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Design and Implementation of a Personalized News System Based on SSM Architecture

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Abstract

In today's information age, personalized recommendations have permeated every aspect of people's lives, becoming an indispensable service on major mainstream websites. By considering users' past interaction habits and preferences, personalized recommendation systems cater to the unique needs of individuals, presenting content that aligns with their interests. However, research on news recommendations, compared to fields such as e-commerce and music, remains relatively scarce and faces significant challenges, particularly in identifying news choices that may engage readers amidst information overload. This study designed and implemented a personalized hot news recommendation mechanism based on collaborative filtering technology. The system was developed using the SSM framework, incorporating software engineering principles with UML modeling. The front-end interface was built and deployed using the Bootstrap framework, while the back-end interface construction was supported by the Layui front-end framework. MySQL served as the storage system for news information. The core services of the personalized news push system include user account creation and login, personal information management, information search, news content evaluation, customized content push, and administrator-end information supervision. The customized push service, in particular, relies on collaborative filtering technology, tag-based recommendation strategies, and mechanisms for tracking current hot topics to achieve its goals.

Keywords: Personalized recommendations, collaborative filtering technology, MySQL database.

1. Introduction

With the rapid enhancement of internet technology capabilities in China, the public's reliance on the internet has deepened[1]. However, this trend has quietly given rise to the dilemma of an information flood, where users often feel overwhelmed by the vast sea of data, making quick and precise targeting increasingly difficult[2]. Traditional search engines only receive commands and passively obey them, requiring users to clearly articulate their needs and input accurate keywords to obtain the desired content. Personalized recommendation systems have emerged to address this problem.[3] Therefore, developing an efficient personalized news recommendation system to enhance user experience is essential[4].

Personalized recommendation technology is now widely applied in various industries, including music, e-commerce, and film[5]. With recommendation systems, users can explore content that matches their interests more smoothly and potentially discover new areas of interest[6]. For platforms, this is not only an effective tool for strengthening user engagement and enhancing market competitiveness but also opens avenues for increasing revenue through personalized advertising strategies. Over time, personalized recommendation systems have been widely deployed on online platforms such as Amazon, YouTube, and Google, profoundly meeting the diverse needs of users while generating significant economic benefits. Statistics show that after launching the recommendation system, Amazon's sales increased by 30%, while Google's clicks increased by 38% after introducing the recommendation system. Jinri Toutiao is a product focused on personalized news recommendations, and as of now, Jinri Toutiao has 470 million active users. The enormous commercial value of personalized recommendation sections is thus evident[7].

When faced with the challenge of a growing number of users, traditional recommendation systems often encounter problems such as decreased recommendation rates and lack of diversity[8]. The personalized news system proposes a hybrid recommendation solution to address these challenges by using user-based and item-based collaborative filtering algorithms, incorporating rating and collection data, and leveraging statistically based hot topic recommendations[9,10].

2. Objectives

Collaborative filtering technology is a widely adopted traditional recommendation method and plays an important role in recommendation systems.[11,12] Despite this, the algorithm still faces the challenges of uneven data distribution and new user cold starts in practical applications.[13,14] Data sparsity refers to when items are newly launched, and user ratings and collection data are few, resulting in a lack of interaction among users, causing some users to be unable to obtain recommendation results[15]. The cold start problem occurs when new users log in for the first time, and due to a lack of rating and collection data, personalized recommendations cannot be made, affecting the recommendation effect and user experience. Therefore, to solve these problems, a news recommendation system can be designed by combining hot recommendations based on user preference tags and collaborative filtering algorithms. This design not only improves the recommendation accuracy and user satisfaction of traditional collaborative filtering algorithms but also has significant reference value in research and practical applications.[16,17]

3. Theoretical Background of Collaborative Filtering Recommendation Algorithms

3.1 Determining recommendation methods based on user behavior

The key basis for selecting a recommendation strategy lies in the variability of user behavior patterns. User behavior can be divided into explicit and implicit behaviors to deepen the insight into user preference trends and behavior logic, precisely matching the most suitable recommendation model. Examples of both types of data are shown in Table 1.

Table 1 Examples of explicit and implicit behavior data.

	Explicit Behavior	Implicit Behavior
News Websites	User ratings on news	User reading logs on news
Video Websites	User ratings on videos	User viewing logs on videos
E-commerce Websites	User ratings on products	User purchase and browsing logs

The user behavior data of the news recommendation system is divided into three main categories:

(1) Data not involving rating activities, serving as parameters for article and user identity confirmation.

