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Theory and Practice of Constructing College Physical Education Curricula Based on Immersive Multimedia Technology

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ABSTRACT

The overload of sports information resources has greatly increased the difficulty for users to choose resources. To solve this problem, this paper proposes a sports digital teaching resource recommendation model based on collaborative filtering algorithm to achieve the optimization of sports teaching mode in the context of big data and multimedia. Based on the detailed analysis of the teaching resource construction platform, the improved algorithm is applied to the teaching resource recommendation platform, and the algorithm effect is verified based on the collected data. The experimental data shows that the error of this method is significantly better than ID3 algorithm, the error is reduced by 26.55%, and the recall rate is 95.72%, which is 12.76% higher than ID3 algorithm. The introduction of personalized recommendation technology into the utilization of sports information resources can improve the efficiency and accuracy of users' access to resources and strengthen the adaptability to the continuous deconstruction and new integration of the higher education system.

KEYWORDS

Big Data, Collaborative Filtering Algorithm, Instructional Resource, Multimedia, Physical Education

INTRODUCTION

The digitalization of sports is fundamental for the execution of national fitness initiatives. It fosters a robust sports service infrastructure, catering to the rising demands of organizing large-scale sports events. This not only elevates the competitive edge in sports but also bolsters their administrative oversight. Given the nature of sports, its informational assets encompass a plethora of semi-structured and unstructured data types, such as videos, images, athlete profiles, event details, and a myriad of multimedia elements. These resources, being multifaceted and intricate, present classification challenges. Users often find it daunting to efficiently pinpoint relevant and valuable content within this expansive data ecosystem. Such a vast resource pool means users may overlook essential information while their engagement wanes, leading to suboptimal utilization of these resources (Varela et al.,

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2020). Traditional search methodologies often fall short in accuracy, delivering redundant results. Ideally, users should have a clear intent when searching, but they often struggle to articulate or even identify their exact needs, rendering conventional search tools less effective.

Amidst educational evolutions, physical education (PE) must proactively tackle the challenges ushered in by the big data era to foster its growth (Zhu, 2021). Historically sidelined and encumbered by outdated teaching models, PE now needs a fresh, modern approach. Multimedia, a cornerstone of contemporary education, has revolutionized classroom experiences. In the digital age, it has seamlessly integrated into PE classes, enhancing the teaching milieu. Such integration invigorates student engagement and amplifies their motivation in PE, paving the way for elevated instructional quality (Grunspan et al., 2020). Universities, capitalizing on the digital era's advantages, must overhaul their PE teaching techniques. Recognizing the pivotal role of PE in academic curricula, they should strive for enhanced teaching outcomes (Zhang & Min, 2020). Embracing multimedia teaching approaches can expedite student immersion in lessons. Nonetheless, given PE's unique characteristics, meticulous planning is paramount—spanning physiological, functional, athletic, neural, and skill-based facets—to achieve desired learning outcomes. Furthermore, fostering positive student sentiment and a fervent passion for sports is integral to optimizing their learning experience.

Effective physical education teaching techniques not only bolster students' physical health but also contribute to their psychological well-being. However, imparting such methods in primary school settings remains a significant challenge for PE teachers. It is imperative for educators to meticulously manage every aspect of the lesson to ensure each student derives joy from the learning experience. Yet, PE classes are not without unforeseen challenges, such as accidents leading to injuries or lack of student engagement, which can be problematic for instructors (Bai & Zhang, 2020). As the educational landscape shifts towards digitization, physical education is delving into the realm of digital resource creation. While this journey has led to the accumulation of some noteworthy insights, there's still a gap in aligning these digital resources with the unique essence of physical education, and a dearth of established models for reference. This paper introduces a recommendation system for digital PE instructional resources, leveraging the Collaborative Filtering (CF) algorithm. This model aims to pave the way for a data-driven, multimedia-rich smart campus, thereby enhancing the physical education instructional framework.

Utilizing online resources in physical education maximizes student engagement, transforming them from mere recipients of knowledge to proactive seekers. This shift facilitates a transition from passive to active learning (Liu et al., 2022). Such an adaptable learning process fosters students' abilities in self-management and independent learning. Traditional physical education methods in universities tend to be repetitive and lack diversity, often leading to diminished student interest. However, integrating multimedia and Information Technology (IT) enhances the presentation of PE content through visuals and videos, sparking student interest and elevating the overall teaching quality.

In sum, this study focuses on the personalized recommendation techniques for digital sports teaching resources. It establishes and refines a recommendation model for sports information resources using the CF algorithm. This research serves as a theoretical foundation for future explorations into personalized recommendation techniques in sports information resources. Additionally, it offers technological backing for the implementation of personalized recommendation services in real-world system platforms. The key innovations and contributions of this research encompass the following:

(1) Tackling the challenge of limited data, this paper introduces a recommendation model that incorporates both user ratings and resource attribute preferences.
(2) The model identifies the nearest neighbors based on the similarity in user attributes. It evaluates the information richness of users' ratings using information entropy. From the neighboring user clusters, the model then chooses the mean value of the ratings with higher information content to serve as the foundation for predicting new user ratings.

