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Research Article

A Personalized Recommendation Method for Ancient Chinese Literary Works Based on a Collaborative Filtering Algorithm

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The works of ancient Chinese literature that rely on Internet technologies are developing quickly. Through mobile phone inspection, ancient Chinese literary masterpieces are becoming more well-known, which encourages readers to read them more regularly. Providers of output literary works are confronted with a conundrum and a challenge, enabling users to quickly discover and attract their own works in the vast body of ancient Chinese literature. Providers of output literature can rely on personalized recommendation technology to find a solution to this issue. The production of works of literature is one of the most significant signs of human civilisation. As Internet technology becomes more widespread, the suggestion of the platform will become a more important factor in determining how the general audience reacts to works of literature. A collaborative filtering (*CF*) algorithm is offered as a method for making the recommendation algorithm for ancient Chinese literature more accurate. The personalized recommendation system's technological support helps to increase the accuracy of recommendations. This system predicts and scores the reading preferences of the readers in a thorough manner, which helps to improve the recommendation's accuracy. It is hoped that the user community will find the analysis and discussion contained in this article to be useful as a reference. The compelling experimental findings show that the recommendation algorithm suggested in this study greatly improves the accuracy of the intelligent recommendation system. These results were found by analyzing the final experimental data.

1. Introduction

Since 1997, Resnick and Varian have been working on the concept of a personalized recommendation system [1–4]. It proposes related product information on the e-commerce platform, according to the actual preferences of users, and it gives users suggestions and guidance. The function of virtual sales significantly simplifies the purchase requirements of users. A comprehensive personalized recommendation system will consist of a number of modules, the most important of which are user behavior records, user data analysis, and recommendation algorithms. These modules will each be responsible for their own unique processing functions. The scope of user information is determined by using the user behavior record, which also assesses the user's preference for similar information. These recommendations are based on the user's online activity, including comments, browsing, time spent on reading, staying on websites, and likings. The relevance of user information recommendations is also assessed using the user behavior record. User data analysis [5–7] involves immediately analyzing the user's activity, determining the user's genuine preferences, and making targeted recommendations for comparable relevant content. The recommendation algorithm serves as the framework upon which the entirety of this process is built, and it is the single most significant component of the system's main technologies in terms of ensuring the correct execution of the process.

Inquiries from clients are processed using technology for information and data retrieval [8–10]. The research on information data retrieval includes two different sorts of technologies. The first is a technology for queries, and the second is a technique for indexes. The second step is to conduct an analysis of the information contained within the resource, after which it is represented to the computer in the form of a data and information structure that it can process.

The first step is to acknowledge the requirements of clients via the user interface. Hence, information data retrieval technology is typically implemented in large-scale database management systems. Nevertheless, these databases are typically unchanging. It is unable to actively provide recommendations for clients and is also unable to uncover other interests held by customers.

In contrast to information retrieval, information filtering considers the requirements of clients over an extended period. Its primary function is to process various forms of textual data. The end goal is to be able to assist clients in processing vast amounts of information. The pursuits and passions of consumers need to inspire the development of this technology. It can be primarily broken down into two categories: the first is based on the technology of filtering content information, and the second is *CF* technology, which combines the characteristics of the information content to be filtered and organically matches the information flow with the customer file and determines the information based on the degree to which it matches. Does the customer derive any benefit from consuming the stream?

Customers work together in this technology to pick out information, which is mostly based on customers who have interests that are comparable to one another, and to make judgments on the information data through the cooperation of these customers. The collaborators are typically consumers' family, friends, coworkers, or other customers who share similar interests. Customers place their trust in these individuals since they recommend information to consumers based on their own personal opinions. The most important advantage of the so-called *CF* technology is that it completes the filtering process after studying client behavior rather than the product itself. People have started to make improvements to *CF* technology by doing ongoing studies and analyses of this technology [11–15]. This has led to the production of a *CF* technology that is automated and intelligent. As a result of the fact that the *CF* technology does not care about the actual content of resources, it is difficult to analyze the content of resources. If you want to use things like music, graphics, videos, or images as resource content, *CF* technology is an excellent option. Consumers are unable to anticipate the recommended content in advance due to the fact that the *CF* technology can uncover resources that have completely diverse appearances in their content. The *CF* technology offers several advantages that cannot be replicated when compared to the traditional methods that were used in the past, and it is also a relatively successful technology that has been employed in personalized recommendation systems up until this point.

