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Article

The application of artificial intelligence in biomechanical feedback and learning effectiveness enhancement in ideological and political education

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Abstract: The application of artificial intelligence (AI) in ideological and political education (IPE) optimizes the learning effect with the help of biomechanical feedback mechanism, and provides technical support for deepening the reform of IPE in colleges and universities. With the help of AI technology, especially its advantages in data analysis and deep learning (DL), accurate matching and personalized recommendation of learning resources can be realized. In this study, an AI-assisted IPE system with biomechanical feedback was constructed. By analyzing students' physiological reactions and behavior patterns in the learning process, the system can evaluate the learning state and adjust teaching strategies. The key findings show that this learning method combined with biomechanical feedback can significantly improve students' learning participation, understanding depth and satisfaction, and make IPE more in line with students' needs.

Keywords: artificial intelligence; ideological and political education; biomechanical feedback; improvement of learning effect

AMS 2020 codes: 00000

1. Introduction

In today's world where globalization and informatization are intertwined, the importance of IPE as a key link in shaping individual ideological concepts and moral qualities is increasingly prominent [1]. It not only carries the mission of inheriting mainstream social values, cultivating civic responsibility and moral sentiments, but also faces the challenge of how to innovate educational models and enhance educational effectiveness in the context of the new era [2]. Traditional IPE often relies on face-to-face classroom teaching. Although this model has advantages in emotional communication and instant feedback, it is limited by the temporal and spatial dimensions and difficult to meet the increasingly diverse and individualized learning needs [3]. With the rapid development of information technology, especially the rise of online learning models, IPE has ushered in unprecedented opportunities for transformation [4]. Online learning, with its flexibility, convenience, abundant resources, and wide coverage, breaks the temporal and spatial boundaries of traditional education models, allowing learners to engage in self-directed learning according to their own pace and interests. This transformation not only greatly broadens the boundaries of learning, but also provides IPE with a broader platform and richer means.

However, the popularity of online learning has also brought new problems, such as knowledge overload, difficulty in information filtering, and insufficient learning motivation. If these problems cannot be effectively solved, they will directly affect the quality and effectiveness of IPE [5]. In this context, the introduction of AI provides new solutions for IPE. Through big data analysis, AI can accurately capture learners' learning behavior characteristics, interest preferences, and knowledge mastery, providing scientific basis for individualized resource recommendations [6,7]. Meanwhile, by utilizing DL algorithms, AI can continuously optimize recommendation strategies, achieve more accurate and efficient matching of learning resources, effectively alleviate knowledge overload problems, and stimulate learners' interest and participation in learning.

However, the popularity of online learning has also brought about the problem of knowledge overload. Faced with a massive amount of learning resources and information, learners often find it difficult to quickly filter out content that meets their own needs. This not only wastes valuable learning time, but may also lead to anxiety due to information overload, affecting learning outcomes. Therefore, developing an individualized resource recommendation system based on AI has become the key to solving this problem. Individualized recommendation system is based on user behavior data and uses algorithm models to predict content or products that users may be interested in. In the field of IPE, building an individualized resource recommendation system based on AI first requires collecting and analyzing students' learning behavior data, including but not limited to learning time, learning progress, interaction frequency, preference types, etc. By utilizing big data analysis techniques, we can deeply mine this data, construct student profiles, and recommend the most suitable learning resources based on the features of the profiles. The innovation points are as follows:

1) This article discusses the wide application potential of AI technology in the field of education, especially in IPE, and focuses on its breakthrough through biomechanical feedback in IPE content innovation.
2) This article constructs an IPE learning resource recommendation system based on big data analysis and deep learning (DL) algorithm, which integrates biomechanical feedback. With the help of accurately capturing students' learning physiological reactions and behavior patterns, the system realizes individualized recommendation of learning resources.
3) The core innovation of this article is that it introduces biomechanical feedback mechanism into the field of IPE, which promotes the development of IPE in a more intelligent, individualized and efficient direction.