RELATED WORK

Currently, there is a notable gap in the research on digital teaching resources for physical education. A significant impediment to the advancement of online physical education is the lack of comprehensive and top-tier digital teaching resources (Batra et al., 2021). Some experts define sports information resources as either sports literature or data resources. They perceive it as an aggregate of diverse media and formats connected to sports—encompassing text, audio-visuals, printed materials, electronic data, databases, and more, specifically tailored to sports (Kos & Umek, 2018). This definition, however, is confined to the sports information in its narrow sense. Broadly, sports information resources encompass a myriad of elements integral to sports information activities (Krizhevsky et al., 2017). This extends beyond just the information, encapsulating associated resources like personnel, equipment, technology, and funding. These resources are distinguished by their immediacy, shareability, value-addition, and transmissibility. Liu and Tsai (2021) examined the present state of information resources in PE teaching, highlighting key challenges in integrating IT into PE. The digital transformation in sports encompasses several main elements, with sports information resources at its heart. The foundation lies in the information network, aiming to merge information technology with resources (LeCun et al., 1998). Supporting this transformation are indispensable components like expertise in sports digitalization, related industries, and guiding policies.

The advent of personalized recommendations can be traced back to 1992, with the first commercial recommendation system emerging in 1994 (Megahed et al., 2022). Paul Resnick and others at the Massachusetts Institute of Technology pioneered this concept by curating content for users based on their interests, sorting messages in the Usenet discussion domain. This innovation marked the dawn of the recommendation system era. By 1996, Yahoo introduced the "My Yahoo" feature, enabling users to customize their content modules, enhancing the information retrieval process and fostering deeper, long-lasting user engagement.

Rissmann (2017) expanded upon this technology, applying personalized recommendation techniques to online distance education. This approach gauged user interests through their personal profiles and tailored recommendations based on resource ratings. Lin et al. (2019) delved deeper into e-learning, examining user needs for such recommendation services, meticulously studying recommendation models and associated technologies. By discerning which recommendation techniques fit specific learning scenarios, they devised an integrated strategy encompassing multiple recommendation service methods.

Smith et al. (2013) introduced a community-centric personalized recommendation platform. Here, user activities were continuously tracked, with data mining employed to scrutinize the accumulated information. The platform then suggested users with aligned interests and behaviors. Zhen (2021) incorporated personalized recommendation technology within instructional resources, streamlining the resource search process for learners, uncovering latent user interests, and enhancing the system's customized service quality.

Bai and Li (2021) emphasized the importance of setting clear, scientific objectives for physical education students' skill development. They advocated for holistic enhancements in students' physical prowess and practical abilities, refining physical education theoretical approaches, and catering to the demands of digitalized teaching evolution. Schultze (2015) crafted a personalized service blueprint for distance learning, leveraging data mining techniques. This model encapsulated the essence, functionalities, and implementation stages of data mining.

At present, there are three major difficulties in the development of China's sports information industry. Sports resources are too scattered. The utilization rate of sports resources is low. The sports system lacks cohesive internal information linkage. The low utilization rate of sports resources is reflected in the fact that only 39.2% of units in China have established an information resource database, of which 78.5% have updated the data only once over the course of more than half a year, and only 36.2% of the units with an information resource database have implemented online sharing.

Compared with the scale of informatization in other industries, the development of China's sports informatization industry remains in its infancy and has a broad scope for improvement.

METHODOLOGY

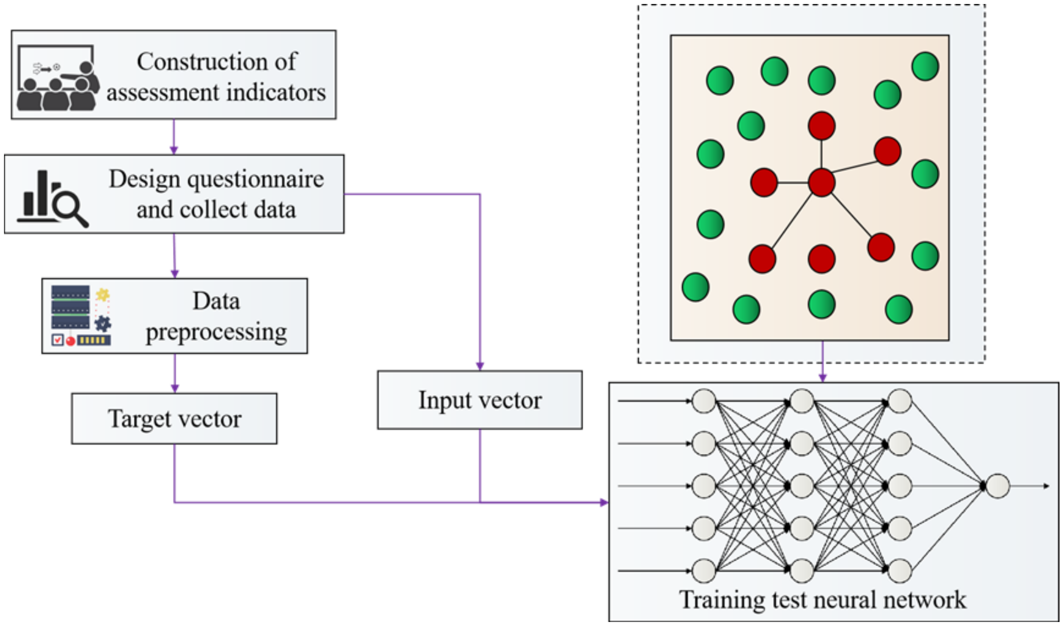
The Value of Informatization of PE Instructional Resources in Schools

