HYBRID PERSONALIZED RECOMMENDATION MODEL FOCUS ON IMPROVED COLLABORATIVE FILTERING

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ABSTRACT

In recent years, the popularity and acceptance of online education and large-scale open online courses (MOOCs) have significantly increased. The widespread acceptance of the Internet education model has led to the emergence of various educational platforms. With the continuous improvement of online education systems, more and more courses have been added to online education platforms, expanding the group of learners who can benefit from online education. This article aims to improve personalized recommendation algorithms based on collaborative filtering to better meet the needs of users. Firstly, various recommendation technologies and algorithms currently used in recommendation systems were introduced, highlighting their respective advantages and disadvantages. This model can learn the historical behavior of users and generate personalized recommendations based on their interests and preferences. In our research, we found that collaborative filtering technology has high accuracy in recommendation systems, but there are also some limitations, such as sparsity and cold start issues. In order to address these issues, in this study, the Learning Resource Model (LRM) and Learner Model (LM) were combined into collaborative filtering algorithms to create a Hybrid Personalized Recommendation Model (HPRM). Experimental results show that our hybrid recommendation model outperforms traditional collaborative filtering methods in terms of accuracy, recall, and F1. In addition, our model can effectively handle sparsity and cold start issues, thereby improving the performance of the recommendation system. In summary, our research provides an effective hybrid recommendation method for the field of recommendation systems and provides useful references for future research.

Keywords: *Learning Process Optimization, Personalized Recommendation, Cognitive Diagnosis, Collaborative Filtering, Hybrid Personalized Recommendation System.*

1. INTRODUCTION

In the current education field, educational resources are continuously expanding, and with the development of the internet, education has transitioned from traditional classroom-based learning to online education. Especially after the outbreak of the COVID-19 pandemic, when face-to-face learning was not possible, online learning has become the preferred mode of education, and the use of online education platforms is increasingly accepted by learners. Data shows that as of December 2022, the user base of online education in China has reached 312 million, accounting for 31.6% of the total internet population in China [1]. This figure peaked in March 2021, reaching 413 million, accounting for a total proportion of 46.8% [2]. The current educational resources can be said to be in a stage of expansion, which often leads to information overload for learners. How to extract useful resources from the vast and complex educational resources has become a question confronting many users.

In this study, propose a hybrid personalized recommendation model based on an improved collaborative filtering approach. To address the limitations of traditional collaborative filtering methods in dealing with sparsity and cold-start issues, we adopt a hybrid model that combines a learner model and a learning resource model.

Specifically, the learning resource model consists of three components: Tag-based Feature Representation of Learning Resources, Bloom's Education Based Labelling, Educational Objectives, and Cognitive Diagnostic Labelling. The learner model includes Learning Style, Knowledge Level, Learning Behavior, and interest Preference. Experimental results show that our method achieves significant performance improvements on multiple datasets, outperforming traditional collaborative filtering methods and other deep learning-based recommendation models.

1.1 Problem Statement

Through the platform's search function can retrieve information, in the search bar to enter the desired search keywords, the search engine will be the results of feedback to the user, but the actual situation, most of the time, the search results are not what need, cannot get 100% to their own interest in the video, sometimes to the search keywords repeatedly search for many times, the user also did not get the resources he wanted, thus having to admit that the search is a failure, so although the search engine is to some extent helpful, but most of the time, the face of the resource fog, the user will still be overwhelmed [3]. Most current recommendation systems take the simpler approach of filling the user-item matrix with a predetermined value that averages the user's ratings of all items. Although this method has improved the final recommendation results, after filling the matrix with values, the matrix can no longer fully reflect the user's preferences, resulting in poor recommendation quality of the final recommendation system [4].

There is no doubt about the importance of accuracy in a recommendation system. A recommendation system that recommends items to users that mostly do not meet their needs that will continue to lose users. However, purely accuracy-based metrics have a negative impact on the recommendation system and may result in users receiving less and less information in subsequent accurate recommendations, ultimately narrowing the user's field of vision [5].

The point of view of the problem statement under discussion can be further understood in the following introspective.

1. How to discover the characteristics of learners' interests, recommend learning resources according to the characteristics, and promote the improvement of professional skills and career development?

2. How to process features based on learners' behavior information to optimize the personalized recommendation efficiency of the system?

3. How to break the old model of traditional e-learning system, design a learner-centered and personalized e-learning system, and improve the accuracy and satisfaction of personalization promotion?

1.2 Research Motivation

Personalized adaptive learning is based on differences in learners' personality traits and can provide different learning services for different learners. It can be seen that the change from active search by learners to automatic recommendation by the learning system is an inherent requirement to realize personalized adaptive learning. At present, the growth rate of educational resources has been high, and with it, the problems of information overload and learning lost. Instead of meeting learners' needs for personalized learning, the vast number of digital resources has led to the embarrassing situation of more and more learning resources, but harder and harder to find learning resources for learners themselves.

To address the above issues, this paper proposes a personalized recommendation algorithm that improves on the user-based collaborative filtering recommendation algorithm by incorporating a learning resource model and learner model, improving the accuracy of user similarity calculation, and introducing the object attribute matrix and rating mapping module into the recommendation process, thereby improving the accuracy of personalized teaching resource recommendations.

1.3 Research Objectives

With the rapid development of information technology constantly updated and iterated, changing the way of life of people and the traditional mode of education. For example, data mining technology can be used in the education sector to analyses students' learning patterns, explore the potential value of the MOOC curriculum and build a personalized learning environment for students. With the support of China's education policies, the development of education informatization is becoming more and more complete and widespread, making the construction of online education platforms and courses increasingly mature, and based on this, online teaching models such as catechism are gradually gaining widespread attention and participation, all of which provide fundamental data support for the development of learning analytics [6].

At the same time, the development of network technology, personalized recommendation technology, the embedding of new teaching models, the promotion of advanced teaching concepts, the diversification of interaction methods, and the return of data analysis technology have all played a relevant

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and important role in the creation and development of learning analytics technology.

This paper uses this feature to optimize the algorithm to optimally classify users by their background information and to achieve an efficient and accurate recommendation service. This research embarks on the following objectives:

1. To study on user modelling techniques and collaborative filtering recommendation algorithms.

2. To develop and implement a hybrid model that classifies learners using an improved collaborative filtering algorithm.

3. To test and evaluate the performance of the proposed hybrid model in terms of the success rate of the recommended results.

2. LITERATURE REVIEW

The first example of collaborative filtering, and the origin of the term, was the Tapestry system developed by Xerox PARC, which allowed its users to make notes and comments on the documents they were reading [7]. Thus, not only can users use the content of the document to manually narrow their search, but they are able to rank subject documents based on their relevance and usefulness once the appropriate number of users has been reached, based on the notes and comments of other users [8]. The collaborative filtering algorithm constructs a recommendation model from a user's previous browsing history of item objects to make recommendations, and the final page's recommendations have a great deal of similarity to the user's previous purchase history. The first personalized recommendation systems were introduced at the Artificial Intelligence Society in the USA and were named LIRA [9]. Personalized recommendation systems are a significant improvement over traditional recommendation systems in terms of providing personalized product recommendations to users. Not only can the recommendation system recommend similar products, but it can also recommend products that the user may be interested in, but that the user has not purchased before, greatly increasing the novelty of the product.

A personalized recommendation system is a data mining platform based on massive amounts of data and is a key component of a recommendation system. A customized recommendation system can predict the preferred content of a target user based on the various information they provide and find the right information from the huge amount of data efficiently, reducing time wastage.

