An Empirical Study on the Phenomenon of Information Narrowing in the Context of Personalized Recommendation

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Abstract. Personalized recommendation services have been widely applied to improve users’ search efficiency, but when filtering information for users, they also hide the risk of the declining in content diversity, which is information narrowing. In this study, comprehensive news and information platforms in China were taken as the empirical research object. The experimental tracking method was used to collect the content data of client end recommended news. Simpson and Shannon-Wiener indexes were used to measure the information narrowing phenomenon. Questionnaires were used to collect users’ data of news and information applications usage, the perception of information overload, and the perception of information narrowing. The data of questionnaire was analyzed and processed by MATLAB and SPSS 20.0, and the hypotheses were tested by statistical methods. The results reveal that there is indeed information narrowing phenomenon in news information personalized recommendation service, but most users are unaware of this.

1. Introduction
The concept of information narrowing was firstly put forward in 2002 by Professor Sunstein from Columbia University. He believes that the Internet have made it easier for people to obtain personally preferred information while resisting the information they do not like that people are actually receiving the “narrowed” information in this procedure [1]. Nowadays, more and more individuals get information through the Internet. According to the digital report of 2019 released by “We Are Social and Hootsuite”, the global population is 7.676 billion, of which 4.388 billion are Internet users [2]. By June 2019, the number of Chinese netizens has reached 854 million [3]. People’s lives are increasingly inseparable from the network, and the vast amount of information in the network is also filled with people's lives. However, due to the limited ability of information processing, people would selectively obtain and digest information, which narrows users' knowledge over time. The development of personalized recommendation intensifies this information acquisition behavior. It helps users initially filter out the information they are not interested in, just like creating a “mono” communication that flattens the information that people receive. As this single planarization accumulates, the individual information environment tends to narrow down or even close. Based on the above, this paper defines “information narrowing” as the following: within the network environment, the service of information notification pushing such as personalized recommendation makes it easier for users to obtain
information of their own preferences, while user have less and less contact with excluded information, and thus leading to a declination in the diversity and depth of received information.

The concept “Filtering Bubble” was firstly formulated by Eli Pariser in his book The Filter Bubble: What the Internet Is Hiding from You [4]. Filtering Bubbles is a mode which is able to continuously strengthen itself by narrowing the user’s content interface. This mode can reduce the user’ motivation to learn new content, weaken the links between groups, and promote the polarization of group. In China, news, social, and video applications based on personalized recommendation provide users with “carefully selected” content. Under this, does the “Filtering Bubble” imperceptibly emerge in the user group and create a phenomenon of information narrowing when users using those applications? At present, there is a lack of research on the impact of information narrowing brought by personalized recommended products in academic circles. Therefore, researching information narrowing based on personalized scenarios, quantifying the degree of information narrowing, and exploring the degree of information narrowing perception from the user side can remind users and Internet enterprises to think over personalized recommendations and help prevent the crowd polarization to some content.

2. Overview of The Quantitative Study on Information Narrowing
In China, most researches on information narrowing are qualitative analysis, especially focus on the influence and causes of information narrowing [5]. Quantitative studies have been ignored that only until recent years a small number of relevant researches emerges. Ye has defined information narrowing as the phenomenon that the notification pushing of a single type of news accounts for more than 50% of the total. 14% of 77 participants users have the issue of information narrowing according to his study [6]. Wang has analyzed three personalized information recommendation platforms, Toutiao, Tiantiankuaiibaio, and Yidianzixun, discussing the degree of information narrowing based on the average degree of pushed information types [7].

