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Molecular & Cellular Biomechanics 2025, 22(1), 852.
https://doi.org/10.62617/mcb852

Article

Human-computer emotional interaction in online education based on biomechanical principles

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CITATION

Liu D. Human-computer emotional interaction in online education based on biomechanical principles. Molecular & Cellular Biomechanics. 2025; 22(1): 852. https://doi.org/10.62617/mcb852

ARTICLE INFO

Received: 21 November 2024
Accepted: 12 December 2024
Available online: 6 January 2025

Abstract: Emotional interactions in traditional online education often face problems such as unnaturalness, lack of personalization, and neglect of body language. This paper aims to optimize the emotional expression of virtual teachers from the perspective of kinematics and mechanics through the principles of biomechanics, improve the naturalness and personalization of emotional interaction, and thus enhance learners' emotional involvement, learning motivation, and learning effects. This paper combines the principles of biomechanics to optimize the human-computer emotional interaction system and enhance the emotional resonance between virtual teachers and students. In the study, inverse kinematics and dynamic models are constructed to ensure that the virtual teachers' movements conform to the laws of human biomechanics and effectively express emotions. Secondly, the facial action coding system is used to model the facial expressions of the virtual teachers, and the coordination of facial expressions and body movements is achieved through a coordinated control algorithm. Finally, an emotion perception and feedback mechanism is designed to enable the virtual teachers to adjust their posture, speech, expression, etc., in real time according to the students' emotional state and provide personalized emotional response. The experimental results show that the optimized virtual teacher emotional interaction system is significantly superior to the traditional education system in terms of human-computer interaction quality, emotional feedback, and learning motivation. Specific data shows that the experimental group scores 4.3 in positive emotions (positive affect, PA), significantly higher than the control group's 3.1. In terms of pleasure scores, the experimental group scores 4.5, while the control group only scores 3.2. In addition, the experimental group is significantly better than the control group in various indicators of learning motivation, and its learning time is significantly longer than that of the control group. Its task completion and number of interactions are also better than those of the control group.

Keywords: biomechanical principles; online education; interpersonal emotional interaction; virtual teacher; emotional feedback

1. Introduction

With the rapid development of information technology, online education has gradually become an important part of modern education [1,2]. Its flexibility, convenience and personalized customization have made it widely used around the world. Especially during the COVID-19 pandemic, the popularity of online education has further accelerated and has become the main way for students to learn. Online education not only provides learners with a more convenient learning channel, but also breaks through the spatial and temporal limitations of the traditional education model, promoting the global sharing of educational resources and the realization of educational equity [3,4]. However, although online education has made significant progress in knowledge transfer and technology application, the existing online education system still faces many challenges in improving learning experience and enhancing learning outcomes, especially in terms of "human-computer emotional interaction" [5]. Traditional online education platforms focus on imparting knowledge and ignore the importance of emotional factors. Studies have shown that emotional interaction plays a vital role in the learning process and can effectively stimulate students' learning motivation, enhance learning investment, and improve learning outcomes. Therefore, how to optimize students' learning experience through effective emotional interaction mechanisms has become a key issue in current online education research [6,7].

Currently, many online education platforms rely on a single method such as voice, facial expressions, or text to provide emotional feedback. Although these methods can convey emotional information, they lack the support of body language, and the emotional response is not personalized, which result in the virtual teachers' emotional expression being unnatural and not vivid enough, making it difficult to arouse students' emotional resonance [8]. In addition, existing systems usually fail to perceive students' emotional states (such as anxiety, confusion, fatigue, etc.) in real time, resulting in the inability to respond to students' emotional needs in a timely manner, which may affect learning motivation and outcomes. Traditional online education systems mainly focus on knowledge transfer and technology application, ignoring the role of emotional interaction, which limits students' emotional involvement and learning motivation. Therefore, improving the quality of human-computer emotional interaction in online education has become an important way to improve learning outcomes.

To address the shortcomings of existing systems, this paper optimizes the emotional expression of virtual teachers by applying biomechanical principles, thereby enhancing the naturalness, personalization, and effectiveness of emotional interaction. Biomechanics, as a discipline that studies human movement and mechanics, provides a theoretical basis for the body language and emotional expression of virtual teachers. Through the application of biomechanics, the virtual teachers' body movements, postures, and facial expressions are adjusted to make them more in line with the laws of natural human movement and the needs of emotional expression, thereby enhancing the realism and interactive effect of emotional interaction. Specifically, biomechanical principles help optimize the emotional feedback of virtual teachers, making the emotions they express more natural and personalized, and making timely adjustments based on the emotional state of students. This biomechanics-based optimization helps virtual teachers establish a deeper emotional resonance with students, stimulate students' learning motivation, and ultimately improve learning outcomes.

This study optimized the emotional interaction system of the virtual teacher by introducing the principles of biomechanics. Using inverse kinematics and dynamic modeling, we ensured that the movements and postures of the virtual teacher conformed to the laws of human biomechanics, enhancing the naturalness and realism of the movements. The facial action coding system (FACS) made the facial expressions of the virtual teacher more detailed and dynamic, while the coordinated control algorithm (CCA) achieved the synchronization of facial expressions and body movements, improving the consistency of emotional expression. In addition, combined with facial expression recognition and speech emotion analysis technology, the system can perceive and respond to students' emotional states in real time and provide personalized emotional feedback. These optimizations enable virtual teachers to establish emotional connections with students more naturally, stimulate learning motivation, and improve learning outcomes.