2.1 Personalized Recommendation Theory

Personality is the sum of specific and stable physiological and psychological characteristics with certain tendencies and dynamics that are formed by individuals on the basis of their genetic heritage and subject to the constraints of their social life environment. Personalized learning means that students are able to choose their own learning content and learning path according to their own personality characteristics and needs. By analyzing the learner's learning style, interests and environment, students are provided with learning content and learning methods that match their own characteristics. It provides students with content and learning methods that are tailored to their individual characteristics [10].

2.2.1Characteristic representation of learning styles

The earliest theory of learning style was proposed by David Kolb [11]. It reflects the physiological and psychological needs of learners, and the study of learning styles provides a basis for the personalized requirements of learner models. Based on the Felder-Silverman learning style model and using the Index of Learning Style Questionnaire (LSQ) as a tool, learners' learning styles are quantified in four dimensions: perception, input, processing, and understanding [12].

At the data collection layer, each new learner must complete a learning style questionnaire, and the results of the LSQ questionnaire are sent to the data and analysis layers to construct learning style features at the representation layer. The specific process of quantification of learning style characteristics is as follows:

Represent the learning style quantification results in the form of a quadruplet $<L, V>$ ($i= \{1, 2, 3, 4\}$).

L, denotes the 4 dimensions of LSQ; V denotes the quantified value of learning style tendencies under the L, dimension, which is defined formally as $Ls= \{(<L1, V1>, <L2, V2>, <L3, V3>, <L4, V4>)\ V \in [-1,1]\}$. Learners fill in the LSQ scale with 44 questions, each containing two options A and B. The value of the answer result is defined as P, where j denotes the question number. The results were filtered and processed according to P, categorize and totaled with the final totaled results denoted by a and b.

Judgement of the magnitude of the values of a and b. If $a>b$, $V=(a-b) *a$; if $a<b$, then $V=(b-a) *a$.

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The test result quadratic Ls of learning style traits is then the quantified result of the learner's learning style traits.

As an important indicator of students' individuality and differentiation, learning style largely influences students' interest and effectiveness in learning, and thus the theoretical guidance of learning styles for online guidance systems cannot be ignored. Students' learning styles are a key factor in the learner profiling phase. In this study, the index of learning style questionnaire (LSQ), which accompanies the Felder-Silverman learning style, will be used to measure students' learning styles. When new users enter the system, they need to fill in the index of learning style questionnaire, thus solving the problem of cold start, which leads to no rating and no recommendation.

2.2 Bloom's Theory of Cognition

Bloom's theory of cognition, also known as Bloom's taxonomy, is a framework for categorizing educational objectives and learning outcomes. The theory was developed by educational psychologist Benjamin Bloom and his colleagues in the 1950s, and it has since been widely used by educators to design and assess instructional activities [13]. The cognitive domain of Bloom's taxonomy consists of six levels of cognitive complexity, arranged in a hierarchical order from lower-order thinking skills to higher-order thinking skills. The six levels are: Remember, Comprehension, Application, Analysis, Evaluation and Create, as shown in Figure 1.

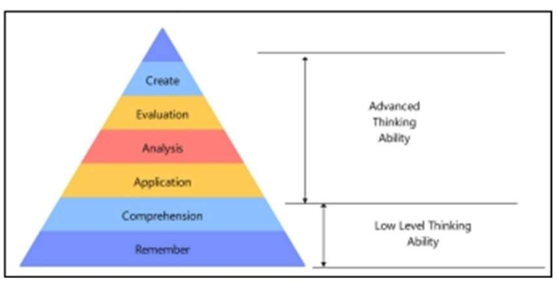

Figure 1: Bloom's Theory of Cognition

2.3 Collaborative Filtering

Collaborative filtering (CF) is a technique used in recommender systems to predict the interests of users by analyzing their interactions with a set of items and the interactions of similar users [14]. The goal of collaborative filtering is to provide personalized recommendations to users based on their past behavior and the behavior of similar users.CF is one of the most widely used and successful recommendation techniques in practice and it has been used in various fields such as e-commerce, social media, music, movies. There are two (2) basic recommendation methods in collaborative filtering, namely user-based recommendation and item-based recommendation, which are described in detail below.

2.3.1 User-based collaborative filtering recommendation

The core idea of User-based Collaborative Filtering Recommendation consists of two (2) points:

First, the similarity between users is calculated using their historical data; secondly, the target user's preference for these items is predicted based on the ratings of the items by users with higher similarity to the target user. The information in the figure shows that learner A chooses learning resources A and B, learner B chooses learning resource B, and learner C chooses learning resources A, B and D. From these user choices, can find that learner A and learner C have similar preferences, and learner C also likes learning resource D. Then the system can infer that learner A may like learning resource D, so resource D can be recommended to learner A [15].

while the User-based Collaborative Filtering mechanism calculates the similarity of users based on their historical preference data. The principle of recommendation is shown in Figure 2.

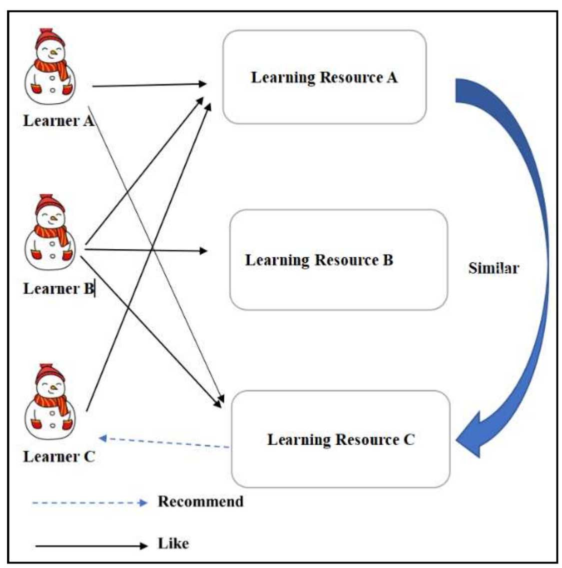

Figure 2: User-based Collaborative Filtering Based Recommendation

2.3.2 Collaborative Item-Based Filtering Recommendations

The item-based collaborative filtering recommendation is similar to the user-based

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collaborative filtering recommendation in that it first calculates the similarity between items, and then recommends the items that are similar to the target user's selection [16]. Learner A chooses resources A and C, learner B chooses resources A, B and C, and learner C chooses resource A. From the historical preferences of these learners, we can assume that learning resource A and learning resource C are relatively similar since both learner A and B like learning resource C. Based on this judgment, we can presume that learner C may also like learning resource C. Therefore, the recommendation system recommends learning resource C to learner C. Item-based collaborative filtering recommendations and content-based recommendations are similar in that they are both based on the similarity of items, but they differ in the method of calculating the similarity, as content-based recommendations obtain information about the attributes of the items themselves, while item-based collaborative filtering recommendations are judged from the user's historical preferences.

Figure 3 shows the basic principle of the item-based collaborative filtering recommendation mechanism.

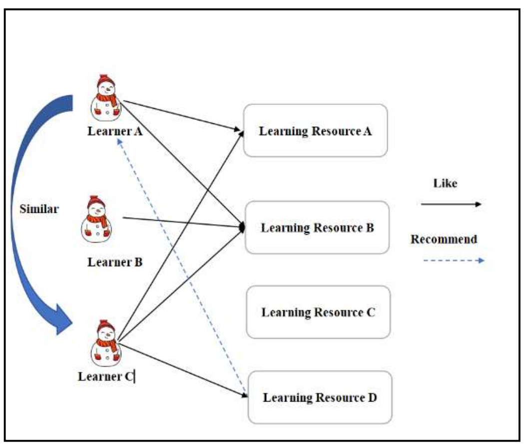

Figure 3: Item-based Collaborative Filtering Based Recommendation.

3. METHODOLOGY

Data extraction and learning style testing must be combined with system models or techniques to generate accurate algorithms and provide an efficient process. A comprehensive step-by-step research procedure was designed that considered the correlation between each research objective, the designation of the research process, and the designation of the research results for the research outcomes.