At present, the application scope of big data has been extended to all aspects of society (Eltawil et al., 2021). In the field of PE teaching, big data can promote the mining of educational data and integrate effective information for learning and analysis. The swift advancement of multimedia technology in IT, coupled with its extensive use in university physical education, has profoundly transformed teaching methodologies and the ways multimedia is delivered and received. This shift has revolutionized instructional approaches, spurring a complete redesign of the teaching stage and even a restructuring of the teaching framework. The traditional instructional model is giving way to a more flexible, dynamic, and innovative networked structure (Yuan, 2020). Educational data mining involves harnessing vast amounts of data, utilizing cloud computing, and constructing models to gain a clearer and more intuitive insight into the relationship between students' physical education performance, their exercise methods, and frequency. This aids in better understanding the future physical education trajectory for learners (Liang & Yin, 2022). Learning analysis entails examining the entirety of a student's physical education journey based on their current achievements in PE. By identifying challenges and providing constructive feedback, it aims to assist students in optimizing their physical education experiences.

In this revamped structure, the computer system will take over the regulatory role traditionally held by the teaching organization and management department. This change will enhance direct communication in the educational process while diminishing the controlling role of the teaching organization, leading to a streamlined teaching management hierarchy and faster integration of multimedia IT in education. Simultaneously, learners will transition into proactive participants in the educational process. The teaching management approach will shift from a control-oriented model to a participatory one, fostering active engagement and empowering both educators and students. The vastness of big data databases allows for timely recording and regular monitoring of learners' physical fitness results. This provides students with real-time insights into their health metrics. Using big data, we can holistically analyze learners' physical development trends over the past five years, capturing shifts in their endurance, explosive strength, and flexibility. This provides insights that are more instructive than merely observational. Integrating multimedia into physical education teaching amplifies results with reduced effort (Smith et al., 2013). Multimedia presents students with vivid moving images, graphics, and sounds that effectively illustrate technical movements. This intensely engages students' auditory and visual senses, sparking their thinking and stimulating their learning enthusiasm. As a result, students can form a comprehensive understanding of the movement. The framework and process for retrieving physical education instructional resources are depicted in Figure 1.

The appropriate application of multimedia-infused teaching techniques can simplify learning and exercise, enhancing students' positive emotional experiences and reinforcing their determination and resilience (Shan & Talha, 2021). It also elevates the quality of instruction. Through multimedia animations, teachers can break down and demonstrate each phase of an action, allowing learners to grasp the core components more intuitively. This deepens their understanding, enabling them to quickly apply these skills during physical education sessions. Teachers have the flexibility to rewind, slow down, pause, and provide detailed explanations, ensuring that learners have a clear and tangible grasp of the content. This maximizes the impact of multimedia in physical education, continually enhancing the proficiency of the teaching process (Pan, 2021). The multimedia learning platform based on big data technology can provide learning resource classification and search functions. The

Figure 1. PE instructional resources retrieval framework



platform uses personalized recommendation technology to conduct data mining on student information and learning records, predict learners' interest in the platform learning resources, and use the learning resources with the top interest ranking as the recommendation results. The recommendation result display module dynamically presents the recommendation results in a form that learners can easily understand and accept, and applies it to their learning process, providing them with personalized learning resources and teaching guidance.

The Recommendation Model of Physical Education Digital Teaching Resources Based on CF Algorithm

A good PE video can greatly stimulate students' active participation, creativity, and interest, thus creating a positive atmosphere for outdoor PE teaching (Nagowah et al., 2021). Using appropriate multimedia tools is crucial for teachers to immerse students quickly into a designated teaching atmosphere, sparking their interest in learning new techniques. For instance, teachers can transform specific technical concepts into research topics. By encouraging students to form groups and utilizing local online educational resources, sports news broadcasts, and classic sports event clips, educators can pinpoint sports scenarios that resonate with these concepts. This approach enables students to grasp the essence of relevant techniques within an engaging and varied teaching setting. The integration of multimedia through the service platform ensures seamless coordination between teaching and learning activities, streamlining the teaching process. This not only enhances the timely communication of multimedia in education but also reduces overheads related to teaching management and coordination. The prompt feedback mechanism fosters better adaptability to learning environments, further energizing the learning spirit of students. It encourages knowledge sharing and experience exchange, paving the way for successful teaching strategies and the attainment of educational objectives. However, as the number of users and items in the system surge, traditional recommendation algorithms may become sluggish in processing data.

