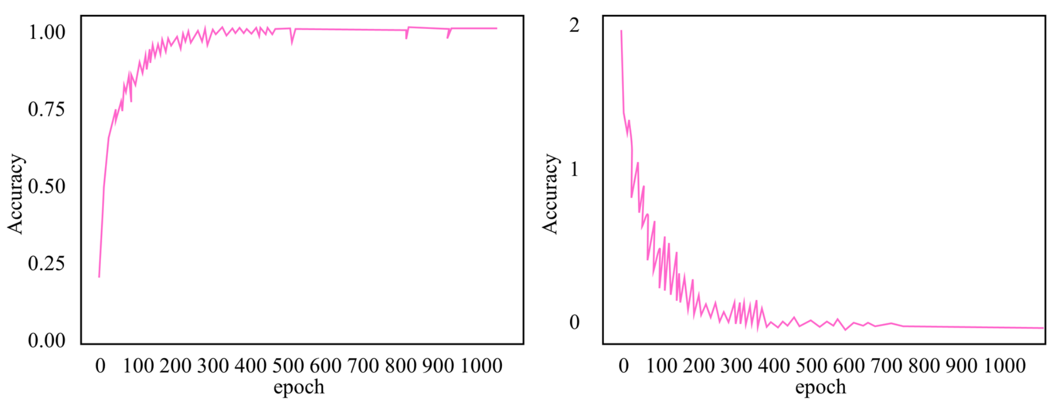
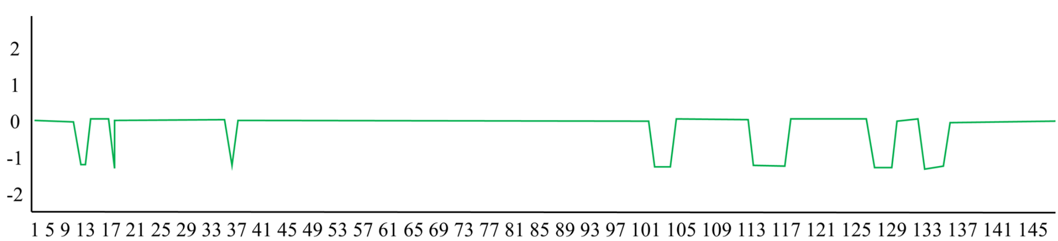


Figure 5.
Sequence Diagram of Learner Learning State



Comparison of Parents' Attitudes Toward Children's Informatization Learning Before and After Large-Scale Online Learning

This study explored students' attitudes toward e-learning in the context of the combination of large-scale online learning and multimedia technology. It took the large-scale online learning experienced by students during the pandemic as its boundary. The study found that parents' attitudes toward their children's e-learning are significantly different before and after large-scale online learning (see Figure 6).

After large-scale online learning, the scores of parents' attitudes toward their children's e-learning showed an overall downward trend. Still, a small number of groups (like parents over the age of 60, parents with junior high school education and below, and parents who had never experienced e-learning before large-scale online learning) had improved attitudes (see Figures 6 and 7). Before large-scale online learning experiences, this group of parents knew little about e-learning (and even held prejudice). However, their attitudes improved when e-learning met the basic needs of their children's learning during a special period.

This study also found that parents' attitudes toward their children's e-learning changed based on the initial stage of e-learning and their perceived advantages of e-learning based on their and their children's basic needs (i.e., safety, ease, and low cost). This showed an increase in attitude scores. However, with the in-depth understanding of e-learning, they will have more diversified demands for e-learning. When the needs go unmet, a negative emotional experience will be generated. In turn, the attitude score declines. This shows that parents' attitudes toward their children's e-learning can change with a different understanding of the stages of e-learning. The change in trend of attitude scores is determined by whether their own growing needs can be met (i.e., less energy consumption, less harm to

Figure 6.
Comparison of Parental Attitude Scores by Gender, Age, Educational Background, Frequency of Informatization Learning, and Work Status