The vast majority of existing recommendation systems favour recommending things that have a high likelihood of being bought. They use methods such as data mining, *CF*, and content-based filtering in their operations. After conducting research to determine the flaws in each algorithm, a number of academics came to the conclusion that the existing algorithms had less direct engagement with clients. Many researchers have focused their attention on the combined recommendation algorithm [16–18], which combines a number of different recommendation techniques in order to address the shortcomings of individual recommendation algorithms while also capitalizing on the benefits offered by those algorithms individually. On the other hand, the majority of the study is founded on two different algorithms: *CF* and content-based filtering. Very few scholars have looked into how interactive design might be used to dynamically compose several recommendation methods.

Customers can have better services by using IoT services. It can enable users to acquire information when it is required. The primary idea behind the proposed plan is to provide recommendations to users whose interests are comparable to one another. In other words, the *CF* algorithms first assess a user's preferences based on the behavioral records that the user has kept, and then they generate recommendations based on the preferences of other individuals who share interests that are comparable to the user's own. When it comes to recommended products, *CF* does not have any specific requirements (such as descriptions or metadata). It can deal with a variety of things, such as books, movies, and music. Because of this, it finds widespread use in a variety of commercial applications. According to a survey that was just released by Ref, the recommendation system on Amazon is responsible for more than 30 percent of purchases. Additionally, recommender systems are an essential component of cloud computing.

2. Related Work

The memory-based *CF* algorithm is a type of filtering algorithm that is based on items as well as the thoughts contributed by the user. It begins by choosing collaborative neighbor users who have concepts that are comparable to those of the user, and then it proposes objects and items based on the associated items of the users who are collaborative neighbors. Scoring things, proposing users, anticipating the likely scoring values of users for these items, and screening the benefits and disadvantages according to the scores are all included in this process. It is important to note that the judgment basis of the algorithm will be the score of the item and that the analogy concept will also be reflected here. These two points are important to note. If the features described above are favored by a sizable majority of users who are collaborative neighbours, then it is assumed that the user will similarly value these qualities and any features that are related to them. The ranking system will demand user participation and will automatically prefer items that are comparable.

The memory-based *CF*algorithm [19] and the model-based *CF* method [20] both have distinctive features that distinguish them from one another. The earlier method tends to build a model first (by combining users' surfing, clicks, purchases, and information read), then look for related and cooperative neighbour users. Make a thorough model of the user's preferences, assess that model in light of the data provided by the nearby users, and use that data to anticipate the user's preferences. When the item set is divided up into numerous modules, the module units of the users who are working together with their neighbors are then categorized according to the user's model, and the user model that best fits the data is chosen. A curated selection of the most relevant modules is used to provide users with content recommendations. This technology has branched out into many different subfields, many of which incorporate the concepts of correlation and comparative analysis in some way. People's aspirations to lead more spiritual lives are growing in tandem with the general rise in the quality of their living conditions, and as a result, libraries have evolved into popular gathering spots for those looking to do so. It is very crucial for individuals to be able to locate the books that they require from among a huge number of books when the technology for wireless mobile network storage has matured to the point where many e-books may be stored in libraries [21–24]. People will have an easier time finding the books they require with the assistance of the library's bibliographic recommendation system, which will lead to a higher rate of resource usage overall. It is for this reason that the development of a library bibliographic recommendation system that has good performance has become an important direction in the field of study concerning libraries.

There is now more interest in location-based recommendations due to improvements in mobile positioning technology. These suggestions can help users find interesting places to visit within a specific distance of where they are right now, as well as propose places to go for food that they would enjoy. In general, information about a user's mobility and spatial location is useful in identifying their preferences. When making recommendations, considering the geographic location of the user can improve speed, as well as give improved scalability to accommodate growing data sizes and latent space dimensions. In general, user behaviors falls somewhere within a predetermined range of possibilities. For instance, when most users consume offline content, they will choose hotels within 50 miles, which demonstrates that user behavior patterns are heavily influenced by geographic regions. This can be seen in the fact that most users will choose hotels within this distance range. Take into account the whereabouts of users across the globe. It is possible to do user portraits with greater accuracy in order to determine user preferences.