CF recommendations derive from a user's resource rating matrix to determine similarities and offer suggestions. This approach is resource-agnostic, leading to a more varied set of recommendation outcomes. Moreover, it leverages machine learning and data mining techniques to construct a unique user model grounded in individual attributes. Based on this user model, resources are recommended. CF thus offers a high level of personalization and automation.

The primary approach entails constructing user interest models and product feature models. This is achieved by analyzing multi-user data and behaviors while integrating item feature analyses. Within the realm of CF personalized recommendation, the contents or entities recommended are termed "items." A pivotal step involves creating a "user-item" score matrix. By leveraging this matrix, similarities between users or items are ascertained. Subsequently, the most similar users or items are collated. By amalgamating the likeness of similar items and scores from akin users, a list of potentially appealing items for the current user is curated. The user's projected scores for these items shape the final list of recommended items.

However, CF faces challenges. Building an accurate user model can be intricate. Furthermore, it grapples with the "cold start" dilemma, meaning when new learners or resources enter the system, the absence of adequate data hinders effective recommendations.

The steps to create the sports teaching recommendation model using the algorithm discussed in this paper are illustrated in Figure 2.

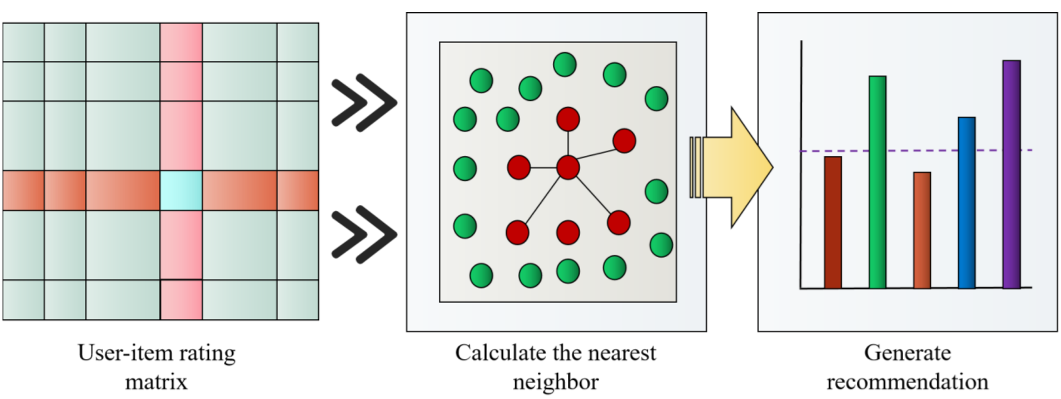
Online instructional resources are diverse and abundant. While content-based recommendation struggles with recommending unstructured resources like audio and video or cross-domain recommendations, association rule–based recommendations lack personalization, often leading to unsatisfactory personalized outcomes. In contrast, CF recommendation techniques are format-agnostic, capable of addressing complex non-structured objects, and offer a high level of automation, effectively identifying users' potential interests.

Data sparsity is the primary factor that affects the quality of recommendation by the CF algorithm (Villegas-Ch et al., 2019). The CF algorithm relies on users' evaluation of items to generate recommendations. If users' evaluation of items is too sparse, it can lead to significant errors in calculating similarity, thereby impacting the quality of personalized recommendation platforms. To determine the similarity between PE instructional resources, one can compute the cosine of the angle between two vectors:

$$sim\left(i,j\right)=\frac{\vec{i}\cdot\vec{j}}{\left\|i\right\|\left\|j\right\|} \tag{1}$$

The correlation degree between two vectors is calculated:

Figure 2. Establishment of PE teaching recommended model



$$sim\left(i,j\right)=\frac{\sum_{u\in U}\left(R_{u,i}-\bar{R}_{i}\right)\left(R_{u,j}-\bar{R}_{j}\right)}{\sqrt{\sum_{u\in U}\left(R_{u,i}-\bar{R}_{i}\right)^{2}}\sqrt{\sum_{k\in R_{mn}}\left(R_{u,j}-\bar{R}_{j}\right)^{2}}} \tag{2}$$

$R_{u,i}$ represents the rating of user u on instructional resource i, and $\bar{R}_i$ represents the average value of the rating of the i-th instructional resource. Eliminate the influence of different users' scoring habits by subtracting the average score of users:

$$sim\left(i,j\right)=\frac{\sum_{u\in U}\left(R_{u,i}-\bar{R}_{u}\right)\left(R_{u,j}-\bar{R}_{u}\right)}{\sqrt{\sum_{u\in U}\left(R_{u,i}-\bar{R}_{u}\right)^{2}}\sqrt{\sum_{k\in R_{mn}}\left(R_{u,j}-\bar{R}_{u}\right)^{2}}} \tag{3}$$

$\bar{R}_u$ is the average value of users' ratings on all instructional resources, and $R_{u,i}$ represents users' u ratings on instructional resources i.

