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Article

Exploration of integrating biomechanical perspective into ideological education management strategy

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Abstract: This paper introduced biomechanical theory into ideological education management, analyzed the impact of educational intervention and optimized intervention strategy by establishing a dynamic prediction model of ideological behavior, aiming to improve educational effect, reduce resource investment, and realize personalized and precise ideological education management. It constructed a dynamic prediction model of thought behavior based on LSTM (Long Short-Term Memory), and used the core concepts of biomechanics to analogize key variables in ideological education management. Thought tendencies can be analogized to state variables, educational interventions can be regarded as external forces, and thought inertia can be corresponded to the internal resistance of thought transformation, thereby revealing the law of change of thought state and providing quantitative basis. In terms of model optimization, GA (Genetic Algorithm) is used to optimize the educational intervention strategy, and the fitness function is used to comprehensively evaluate the degree of ideological transformation and resource costs to achieve a multi-objective balance. The experimental results show that the proposed strategy shows high accuracy in the prediction of ideological tendency scores, with an average RMSE (Root Mean Square Error) of 0.12 and an average MAE (Mean Absolute Error) of 0.08. It is superior to traditional strategies in improving class participation rate, learning management system login frequency, and reducing educational intervention costs. The ideological education management strategy based on the biomechanical perspective can provide accurate predictions of ideological states and achieve efficient use of educational resources by optimizing intervention design, which verifies the theoretical innovation and practical application value of this method.

Keywords: ideological education; management strategy; biomechanics analysis; long short-term memory; genetic algorithm

1. Introduction

In the current rapidly changing social environment, ideological education management faces challenges of complexity and diversity. The traditional education model is difficult to meet the individualized and dynamic ideological education needs. Ideological behavior [1,2] is essentially a dynamic process, which is affected by multiple internal and external factors. Its changing law is similar to the interaction between force and state in biomechanical systems. Integrating biomechanics [3,4] theory into ideological education management provides a new perspective. Biomechanics [5,6], as a discipline that studies the impact of forces on the behavior and structure of organisms, emphasizes dynamic feedback and adaptive regulation, which is highly consistent with the goal of ideological education to focus on the dynamic changes of individual thoughts and their influencing mechanisms. The current ideological education practice is usually based on static evaluation, lacking in-depth research on the dynamic laws of ideological behavior and real-time intervention mechanisms, making it difficult to accurately manage individual characteristics. The development of intelligent technology has provided a new opportunity for ideological education. By combining dynamic modeling and optimization algorithms, it can achieve real-time monitoring, accurate prediction and personalized intervention of ideological behavior. In particular, dynamic models based on deep learning methods such as LSTM can effectively capture the temporal changes in thoughts and behaviors, and optimization algorithms can help design efficient and low-cost educational intervention strategies. The introduction of biomechanical data, through the collection of psychological and physiological signals such as heart rate and respiratory rate by wearable devices, can provide more comprehensive data support for the monitoring of thoughts and behaviors. This interdisciplinary integration method can not only reveal the inherent laws of ideological and behavioral changes, but also provide a scientific basis for the design of ideological education management strategies, and promote the personalization, precision and efficiency of educational intervention. Therefore, based on biomechanics theory, this study explores a new model of intelligent ideological education management for the future through the combination of dynamic modeling and optimization algorithms, providing an innovative path for the theoretical research and practical application of ideological education.

This paper introduces biomechanical theory into ideological education management, innovatively establishes a dynamic prediction model of ideological behavior and optimizes educational intervention strategies, bringing a new scientific perspective and practical methods to the traditional ideological education field. By analogizing the state of ideological tendency to the state variables in the physical system, educational intervention to the action of external force, and ideological inertia to the inherent resistance to ideological transformation, the paper redefines and analyzes the laws of ideological change in a dynamic system manner, thereby achieving quantitative and scientific modeling of ideological tendencies. This cross-domain integration provides a theoretical innovation foundation for ideological education research. By introducing the LSTM model to achieve high-precision prediction of ideological states, the effectiveness of educational intervention has been significantly improved. In terms of optimization strategy, GA is used to weigh and optimize the allocation of educational resources and the magnitude of ideological transformation, so that the intervention strategy achieves a balance between ideological education effects and resource input. This practical breakthrough not only enhances the level of intelligent education management, but also expands the application scenarios of algorithms in the field of ideological education. This paper verifies the actual effect of the proposed strategy through experiments, including improving students' classroom participation, learning management system login frequency and ideological tendency scores, while reducing the consumption of educational resources. This provides important theoretical support and practical reference for intelligent education management. This strategy emphasizes the personalization, dynamism and data-driven decision support of ideological education, opening up a new direction for the integrated application of educational informatization and artificial intelligence technology in the future.

2. Related work

As an important means to shape individual ideology and values, ideological education management has always been a research focus in the field of education. With the changes in social environment and educational objects, ideological education management strategies [7] have gradually shifted from traditional indoctrination education to personalized, interactive and scientific education. Researchers emphasize that ideological education [8] should be based on the individual psychological needs of students and the dynamic changes in the social environment, and focus on the synergy between emotional experience and cognitive process. Ideological education strategies based on humanistic theory [9] advocate taking the individual as the center and improving students' ideological awareness through empathy and guidance. System dynamics models [10] are gradually being applied to ideological education to simulate the spread and change of ideological behavior and provide data support for the design of educational strategies. The development of information technology has also promoted the intelligentization of ideological education management. By using learning analysis technology and big data platforms, educational managers can more accurately monitor students' ideological dynamics and conduct personalized interventions. Most existing studies remain within the framework of psychology and educational theory, lacking interdisciplinary method support, especially in terms of dynamics, feedback, and intervention effectiveness.

With the rapid development of information technology, ideological education management strategies are gradually integrating intelligent technology and algorithm models to form a series of data-driven management methods. Big data technology is widely used in ideological education. Through data mining [11,12] and analysis, real-time monitoring and personalized prediction of students' ideological states can be achieved. Educational data analysis models based on machine learning [13,14] can dynamically evaluate students' ideological tendencies and provide a scientific basis for educational intervention. Artificial intelligence technologies such as natural language processing are also used to analyze students' text feedback to reveal their deep ideological states. The ideological education simulation model based on multi-agent system [15] builds a virtual student group and simulates the propagation law of ideological behavior in the group, providing a reference for educational policy making. However, most of these technical applications are currently limited to a single data source or static analysis, and fail to fully consider the complex dynamic characteristics of ideological behavior. The introduction of multi-source data fusion and dynamic modeling technology into ideological education management and the exploration of systematic and intelligent intervention strategies have become an important direction of current research. This method requires the development of interdisciplinary integration models in combination with the core goals of ideological education to comprehensively improve the accuracy and effectiveness of educational intervention.