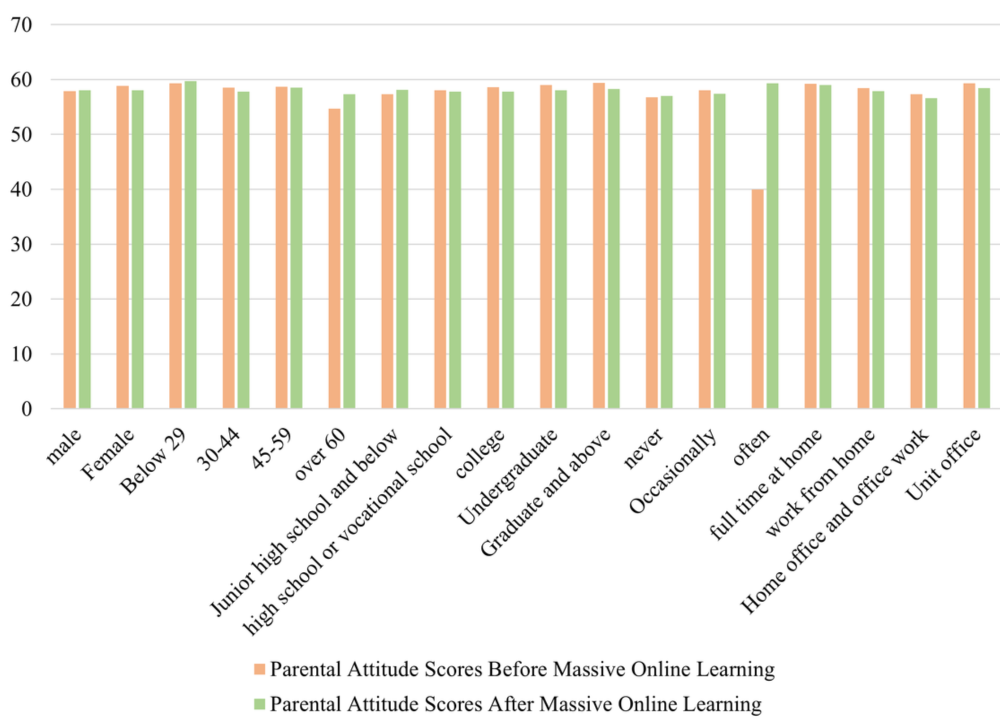


Figure 7.
Comparison of Attitude Scores of Parents with Different Children's Gender, Grade, Academic Level, and Frequency of Children's Informatization Learning

their children's physical and mental health, and improvement of their children's academic performance). Parents' attitudes toward their children's e-learning is, therefore, characterized by distinct stages.

CONCLUSION

In the context of large-scale online learning and multimedia technology, this study explored whether online learning affected parents' attitudes toward their children's e-learning. Based on the classical convolutional neural network and CK+ dataset, this article proposes a convolutional neural network model to evaluate parents' attitudes toward e-learning in the context of large-scale online learning and multimedia technology.

The experiment shows that the convolutional neural network model proposed in this article can accurately recognize the facial information of learners in the live classroom. Teachers can adjust teaching strategies in real time according to learners' emotional changes. This will improve the teaching process. The study also found that the change of parents' attitudes toward e-learning was affected by parents' gender, age, educational background, frequency of e-learning, and working status. The frequency of their children's e-learning, gender, whether they were only children, school grade, and academic level also affected parents' attitudes. Prior studies have shown that young parents are more worried about the negative impact of e-learning on their children. However, the current study found that this group has a more positive attitude toward e-learning. The reason may be that parents have different values in different times or backgrounds.

This study found many factors that affect parents' attitudes toward their children's e-learning. The research is based on in-depth interviews. However, it failed to fully present the formation mechanism of parents' attitudes toward their children's e-learning. This will be discussed in a follow-up study.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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