

# Design of Personalized Recommendation and Sharing Management System for Science and Technology Achievements based on WEBSOCKET Technology

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**Abstracts**—Scientific research is becoming more and more crucial to contemporary society as the backbone of the nation's innovation-driven development. The rapid growth of information technology and the rise of information technology in scientific research both contribute to the globalization of scientific research. Small research groups still don't have a place to showcase and share their accomplishments, though. In order to integrate scientific research information and combine personalised recommendation technology to suggest developments of interest to users through their historical behaviour data, the study proposes a personalised recommendation and sharing management system for scientific and technological achievements based on the Ruby on Rails framework. According to the testing results, the system had a 299ms request response time, a maximum 1KB request resource size, and a 20ms data transfer time. Additionally, the study's user-based collaborative filtering recommendation algorithm has an accuracy rate of 41% when the nearest neighbor parameter is set to 50, there are 10 information suggestions, and there are 0.7 training sets, which essentially satisfies the system criteria. In conclusion, the research suggested that a personalised recommendation and sharing management system for scientific and technological accomplishments can essentially satisfy the needs of small research teams to communicate and share scientific accomplishments, as well as realise the sharing of scientific achievements.

**Keywords**—Research management; personalised recommendations; WebSocket; ruby on rails; informatization

## I. INTRODUCTION

As the scope and extent of scientific research grow with the advancements in information technology and [1] technology, research has become increasingly diverse and intricate. Along with managing projects and delivering their results, researchers need to scrutinise data, design experiments and locate literature from a vast range of information [2]. In this scenario, research management systems (RMS) offer an efficient, automated and standardised alternative [3]. In order to automate and standardise research management, an RMS can aid researchers in managing information, designing experiments, analysing data, managing projects, and efficiently presenting research results [4]. Nevertheless, the current state of RMS in China is still nascent, and a shortage of academic platforms for the exchange of innovative research between teams makes it difficult to adapt research outcomes

[5].

## II. RELATED WORK

Real-time push and real-time communication are enabled by WebSocket technology, which is widely used in web applications that require a high degree of real-time, such as live chat, games, stock quotes, etc. Bisták P. proposes a new architecture for building virtual and remote laboratories using WebSocket communication technology to develop a remote control laboratory for three-tank hydraulic systems. The results showed that the remote laboratory had been visualised in 3D on the client side and was capable of comparing non-linear feedback control with dynamic feed-forward control [6]. To address the issue of exponential growth in IoT data traffic, Al-Joboury I.M. et al. proposed an IoT blockchain architecture using WebSocket communication. They found that proof-of-stake is more streamlined and advantageous for IoT applications than proof-of-work and Byzantine fault tolerance [7]. Pala Z et al. designed a network using machine learning to overcome the problem of synchronous system operation, which affects application efficiency, by analysing and transmitting data using WebSocket technology [8]. Abdelfattah A. S. et al. suggested a dependable approach using middleware and WebSockets technology to address the problem of Web service request timeouts in the mobile experience. The methodology improved the mobile experience by reducing network consumption time to seven times that of the straight cloud approach, according to the results [9]. To promote a multi-user real-time co-reading system using WebSocket technology, Chang C.T. et al. proposed a collaborative learning co-reading performance. Experiments revealed that the system significantly impacted students' learning outcomes during co-reading and that six out of seven hypotheses were supported [10].

In e-commerce, social networking, music, and other industries, CFRA, or a Personalised Recommendation Algorithm (PRA), is frequently utilised. When evaluated using independent datasets, Lim H et al.'s newly proposed Weighted Impulse Neighbourhood Regularised Three-Factor Decomposition One-Class Collaborative Filtering algorithm (CFA) demonstrated accuracy of the first 37 predicted associations of 8.495% with an enrichment factor of 4.19 compared to random guesses [11]. A recommendation framework that integrates local differential privacy (LDP)

with collaborative filtering has been developed by Bao T et al. to address the problem of dishonest server behavior or user privacy disclosure in case of failure. The results showed that the method outperformed other differential private recommendation methods [12]. In contrast to other fuzzy algorithms and traditional algorithms, Wu Y et al. proposed an interval fuzzy number-based CFRA. This algorithm is experimentally proven to be more effective and practical in sparse datasets with more users than items, and effective in improving prediction accuracy and ranking accuracy [13]. To address the issue of malicious user reviews and the issue of a small number of reviews affecting the accuracy of recommendations, Zheng G et al. proposed a CFRA with item labelling features [14]. Experiments revealed that the algorithm could successfully address the issue of cold-start data and that the interpretation of recommendation results was convincing. Zhang J et al. suggested a unique CFRA with item labelling features, and studies revealed that the proposed method was superior to existing methods [15].

The utilization of Websecurity technology and CFA is currently under investigation by various researchers from multiple perspectives; however, its practical application design in RMS is uncommon. To construct an RMS for scientific information PR, this study incorporates Websocket technology built on the Ruby on Rails framework and ronAJAX technology for CFRA. This study analyses the use of personalised recommendation (PR) algorithms based on WebSocket technology to recommend scientific and technological achievements of interest to users. The aim is to develop a management system for PR and information sharing that is objective, comprehensible, and logically structured. The conventional dissemination of scientific and technological advancements is frequently disseminated without sufficient personalized services. This research employs a customised recommendation system founded on network socket technology, which supplies individualised suggestions for scientific and technological advancements according to the users' requirements. This initiative aims to elevate users' curiosity and acceptance of scientific and technological developments, hence improving their utilization and market penetration. The research is categorised into four primary sections: analysis of pertinent research findings, core technology design and architecture, feasibility confirmation of the recommendation system, and a summary of the obtained results.

### III. DESIGN OF A PR AND SHARING MANAGEMENT SYSTEM FOR SCIENTIFIC AND TECHNOLOGICAL ACHIEVEMENTS BASED ON WEBSOCKET TECHNOLOGY

The sharing and interchange of scientific and technological advancements has become a crucial component of the growth of the scientific research area as a result of the ongoing development of data processing and artificial intelligence technologies. This part compares the benefits and drawbacks of popular recommendation algorithms (RA) in order to further choose the best RA for the research system. It also focuses on the essential technologies and architectural design of the research sharing management system.