As a discipline that studies the laws of motion and behavior of organisms under the action of forces, biomechanics has been widely used in many fields in recent years. The core of this approach is to reveal the internal mechanism of biological behavior through mechanical models [16], and to provide theoretical support for system optimization and intervention. In the field of education [17], some studies have attempted to explore the relationship between stress and learning behavior by collecting students' psychological and physiological signals, including heart rate variability and skin galvanic response, and combining them with biomechanical analysis models. Most of these studies focus on the correlation analysis between behavior and physiological response, and fail to further integrate into the education management system. The feedback control theory of biomechanics [18] emphasizes regulating the system state through real-time data feedback. This concept is highly consistent with the "intervention-response-adjustment" closed-loop model in ideological education management. Therefore, introducing biomechanics theory into ideological education management can not only enrich the theoretical basis of ideological education management, but also optimize educational intervention strategies through real-time data collection and analysis, and ultimately achieve more precise and efficient ideological education management. This cross-disciplinary research method has opened up a new direction for ideological education, and at the same time has put forward higher requirements for the research of multidisciplinary integration.

3. Methods

3.1. Integration framework of biomechanics and ideological education management

Ideological behavior is modeled as a dynamic system, and the core concepts of mechanical theory are used to analogize the key variables in ideological education management, revealing the laws of ideological changes and providing a scientific basis for educational intervention strategies. Thought tendency is the core variable that describes the current thought and behavior state of an individual. It is analogous to the "state variable" in the mechanical system, reflecting the dynamic changes and characteristics of the thought state.

A standardized scale can be used to quantify the thought tendency into a numerical score to describe the current thought state. And by recording behavioral data such as class participation rate, homework completion, and task performance, the thought tendency can be indirectly reflected.

External force refers to the force exerted on students' ideological tendencies through intervention in the process of ideological education, including course content, teacher-student interaction, activity design, etc., exerting positive or negative force on the ideological state.

Ideological inertia refers to the characteristic of individual ideological tendencies to maintain the current state and resist changes in external forces, which is analogous to the resistance in physical systems. The degree to which students' original ideas are deeply rooted, such as religious beliefs and family education background, has a great hindering effect on ideological change. By analyzing the trajectory of students' ideological changes in the past education process, the ideological inertia coefficient is estimated.

The resistance model of dynamic systems is used to describe the effect of ideological inertia on the change of state variables.

$$F_z = -k_d \times v \tag{1}$$

In Equation (1), k_d represents the resistance coefficient, and v represents the rate of change of thought tendency.

Elastic resilience refers to the ability of students to return to their original state of mind after being affected by external forces, which is analogous to the elastic coefficient in mechanics. It is used to quantify the resilience of thought. The larger the value, the more likely the student is to maintain his original state of mind and the stronger the ability to return.

$$F_t = -k_s \times \Delta x \tag{2}$$

In Equation (2), k_s represents the elastic coefficient, and Δx represents the deviation value of the thought tendency.

Construct the mechanical equation of the thought state:

$$m \times a = F_j - F_z - F_t \tag{3}$$

In Equation (3), m is the "quality" of thought behavior, describing the difficulty of thought change. a represents the acceleration of thought tendency, reflecting the rate of change of thought change. F_j represents the power of educational intervention.

In order to improve the scientific nature and dynamic adaptability of ideological education management, the feedback control model in biomechanics is introduced to construct a closed-loop management strategy of "intervention-response-adjustment". This mechanism achieves precise intervention in ideological education and dynamically optimizes the management process through analysis and adjustment of feedback signals.

Integrating the biomechanical perspective into the exploration of ideological education management strategies, by analogy between the biomechanical principles and the key elements in the ideological education process, new management ideas and intervention methods are revealed. The thinking tendency in biomechanics can be analogized to the state variables of the system, representing the cognitive state and behavioral tendency of individuals in ideological education. For example, the values and attitudes of individuals can be regarded as dynamically changing variables. Educational intervention is analogized to the action of external forces. In biomechanics, external forces can change the motion state of objects, while educational intervention exerts influence on individual cognition through curriculum design, behavioral guidance, etc., thereby changing their ideological tendencies. Positive educational intervention is similar to the continuous application of external forces, which can prompt individuals to develop in a positive direction. The analogy between thinking inertia and the inherent resistance to thinking change reveals the inherent obstacles of individuals to accept new ideas. In physics, inertia is manifested as the tendency of objects to maintain the status quo, while in ideological education, it is manifested as the rejection of new ideas by individuals' inherent concepts. Through these analogies, strategies can be borrowed from the theory of biomechanics, such as gradually overcoming "internal resistance" by applying "external forces" in stages to achieve ideological change. This interdisciplinary perspective provides new theoretical basis and practical guidance for ideological education, further enhancing its scientific nature and systematic nature.

The intervention-response-adjustment closed-loop model is shown in **Figure 1**.

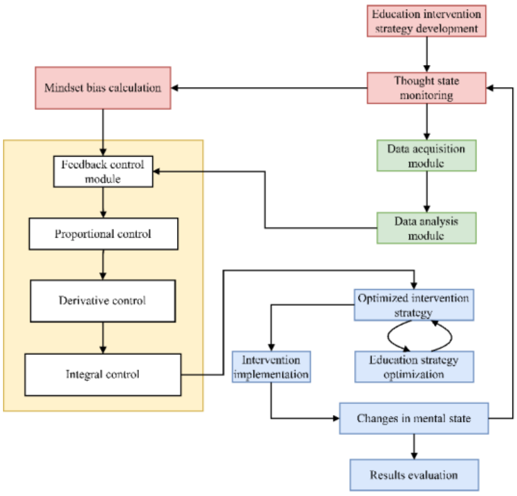

Figure 1. Intervention-response-adjustment closed-loop model.

Educators apply appropriate educational intervention measures based on the state of students' ideological tendencies, including curriculum design, activity arrangements, etc. Students' performance in ideological behavior, including classroom participation and changes in ideological tendency questionnaire scores, reflects the effectiveness of educational intervention. Based on the deviation between student responses and expected goals, the educational strategy is optimized in real time, and more precise intervention measures are re-applied to form a closed loop.

