Research on Personalized Recommendation of High-Quality Academic Resources based on user Portrait

Jianhui Xu[1], Mustafa Man[2]*, Ily Amalina Ahmad Sabri[3]*, Guoyi Li[4], Chao Yang[5], Mingxue Jin[6]
Faculty of Ocean Engineering Technology and Informatics, Universiti Malaysia Terengganu, Terengganu, Malaysia[1, 2, 3]
Department of Physical Education, Shenyang Medical College, Shenyang China[4]
Faculty of Ethnic Culture and Vocational Education, Liaoning National Normal College, Shenyang China[5, 6]

***Abstract*—With the advent of the era of big data, the phenomenon of information overload is becoming increasingly serious. It is difficult for academic users to obtain the information they want quickly and accurately in the face of massive academic resources. Aiming at the optimization of academic resource recommendation services, this paper constructs a multi-dimensional academic user portrait model and proposes an Academic Resource Recommendation Algorithm Based on user portrait. This paper first, combs the relevant literature and information; Secondly, to obtain the attribute tags of multi-dimensional user portraits, a set of questionnaires are designed to collect the real information of academic users, and the corresponding academic user portrait model is constructed; Then, the collected data is processed through certain rules, and the user is quantitatively modeled based on the data through mathematical means; Finally, through the construction of the completed academic user portrait model, combined with collaborative filtering algorithm, provide personalized academic resource recommendation services for academic users. Through the verification and analysis of simulation experiments, the Academic Resource Recommendation Algorithm Based on the user portrait proposed in this paper plays a great role in expanding users' interest fields and discovering new hobbies across fields and disciplines.**

Keywords*—*Personalized recommendation system; user portrait; academic resources; collaborative filtering

I. INTRODUCTION

Academic users are increasingly finding it difficult to obtain the information they want quickly and accurately in the face of massive academic resources, which often require a lot of time and energy. Therefore, the research of personalized recommendation services for academic resources is particularly important. Personalized recommendation services of academic resources can mine users' potential interests according to the personalized attributes of academic users, to actively recommend the academic resources users need [1]. Therefore, personalized recommendation service of academic resources has greatly improved the shortcomings of traditional retrieval systems, such as redundant information and difficult screening, and can meet various preferences and needs of academic users.

A. The Statement of the Research Problem

At present, most of the recommendation systems in the academic field adopt Content-Based Recommendation methods. The Content-Based Recommendation method focuses on the similarity of content features, which ignores most user preference features, such as the level of academic resources, the author of academic resources, etc. There are still many common problems in the recommendation of academic resources. For example, the recommendation of multiple types of academic resources, the preferences and needs of users with different identities, etc., resulting in unsatisfactory recommendation results [2].

1) Traditional search engines rely too much on keywords, and do not take into account the retrieval users' own attributes, such as interest preferences, research fields, retrieval purposes and other factors, which do not meet the requirements of personalized recommendation services.

2) The diversity of academic resources in the existing academic recommendation system is low, and it is impossible to recommend interdisciplinary and heuristic resources.

B. Research Objectives

1) To study the existing personalized recommendation algorithms of academic user modeling, academic resource modeling and academic resources.

2) To propose appropriate academic resource recommendation strategies, find the deep connection between user personalization and literature diversity, and recommend users with personalized and diversified recommendation results.

3) Accurately reflect user characteristics, meet users' diverse reading needs, build a multi-dimensional academic user portrait model, and form an Academic Resource Recommendation Algorithm Based on user portrait on the basis of collaborative filtering algorithm.

C. Research Question

There are two important issues that need to be addressed. First, how to calculate the similarity between students through behavioral data, and require that the similarity reflect the interests and learning characteristics of student strengths. Second, after identifying a new sample of near-neighbor students, how to determine the set of recommended courses to be selected based on the near-neighbor students' course selection records [3].

D. Rationale of the Study

In view of the insufficient characteristic information of the current academic resource database, which leads to the incomplete recommendation system, based on the current relatively mature database, this paper uses the literature research method, questionnaire survey method, big data

*Corresponding Author.

analysis and other related research technologies to lay the foundation for the follow-up recommendation system research. At present, the existing recommendation methods are mainly divided into content-based recommendation methods, collaborative filtering-based recommendation methods and hybrid recommendation methods. Based on the previous research, this paper builds a multi-dimensional academic user portrait for academic users, adopts the optimized collaborative filtering recommendation model, and tries to find cross domain academic resources that users are potentially interested in and have certain guiding significance for users [4].

E. Research Gap

From the current status of research, we can see that in recent years, there have been numerous studies on recommendation in education at home and abroad, but most of these studies are on K12 education, i.e., basic education, and fewer studies on learning resource recommendation algorithms for students in higher education. Therefore, it is more difficult to recommend learning resources for students in higher education than for students in basic education. In previous studies on learning resource recommendation, most of them improve the classical collaborative filtering algorithm to achieve the effect of improving the recommendation accuracy, and the user profile is not systematically utilized, which will be affected by factors such as cold start and sparse data matrix, resulting in poor recommendation effect.

To sum up, recommendation system is very crucial to solve the problem of resource overload, which attracts the majority of enterprises and scholars to conduct research. However, the application of recommendation system in the field of online education is not widespread and the recommendation algorithm is not perfect, and there is no integration of user portrait into the process of recommendation algorithm, especially there is no recommendation algorithm of learning resources for college students, and college students, as the backbone of online education, are an important part of online learning users, so it is necessary to realize the recommendation algorithm of learning resources integrating user portrait for college students, and Complete the design and development of the learning resource recommendation platform.