#### A. Design of the Key Technology and Overall Architecture of the Research Sharing Management System

The main objective of the Research Sharing Management System is to enhance collaboration and information sharing among researchers, while facilitating the advancement of scientific research. It serves as a platform for storing, managing and sharing the results of scientific research. In order to help small research teams achieve result sharing and communication, the study will design the Research Sharing Management System from three aspects: system requirements, key technologies, and overall architecture. The system requirements are divided into two sections: business requirements and performance index requirements. The business requirements need to meet the purpose of research users to use information to achieve resource sharing, so the study adopts web research sharing system with simple interaction and unified interface. The system is divided into five modules: user authentication, team management, dynamic management, RA and private information management, and the specific structure is shown in Fig. 1.

The performance indicator requirements mainly meet the user experience, so the study combines the characteristics of the research system to design a system that should meet the performance requirements of strong real-time, operability, high reliability and high security during operation. After determining the system framework through requirements analysis, a number of development techniques are required to realise the submission, acquisition, storage, publication and notification of information. The first study uses Asynchronous JavaScript and XML (AJAX) asynchronous request technology to count user likes, favourites and comments, with page content rendered in HTML and CSS, dynamic display and interaction implemented by the DOM, and data exchanged between the browser and web server in JSON data exchange format. AJAX data exchange works with several technologies to load the system on demand, reducing unnecessary data transfer and thus speeding up the response time of the interface. The study then uses WebSocket technology to synchronise information between the browser and the server. The information transfer process between the browser and the web server is shown in Fig. 2.

The research then uses a recommendation system to complete the information filtering, which builds a user preference model based on user interaction data to recommend content of interest to the user. The RA essentially connects the user to information in a certain way, helping the user to discover content of interest while pushing content to the user, often in the form of friend recommendations, history, user characteristics and personal information. The final study uses Ruby on Rails framework technology to integrate AJAX technology, WebSocket technology, RA technology and other unmentioned technologies in an orderly manner, while abstracting simple and reusable design artefacts. The Ruby on Rails framework is designed with agile development ideas such as convention over configuration, chef selection and do not repeat. It is a typical Model View Controller (MVC) framework for mapping traditional input, processing and output logic. When a user submits a request via a browser, the server uses a route to locate the appropriate controller, which

then parses the user's request and interacts with the database using the model. Once the data has been retrieved, the controller provides the information to the view layer. This information is used by the view layer to create the finished web page, which is then returned to the browser as resources such as HTML, CSS and JavaScript. Fig. 3 shows the overall system architecture after integrating the core technologies to build the RMS.

As shown in Fig. 3, the study combines the business requirements and key technologies of the system based on following the design principles of the application while meeting the requirements of scalability, high stability, ease of operation and practicality, using the ActiveJob backend job module of the Ruby on Rails framework to create the PR system.

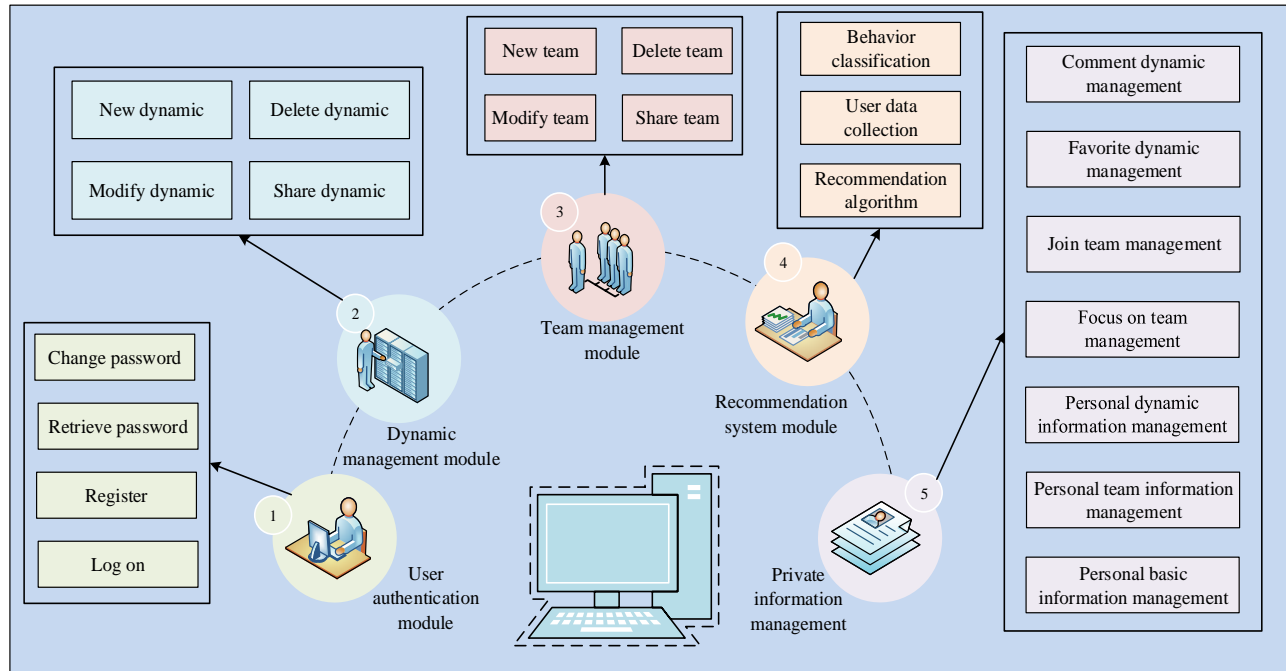


Fig. 1. Functional block diagram of scientific research sharing management platform.