(2) Users' direct feedback information, which can serve as information interacting with the system.

(3) Feedback information integrating user characteristic data.

3.2 Similarity calculation schemes

3.2.1 Jaccard similarity

Jaccard similarity measures the correlation between two sets, ranging from 0 to 1, with higher values indicating higher similarity. Calculating the Jaccard similarity method of two user information involves obtaining the number of intersection elements between them and dividing it by the total number of elements in the union set. The Jaccard similarity formula is shown in Equation 1:

$$J(A, B) = \frac{A \cap B}{A \cup B} \tag{1}$$

3.2.2 Cosine similarity

Cosine similarity is a measurement method to evaluate the similarity of directions between two vectors. The range of values is between 0 and 1, with values closer to 1 indicating a high degree of similarity between the calculated vectors. In the collaborative filtering mechanism, cosine similarity is generally adopted as a metric benchmark to evaluate user similarity, driving the implementation of personalized recommendation strategies. The cosine similarity formula is shown in Equation 2:

$$\mathrm{sim}(A,B) = \cos(a,b) = \frac{a \cdot b}{||a|| \cdot ||b||} \tag{2}$$

3.2.3 Pearson correlation coefficient

The Pearson correlation coefficient can be adopted when evaluating the degree of linear association between two variables. Compared to cosine similarity, which only focuses on directional consistency, it delves deeper into the subtle differences in ratings among raters. The Pearson correlation coefficient formula is shown in Equation 3:

$$r = \frac{\sum_{i=1}^{n}(X_i-\bar{X})(Y_i-\bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i-\bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i-\bar{Y})^2}} \tag{3}$$

3.3 Two types of collaborative filtering algorithms

3.3.1 User-based collaborative filtering algorithm

User-based collaborative filtering algorithm (UserCF): Focuses on discovering groups of other users with shared preferences, and based on this, recommends interest points favored by similar user groups to the target user. As shown in Figure 1, this concept revolves around the user collaborative filtering recommendation mechanism.

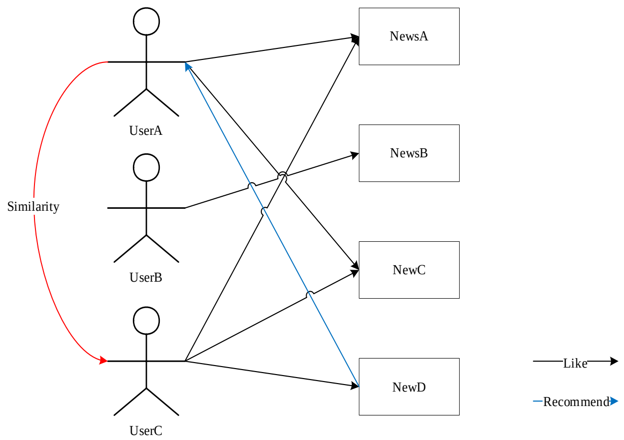

Figure 1 User-based collaborative filtering recommendation concept diagram

3.3.2 Item-based collaborative filtering algorithm

The Item-Based Collaborative Filtering Algorithm (ItemCF) involves deeply exploring users' past activity patterns, collecting and organizing user behavior logs, and evaluating the correlations between various items to accurately push content that target users might be interested in or prefer. As shown in Figure 2, the concept of the item-based collaborative filtering recommendation mechanism is illustrated.

3.4 Cold start and data sparsity problems

The initial challenge faced by new users, particularly in the application of collaborative filtering strategies, is the so-called cold start problem. This occurs when the system lacks sufficient behavioral records for users, specifically when users have not yet adequately rated news. The similarity indices displayed through formulas are notably low, revealing little substantive reference value. The sparse nature of data distribution is attributed to the lack of user engagement during the system's startup phase. In this context, the primary initiative of collaborative filtering algorithms is to construct a matrix framework designed to map the relationship between users and their corresponding ratings as an initial step. Within the framework of the system, the news recommendation mechanism must measure the constant flow of information. The news items users engage with in this system are only a small fraction of the system's content, leading to a matrix structure that is significantly sparse.