II. LITERATURE REVIEW

Academic resource recommendation service is a relatively mature service in the field of scientific research, and the existing research focuses on different aspects, which cannot meet the diversified needs of users. For example, CiteULiket focuses on maintaining the citation relationship of papers, Google Academic provides a complete paper search function, and Aminer platform uses data mining algorithms and analyzes social networks to provide academic users with not only basic academic resource retrieval services, but also current hot academic topics, visualization of trends in research directions, and deep mining of scholars' social networks and other functions. In order to further improve the academic resource recommendation service.Scholars build recommendation algorithms for academic resources by studying users' academic behaviors to tap users' interests, research directions and other academic preferences. S. Bhaskaran et al. used content filtering algorithms to analyze user behavior, such as citing papers and displaying ratings, to recommend academic papers of interest to users [5]. M. Venkatesh et al. used machine learning algorithms to construct a user requirements model that can adaptively match user preferences with a target library repository to complete user-oriented personalized recommendations of digital library resources [6].

In recent years, research trends in information behavior models have shown the following four aspects.

First, the research content is further refined, both for a certain type of information behavior and for the characteristics of information behavior models; Second, the research object is further subdivided, the academic user group is divided into multi-level and multi-dimensional, and information behavior models for different subject areas; Third, the factors affecting information behavior are more explored, and efforts are made to explore the micro-level; Fourth, the research methods are diversified, mainly survey and interview methods are used in data collection, supplemented by literature analysis and experimental methods, etc.

In general, the existing domestic and foreign academic resource recommendation systems and recommendation algorithms have met users' personalized needs to a certain extent. However, there are still some problems: firstly, the recommendation algorithms are mostly based on users' academic preferences, which makes the range of academic resources recommended relatively single and the diversity of academic resources low. First, the recommendation algorithms are mostly based on users' academic preferences, which makes the range of academic resources recommendation results relatively single and the diversity of academic resources low, and cannot achieve cross-disciplinary and cross-domain heuristic resources. The recommendation algorithm is mostly based on users' academic preferences. Secondly, in the face of the growth of massive academic resource data, the processing capability and machine learning capability of the system have become the key issues that must be addressed in the future academic resource recommendation system. In the future, the processing capability and machine learning capability of the system become the challenges that must be solved for academic resource recommendation systems.

This section will elaborate and introduce the relevant background knowledge of this research content, including personalized recommendation and user portrait theory and their application in the field of academic resources. Finally, the commonly used evaluation indicators of the recommendation system and the subsequent chapters of this paper are briefly explained, which paves the way for the proof of measuring the scientific effectiveness of this paper.

A. Personalized Recommendation Theory

The purpose of the recommendation system is to use the collected user information and item information to establish user models and item models, and match them according to specific rules. The recommendation algorithm plays a bridge role in this matching rule. Finally, the rules contained in the algorithm are used to filter the calculation results, to find the products that users may be interested in, and recommend them to users. This section selects three types of recommendation systems related to the research content of this paper for a brief introduction, which are: content-based recommendation system, collaborative filtering-based recommendation system, and hybrid recommendation algorithm.

1) Content-based recommendation system: Content based recommendation is also called attribute based on recommendation. In the process of recommendation system, it can be seen that both items and users contain certain attribute information. Because the attribute information of items is relatively static and objective, it is very easy to calculate the correlation between the degrees of similarity. The content-based recommendation algorithm is to discuss whether the actual attributes of the two items to be recommended are similar. As the basis for judging whether to recommend or not, the core task of the algorithm is to calculate the similarity of the attributes of the items as shown in Fig. 1.

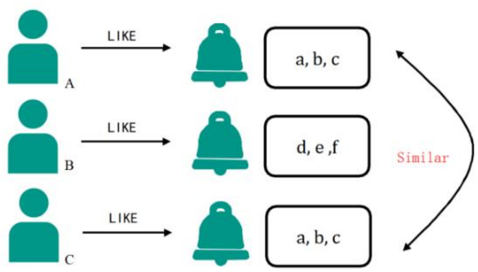

Fig. 1. Content based Recommendation System.

The disadvantages of content-based recommendation are as follows:

a) Relying on the classification of the objects to be recommended, the quality of recommendation is greatly affected by the nature of the objects to be recommended.

b) For users, the recommendation process is based on the analysis of existing content, and the recommendation results are difficult to innovate. Therefore, it is difficult to develop new product fields, and the ability to inspire users' interests and hobbies and promote users to contact new things is insufficient.

c) In front of a new user who has no historical reading record at all, there is no interactive item record, and there is no way to analyze the characteristics of items, so it is impossible to match the content to achieve recommendations, and only provide content to users in a way similar to the "popular list".

d) It requires a large amount of data of the object to be recommended, takes up large storage and computing space, and increases the cost of recommendation services.

2) Recommendation system based on collaborative filtering: In the field of Resource Recommendation Based on collaborative filtering, resources are mainly based on traditional collaborative filtering algorithms. Recommendation work, establish user documents based on the semantic analysis of users' reading literature, find similar user documents and predict users' interests through traditional collaborative filtering methods, and realize personalized recommendation the accuracy of such recommendation algorithms is vulnerable to data sparsity and cold start problems [7]. Therefore, integrate users according to the types of scoring items and user scoring items, the user similarity is calculated, and the corresponding collaborative filtering algorithm is designed to improve the accuracy of recommendation results [8]. Niu et al. used three different types of information (users, items, user items) to deal with the problem of data sparsity, predicted the item score, and produced high-quality recommendation results [9]. L. Antony Rosewelt et al. proposed to integrate the intimate relationship between friends into the recommendation model to recommend resources for new users under the same interest topic [10].