The success of the venue recommendation process is heavily dependent on the methods that are utilized to obtain information regarding the user's environment or preferences. However, it is difficult to collect complete knowledge about user preferences, and furthermore, user preferences have a tendency to vary from person to person (i.e., some preferences are common to all users, while others are dynamic and diverse). Venue-based recommendation algorithms [25, 26] typically suggest the most well-known, inexpensive, or conveniently located venues based on a few pieces of contextual information. In addition to taking into account the user's location, it is imperative to also consider the user's other interests and preferences. The preferences of users are influenced by a wide variety of factors, including proximity, familiarity, and overlap in areas of interest [26]. Therefore, it is vital to take into account distance in addition to other criteria of interest that include several dimensions when making individualized recommendations for crowdfunding projects.

In recommender systems, users and goods each have their own unique set of multidimensional characteristics. The degree to which objects and users match up can be improved, as well as the effectiveness of recommendations, by the utilization of multifeature similarity [27]. Therefore, when it comes to financial things found on the Internet, taking into account the multidimensional characteristics of both items and users and matching them can considerably increase the identification of user preferences. Studies that already exist have shown that there is a local bias in the behavior of online investors. This means that investors favor projects that are located in closer proximity to them. This preference of investors violates the limitation of geographical location, and it is a completely different scenario from the suggestion of venue projects. Because of this, a recommendation system that is based on local preferences needs to be reconstructed.

Due to the fact that the majority of consumers only buy a few goods, there is a problem with data sparsity. Utilizing various forms of implicit feedback data, such as the ratings and comments left by customers on online retailers' websites, is one potential answer. One such possibility is to make use of a network graph to determine the overall degree of similarity that exists between users and products.

The location of the user is one of the fundamental features. Other user attributes are diverse. Recommender systems have evolved in recent years to take into consideration the multidimensional features of consumers. However, this type of group recommendation treats users in the same group as if they were all identical, does not include any sort of personalisation, and has a performance that is restricted by the degree to which clustering is accurate.

3. Research Design

The analysis of its working process reveals, as shown in Figure 1, that the user's individual needs are analyzed first and then the relevant information regarding ancient Chinese literary works is extracted from the database. Finally, a portion of the information is preprocessed and categorized, and the classification outcomes are saved in the database. All this is completed prior to the classification results being saved in the database. The next step is to make use of *CF* to determine the degree of similarity between users and works, as well as to mine the relationship between the two. Next, create tailored recommendation association rules, and then ultimately show the results of the recommendations made.

3.1. Data Sources. The source of our data is a database of the ancient Chinese literary works on a domestic literary website. This database contains readers' ratings of the ancient Chinese literary works as well as their comments on these works. Separate the data into a training set and a test set, with the former accounting for eighty percent of the total and the latter for twenty percent.

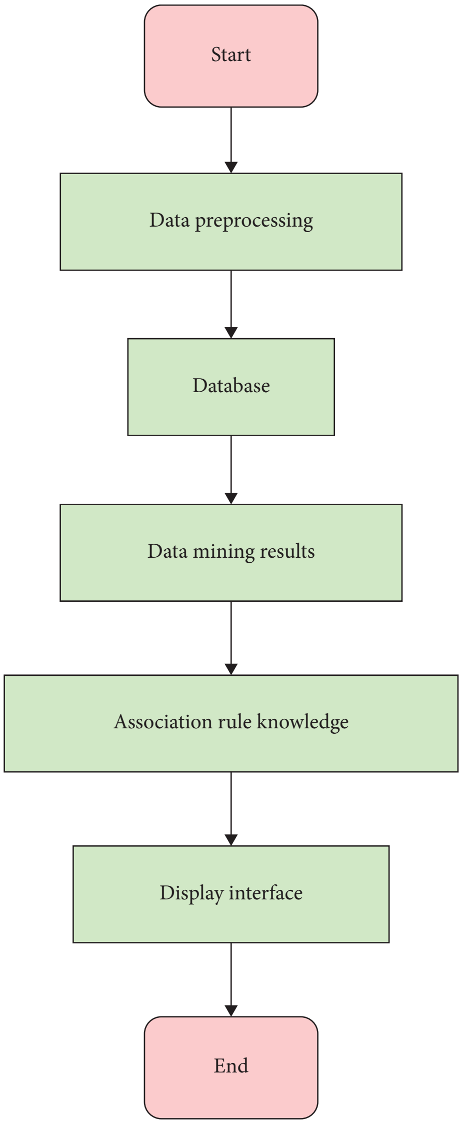

Figure 1: The workflow of a personalized recommendation system.