2. Related work

In recent years, with the rapid development of online education, the role of emotional interaction in improving learning experience and results has gradually been valued [9,10]. Traditional online education platforms usually focus on imparting knowledge, and research on emotional interaction started relatively late. Existing virtual teachers and educational robots mostly rely on single emotional feedback methods such as voice and facial expressions. Although these technologies can convey emotions to a certain extent, the naturalness and vividness of their expressions are relatively limited [11]. In particular, traditional systems lack body language and personalized emotional responses, and the emotional expression of virtual teachers is relatively mechanical, so it is difficult for students to have real emotional resonance with virtual teachers [12]. In addition, existing systems are usually unable to perceive students' emotional states in real time and fail to make dynamic adjustments based on their emotional needs, which means that students' emotional needs often cannot be responded to in a timely manner, in turn affecting their learning motivation and learning outcomes. Therefore, how to improve the naturalness and personalization of emotional interaction has become a key issue in improving the effectiveness of online education systems.

The application of biomechanical principles in emotional interaction provides a new approach to solving this problem [13]. As a discipline that studies human movement and mechanics, biomechanics reveals the natural movement patterns of the human body in emotional expression. Non-verbal signals such as human posture, movement, and body language change with emotional state. These physiological reactions help convey emotional information and enhance the authenticity of communication [14,15]. In emotional interaction, biomechanics optimizes the virtual teachers' body languages and facial expressions to make them more consistent with the laws of natural movement and enhance the effect of emotional feedback [16]. By applying biomechanics, it is possible to adjust the virtual teachers' range of motion, posture, and expression, and provide personalized feedback based on the students' emotional state. For example, when students are anxious or confused, virtual teachers can ease emotions through body languages and encouraging gestures to improve the learning experience. The application of biomechanics can help to establish a more realistic emotional connection between virtual teachers and students, thereby promoting the improvement of learning motivation and effectiveness [17,18].

3. Methods and implementation

3.1. Application of biomechanical principles in emotional interaction

3.1.1. Action and posture optimization

(1) Construction and application of inverse kinematics model

This paper adopts the inverse kinematics (IK) model to reversely calculate the target position of the end effector of the virtual teachers' limbs and infer the rotation angle of each joint, thereby ensuring the naturalness and accuracy of limb movements. When constructing the IK model, the skeleton structure of the virtual teachers is first defined, including the connection between joints and skeleton segments [19]. The rotation axis, range of motion, and movement limit of each joint are reasonably set according to the human anatomical structure. The specific settings are shown in **Table 1**:

Table 1. Settings of human joints of IK model.

Location	Joint type	Rotation axis direction	Range of motion
Shoulder joint	Ball-and-socket joint	*X* axis (horizontal), *Y* axis (vertical)	180° front and rear, 180° horizontal rotation
Elbow joint	Pivot joint	*X*-axis (vertical)	0°–150° (bend angle)
Wrist joint	Ball-and-socket joint	*Y* axis (vertical), *Z* axis (horizontal)	Rotate 45°, bend 90°, extend 80°
Knee joint	Pivot joint	*X*-axis (vertical)	0°–150° (bend angle)
Ankle joint	Gear joint	*Y* axis (vertical)	0°–60° (dorsiflexion and plantar flexion angles)
Spinal joint	Ball-and-socket joint	*X* axis (front and back), *Y* axis (left and right)	30° front and rear, 15° left and right
Neck joint	Ball-and-socket joint	*X*-axis (up and down), *Y*-axis (left and right)	Neck front and back 30°, left and right 45°

The key to IK solution is to calculate the relationship between joint angles and target positions. Common IK solution methods include Jacobian inverse method and gradient descent method [20]. This paper adopts the Jacobian inverse method, which is based on the linearized model and describes the relationship between the joint angle and the end effector position change through the Jacobian matrix. The Jacobian inverse method calculates the angle of each joint through inverse operation, so that the end effector gradually approaches the target position, and adjusts the joint angle through iteration until the target error is less than the preset threshold. In IK solution, the Jacobian matrix J describes the relationship between each joint angle and the change in the end effector position [21]. If the end effector position is p and the joint angle is θ, then the following relationship holds:

$$\Delta p = J(\theta) \cdot \Delta\theta \tag{1}$$

In Equation (1), Δp is the change of the end effector position; $\Delta\theta$ is the change of the joint angle; $J(\theta)$ is the Jacobian matrix, which represents the effect of the joint angle change on the end effector position change. The solution process of the Jacobian inverse method is:

$$\Delta\theta = J^{-1}(\theta) \cdot \Delta p \tag{2}$$

In Equation (2),$\Delta\theta$ is computed through iterative optimization, and the joint angle is gradually adjusted until the error of the target position is less than the set threshold. The Jacobian inverse method solution process is shown in **Figure 1**:

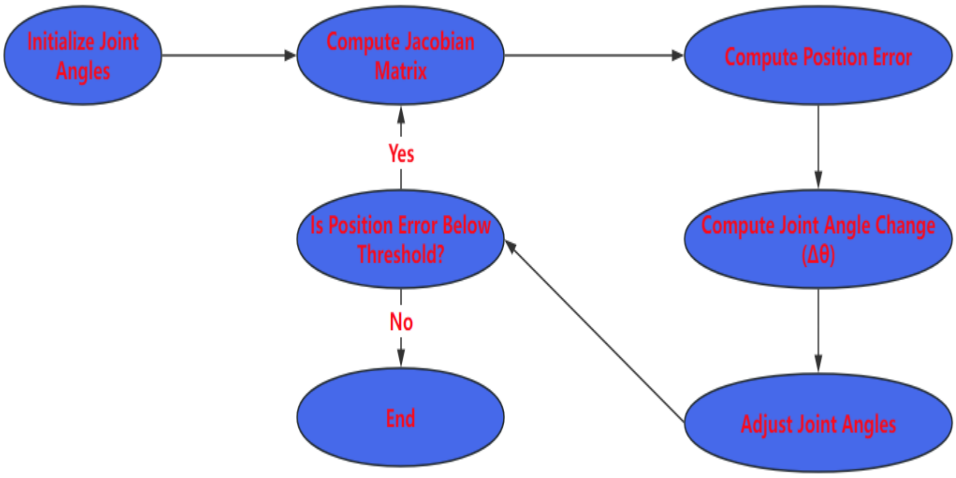

Figure 1. Jacobian inverse method solution flow chart.