The first objective is to study on learning behaviour and modelling techniques and recommendation algorithms and their related issues. The mostly highlighted method is the collaborative filtering recommendation algorithms. The second objective is to develop and implement a hybrid model that classifies learners using an improved algorithm, the similarity rating for personalized recommendation to learners. The third objective is to test and evaluate the performance of the developed hybrid model in terms of extraction time by using a pre-determined datasets as the benchmark. The related research question is the process of validating the proposed models. In addition, the analysis of performance provides the knowledge explored by the proposed models.

3.1 Personalized Online Learning Process Optimization Methods

Based on the problems and causes in the online learning process, this article explores corresponding methods for optimizing the online learning process from several aspects, including identifying learning style, knowledge cognition, resource description, resource classification, and recommendation mechanism.

Resource description and classification can also be determined based on the learner model. In the recommendation mechanism, cognitive diagnosis can be integrated into collaborative filtering to achieve personalized recommendations based on cognitive diagnosis. Finally, a Hybrid Personalized Recommendation Model (HPRM) can be constructed and applied with a three-level adaptive recommendation to learners.

3.2 Hybrid Personalized Recommendation Model (HPRM)

The Hybrid Personalized Recommendation Model (HPRM) is based on collaborative filtering as a technique to integrate the learner model with the learning resource model. The recommendation flow diagram is shown in Figure 4 below.

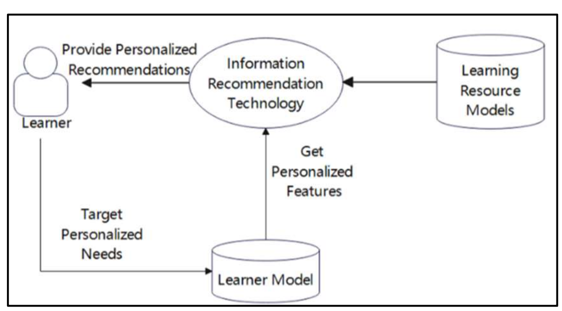

Figure 4: General Model Process.

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Learners' personalities are different, and the learning resources they need are also different; learners' learning goals and cognitive abilities may influence the choice of learning paths, learners' knowledge level needs to match the difficulty of the learning resources, and learning styles will eventually influence the type of learning resources obtained, etc.

In order to improve the quality of resource information and ultimately enhance learning effectiveness, many aspects of learner's personality characteristics need to be considered.

In this chapter, a user-based collaborative filtering algorithm is designed, combing learner's learning style, preference and cognitive levels. A hybrid personalized recommendation model based on learner model and learning resource model is also built.

3.2.1 Learning resources model (LRM)

The Learning Resource Model (LRM) consists of three components: Knowledge Point Labels, Bloom's Education Based Labeling Educational Objectives, and Cognitive Diagnostic Labeling.

- Labeling educational objectives based on bloom's theory

In a learning resource library, learning resources are like the trunk of a tree, consisting of several branches, with resources on a particular type of knowledge topic clinging to their respective main trunk branches like leaves, with each branch eventually forming a trunk. The very top of the tree is like a pyramid and the bottom end is where the most basic knowledge is learnt, with each category of knowledge having a corresponding marker point. In this paper, the knowledge resources are marked with the appropriate distinction in relation to Bloom's cognitive theory.

In this paper, to adopt Bloom's taxonomy theory and classify the core knowledge points into six levels {Remember, Comprehension, Application, Analysis, Evaluation and Create} to indicate the learners' cognitive level of the core knowledge points. During the learning process, chapter knowledge tests provide a more accurate diagnosis of the learner's level of knowledge and can provide personalized learning resources to match the learner's current cognitive level. The cognitive level features reflect the levels required by the learning objectives and are mapped to the values of hi {1,2,3,4,5,6}, as shown in Figure5.

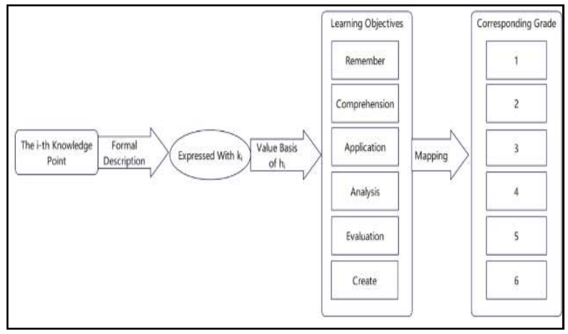

Figure 5: Representation of the Level of Resource Knowledge Mastery.

- Tagging learning resources knowledge points

In this paper, data elements for describing the content of resources are used as keywords for video annotation. A candidate word library for describing video content is established in advance and loaded into the annotation interface. This replaces the tedious process of subjective summarization and manual text input, greatly improving the efficiency of annotation compared to pure text annotation. The main method of annotation information input is to select entries from the word library, with custom text input as a supplement.

Currently, the requirements for using artificial intelligence to intelligently analyse video content are high, and it cannot guarantee the accuracy of information extraction. The feasibility of automatic retrieval is not significant. On the other hand, if human annotation is used to annotate video content, there is not yet a widely accepted formatted language in the industry. Considering the feasibility and maturity of existing technologies, this article chooses the direction of technology based on manual annotation as an auxiliary for the learning resource model, as shown in the Table 1.

Table 1: Data elements for describing the content of resources.

Data Elements	*Description*
Term	Definition
Title	The title given to a resource.
Subject	The subject description related to the content of the resource.
Keywords	The keyword description related to the content of the resource.
Learning Objectives	Tagging learning objectives related to the learning resource.
Target Audience	The intended audience for the resource.

The manual annotation model for video resource knowledge is the process of manually annotating video resources using specific knowledge points based on the content of the video resources. Knowledge point annotation involves identifying the specific knowledge points covered by each unit of the chapter or segment, and then manually assigning knowledge points based on the content covered by each unit.

The video resource knowledge manual marking model requires subject-specific expertise and understanding of the expected learning outcomes for the video resource. Subject matter experts can manually mark the knowledge points of video resources by viewing the content and identifying the key concepts or ideas covered in each segment. The annotated knowledge points are then encoded into an indexed database, thereby improving the learning resource model.

- Cognitive diagnostic labelling

The media that learners use to learn and communicate during the learning process belong to learning resources. Representing learning resources in an appropriate manner is a necessary prerequisite for personalized learning. Currently, the representation of most learning resources is based on the learners' needs, only considering some features of the learning resources themselves, and annotating these features from the learners' perspective. The connection between learning resources is loose, which is not conducive to resource management and recommendation.

This article starts from the connection between resources, combines with the characteristics of learning resources themselves, and chooses to represent learning resources in a set-based manner. Learning resources Z = {z1, z2, z3, z4, z5} = {resource ID, resource name, taught knowledge points, resource type, teaching objectives}, where taught knowledge points represent the main topics covered by the resource; resource type includes text documents and videos, represented by 0 and 1 respectively.

This article adopts a goal-levelling method to divide the mastery of knowledge points. After testing, the learners' scores are divided into three levels: Score ∈ [80, 100], Score ∈ [60, 80], Score < 60, which are mapped to the three levels of proficiency represented by 1, 2, and 3, respectively. The level of a knowledge point, L_i, depends on the test score of the knowledge point, Score (K_i), which represents the test score of the knowledge point K_i for the learner, as shown in Figure7 below.