The target user's prediction score of resource entry i is:

$$P_{x,i}=\bar{S}_{x}+\frac{\sum_{y\in U}\left(sim\left(x,y\right)\times\left(S_{y,i}-\bar{S}_{y}\right)\right)}{\sum_{y\in U}\left(sim\left(x,y\right)\right)} \tag{4}$$

$sim\left(x,y\right)$ represents the similarity measure between user x and user y, $S_{y,i}$ represents the rating of user y on resource item i, and $\bar{S}_x$ and $\bar{S}_y$ represent the average resource rating of user x and y users, respectively.

There are both registered and unregistered users in the personalized recommendation platform of instructional resources, and unregistered users can search and browse resources and personalized recommendation services (Bates & Friday, 2017). Registered users can evaluate resources and manage personal information, in addition to accessing the same features as unregistered users. At the stage of interaction with users, the multimedia information retrieval service generally does not express, analyze, or utilize the knowledge of users' historical interests. The document outlining learners' interest preferences in PE can be expressed as:

$$D=\left\{M,N\right\} \tag{5}$$

Where M represents short-term study interest, and N represents long-term study interest. M and N are respectively represented as:

$$M=\left\{S_{1},S_{2},\ldots,S_{n}\right\} \tag{6}$$

$$N=\left\{L_{1},L_{2},\ldots,L_{n}\right\} \tag{7}$$

Students' interest preferences are expressed as follows:

$$U = \left\{S_1, S_2, \ldots, S_n, L_1, L_2, \ldots, L_n\right\} \tag{8}$$

For each S_i, L_j, category attribute variables E_i, E_j and weight attribute variables F_i, F_j are introduced. Therefore, S_i and L_j are expressed as:

$$S_i = \left\langle S_i, F_i, E_i \right\rangle, i = 1,2,\ldots,m \tag{9}$$

$$L_i = \left\langle L_j, F_j, E_j \right\rangle, i = 1,2,\ldots,n \tag{10}$$

Students' study interest preference documents can be expressed in the form of a two-dimensional table:

$$D = \begin{Bmatrix} S_1 & S_2 & \ldots S_m & L_1 & L_2 & L_n \\ F_1 & F_2 & \ldots F_m & F_{m+1} & L_{m+2} & L_{m+n} \\ E_1 & E_2 & \ldots E_m & E_{m+1} & E_{m+2} & E_{m+n} \end{Bmatrix} \tag{11}$$

S_m and L_m are the attribute values of short-term and long-term study interest, respectively; E_{m+n} represents the resource category of PE instructional resources corresponding to students' study interest; learning interest weight of vocabulary is represented as F_{m+n} attribute value.

Computing the user's information value within the cluster of neighboring users not only streamlines the calculation of user information entropy but also considers both the user's rating and the attributes of the resource. Selecting users with high information entropy regarding specific resources serves as a foundation for predicting scores for new users. Subsequently, the average ratings these users give to resources become the predicted scores for the newcomers. The refined algorithm introduces a similarity measure grounded in user preferences for resource attributes, merging user ratings with resource attribute preferences to determine user similarity. This approach somewhat mitigates the sparsity of the user-resource rating matrix.

RESULT ANALYSIS AND DISCUSSION

The personalized teaching resource recommendation platform consists of data collection and preprocessing modules. These modules gather students' learning records, such as course visitation times, reading frequency, duration of stay, and visited URLs. Such historical logs furnish a wealth of foundational data for recommendations. Subsequent steps involve consolidating pertinent data, eliminating duplications, filtering out superfluous data entries, pinpointing users via unique identifiers, and supplying structured data for subsequent analysis.

In the recommendation platform, the distribution of users' ratings is different, so the amount of information for users' ratings also differs. Some users' ratings contain more information; that is, users' ratings are more average. Some users' scoring contains less information; that is, the scores are concentrated. Therefore, in dealing with new users' problems, some users are selected according to learners' information, and the average score of these users on a certain resource is calculated as the predicted score of new users on this resource. Within the system, users with existing rating data are recommended by a preference recommendation model based on rating and resource attributes, and new users are recommended by a recommendation model based on user characteristics and information entropy. In order to avoid the loss of important information caused by the rejection of special data, the quantitative data with large differences in data distribution intervals are processed by interval discretization. Data outlier removal processing is shown in Figure 3.

Abnormal value is a special case that we often encounter in data analysis. Abnormal data will affect our normal analysis results. There are several methods to deal with normal outliers: delete outliers, replace the abnormal value as the missing value, and replace it with 0 or the average value. Using these data to train the designed network can result in improved network weights. Then, substituting the obtained network weight into the network can become the basic model of PE instructional resource recommendation. In increasing the use of digital resources, we must closely consider the particular context of PE teaching and work to meet its requirements. Simultaneously, it's essential to enhance the utilization of hardware equipment in PE teaching, adapt the management approach for such hardware, and ensure logical layout and instructional planning.