However, during the IK solution process, the adjustment of joint angles may cause sudden or discontinuous movements, making the virtual teachers' body movements appear unnatural. Therefore, based on the joint angles obtained by IK solution, this paper further uses the Bézier curve to smooth the movements [22]. The Bézier curve is a classic smooth curve interpolation method in computer graphics. It generates a smooth trajectory through control points to ensure that the transition between the starting point and the end point of the movements is natural and continuous. To ensure that the virtual teachers' body movements are physiologically consistent and smooth, this paper selects the cubic Bézier curve, which defines the smooth transition of the movements through four control points. On this basis, the joint angles obtained by IK solution are used as the starting and end points of the Bézier curve, and the control points are set according to the speed requirements at the beginning and end of the movements to ensure a natural and smooth transition of the movement trajectories. The parametric equation of the cubic Bézier curve is:

$$B(t) = (1-t)^3 \cdot P_0 + 3(1-t)^2 \cdot t \cdot P_1 + 3(1-t) \cdot t^2 \cdot P_2 + t^3 \cdot P_3 \tag{3}$$

In Equation (3), t is the parameter, and P_0, P_1, P_2, and P_3 are control points, which determine the start, end, and transition path of the curve. In this paper, the smoothing process using the cubic Bézier curve is shown in **Figure 2**:

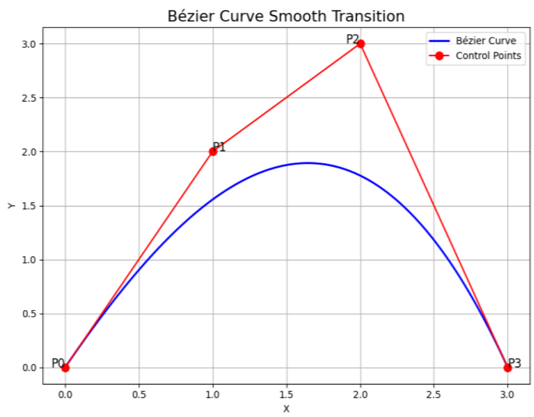

Figure 2. Bézier curve smooth transition diagram.

In addition, to further improve the naturalness and continuity of the movements, this paper also uses the natural spline curve to optimize the transition of limb movements. Unlike the Bézier curve, the spline curve can automatically take into account boundary conditions and generate smooth curves, ensuring that there are no drastic accelerations or speed changes during the movement. During the computing process, the natural spline curve can effectively reduce the abruptness of the movement by conditionally constraining the start and end of the movement, making the virtual teachers' body movements smoother and in line with physiological laws.

$$S(t) = \sum_{i=1}^{n} N_i(t) \cdot y_i \tag{4}$$

In Equation (4), $S(t)$ is the spline curve; $N_i(t)$ is the spline basis function; y_i is the value of the spline node. By properly selecting boundary conditions and node values, the spline curve can smoothly connect various movement nodes and ensure a natural transition of limb movements.

(2) Dynamic modeling and movement optimization

In this paper, the core task of dynamic modeling is to simulate the mechanical response of each joint and part when the virtual teachers perform body movements, covering multiple factors such as inertia, gravity, muscle tension, etc. This paper uses the Lagrange equation for dynamic modeling.

In Lagrangian dynamic modeling, the skeleton structure of virtual teachers needs to be considered as a multi-rigid body system first [23,24]. Each joint is regarded as a rigid body with physical properties such as mass and moment of inertia, and the interconnection between bone segments is realized through joints. Therefore, each joint of the virtual teachers can be regarded as an independent rigid body and has its own degree of freedom of movement. The basic form of the Lagrange equation is:

$$L = T - V \tag{5}$$

In Equation (5), L is the Lagrangian; T is the kinetic energy of the system; V is the potential energy of the system. The expression for kinetic energy is as follows:

$$T = \frac{1}{2}\sum_{i=1}^{n} m_i v_i^2 \tag{6}$$

In Equation (6), m_i is the mass of the i-th rigid body, and v_i is the velocity of the i-th rigid body. The potential energy takes into account the effect of gravity and can be expressed as:

$$V = \sum_{i=1}^{n} m_i g h_i \tag{7}$$

In Equation (7), g is the acceleration due to gravity, and h_i is the height of the i-th rigid body. Through the Lagrange equation, the motion equation of the virtual teachers is constructed, and the dynamic characteristics of the system are derived, thereby obtaining the force conditions and torques of each joint. Specifically, by deriving the Lagrange equation of each rigid body and differentiating the joint angle, the dynamic equation related to the joint motion is obtained, which can describe the acceleration, velocity, and mechanical response of each joint.

In the process of dynamic modeling, the optimization of the movements must not only ensure that they conform to physiological laws, but also avoid excessive mechanical burden during the movements, especially when performing complex movements, such as reaching out to hug, which involve the coordinated movement of multiple joints. Through the Lagrange equation, the moment of inertia and torque of each joint can be precisely calculated, and the interaction forces between joints can be analyzed, so as to optimize the force conditions of the joints and avoid excessive loads on certain joints or abrupt movements. For example, when the shoulder, elbow, and wrist joints are extending, the force on each joint must be reasonably distributed to avoid excessive load on local joints. By modeling and optimizing the mechanical relationship between joints, it can be ensured that the load on each joint during the movement is within a reasonable range, avoiding uncoordinated movements caused by uneven loads.