Collaborative filtering recommendation research has obvious deficiencies in two aspects:

On the one hand, these studies mainly use users' explicit and implicit behavior data to model users' interests, which is prone to the problem of data sparsity; on the other hand, these studies are often based on static scenarios, and it is difficult to cope with the real needs of online mobile recommendation of academic resources under the situation of constantly updating user data and changing user needs.

B. Academic user Portrait

User portraits for academic users are more focused. In order to more accurately recommend academic resources, it is necessary to obtain and describe the characteristics of academic users' interest in academic resources, so as to depict accurate academic user portraits. All the interest characteristics of users can be divided into different types [11]. One classification method is to divide user portraits into explicit features and implicit features according to different acquisition methods. Explicit features refer to a kind of academic user features that can be obtained directly without deep mining, such as name, age, education, major, identity, etc., and also include research directions and research fields independently defined by users. Such features can be collected manually, or automatically retrieved by software on the basis of user consent. The implicit feature is the feature attribute calculated and analyzed after deep mining a series of academic behavior and other information of academic users. Generally, it needs to be collected by software such as web crawlers and obtained by using the relevant algorithms of data mining. Explicit features are simple and fast to obtain, but the level is shallow and the flexibility is not high. Implicit features can mine more interesting features of users, but rely on higher cost calculation, which is a complementary role of explicit features. Users' academic behavior refers to academic related interaction behavior, which can be the retrieval, download, collection, quotation and other behaviors of academic resources. The purpose of analyzing these academic behaviors is to infer users' academic interest tendency, further supplement users' interest characteristics, and improve academic user portraits. The purpose of analyzing these academic behaviors is to infer users' academic interest tendency, further supplement users' interest characteristics, and improve academic user portraits [12].

Before designing an academic resource, recommendation service based on user portrait, it is necessary to establish a multi-dimensional academic user portrait model, which can obtain user attributes in an all-round and multi-level way, accurately reflect user characteristics, and meet users' diverse reading needs. The multi-dimensional academic user portrait is mainly composed of two parts: dimensional analysis and model construction.

C. Dimension Analysis of Academic User Portrait

The establishment of user portrait dimension is the basis of establishing user portrait model. An ordinary academic user will have a series of information that can affect the acquisition of academic resources, including the most basic attributes of a person, as well as academic preferences fed back from academic behavior. In addition, there are some additional factors that can be defined and distinguished, user information that can optimize the recommendation service of academic resources. This kind of information has obvious personal style, so this paper calls this kind of dimension "academic personality"[13-17].

Accordingly, this paper selects the following three dimensions: basic information, behavioral characteristics and academic personality as the components of the multi-dimensional academic user portrait as shown in Fig. 2.

D. Construction of Multi-dimensional Academic User Portrait Model (MAUPM)

In order to obtain the real data needed in the process of academic user portrait modeling, this paper designs a set of questionnaires for data collection. For the two dimensions of basic information and academic personality, the questionnaire is divided into two parts: The first part mainly adopts the form of multiple-choice questions, including age, gender, education background, major, identity, time engaged in scientific research, research direction and other questions, which are used to collect basic information. In the second part, through the further investigation of users, including the scientific research progress and the proficiency of using the academic resource platform, combined with the identity, professional title, working time and other information obtained in the first part, we can get the users' academic motivation and domain knowledge. For the investigation of cognitive style, the scale test commonly used in the field of psychology is used to set up eight scenarios and let users choose the situation that is consistent with themselves. In order to supplement and verify the authenticity of the results of the scale, the questionnaire also set up a mosaic graphic experiment, which requires users to find the specified simple graphics in a complex graphics. Users who prefer field independent cognitive style can find simple graphics in complex graphics faster [18].

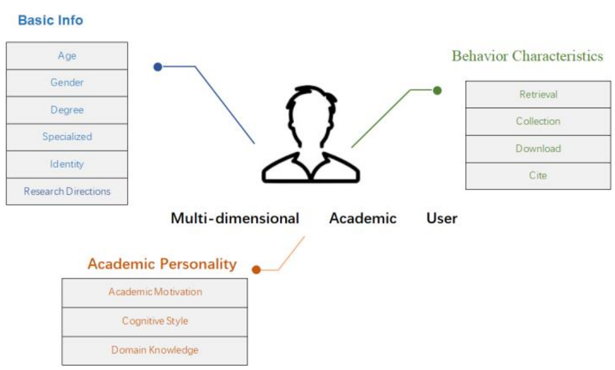

Fig. 2. Multi-dimensional Academic user Portrait Structure.

The results of these questions can finally feedback the "academic personality" of the surveyed users. For the dimension of behavior characteristics, it is obtained by viewing the behavior logs of academic users on the academic resource platform. Based on the collected data, this paper constructs a multi-dimensional academic user portrait model [19].

1) Basic information model: It is divided into six sub dimensions: age, gender, education, major, identity and research direction. In order to simplify the information, the age dimension adopts the form of age group, and the research direction is described by the data filled in by users in the questionnaire. The basic information model is shown in Table I.

TABLE I. BASIC INFORMATION MODEL

Sub Dimension	Value
Age	Under 30 years old, 31-40 years old, 41-50 years old, 51-60 years old, under 60 years old
Sex	Male / Female
Education	Bachelor's degree or below, Bachelor's degree, Master's degree, Doctor's degree or above
Profession	Philosophy, Economics, Law, Pedagogy, Literature, History, Science, Engineering, Agriculture, Medicine
Identity	Students, Teachers
Research Direction	Fill in by yourself, such as "control theory".

Behaviour characteristics are composed of four dimensions: user's retrieval, collection, download and reference.

The values of each dimension are as follows:

- Search dimension: the user's search term K, the time to visit the page t (unit: minutes), and the document name P of the search page.
- Collection dimension: user's collection page document name C.
- Download page: user's download page document name D.
- Citation dimension: user's citation name R.