There are relatively more quantitative researches on information narrowing in foreign countries. Dillahunt et al. [8] were the first attempting to measure and describe filter bubbles: research subjects were asked to search same contents on Google and Bing. Search results were data analyzed and compared. The experiment found that filter bubbles did exist and visualized them through a graphical display. Nguyen et al. [9] investigated the influence of the recommendation system based on collaborative filtering on users. By analyzing the movie recommendation data of the users on the website MovieLens, they found that as time goes by, the content range provided by the recommendation system to users would slightly reduce, but the user experience of using the recommended products became slightly worse. Cozza et al. [10] also carried out a study of search engines. By measuring the personalized recommendation level of web search, they studied the possibility of users falling into the filter bubble. The results showed that the main content of Google News page for users with training experience and new users were exactly the same. The expected personalization effect was significant: the news recommended by the “Suggest for account” section varies in both content and quantity according to the interaction area and frequency between the user and the platform.

2.1. Data Collection Methods of Information Narrowing
We found that there are two methods to collect data in these researches of information narrowing: experimental tracking method and data mining. The number of data collected by experimental tracking method is limited, generally within a few thousand, and the time span of collection is short which is less than one month, but this method is highly feasible. On the contrary, the magnitude of the data collected by data mining is much higher than the experimental tracking method, and the collection time span is normally more than one year. However, because of the enterprise not making the user data public, the feasibility of data mining is low. Therefore, this study intends to use the experimental tracking method for data collection.

When studying the influencing factors of information narrowing, Han [11] took the breadth and depth of the information receipted by users as the criterion for measuring the degree of information narrowing. The information reception breadth refers to the number of information type obtained by the
user, and the information reception depth refers to the amount of information obtained by the user. Combining relevant literatures and Han Linjie’s research on information narrowing, it is clear that the measurement of information narrowing focuses more on the information breadth, that is, the information or content diversity. Therefore, this paper has also conducted research on content diversity. If the content diversity is significantly reduced, it is considered the information narrowing occurs.

2.2. Measurement Methods of Information Narrowing Based on Content Diversity

The concept of diversity was first put forward in the field of biology referring to biodiversity and ecological diversity [12]. Subsequently, diversity was also applied in other fields, such as population diversity and cultural diversity. In the field of information content provision, such as music, books, games, movies, TV broadcasts, etc., diversity are featured to attract audiences. Content diversity measures the degree of differentiation between a group of content objects and the degree of diversity shown as a whole.

2.2.1. Simpson and Shannon-Wiener Indexes. In the researches on content diversity, scholars often use the diversity index to measure content diversity. One of the common calculation methods is the Simpson diversity index [13], which was proposed by Simpson in 1949. The calculation formula is as follows:

\[ D = 1 - \sum_{i=1}^{S} P_i^2 \] (1)

In the formula, \( S \) refers to the number of sample types and \( P_i \) refers to the proportion of a category \( i \) in the population. This formula is used to measure the proportion of different categories. It is considered to be the best measurement of diversity and the operation is simple. The Simpson diversity index is derived from the field of biological species diversity research. Similar formula such as Shannon-Wiener index [13] is showed below (the parameters in the formula are the same as those in formula 1):

\[ H = \sum_{i=1}^{S} P_i \log_2 P_i \] (2)

2.2.2. Label Vector Coding. In practice, label vector coding method is often used to measure the content diversity of recommendation information. Lee and Hwang [14] used this method to measure the impact of large recommendation platforms on content diversity. From the perspective of feasibility, label vector coding is a suitable method of processing binary data. The formula is as follows:

\[ I = \sum_{i=1}^{N} \sum_{j=1}^{P} (x_{ij} - c_i) \] (3)

2.2.3. Label-Content Matrix Method. In the research of Nguyen [9], information narrowing was measured by the highly reliable labeled label-movie explanatory matrix provided by Movielens. The calculation method is as follows:

\[ d_{(m_i,m_j)} = \sqrt{\sum_{k=1}^{m} [rel(t_k,m_i) - rel(t_k,m_j)]^2} \] (4)

Because of simple operation and pellucid formula, the calculation method Simpson and Shannon-Wiener indexes, which originate from the biological perspective, are often used in academic research related to information narrowing and content diversity. The latter two methods are the calculation indexes from the perspective of algorithm evaluation. Because they are used in the research of enterprise practice, the standard of data format is usually higher than others.