In addition, the smoothness of the movement is also an important goal in the optimization process. By adjusting the range of motion, acceleration, and speed of each joint, it can be ensured that there are no abrupt pauses or incoherent acceleration during the execution of the movements. Especially in some movements that require smooth transitions, such as when the virtual teachers perform some complex body movements, the coordination and smoothness of the movements of each joint must be ensured. The Lagrange equation can help calculate the equations of motion for each joint and optimize the motion process as needed to eliminate possible skips or unsmooth transitions. Through precise dynamic modeling and optimization, the virtual teachers' movements are made natural and physiologically reasonable, avoiding excessive speed changes or unnatural movement mutations.

(3) Emotional expression through movement optimization

In the process of motion optimization, in addition to improving naturalness, another important goal is to ensure that body movements effectively convey emotional information. The virtual teachers express emotions such as care, understanding, and encouragement through body movements, postures, and facial expressions. Therefore, motion optimization must not only follow physiological and mechanical laws, but also accurately reflect emotional characteristics. This paper combines inverse kinematics and dynamic modeling to ensure that the virtual teachers' body movements are natural and smooth and can effectively convey emotions.

For example, when expressing "care" or "comfort", the virtual teachers' movements should be gentle and soothing. At this time, the body movements should avoid being abrupt, but should be gradual and gentle. To this end, the IK model and the dynamic model work together to optimize the starting angle, amplitude, and acceleration of the movement to ensure that the movement not only meets physiological requirements and avoids excessive tension or unnatural mutations, but also shows emotional softness. Specifically, IK solution provides the preliminary angle and target position of limb movements, while dynamic modeling optimizes the mechanical properties during the movements to ensure that the movements are smooth and meets the requirements of emotional expression.

Relatively speaking, when expressing "encouragement", virtual teachers' body movements need to show more vitality and strength, such as waving, patting shoulders, etc. At this point, the synergy between the IK model and the dynamic model is mainly reflected in adjusting the amplitude and speed of movements so that the movements are both dynamic and meet the requirements of physiology and mechanics. By fine-tuning these details, virtual teachers' body languages can be made more vivid and expressive, thereby enhancing learners' emotional resonance, stimulating their learning motivation, and ultimately improving learning outcomes.

By combining inverse kinematics and dynamic modeling, this paper can precisely optimize each body movement of virtual teachers to ensure that it conforms to physiological and physical laws and can accurately convey emotional information. Such optimization not only improves the naturalness of virtual teachers' movements, but also enhances the depth and effectiveness of their emotional expression, helps to establish more effective emotional interactions, and thus promotes learners' emotional involvement and learning outcomes.

3.1.2. Combination of facial expressions and body language

(1) Facial expression modeling

Facial expressions are an important dimension of emotional expression of virtual teachers. To accurately convey emotions (such as smile, frown, surprise, etc.), this paper uses the facial action coding system (FACS) to model the facial expressions of virtual teachers. FACS divides facial expressions into a set of basic action units (AU) based on facial muscle movements, each of which represents the muscle activity in a specific area of the face [25]. By activating different action units, virtual teachers can show a variety of emotional expressions. The action unit settings for common emotional expressions are shown in **Table 2**:

Table 2. Action unit settings for common emotional expressions.

Emotional Expression	AU	Emotional Expression	AU
Smile	AU6 (muscles of malar elevation) AU12 (levator labii superioris)	Anger	AU4 (muscles of the glabella)
Surprise	AU1 (eyebrow elevating muscles) AU5 (muscles that enlarge the eyes)	Happiness	AU23 (lips tightly closed)
Frown	AU4 (muscles of the glabella) AU15 (muscles that depress the mouth corners)	Shyness	AU25 (chin tension)
Sadness	AU15 (muscles that depress the mouth corners) AU1 (eyebrow elevating muscles)	Suspicion	AU4 (muscles of the glabella) AU14 (muscles that depress the eyelids)

(2) Coordination of facial expressions and body movements

The transmission of emotions does not only rely on facial expressions, body language also plays a vital role in the emotional expression of virtual teachers. To ensure that the facial expressions and body movements of virtual teachers remain consistent in the same situation, this paper adopts the coordinated control algorithm (CCA) to achieve synchronization between the two. The core idea of the coordinated control algorithm is to automatically adjust the body language movements according to the changes in facial expressions, so that the facial and body expressions complement each other in conveying emotions and avoid conflicts or inconsistencies in emotional signals. During the implementation process, the algorithm first uses FACS to extract the facial expression features of virtual teachers through facial action recognition. Based on the intensity, duration, and type of emotions in the facial expressions, the algorithm computes the corresponding body language patterns.

In the actual process, it is assumed that the feature vector of facial expression is $F = [f_1, f_2, \ldots, f_n]$, where each f_i represents the activation degree of different facial action units. According to these facial features, the coordinated control algorithm defines the mapping relationship of body language movements, namely:

$$L = \mathcal{M}(F) \tag{8}$$

In Equation (8), $\mathcal{M}(\cdot)$ is a mapping function that maps the features of facial expressions to the movement space of body language L and selects different body language patterns according to the emotion type. To ensure coordinated movements, the coordinated control algorithm dynamically adjusts the amplitude, speed, and rhythm of limb movements based on facial expressions. Assuming that $A(t)$ is the amplitude function of the body movement; $V(t)$ is the speed function of the movement; t is the duration of the movement, under the influence of the facial expression input $F(t)$, the amplitude and speed of the body movements are adjusted by the following Equations:

$$A(t) = \alpha \cdot A_0 \cdot F(t) \tag{9}$$

$$V(t) = \beta \cdot V_0 \cdot F(t) \tag{10}$$

In Equations (9) and (10), α and β are adjustment parameters, and A_0 and V_0 represent the default movement amplitude and speed respectively. The intensity and type of facial expressions affect parameter changes. For example, when smiling, the algorithm adjusts the softness and rhythm of the movement to avoid abrupt or violent movements. This method ensures precise matching of facial expressions and body language, improving the naturalness and consistency of emotional expression. Overall, the coordinated control algorithm ensures that virtual teachers' emotional communication in emotional interaction is both coordinated and natural, avoiding inconsistency or conflict in emotional signals, by adjusting the synergy between body language and facial expressions in real time.