The behavioural characteristic model is shown in Table II.

TABLE II. BEHAVIORAL CHARACTERISTIC MODEL

Sub Dimension	Value
Retrieval	Search term K
	Access time T
	Search page document name P
Collection	Collection page document name C
Download	Download page document name D
Quote	Reference name R

2) Academic personality model: The three sub dimensions of academic motivation, cognitive style and domain knowledge are described by the data obtained from the questionnaire, in which academic motivation and domain knowledge can be obtained directly from the results checked by users. The academic personality model is shown in Table III.

TABLE III. ACADEMIC PERSONALITY MODEL

Sub Dimension	Value
Academic Motivation	Explicit, Fuzzy
Cognitive Style	Field Independent, Field Dependent
Domain Knowledge	Junior User, Experienced User

In order to accurately judge the cognitive style of academic users, this paper converts some literality in the questionnaire into specific values (scores). Three variables were defined: scale value n, speed value V and cognitive style index s. The n value represents the score of the user in the scale test. The higher the score of each question, the more consistent it is with the described situation, and the user is more inclined to the field independent cognitive style in the situation of this question; The V value represents the user's response in the mosaic graphic experiment. The faster the user completes the mosaic graphic experiment, the more it can reflect the user's field independent cognitive trend; the cognitive style index s reflects the final situation of the user's cognitive style. The higher the s value of the user, the more the user prefers the field independent cognitive style. The lower the S value, the more the user prefers the field dependent cognitive style [20-22]. S value is positively correlated with n value and V value, and the calculation formula of s value is $S = N \times V$.

S is the cognitive style index, n is the score of the scale test questions, and V is the score of the graphic mosaic experiment.

It can be predicted that with the development of new technology, academic personalized recommendation will produce new ideas, models and methods, and the results of recommendation will be more and more satisfactory. In order to solve the problem of information overload, this method will become one of the research contents in the academic field for a long time [23].

III. METHODOLOGY

The portrait constructed above is a three-dimensional map based on semantic information. This chapter will quantify all dimensions in the three-dimensional map, fuse and reconstruct, store each user's information in the form of vectors, and construct a vector-based user portrait. Then, combined with the user based collaborative filtering algorithm, the similarity between vectors is calculated, so as to predict the list of academic resources recommended by users to be recommended [24].

A. User Attribute Vector

This paper divides the academic user portrait into three dimensions: basic attributes, academic personality and behavioral characteristics. Among them, the basic attribute and academic personality are relatively static objective attributes, which can reflect the user's personal attributes over a period of time, and can be clearly expressed through discrete and unique values, for example, the gender can only be "male" or "female". Therefore, in the process of practical application, the basic attributes and academic personality dimensions are combined and deleted to form the user attribute vector. User Info={Age, Gender, Education, Profession, Identity, Motivation, Style}There are two (2) parts deleted: 1. Change the "age" label to "age range" in order to reduce the number of discrete data and reduce the amount of calculation; 2. The sub dimension of "domain knowledge" is deleted because the domain knowledge level of an academic user has been reflected in the attributes of age, identity, education and major. Deleting this dimension can reduce the workload and avoid defining evaluation indicators, so as to avoid the error loss caused by subjective judgment [25]. According to the multi-dimensional academic user portrait model, the reconstructed and fused user attribute vector and its values are shown in Table IV.

Because the total number of dimensions of user attributes is not large, this paper uses "one-hot" to encode vectors. One hot encoding, alias is an effective bit encoding. The encoding idea is to set n-bit status registers to represent in different states. Each bit register has only "0" and "1" states. No matter how many bits the register has, when representing each state, only one bit is valid, that is, the position representing the state is "1", and the other positions are "0"[26]. For example, if the "age range" attribute has five values, the attribute code form is a Five-Dimensional vector. When the value is "under 30 years old", the attribute code is: age = {1, 0, 0, 0, 0}. When the value is "over 60 years old", the code is: age= {0, 0, 0, 1}.

TABLE IV. USER ATTRIBUTE VECTOR VALUE AND CODING

User Attribute Vector	Value	Code
Age Group	Under 30 years old	{1，0，0，0，0}
	31-40 years old	{0，1，0，0，0}
	41-50 years old	{0，0，1，0，0}
	51-60 years old	{0，0，0，1，0}
Sex	Male	{1，0}
	Female	{0，1}
Education	Below bachelor degree	{1，0，0，0，0}
	bachelor degree	{0，1，0，0，0}
	Master degree	{0，0，1，0，0}
	Doctor degree	{0，0，0，1，0}
Profession	Philosophy	{1，0，0，0，0，0，0，0，0，0，0，0}
	Economics	{0，1，0，0，0，0，0，0，0，0，0，0}
	Law	{0，0，1，0，0，0，0，0，0，0，0，0}
	...	...
Identity	Student	{1，0，0，0，0}
	Assistant	{0，1，0，0，0}
	Lecturer	{0，0，1，0，0}
	Associate Professor	{0，0，0，1，0}
	Professor	{0，0，0，0，1}
Academic motivation	Explicit Type	{1，0}
	Fuzzy Type	{0，1}
Cognitive style	Field Dependence	{1，0}
	Field Independent Type	{0，1}

B. Similarity Calculation

The cosine similarity formula is used in this paper, so the similarity formula of user attribute vector is:

$$\text{Sim\_Info(a, b)} = \cos(A, B) = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}} \quad (1)$$

where, a and B are the user attribute vectors of a and B users, and A_i and B_i are the attribute values of each dimension of the two users respectively. The formula of vector similarity in the research field is:

$$\text{Sim\_Area(a, b)} = \cos(X, Y) = \frac{N(X) \cap N(Y)}{\sqrt{N(X) \times N(Y)}} \quad (2)$$

N(X) and N(Y) are the number of keywords in the research field vector of users a and B respectively. Suppose that the research field vectors of users a and B are respectively: User_area_a = {User portrait, Recommendation system, Education system} User_area_b = {User portrait, Marketing, Business Administration} The denominator is $\sqrt{N(A)} \times \sqrt{N(B)}$ in form according to the similarity formula. [27].