The mathematical expression of the feedback control Equation is as follows:

$$F_a = K_p \times e + K_d \times \frac{de}{dt} + K_i \times \int edt \tag{4}$$

F_a is the intensity of the adjustment strategy, which is used to dynamically optimize the intensity and direction of intervention measures. e represents the mental state deviation, that is, the difference between the target mental state and the current state. K_p is the proportional coefficient, which directly adjusts the intervention intensity according to the deviation size, reflecting the gap between the current state and the target value. K_d is the differential coefficient, which adjusts the intervention according to the rate of change of the deviation and strengthens the ability to respond to rapidly changing mental states. K_i is the integral coefficient, which accumulates past deviations, optimizes the intervention strategy in the long term, and avoids the negative impact of long-term deviation accumulation.

In classroom teaching, in order to improve students' cognition and acceptance of core values, the operant conditioning theory in behavioral science and biomechanical monitoring technology can be combined. Teachers design task-based teaching activities to evaluate students' concentration and emotional fluctuations in tasks by recording students' heart rate variability, skin galvanic response and breathing rate in real time. If biological signals show that students are in a state of high anxiety or low participation, emotional regulation strategies in educational psychology (deep breathing training or positive feedback) can be introduced to improve students' psychological state and enhance learning effects. Combining behavioral observation records with biomechanical data, the frequency and quality of students' classroom participation behaviors, such as answering questions and completing tasks, can be quantified. Through data analysis, it was found that certain teaching links or methods may cause students to be distracted or depressed. Teachers can adjust teaching strategies accordingly, increase interactive links or adopt situational teaching methods to improve students' sense of participation and identity.

3.2. Data collection and preprocessing

It can measure the individual's acceptance of core values and educational content, and record the dynamic changes of students' thoughts through Likert scale. This paper regularly tracks the cognitive changes of students in the learning process. This paper designs a 5-point scoring questionnaire scale, covering 20 dimensions (including open-mindedness, critical thinking, etc.), 1 means completely disagree and 5 means completely agree.

The intervention effect is analyzed once before, during, and after the start of the educational activity, providing quantitative basis for ideological dynamics and data support for the optimization of educational strategies. This paper records the actual frequency of students' interactions in class, quantifies the situation of students completing homework or projects on time, and reflects the degree of ideological involvement.

The system automatically records students' login time, homework submission, and online discussion participation on the platform. Educators observe and record students' participation behaviors to make up for details that cannot be captured in the learning management system. The learning management system data can be combined with the observation log to conduct trend analysis and establish a student behavior characteristic profile. The behavioral data is combined with the ideological tendency data to form a multidimensional ideological and behavioral model to provide a decision-making basis for personalized intervention.

Biomechanical data can be collected, including heart rate variability, skin galvanic response, and respiratory rate. Heart rate variability [19,20] reflects students' emotional fluctuations and psychological stress by measuring changes in heartbeat intervals. Galvanic skin response detects students' psychological fluctuations through small changes in the conductivity of the skin surface. Respiratory rate evaluates changes in students' mental activity in different teaching sessions by detecting the speed and depth of breathing.

The sampling frequency can be set to 1–2 times per second to ensure high time resolution synchronization between dynamic thought changes and biological signals. Data is transmitted to the central database in real time, and devices are interconnected through wireless connection. Combined with heart rate variability, skin galvanic response, and respiratory rate, a real-time biomechanical characteristic model of students' mental state is constructed.

Missing values are an inevitable problem in data collection, caused by sensor failure, network interruption, or human negligence. The purpose of missing value processing is to fill in the gaps and reduce the deviation caused by missing data. For missing values, mean interpolation is used.

$$x_{\text{new}} = \frac{\sum_{i=l}^{n} x_i}{n} \tag{5}$$

In Equation (5), x_i represents the existing non-missing values, and n represents the number of non-missing values.

The biological signal acquisition process is susceptible to environmental interference and requires noise reduction to improve data quality. Wavelet transform is used to decompose the signal into components of different frequencies, retaining useful signals and removing noise. The wavelet decomposition Equation is:

$$f(t) = \sum_{a} \sum_{b} c(a,b)\psi_{a,b}(t) \tag{6}$$

$\psi_{a,b}(t)$ represents the wavelet basis function of scale a and position b, and $c(a,b)$ represents the corresponding coefficient.

Since the dimensions and numerical ranges of thought and behavior characteristic data and biological signals are different, standardization can eliminate the numerical scale differences and make the variables comparable. The data is converted into a distribution with a mean of 0 and a standard deviation of 1, and the Equation is:

$$z = \frac{x - u}{\sigma} \tag{7}$$

In Equation (7), u and σ are the mean and standard deviation, respectively. Data preprocessing can effectively improve data quality and ensure the scientificity and accuracy of thought and behavior modeling and educational intervention strategy optimization.

3.3. Dynamic thought and behavior modeling and optimization

LSTM [21,22] is a deep learning model based on recurrent neural networks, which is specifically designed to solve the long-term dependency problem in time series data. In the modeling of thought behavior, the ability of LSTM can be used to analyze the dynamic interaction between historical thought states, real-time biomechanical signals and external educational interventions, and predict the changing trend of students' thought states. The input features of the LSTM model are designed to capture the core variables that affect the changes in students' thought states, including historical states, real-time biomechanical signals and external interventions.

The process of thought tendency prediction and optimization is shown in **Figure 2**.

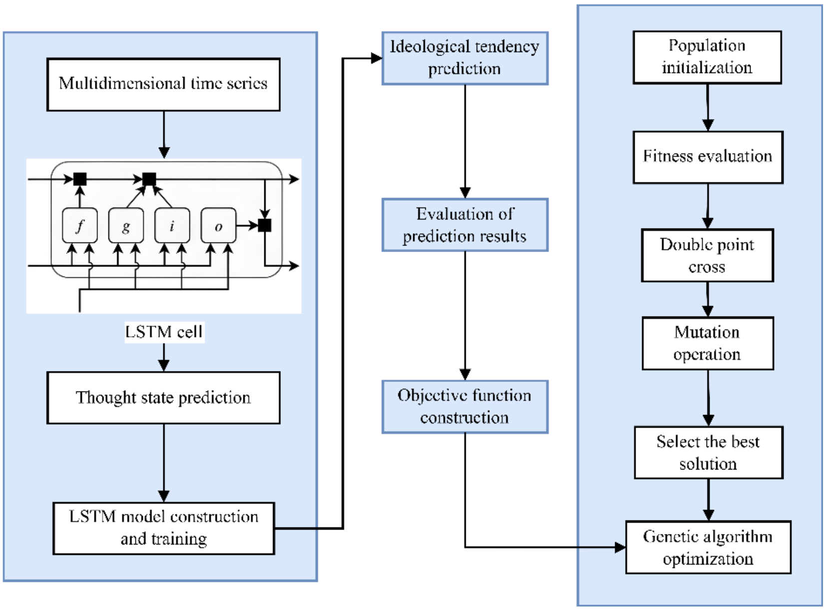

Figure 2. The process of predicting and optimizing thoughts and behaviors.