3.2. Emotional perception and feedback mechanism

3.2.1. Facial expression recognition

In this paper, the core tool for facial expression recognition is OpenFace, a powerful open source facial expression analysis system. OpenFace is designed for real-time and precise facial expression analysis, and can achieve robust facial recognition, facial feature point detection, expression analysis, etc., in complex environments. The recognition process of OpenFace mainly includes three key steps: facial detection, feature point location, and action unit analysis.

First, OpenFace uses convolutional neural networks (CNN) to perform facial detection, that is, to identify and locate facial areas. The input image is set to be I, and its pixel is set to be $P = \{p_1, p_2, \ldots, p_n\}$. CNN generates a facial recognition model *M* during training:

$$M(I) = R \tag{11}$$

In Equation (11), R represents the bounding box coordinates of the face region. After being trained with a large amount of data, the detection algorithm is able to extract facial contours from complex environments, has good adaptability, and can accurately identify faces in conditions of uneven lighting, facial occlusion, or tilt. This relies on the feature extraction capabilities of deep learning to ensure that the system can run in real time and robustly in a variety of real scenarios.

After completing facial detection, OpenFace enters the feature point positioning stage and uses the ensemble of regression trees (ERT) algorithm to mark 68 key facial feature points. The position of each feature point is (x_i, y_i), and the facial feature point set is represented by $\{(x_1, y_1), (x_2, y_2), \ldots, (x_{68}, y_{68})\}$. The ERT algorithm optimizes the prediction loss function by iteratively training the decision tree. The Equation is as follows:

$$\mathscr{L} = \sum_{i=1}^{68} \|\hat{p}_i - p_i\|^2 \tag{12}$$

In Equation (12), $\hat{p}_i$ is the feature point coordinates predicted by the model, and p_i is the true coordinates. Through decision tree optimization within a few milliseconds, the precise positioning of feature points is completed. This feature point layout lays the foundation for the system to further analyze facial expressions because it can capture the fine movements of various facial areas. OpenFace can stably and continuously track the changes in the positions of these feature points in each frame of the video, providing the necessary motion data for subsequent action unit analysis.

Based on the location of feature points, OpenFace further uses action units in FACS to recognize facial expressions. Action unit detection uses the dynamic changes in feature point coordinates to identify the amplitude of facial muscle activity. For each AU, OpenFace calculates an intensity score S_{AU} of the muscle activity, which typically ranges from 0 to 5. Assuming that the changes in the feature point position at time *t* and *t*+1 are $\Delta x = x_{t+1} - x_t$ and $\Delta y = y_{t+1} - y_t$, the intensity score S_{AU} of each AU can be expressed by the facial motion feature function *f*, that is:

$$S_{\mathrm{AU}} = f\left(\sum_{i=1}^{n_j} \sqrt{(\Delta x_i)^2 + (\Delta y_i)^2}\right) \tag{13}$$

In Equation (13), n_j represents the number of feature points associated with the AU, and f is the score mapping function of the model.

OpenFace computes the intensity score of each AU through a machine learning model. In this paper, this value ranges from 0 to 5, which reflects the intensity of muscle activity. In this way, OpenFace can make a detailed and continuous record of various emotional changes on the face. Once these action units are detected and quantified, OpenFace provides this data as an emotion indicator to the emotion feedback system. On this basis, the feedback system of virtual teachers can dynamically adjust according to the current emotional state of students.

3.2.2. Speech sentiment analysis

This paper aims to achieve emotionally resonant human-computer interaction by analyzing students' voice signals in real time, recognizing their emotional states, and adjusting the virtual teachers' tone, speaking speed, and intonation. These features together reflect the speakers' emotional states, so accurately recognizing and parsing these features is crucial for emotional interaction.

To achieve precise speech emotion recognition, this paper adopts an emotion recognition model based on deep learning, which mainly includes convolutional neural networks and recurrent neural networks. These models automatically extract key features in speech, such as pitch, volume, speaking speed, and intonation, and use them to determine the type and intensity of students' emotions, such as anxiety, confusion, or joy.

3.2.3. Design of virtual teachers' feedback mechanism

The feedback mechanism of the virtual teacher relies on multimodal emotion perception technology, including facial expression analysis, voice emotion analysis, and body language perception. OpenFace technology recognizes emotions by capturing subtle facial changes, voice emotion analysis extracts voice features to recognize emotions, and body language perception adds a dimension to emotional expression. This study combines the random forest algorithm to extract features and assign weights to the data of facial expression analysis, voice emotion analysis, and body language perception to achieve the fusion of multimodal data, thereby obtaining a more comprehensive and accurate assessment of emotional state. Combining these technologies, the virtual teacher can perceive students' emotions in real time and provide personalized feedback to ensure that the assessment of emotional state is comprehensive and accurate.

The virtual teachers' feedback mechanism relies on multi-modal emotion perception technology, including facial expression analysis, speech sentiment analysis, and body language perception. OpenFace technology recognizes emotions by capturing subtle facial changes. Speech sentiment analysis extracts voice features to recognize emotions. Body language perception adds dimensions to emotional expression. Combining these technologies, virtual teachers can perceive students' emotions in real time and provide personalized feedback, ensuring comprehensive and precise evaluation of emotional states.

Based on emotion perception, virtual teachers adjust feedback behavior in real time. When students show anxiety or confusion, virtual teachers sooth them by adjusting their speaking speed, tone, facial expressions, and body languages, such as using a gentle tone, slow speech speed, smiles, and soft gestures (such as nodding slightly). When students show positive emotions such as joy, virtual teachers encourage them by increasing their speaking speed, strengthening their tone, and showing an open gesture. In addition, the virtual teachers' feedback mechanism is personalized and optimized based on students' emotional history data to adapt to different emotional needs. Soothing feedback is provided to anxious students, and motivational strategies are adopted for emotionally positive students. When designing feedback mechanisms, biomechanical principles must also be considered to ensure that limb movements are natural and smooth, in line with physiological laws, avoid inappropriate movements, and ensure physiological comfort and visual naturalness.