C. Generate Recommendation List

Finally, the user group with high similarity to the users to be recommended is called the "most similar user set", and the academic resources that the "most similar user set" likes but the users to be recommended have not interacted with are recommended to them. Let user A mark the thesis set as P_A, the most similar user set of a as U_A, the recommended thesis set as R, and the thesis set as P. Then user A's recommended thesis collection is $R_A = \{p \mid p \in Pi, i \in UA, \ p \notin PA\}$.

This recommendation algorithm does not consider the users' scores on the papers, because the collection of papers adopts a single implicit feedback data, and takes the "interaction" between collections, downloads and academic resources as the basis of users' interest [28].

IV. Analysis and Results

A. Experimental Environment

Experimental Platform: Windows10 64-bit operating system，11th Gen Intel(R) Core (TM) i7-11800H @ 2.30GHz 2.30 GHz3.40GHz，16.0 GB RAM. Tools：Java，Python, SPSS.

B. Data Acquisition and Processing

In order to verify the accuracy of the academic resource’s recommendation algorithm proposed in this chapter, 100 users of the questionnaire were selected, and the historical reading list of academic resources was manually collected from them. Each person had a total of five documents, including title, abstract and keyword information. Three of the five papers are used as training sets and two test sets, that is, three papers are the user's "historical reading list" and two papers are the "future real reading list". The questionnaire survey results are obtained from the "questionnaire star" website background management system, stored in SPSS files, and the user attribute vector of each user can be obtained after encoding the data. From the data, the selected 100 users have the same educational background, major and identity, which provides a practical basis for subsequent recommendations based on collaborative filtering. After grouping and numbering the manually collected user history reading papers, we use python3.0 programming language and TF-IDF algorithm to extract keywords from the title and abstract of the literature. Combined with the keyword information of the literature itself and manual verification, after duplication and error correction, a total of 689 keywords of 350 documents were finally obtained.

1) Collect questionnaire analysis: From the questionnaire collected, the proportion of men and women in the surveyed population is 55.48% to 44.52%, about 1:1; Users' majors are mainly engineering, and they are academic users of philosophy, law, pedagogy, science, medicine and management; In terms of academic qualifications, 81.66% are masters, 19.34% are undergraduates, and the user groups are students. The following mainly analyzes the survey results of the third dimension "academic personality" in the user portrait proposed in this paper.

In the survey results of the scientific research stage of this questionnaire, 39.93% of users choose the scientific research preparation stage, 49.72% of users choose the scientific research progress stage, and 10.35% of users choose the scientific research publication stage. It can be seen that academic users will indeed experience different stages of scientific research on the road of scientific research, and they will also have different academic motives in the search process of academic resources. Count the cognitive style index s of the surveyed users and calculate the benchmark value $\dot{s}$ = 11.316, the results show that 55.17% of the academic users participating in the survey have field independent cognitive style, and 44.82 % of the users have field dependent cognitive style. For the statistics of domain knowledge level, the information sources include the user's age, education background, professional title, time engaged in scientific research, proficiency in using academic resource platform, etc. In this questionnaire survey, users with bachelor's degrees without exception chose "directly use one or several keywords to search and try to expand the search scope", while nearly half of users with master's degrees chose the same common search methods as users with bachelor's degrees, and 38.46% of users chose "select certain restrictions (phrases, tags, etc.) while using keywords", Another 11.54% of users made the choice of "traversing relevant academic resources with the author or publishing unit and the journal as the search tag". It can be seen that with the gradual accumulation of scientific research experience, academic users' domain knowledge is also expanding, and there are certain differences between primary users and experienced users in the acquisition of academic resources. Therefore, it is essential to integrate the academic experience level of academic users into user portraits. Through the analysis of the questionnaire results, academic users have different academic personalities, and the user portrait integrated into academic personality is more three-dimensional, which can greatly improve the personalization and accuracy of academic resource recommendation services.

C. 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.

Based on the above, the complete recommendation steps for a user to be recommended is shown in Fig. 3.

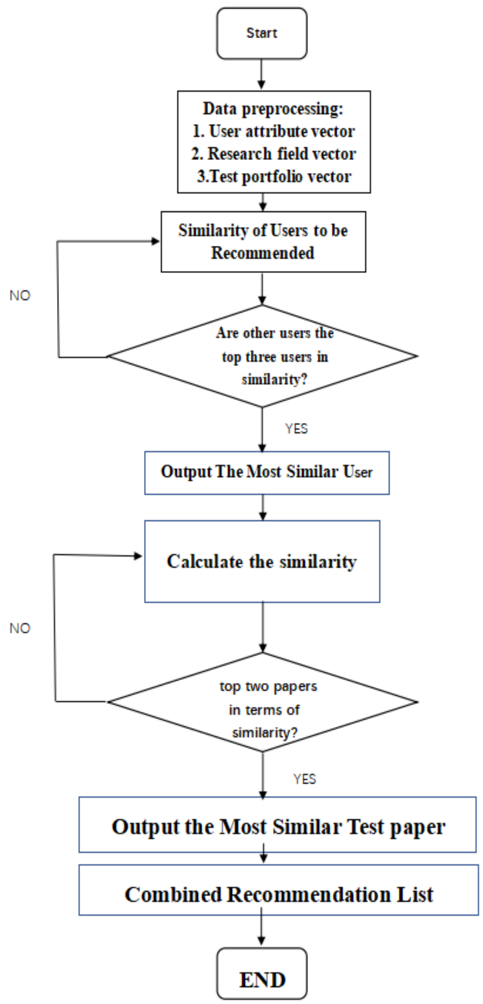

Fig. 3. Algorithm Experiment flow Chart.