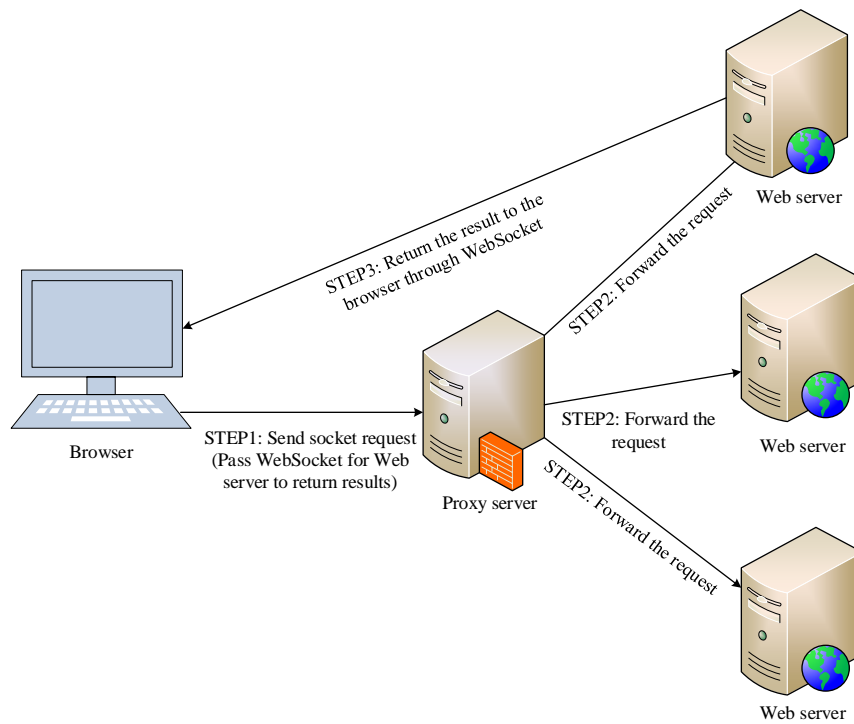


Fig. 2. Information transfer process between browser and web server.

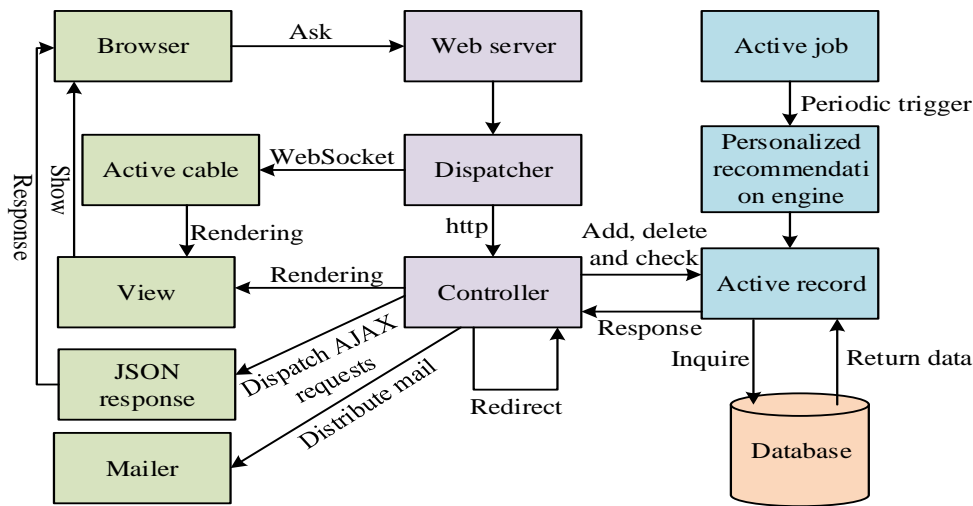


Fig. 3. System architecture design.

**B. PRA Design for Scientific and Technological Achievements based on WEBSOCKET Technology**

After developing the shared management system's architecture, the study progresses to incorporate socket technology to enhance and design PRA technology accomplishments. Research users have relatively fixed research areas when doing research activities, resulting in a tendency to overlap information when searching for keywords and retrieve less available information. Although PRA serves as the foundation of PR technology, each algorithm has a unique application scenario, making it crucial to pick the best RA to suit research users' demands. Content-based algorithms, tag-based algorithms, knowledge-based algorithms, and CFRA are some examples of common RAs. The similarities between feature vectors and user preference vectors are computed by content-based RAs, which gather features from both people and items before making suggestions. Cosine similarity, as in Eq. (1) [16], is the formula used to determine similarity most frequently.

$$\cos(F_u, F_i) = \frac{F_u \cdot F_i}{\|F_u\| \times \|F_i\|} \quad (1)$$

In Eq. (1),  $F_u$  is the preference feature of a user and  $F_i$  is the preference feature of a candidate item. The closer the cosine similarity value is to 1, the closer the candidate item is to the user's preference, and the closer its value is to -1, the less suitable the candidate item is for that user. The advantages of content-based PRA are that only the user's interest features and resource attributes need to be compared online, and the similarity can be performed offline. The disadvantages are the difficulty of extracting information features from complex resources and the inability to detect similarities between similar synonyms [17]. The user's interest in the resource is determined using Eq. (2), and the tag-based RA analyzes the user's level of interest based on the number of times the user has tagged the resource. The tag-based RA then generates suggestions based on the interest matrix between the user and the resource.

$$p(u, i) = \sum_b n_{u,b} n_{b,i} \quad (2)$$

In Eq. (2),  $u$  is the user,  $i$  is the resource,  $b$  is the tag,  $n_{b,i}$  is the number of times the resource has been tagged, and  $n_{u,b}$  is the number of times the user has been tagged. The tag-based RA has the benefit of being able to comprehend the user's interests and easily obtaining the user's tags, but the drawback is that it requires work to develop the habit of tagging resources and the research user is not motivated to tag [18]. The knowledge-based RA is a system that provides a solution in response to the user's stated demands. Fig. 4 [19] illustrates the precise suggestion process.

Knowledge-based RAs are mainly applicable to specific domains and have a high recommendation accuracy rate, but the implementation process is complicated for users and not suitable for scientific users. Collaborative Filtering Architecture (CFA) is based on the user's evaluation of resources to jointly filter information and recommend content of interest to the user, which is mainly divided into user-based CFRA and item-based collaborative filtering recommendations [20]. User-based collaborative filtering uses the user's interest similarity score to make recommendations, which has no special requirements for recommended resources and can handle a variety of complex objects, while item-based CFA uses the similarity of items to make recommendations. A comparison of the advantages and disadvantages of each RA, combined with the usage scenario of the system, the study selected user-based CFRA and the specific algorithm recommendation process is shown in Fig. 5.