4. Test of optimization of performance of human-computer emotional interaction system by combining biomechanical principles

In order to compare the effects of the virtual teacher emotional interaction system based on biomechanical optimization and the traditional education system on students' emotional experience, learning motivation and learning effect, this paper conducted evaluation experiments in university laboratories and online education platforms. The experimental subjects were 120 undergraduates aged between 18 and 22, covering undergraduates from different disciplines, including computer science, liberal arts, science, engineering and business. Before the formal experiment, the subjects' learning ability and computer operation proficiency were evaluated through pre-tests to reduce the errors caused by other variables. All subjects were divided into experimental and control groups by lottery through a random number generator, with 60 people in each group. All students conducted experiments under the same tasks and time limits to ensure the consistency of learning content and environment, and collected data in a controlled environment to ensure the effectiveness and fairness of the experiment.

(1) Emotional experience evaluation experiment

To evaluate the impact of the virtual teacher emotional interaction system based on biomechanical optimization on students' emotional experience, this experiment combines the subjective emotion scale and physiological indicator monitoring method. Before the experiment, all participants receive brief training to familiarize themselves with the operating interface and task requirements. Before the experiment, all participants received 30 min of training, including system operation introduction, task requirements explanation, experimental process description and practical operation drills to ensure that they can complete the experimental tasks proficiently. Basic emotional data are collected using the positive and negative affect schedule (PANAS) scale and physiological monitoring equipment (recording heart rate and galvanic skin response). The physiological monitoring equipment used included the Polar H10 heart rate monitor with a heart rate monitoring accuracy of ±1 beats/minute and the EDA sensor equipped with the Biopac MP150 system, which can monitor the skin galvanic response (EDA) with an accuracy of 0.01 micro-Siemens (μS). The experimental group uses the optimized virtual teacher system, and the control group uses the traditional education system. Both complete the same online learning modules, including video explanations, interactive questions and answers, and quizzes. The emotional experience evaluation process includes two aspects: subjective evaluation and physiological evaluation. During and after the learning process, participants are required to fill out an emotional evaluation questionnaire covering dimensions such as emotional state, anxiety, pleasure, and learning engagement. At the same time, physiological data such as heart rate and galvanic skin response are continuously recorded through physiological monitoring equipment to quantify emotional fluctuations during the learning process. At the same time, the physiological monitoring equipment continuously recorded heart rate data at a frequency of 1 Hz; the galvanic skin response (EDA) data was recorded at a frequency of 0.5 Hz. After the experiment, the researchers collect and analyze the subjective evaluation data from the emotional questionnaire and the objective data from the physiological monitoring equipment. The experimental results are shown in **Figures 3** and **4**:

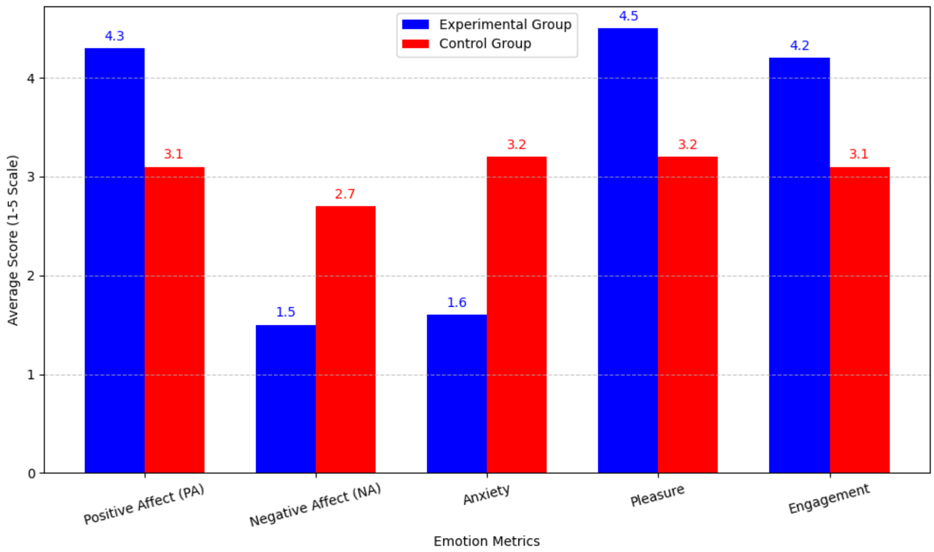

Figure 3. Emotional index results of the experiment.

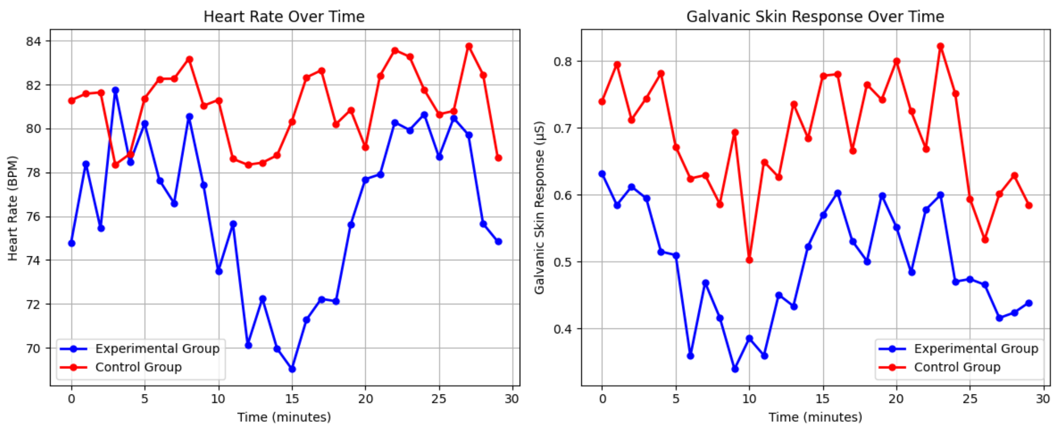

Figure 4. Heart rate and galvanic skin response changes.