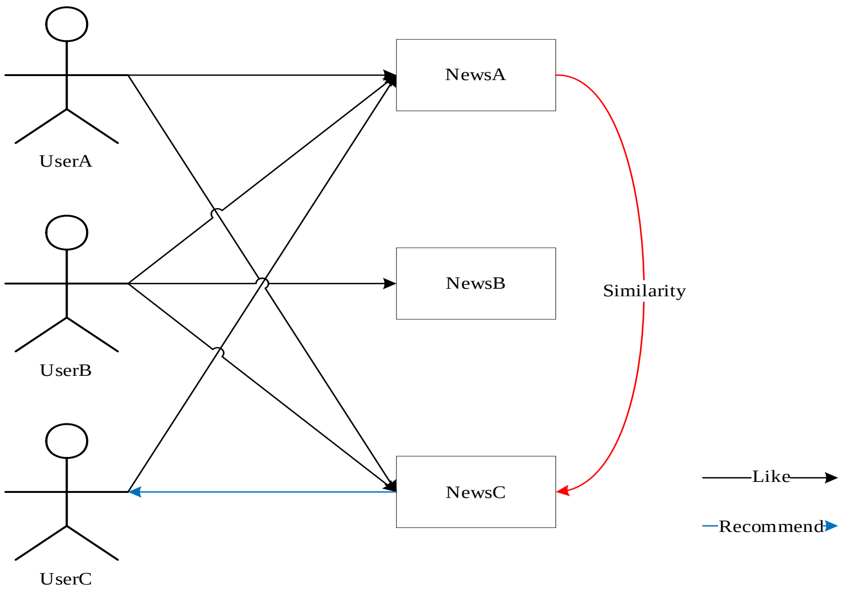

Figure 2 Item-based collaborative filtering recommendation concept diagram

The system adopts a method where new users initially select preference categories, and then recommendations are made based on their interest tags. Once users accumulate a certain history of operations, the system switches to using collaborative filtering to provide recommended content, effectively addressing the challenge of recommending content when new users join.

3.5 Comparison of two collaborative filtering algorithms

A summary comparison of the two algorithms is shown in Table 2:

Table 2 Comparison of UserCF and ItemCF.

	Explicit Behavior	Implicit Behavior
Performance	Suitable for scenarios with fewer users	Suitable for scenarios with fewer items
Field	Strong timeliness, emphasizing commonality between people	Richer user personalization
Real-time	No immediate change when users have new behavior	Immediate change
Cold Start	Cannot immediately provide personalized recommendations when user data is scarce	Begins recommending when behavior occurs on an item
New Items	New items can be immediately included in the recommendation list	Requires offline updates

From the table, it can be seen that the two algorithms have their strengths and weaknesses and are suitable for different problem models. In a news recommendation system, the number of users is far fewer than the number of news items. Therefore, UserCF is more suitable for news recommendation systems.

4. System Function Structure

4.1 User function structure

The user system architecture is divided into three main parts: user management, personalized recommendation, and news information. User management includes registration, login, and personal profile editing. Personalized recommendations are tailored for different users: anonymous users see popular content, new users receive recommendations based on interest tags, and old users receive personalized content through collaborative filtering algorithms. The news information section integrates search functionality for retrieving news, allowing users to explore news details in depth and engage with news through comments and collections, promoting multidimensional interaction between users and news. The user function structure diagram is shown in Figure 3.

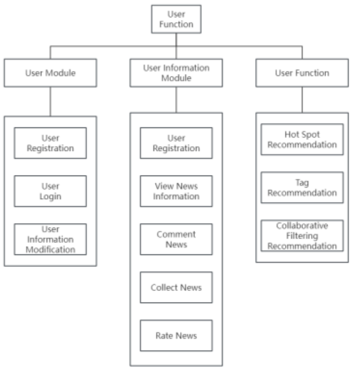

Figure 3 User function structure diagram

4.2 Administrator function structure

The administrator interface includes the following modules: user management, news classification, information review, tag system, rating monitoring, content quality, comment management, browsing analysis, and permission control, as shown in Figure 4.