Multi-dimensional data of thoughts and behaviors are collected through questionnaires, behavioral data, and biomechanical signals to fully reflect the students' thought states and related dynamic characteristics. In the data preprocessing stage, missing values are filled, signal noise is reduced, and standardization is performed on the collected data to ensure data quality and comparability between dimensions. The feature extraction technology is used to extract historical thought states, real-time biological signals, and external intervention variables as inputs to the LSTM model. The LSTM model uses its powerful time series learning capabilities to capture short-term and long-term dynamic trends in thought states and provide high-precision prediction support for optimization strategies. Based on the objective function, a GA is designed to generate diversified intervention strategies through population initialization, fitness evaluation, crossover and mutation operations, and finally select the optimal solution. The overall process forms a closed-loop system of intervention-prediction-optimization, providing precise and efficient scientific support for dynamic ideological education management.

The design and implementation of educational strategies include course content, teacher-student interaction, and the intensity of educational activities. The output of LSTM is a prediction of the trend of changes in the state of mind in the short and long term. It predicts the fluctuation of the student's state of mind in the next few time steps, and the long-term prediction is the overall trend of changes in the state of mind.

The mathematical expression of LSTM is the core of its modeling idea, and the forget gate determines which historical information needs to be discarded.

$$f_t = \sigma(W_f \times [x_t, h_{t-1}] + b_f) \tag{8}$$

f_t represents the output of the forget gate, W_f represents the weight matrix. b_f represents the bias term.

The input gate [23,24] determines which new input information needs to be added.

$$i_t = \sigma(W_i \times [x_t, h_{t-1}] + b_i) \tag{9}$$

$$\tilde{C}_t = \tanh\left(W_C \times [x_t, h_{t-1}] + b_C\right) \tag{10}$$

Cell status update:

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \tag{11}$$

The output gate controls the hidden state output at the current moment.

$$o_t = \sigma(W_o \times [x_t, h_{t-1}] + b_o) \tag{12}$$

$$h_t = o_t \times \tanh\left(C_t\right) \tag{13}$$

Current hidden status:

$$h_t = \sigma(W_{h_x} x_t + W_{h_h} h_{t-1} + b_h) \tag{14}$$

Combining multiple feature inputs:

$$h_t = \sigma(W_x \times \mathrm{X}_t + W_u \times \mathrm{U}_t + W_h \times h_{t-1} + b) \tag{15}$$

The mean squared error is used to measure the deviation of the predicted and actual state of mind:

$$\mathscr{L} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{16}$$

The Adam optimizer was used to adjust the model parameters, and the learning rate was set to 0.001. The number of LSTM units, time step, regularization parameters, etc., were determined through grid search.

GA [25,26] is a global optimization algorithm based on natural selection and genetic mechanism. It simulates the biological evolution process and gradually finds the optimal solution. Each chromosome represents a combination of educational intervention strategies. A certain number of chromosomes are randomly generated to form an initial population.

The fitness function is:

$$f = \alpha \times \Delta S - \beta \times G \tag{17}$$

In Equation (17), ΔS represents the thought score and G represents the intervention cost.

For each individual, the fitness value is calculated. The higher the fitness value, the better the strategy combination of the individual. Using the roulette algorithm, the next generation parent individuals are randomly selected according to the proportion of the individual fitness value to the overall fitness value. It can ensure that individuals with high fitness have a greater probability of passing on genes, while retaining some individuals with low fitness to increase diversity.

This paper adopts the two-point crossover strategy [27,28], randomly selects two parent individuals, and exchanges gene fragments at two points. The crossover probability can be set to 0.8, randomly changes one gene value of the individual, and sets the mutation probability to 0.1 to prevent premature convergence.

The parameter settings of the GA are shown in **Table 1**.

Table 1. Parameter settings of the GA.

Parameter name	Value	Description
Population size	100	Each generation contains 100 candidate solutions to ensure the diversity of solutions while taking into account computational efficiency.
Chromosome length	10	Each chromosome consists of 10 genes, representing different variables in intervention strategies.
Max generations	200	The algorithm runs for 200 generations to balance computational cost and optimization effect.
Crossover probability	0.8	Ensure that most chromosomes generate new solutions through crossover operations to enhance the diversity of the population.
Mutation probability	0.1	Ensure population diversity and avoid local optimal solutions, but the probability should not be too high to avoid destroying good solutions.
Fitness weight α	0.7	In the fitness function, the weight of the magnitude of thought change is 0.7, emphasizing the importance of educational effects.
Fitness weight β	0.3	The weight of intervention costs is 0.3 to ensure that resource use efficiency is not ignored.
Initial population generation	Uniform random distribution	The initial solutions are evenly distributed within the scope of the problem definition to cover a wide area of the search space.
Stopping criterion	Fitness change is less than 0.001	Set the stopping condition as no significant improvement in fitness for 10 consecutive generations to prevent the algorithm from stopping prematurely or running for too long.

3.4. Experimental design and indicator evaluation

The data collected in this paper include students' behavioral data in the learning management system (such as login time, homework submission, online discussion participation), educator observation logs, Likert scale questionnaires, and biomechanical sensor data (heart rate variability, skin galvanic response, respiratory rate). The sample size is 500 students to ensure statistical significance and model generalization ability. Feature selection uses principal component analysis and recursive feature elimination to screen key variables, covering ideological tendencies, behavioral characteristics, and biological signals. Model training uses LSTM to capture the dynamic characteristics of time series data, and GA optimizes LSTM hyperparameters (learning rate, number of hidden layer nodes, etc.). In the experimental setting, the data is divided into training set and test set with a ratio of 8:2, and cross-validation is used to evaluate the stability of the model. Parameter adjustment combines grid search and Bayesian optimization to achieve optimal hyperparameter selection.

