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Article

Personalized college physical education curriculum generation via hierarchical recommendation algorithm with biomechanics-driven optimization

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Abstract: With the rapid development of modern communication technology and multimedia technology, learners can obtain various learning resources in various ways. But the problem that comes with it is to obtain the knowledge needed by learners from many resources efficiently, quickly and effectively, so as to complete the systematic study of college physical education personalized courses. Since 1980s, personalized learning and personalized service in the network learning environment have been studied accordingly. The related research involves many information science fields such as information retrieval, data mining, artificial intelligence, computer communication and network, but the research on the generation of personalized curriculum of college physical education is relatively few. This paper mainly focuses on the research and realization of personalized curriculum generation technology of college physical education, and explores the solution to realize the individualization of college physical education learning content in the process of large-scale online education. A hierarchical recommendation algorithm based on multi-dimensional feature vector is proposed, with a unique emphasis on integrating biomechanics. By analyzing biomechanical indicators like joint mobility, muscle strength, and body coordination of students, the algorithm can accurately assess their physical conditions. This integration can not only help physical education teachers make the overall teaching plan, but also meet the needs of college students' individual knowledge and ability characteristics for curriculum learning. In addition, the hierarchical implementation of the recommendation algorithm distributes the recommendation of large-scale knowledge base and resource base at different levels, which effectively reduces the dimension, reduces the amount of calculation and improves the efficiency of the implementation of the personalized curriculum generation algorithm of college physical education. Biomechanics-driven optimization ensures that the recommended courses are not only knowledge - based but also safe and effective for students from a biomechanical perspective, enhancing the overall quality of personalized PE curricula.

Keywords: hierarchical recommendation algorithm; college physical education; curriculum generation, Biomechanics-driven optimization

1. Introduction

With the rapid development of computer, Internet, and related technologies, providing personalized services in modern distance education has become one of the mainstream approaches in online learning [1]. In the context of college physical education, individualized curricula are increasingly seen as essential. The learning process should be tailored to students' individual personality characteristics and developmental potential, incorporating appropriate methods, means, content, starting points, processes, and evaluation methods to foster students' personal growth. Recent studies indicate that personalized learning in physical education not only enhances engagement but also improves long-term physical activity adherence [2]. For example, a study conducted by the National Institute of Health found that tailored exercise programs significantly increased physical activity levels among college students compared to one-size-fits-all approaches [3].

Individualized learning in physical education curricula has several key characteristics: multi-dimensional learning resources, a variety of value pursuits, unique learning styles, and an emphasis on lifelong learning, autonomy, cooperation, and inquiry-based methods [4]. However, the learning process is not merely about the educator's transmission of knowledge. It also involves a deep, individualized understanding of the subject matter. In the case of physical education, personalized learning becomes increasingly complex due to the diversity and complexity of learning data. As more data is collected from various sources, the difficulty in interpreting and utilizing this data grows.

When generating learning content for physical education curricula, several factors must be considered, including teaching objectives, curriculum requirements at different levels, the teaching syllabus, and the diverse expertise of physical education instructors. Personalized learning requires adapting to these multiple variables, especially given that curriculum resources are developed and constructed by educators from various disciplines [5]. Recent research suggests that personalized learning models based on big data analytics and machine learning algorithms can enhance the accuracy and effectiveness of these individualized curricula, addressing the growing demand for customized learning pathways in physical education.

To improve the accuracy and relevance of research in this field, this paper proposes the construction of an effective dynamic algorithm. This algorithm builds on an understanding of students and their individual learning needs within the context of physical education courses. The aim is to develop a recommendation-based system that can automatically generate and evolve physical education curricula, allowing for real-time adaptation to individual learner needs. This approach seeks to solve the challenges of large-scale curriculum generation and evolution in distance learning environments, responding to the urgent need for appropriate learning resources and addressing the gap where many instructors lack the technical expertise to develop such systems.

2. Related work

2.1. Curriculum generation based on statistical methods

Curriculum generation methods have evolved significantly, and one of the recent innovations is the use of statistical methods to optimize the learning path for learners. Traditional approaches to curriculum generation typically involve selecting concepts first and then matching each concept with appropriate learning resources. However, this method often lacks a holistic view of the curriculum structure and learner needs. To address this limitation, statistical methods offer an alternative where the learning path is constructed by calculating all possible courses for a set of concepts, and then selecting the most suitable one based on a utility function [4].