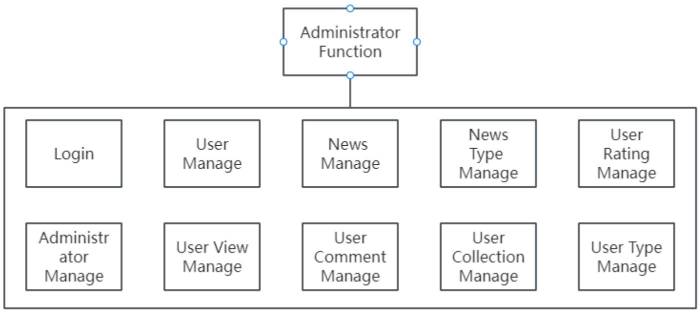

Figure 4 Administrator function structure diagram

4.3 Logical design of the database

The interest tags table records users' preference tags, as shown in Table 3.

Table 3 Interest tags.

Field Name	Field Type	Primary Key	Allow Null	Remark
id	int(11)	Yes	No	Primary Key ID
userid	int(11)	No	Yes	User Primary Key
newstypeid	int(11)	No	Yes	News Type Primary Key
createtime	varchar(50)	No	Yes	Add Time

The user table is designed to encapsulate key elements of the user's personal identification, such as name, password, gender attributes, contact number, and email address, as shown in Table 4.

The administrator table is designed to manage core information such as the administrator's username, access code, contact phone number, and email address, as shown in Table 5.

The news table is used to store news information, as shown in Table 6.

The rating table stores user rating records, as shown in Table 7.

The comment table stores user comment records, as shown in Table 8.

Table 4 User.

Field Name	Field Type	Primary Key	Allow Null	Remark
id	int(4)	Yes	No	User ID
username	varchar(50)	No	Yes	User Login Name
password	varchar(50)	No	Yes	Login Password
gender	varchar(50)	No	Yes	Gender
header	varchar(50)	No	Yes	Avatar
phone	varchar(50)	No	Yes	Phone
email	varchar(50)	No	Yes	Email
createtime	varchar(50)	No	Yes	Registration Time

Table 5 Administrator.

Field Name	Field Type	Primary Key	Allow Null	Remark
id	int(4)	Yes	No	User ID
username	varchar(50)	No	Yes	User Login Name
password	varchar(50)	No	Yes	Login Password
phone	varchar(50)	No	Yes	Phone
email	varchar(50)	No	Yes	Email
createtime	varchar(50)	No	Yes	Registration Time

Table 6 News.

Field Name	Field Type	Primary Key	Allow Null	Remark
id	int(4)	Yes	No	News ID
username	varchar(50)	No	Yes	News Title
newstypeid	int(11)	No	Yes	News Type Foreign Key
image	varchar(255)	No	Yes	News Cover
content	text(2000)	No	Yes	News Content
wid	varchar(50)	No	Yes	Global Times News ID
createtime	varchar(50)	No	Yes	Creation Time

Table 7 Rating.

Field Name	Field Type	Primary Key	Allow Null	Remark
id	int(11)	Yes	No	Primary Key
userid	int(11)	No	Yes	User Foreign Key
newsid	int(11)	No	Yes	News Foreign Key
score	int(11)	No	Yes	News Rating
createtime	varchar(50)	No	Yes	Rating Time

Table 8 Comment.

Field Name	Field Type	Primary Key	Allow Null	Remark
id	int(11)	Yes	No	Primary Key
userid	int(11)	No	Yes	User Foreign Key
newsid	int(11)	No	Yes	News Foreign Key
content	varchar(50)	No	Yes	Comment Content
createtime	varchar(50)	No	Yes	Comment Time

The collection table stores user collection records, as shown in Table 9.

Table 9 News collection.

Field Name	Field Type	Primary Key	Allow Null	Remark
id	int(11)	Yes	No	Primary Key
userid	int(11)	No	Yes	User Foreign Key
newsid	int(11)	No	Yes	News Foreign Key
createtime	varchar(50)	No	Yes	Comment Content

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The browsing records table stores user browsing records, as shown in Table 10.

Table 10 News browsing records table.

Field Name	Field Type	Primary Key	Allow Null	Remark
id	int(11)	Yes	No	Primary Key ID
userid	int(11)	No	Yes	User Foreign Key
newsid	int(11)	No	Yes	News Foreign Key
createtime	varchar(50)	No	Yes	Browsing Time

The news type table stores the news types, as shown in Table 11.

Table 11 News type.