The complete collaborative filtering recommendation system consists of three modules: behaviour collection for collecting user information, a model for analyzing user interests, and an RA. The behaviour collection module mainly collects and classifies the operation behaviour of the user interface, and the research designs a user behaviour collection form to collect the user's research direction, likes, favourites, comments and other historical data, which is transferred to the server and then stored in the database through interface

interaction after collection. The study adopts a weighted average to infer the user's interest level, calculated as in Eq. (3).

$$\bar{p} = \frac{\sum_{i=0}^n m_i f_i(x_i)}{\sum_{i=0}^n f_i(x_i)} \quad (3)$$

In Eq. (3),  $n$  is the user action behaviour,  $m_i$  is the corresponding action behaviour weight, and  $f_i(x_i)$  is the corresponding score of the user action behaviour. The user browsing behaviour is calculated as in Eq. (4).

$$f_i(x) = \begin{cases} 1, & (\text{has viewed}) \\ 0, & (\text{has't viewed}) \end{cases} \quad (4)$$

The calculation of users' liking, favouriting and sharing behaviour is shown in Eq. (5).

$$f_i = \begin{cases} f_i(x), & (\text{thumb up}) \\ 0, & (\text{thumb down}) \end{cases}, \quad (i = 2, 3) \quad (5)$$

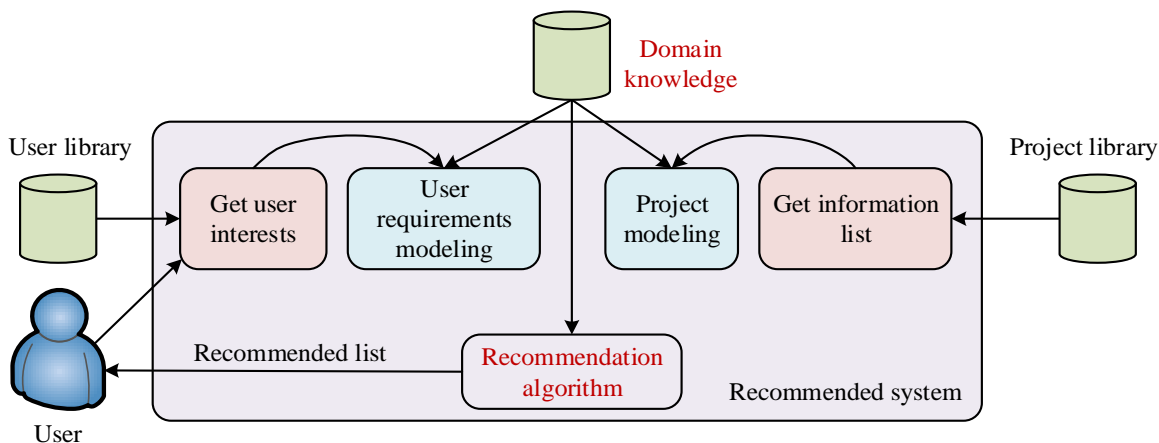


Fig. 4. Knowledge-based recommendation block diagram.

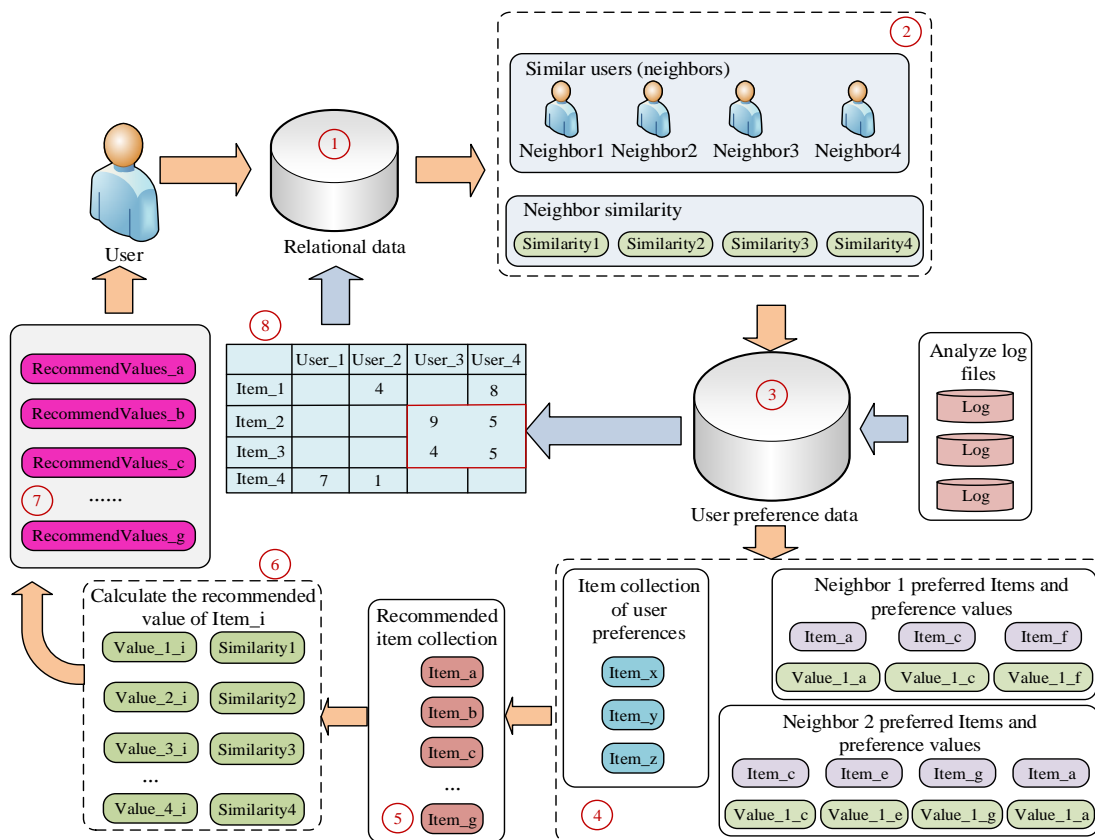


Fig. 5. CFRA structure diagram.

User objection to comment behaviour is calculated as in Eq. (6).

$$f_4(x) = x, (\text{comment statistics}) \quad (6)$$

The Euclidean distance was utilized to determine the similarity between users after the study generated the users' score matrices for each dynamic via the weighted average approach, as shown in Fig. 6. The Euclidean distance refers to  $n$  as the actual distance between two points in space.

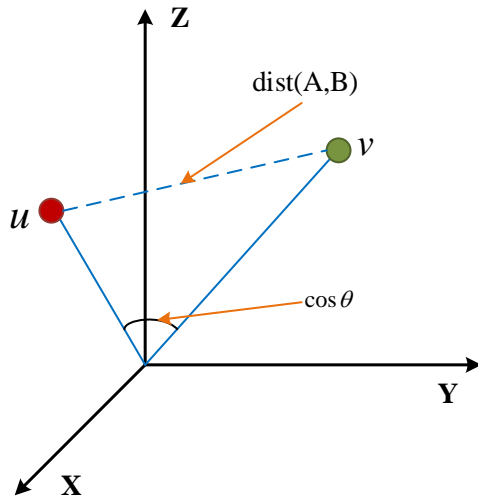


Fig. 6. Schematic diagram of the distance between two points in the three-dimensional space coordinate system.