V. Result and Discussion

A. Offline Test

Finally, each 100 users will get six recommended papers, and a total of 600 papers will be generated from the recommendation list number the test papers from 1 to 600, and the number of the recommended papers of 100 users and their corresponding test papers, that is, the number of "future real reading list", is shown in Table V.

In this article, "recall rate" and "accuracy rate" will be used as the basis for scoring. Let R (u) represent the user's real reading list in the future, that is, the test paper collection, and T(u) represent the recommendation list finally predicted by the algorithm.

$$\text{Recall}=\frac{\sum_{u\in U}|R(u)\cap T(u)|}{|T(u)|} \quad (3)$$

$$\text{Precision}=\frac{\sum_{u\in U}|R(u)\cap T(u)|}{|T(u)|} \quad (4)$$

TABLE V. Comparison between Recommended Papers List and Real Reading List

No.	Recommended Paper No.	Real reading paper No.	Number of Correct Predictions
1	20,12,3,19,3,15	1 2	0
2	8,6,11,9,3,20	3 4	1
3	9,1,14,13,17,18	5 6	0
4	8,6,9,1,14,13	7 8	1
5	6,5,14,13,17,18	9 10	0
6	8,6,20,12,3,15	11 12	1
7	6,5,9,1,17,18	5,9,17	3
8	8,6,9,1,14,13	6,9,13,14	4
9	6,5,9,1,14,13	1,18	1
10	8,6,9,1,3,20	19 20	1
...	...	...	...

It is calculated that the recall rate of the proposed algorithm in the offline test is 70% and the accuracy rate is 78.7%.

B. User Research Method

This article will pay a return visit to 80 test users. The recommendation list generated by the algorithm is conveyed to the test users to collect their real evaluation. The contents of the return visit and investigation include the following:

1) Satisfaction with the number of papers: Are you satisfied with the number of papers in the recommendation list (Dissatisfied, Generally Satisfied, Relatively Satisfied, Very Satisfied).

2) Thesis title reading interest evaluation: Just observe the title of the paper in the recommendation list. Do you want to click to read it? (No, generally, quiet, very much).

3) Cross domain reading interest evaluation: Have you found any papers that are different from the current research field but still interested in from the list of recommendations? (In conformity, general conformity, relatively conformity, very conformity).

The return visit results are shown in Fig. 4.

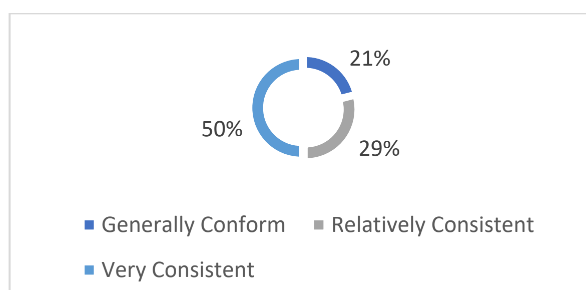

Fig. 4. Satisfaction with the Number of Papers and Reading Interest Evaluation.

The result analysis of the three problems has the following conclusions.

Most of the revisited users are very satisfied with the number of papers in the recommendation list, indicating that the number of five to six recommended papers can meet the reading needs of ordinary academic users. On the academic resources of retrieval website, the most intuitive part presented to users is the title of the paper. Most revisiting users are satisfied with the recommendation results from the perspective of the title of the paper, of which 84% of the recommended papers are favored by users. 3.53.7% of the revisited users believed that the literature resources in the recommendation list were different from the current research field, but they still had great interest, and 39% of the users were also more willing to read the recommended papers in the interdisciplinary field. It can be seen that the Academic Resource Recommendation Algorithm Based on user portrait proposed in this paper can expand users' research interests, improve users' interdisciplinary and interdisciplinary reading tendency, and help academic users inspire new research directions.

C. Innovation Points

Aiming at the current trend of more and more cross domain cooperation in scientific research, this paper explores the potential interests of users, analyzes the cognitive style trend of users from the perspective of psychology, so as to measure the cross domain academic resource needs of academic users, expand the factors of academic resource recommendation, and further improve the theoretical system of personalized recommendation of academic information resources.

This paper adopts interdisciplinary research, combines computer related technologies such as statistics, psychology, library and information science and data mining, adopts research methods such as questionnaire survey and empirical analysis, and integrates the research ideas of social science into the research of recommendation system, which has strong progressiveness and applicability.

D. Future Work

In the research process, the real user data used are phased static data, and the dynamic time factor is not considered, so the changes of academic users cannot be reflected in the user portrait. In the next work, it can use the existing computer technology to realize the dynamic tracking of user information, which can make up for this shortcoming.

VI. User Interface of the System (GUI)

The implementation effect of the academic resource module based on personalized user portrait is shown in Fig 5.-Fig 7.

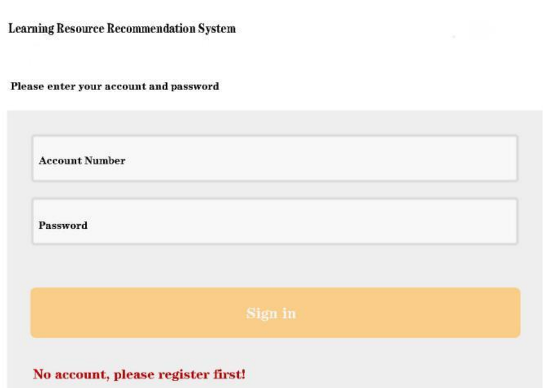

Fig. 5. Learning Resource Recommendation Login Interface.