Field Name	Field Type	Primary Key	Allow Null	Remark
id	int(11)	Yes	No	Primary Key
typename	varchar(50)	No	Yes	News Type Name

5. System Implementation

5.1 System entry page

As shown in Figure 5, the upper center of the system front-end interface has a search input area, while the right side has a series of function buttons, covering user login, account creation, and other operations. Below are the news category buttons, allowing users to browse news by category.

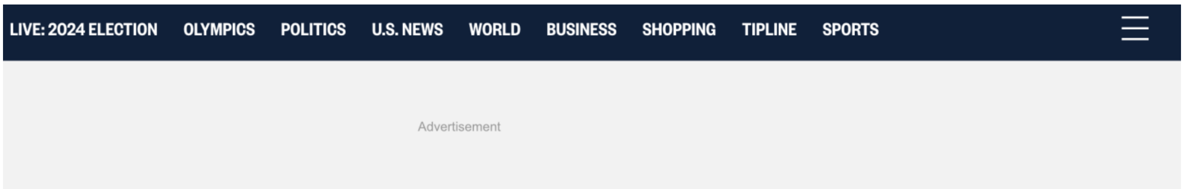

Figure 5 News search and news category browsing interface

As shown in Figure 6, the right side is the hot recommendation/personalized recommendation section. Recommendations for unlogged users are based on news ratings and collection numbers. New users will see a customized recommendation list based on interest tags after logging in. For active old users, the system provides more advanced personalized recommendations based on collaborative behavior analysis among users.

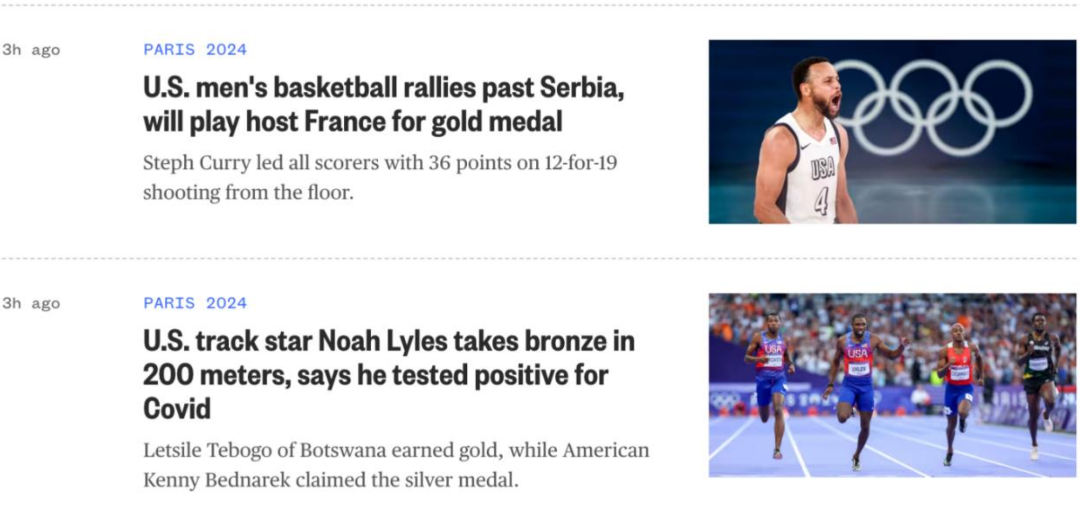

Figure 6 Hot recommendation/personalized recommendation interface

5.2 User registration and login module

Visitors can create accounts through the website's homepage portal to become platform members. During account creation, user identifiers, contact numbers, and email addresses must be submitted. Once the registration verification is correct, the system will seamlessly transition to the login interface. During the login process, users are encouraged to select personal preference tags to help the system accurately push customized tag suggestions. After registration and verification, users immediately unlock permissions for personal profile management, news article storage, opinion expression, and evaluation. The operation process from registration to login is shown in detail in Figure 7.