3.2. CF Algorithm. The *CF* algorithm establishes the relevance of the keywords found in the works of classical literature from the mediaeval times. Currently, a number of methods can be used to determine the keyword weights of literature from the mediaeval and classical periods. This method is more scientific and reasonable when compared to other methods, and it may be used to determine the relative importance of keywords in literary works from the Middle Ages and the classical period. As a result, the focus of this article will be on determining the relative importance of keywords in classical and medieval literary works. The importance of keywords to medieval and classical literary works is represented by the *WF*, which stands for the word frequency of medieval and classical literary works and is used to describe the importance of keywords. The word used to describe the significance of keys around the world is Inverse Document Frequency (*IDF*) of medieval classical literary works. Assuming that there are F keywords in books of medieval and classical literature and that the number of times they appear in books of medieval and classical literature is K, then WF may be represented as a formula, provided that there are F keywords in books of medieval and classical literature.

$$WF = \frac{K}{F}. \tag{1}$$

If we assume that the total number of the ancient Chinese literary works is N, and that the number of ancient Chinese literary works that contain a certain keyword is k, then the information distribution function can be stated as the following formula:

$$IDF = \log_{10}^{N/k+1}. \tag{2}$$

It is possible to determine the keyword weight of the ancient Chinese literary works using this method, and this weight may be stated using the following formula:

$$WF - IDF = WF \times IDF. \tag{3}$$

The keyword weights of the ancient Chinese literary works are used next in order to determine the similarity between the works being compared. h is the number of common keywords that may be found in literary works from ancient China such as A_i and A_j. Since the weights of the kth keyword are ω_{ik} and ω_{jk}, respectively, for the literary works A_i and A_j, the formula for determining the degree of similarity between these two sets of works is as follows:

$$\mathrm{sim}\left(A_i, A_j\right) = \sum_{k=1}^{h} \omega_{ik} \times \omega_{jk}. \tag{4}$$

After that, compute the user's degree of overlap. Numeric and text kinds are both considered user characteristics. Let's call the degree to which the numerical characteristics of user U_i and user U_j are alike $\mathrm{sim}_{n(i,j)}$. The similarity between user U_i and U_j's text attributes is denoted by $\mathrm{sim}_{h(i,j)}$, and the similarity between user attributes is denoted by the following formula:

$$\mathrm{sim}_{a(i,j)} = \mathrm{sim}_{n(i,j)} + \mathrm{sim}_{h(i,j)}. \tag{5}$$

Determine the degree of user activity overlap. The number of dynamic pieces of information that are shared between user U_i and U_j is equal to m, and the weight of the kth dynamic piece of information is denoted by U_{ik} and U_{jk}, respectively. The sim_{ac} model is based on user activity similarities, as shown in the following equation:

$$\mathrm{sim}_{ac(i,j)} = \sum_{k=1}^{m} U_{ik} + U_{jk}. \tag{6}$$

The concept of user similarity refers to two distinct aspects: attribute similarity and activity similarity. The overall degree of overlap between users U_i and U_j can be calculated using the following formula:

$$\mathrm{sim}\left(U_i, U_j\right) = \gamma \mathrm{sim}_{a(i,j)} + \eta \mathrm{sim}_{ac(i,j)}. \tag{7}$$

Determine the degree of association between users and classic works of Chinese literature. If we make the assumption that there are connections between the user U_i and the work A_j, then the formula used to determine the nature of the link between the user U_i and the work A_j is as follows:

$$\mathrm{sim}_{ua} = \sum_{k=1}^{c} R_{ik}. \tag{8}$$

The value that corresponds to the kth connection between U_i and work A_j is denoted by R_{ik} in the formula.