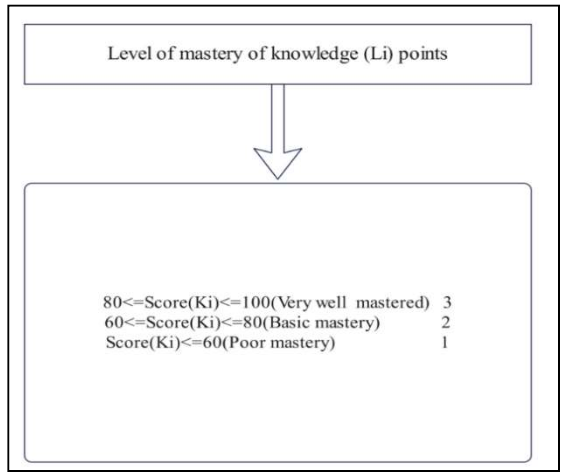

Figure 7: Representation of the Level of Resource Knowledge Mastery.

- Bloom's Education Based Labelling Educational Objectives

To design knowledge points for each level of Bloom's taxonomy, we need to understand the skills and knowledge required at each level. Here are some knowledge points for each level, specifically tailored to a C Language course, as shown Table 2.

Table 2 C language course bloom's educational objectives.

Data Elements	*Description*
Term	Definition
Title	The title given to a resource.
Subject	The subject description related to the content of the resource.
Keywords	The keyword description related to the content of the resource.
Learning Objectives	Tagging learning objectives related to the learning resource.
Target Audience	The intended audience for the resource.

To design knowledge points for each level of Bloom's taxonomy, need to understand the skills and knowledge required at each level. The Bloom's Taxonomy is integrated to tag the course resources of this course by using, for example, C Programming as a classification indicator. The first step is the classification of the basic chapter of C Programming as presented in Figure 8 below.

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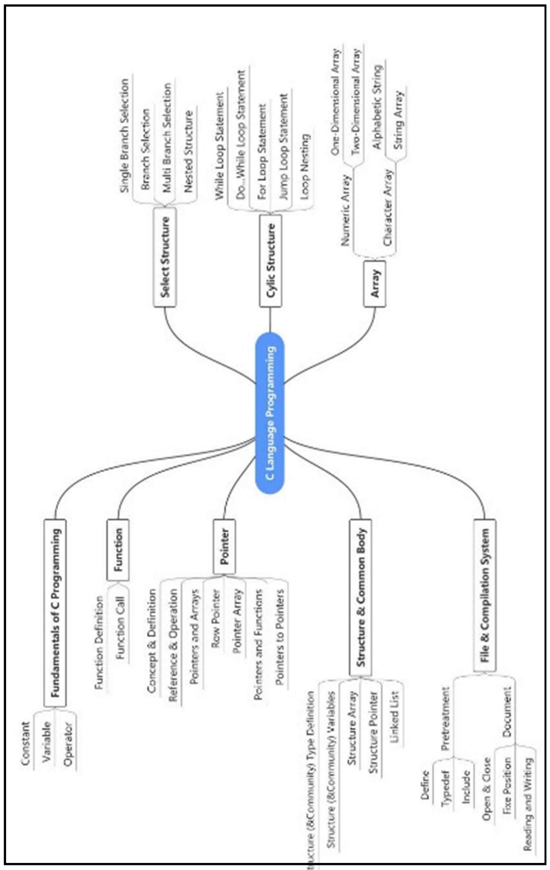

Figure 8: C programming course resource structure

3.2.2 Learner Model (LRM)

In the field of educational resource recommendation research, learner personality refers to a number of characteristic attributes that distinguish learners from other individuals in relation to their learning, mainly involving aspects such as the learner's learning goals, user interests and preferences, and learning style. From these aspects that the learner's personalized learning needs are reflected. Basic information about the learner, such as the learner's name, gender, date of birth, etc. are basic attributes of the learner.

Meanwhile the information about learner's education level, grade, class and school belong to higher level attributes, these serve as reference to determine the learner's learning level and content range and further provides personalized education resource recommendation services for learners, as shown in the Figure 9 below.

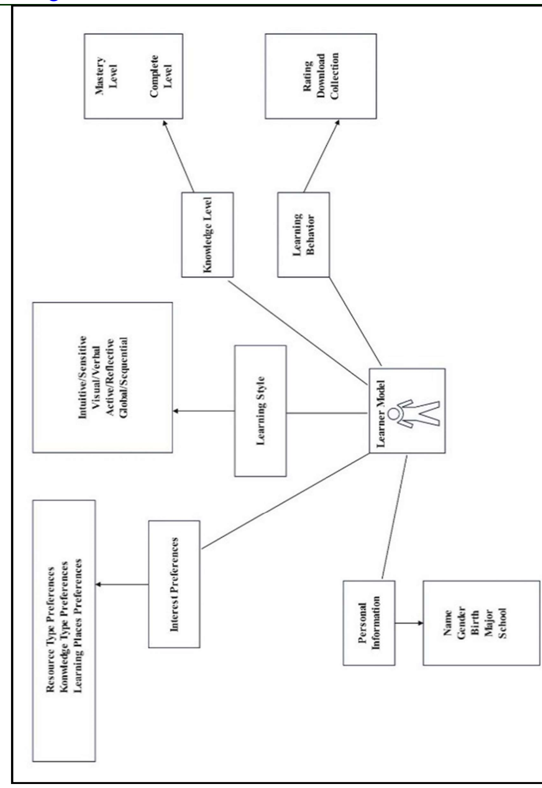

Figure 9: C programming course resource structure

3.2.2.1 Learning Style

The learning style based on E-Learning is the unique learning preference formed by learners during the learning process, which may be influenced by various factors such as the learning environment, learning needs, and learning cognition.

The learner's learning content and learning path also have a certain personalized tendency. Learning style reflects the individual learning behaviour preferences of learners and is also the manifestation of their uniqueness. The following characteristics can be summarized through research on learning styles (Wang,2020).

In summary, the learning style based on E-Learning is a personalized and stable expression of learning behaviour formed by learners during the learning process, and is the basis for studying personalized learning resource recommendation. To better construct personalized online learning platforms and make them more intelligent and convenient, research on learning styles is of great importance and significance.

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The Solomon Learning Style Inventory was designed by Felder and Soloman based on the Felder-Silverman Learning Style Model. The scale is generally used in the pre-test of learning systems to initialize learners' learning styles, and it has been adopted by more and more researchers adaptive learning systems, making the scale certified by a large amount of experimental data, confirming the scale's adaptability in online teaching platforms.

Online teaching platform has good reliability and validity, and has strong adaptability. The Solomon Learning Style Inventory has 11 questions for each of the 4 dimensions of the model, making a total of 44 questions. Each question has two (2) options, a and b, for each of the two (2) style types under that dimension. From dimension as shown in Table 3 below.

Table 3 Learning style inventory.

Questions	Description										
	Active/Reflective		Intuitive/Sensitive			Visual/Verbal			Global/Sequential		
Question	A	B	Question	A	B	Question	A	B	Question	A	B
1			2			3			4		
5			6			7			8		
9			10			11			12		
13			14			15			16		
17			18			19			20		
21			22			23			24		
25			26			27			28		
29			30			31			32		
33			34			35			36		
37			38			39			40		
41			42			43			44		
SUM			SUM			SUM			SUM		

The specific acquisition process of learning styles is summarized below.

1.Fill in the corresponding place in the table with 1.

2.Count the total number of items in each column and enter them in the total column at the bottom.

3.Subtract the smaller value from the larger value of the total and write down their result (difference).

4.The other three (3) scales were used to calculate the difference and determine the type of learning style to which they belonged.