Figure 3 shows the difference in scores on the emotional experience index between the experimental group (virtual teacher emotional interaction system based on biomechanical optimization) and the control group (traditional education system). The results show that in terms of positive emotions (positive affect, PA), the score of the experimental group is 4.3, which is significantly higher than the 3.1 of the control group, indicating that the virtual teacher system can effectively stimulate students' positive emotions. In terms of pleasure, the experimental group scores 4.5, which is significantly higher than the control group's 3.2, showing its advantage in enhancing the pleasure of learning. For negative emotions (negative affect, NA) and anxiety, the experimental group scores lower, 1.5 and 1.6 respectively, while the control group scores higher, 2.7 and 3.2 respectively, indicating that the virtual teacher system effectively alleviates students' negative emotions and anxiety. Finally, the learning engagement of the experimental group is 4.2, significantly higher than the 3.1 of the control group, reflecting that the system not only improves emotional experience but also enhances learning motivation and concentration. In summary, the virtual teacher emotional interaction system based on biomechanical optimization is superior to the traditional education system in stimulating positive emotions, reducing negative emotions and anxiety, and enhancing pleasure and learning engagement.

During the test, the heart rate and galvanic skin response changes of the students in the experimental group and the control group are shown in **Figure 4**.

As shown in **Figure 4**, in the heart rate change curves, the average heart rate of the experimental group is significantly lower than that of the control group, indicating that the virtual teacher emotional interaction system optimized based on biomechanical principles has a more effective emotional relief effect on the overall learners, putting them in a more relaxed physiological state. However, the heart rate variation of the experimental group is relatively large, which indicates that although the overall heart rate is low, the heart rate of the experimental group may fluctuate significantly when encountering new learning tasks or interactive situations. Such fluctuations may reflect that the emotional interaction system makes students more sensitive and immediate in their response to emotional feedback. This suggests that the virtual teachers' emotional interaction can stimulate students' short-term interest and attention, causing their heart rate to fluctuate slightly without causing sustained physiological tension.

In contrast, the heart rate curve of the control group is higher than that of the experimental group most of the time, indicating that the traditional system is generally ineffective in relieving students' emotional stress during the learning process, keeping the heart rate at a high level for a long time. The heart rate variation of the control group is relatively small, which may be because there is less emotional interaction in the traditional system, and students do not get the opportunity to relieve their emotions. Their physiological state is in a state of continuous tension, and their heart rate fluctuations are relatively stable but high.

In the galvanic skin response change curves, the galvanic skin response value of the experimental group is always lower than that of the control group, indicating that with the support of the emotional interaction system, students' physiological stress response is weaker, and they present a more relaxed physiological state. Galvanic skin response is usually associated with emotional excitement and tension. The galvanic skin response value of the control group is higher and the change trend is similar to that of the experimental group, indicating that the two groups have the same emotional fluctuations when dealing with similar learning content, but the experimental group can maintain a lower stress level with the support of the interaction system.

Overall, the virtual teacher emotional interaction system based on biomechanical optimization can effectively help students maintain a low average heart rate and galvanic skin response during the learning process, significantly relieve continuous emotional stress, and optimize the physiological state. The large fluctuation range of the heart rate in the experimental group shows that the system stimulates students' emotional participation to a certain extent, causing them to have a positive physiological response to the learning task without causing a continuous state of tension.

(2) Learning motivation evaluation experiment

In order to evaluate the effect of the virtual teacher emotional interaction system optimized based on biomechanical principles on students' learning motivation, this experiment adopted a method combining subjective evaluation with objective behavior quantification. The experimental group used the optimized virtual teacher emotional interaction system, while the control group used the traditional education system. Both groups of students were required to complete the same online learning module, including video explanations, interactive questions and answers, and quizzes. After the experiment, the participants filled out a learning motivation questionnaire based on the Motivated Strategies for Learning Questionnaire (MSLQ) or the Learning Motivation Scale (LMS), and the evaluation dimensions included learning goal clarity, learning interest and participation, achievement motivation, and self-efficacy. In addition, the researchers further quantified students' learning participation and motivation performance through behavioral data analysis, such as learning time, task completion, and number of interactions. The experimental data were statistically analyzed by independent sample T test to determine whether the difference in learning motivation between the experimental group and the control group was statistically significant. When conducting the T test, this study set the significance level (p value) to 0.05 to determine the significance of the results. This means that if the p value is less than or equal to 0.05, the difference between the two groups will be considered statistically significant, indicating that the virtual teacher emotional interaction system is effective in improving students' learning motivation. The experimental results are shown in **Table 3** below:

Table 3. Results of the learning motivation evaluation experiment.