The beginning of this article elaborates on the macro background and profound significance of the research, and further explores the cutting-edge applications of AI in the field of IPE content innovation. Subsequently, the core part of the article revealed in detail an IPE learning resource recommendation system that integrates AI. In order to verify the effectiveness and practical feasibility of this innovative system, we carefully designed experiments and conducted comprehensive verification. At the end of the article, the conclusion not only systematically summarizes the main research findings and contributions of this study, but also deeply reflects on the limitations and shortcomings of the research, and based on this, prospectively points out the direction and improvement suggestions for future research, aiming to contribute new wisdom and strength to the continuous progress and development of the IPE field.

2. Related work

In order to further improve the accuracy of individualized resource recommendations, many scholars have devoted themselves to in-depth exploration of learners' personal preferences, learning styles, and cognitive abilities, and are committed to establishing effective connections between these characteristics and diverse learning resources. In this field, Rong et al. [8] first proposed a collaborative filtering recommendation method for teaching resources, which utilizes clustering algorithms to finely divide user groups, thereby significantly improving the scalability of recommendation systems. However, Zhang et al. [9] did not fully consider the dynamic characteristics of user learning data when using collaborative filtering algorithms for user recommendation, resulting in the recommendation effect not meeting expectations. In response to the challenges in learning resource recommendation, Qi et al. [10] took a unique approach and proposed a new collaborative filtering recommendation method based on learners' social network information. At the same time, Geng et al. [11] integrated topic analysis techniques into content-based recommendation algorithms to accurately grade courses and professors, and based on this, recommend relevant courses tailored to learners. Liu et al. [12] took a different approach by using DL methods for individualized recommendations and cleverly incorporating blockchain technology in the recommendation process to enhance the security of data in the recommendation system, thereby significantly improving the overall performance of the recommendation system.

The research of Tong et al. [13] reveals the influence of height and load on running biomechanics through data analysis. In IPE, we can also use big data and artificial intelligence technology to analyze students' learning behavior and interest preferences, and realize individualized customization of educational content. Wu et al. [14] introduced DL technology into recommendation systems and effectively solved the problem of data sparsity in the system by utilizing its excellent feature extraction ability. Wang [15] proposed a learning resource recommendation algorithm based on deep neural networks (DNN), which has excellent recognition and classification capabilities for multi feature attributes of resource details. In addition, Deng et al. [16] achieved individualized resource recommendations by calculating the similarity between adjacent students and using collaborative filtering algorithms. Matveichuk et al [17] pointed out the challenges in the diagnosis and treatment of musculoskeletal system and emphasized the importance of interdisciplinary cooperation. Yongli et al. [18] constructed an education system based on AI. The system evaluates students' learning status in real time by collecting and analyzing students' learning behavior data. Wang [19] proposed a theoretical framework combining big data and cognitive psychology to explain and predict students' learning process and learning effect in ideological education. Angskun et al. [20] integrated AI technology with pedagogy, psychology and other disciplines, and explored the diversified application of AI in ideological education. Li et al. [21] proposed that AI can be used not only for personalized teaching, but also for learning evaluation, teaching resource management, students' emotional support and many other aspects. Vidal-Silva et al. [22] applied the teaching method combined with AI to students in different grades and regions, and verified the universal applicability of this method. IPE can also learn from the theories and methods of other disciplines for interdisciplinary integration and innovation of educational content.

The AI based IPE learning resource recommendation system proposed in this article is an effective solution for IPE to adapt to the era of online learning and cope with the challenge of knowledge overload. It can not only improve learning efficiency and optimize the learning experience, but also promote the individualized and intelligent development of IPE, making education closer to the actual needs of learners and truly achieving individualized teaching.

3. Biomechanical feedback application of AI in IPE

3.1. AI

In today's information age, the wave of big data with AI at its core is sweeping the globe at an unprecedented speed, profoundly changing the way humans produce, live, and operate society. The integration of AI has provided unprecedented possibilities for the richness of IPE content. Through the analysis and processing of massive data using DL algorithms, AI can accurately capture social hotspots, current events, and student interests, and organically integrate these elements into IPE content, making teaching content more realistic, close to life, and close to students, greatly enhancing the attractiveness and infectiousness of education [23]. At the same time, AI can customize differentiated teaching content based on students' learning habits, understanding abilities, and other individualized characteristics, achieving individualized teaching and improving the pertinence and effectiveness of education. In terms of educational methods, the introduction of AI has promoted the development of IPE towards multimodality and interactivity [24]. AI can aggregate and create educational resource libraries in various forms including text, images, audio, video, etc., providing educators with diverse teaching methods.