The specific rules for calculating the learning style dimensions are as follows: firstly, each dimension corresponds to 11 questions and contains two (2) options: a and b. If the learner chooses a, a column is scored as 1 and the b column is scored as 1. If the learner chooses a, a column is scored as 1 and the b column is scored as 1. The sum of the columns is then compared and the smaller value is subtracted from the larger one, and the value is marked with the letter of the larger learning style dimension. The specific formula is as follows:

Each question has two options, a and b, for each of the two (2) style types under that dimension. The total number of a and b options is obtained by counting the answers for each dimension in the learning style scale and taking the difference between them to obtain one of the cases 11a, 9a, 5a, 3a, 1a and 1b, 3b, 5b, 7b, 9b, 11b. These 12 cases were then further divided into three (3) different types. The final results are as follows: 11a, 9a, 7a, and 5a are classified as active; 3a, 1a, 1b, and 3b are classified as balanced; and 5b, 7b, 9b, and 11b are classified as contemplative.

Therefore, the basis for designing a personalized learning recommendation system based on E-Learning is to build a learning style prediction model for learners. By analyzing the different learning styles of different online learners, a better understanding of their personalized needs can be achieved, thereby providing better services to users. The Felder-Silverman learning style scale was proposed in a traditional teaching environment and is currently widely used in learning style prediction models. This study is based on the Felder-Silverman experiential learning theory, and has been conducted in details and in-depth study of prediction models of learning styles both domestically and internationally. It was found that the interactive behaviour generated by learners during the learning process to some extent expresses a tendency towards a certain learning style.

In order to better understand the learner's personality, the first step to be carried out is data collection, combined with a learning style test form to obtain basic information from the database of the online teaching platform.

The second step is data pre-processing, that is, data filtering, which filters out garbage data and data containing many useless characters, such as test and 11. This is to protect the accuracy of the data source and provide an effective database for subsequent personalized recommendations.

The third step is data transformation. Due to the inconsistent data format from different dimensions

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and data sources, the data needs to be transformed and stored in a common space to enable the construction of a mixed model in the future. The learner's basic information and learning style data are constructed into a learner model in the fourth step, and a new mixed recommendation model (HPRM) is generated by combining the learner model with the learning resource model and the improved collaborative filtering algorithm. Chapter 5 further discusses the advantages of the proposed HPRM model relative to existing models using accuracy, recall, and F1.

3.2.2.2 Learning Behaviour

Learning behaviour can be seen as the external manifestation of the learning process, from which one can obtain the learning characteristics and behaviour patterns of the learner. Therefore, the analysis of learning behaviour records can better understand the needs of learners and provide data support for adaptive recommendation of learning resources (Yan et al., 2018). At the same time, based on learning behaviour, the preferences of learners can be dynamically reflected, and various aspects of learner needs can be obtained, thus continuously improving the learner model, as shown in Table 4.

Table 4 Learning style inventory.

User Behaviour	*Classification*
Collection	Explicit
Rating	Explicit
Like	Explicit
Share	Explicit
Browsing History	Explicit

3.3 Summary

This chapter discusses the construction of online learning resource model and learner model in personalized recommendation of learning resources. Firstly, to accurately obtain the basic data of learners' cognitive level characteristics and interest preference characteristics, the construction of the model of e-learning resources is completed, and on this basis, the representation method of e-learning resources characteristics is proposed.

Then, through learner feature analysis, learner feature data collection and learner feature representation method research, we complete the construction of learner model, and provide the basis for the personalized recommendation method of online learning resources in the next chapter.

4. DATA ACQUISITION AND IMPLEMENT

The data of both performance testing and user's satisfaction were taken from online teaching platform of Liaoning National Normal College. The data covers the period of three years, from 2019-2022.

4.1 Data Acquisition

Adaptive recommendation of learning resources is an important service in recommendation systems. A reasonable and effective recommendation system can not only push appropriate resources to learners, providing them with an autonomous learning environment, but also record the dynamic behaviors of learners during learning, constantly updating their feature information and providing suitable and effective learning resources. Based on the above objectives and the constructed adaptive recommendation model for online learning resources, this paper first establishes a learning resource library that meets the needs and feature attributes of learners, proposes an adaptive strategy for recommending similar learning resources, and finally implements personalized recommendation of online learning resources based on the basic principles of user collaborative filtering algorithm. The three-year data from Liaoning National Normal College will be used as the research object. Due to the outbreak of COVID-19 in China from 2019 to 2022, all courses were conducted online, which provided us with a great deal of data support.

4.2 Preparation

Firstly, the content of the course materials will be processed into digital resources and stored on the online learning platform. For the course resources that are uploaded into the system for the first time, the system will provide initial tags and annotations. The system will also identify the knowledge points and Bloom's educational objective levels of the learning resources, and then label them. The labeled learning resources will be stored in the resource attribute tag library for later use in recommending learning resources. Finally, the online learning resource recommendation system will actively recommend learning resources to learners based on their characteristics and learning needs, using corresponding tags from the tag library. Learners can select resources that meet their needs from the recommended list. After completing the learning, learners need to rate the resources they have learned. The rated learning resources will be stored in the

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rated learning resource library, providing dynamic data to enrich and update the characteristics and attributes of the resource tag library. This will improve the learning resource library and provide verified learning resources for new users [17].

4.3 Implementation of Recommendation Algorithm

The test papers contain the user's real reading list in the future, which can analyze and verify the predicted value and the real value to obtain the accuracy of the recommended algorithm, as shown Figure 10.

```java
import java.util.HashMap;
import java.util.HashSet;
import java.util.Map;
import java.util.Set;
public class ImprovedRecommendationAlgorithm {
    private int numLearners;
    private int numResources;
    private Map<Integer, Map<Integer, Double>> learnerResourceMatrix;
    private Map<Integer, Set<Integer>> learnerResourceMap;
    private Map<Integer, Set<Integer>> resourceLearnerMap;
    private Map<Integer, Double> resourceSimilarities;
    private Map<Integer, Map<String, Double>> learnerAttributes;

    public ImprovedRecommendationAlgorithm(int numLearners, int numResources) {
        this.numLearners = numLearners;
        this.numResources = numResources;
        this.learnerResourceMatrix = new HashMap<>();
        this.learnerResourceMap = new HashMap<>();
        this.resourceLearnerMap = new HashMap<>();
        this.resourceSimilarities = new HashMap<>();
        this.learnerAttributes = new HashMap<>();
    }
    // Add a learner-resource rating pair to the learner-resource matrix
    public void addRating(int learnerId, int resourceId, double rating) {
        if (!learnerResourceMatrix.containsKey(learnerId)) {
            learnerResourceMatrix.put(learnerId, new HashMap<>());
            learnerResourceMap.put(learnerId, new HashSet<>());
        }
        learnerResourceMatrix.get(learnerId).put(resourceId, rating);
        learnerResourceMap.get(learnerId).add(resourceId);
        if (!resourceLearnerMap.containsKey(resourceId)) {
            resourceLearnerMap.put(resourceId, new HashSet<>());
        }
        resourceLearnerMap.get(resourceId).add(learnerId);
    }
```

Figure 10: Hybrid Recommendation Sample Code

5. ANALYSIS DAN RESULT

The evaluation phase consists of two steps: performance testing and user satisfaction. In this paper, a mature collaborative filtering algorithm is used as the basis and combined with a learner model and a learning resource model to create a hybrid HPRM recommendation model for personalized recommendations on a web-based educational platform. Performance testing is conducted using Precision, Recall, and F1 measures, while user satisfaction is assessed using questionnaires and interviews [18].

Precision, recall, f1 are three (3) metrics widely used in the fields of information retrieval and statistical classification to evaluate the quality of results. Precision is the ratio of the number of relevant documents retrieved to the total number of documents retrieved, and measures the accuracy of the retrieval system; Recall is the ratio of the number of relevant documents retrieved to the number of all relevant documents in the document library, and measures the completeness of the retrieval system. Precision, recall and F-Measure are important evaluation metrics for selecting targets in a mixed environment. Assuming that for a user, the set of learning resource records used as a test sample is Stest and the set of recommendation lists constructed by the recommender system for the user is Srec, the precision, recall and F-Measure are calculated as follows.

$$Precision = \frac{|Stest \cap Srec|}{|Srec|} \quad (1)$$

$$Recall = \frac{|Stest \cap Srec|}{|Stest|} \quad (2)$$

$$F1\ Value = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (3)$$

5.1 Recall

In order to compare the effectiveness of the UserCF algorithm, ItemCF algorithm, and HPRM strategy proposed in this paper for all users, both UserCF and ItemCF algorithms are applied to users to generate recommendation lists. Then, F1 values are calculated and the recommendation algorithm for the current user is selected based on the Recall value. The results of the experiment are shown in the Figure 10, where N represents the number of recommended resources.