In order to evaluate the performance of the LSTM model in predicting ideological tendency scores, RMSE and MAE are used for evaluation. The root mean square error is used to measure the average difference between the predicted value and the true value. The smaller the value, the better the prediction performance. The Equation is:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{18}$$

y_i and $\hat{y}_i$ represent the i-th true value and the i-th predicted value respectively, and n is the total number of samples.

MAE represents the average of the absolute differences between the predicted value and the true value, and the Equation is as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{19}$$

MAE more directly reflects the average deviation between the predicted value and the true value, which is convenient for explaining the model performance.

Introducing biomechanics theory into ideological education management [29,30] provides a scientific and accurate quantitative tool for the educational process. By constructing a dynamic prediction model of ideological behavior, it simulates the change process of students' ideological tendencies and analyzes the specific impact of external intervention. This paper compares the mental state to the state variable in mechanics, introduces concepts such as external force, resistance and elastic recovery force, and models the educational intervention strategy as an external force to intuitively evaluate the positive and negative effects of intervention measures on mental transformation. By collecting biomechanical data and combining it with the characteristics of thought and behavior, real-time tracking and feedback of students' mental state can be achieved, thereby enhancing the pertinence and effectiveness of intervention strategies. The optimization algorithm is used to iteratively optimize the intervention strategy, achieve a balance between the ideological tendency score and the cost of educational resource investment, and improve the scientificity and efficiency of educational management.

This paper adopts the intelligent education management strategy supported by the dynamic ideological behavior model and the optimization algorithm, and compares it with the traditional ideological education strategy. 120 students were selected for analysis, and the basic information of the selected students is shown in **Table 2**.

Table 2. Basic information of selected students.

Indicator	Category	This paper strategy	Traditional strategy
Gender	Male	30	30
	Female	32	28
Age	< 18	20	20
	18–22	23	17
	> 22	19	21
Educational stage	Junior college	31	29
	Bachelor's degree	31	29

From the selected student subjects, it can be seen that the students in this strategy and the traditional strategy have a balanced number in terms of gender, age, education stage, etc. The experimental period is set for 1–12 months to observe the long-term effect of ideological changes.

The performance of this ideological education management strategy is reflected by the change of ideological tendency scores, educational intervention costs, and student learning participation. The participation of students in learning is reflected in the number of times students speak in class and the frequency of logging into the learning management system.

4. Results

4.1. Prediction performance of ideological tendency score

The prediction of ideological tendency score can provide a scientific basis for educational management and psychological intervention. By predicting the changing trend of ideological tendency, it can help educators identify the potential fluctuations of students' ideological state in advance, so as to formulate more targeted educational intervention strategies and improve the effectiveness of ideological education. Ideological tendency prediction can also support the implementation of personalized education. By dynamically monitoring students' ideological states, the content and form of education can be adjusted in a timely manner to meet individual development needs. The performance of using LSTM to predict ideological tendency scores is shown in **Figure 3**.

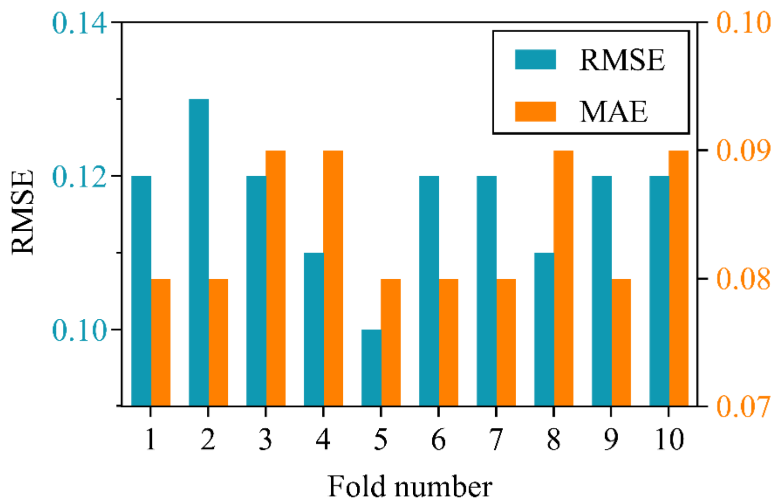

Figure 3. Ideological tendency score prediction

When using the LSTM model to predict ideological tendency scores, the performance indicators obtained through 10-fold cross-validation show that the LSTM model has high prediction accuracy and stability. The fluctuation range of RMSE is 0.10 to 0.13, and the range of MAE is 0.08 to 0.09. The overall indicators show that the model performs relatively consistently under different data segmentations and has a small error. This performance is achieved thanks to the LSTM model's powerful ability to process time series data and capture dynamic changes. In data with a certain degree of time dependence, such as ideological tendency scores, LSTM can effectively learn the long-term and short-term dependencies between features, thereby accurately predicting the changing trend of ideological states. The good performance of the LSTM model is also closely related to the selection of input features and data preprocessing. In this study, multimodal inputs were combined, including historical thought states, real-time biomechanical signals, and external intervention variables, to construct a comprehensive feature set, providing a rich information basis for the model. Preprocessing steps such as data standardization and noise reduction reduced the noise and interference of the input data, further improving the generalization performance of the model. Thanks to the cross-validation strategy, this paper tests the model performance under the condition of diversified data distribution, which not only effectively reduces the impact of data partitioning on the results, but also proves the robustness of the model to unseen data. In the task of predicting ideological tendency scores, LSTM achieves accurate prediction of ideological states in complex educational intervention environments through efficient modeling of time series and comprehensive use of feature information, providing strong support for the optimization of personalized education strategies.

4.2. Strategy optimization convergence performance

This paper uses GAs for educational strategy optimization and evaluates the efficiency and stability of the algorithm in searching for the optimal strategy by analyzing the convergence performance. The number of convergences reflects the number of iterations required for the algorithm to find the global optimal solution, which directly affects the computational cost of optimization; the convergence time measures the actual execution efficiency of the optimization process and is closely related to the feasibility of practical applications. Comparing GA with other optimization algorithms, the convergence performance of strategy optimization is shown in **Figure 4**.