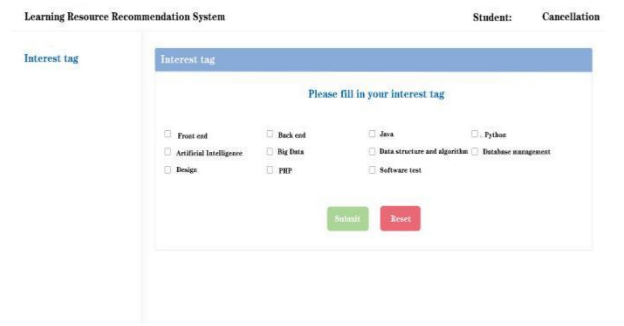

Fig. 6. User Interest Tag Acquisition.

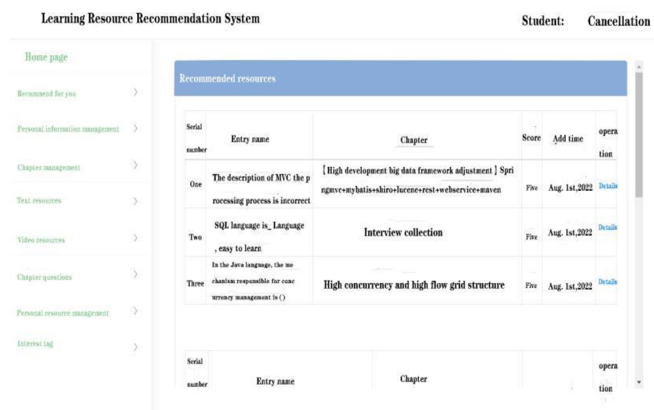

Fig. 7. Personalized Academic Resources Recommendation Display Interface.

VII. Conclusion

In recent years, it is more and more difficult for academic users to obtain the information they want quickly and accurately in the face of massive academic resources. Personalized recommendation system can solve this problem. The existing personalized recommendation system improves the shortcomings of the traditional retrieval system, such as information redundancy and difficulty in screening. To a certain extent, it can meet the various preferences and needs of academic users, but it also lacks the deep characterization of users' personal attributes. Therefore, from a new perspective, this paper attempts to mine the attributes of individual users, broaden the dimension of academic user portraits, and enhance the objectivity of academic resource recommendation services. Firstly, this paper studies the relevant knowledge of personalized recommendation system and user portrait theory, focusing on the definition, classification and evaluation indicators of recommendation system, and the construction method of user portrait. Then, in order to integrate the idea of user portrait into the personalized recommendation service of academic resources, based on the construction of a diversified and three-dimensional academic user portrait, the concept of "academic personality" is proposed on the basis of two basic dimensions of users' basic attributes and behavioral characteristics." Academic personality" includes three parts: users' academic motivation, cognitive style and domain knowledge. Through the infiltration of psychological theory, it further complements the portrait dimension of academic users and constructs a multi-dimensional academic user portrait model.

Finally, using the constructed multi-dimensional academic user portrait model, combined with the user based collaborative filtering method, an Academic Resource Recommendation Algorithm Based on user portrait is proposed, which optimizes the existing academic resource recommendation strategies. The experimental results show that the Academic Resource Recommendation Algorithm Based on user portrait proposed in this paper can play a great role in expanding users' interest fields and finding new hobbies across fields and disciplines.

REFERENCES

[1] Al-Salman, S., & Haider, A. S. Jordanian University Students' Views on Emergency Online Learning during COVID-19. Online Learning, 25(1) pp286-302,2021.

[2] Mabude, C. N., Awoyelu, I. O., Akinyemi, B. O., & Aderounmu, G. A. An integrated approach to research paper and expertise recommendation in academic research. International Journal of Advanced Computer Science and Applications, 13(4) doi:https://doi.org/10.14569/IJACSA.2022.0130456,2022.

[3] Adenariwo, F. K., & Sulyman, A. S. Availability and accessibility of electronic information resources in academic libraries as predictors of academic performance of students. Library Philosophy and Practice, , 1-10. Retrieved from https://www.proquest.com/scholarly-journals/availability-accessibility-electronic-information/docview/2705446808/se-2,2022.

[4] S. S. Khanal, P. W. C. Prasad, A. Alsadoon, A. Maag, "A systematic review: machine learning based recommendation systems for e-learning," Education and Information Technologies, vol. 25 no. 4, pp. 2635-2664, DOI: 10.1007/s10639-019-10063-9, 2020.

[5] M. Venkatesh, S. Sathyalakshmi, "Smart learning using personalized recommendations in web-based learning systems using artificial bee colony algorithm to improve learning performance," Electronic Government, an International Journal, vol. 16 no. 1/2, pp. 101-117, DOI: 10.1504/EG.2020.105253, 2020.

[6] S. Bhaskaran, R. Marappan, B. Santhi, "Design and analysis of a cluster-based intelligent hybrid recommendation system for e-learning applications," Mathematics, vol. 9 no. 2, DOI: 10.3390/math9020197, 2021.

[7] A. Klašnja-Milićević, M. Ivanović, B. Vesin, Z. Budimac, "Enhancing e-learning systems with personalized recommendation based on collaborative tagging techniques," Applied Intelligence, vol. 48 no. 6, pp. 1519-1535, DOI: 10.1007/s10489-017-1051-8, 2020.