A utility function, in this context, is used to evaluate whether a particular teaching resource is appropriate for the target learners. It matches the characteristics of learning resources with those of the learners, ensuring that the resources align with their current knowledge level, learning goals, and learning preferences [3]. Instructional designers evaluate a pool of teaching resources based on their practicality, and the data derived from these evaluations are used to train and assess the utility function [6]. Once the utility function is established, the edges of the learning path graph are weighted according to the reciprocal of the utility function—meaning that more suitable teaching resources are given smaller weights. Subsequently, a minimum path algorithm is applied to identify the optimal learning path from the weighted graph.

Although this statistical approach represents an innovative advancement in curriculum generation, several challenges hinder its practical application. A primary limitation is that learning resources are often predetermined by instructional designers based on standardized learner assessments. This does not account for the fact that individual learners may have vastly different learning objectives, making a one-size-fits-all approach problematic [7]. Moreover, the model assumes that only resources with direct relationships can be grouped together in a course. However, in real learning environments, two seemingly unrelated resources may both contribute to the same learning outcome. For example, two exercises with different difficulty levels targeting the same concept may be incorrectly excluded from the same course due to the lack of a direct relationship between them [8]. These shortcomings highlight the need for more flexible and adaptive curriculum generation models that can account for diverse learner needs.

2.2. Recommendation technologies and curriculum generation

With the rapid expansion of digital learning resources, particularly online educational content, learners often face the challenge of information overload, which can lead to cognitive overload and a sense of being lost in a "learning maze" [9]. This issue is compounded by the explosion of network information, which makes it difficult for learners to efficiently access resources that match their specific learning needs. In response to this, recommendation systems have become an essential tool for personalizing content delivery, helping users navigate the vast amount of available resources by automatically recommending items based on their preferences and needs [10].

In the context of personalized learning, recommendation systems have been widely explored as a way to match learners with relevant educational resources. These systems typically rely on user models that are based on learners' interests and preferences, with recommended resources selected by measuring the similarity between the learner's interest profile and the resources available [11]. While this approach has proven effective in informal learning contexts, where the goal is to engage learners with content they are interested in, it falls short in formal learning environments. In academic education, particularly for curriculum-based learning, this method does not fully address the need for systematic learning or the achievement of predefined learning objectives within a specific subject area.

Several personalized learning models have been proposed in recent years, which aim to improve the efficiency of the curriculum generation process. These models integrate not only the learners' interests but also cognitive attributes, such as prior knowledge and learning behavior, to create a more comprehensive profile that better reflects the learner's educational needs. For instance, models based on collaborative filtering and content-based filtering are commonly used, but they face challenges in terms of scalability and adaptability to evolving learner profiles. Collaborative filtering relies on learner interactions with content (e.g., ratings, clicks) to recommend resources, but it can struggle with cold-start problems when limited learner data is available. Content-based filtering, on the other hand, uses the features of learning resources to recommend similar content, but this method often fails to account for the diverse learning styles and evolving needs of individual learners [12].

Recent advancements have sought to combine these methods with context-aware recommendation systems, which incorporate contextual factors such as time, learner's progress, and the specific goals of the learning session [13]. These systems aim to provide recommendations that are not just based on static learner profiles, but also adapt to the learner's real-time learning needs and behaviors. However, these approaches remain largely experimental and have yet to achieve widespread adoption in formal educational settings due to challenges in their implementation and the complexity of integrating diverse data sources.

2.3. Comparative analysis of personalized curriculum generation methods

The field of personalized curriculum generation is diverse, with various methods that aim to cater to individual learning needs. Traditional methods, such as heuristic-based curriculum generation, rely on predefined rules and expert input to select learning resources [14]. However, these methods often lack the flexibility to adapt to individual learners or changing learning contexts. In contrast, statistical methods provide a data-driven approach by using utility functions to evaluate the suitability of learning resources based on learner characteristics [15]. While this approach improves the adaptability of the curriculum, it still faces challenges in capturing the dynamic nature of learners' goals and the complex relationships between learning resources.

Recommendation-based methods, such as collaborative and content-based filtering, have been widely explored, but they primarily focus on interest and engagement, which may not align with formal learning objectives [16,17]. Moreover, these methods are often unable to integrate a learner's evolving needs or provide a systematic path toward achieving specific learning goals.