The Euclidean distance between the user score vectors is given by Eq. (7), since the user score for each dynamic can be regarded as a multidimensional vector.

$$D(u, v) = \sqrt{\sum_{k=1}^n (x_k - y_k)^2} \quad (7)$$

The  $u$ ,  $v$  in Eq. (7) are the sets of user  $u$ ,  $v$ 's ratings of all resource actions, and  $x_i$ ,  $y_i$  are the vectors of user  $u$ ,  $v$ 's ratings of all resources respectively. The closer the Euclidean distance, the higher the similarity, and for the convenience of calculation the normalisation process is performed as in Eq. (8).

$$\begin{cases} s(u, v) = \frac{1}{1 + D(u, v)} \\ 0 \leq s(u, v) \leq 1 \end{cases} \quad (8)$$

The user with the highest similarity to the user is identified and the difference set of the rating dynamics between these two users is determined. This process is repeated until all users have been compared. The study uses accuracy, recall, coverage and Mean Absolute Error (MAE) as performance indicators to evaluate the RA. Accuracy is assessed using Eq. (9).

$$\text{Accuracy} = \frac{\sum_u |R(u) \cap T(u)|}{\sum_u T(u)} \quad (9)$$

In Eq. (9)  $R(u)$  is the set of  $N$  resources recommended to user  $u$ , and  $T(u)$  is the set of resources preferred by user  $u$  on the test set. The recall is calculated as in Eq. (10).

$$\text{Recall} = \frac{\sum_u |T(u) \cap R(u)|}{\sum_u |T(u)|} \quad (10)$$

The coverage ratio is calculated as in Eq. (11).

$$\text{Coverage} = \frac{U_{u \in U} R(u)}{|I|} \quad (11)$$

In Eq. (11),  $U$  is the set of users and  $I$  is the total number of resources.  $MAE$  is calculated as in Eq. (12).

$$MAE = \frac{\sum_{r_{u,i} \in T} |p_{u,i} - r_{u,i}|}{r_{u,i}} \quad (12)$$

In Eq. (12),  $T$  is the test set and  $r_{u,i}$  is the rating of item  $i$  by user  $u$ . In conclusion, the system RA's analysis and design are finished.

#### IV. PERFORMANCE ANALYSIS OF A PR AND SHARING MANAGEMENT SYSTEM FOR SCIENTIFIC AND TECHNOLOGICAL ACHIEVEMENTS BASED ON WEBSOCKET TECHNOLOGY

To verify the effectiveness of the designed RMS and the feasibility of the PRA, this section is designed for comparative experiments of key system technologies and tests of the accuracy and resistance to attack of the user-based CFA.

##### A. Performance Analysis of Key Technologies for Technology Sharing Management System

To verify the feasibility of the AJAX data exchange technology selected for the study, the study used AJAX and traditional HTTP on the system to respond to the same operation respectively, and the response results of both were counted. The training of the model utilises Adam as the optimizer and employs a preheating training methodology. The batch size has been established as 254, with a total iteration count of 3000 and an initial learning rate of 0.0001.

Table I shows a comparison of the results of AJAX and HTTP request responses. The comparison shows that the response time for a single HTTP request is 1613ms and the request resource size is above 40KB, while the response time for AJAX containing the request header and request body is 299ms and the request resource size is no more than 1KB. The results show that AJAX has no additional data transfer of HTML and CSS resources during page loading, which speeds up the response speed of the interface and the study. The use of AJAX data exchange instead of traditional HTTP request

interfaces is effective. To verify the efficiency of the WebSocket real-time push technology selected for the study, the study was tested at a broadband of 30MB/s, counting the throughput of the AJAX polling and WebSocket networks and the data transfer time of the HTTP and WebSocket protocols.

Fig. 7(a) shows the comparison between AJAX polling and WebSocket network throughput. Compared to AJAX polling, WebSocket data requirements are smaller for concurrent client requests below one million and minimal for concurrent requests above one million. In terms of the amount of data communicated, WebSocket has a significant advantage with better concurrency performance. Fig. 7(b) shows the data transfer time comparison between HTTP protocol and WebSocket protocol, the data transfer time in HTTP protocol is basically around 35ms, the transfer time starts to increase when the concurrent working time is 5min and then decreases to around 30 when the data transfer time is mid 10min. The data transfer time in the WebSocket protocol is around 20ms, which varies in line with the HTTP protocol, which is known to consume time each time a connection is established and released during the transfer process. The comparison between the two shows that the WebSocket protocol has a faster

transmission time and faster real-time push. The study divided the generated CiteULike-a dataset into test sets A and B based on user-document interaction records in the CiteULike document management platform, each test set includes 2500 users, 7000 papers and 100000 user-document interaction records, the study proposed the system with the traditional RMS in two the test set was tested on two test sets, using ROC and AUC as evaluation metrics, with AUC being the area below the ROC curve.

The ROC curves and AUC values for the two systems on test sets A and B are displayed in Fig. 8. The findings reveal that on test sets A and B, the suggested RMS has AUC values of 0.973 and 0.986, compared to 0.726 and 0.667 for the conventional RMS. The results show that the AUC values of the proposed RMS on test sets A and B were 0.973 and 0.986 respectively, compared to 0.726 and 0.667 for the conventional RMS. The AUC values of the proposed system increased by 34% and 48%, indicating that the improvement of key technologies has improved the accuracy of the system recommendations and made it easier for researchers to share information and communicate their results.