Finally, it comes down to the recommendation rules for the ancient Chinese literary works from the users. The collection of the ancient Chinese literary works should be denoted by the letter $X = \{X_1, X_2, \ldots, X_m\}$, and the collection of transaction records should be denoted by the letter $Y = (y_1, y_2, \ldots, y_n)$. In accordance with the matching tree method, the levels of support and confidence are derived from the following formulas:

$$S(X_i) = \frac{\left|\{y \in Y | X_i \in X\}\right|}{|Y|}, \tag{9}$$

$$\mathrm{Con}\left(X_p \longrightarrow X_q\right) = \frac{S\left(X_p \cup X_q\right)}{S\left(X_p\right)}. \tag{10}$$

The K-Means clustering algorithm is utilized in the process of analyzing the ancient Chinese literary works and classifying them into a set of K categories. The matching rules for the numerous literary works are formed according to the matching tree technique, and the minimal support and minimum confidence are computed after that. Finally, based on the minimal amount of support and minimum amount of confidence, the bibliography is recommended to users.

4. Results

To begin, we stipulate a condition regarding the rating index of the personalized recommendation system's procedure. Early recommendation systems are frequently based on their evaluation of their ability to anticipate whether users will read a certain work of literature or not. As a result, the accuracy rate becomes a crucial measure. Later research concluded that basing the development of recommender systems primarily on accuracy would result in unintended consequences. As an illustration, the accuracy rate will be quite high when it comes to the recommendation of well-known products. Users will still purchase these kinds of products even though they are not recommended. When users promote things to other users who are unfamiliar with but are interested in, they express higher levels of enjoyment. On the other hand, experience has shown that a massive collection of outstanding literary works will significantly affect sales. In order to accomplish this, precision and recall are divided into two separate areas when evaluating recommender systems. In the formulas (11) and (12), which are listed in that order, there are the steps for calculating the two different types of indicators.

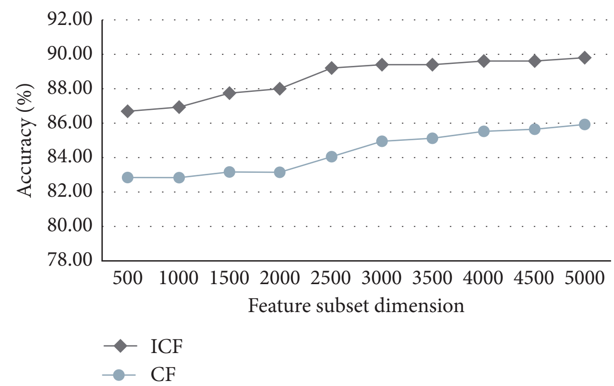

Figure 2: The accuracy of the two algorithms.

$$p = \frac{TP}{TP + FP}, \tag{11}$$

$$r = \frac{TP}{TP + FN}. \tag{12}$$

As can be seen in Figure 2, we evaluate the performance of the improved collaborative filtering algorithm (*ICF*) in contrast to the conventional *CF*. The accuracy of the *ICF* algorithm is substantially higher than that of the *CF* algorithm, as can be seen from the observation figure. This is a major difference between the two algorithms. When the dimension of the feature subset is 500 dimensions, the accuracy of the *ICF* algorithm is higher than that of the *CF* algorithm. When the dimension of the feature subset reaches 4000 dimensions, the accuracy of the two algorithms tends to be stable, and the final accuracy of the *ICF* algorithm is stable. When the dimension of the feature subset is 500 dimensions, the accuracy of the *CF* algorithm is higher than that of the *ICF* algorithm. It is approximately 89.6 percent, but the accuracy of the *CF* algorithm remains relatively constant at approximately 85.8 percent.

Figure 3 displays the recall results obtained using the two different techniques. It has been found that the recall rate of the *ICF* method is greater than that of the *CF* algorithm when the feature subset dimension is set to 500 dimensions. The recall rate of the *ICF* algorithm tends to be stable when the dimension of the feature subset reaches 1500, but the recall rate of the *CF* method is steady when the dimension of the feature subset reaches 3500. The ultimate recall rate of the *ICF* algorithm has been found to be steady at approximately 89.1%, which is higher than the *CF* algorithm's recall rate of 85%.

Figure 4 depicts the outcomes of the calculations for the *F* value performed by the algorithm for the analysis of reader text comments. It is clear from looking at the figure that as the feature subset dimension gets larger, the *F* value of the *ICF* algorithm goes up from 85.9% to 88.7%, and the *F* value of the *CF* method also goes up from 82.5% to 84.7%. When the dimension of the feature subset approaches 3500, the *F* value of the two algorithms has a greater likelihood of being stable. In general, the performance of the *ICF* algorithm is noticeably superior to that of the *CF* method.