3. Research Design

3.1. Research Approach

By analyzing the literature of information narrowing in personalized recommendation, it can be seen that different scholars have differing opinions about the existence and adverse effects of information narrowing, and there are few literatures that studied the information narrowing from the users’
perception side. Therefore, the research design of this paper includes two parts. The first part measures whether personalized recommendation brings information narrowing to the user based on user behavior data. The second part studies whether users perceive information narrowing when using personalized recommendation based on user perception and its impact on users. In the study of the narrowing phenomenon, it is necessary to classify the information and examine the existence of information narrowing by measuring the diversity of information. For the research on user perception, the main work is collecting user feedback data through questionnaire and conducting relevant analysis based on the collected questionnaire data. The specific research path is shown in figure 1.

Figure 1. Research Approach.

3.2. Research Hypotheses
(1) Whether personalized recommendation brings information narrowing to the user.

A large number of articles related to "information cocoon room" in the field of communications has showed that personalized recommendation does have the risk of information narrowing, and scholars such as Ye have already begun to study the forming factors and preventive solutions of information narrowing. Besides, in order to improve the level of the content diversity of recommendation system, there are scholars of computer field who specialized in the progress of the researches of personalized recommendation system diversity [15], which indicates that personalized recommendation do have deficiencies in diversity.

Various studies have shown there is probability that information narrowing exists in certain areas. As the depth and intensity of personalized recommendation accumulates, users may gradually fall into a relatively “narrow” set of recommended content results. Potential information that users might be interested in or should know will be ignored, therefore the content received is the result of being “narrowed”. Thus, the following hypothesis is putting forward:

H1: Personalized recommendation brings information narrowing to users.

(2) Whether users perceive information narrowing when using personalized recommendation and its impact on users.

Information narrowing homogenizations the information content obtained by users [16]. In order to explore the degree of homogeneity, starting from the information needs of users, this paper measured the impact of information narrowing by collecting the user's evaluation of personalized recommended content. The personalized recommendation evaluation indicator system is a tool to evaluate the effectiveness of personalized recommendation. Recommendation accuracy and recommendation efficiency were the two commonly used indicators measuring the effectiveness of personalized recommendations from the initial [17]. Gradually, other indicators proposed by scholars considering
user satisfaction emerged, such as coverage [18] and the diversity of suggestion list [19-21]. At present, the most authoritative and perfected personalized recommendation evaluation indicator system is proposed by Zhou et al. [22], including six indicators: accuracy, coverage, diversity, novelty, etc.

Li et al. [23] have pointed out that enterprises cannot design recommendation systems solely on the basis of accuracy indicators, because users’ behaviors in selection or purchase are not always related to high recommendation accuracy, that is, different users have different perceptions of the importance of evaluation indicators. What is more, the evaluation of personalized recommendation system based on user perception is more authentic [24]. Therefore, in order to study the user's evaluation of personalized recommendation content and analyze the evaluation effect more objectively, it is necessary to explore the relationship between the user's perception of the importance of evaluation indicators and the evaluation result, thus the following hypothesis is proposed:

H2: The perception of the importance of evaluation indicators is related to the evaluation of personalized recommendation content and has a positive impact on the evaluation of personalized recommendation content.

Whether information narrowing occurs in the process of user’s access to information and whether it affects the user’s information acquisition dimension and quantity are the matter of concern [25]. Therefore, it is necessary to analyze the user’s perception of information narrowing from the user’s perspective. Based on the data of evaluation of the personalized recommendation content and the perception for impact of recommendation, it can be explored whether the user's evaluation of the recommendation is related to the perception of the impact of the recommendation. Thus, the following hypotheses are proposed:

H3: Evaluation of personalized recommendation content is related to the perception of the impact of recommendation.

H4: Evaluation of personalized recommendation content, the perception of the impact of the recommendation, and the perception of information narrowing are correlated.

3.3. Experimental Design and Implementation

In order to examine the hypotheses proposed above, the corresponding experimental designs have been carried out below.