Figure 4 shows the scatter diagram of the predicted value and the actual value of the test sample used by the model in this article. Figure 5 shows the scatter diagram of the predicted value and the actual value of the test sample utilized by the PE instructional resource recommendation model based on the ID3 algorithm.

The scatter chart graphically displays the actual value in the data and the predicted value of the model. It displays the actual value along the X axis and the predicted value along the Y axis. The figure also depicts a line showing perfect prediction, on which the predicted value and the actual value exactly match. The distance between a point and the ideal 45–degree angle line indicates the accuracy of the prediction. It can be concluded that the PE instructional resource recommendation model based on the improved CF algorithm outperforms ID3 in terms of time measurement accuracy and efficiency.

Multimedia IT offers an open platform, allowing teachers to easily access and present PE instructional content. This not only enhances the convenience of PE instruction but also simplifies the learning process for students. Implementing multimedia IT in teaching boosts instructional

Figure 3. Data outlier removal processing

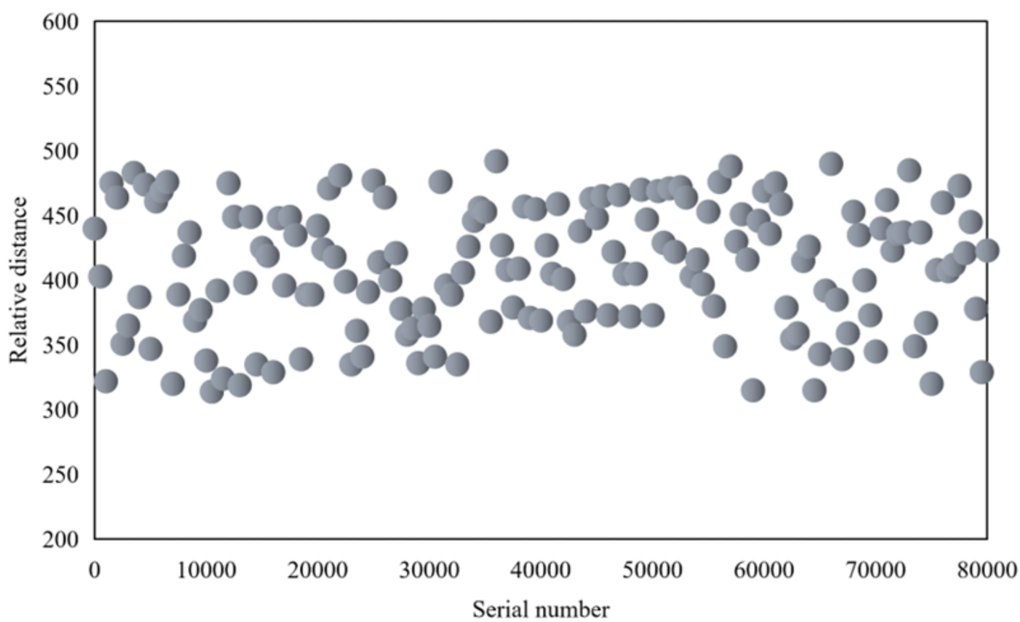


Figure 4. Scatter chart of improved CF actual value and predicted value

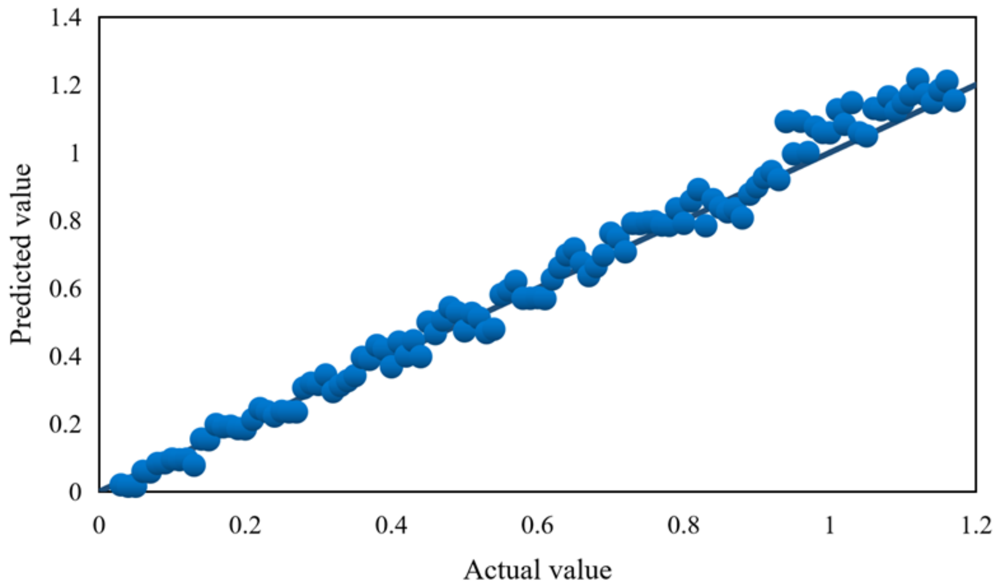
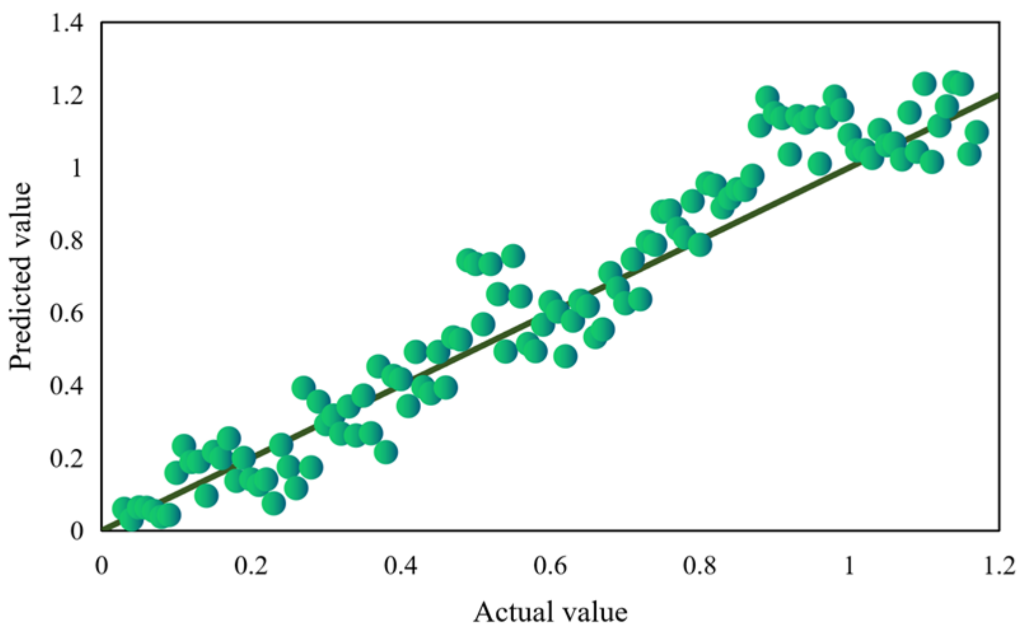


Figure 5. Scatter diagram of ID3 actual value and predicted value



efficiency, streamlines lesson durations, and ensures optimal allocation of educational resources. Within an educational framework powered by big data, Figure 6

According to the ID3 algorithm, the attribute with the largest information gain will be the root node, while the improved algorithm will take the attribute with the smallest information entropy as

Figure 6. Prediction accuracy of different algorithms in the efficiency analysis algorithm: (a) improved CF, (b) ID3