By utilizing advanced technologies such as virtual reality (VR) and augmented reality (AR), immersive learning scenarios are constructed, allowing students to experience and comprehend in simulated situations, thereby deepening their understanding and application of theoretical knowledge, making educational methods more flexible and varied, and learning experiences more vivid and interesting (as shown in **Figure 1**). More importantly, the application of AI has activated students' autonomy and initiative in the learning process. Through intelligent recommendation systems, online interactive platforms, and other tools, students can independently choose learning content, control their learning progress, and even participate in the co creation of course content. This active exploration learning mode greatly stimulates students' interest and creativity in learning. At the same time, AI can also assist educators in better playing a leading role, timely grasp students' learning situation through data analysis, accurately implement policies, optimize teaching strategies, and further improve the quality and effectiveness of IPE.

Figure 1. Application of AI.

3.2. Specific applications

In recent years, DL technology has achieved rapid development and has made significant achievements in many application fields, such as speech recognition and image processing. The DN-CBR model, as a recommendation system based on DNN, cleverly integrates the attribute information of users and items as well as the textual information of items [25]. Specifically, the model extracts attribute features of users and items separately through DNN, and uses convolutional neural networks (CNN) to vectorize the text information of items to extract their text features. Subsequently, these features are synthesized to form the final item features, and individualized recommendation services based on ratings are provided to users through the interaction between users and item feature vectors to predict ratings. The core advantage of the DN-CBR model lies in its utilization of the efficient feature extraction and combination capabilities of DNN, which deeply explores the complex associations between users and items through multi-layer networks and numerous neurons. Multilayer perceptron (MLP), as an evolved version of perceptron, is characterized by containing multiple neural layers and is adept at processing nonlinear data.

This article cleverly utilizes the advantages of MLP in processing nonlinear data to improve the DN-CBR model, upgrading the original simple vector multiplication method to predict scores through MLP. This improvement enables user features and item features to interact through the deep network structure of MLP, resulting in more accurate predictive ratings. This article proposes the UDN-CBR model for learning resource recommendation in IPE, which is a learning resource recommendation algorithm based on an improved DN-CBR model. UDN-CBR model integrates the information of learners and learning resources, and uses DNN to deeply learn the nonlinear relationship between them (**Figure 2**). Its case-based reasoning workflow includes four stages: Obtaining features, CNN extracting text features, forming comprehensive features and MLP score prediction.