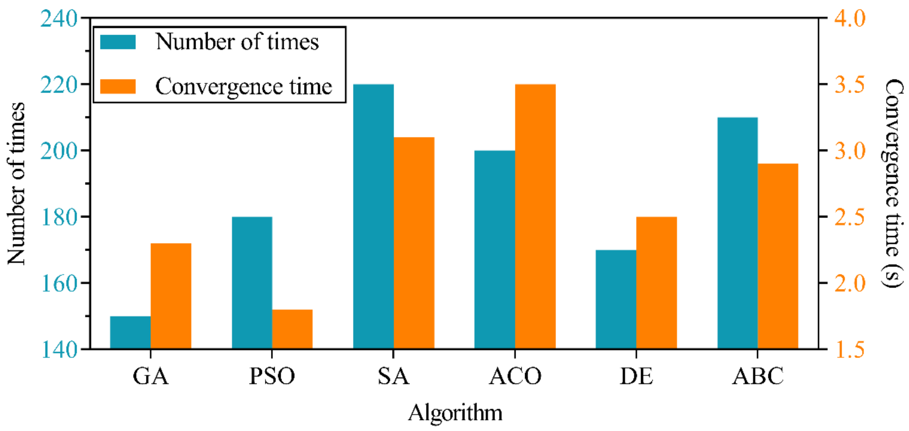

Figure 4. Strategy optimization convergence performance.

In the convergence analysis, GA showed better performance, with a convergence number of 150 times, the lowest among all algorithms, and a convergence time of 2.3 s, which was at a medium level, showing a balanced optimization efficiency and computational cost. This shows that GA is efficient in searching for the optimal solution of educational intervention strategy, can find the global optimal solution in fewer iterations, and is suitable for dealing with dynamic and complex ideological education problems. In contrast, PSO (Particle Swarm Optimization) has the shortest convergence time of 1.8 s, but the number of convergences is relatively high at 180 times, showing a faster single calculation, but its global search efficiency is slightly inferior. SA (Simulated Annealing) and ACO (Ant Colony Optimization) both performed averagely in terms of convergence times and time, which were 220 times and 3.1 s and 200 times and 3.5 s respectively, reflecting their insufficient adaptability to large-scale complex problems and the tendency to fall into local optimality. DE (Differential Evolution) and ABC (Artificial Bee Colony) are close in convergence, with convergence times of 2.5 seconds and 2.9 s respectively. In general, the advantages of GA lie in the extensiveness of the search space and the robustness of the evolutionary process. In the optimization of ideological education intervention strategies, its fast convergence characteristics help to cope with the actual needs of multi-dimensional variables, dynamic constraints and complex objective functions. Its convergence performance reflects the ability of the algorithm to balance global exploration and local development through operations such as selection, crossover, and mutation, so that the intervention strategy is close to the optimal solution within a controllable time. The optimization process is more suitable for real-time education scenarios, highlighting the practical application value of GA in strategy design.

4.3. Changes in ideological tendency scores

The strategy in this paper integrates biomechanics. The strategy in this paper is compared with the traditional strategy to observe the changes in students' ideological tendency scores from January to December. The full score is 100 points. The results of the changes in ideological tendency scores are shown in **Figure 5**.

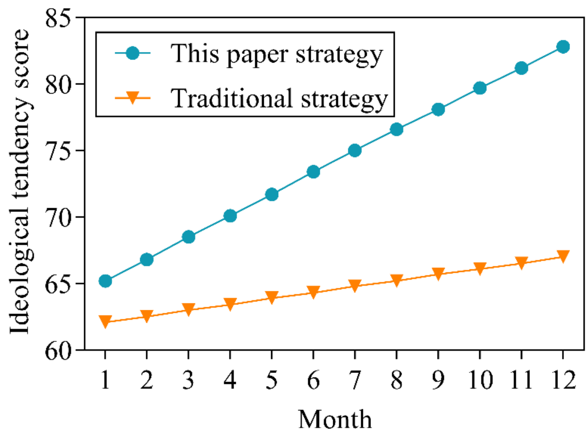

Figure 5. Changes in ideological tendency scores.

The ideological tendency scores of students using the strategies in this paper showed a clear linear growth from January to December, from 65.2 points to 82.8 points, an increase of 17.6 points. The ideological tendency scores of students using traditional strategies only increased from 62.1 points to 67.0 points, an increase of only 4.9 points. The significant superiority of this strategy is reflected in the score growth rate and the overall improvement of ideological tendencies throughout the year. Compared with the traditional strategy, the score curve of this strategy is steeper, which shows that this strategy is effective in the early optimization of ideological tendencies.

This strategy combines biomechanical signals to conduct real-time analysis and feedback on students' emotional state and behavioral data, dynamically predicts students' ideological change trends through LSTM, and uses GA to optimize intervention strategies to ensure the accuracy and adaptability of educational intervention. In contrast, traditional strategies lack dynamic perception and real-time optimization of individual thought states, and the intervention methods are relatively single and fixed, making it difficult to cope with students' complex and diverse thought characteristics. The strategy in this paper can effectively use emotional fluctuation data and thought and behavior trajectories to adjust the intensity of education according to the needs of students at different stages, while traditional methods adopt a unified education model that cannot fully stimulate students' thought potential. The strategy in this paper shows great application potential. It can not only significantly improve students' ideological tendency scores, but also provide a scientific and personalized solution for ideological education management.

4.4. Cost of educational intervention

The analysis of educational intervention cost can quantify the investment efficiency of educational resources in ideological education management, and provide a key basis for the optimization of intervention strategies. By analyzing the intervention costs, it can evaluate whether resource allocation is reasonable, avoid excessive or insufficient intervention, and ensure the efficient implementation of ideological education activities. The combination of intervention cost measurement and ideological tendency improvement effect can help to build a more economical and efficient education model, achieve the best balance between input and output, and improve the scientific nature and sustainability of overall education management. The results of the changes in education intervention costs are shown in **Figure 6**.