TABLE I. AJAX RESPONSE COMPARED TO HTTP RESPONSE

Request	HTTP			AJAX		
	Index	Application.css	Application.js	Comments	Likeables	Collects
Name	Index	Application.css	Application.js	Comments	Likeables	Collects
Status	200	200	200	200	200	200
Protocol	h2	h2	h2	h2	h2	h2
Type	Document	Stylesheet	Script	xhr	xhr	xhr
Initiator	Other	Index	Index	Jquery.min.js	Jquery.min.js	Jquery.min.js
Size	46.1KB	103KB	82KB	864B	776B	769B
Time	456 ms	834 ms	323 ms	167 ms	65 ms	67 ms
Total	1613 ms			299 ms		

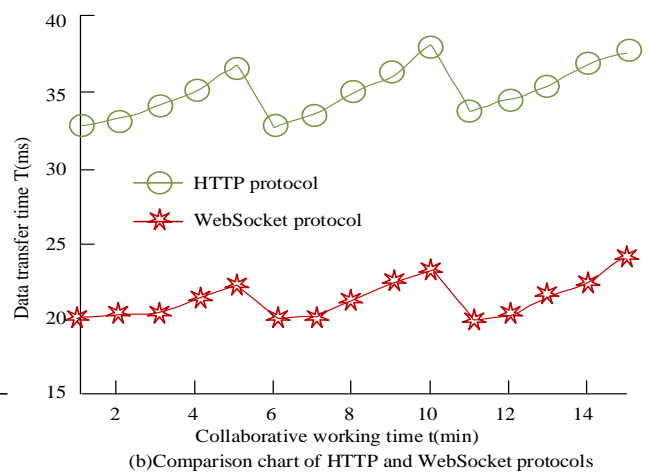
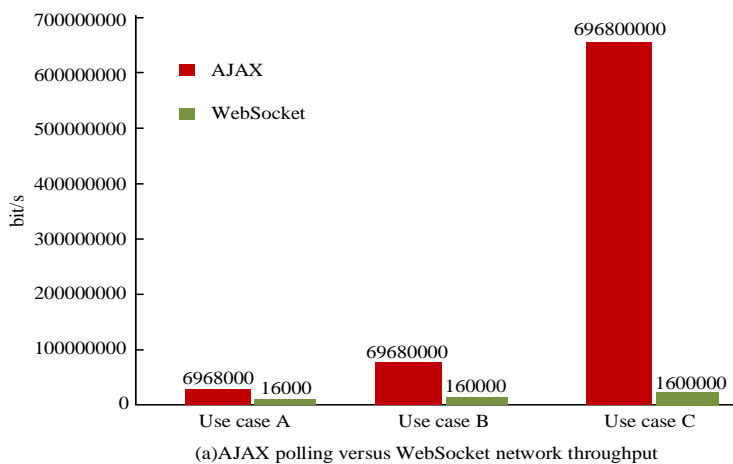


Fig. 7. AJAX polling and WebSocket network throughput and data transmission time comparison of HTTP protocol and WebSocket protocol.

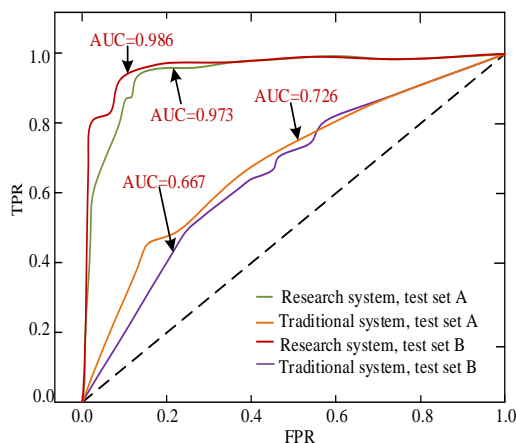


Fig. 8. ROC curves and AUC values of the two systems.

**B. Performance Analysis of the PRA for Scientific and Technical Achievements**

To verify the effectiveness of the user-based CFRA selected for the study, offline experiments were conducted on the Movielen dataset to generate TopN recommendations for each user, using accuracy, recall, coverage and popularity as performance measures, specifying the nearest neighbour parameter as the K users with the most similar interests to the recommended user, and recording the test results.

Table II shows the results of the experimental tests using user-based CFRA. The experimental results show that the accuracy of information recommendation increases with the increase of the nearest neighbour parameter K. The best recommendation is achieved when K=50. When K is constant, the accuracy of information recommendation decreases and the recall, coverage and popularity increase as the number of resources recommended to the user increases. When the training set is 0.7, the accuracy of information recommendation can basically reach 41%. In conclusion, the

accuracy of information recommendations may essentially satisfy the system requirements when K=50, the number of information suggestions is 10, and the training set is 0.7. The study included the classic CFRA based on user (CF), CFRA based on user (UserCF), content-based recommendations (CB), and knowledge-based recommendation algorithm (KR) were tested on test sets A and B to confirm the algorithms' accuracy in making recommendations. The four algorithms' recommendation accuracy was compared using the MAE as a performance evaluation metric.

Fig. 9(a) and (b) show a comparison of the recommendation accuracy of the four RAs on test sets A and B. The results show that the MAE values of UserCF on the two test sets are significantly smaller than those of CF, CB and KR algorithms, and its recommendation accuracy is the highest, with the recommendation accuracy of UserCF improving by about 13.46% compared to KR, and its recommendation accuracy improving by about 10.38% compared to CB. This shows that the research selection of UserCF algorithm can meet the needs of RMS and improve the quality of system information recommendation. To further compare the attack resistance of the four algorithms, the study added mixed attack data to the original Movielen dataset, selected K=50, with fill size of 3%, 5% and 10%, and attack size of 1%, 2%, 3%, 4%, 5%, 6%, 7%, 8%, 9% and 10%, and tested the change of recommendation accuracy of the four algorithms as the fill size and attack size kept increasing situation.

Fig. 10(a) to (c) show a comparison of the prediction bias of the four algorithms at 3%, 5% and 10% fill size. The results show that when the fill size is the same, the prediction deviation of the four algorithms fluctuates more as the attack size increases. In conclusion, the user-based CFA used for the study is better suited for RMS, which can increase the accuracy of the system's recommendations and satisfy the demands of scientific user information sharing.

TABLE II. CFRA EXPERIMENTAL TEST RESULTS

Serial Number	Parameter			Performance			
	Neighbor Parameter	Proportion Of Training Set	Recommended Quantity	Accuracy	Recall	Coverage	Popularity
1	10	0.7	10	0.3373	0.0680	0.4094	6.7834
2	20	0.7	10	0.3766	0.0759	0.3175	6.9195
3	40	0.7	10	0.4040	0.0814	0.2395	7.0310
4	50	0.7	10	0.4083	0.0823	0.2237	7.0630
5	60	0.7	10	0.4130	0.0823	0.2095	7.0882
6	50	0.6	10	0.4623	0.0699	0.2187	6.9349
7	50	0.8	10	0.3314	0.1002	0.2325	7.1696
8	50	0.9	10	0.2119	0.1280	0.2406	7.2500
9	50	0.7	5	0.4629	0.0466	0.1691	7.1538
10	50	0.7	20	0.3468	0.1398	0.2957	6.9506
11	50	0.7	30	0.3077	0.1860	0.3505	6.8740
12	50	0.7	40	0.2790	0.2249	0.3961	6.8152
13	50	0.7	50	0.2573	0.2592	0.4233	6.7601
14	50	0.7	60	0.2396	0.2896	0.4506	6.7253