Hybrid models, which combine the strengths of statistical methods and recommendation systems, offer a promising avenue for improving personalized curriculum generation. These models leverage both content-based and user-based data, adapting the curriculum to the learner's preferences while ensuring alignment with predefined learning objectives. However, the complexity of integrating multiple data sources and maintaining system efficiency remains a significant challenge [18].

The proposed hierarchical recommendation algorithm, as discussed in this paper, combines these approaches by introducing a more dynamic, context-aware mechanism that adjusts learning resources based on real-time learner behavior and feedback [19]. By integrating both the learner's individual preferences and the curriculum's learning goals, this approach aims to bridge the gap between informal learning and the structured nature of academic education, offering a more effective and personalized curriculum generation process.

3. Construction of personalized curriculum generation algorithm of college physical education based on hierarchical recommendation algorithm

In the learning process of personalized physical education courses, Because of the differences among college students, there are different local learning plans and learning objectives in different learning stages.

3.1. Model overview

In order to complete the automatic generation of Web-based online courses, First of all, it is necessary to provide a platform for physical education teachers, knowledge experts and instructional designers, so that knowledge experts can build concepts in knowledge domain structure, initialize various constraints among concepts, and build knowledge domain structure diagram. Through the above work, the construction of knowledge base and resource base can be completed in the system. In the formal learning process, such as the teaching plan of a certain academic education, there are many established subjects, and the content learning of each subject is the learning of a course, which ultimately needs to reach an established ability level. This paper puts forward the recommendation process of realizing the recommendation of learning concepts and learning objects step by step, and realizing the teaching objectives of physical education teachers and the learning needs of college students' personalized physical education courses separately. That is, a hierarchical implementation structure based on recommendation algorithm, which divides the implementation of sports personalized curriculum recommendation algorithm into three layers. The specific structure is as follows:

The first layer: the overall teaching plan for physical education teachers, extracting concepts related to curriculum subject keywords from the system knowledge base, and inheriting the existing relations in the knowledge base, constitutes a knowledge structure diagram based on teachers' teaching plan, that is, the knowledge base of physical education courses.

The second layer: based on the target users of physical education curriculum, that is, the initial personality characteristics of students, on the one hand, the personalized knowledge structure diagram composed of concepts and relationships suitable for users' current knowledge and ability level is filtered from the curriculum knowledge base;

The third layer: based on the personalized knowledge structure diagram, extracting the learning objects related to the concepts in the current knowledge diagram, and forming a structured college physical education personalized curriculum.

Figure 1 shows the structural framework of the personalized course recommendation algorithm, which is divided into three levels.

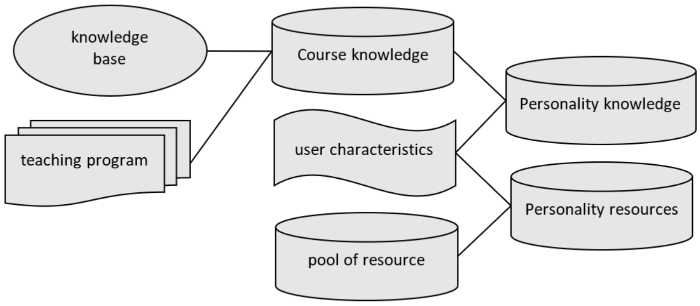

Figure 1. Schematic diagram of the structural framework of hierarchical recommendation algorithm.1

3.2. Personalized curriculum generation algorithm of college physical education based on hierarchical recommendation algorithm

This chapter will propose three algorithms to be defined according to the following contents, namely, the algorithm for generating physical education curriculum knowledge structure oriented to the overall goal and initial personality characteristics (Algorithm 1), the algorithm for generating personalized knowledge structure based on personality knowledge characteristics (Algorithm 2), and the algorithm for generating learning objects based on user personality characteristics (Algorithm 3).

3.2.1. Algorithm for generating knowledge structure of physical education curriculum oriented to overall goal and initial personality characteristics

When a teacher needs to offer a new personalized physical education course for students, First of all, physical education teachers are required to set teaching plans and submit teaching documents in a certain format according to the requirements of personalized college physical education courses, According to the teaching plan, the system can tailor a concept set suitable for teachers' needs, including the set of knowledge points needed to complete the target learning of the course, and the local learning objectives for each knowledge point, such as general mastery (basic learning), proficiency mastery (applied learning) or in-depth mastery (discovery learning) [20]. This process is equivalent to formalizing the teacher's teaching plan through the concept map of knowledge structure and the conceptual metadata model predefined by the system, which lays a good foundation for the next personalized recommendation.