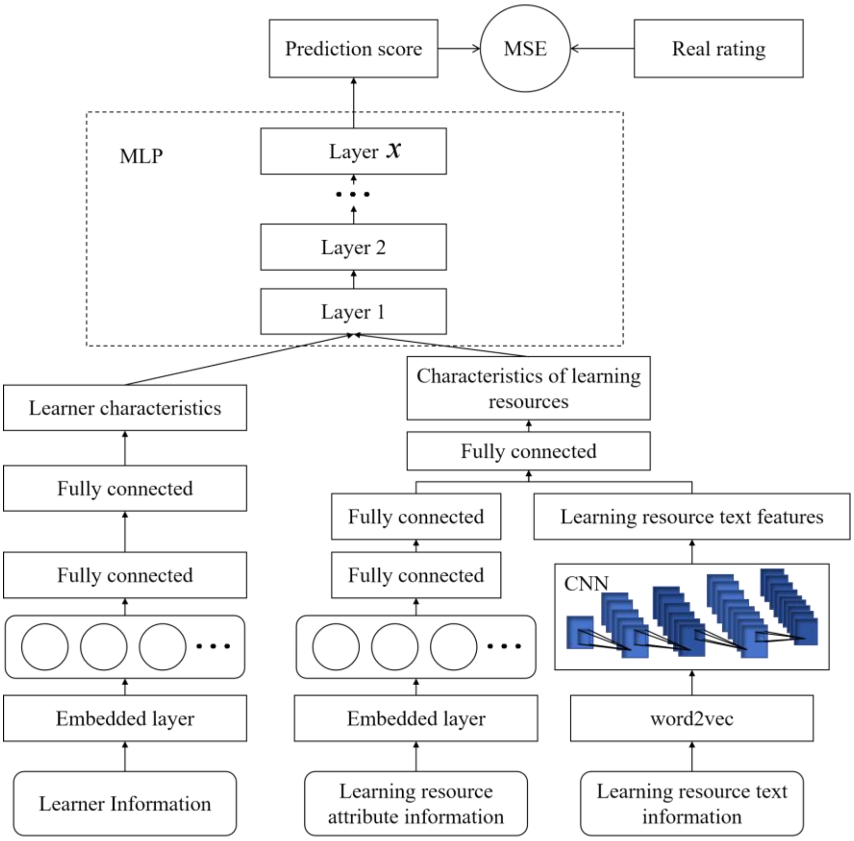

Figure 2. UDN-CBR model structure.

4. Recommendation of IPE learning resources based on AI and biomechanical feedback

4.1. System construction

The core of an individualized resource recommendation system lies in its accuracy and personalization. It is not just a simple information filtering tool, but an intelligent assistant that can deeply understand learners' needs, interests, and even learning styles. The system collects and analyzes multidimensional data such as learners' basic information, learning history, preference tendencies, and learning outcomes through user modules, and constructs a detailed user profile. During this process, DL algorithms play a crucial role in mining potential correlations between data, predicting learners' future needs, and achieving customized push of learning resources.

The learning resource module is a vast resource library that covers various forms of learning materials from basic education to higher education, including courses, papers, video tutorials, online discussions, and more [26]. The recommendation system module is a bridge connecting users and learning resources. It uses advanced recommendation algorithms to dynamically adjust the recommendation list based on the user's current learning status and goals, ensuring that each recommendation can accurately reach the learner's "knowledge blind spot" or interest point, effectively avoiding cognitive overload and learning confusion [27]. In addition, the system also has the ability of self-learning and optimization, which can continuously adjust recommendation strategies based on user feedback, achieving a more user-friendly interactive experience. In the long run, individualized resource recommendation systems based on AI can not only greatly improve learning efficiency and quality, but also promote educational equity, allowing everyone to enjoy the most suitable educational resources for themselves and contribute to the construction of a lifelong learning society.

4.2. Algorithm principle

In building a learning resource recommendation system based on the UDN-CBR model, we first need to take learner information and learning resource attribute information as inputs to extract their respective attribute features. Specifically, assuming the learner's attribute set is $x = \{x_1, x_2, \cdots, x_m\}$, where x_i represents a specific attribute of the learner, such as learner ID, which serves as a unique identifier that can distinguish different individual learners. Correspondingly, the attribute set of learning resources can be represented as $y = \{y_1, y_2, \cdots, y_n\}$, where y_i corresponds to a specific attribute of the learning resource, such as the learning resource ID, which also serves to distinguish different learning resources. Next, in order to transform these discrete attribute information into continuous feature vectors that can be used for deep learning, we input the attributes of the learner and learning resources into the embedding layer. In this layer, each attribute is mapped to a high-dimensional vector space, generating learner and learning resource attribute feature vectors $\bar{x}, \bar{y}$. This process can be summarized by the following formula:

$$\bar{x} = f(w_1 x + b_1) \tag{1}$$

$$\bar{y} = f(w_2 y + b_2) \tag{2}$$

Among them, w_1, w_2 represents weight parameters, which play a key role in adjusting the importance of features during the learning process; b_1, b_2 stands for bias term, which is used to introduce nonlinear factors into the model. $f(\cdot)$ is an activation function that can introduce nonlinear characteristics into the model, thereby enhancing its expressive and generalization abilities. After obtaining the various attribute features of learners, we effectively fuse these features using the $concatenate(\cdot)$ function. u_i, s_j as a vector representation of learner characteristics and learning resources, provides accurate and comprehensive information support for subsequent learning resource recommendations.

$$u_i = concatenate(\bar{x}) \tag{3}$$

$$s_j = concatenate(\bar{y}) \tag{4}$$

The hotspots of learning can be accurately captured by analyzing the learning resource frequency matrix. Firstly, we will perform detailed numerical encoding on the features in the matrix, which ensures the accuracy and computability of the information. Subsequently, through in-depth feature comparison, we calculate the difference values between features, which can reveal the intrinsic connections and differences between different features. Based on this analysis, we have constructed six key feature difference functions $S_i(i = 1,2, \cdots, 6)$, which provide us with a profound understanding of the changing demands for learning resources. On this basis, the objective function of the recommendation model is established.

$$min\, S = \sum_{i=1}^{6} \omega_i S_i \tag{5}$$

In the formula, ω_i represents the weight of different difference functions on the overall recommendation model.