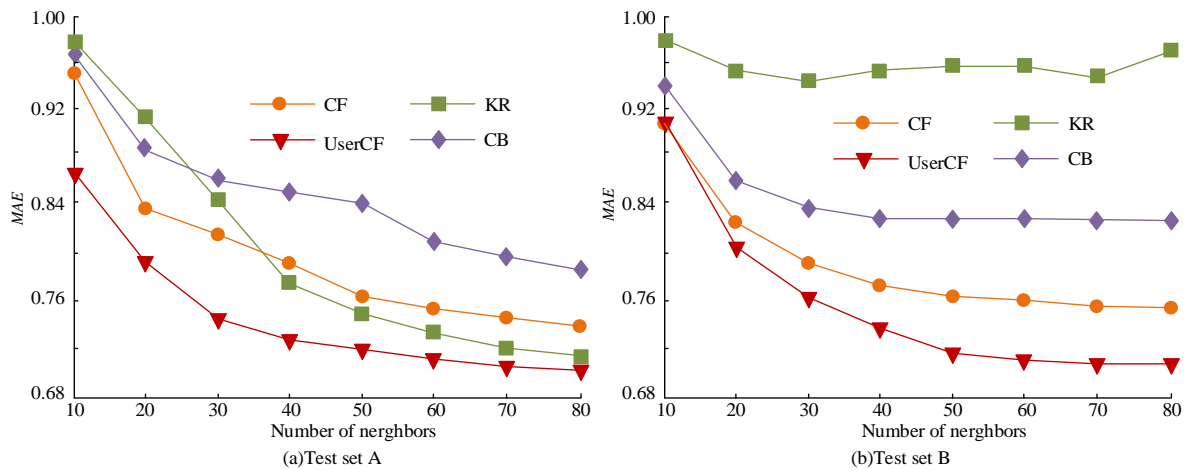


Fig. 9. Comparison of recommendation precision with different datasets.

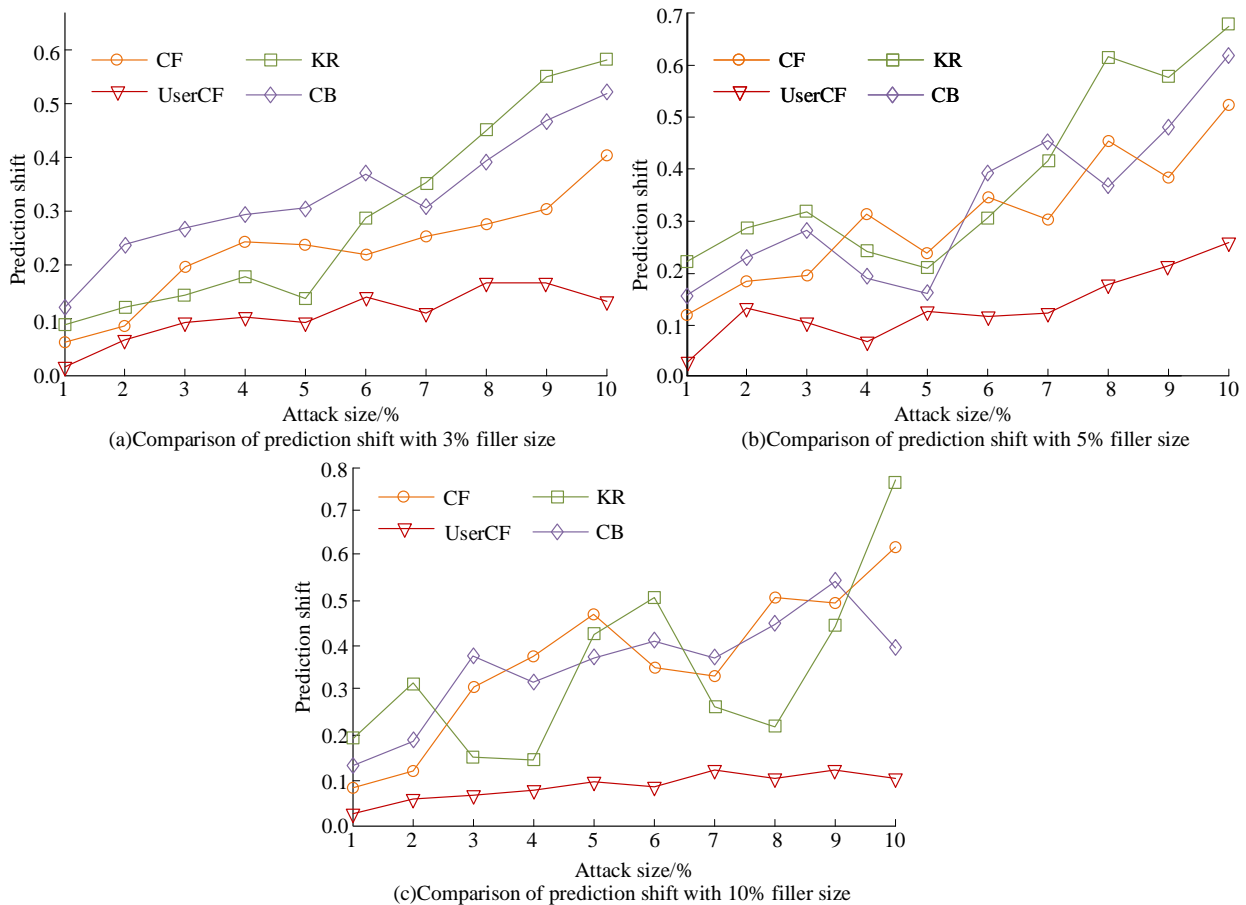


Fig. 10. Comparison of the prediction deviation of the algorithm at different filling scales.

## V. RESULTS AND DISCUSSION

With the ongoing advancements in science and technology and the rising prevalence of intelligent devices, there is a growing desire for personalized recommendations and shared management of scientific and technological accomplishments. The conventional approach to recommending and managing these accomplishments presents challenges such as information imbalance, imprecise recommendations, and burdensome administration. Designing a personalised system

for recommending and sharing scientific and technological achievements based on network socket technology has the potential to address these issues effectively, enhancing the efficiency of utilisation and improving the overall user experience. The study's experimental results demonstrated that implementing AJAX and WebSocket technologies can substantially enhance the system's response time and data transfer efficiency. Additionally, the UserCF approach proved to be more accurate in terms of information recommendation

and MAE value. The study adopted network socket technology and proposed corresponding system design and algorithm optimization based on the requirements of personalized recommendation and shared management. This holds immense importance in driving innovation and utilization of network socket technology, while also playing a guiding and exemplifying role in advancing the dissemination and collaboration of scientific and technological progress.