The teaching plan of PE teachers is divided into several records according to the format, each record is represented as an independent document, and the concepts in the knowledge base are regarded as characteristic keywords. The recommendation algorithm is based on TF-IDF method to generate feature keywords for the needs of college physical education teachers. The algorithm described here is oriented to the teaching plan made by physical education teachers according to the level of target learners and the ultimate degree goal, and extracts the knowledge structure diagram of specific university physical education courses from the system knowledge base.

The system knowledge base is a concept map containing concepts and their mutual constraints, which is expressed by binary groups as:

$$\text{Knowledge Domain} = \{C, R\} \tag{1}$$

They are expressed by different keywords as:

$$C = (c_1, c_2, \cdots, c_N) \tag{2}$$

3.2.2. Personalized knowledge structure generation algorithm based on personality knowledge characteristics

Using algorithm 1, we get the knowledge domain of a course facing the target needs of physical education teachers. However, when teachers make teaching plans, Only the group goal characteristics of the target learners can be considered, For example, the educational level requirements, the overall average knowledge level, and the general evaluation of the learning ability of the group, etc. However, in the large-scale personalized physical education curriculum learning, the individual level and ability differences of each learner cannot be reflected in this teaching plan, and teachers cannot make different teaching plans for different learners. However, due to the individual differences of learners, from the beginning of learning to the whole learning process, the learning content and learning methods are different. Therefore, at the beginning of learning, it is necessary to generate courses for different learners to adapt to their initial knowledge background and ability level.

Among them, the difficulty coefficient is used to weigh the learning difficulty of concepts and match the learning ability of learners; The time coefficient is used to weigh the time needed for concept learning and match the learner's goal; Type parameters are used to weigh the goals of concept learning and match the goals of learners. The target user of the course, that is, the model of learners, is defined as before. According to the pre-test results, after collecting data and analyzing, the preparatory knowledge level and learning ability of learners before learning the course are obtained, and their learning goals are obtained by displaying feedback, as shown in **Table 1** below. The goal of user model definition in this paper is to match user characteristics with concept characteristics and resource characteristics adaptively from different angles.

Table 1. User personality trait model.1

User Personality Trait Model	$User_1$	$User_2$	…	$User_i$	…	$User_n$
Conceptual feature C	c_1	c_2	...	c_i	...	c_n
Knowledge feature S	s_1	s_2	...	s_i	...	s_n
Competency characteristic B	b_1	b_2	...	b_i	...	b_n
Target feature O	o_1	o_2	...	o_i	...	o_n

Conceptual Features: These are related to the learner's cognitive understanding of core concepts. We quantify them through self-assessment surveys where learners rate their understanding on a standardized scale. Additionally, concept maps or open-ended assessments are analyzed to measure the learner's ability to link and organize concepts.

Knowledge Features: These refer to the learner's factual and procedural knowledge. We quantify these through scores from knowledge tests designed to assess subject mastery. Data from Learning Management Systems (LMS), such as assignment completion rates and quiz scores, are also used to measure the learner's knowledge progression.

Other Parameters: Additional learner traits, such as learning preferences and behavior patterns, are captured through analytics from online interactions, including participation in discussions or response times to assignments. These data points are integrated into the model to offer a more holistic view of the learner.

Based on the above definition, the conceptual model for designing Algorithm is as follows:

Set the curriculum knowledge structure as follows:

$$KD' = \{C', R'\} \tag{3}$$

For the target user *U*, the user descriptions based on knowledge characteristics and ability characteristics are as follows:

$$S^u = (s_1^u, s_2^u, \cdots, s_n^u) \tag{4}$$

$$B^u = (b_1^u, b_2^u, \cdots, b_n^u) \tag{5}$$

For the *n* concepts in the curriculum knowledge concept map, the features based on difficulty coefficient are described as:

$$Cdif = (cdif_1, cdif_2, \cdots, cdif_n) \tag{6}$$

3.2.3. Learning object generation algorithm based on user personality characteristics

Applying algorithm 1, we get the set of curriculum concepts which is suitable for the teaching plan of college physical education teachers, and algorithm 2 recommends the personalized knowledge domain which is suitable for learners' personality characteristics. The course content is composed of a series of learning objects that support concept learning. Therefore, this section uses the relationship between concepts and learning objects to further recommend the appropriate set of learning objects and generate a structured course. The algorithm realizes the third and fourth steps of hierarchical recommendation.