The embedding layer plays a key role in transforming the textual information of learning resources into an embedding matrix in a high-dimensional space. In this conversion process, each word segmentation element in the text is mapped to a fixed dimensional vector. For example, if the text contains a total of 7 words, and each word is accurately represented as a 5-dimensional vector, then we will ultimately obtain a 7 × 5-dimensional embedding matrix. This matrix, like an image containing textual information, provides rich input data for subsequent convolutional layers. Here, the text matrix $D \in R^{n \times m}$ of the learning resources is:

$$\begin{bmatrix} w_{11} & \cdots & w_{1i} & \cdots & w_{1m} \\ w_{21} & \cdots & w_{2i} & \cdots & w_{2m} \\ \vdots & \vdots & \vdots & & \\ w_{n1} & \cdots & w_{ni} & \cdots & w_{nm} \end{bmatrix} \tag{6}$$

Among them, m represents the dimension of embedding; n represents the number of words; $w_{[i,1:m]}$ represents the vector form of the i word.

When evaluating the level of interaction between learning resources and learners, we mainly rely on two criteria: The frequency of viewing learning resources and the amount of time learners invest in watching. Specifically, S_{ij} represents the actual viewing time of learner i on learning resource j, while viewing frequency ω intuitively reflects the degree of repeated access of learners to the same resource, reflecting their interest or demand intensity for that resource. In order to quantify this interaction, an implicit scoring mechanism is introduced:

$$\alpha_{ij} = \frac{\sum_{\sigma=1}^{\omega} S_{ij}^{\sigma}}{\omega T_j} \tag{7}$$

This mechanism divides learners i' preferences for different resources into ten levels based on the ratio a_{ij} of their average viewing time S_h to the total viewing time T_j of learning resources j. This division not only considers learners' time investment in resources, but also implies an indirect evaluation of the quality of resource content. In addition, we also considered the b_j rating obtained for learning resource j in online learning platforms, as well as the explicit rating of resource j by learner i based on personal experience. Ultimately, the comprehensive rating of learners is the average of explicit and implicit ratings:

$$f(i,j) = 5\left(a_{ij} + b_j\right) \times 100\%, 0 \le a_{ij} \le 1, 0 \le b_j \le 1 \tag{8}$$

This comprehensive rating mechanism aims to comprehensively and objectively reflect learners' overall evaluation of learning resources and provide a strong basis for personalized recommendation.

5. Result analysis and discussion

In order to further evaluate the effectiveness of the learning resource recommendation system based on the UDN-CBR model proposed in this article, we specially arranged a comparative test with the traditional recurrent neural network (RNN) recommendation system. Data collection mainly captures students' physiological reactions and behavior patterns in real time through AI-assisted IPE system, and collects students' subjective feedback through questionnaires and interviews. In the data analysis stage, various algorithms and techniques are adopted: Signal processing algorithm is used to filter out physiological data noise and extract features, such as heart rate variability (HRV) analysis to evaluate stress response; Apply computer vision and machine learning algorithms to identify and analyze behavior patterns, such as eye tracking algorithm to track gaze points; Text mining and sentiment analysis algorithms are used to extract key information and sentiment tendency from subjective feedback. These algorithms are closely related to the goal of this study, which provides strong support for accurately evaluating students' learning state, deeply understanding learning behavior and improving teaching.

Figure 3 clearly reveals the significant difference in the accuracy of IPE learning resource recommendation between the two, indicating that our system has higher accuracy. This superior performance is mainly attributed to the ingenious integration of the UDN-CBR model, which not only incorporates the excellent data fitting characteristics of MLP, but also integrates the deep feature learning ability of DNN. The introduction of MLP enhances the system's ability to capture complex associations between learners and resources, while DNN deepens the mining of potential features. The two work together to significantly improve the accuracy of recommendations. In addition, the UDN-CBR model cleverly utilizes user historical behavior data, combined with deep learning and collaborative filtering techniques, to accurately capture and update user preferences in real-time, thereby providing users with more individualized and tailored learning resources.