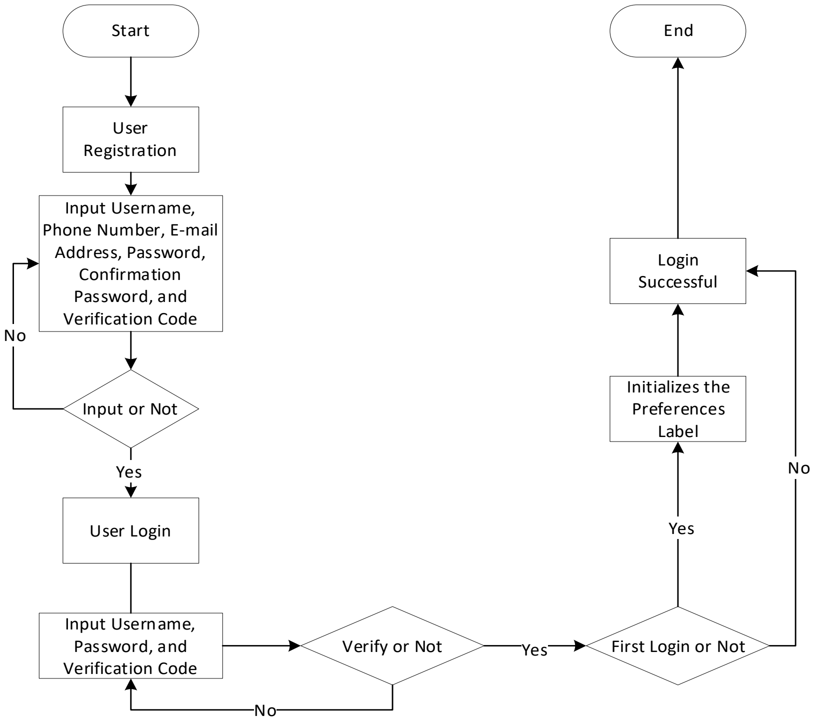

Figure 7 User registration and login flowchart

5.3 News details module

After logging in, users can access the detailed news display area by simply tapping the news link on the homepage. This page unfolds deeply, revealing the title, main text, and release time of the news, while granting users multiple interaction permissions: collection, rating, and even writing personal insights. They can view other users' ratings and comments on the news.

5.4 Implementation of recommendation function

The system adopts the Mahout algorithm toolbox, utilizing user-oriented and item-oriented collaborative filtering techniques to filter and push news content. The processes of the two collaborative filtering methods are generally similar, and this document will focus on detailing the specific implementation details of the user-based collaborative filtering recommendation mechanism. Implementing this recommendation strategy can be subdivided into four stages:

Information Pre-Processing: Construct a user-item evaluation matrix that maps the user's rating status for each item.

Evaluating User Interrelatedness: This involves measuring their similarity, commonly adopting algorithms covering Pearson correlation and cosine similarity analysis. By meticulously analyzing the intersection of user rating activities, a matrix mapping user-to-user similarity can be constructed.

Proposing Candidate Items: By leveraging users' past evaluation records and the constructed similarity matrix, a group of other users most akin to the target individual can be selected as "neighbor partners." Subsequently, from these "neighbor partners'" evaluation experiences, items not yet touched by the target user but highly rated can be identified as potential recommendations.

Ranking Recommendations and Creation: According to the criteria or key indicators for evaluating recommended candidate items, optimize the sequence arrangement, ensuring that the most highly rated or highly related items are accurately connected to the target user group.

5.5 Administrator module

The operation sequence of the administrator interface is divided into three core stages:

System Entry: Requires administrators to submit precise authentication credentials, only allowing access when these credentials are verified as correct. If discrepancies are encountered, the system immediately redirects to the login interface and prompts the administrator to recursively input data until the login process is complete.

Post-Login Verification: Once validated, the system automatically guides the administrator to the main interface, displaying core statistical data including total registered users, diversity count of news categories, total news items, richness of user identity tags, and the number of user rating activities.

Administrator Operations: Administrators can perform various operations, covering user information maintenance, news classification and content management, and user rating supervision.

These steps form the core operation process of the management terminal, allowing administrators to effectively manage the system. The process flow of administrator news information management is shown in Figure 8.