Step 1: According to the association matrix established between each learning object r_i in the learning resource set and each concept c_i in the concept set, an association matrix based on the learning resource and the concept sequence is generated, then the association relationship vector between a learning object in the curriculum resource and the concept in the concept sequence can be expressed as:

$$r_i^u = (v_{i1}^u, v_{i2}^u, \ \cdots, v_{ip}^u) \tag{7}$$

The second step is to generate a learning object set supporting the target concept set according to the association relationship, and calculate the association degree between the learning object and the concept set:

$$\eta_{ip}^{u} = \sum_{k=1}^{p} v_{ik}^{u} \tag{8}$$

$$R' = \{r_i | r_i \in R, r_i^u \in R, \eta_{ip}^u \neq 0\} \tag{9}$$

Step 3: Based on the ability characteristics of users' personality characteristics, the learning object resource set is generated. By finding the distance between the ability feature vector in personality characteristics and the feature vector of each learning object, the learning objects exceeding a certain threshold are eliminated. The difficulty of learning resources is consistent with the characteristics of users' abilities, that is, when the distance is equal, the learning objects have better adaptability; However, the difficulty of learning resources is too simple or too difficult compared with the user's ability, which is a resource with poor adaptability and is not suitable for generating courses.

Step 4: Based on the target characteristics in the user's personality characteristics, further filter and generate the learning object set; By calculating the distance between the user's target feature vector and the learning object type feature vector, the learning objects whose distance exceeds a certain threshold are further eliminated, and finally the suitable concept set is obtained.

Feature extraction from the teachers' teaching plan documents is achieved through the application of the TF-IDF (Term Frequency-Inverse Document Frequency) method. This method is widely used in text mining and natural language processing to evaluate the importance of words in a document relative to the entire corpus. TF-IDF helps to highlight terms that are significant to specific documents while down-weighting common terms across the entire dataset.

The TF-IDF method consists of two main components:

Term Frequency (TF): This measures how frequently a term appears in a specific document. The assumption is that the more often a term appears in a document, the more important it is to that document. The term frequency is calculated using the formula:

$$TF(t,d) = \frac{\text{Number of times term} t \text{appears in document} d}{\text{Total number of terms in document} d} \tag{10}$$

where t represents the term and d represents the document.

Inverse Document Frequency (IDF): This measures how important a term is within the entire document corpus. Words that appear frequently across many documents are given less weight, as they are less informative about any specific document. IDF is calculated using the formula:

$$IDF(t,D) = \log\left(\frac{|D|}{1+\mathrm{DF}(t)}\right) \tag{11}$$

where $|D|$ is the total number of documents in the corpus, and DF(t) is the number of documents containing the term t. The formula ensures that terms appearing in many documents (and thus are less informative) receive a lower IDF score.

TF-IDF Weight Calculation: Finally, the TF-IDF weight for each term is calculated by multiplying the Term Frequency (TF) and the Inverse Document Frequency (IDF):

$$\begin{aligned} TF-IDF(t,d,D) &= TF(t,d)\text{-}IDF(t,D)\text{TF-IDF}(t,d,D) \\ &= TF(t,d)\times IDF(t,D)TF-IDF(t,d,D) \\ &= TF(t,d)\text{-}IDF(t,D) \end{aligned} \tag{12}$$

This value reflects the importance of the term in the document, considering both its frequency within the document and its rarity across the document corpus. Higher TF-IDF scores indicate more important terms for a specific document.

4. Analysis of experimental results

4.1. Overview of experimental process

In order to test and verify the hierarchical recommendation algorithm, we first organize teachers engaged in physical education to build a domain knowledge base in the system, and build a knowledge base with 849 knowledge points on 100 topics in the field. According to PCG-LRS algorithm, it needs to be realized hierarchically to realize individual courses for 100 college physical education students, and at the same time, it needs to complete the learning objectives stipulated by the teaching plan formulated by physical education teachers.