Evaluation indicators	**Experimental group**	**Control group**	***p*-value**
Learning objectives	4.2 ± 0.5	3.5 ± 0.7	< 0.05
Study interests	4.5 ± 0.6	3.8 ± 0.8	< 0.05
Achievement motivation	4.1 ± 0.7	3.3 ± 0.9	< 0.05
Self-efficacy	4.4 ± 0.6	3.7 ± 0.8	< 0.05
Study time (minutes)	45.2 ± 5.1	38.5 ± 6.3	< 0.05
Task completion rate (%)	94.3 ± 3.6	82.1 ± 6.2	< 0.05
Number of interactions	25 ± 4	18 ± 5	< 0.05

According to the data in **Table 3**, the experimental group is significantly better than the control group in various indicators of learning motivation, indicating that the virtual teacher's emotional interaction system optimized based on biomechanical principles has a significant effect on improving students' learning motivation. In terms of clarity of learning goals and learning interest and participation, the mean values of the experimental group were 4.2 and 4.5 respectively, which were significantly higher than the 3.5 and 3.8 of the control group, and the fluctuations were small, indicating that the system effectively helped students clarify and maintain learning goals. Higher interest. The scores of the experimental group on achievement motivation and self-efficacy were 4.1 and 4.4 respectively, which were significantly better than the 3.3 and 3.7 of the control group, indicating that the system enhanced students' intrinsic motivation and self-confidence. In addition, the experimental group's learning time was 45.2 minutes, which was significantly higher than the 38.5 minutes of the control group, and was also better than the control group in terms of task completion and number of interactions, further proving that the virtual teacher system can improve student learning engagement and efficiency advantages. Overall, the experimental group performed better in all dimensions of learning motivation, and the p values were all less than 0.05, indicating that the statistical results were significant, indicating that the virtual teacher emotional interaction system effectively enhanced students' learning motivation and promoted positive Engage and learn effectively.

(3) Human-computer interaction experience evaluation experiment

To evaluate the impact of the virtual teacher emotional interaction system optimized based on biomechanical principles on students' human-computer interaction experience, this paper arranges researchers to observe and record the interaction frequency, response time, and emotional feedback between the experimental group and the control group students and the virtual teachers during the learning process, so as to objectively quantify the quality of human-computer interaction. After learning, the participants fill out a questionnaire about the human-computer interaction experience, and the evaluation dimensions cover interaction fluency, system responsiveness, teacher role identity, and system usability. The experimental results are shown in **Table 4**:

Table 4. Results of human-computer interaction experience evaluation.

Evaluation indicators	**Experimental group**		**Control group**	
	Mean	**Standard deviation**	**Mean**	**Standard deviation**
Interaction fluency	4.5	0.6	3.2	0.8
System responsiveness	4.6	0.5	3.4	0.7
Teacher role identity	4.3	0.6	3.1	0.9
System usability	4.4	0.5	3.3	0.8
Interaction frequency (times/minute)	3.8	1.1	2.4	1.0
Response time (seconds)	1.2	0.4	1.9	0.6
Emotional feedback positivity	4.7	0.5	3.5	0.7

According to the data in **Table 4**, the virtual teacher emotional interaction system based on biomechanical optimization is significantly superior to the traditional education system in terms of human-computer interaction quality. The experimental group scores higher than the control group (3.2, 3.4, and 3.1) in interaction fluency (4.5), system responsiveness (4.6), and teacher role identity (4.3), indicating that the optimized system provides smoother and more timely interactions and enhances students' emotional identification. The experimental group also scores significantly higher on system usability (4.4) than the control group (3.3), indicating that the system is more convenient to operate. The interaction frequency (3.8 times/minute) and response time (1.2 s) of the experimental group are better than those of the control group (2.4 times/minute and 1.9 seconds), indicating that the optimized system can respond to student input more quickly and promote participation. Finally, the experimental group scores significantly higher on the positivity of emotional feedback (4.7) than the control group (3.5), indicating that the system is more effective in stimulating students' emotional resonance and enhancing their emotional involvement. Overall, the optimized system performs superiorly in terms of human-computer interaction experience, emotional engagement, and learning effects.

5. Discussion

This study is limited by a small sample size, mainly from undergraduate students majoring in computer science, which may affect the general applicability of the results. Future research should expand the sample range to include students from different disciplines and cultural backgrounds to explore the impact of potential confounding variables such as subject preferences and cultural differences on the virtual teacher emotional interaction system. Increasing the sample size can not only enhance the robustness of the statistical analysis, but also improve the universality and adaptability of the model. Our results provide a basis for future research, but need to be verified in a wider range of educational settings to ensure the universality and effectiveness of the design of the virtual teacher emotional interaction system.

6. Conclusion

This paper combines biomechanical principles into the virtual teacher emotional interaction system, aiming to solve the problems of unnatural performance, lack of personalization, and neglect of body language in the traditional online education system. Based on the principles of kinematics and mechanics, this paper optimizes the emotional expression of virtual teachers to improve the naturalness, personalization and vividness of human-computer interaction, thereby enhancing students' emotional involvement, stimulating learning motivation, and improving learning effects. The experimental results show that the virtual teacher system based on biomechanical optimization is significantly superior to the traditional education system in terms of human-computer interaction quality, emotional feedback, learning motivation, and learning effects.

Specifically, the optimized virtual teacher system not only provides a smoother and more timely interaction experience, but also effectively enhances students' sense of identity with the teachers' roles, and improves their interest in learning and class participation. In terms of learning motivation and emotional experience, the experimental group shows significant advantages in the dimensions of learning goal clarity, achievement motivation, and pleasure, showing higher learning engagement and more positive emotional reactions. In addition, the optimized system helps students maintain lower emotional stress during the learning process through real-time emotional feedback and interaction, and improves their learning participation, thereby further promoting the improvement of learning effects.

Although this paper achieves remarkable results, there are still some limitations. The sample size of the experiment is small and mainly focuses on the application of specific learning modules, lacking verification of a wider learning environment and different learning content. Future research should expand the sample size and explore the applicability of the system in a wider range of learning situations, especially in diversified learning content and task settings. In addition, with the rapid development of virtual reality and artificial intelligence technologies, it is expected to integrate these technologies so as to further optimize the interactivity, adaptability, and personalization of virtual teachers, thereby promoting innovation and development in the field of education.

Funding: This work was supported by the Project of “Research on the Enhancement of Human Resources through School Enterprise Cooperation for Cultivating the Core Competitiveness of Pre-service English Teachers” of the Ministry of Education in 2024 (Project No.: 2023122592380).

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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