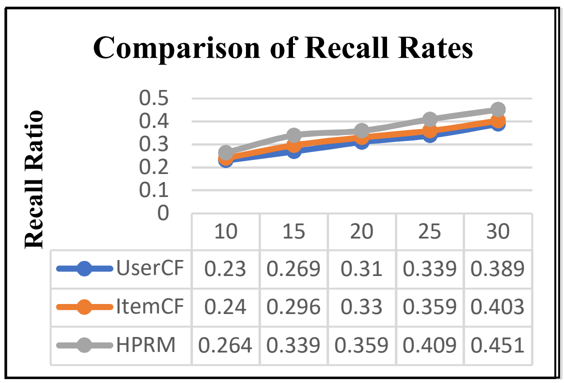

Figure 11: Hybrid Recommendation Sample Code

5.2 Precision

Precision is defined as the ratio of all items in the test set to the number of items in the recommended list that the learner is actually interested in. The higher the number of correct recommendations in the overlap between the user's actual interactions and the recommended items, the higher the accuracy rate [19]. This section aims to verify that the mixed-mode HPRM recommendation method proposed in this chapter performs better than the content-based filtering algorithm and the item-based collaborative filtering recommendation algorithm. To this end, a representative dataset is selected, and the online teaching platform dataset of

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Liaoning National Normal College is used for experimental verification. The evaluation index selected in this section is Precision.

To test the improvement of the HPRM recommendation algorithm over the content-based filtering recommendation algorithm and the user-based collaborative filtering recommendation algorithm in terms of recommendation efficiency and accuracy, the following experiments were designed: The dataset of Liaoning National Normal College of Higher Education was used to conduct the experiments, and the accuracy rate change pattern of the mixed-mode HPRM recommendation algorithm was observed during the experiments to verify whether the proposed hybrid recommendation algorithm has any improvement according to the experimental results. The results are shown in Figure 12.

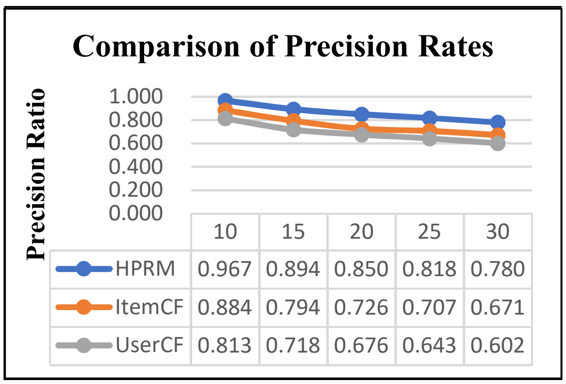

Figure 12: Hybrid Recommendation Sample Code

5.3 F1 Value

In order to compare the recommendation effectiveness of the UserCF algorithm, ItemCF algorithm, and the HPRM strategy proposed in this paper for all users, both UserCF and ItemCF algorithms were applied to the users, and recommendation lists were generated. F1 values were then calculated, and the recommendation algorithm for the current user was selected based on the F1 value. The results of the experiment are presented in the Figure13, where N represents the number of recommended resources.

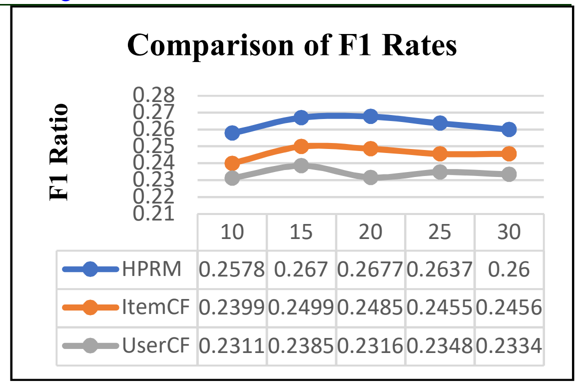

Figure 13: Hybrid Recommendation Sample Code

5.4 User Satisfaction

The purpose of this study is to summarize the status of online learning development through literature combing, and to encapsulate the dimensions that influence college students' online learning satisfaction. Taking the students of Liaoning National Normal College as the subjects, the empirical research was conducted to take different subjects' perspectives on the precise personalized recommended content that would have a significant impact on their online resource system [20].

Due to the random and uncontrollable nature of the survey respondents, the questionnaire method was used in order to obtain the research data efficiently. The questionnaire survey must clarify the basic information of the respondents, the basic situation of online learning, the degree of satisfaction of online learning, etc., to understand the real feelings of students after online learning. The questionnaire was semi-structured and open-ended questions were set at the end for students to talk about their real feelings after online learning.

5.4.1 Course satisfaction pass rate

The overall satisfaction of each user towards each of the 10 courses was calculated using the following formula:

$$Pass\ Rate = \frac{Sum\ of\ Satisfied\ and\ Very\ Satisfied\ Courses}{Total\ Number\ of\ Recommende\ \ Courses} \quad (4)$$

The satisfaction rate of all 50 random users is presented in Figure 14. The tabulated results show that the satisfaction rate is high 70% and only two (2) users had a satisfaction rate of 70% and below.

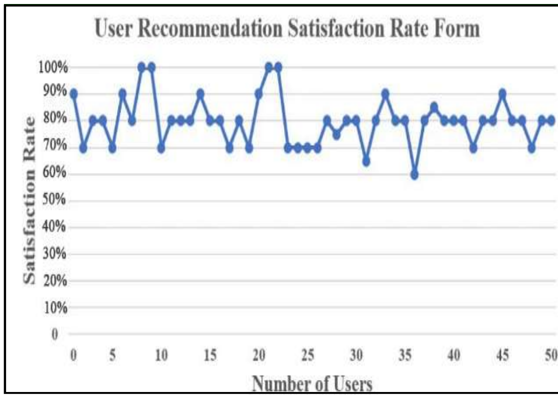

Figure 14: Hybrid Recommendation Sample Code

5.4.2 Questionnaires for overall HPRM satisfaction

In order to understand the actual needs of teachers and students of Liaoning National Normal College on the current online teaching platform, questionnaires were disseminated and interviews were conducted with students and teachers. At the beginning of the questionnaire development, the author consulted expertise and professors in the related industry. The author also conferred some students who have been using the online platform learning for a long period of time. The structure of the questionnaire was adjusted from the perspectives of the rigor of the survey research and the actual needs of teachers and students. This study focuses on the adaptation of higher education students to online learning during the epidemic. The study was conducted with a sample of full-time higher education students from Liaoning National Normal College. Students were invited to fill in the questionnaire. A total of 230 questionnaires were returned and 210 valid questionnaires were obtained by removing the questionnaires that were answered within a very short period of time and those that were filled in indiscriminately. The basic information of the sample is shown in Table 5 below.

Table 5: Distribution and Collection of Questionnaires.