Through algorithm 1, the personalized curriculum generation for college physical education teachers is completed. The distance between the curriculum generated by teacher feedback and its expected curriculum is evaluated by double evaluation of knowledge domain and learning resources, and each knowledge point (concept) and each learning object are evaluated respectively. Finally, the average absolute deviation is obtained, thus judging the accuracy of algorithm 1. On the other hand, Choose a physical education course, Select 100 students to study this course, Through the distance between the curriculum generated by the student feedback system and its expected curriculum, and through the double evaluation of knowledge domain and learning resources, each concept and each learning object are evaluated respectively, and finally the average absolute deviation is obtained, so as to judge the accuracy of the above algorithm 2 and algorithm 3 for personalized curriculum of college physical education.

4.2. Verification of experimental results

4.2.1. The value of threshold d varies the accuracy of the algorithm

The threshold d controls the sensitivity of the algorithm in connecting learning resources. In Algorithm 1, a concept subset related to the teaching plan documents is recommended from the knowledge base. The effectiveness of the algorithm is largely determined by whether the concept subset meets the teachers' teaching objectives and requirements. The weight of the concept subset C in the knowledge base to the teaching plan document D is the basis for the implementation of the algorithm. Therefore, different values for the weights are tested in the experiment to detect teacher satisfaction with the results, and a threshold d is set for the algorithm. If d is too high, only highly similar resources are connected, potentially missing relevant but less obvious connections. Conversely, a very low d results in overly broad connections, leading to a dense graph of unrelated resources that could reduce the quality of recommendations. The choice of d should reflect the distribution of resource similarities, balancing meaningful connections with flexibility to adapt to various teaching needs. A threshold that is too stringent may limit the algorithm's ability to identify diverse but valuable learning paths, while a threshold set too leniently risks recommending irrelevant or redundant resources, reducing the overall effectiveness of the curriculum.

The analysis of different threshold settings, therefore, aims to identify the optimal balance between specificity and comprehensiveness. As d determines the minimum similarity required for linking resources, its value directly influences both the precision of the recommendations and their diversity. By fine-tuning d, the algorithm can be adapted to different teaching contexts, ensuring that the recommended concept subsets not only meet the teacher's learning objectives but also provide a broad enough range of resources to foster a comprehensive learning experience.

According to the evaluation of the generated curriculum concept domain by 16 teachers, the average deviation when setting different thresholds is calculated as shown in **Table 2**.

Table 2. The influence of threshold value in algorithm 3–1 on the accuracy of the algorithm.2

Syllabus	$\boldsymbol{Avg_d}$	$\boldsymbol{1.5Avg_d}$	$\boldsymbol{2Avg_d}$	$\boldsymbol{2.5Avg_d}$	$\boldsymbol{3Avg_d}$	$\boldsymbol{3.5Avg_d}$
D1	0.52	0.63	0.89	0.87	0.78	0.6
D2	0.37	0.58	0.78	0.85	0.81	0.59
D3	0.42	0.61	0.85	0.83	0.78	0.71
D4	0.42	0.52	0.87	0.84	0.79	0.56
D5	0.39	0.59	0.79	0.8	0.71	0.61
...	...	...	...	...	...	...
D15	0.29	0.45	0.69	0.85	0.75	0.63
D16	0.43	0.59	0.82	0.86	0.69	0.68
Average	0.43125	0.5775	0.805	0.84125	0.75375	0.64

The experimental results are shown in **Figure 2**. When the threshold is taken as the average weight, that is to say, when the weight of the concept for the teaching plan is greater than the average weight, that is, it is recommended as the curriculum knowledge domain, the teacher's overall satisfaction with it is only 43%; When the threshold value increases to 1.5 times, 2 times and 2.5 times of the average weight value, teachers' satisfaction with the generated curriculum knowledge domain increases continuously; However, when the threshold value continues to increase, reaching 3 times and 3.5 times of the average weight value, the satisfaction of the corresponding generated curriculum knowledge domain is declining. Therefore, according to the experimental results, the threshold value is $2.5Avg_d$ in this paper.

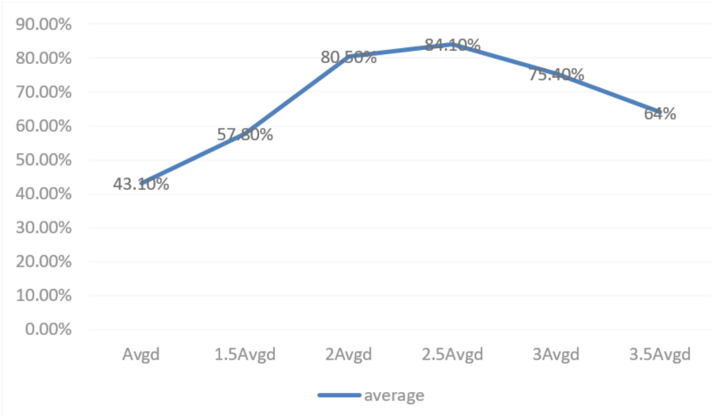

Figure 2. Effect of threshold d in algorithm 3–1 on algorithm accuracy.