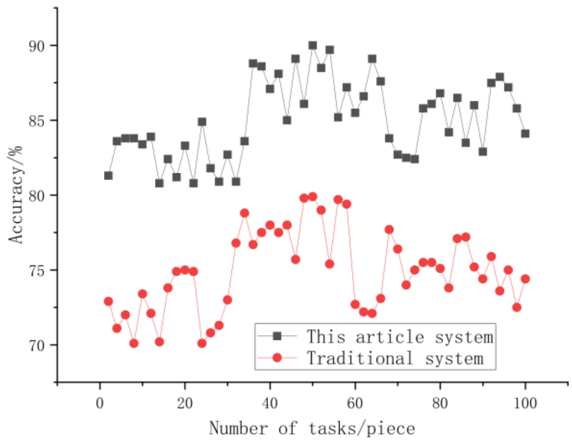

Figure 3. Comparison of recommended accuracy.

Figure 4 visually compares the time difference between the innovative system proposed in this article and the traditional RNN based system in performing IPE learning resource recommendation tasks. The diagram clearly reveals that compared to classical RNN systems, the system designed in this article takes less time to complete the same recommendation task and significantly improves efficiency. The core of this progress lies in the UDN-CBR model adopted by the system, which combines the advantages of MLP and DNN. With the excellent data fitting characteristics of MLP and the deep feature analysis ability of DNN, it achieves efficient analysis of user preferences and learning resource features. This efficient parsing not only enhances the accuracy of recommendations, but also significantly reduces the time cost of the recommendation process. Furthermore, the UDN-CBR model deeply mines user historical behavior data and combines DL and collaborative filtering techniques to achieve precise capture and real-time updates of user preferences.

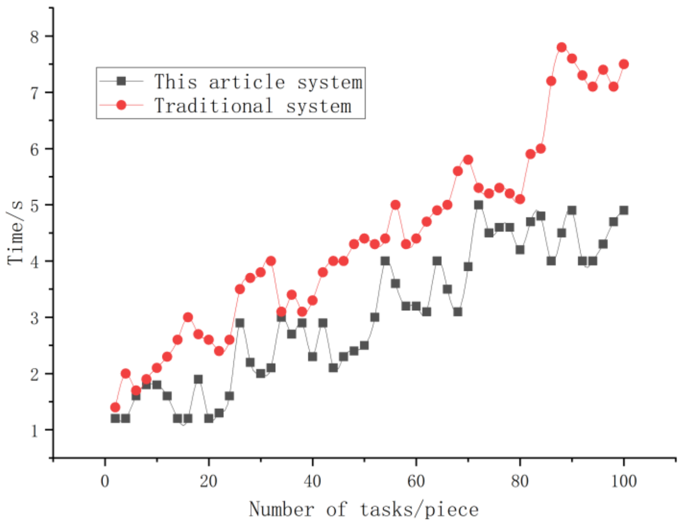

Figure 4. Time comparison.

Figure 5 visually compares the recall performance of the proposed system and traditional RNN system in IPE learning resource recommendation tasks. Recall rate, as a key indicator for evaluating the effectiveness of recommendation systems, reveals the proportional relationship between successfully recommended resources and all relevant resources. The diagram clearly shows that compared to traditional RNN systems, our system exhibits a higher recall rate when performing the same recommendation task, indicating that our system can cover a wider range of learning resources that users may be interested in. The significant improvement in this recall rate is mainly attributed to the UDN-CBR model introduced by the system in this article. UDN-CBR, as an innovative recommendation algorithm, cleverly integrates the advantages of MLP and DNN. MLP, with its powerful data fitting ability, accurately captures the complex connections between user behavior and learning resource features; DNN utilizes deep feature extraction to uncover the potential value behind data. The combination of the two enables the UDN-CBR model to have a deeper understanding of user preferences, thereby more accurately recommending learning resources that meet user needs.