Index	*Number*
Number of Questionnaires Distributed (Copies)	230
Number of Copies Collected (Copies)	215
Recycling Rate	93.48%
Number of Valid Questionnaires (Copies)	210
Valid Questionnaire Rate	91.30%

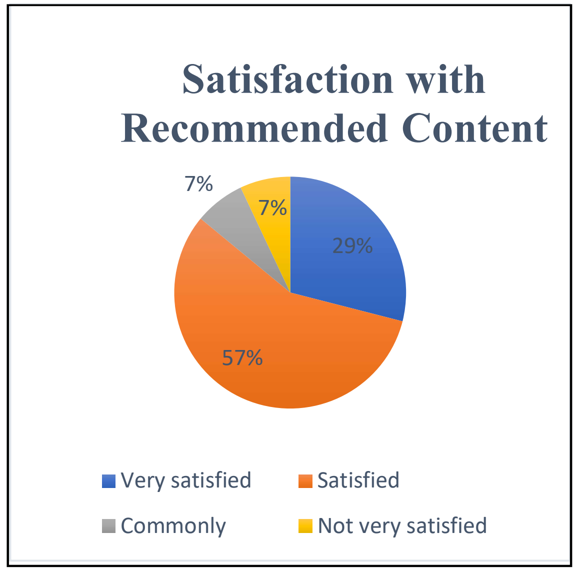

Figure 15: Satisfaction with Recommended Content

Based on Figure 15 majority of respondents (62%) were satisfied with the recommended content. 26% of respondents were Very satisfied and 7% were commonly satisfied. Only 5% of respondents were Not very satisfied. Overall, it seems that the recommended content was well received by the majority of respondents, with a high level of satisfaction among most of the surveyed individuals.

5.5 Validation of Optimization Results

This experiment focused on 60 online learners of C programming language course. These learners, came from different major, thus they had with varying majors, different learning foundations, and different learning goals regarding the knowledge module. By collecting the data generated during their online learning process using appropriate evaluation metrics, the learning process was evaluated.

5.5.1 Experimental steps

Firstly, the 60 learners were divided into three groups (Group A, Group B, and Group C) based on their learning goals and backgrounds. There were 20 learners in each group numbered from 1 to 20. Then, different learning processes were selected for the three groups of learners.

Group A: During the online learning process, the learning system recommended learning resources to the learners based on their historical information using a general traditional content-based collaborative filtering recommendation method.

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Group B: The personalized learning process was implemented using the HPRM recommendation approach. Based on the ratings of similar users for filtered resources, the learners' needs were predicted, and learning resources were recommended accordingly.

Group C: The learners in this group were not given any recommendations and were required to independently select the learning resources they needed through methods such as keyword search.

All three groups of learners started learning the C language programming knowledge module simultaneously and then took a standardized test. The behavioral data generated during the learning process and the test scores were collected for all groups of learners. Relevant data was selected to create charts and conduct analyses based on evaluation indicators.

5.5.2 Analysis of experimental data

The personalized recommendation-based online learning process optimization method proposed in this paper, aims to optimize the learning process, reduce online learning time, improve learning efficiency, and enhance learners' satisfaction with the learning experience. It was compared with the traditional collaborative filtering-based online learning process for performance testing. The learning data generated by the three groups of learners in the online learning process are presented in Tables 6, 7 and 8 for Group A, Group B, and Group C, respectively.

Table 6: Data on the Learning Process of Learners in Group A.

Learners	Accuracy	Hours	Score	Satisfaction
a1	0.54	145	73	2
a2	0.47	150	66	1
a3	0.62	138	91	3
a4	0.65	129	79	3
a5	0.69	149	90	4
a6	0.77	150	78	3
a7	0.66	151	89	4
a8	0.74	152	80	3
a9	0.66	144	81	4
a10	0.82	154	82	2
a11	0.68	120	87	4
a12	0.75	121	76	3
a13	0.82	122	66	2
a14	0.60	137	86	4
a15	0.64	124	78	3
a16	0.67	139	80	2
a17	0.63	144	79	3
a18	0.70	129	90	4
a19	0.83	128	79	3
a20	0.65	135	86	3

Table 7: Data on the Learning Process of Learners in Group B.

Learners	Accuracy	Hours	Score	Satisfaction
b1	0.82	145	86	3
b2	0.83	150	87	4
b3	0.82	138	91	5
b4	0.74	129	79	4
b5	0.89	130	90	5
b6	0.83	137	78	3
b7	0.64	121	89	5
b8	0.80	132	80	4
b9	0.68	134	81	4
b10	0.81	124	82	3
b11	0.88	120	87	4
b12	0.77	121	76	4
b13	0.63	112	66	3
b14	0.88	137	86	4
b15	0.86	124	78	4
b16	0.77	139	80	3
b17	0.88	122	79	4
b18	0.91	129	90	5
b19	0.86	128	79	3
b20	0.91	120	86	3

Table 8: Data on the Learning Process of Learners in Group C.

Learners	Accuracy	Hours	Score	Satisfaction
C1	0.54	145	62	2
C2	0.47	150	71	2
C3	0.62	138	57	2
C4	0.65	129	71	4
C5	0.69	149	59	1
C6	0.77	150	78	1
C7	0.66	151	79	3
C8	0.74	152	54	2
C9	0.66	144	61	4
C10	0.82	154	72	1
C11	0.68	120	73	3
C12	0.75	121	76	1
C13	0.82	122	66	3
C14	0.60	137	62	2
C15	0.64	124	58	1
C16	0.67	139	80	3
C17	0.63	144	79	3
C18	0.70	129	80	4
C19	0.83	128	79	2
C20	0.65	135	76	3

Direct observation of learner data does not reveal the differences between the two groups of learners in different learning processes. Therefore, it is necessary to classify and organize the raw data for observation and analysis. The following is a comparison chart of learner learning data. The comparison of the predictive rating accuracy between groups A and B is shown in Figure 16.

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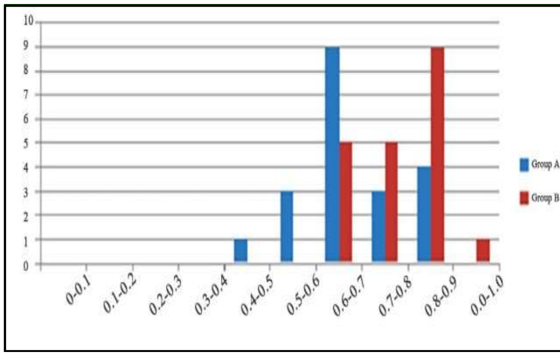

Figure 16: Comparison of the Accuracy of Prediction Scores Between Groups A and B

The length of online learning for learners in groups A and B compared to those in groups B and C is shown in Figure17.

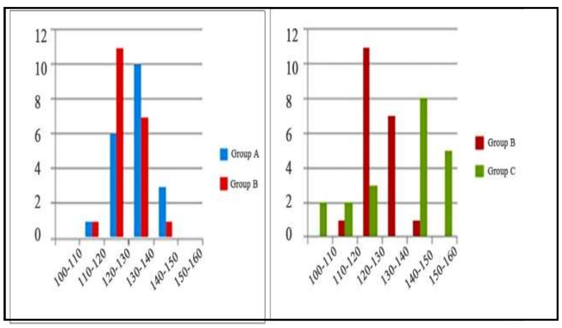

Figure 17: Online Learning Hours of Learners in Groups A and B Compared with Those in Groups B and C

A comparison of the module knowledge test scores of learners in groups A and B with those in groups B and C is shown in Figure 18.

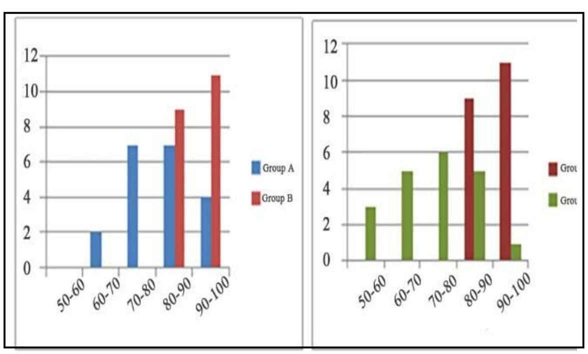

Figure 18: Comparison of the Module Knowledge Test Scores of Learners in Groups A and B with Those in Groups B and C

The comparison of satisfaction levels between group A and B, and between group B and C, can be seen in Figure 19.