the root node. According to the gain, one must select the node and generate the decision tree. The enhanced ID3 algorithm eliminates the need for multiple log function calls. Instead of calculating the information gain, it directly selects the attribute with the lowest information entropy as the dividing attribute by comparing their respective entropies. This improves the efficiency of establishing the decision tree. The personalized recommendation platform of instructional resources integrates the service system of sharing instructional resources and personalized recommendation. The system should provide personalized service for users, recommend the required resources for users, and solve the problem of information overload in the network instructional resource system. On the basis of clustering, the recommendation model based on rating and resource attribute preference is used to recommend users, which alleviates the problem of data sparsity. For new users, their scores are predicted according to the similarity of user characteristics and information entropy.

The improved CF recommendation algorithm mainly focuses on user clustering, rating, and resource attribute preference models, when providing personalized recommendations for users with historical rating data; and it relies on user characteristics and the information entropy model to provide personalized recommendations for new users. Figures 7 and 8 show the results of comparing the ID3 model with the average absolute error and recall of the PE instructional resource recommendation algorithm used for this article.

It's easy to see from Figure 7 and Figure 8 that after many iterations, the error generated by the proposed method is obviously an improvement over that produced by the algorithm used for comparison in this analysis, with the error reduced by 26.55% and the recall reaching 95.72%, which is 12.76% higher than that of the comparison algorithm. Therefore, the sports teaching resource recommendation algorithm based on the algorithm in this paper is a reasonable and viable recommendation model, which can provide theoretical support for the construction of a smart campus and the optimization of sports teaching practice. Unlike traditional online learning resource systems, this paper's proposed personalized recommendation platform emphasizes individual learners. It recognizes the unique