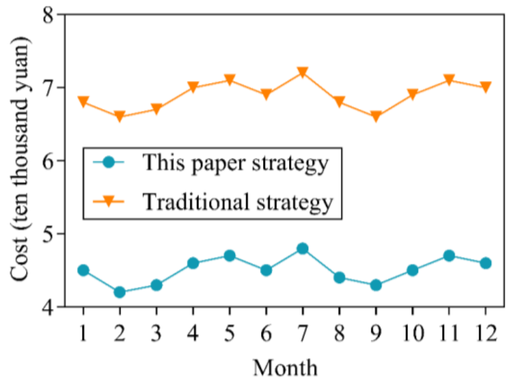

Figure 6. Changes in educational intervention costs

The educational intervention costs using the strategy in this paper are always lower than those of the traditional strategy, reflecting the resource-saving advantages of the optimized intervention strategy. In 12 months, the average monthly intervention cost using the strategy in this paper was 45,000 yuan, while the traditional strategy was 69,000 yuan. The cost control of this strategy is mainly reflected in the following aspects: by introducing biomechanical modeling and dynamic optimization methods, this strategy can effectively predict the trend of ideological tendencies, making intervention more targeted and accurate, thereby reducing unnecessary repeated resource investment. The intervention strategy adjustment based on the GA optimization algorithm can dynamically adjust the intensity and frequency of intervention, making the distribution of educational resources among different student groups more balanced, and effectively avoiding the phenomenon of excessive intervention in traditional methods. The application of intelligent means reduces the need for manual participation and reduces labor costs. Although traditional strategies are highly efficient in the short term or in a single activity, they rely too much on fixed patterns and lack the ability to respond to real-time changes in students' ideological tendencies, resulting in a waste of intervention resources. The performance of this strategy also benefits from the data-driven feedback mechanism, which can quickly discover and correct inefficient links in the strategy, further improving the efficiency of resource utilization. The educational management strategy supported by biomechanical modeling and optimization algorithms can not only effectively improve the efficiency of ideological education, but also significantly reduce costs, providing a scientific basis for the allocation of educational resources.

4.5. Student learning participation

The analysis of student learning participation plays an important role in evaluating the effectiveness of educational intervention strategies. By counting the number of times students speak in class and the frequency of logging into the learning management system, it directly reflects the students' learning initiative and involvement. These indicators are the key basis for measuring the effectiveness of ideological education. Changes in participation can help educators identify deficiencies in teaching strategies and improve them, thereby improving teaching efficiency. High participation is associated with positive changes in students' ideological tendencies and better learning outcomes. By analyzing participation data, scientific support can be provided for optimizing the allocation of educational resources and formulating personalized teaching strategies, thereby achieving an overall improvement in the quality of education.

The results of the number of times students spoke in class are shown in **Table 3**.

Table 3. Number of times students spoke in class.

Month	This paper strategy	Traditional strategy
1	2	1
2	2	1
3	2	1
4	3	1
5	4	2
6	5	2
7	5	3
8	6	2
9	6	3
10	6	2
11	7	3
12	7	3

The students who adopted the strategy in this paper spoke significantly more in class than those who used the traditional strategy, and the gap gradually widened in the subsequent months. This trend shows that the strategy in this paper can significantly improve students' classroom participation. In January-April, the difference between the proposed strategy and the traditional strategy in the number of student speeches was small, but as time went on, the advantage of the proposed strategy became more and more obvious. In December, the number of students spoke reached 7 times, while the traditional strategy only spoke 3 times, showing the difference between the two in improving student interactivity. The higher number of classroom speeches in this strategy is attributed to the introduction of biomechanical theory and dynamic thought behavior prediction model in ideological education. By using biomechanical heart rate variability, skin galvanic response and other signals to dynamically monitor students' emotional fluctuations and psychological states, teachers can timely identify the degree of students' ideological activity and stimulate students' learning motivation through customized educational intervention strategies. When biomechanical data indicates that students are in high spirits, strategies can be used to design more interactive classroom activities to promote speaking and discussion; when students are in low spirits, strategies can be used to provide appropriate psychological support and encouragement to gradually improve students' participation. The LSTM model's prediction of ideological tendency scores provides a basis for the precision of educational intervention, ensuring that monthly strategy adjustments are adapted to changes in students' ideological states. Traditional strategies lack dynamic analysis of students' thoughts and emotional states, and cannot adjust teaching methods in a targeted manner, making it difficult to maintain students' long-term classroom participation. The intelligent features of this strategy effectively reduce the pressure on teachers in classroom management, allowing them to focus on students' ideological interaction and the implementation of incentive mechanisms. These factors work together to make the students who adopt the strategy in this paper have a significant advantage in the number of speeches, which further proves that the educational strategy combining biomechanics and intelligent algorithms can improve students' learning experience and active thinking, and promote the two-way achievement of classroom interaction and ideological education goals.

The comparison of the number of speeches by different student categories is shown in **Table 4**.

Table 4. Comparison of the number of speeches by different student categories.

Category	This paper strategy	Traditional strategy
Male	6	2
Female	5	2
< 18	5	1
18–22	6	1
> 22	4	2
Junior college	5	2
Bachelor's degree	5	2

As can be seen from **Table 4**, the number of speeches of the proposed strategy in all student categories is significantly higher than that of the traditional strategy, which reflects its advantage in stimulating students' classroom participation. The number of speeches of male and female students increased from 2 times in the traditional strategy to 6 times and 5 times, respectively, indicating that the proposed strategy has a positive effect on students of different genders. In the age group, the number of speeches of students under 18 years old and 18–22 years old increased to 5 times and 6 times, respectively, indicating that the strategy is particularly effective in improving the classroom participation of young students. In terms of educational background, the number of speeches of both junior college students and undergraduates increased from 2 times in the traditional strategy to 5 times, indicating that the proposed strategy can generally stimulate the willingness of students of different academic qualifications to express themselves. This shows that the teaching method combining biomechanics and educational psychology can effectively improve students' classroom participation and interactivity, and has significant teaching advantages.

The login frequency of the learning management system in the 12th month of ideological education strategy intervention is shown in **Figure 7**.

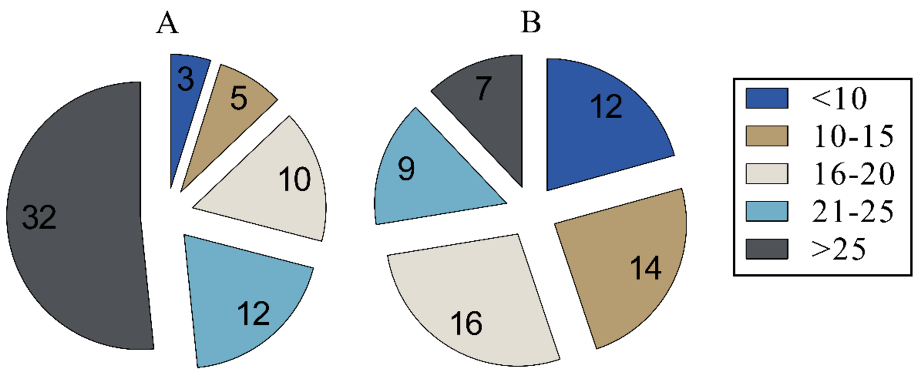

Figure 7. Login frequency distribution (times/month): **(A)** Login frequency distribution of this strategy; **(B)** Login frequency distribution of traditional strategy.