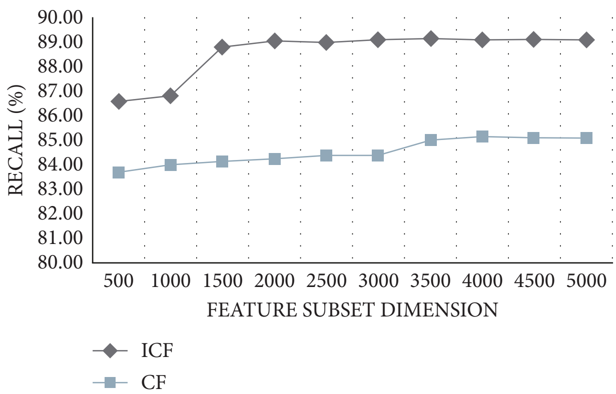

Figure 3: The recall of the two algorithms.

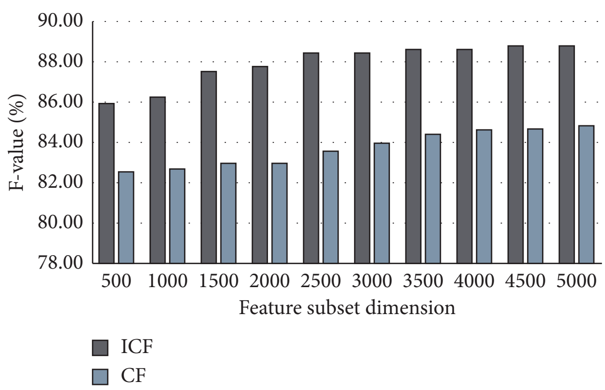

Figure 4: The F value of the two algorithms.

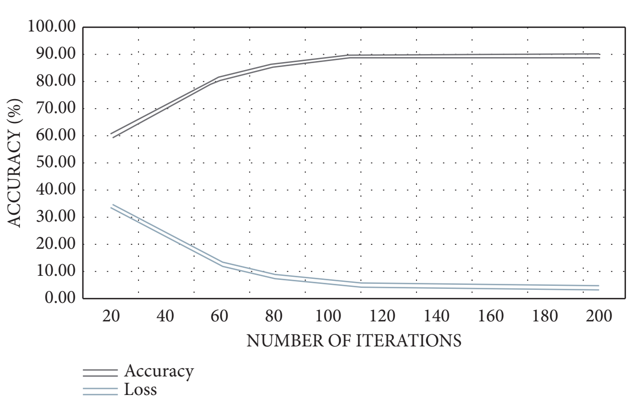

Figure 5: Accuracy and loss as a function of iterations.

As can be seen in Figure 5, both the accuracy and the loss of the *ICF* algorithm shift as more and more rounds are performed. When the number of iterations is close to 120, we can observe that the *ICF* algorithm is getting close to convergent. At this point, both the accuracy and the loss are fluctuating within a relatively small range.

5. Conclusion

We will discuss the *CF* algorithm and the personalized recommendation system, as well as elaborate on the correlation between the two. Our primary focus will be on the structure, classification, advantages, and disadvantages of the personalized recommendation system that is based on the collaborative recommendation algorithm. In addition, we will expand on and introduce the method for improving the algorithm. The classification of model-based filtering algorithms is comparable to that of personalized recommender systems, in that it is user-centric and has similarities to the aforementioned categorization. The *CF* algorithm is the backbone of the system that generates tailored recommendations. Its fundamental premise is that it should be possible to conduct an efficient search for neighbor users who share use'r preferences in a short amount of time, to filter and sort objects according to the preferences of the neighbor users, and to recommend the results of the search to the initial users. It is composed of an offline system and an online system, both of which are connected to one another and work in conjunction with one another. A lack of data, insufficient sample richness, limited system computing capacity, new users, new product interference, and other issues are also present in the process of its development. Improvements can be made, respectively, to the user-led recommendation and the project-guided recommendation systems in response to the issues described above.

We have developed a personalized recommendation algorithm for the ancient Chinese literature that is based on the *ICF* method. This algorithm was created to assist users who are interested in ancient Chinese literature in swiftly locating the literature that best suits their interests. Help more readers get their tailored text while saving time and effort, providing users with a better experience, and giving users more options.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

Declares that he has no conflict of interest.

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