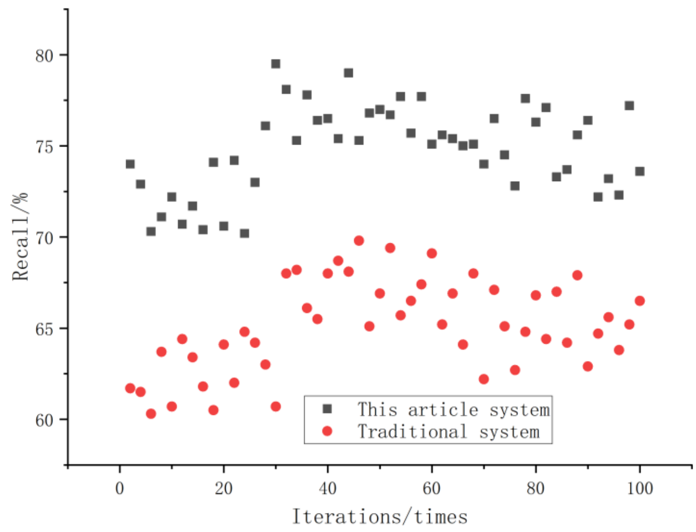

Figure 5. Comparison of recall rates.

Figure 6 directly compares the F1 values of our system and traditional RNN system in the IPE learning resource recommendation task. The F1 score, as an indicator for comprehensive evaluation of the accuracy and recall of recommendation systems, comprehensively reflects the effectiveness of the system's recommendation. The diagram clearly shows that compared with traditional RNN systems, our system has a higher F1 value when performing the same recommendation task, indicating that it is superior in recommendation accuracy, effectively balancing accuracy and recall, and providing users with higher quality learning resource recommendation services. The significant improvement in F1 value is attributed to the UDN-CBR model adopted by the system in this article. UDN-CBR, as an innovative recommendation algorithm, cleverly integrates the advantages of MLP and DNN. MLP, with its powerful data fitting ability, accurately captures the complex connections between user behavior and learning resource features; DNN utilizes deep feature extraction to uncover hidden deep information in data.

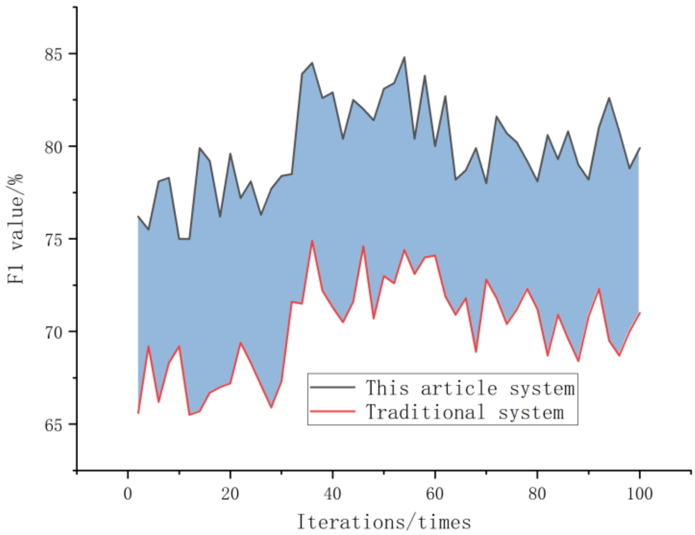

Figure 6. Comparison of F1 values.

Figure 7 compares the performance of our system with traditional RNN systems in terms of user satisfaction. The diagram clearly shows that compared with traditional RNN systems, our system has higher user satisfaction when performing the same recommendation task, indicating that our system performs well in providing individualized and high-quality learning resource recommendations, and can better meet the learning needs of users. The improvement in user satisfaction is mainly attributed to the UDN-CBR model adopted by the system in this article. UDN-CBR, as an innovative recommendation algorithm, cleverly integrates the advantages of MLP and DNN. The combination of the two enables the UDN-CBR model to better understand user preferences and provide learning resource recommendations that better meet their needs, thereby achieving a significant improvement in user satisfaction and increasing student engagement.