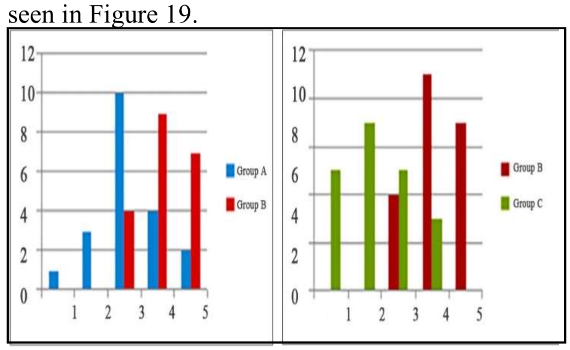

Figure 19: Graph of Learner Satisfaction for Groups A and B Compared to Groups B and C

Observing Figures 16, 17, 18, and 19, the following can be noticed:

1. The predicted rating accuracy of A group learners during the learning process is mainly concentrated in the range of 0.6 to 0.7, while that of B group learners is mainly concentrated in the range of 0.8 to 0.9. The predicted rating accuracy of A group is significantly lower than that of B group.
2. The learning time of B group learners is relatively shorter compared to A and C groups.
3. A and C group of learners have few high scores, more medium scores, and an average score in the medium range, and C group has some learners who failed. The learners of B group have scores of 80 or above, and the average score is significantly higher than that of A and C groups.
4. A group of learners have a general feeling towards the recommended learning resources during the online learning process, with moderate score between satisfied and dissatisfied. B group learners are generally satisfied with the recommended learning resources during the online learning process. However, more than half of the learners in C group are dissatisfied with the learning process.

Therefore, it can be concluded that the online learning process optimization method based on personalized recommendation can optimize the online learning process.

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Compare the benchmark for MOOC Stanford and Chaoxing MOOC, as shown in Figure 20 below.

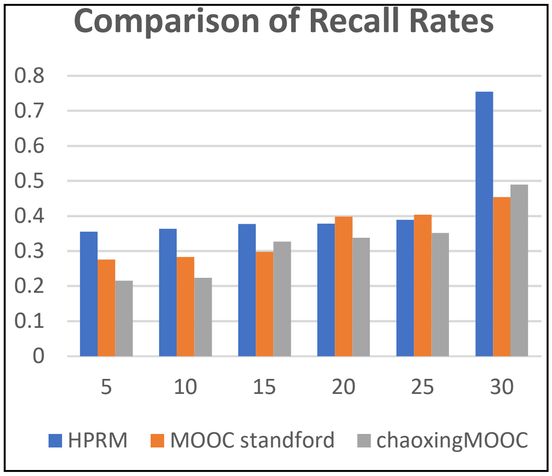

Figure 20: Comparison of the Recall Rates for the benchmark.

As can be seen from the Figure 21, the HPRM model has positive effects on the satisfaction. All satisfaction scores are more than 3, which indicates that most users are satisfied with the recommendations.

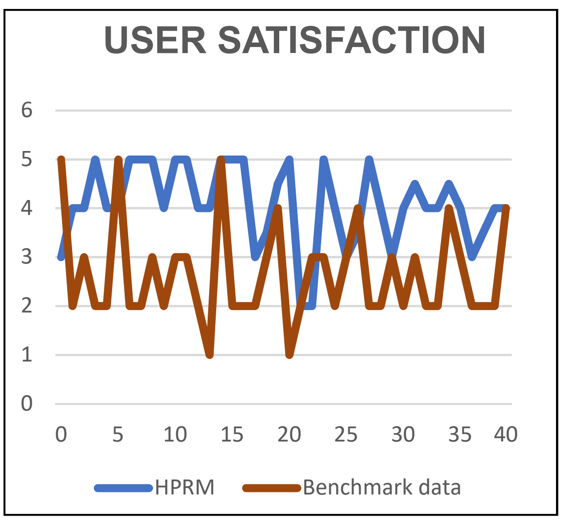

Figure 21: Compare the HPRM and Benchmark Data for User Satisfaction.

6. INNOVATION AND FUTURE WORK

The study takes digital learning resources as the research object, and based on the understanding and grasp of the concepts of integration, digital resource integration and digital learning resource integration, it identifies the theoretical basis for the dynamic integration of digital learning resources. On this basis, the definition of dynamic integration of digital learning resources was defined under the guidance of activity theory, and a Hybrid Personalized Recommendation Mode (HPRM) was constructed using design-based research methods and literature research methods. In order to test the validity of the theoretical model, this study incorporated the HPRM model into the design of the online education comprehensive platform of Liaoning National Normal College, and put the theoretical model of dynamic integration of digital learning resources into teaching practice.

6.1 Innovation

First, starting from the research question, this study provides an overview on the integration of digital learning resources. Based on this overview the static learning styles of first-time users within the framework of the Felder-Soloman Learning Styles Questionnaire (LSQ), which clarifies the core concepts of the study is defined. This also serves as the foundation for the construction of a model for the dynamic integration of digital learning resources and the development of teaching applications.

Finally, after defining the concept of dynamic integration of digital learning resources, this study places dynamic integration of digital learning resources in a broader field of research and education. Guided by activity theory, knowledge organization theory and feedback principles, it adopts research methods such as design-based research methods and literature research methods, constructs the HPRM model, discusses the key elements of dynamic integration of digital learning resources from different dimensions, analyses and explores the logical relationships between the key elements in different dimensions, and provides references for research on the teaching and application of dynamic integration of digital learning resources.

6.2 Limitation

In terms of the organization and management of digital learning resources, these are certain limitations in the selection of tools and techniques. In this study the dynamic integration of digital learning resources was done based on the general process and method of knowledge organization, focusing on the processing of existing knowledge content in the resources. However, for some new types of resources or learners' generative

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information in the learning process, so there is still a need to explore the use of new information technology to incorporate these digital learning resources and knowledge content into the digital learning resource system

6.3 Future Work

Firstly, the adaptive recommendation model for learning resources in this study includes the construction of both a learner model and a knowledge model. The construction of the learner model primarily relies on the learner's interests, learning style, knowledge level, and learning behavior characteristics, focusing more on external and noticeable features, while neglecting the influence of the learner's internal learning emotions and contextual factors. Therefore, in the next step of the work, the learner's internal factors can be considered in the model design, to better meet the real needs of the learner and continuously optimize the learner model.

Secondly, regarding the construction of the learning resource model, this study mainly focuses on textbooks, constructing knowledge sub-models based on the characteristics of course knowledge points. However, the coherence framework between knowledge points needs to be further strengthened, and the positioning of knowledge points to resources is not yet stable. In future work, it is necessary to improve the network framework of the knowledge model and enhance the systematization of the model.

7. CONCLUSION

In this study, took Liaoning National Normal College as the case study. Through the analysis of the theoretical study of online learning, data survey and interview of students, the current situation and problems of online learning were addressed. By analyzing these presented problems, HPRM personalization model, was suggest to assist and optimize the quality of online learning platform.

HPRM, is a general learning system recommendation framework that aims not only to cater to learners' preferences for recommendations, but also to obtain learners' knowledge mastery and knowledge gaps by modeling learners and learning resources, and to recommend the same learning resources and learning paths to learners with matching personalized parameters through a user-based collaborative filtering algorithm. The goal is to improve the completion rate and learning effect of online courses by recommending the same learning resources and learning paths to learners with matching personalized parameters, thus stimulating learners' learning motivation, and enhancing the enthusiasm of online learning.

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