To further demonstrate the effectiveness and innovation of the proposed hierarchical recommendation algorithm, we conduct a comparative experiment with traditional recommendation algorithms, such as Collaborative Filtering (CF) and Content-Based Filtering (CBF). The comparison focuses on key performance metrics, including recommendation accuracy, computational efficiency, and adaptability to personalized curriculum generation. As shown in **Table 3**, the performance comparison of different recommendation algorithms reveals that our hierarchical recommendation algorithm outperforms both CF and CBF in terms of precision, recall, and F1-score.

Table 3. Performance comparison of different recommendation algorithms.

Algorithm	Precision	Recall	F1-Score
Hierarchical Recommendation	0.92	0.89	0.90
Collaborative Filtering (CF)	0.80	0.78	0.79
Content-Based Filtering (CBF)	0.85	0.82	0.83

The hierarchical recommendation algorithm outperforms both CF and CBF in terms of precision, recall, and F1-score. This demonstrates its superior ability to generate personalized curricula tailored to individual learner profiles. Unlike CF, which suffers from high computational costs in large datasets, the hierarchical approach achieves a good balance between accuracy and computational efficiency, making it scalable for large-scale educational environments.

4.2.2. Students' evaluation of curriculum generated by different methods

In algorithm 2, because learning content is not easy, too difficult or too easy, it is necessary to calculate the difference between the user's ability vector and the difficulty coefficient vector of the concept subset generated by the concept. The calculation method of this difference plays a key role in the whole algorithm and is very important for the accuracy of algorithm recommendation. And when measuring fitness, the distance is the smallest in theory, which means that the average difficulty of the concept set is closest to the user's ability and is most suitable for users 13. During the study period, every student hopes to realize himself through certain challenges, which is also one of the important contents of the personalized university sports curriculum.

However, the difficulty setting still needs to take students 'acceptance ability and level as a reference to maximize students' recognition of the course. Therefore, it is more appropriate to choose a difficulty distance slightly higher than the minimum value. How to get a suitable value is the goal of this experiment. Therefore, 100 students participated in the experiment. The students were randomly divided into 4 groups with 25 students in each group. Different methods were adopted for different groups of students, and the average accuracy of each group of course recommendation was obtained through the actual feedback of students. According to the evaluation data of each student in the first group on the concept subset generated by different strategies, the results of "average difficulty deviation" of each strategy are shown in **Table 4**.

Table 4. Statistical results of the first set of feedback data.3

Method	**1. Minimum absolute ability deviation**	**2. Hard**	**3. Easier**	**4. Most similarity**
S1	0.55	0.85	0.63	0.5
S2	0.47	0.93	0.4	0.41
S3	0.51	0.88	0.41	0.46
S4	0.56	0.81	0.43	0.43
S5	0.39	0.84	0.45	0.4
...	...	...	...	...
S24	0.53	0.7	0.54	0.41
S25	0.61	0.87	0.6	0.65
Average	0.5252	0.7936	0.5032	0.4868

From the comparative data, we can see that the fourth strategy, that is, the "most similar" strategy, has the smallest deviation in average difficulty, that is to say, the easier strategy is the recommended strategy that is more suitable for the first group of students.

The statistical results of feedback data from four groups of students on different strategies are shown in **Figure 3**.

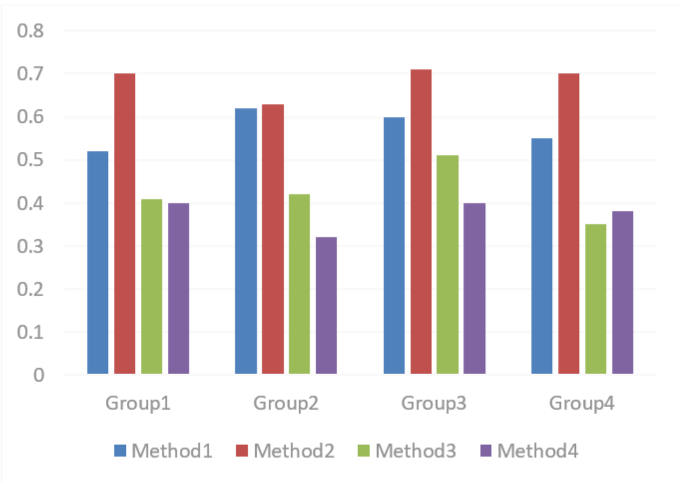

Figure 3. Comparison of evaluation data of different groups of students on courses generated by different methods.