The highest percentage of login frequency of the learning management system of this strategy is more than 25 times per month, and the number of people with less than 10, 10–15, 16–20, 21–25, and more than 25 are 3, 5, 10, 12, and 32 respectively. Compared with traditional strategies, the strategy in this paper effectively increases the number of people with high login frequency. Compared with traditional strategies, the strategy in this paper significantly increases the login frequency of the learning management system. This paper models ideological behavior as a dynamic system and uses the core concepts of mechanics theory to analogize the key variables in ideological education management, making educational intervention more accurate and efficient. This paper takes ideological tendency as the core variable, analogous to the state variable in mechanics, and dynamically monitors the changes in students' ideological states through quantified ideological tendency scores. Ideological inertia can be regarded as a barrier to ideological change. By deeply analyzing the trajectory of individual ideological changes, the degree of students' adaptation to new intervention methods can be effectively quantified, and the size and direction of external forces can be dynamically adjusted, so that students can gradually overcome ideological inertia. The dynamic strategy design centered on the law of changes in ideological state significantly enhances students' perceived value and sense of identity of learning tasks. This further encourages students to log in to the learning management system more frequently and actively participate in the use and management of learning resources, thereby achieving the dual optimization effect of ideological education management and learning behavior improvement.

5. Discussions

This paper integrates the perspective of biomechanics into the ideological education management strategy, reveals the law of ideological tendency changes from a scientific and quantitative perspective, and optimizes the effect of educational intervention. Traditional ideological education is mostly based on experience, lacking systematic and scientific research on the dynamics of individual thoughts. By introducing the concepts of biomechanics, including state variables, external forces and inertia, this paper constructs a dynamic prediction model for thought behavior, and provides a new theoretical framework and tools based on the changing laws of thought states. Ideological tendencies are analogized to state variables, and their numerical models enable educational management to be described in the form of a dynamic system, thus breaking away from the limitations of a single static evaluation method. By introducing the variable of external force, the specific action path of intervention measures in changing ideological tendencies is clarified, and theoretically explain why different intervention strategies can produce different effects. The concept of inertia further reveals the resistance effect in the process of changing ideological tendencies, provides important insights into the difficulties of educational intervention, and helps students overcome the resistance or hysteresis caused by ideological inertia. The strategy in this paper has a driving effect on the theoretical development of ideological education, and also provides practitioners with a scientific basis for systematic optimization of intervention methods, especially showing significant advantages in changing students' thoughts and improving their learning behaviors. Through the combined analysis of behavioral data and biomechanical data, this paper proves that the dynamic prediction model can capture the changing trends of students' ideological tendencies with high accuracy and further optimize the intervention strategy, making up for the shortcomings of traditional ideological education in responding to personalized needs.

In the strategy optimization process proposed in this paper, the application of GA provides strong technical support for the optimization of ideological education management strategy. By setting a scientific fitness function, GA can weigh the degree of ideological transformation and the cost of educational resource investment, making educational management decisions more economical and feasible. The research in this paper shows that in the simulated intervention strategy optimization, GA exhibits a strong convergence ability and can find an intervention plan close to the global optimal within a limited number of iterations. Compared with traditional experience-driven strategy design, the use of GA ensures the scientificity and accuracy of the ideological education management process. Especially when educational resources are limited, the optimized strategy can not only effectively enhance the positive development of students' ideological tendencies, but also significantly reduce time, financial and human costs. By incorporating the output of the dynamic prediction model into the fitness function of GA, the intervention strategy can adapt to the changes in students' ideological state in real time, improving the responsiveness and flexibility of education management. The ideological education management system constructed in this paper from the perspective of biomechanics is not only a theoretical innovation, but also realizes the scientific and intelligent design of educational intervention strategies in technical application, providing support for diversified educational needs and further improving the efficiency of ideological education management.

The refinement of personalized intervention strategies is an important way to improve the effectiveness of educational intervention. Based on multi-dimensional data such as students' specific psychological state, learning style, cognitive ability, etc., targeted educational programs are formulated. By constructing a more detailed student portrait, comprehensively analyzing behavioral data, thought dynamics and biomechanical characteristics, the learning characteristics and needs of students are fully portrayed. On this basis, a variety of educational intervention models are designed. For students with strong cognitive abilities but low participation, more challenging tasks are provided and interactive incentives are enhanced; for students with greater psychological pressure, emotional management support and psychological counseling are increased. A continuous tracking and real-time feedback mechanism is introduced. Through the learning management system and biosensor equipment, the dynamic changes of students are monitored in real time, and the intervention strategy is adjusted in time to ensure the accuracy and adaptability of the program. According to the real-time monitored heart rate variability or classroom participation behavior, the teaching rhythm or content difficulty is dynamically adjusted to better meet the immediate needs of students. Through this highly personalized and dynamically optimized intervention method, the students' learning experience and effect are significantly improved, so that each student can maximize their development potential in an educational environment suitable for their own characteristics.

6. Conclusions

This paper integrates biomechanics theory into ideological education management strategies, proposes a dynamic prediction model for ideological behavior, and combines it with GAs to optimize educational intervention strategies, achieving remarkable research results. Research shows that the model in this paper can accurately predict the dynamic changes of students' ideological tendencies. The fitness function design balances the degree of ideological change and the cost of educational resources, so that the optimization strategy reduces resource input while improving the efficiency of ideological change. Through quantitative analysis of behavioral data such as class participation rate and frequency of use of learning management system, the effectiveness of the strategy in this paper in improving students' ideological tendency scores and participation was verified, further demonstrating the potential of the ideological management system based on the biomechanical perspective in theoretical innovation and practical optimization. The contribution of this study is that it introduces the core concepts of dynamic system modeling and biomechanics into the field of ideological education for the first time, providing a new path for the quantification of ideological tendencies and the optimization of educational interventions, which has far-reaching practical significance for precision and personalized education. The study also has certain limitations. The estimation of the inertial parameters of ideological tendencies depends on the quality of historical data, and the adaptability of the model in complex educational scenarios needs further verification. Future research can introduce richer biomechanical data and artificial intelligence technology to further improve the accuracy and universality of the model, while exploring its application potential in diverse educational scenarios, laying a more solid foundation for realizing intelligent and personalized education management.

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