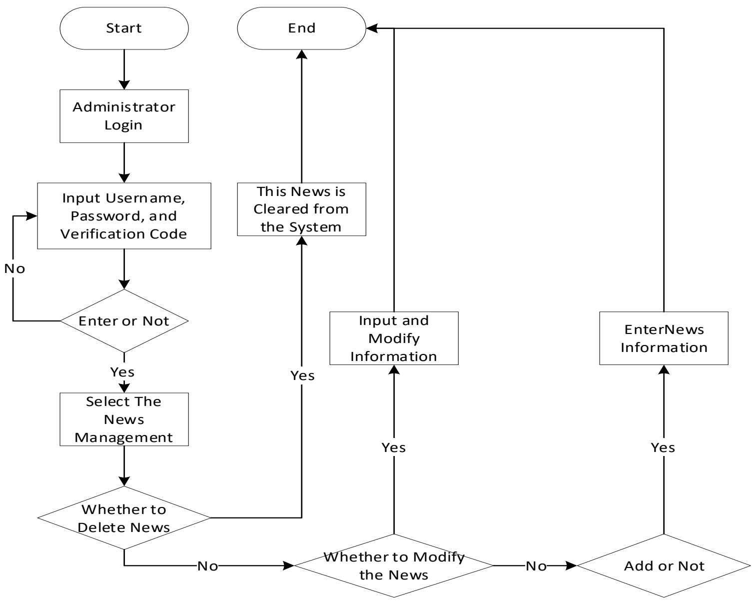

Figure 8 Administrator news information process diagram

6. Test Cases Results

Test cases results for the hot recommendation and personalized recommendation functions are shown in Table 12.

This chapter focuses on in-depth functional testing results of the system's core functions, hot recommendations, and personalized recommendations. For unregistered visitors, the system provides hot recommendations, while personalized recommendations are provided for registered users. In particular, new users receive customized recommendations based on their interest tags and collaborative filtering algorithms, while experienced users primarily rely on collaborative filtering for recommendation content. The test results show that the system performs well in the recommendation function, with no issues affecting the user experience, demonstrating the system's stability and reliability. Overall, the system can meet users' recommendation service needs.

Table 12 Test cases results for hot recommendation and personalized recommendation functions

Type	Functional Test
Test Function	Hot Recommendation, Personalized Recommendation
Description	Test the hot and personalized recommendation functions, providing different news recommendations based on user login status
Serial Number	Operation Steps
01	Access the system homepage as a guest and view the news list displayed in the hot recommendation/personalized recommendation section.
02	Log in with a new account, select the interest tag "Art," access the system homepage, and view the news list displayed in the hot recommendation/personalized recommendation section.
03	Log in with a new account, select the interest tag "Finance," access the system homepage, and view the news list displayed in the hot recommendation/personalized recommendation section.
04	Log in with a new account, select the interest tag "Art," rate a finance-related news item, access the system homepage, and view the news list displayed in the hot recommendation/personalized recommendation section.
05	Log in with a new account, select the interest tag "Finance," collect an art-related news item, access the system homepage, and view the news list displayed in the hot recommendation/personalized recommendation section.
06	Log in with a new account, select the interest tag "Finance," rate a car-related news item, collect an art-related news item, access the system homepage, and view the news list displayed in the hot recommendation/personalized recommendation section.

7. Discussion

This paper focuses on the design and implementation of a personalized news system based on SSM, emphasizing functions such as hot list, personalized recommendations, related recommendations, and recent news. The following work was completed:

1) A more comprehensive recommendation function was used to design the system's functionality and improve the recommendation effect, such as hot list recommendations and recent news recommendations, and related recommendations.

2) A recommendation algorithm based on user interest tags was adopted to better customize news push for users when there is insufficient user rating and collection data, aiming to solve the initial recommendation problem.

3) When new visitors encounter a lack of recommendations in a user and item-based collaborative filtering recommendation system, a descending order recommendation method based on total scores and total collections of news under the login user's preference tags is introduced. This method increases user satisfaction by recommending news related to their tags based on user interest preferences.

Through the above work, user satisfaction and interest have been increased. At the same time, these efforts have further improved the recommendation accuracy and coverage of the system.

The core contribution of this research is that, through an in-depth exploration of various recommendation strategies (such as content-based and collaborative filtering), it was found that in the field of collaborative filtering, a user-centered recommendation mechanism is highly consistent with the framework of the news recommendation system. By using the user rating matrix as a starting point, calculating cosine similarity measurements, and identifying the most matching neighboring users, the evaluation information of neighboring users is used to predict the evaluation of each news item, effectively solving the cold start problem and enabling the implementation of the news recommendation mechanism. Nevertheless, the system still has some limitations that need further improvement. A potential enhancement strategy is to integrate multiple recommendation mechanisms to achieve composite recommendations, by integrating recommendation algorithms from different dimensions, such as recommendation logic using content attributes and deep fusion learning recommendation models, aiming to deepen the efficiency and comprehensiveness of the system's recommendations.

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