Figure 3 presents the statistical analysis of feedback from four groups of students who evaluated different recommendation strategies. The results clearly show that the majority of students across all groups found Method 4 to be the most suitable recommendation strategy. This method, characterized by its alignment with student preferences and learning styles, consistently received the highest ratings in terms of satisfaction and perceived effectiveness.

The feedback data reveals that students generally agreed that the strategy used in Method 4 most closely matched their learning needs, as indicated by the higher positive feedback scores compared to other methods. While other strategies also garnered favorable responses, Method 4 stood out for its ability to provide tailored, relevant content that resonated with students' individual learning goals.

4.2.3. Evaluating strategies for learning objects

In order to determine what kind of learning resources learners are satisfied with, this experiment first defines the difficulty level. First, we define the distance between the difficulty of learning object r_i^u and the learning ability of the concept c_i^u that students need to know about this object d indicates the learning ability gap:

$$d = dif_{r_i^u} \times 2/10 - b_{c_j^u} \tag{13}$$

Redefine the difficulty level as shown in **Table 5** below:

Table 5. Learning object difficulty definition.4

Difficulty level	Difficulty description	Learning ability gap for learning objects
"−2"	Relatively easy	[−0.25, −0.15]
"−1"	Slightly easy	[−0.15, −0.05)
"O"	No difficulty	[−0.05, 0.05]
"1"	Slightly difficult	(0.05, 0.15)
[2]	It's more difficult	(0.15, 0.25)

Then, the students are divided into five groups, each group generates learning resources with different difficulties, and the students evaluate the satisfaction of each learning object. Considering that students may be satisfied with each learning object in the generated learning resources, but they are not satisfied with these resources and hope for more resources, students are invited to make a comprehensive evaluation and give suggestions.

Local satisfaction: The evaluation of college students' satisfaction with each learning object in the course generated by the system.

Global satisfaction: The evaluation of college students' overall satisfaction with the learning resources of the generated courses.

Mean of local satisfaction within the group: the average value of local satisfaction evaluation of each university student in the group.

Intra-group average global satisfaction: the average value of global satisfaction evaluation of all college students in the group.

The results are shown in **Table 6**. After comprehensive consideration, we selected all the learning resources with difficulty "0" and difficulty "1".

Table 6. Statistics of college students' feedback information on the difficulty of learning objects.5

Group	Average local satisfaction	Average global satisfaction	Recommendations
Group "−2"	0.45	0.52	Too simple, not helpful
Group "−1"	0.65	0.61	It is easier to learn, and I hope to improve more
Group "O"	0.89	0.68	Resources with appropriate difficulty and hope to expand more
Group "1"	0.85	0.76	The difficulty is appropriate, and the basic exercises are a little less
Group "2"	0.77	0.79	It's difficult. I hope to have more basic exercises

5. Conclusion

With the rapid development of modern communication technology, multimedia technology and Internet technology, learners can obtain various learning resources through various quick and convenient ways, but the following problem is how to ensure the accuracy of resources, so as to complete the learning of physical education personalized courses in formal learning. Through the combined application of content-based recommendation and recommendation algorithms, This paper puts forward a college physical education personalized curriculum generation (PCG-LRS) algorithm based on multi-dimensional feature vector hierarchical recommendation algorithm, According to the college PE specialization course algorithm proposed in this paper, the course knowledge base is constructed, and the students' knowledge characteristics are analyzed, and further realize the personalized curriculum generation in the preparation stage. This method not only satisfies the overall teaching plan made by physical education teachers to help teachers realize the automatic generation of courses, but also meets the needs of college students' individual knowledge and ability characteristics for curriculum learning. In addition, the layered recommendation algorithm distributes the content recommendation of large-scale knowledge base and resource base at different levels, and divides the recommendation algorithm of college physical education personalized course into several steps, which effectively reduces the dimension, reduces the calculation amount and improves the implementation efficiency of the algorithm of college physical education personalized course generation.

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