[8] X. Liu, "A collaborative filtering recommendation algorithm based on the influence sets of e-learning group's behavior," Cluster Computing, vol. 22 no. S2, pp. 2823-2833, DOI: 10.1007/s10586-017-1560-6, 2020.

[9] P. Gao, J. Li, S. Liu, "An introduction to key technology in artificial intelligence and big data driven e-learning and e-education," Mobile Networks and Applications, vol. 26 no. 5, pp. 2123-2126, DOI: 10.1007/s11036-021-01777-7, 2021.

[10] L. Antony Rosewelt, R. J. Arokia, "A content recommendation system for effective e-learning using embedded feature selection and fuzzy DT based CNN," Journal of Intelligent & Fuzzy Systems, vol. 39 no. 1, pp. 795-808, DOI: 10.3233/JIFS-191721, 2020.

[11] J. Jeevamol, V. G. Renumol, "An ontology-based hybrid e-learning content recommender system for alleviating the cold-start problem," Education and Information Technologies, vol. 26 no. 4, pp. 4993-5022, DOI: 10.1007/s10639-021-10508-0, 2021.

[12] Y. Han, H. Yao, F. Zhou, "Research on the intelligent ecology of modern vocational education system," Modern Educational Technology, vol. 28 no. 1, pp. 114-120, 2020.

[13] Mabude, C. N., Awoyelu, I. O., Akinyemi, B. O., & Aderounmu, G. A. An integrated approach to research paper and expertise recommendation in academic research. International Journal of Advanced Computer Science and Applications, 13(4) doi:https://doi.org/10.14569/IJACSA.2022.0130456,2022.

[14] H. Chen, C. Yin, R. Li, W. Rong, Z. Xiong, B. David, "Enhanced learning resource recommendation based on online learning style model," Tsinghua Science and Technology, vol. 25 no. 3, pp. 348-356, DOI: 10.26599/TST.2019.9010014, 2020.

[15] S. Wan, Z. Niu, "A hybrid e-learning recommendation approach based on learners influence propagation," IEEE Transactions on Knowledge and Data Engineering, vol. 32 no. 5, pp. 827-840, 2020.

[16] Y. Zhou, C. Huang, Q. Hu, J. Zhu, Y. Tang, "Personalized learning full-path recommendation model based on LSTM neural networks [J]," Information Sciences, vol. 444 no. 3, pp. 135-152, DOI: 10.1016/j.ins.2018.02.053, 2020.

[17] K. Dahdouh, A. Dakkak, L. Oughdir, A. Ibriz, "Large-scale e-learning recommender system based on Spark and Hadoop," Journal of Big Data, vol. 6 no. 1,DOI: 10.1186/s40537-019-0169-4, 2021.

[18] Gray, J. L. Identifying the academic and emotional risk and resource factors of underrepresented students in accelerated coursework (Order No. 28154177). Available from ProQuest Dissertations & Theses Global. (2485082910). Retrieved from https://www.proquest.com/dissertations-theses/identifying-academic-emotional-risk-resource/docview/24850 82910/se-2,2022.

[19] M. U. Hulla, M. Hammer, H. Karre, C. Ramsauer, "A case study-based digitalization training for learning factories," Procedia Manufacturing, vol. 31, pp. 169-174, DOI: 10.1016/j.promfg.2019.03.027, 2020.

[20] A. V. Nesterov, "Digitalization of society and the economy: systematization of personal data in information systems," Scientific and Technical Information Processing, vol. 47 no. 2, pp. 133-138, DOI: 10.3103/S0147688220020124, 2020.

[21] T. B. Lalitha, P. S. Sreeja, "Personalised self-directed learning recommendation system [J]," Procedia Computer Science, vol. 171, pp. 583-592, DOI: 10.1016/j.procs.2020.04.063, 2020.

[22] Z. Wei, L. Sun, "How to leverage manufacturing digitalization for green process innovation: an information processing perspective," Industrial Management and Data Systems, vol. 121 no. 5, pp. 1026-1044, DOI: 10.1108/IMDS-08-2020-0459, 2021.

[23] F. Tian, Q. Zheng, K. M. Chao, "Current and future of technologies and services in smart e-learning," Service Oriented Computing and Applications, vol. 14 no. 1,DOI: 10.1007/s11761-020-00288-9, 2020.

[24] H. Ezaldeen, R. Misra, R. Alatrash, R. Priyadarshini, "Semantically enhanced machine learning approach to recommend e-learning content," International Journal of Electronic Business, vol. 15 no. 4, pp. 389-413, DOI: 10.1504/IJEB.2020.111095, 2020.

[25] J. Sun, J. Geng, X. Cheng, M. Zhu, Q. Xu, Y. Liu, "Leveraging personality information to improve community recommendation in e-learning platforms [J]," British Journal of Educational Technology, vol. 51 no. 5, pp. 1711-1733, DOI: 10.1111/bjet.13011, 2020.

[26] D. D. Koffi, N. Ouattara, D. M. Mambe, S. Oumtanaga, A. Adje, "Courses recommendation algorithm based on performance prediction in E-learning," International Journal of Computer Science & Network Security, vol. 21 no. 2, pp. 148-157, 2021.

[27] L. Wu, Q. Liu, W. Zhou, G. Mao, J. Huang, H. Huang, "A semantic web-based recommendation framework of educational resources in E-learning," Technology, Knowledge and Learning, vol. 25 no. 4, pp. 811-833, DOI: 10.1007/s10758-018-9395-7, 2020.

[28] X. Jiang, "Computer aided teaching system based on wechat public platform," Modern Scientific Instruments, vol. 3, pp. 44-49, 2020.