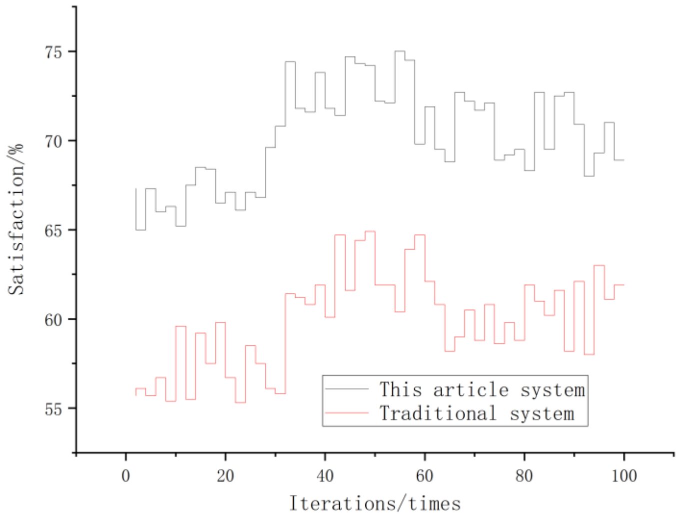

Figure 7. Satisfaction comparison.

Figure 8 shows the comparison between the proposed system and the traditional RNN system in terms of mean square error (MSE) in IPE learning resource recommendation. MSE is a key indicator for measuring the prediction accuracy of recommendation systems. The lower the value, the closer the prediction is to the true result, indicating that the recommendation is more accurate. As shown intuitively in the figure, compared with traditional RNN systems, the MSE value of our system is lower when performing the same task, which means that our system has higher accuracy in predicting user interest learning resources and can better meet individualized learning needs. The significant decrease in MSE value is attributed to the UDN-CBR model adopted by the system in this article, which cleverly integrates the advantages of MLP and DNN, comprehensively understands user preferences, improves the accuracy of learning resource recommendation, and thus reduces MSE value.

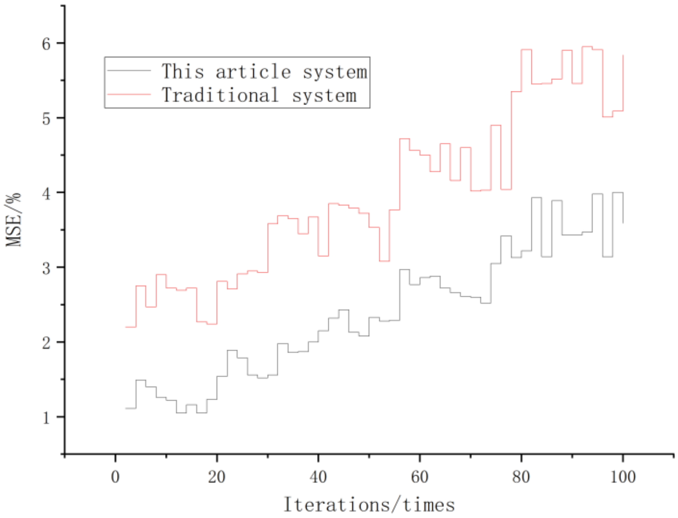

Figure 8. MSE comparison.

6. Conclusion

This article innovatively explores the biomechanical feedback application of AI in IPE, and develops an IPE learning resource recommendation system that integrates big data analysis and deep learning algorithm. By carefully capturing and analyzing students' learning behavior, interest preference, knowledge mastery and biomechanical feedback signals, the system constructs a comprehensive and accurate portrait of students' learning. Based on this portrait, the system can intelligently and personally recommend learning resources for students, which improves the accuracy of recommendation and learning efficiency. The application of the system not only improves students' learning participation and satisfaction, but also enables students to have a deeper understanding and recognition of the party's theoretical line, principles and policies while enjoying personalized learning experience.

Although the current system has made some achievements, there are still some limitations. Although some progress has been made in data processing, the algorithm still needs to be further optimized to improve the accuracy and real-time performance of recommendation. At the same time, the user interface and user experience of the system need to be improved to better meet students' habits and needs. In view of these findings and limitations in research, future research can strive to provide students with more efficient, convenient and personalized IPE learning resource recommendation services through these efforts, and contribute more to the reform and development of IPE.

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

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