## VI. CONCLUSION

With the continuous development of science and technology, China has made significant progress in the field of scientific research. However, while the field of scientific research is steadily developing, the management of scientific research faces the problem of insufficient standardisation, automation and information management, so the construction and promotion of RMS is imperative. This paper proposes a scientific and technological achievement publicity and sharing management system based on WEBSOCKET technology to solve the problem of the lack of a professional platform for scientific communication and exchange among small scientific research teams. The trial results demonstrated that the system using AJAX technology has a response time that is 1314ms faster than that of traditional HTTP, that no request resource exceeds 1KB in size, and that the WebSocket technology used to transmit data demands is more efficient, with data transmission times of roughly 20ms. According to the study, the system has AUC values of 0.973 and 0.986 on the same test set, which is an improvement of 34% and 48% over conventional RMS, respectively. The UserCF method selected for the study also satisfies the system requirements for scientific research with an accuracy rate of about 41% for information recommendations at K=50, several information recommendations of 10, and a training set of 0.7. The recommendation accuracy of UserCF is around 13.46% higher compared to KR and about 10.38% higher compared to CB, which has the highest recommendation accuracy and the strongest resilience to attacks. The MAE of UserCF on the test set is much lower than that of the CF, CB and KR algorithms. In conclusion, the study claims that RMS-based systems can facilitate communication between small research teams and enable the dissemination of results. However, the study still has some shortcomings in that it collected too little information about users' personal lives, making it difficult to provide non-personalised dynamic recommendations. Future research can focus on the front-end interface of the system, user interaction, data collection and other in-depth research topics.

## FUNDINGS

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## REFERENCE

[1] Zan J. Research on robot path perception and optimization technology based on whale optimization algorithm. *Journal of Computational and Cognitive Engineering*, 2022, 1(4):201-208.

- [2] Shahmirzadi T. Feasibility study of Scientific Information Visualization System of Agricultural Research, Education and Extension Organization. *Agricultural Information Sciences and Technology*, 2020, 3(5):31-40.
- [3] Ding J, Wu Y, Ni X, Wang Q, Chen Y, Ye Y, Zhang X, Ma Y, Yang W. A direct coupling analysis method and its application to the Scientific Research and Demonstration Platform. *Journal of Hydrodynamics*, 2021, 33(1):13-23.
- [4] Zhao L. Problems and Suggestions for the Scientific Research Management System of Universities. *Journal of Contemporary Educational Research*, 2021, 5(6):31-35.
- [5] Mashizume Y, Watanabe M, Fukase Y, Zenba Y. Experiences within a cross-cultural academic exchange programme and impacts on personal and professional development. *British Journal of Occupational Therapy*, 2020, 83(12):741-751.
- [6] Bisták P. Remote control laboratory for three-tank hydraulic system using matlab, websockets and javascript. *IFAC-PapersOnLine*, 2020, 53(2):17240-17245.
- [7] Al-Joboury I M, Al-Hemiary E H. Consensus algorithms based blockchain of things for distributed healthcare. *Iraqi Journal of Information and communication technology*, 2020, 3(4):33-46.
- [8] Pala Z, Şana M. Attackdet: Combining web data parsing and real-time analysis with machine learning. *J. Adv. Technol. Eng. Res*, 2020, 6(1):37-45.
- [9] Abdelfattah A S, Abdelkader T, EI-Horbaty E I S M. RAMWS: Reliable approach using middleware and WebSockets in mobile cloud computing. *Ain Shams Engineering Journal*, 2020, 11(4):1083-1092.
- [10] Chang C T, Tsai C Y, Tsai H H, Li Y J, Yu P T. An online multi-user real-time seamless co-reading system for collaborative group learning. *International Journal of Distance Education Technologies (IJDET)*, 2020, 18(4):51-70.
- [11] Lim H, Xie L. A new weighted imputed neighborhood-regularized tri-factorization one-class collaborative filtering algorithm: Application to target gene prediction of transcription factors. *IEEE/ACM transactions on computational biology and bioinformatics*, 2020, 18(1):126-137.
- [12] Bao T, Xu L, Zhu L, Wang L, Li R, Li T. Privacy-preserving collaborative filtering algorithm based on local differential privacy. *China Communications*, 2021, 18(11):42-60.
- [13] Wu Y, ZHao Y, Wei S. Collaborative filtering recommendation algorithm based on interval-valued fuzzy numbers. *Applied Intelligence*, 2020, 50(9):2663-2675.
- [14] Zheng G, Yu H, Xu W. Collaborative filtering recommendation algorithm with item label features. *International Core Journal of Engineering*, 2020, 6(1):160-170.
- [15] Zhang J, Yang J, Wang L, Jiang Y, Qian P, Liu Y. A novel collaborative filtering algorithm and its application for recommendations in e-commerce. *Computer Modeling in Engineering & Sciences*, 2021, 126(3):1275-1291.
- [16] Ejegwa P A, Agbetayo J M. Similarity-distance decision-making technique and its applications via intuitionistic fuzzy pairs. *Journal of Computational and Cognitive Engineering*, 2023, 2(1):68-74.
- [17] Ohtomo K, Harakawa R, Ogawa T, Haseyama M, Iwahashi M. Personalized Recommendation of Tumblr Posts Using Graph Convolutional Networks with Preference-aware Multimodal Features. *ITE Transactions on Media Technology and Applications*, 2021, 9(1):54-61.
- [18] Huang Y, Huang W J, Xiang X L, Yan J J. An empirical study of personalized advertising recommendation based on DBSCAN clustering of sina weibo user-generated content. *Procedia Computer Science*, 2021, 183(8):303-310.
- [19] Chen X, Xue Y, Shiue Y. Rule based Semantic Reasoning for Personalized Recommendation in Indoor O2O e-commerce. *International Core Journal of Engineering*, 2020, 6(1):309-318.
- [20] Zheng K, Yang X, Wang Y, Zheng X. Collaborative filtering recommendation algorithm based on variational inference. *International Journal of Crowd Science*, 2020, 4(1):31-44.