Figure 7. MAE comparison

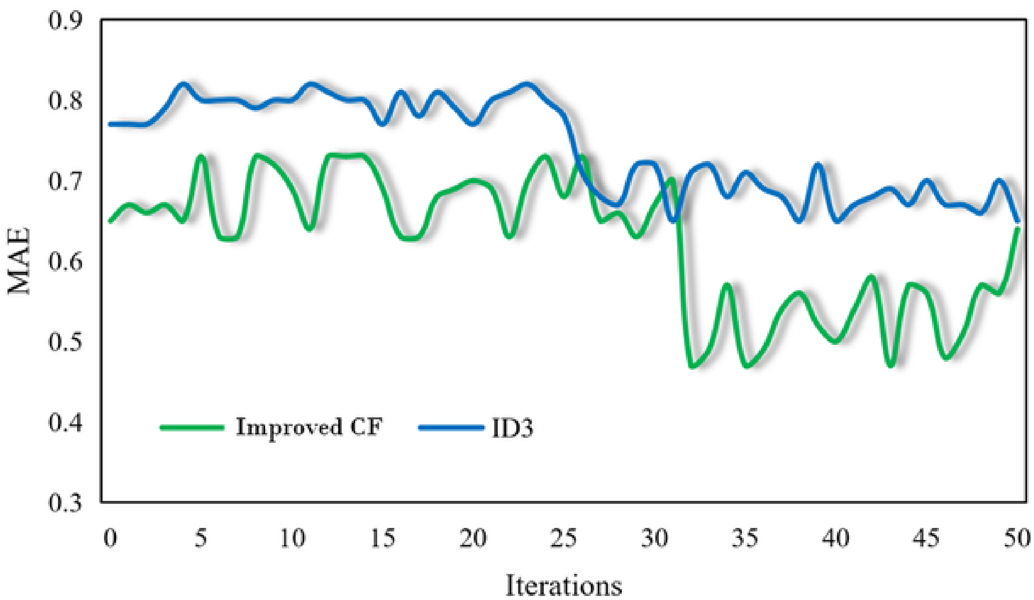
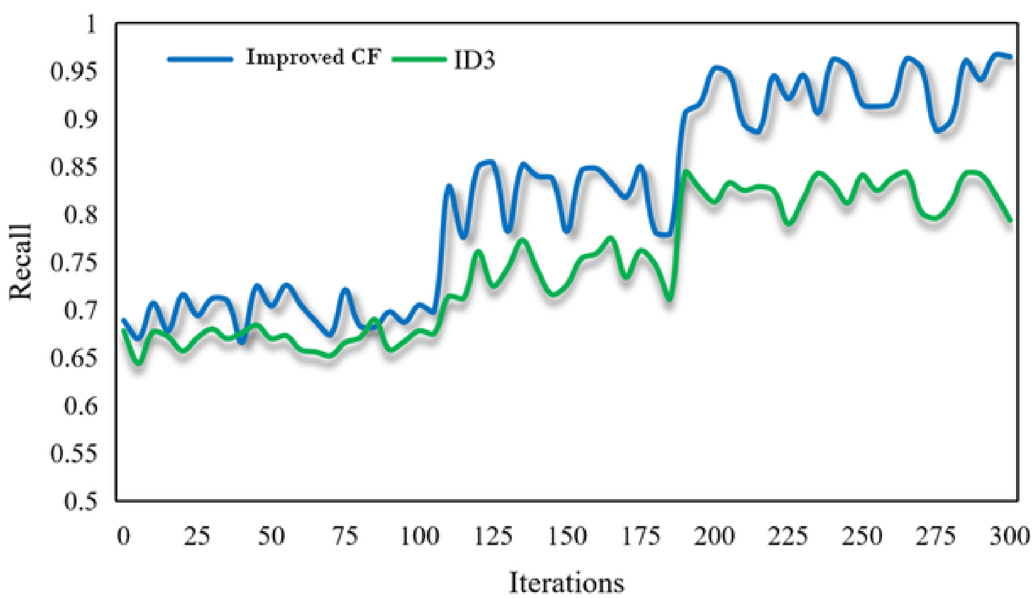


Figure 8. Comparison of recall



differences among learners and offers tailored resource recommendations to align with their interests and preferences.

Interest is a vital motivator in sports learning. PE teachers should tap into students' interests, leverage available sports equipment and facilities, and refresh classroom content. One approach is to survey students' preferences beforehand, group them based on this data, and offer targeted sports training. In the digital age, elevating the quality of physical education requires shifting from traditional teaching mindsets. Enhancing PE teachers' comprehensive skills is key. They should recognize the significance of integrating information technology into their curriculum, continuously update their knowledge, and hone their tech skills to stay contemporary and optimally support students.

CONCLUSION

In light of modern educational reforms, physical education must proactively address challenges introduced by the advent of big data to foster its evolution. We propose a recommendation model for sports digital teaching resources, integrating deep learning and the CF algorithm. This facilitates the development of a smart campus backed by big data and multimedia, enhancing the sports teaching methodology. After multiple iterations, this method's analysis error markedly outperforms its counterpart algorithm. The error is reduced by 26.55%, and the recall rate reaches 95.72%, which is 12.76% higher than the comparison algorithm. Therefore, the sports teaching resource recommendation model based on the CF algorithm is effective and can provide theoretical support for the optimization of sports teaching models.

While this study addresses personalized recommendations for physical education teaching resources, there remain areas for enhancement. The recommendation algorithm presented here primarily addresses the user cold start issue, but the challenge with new projects remains unresolved. Currently, the system recommends based on the most recent resources. Future work will require deeper exploration.

AUTHOR NOTE

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