3.3.1. Hypothesis one: Experimental Tracking Method. Represented by Toutiao, many personalized news and information recommendation platforms have profoundly changed people’s reading habits and information acquisition methods and have affected people’s information world and cognitive construction. Within the comprehensive news and information industry, recommendation algorithm distribution has become a consensus that enterprises take personalized recommendation as a powerful tool to attract users. Therefore, this paper took the platforms of news and information recommendation as the formal research object. In order to improve the research results and select an appropriate measurement method, a preliminary research on personalized recommendation in the context of entertainment information acquisition was conducted before the formal study.

(1) Preliminary Research

The film section of Douban App was the platform of preliminary research. In this section, personalized recommendation is embedded in the column named “you might be interested”. Through content-based recommendation algorithm and collaborative filtering recommendation algorithms, “you might be interested” provides recommendations standing high in user’s favor. Besides, no other applications can defeat Douban’s film tag database, from which one or more representative tags of every film can be extracted. For these reasons, choosing Douban film as the research platform has a great reference value. Participants were asked to upload their screenshots of the first 8 films recommended by the column “you may be interested” to the WeChat public platform. There were 66 volunteers who participated in the preliminary research, with a male-to-female ratio of 9:13, and the proportion of those aged between 18-25 was 89.4%, which means most were young users.

The R language was used to process the text dataset which contains the tags of eight films inputted by
each volunteer. Then, content diversity was measured by the label vector coding method (equation (3)) which has been most commonly used by other researchers. Table 1 shows the results of the double sample T-testing on the first day and the seventh day, the first three days and the last three days of the movie content diversity among these users. The data of the first three days and the last three days were the mean value of the three days’ content diversity. It can be seen from the experimental results that at the confidence level of 5%, the content diversity of preliminary research users on the seventh day significantly decreased compared to the first day, and the content diversity of the last three days significantly decreased compared to the first three days. So far, the results of statistical test indicate that information narrowing has occurred when those users used the personalized movie content recommendation service under the column named “you may be interested”.

Table 1. Summary of T-testing results.

|               | First day | Seventh day | P-value | First three days | Last three days | P-value |
|---------------|-----------|-------------|---------|-----------------|-----------------|---------|
| Content diversity | 11.74     | 10.78       | 0.0031  | 11.30           | 10.64           | 0.0038  |

The results of the preliminary research have verified the existence of information narrowing in the context of personalized entertainment recommendation from the perspective of statistics, and also demonstrated the reliability of the method of data collection, experimental tracking method, which laid a foundation for formal research. Through preliminary research, it was found that the label coding method has high requirements on data format and does not measure content diversity from the field of communication and informatics. Therefore, Simpson index and Shannon-Wiener index were selected to measure the content diversity of news recommended in the formal research.

(2) Formal Research

In view of the need to quantify the content diversity from the perspective of information breadth, synthesizing literature research and news applications, this paper classifies news information into 16 categories based on the scientific, complete and mutually exclusive classification principles: current affairs politics, international affairs, military affairs, social / natural disasters, finance and economics / finance / industry / economics, real estate / infrastructure construction, labor/agriculture/ fishery/ animal husbandry/ forestry, environmental protection / energy / natural resources, automobile / transportation, consumption / tourism / fashion, education / science / culture / art, science and technology / Internet, life and leisure, film and television entertainment, medicine and health, and sports.

News platforms related to this research include Toutiao, NetEase News, Tencent News and other comprehensive News App with the function of recommendation. In order to collect the recommended content, each volunteer was required to upload 6-10 screenshots of the recommendation section in the news App every day. To ensure the validity of the calculation results, the experiment requires each volunteer to upload at least 20 news a day. The experiment lasts 15 days and 44 people completed the experiment effectively. A total of 12,112 data were collected. The descriptive statistical information is shown in table 2. “New user” refers to the volunteer who had never used the News App before participated in this experiment.
Table 2. Descriptive statistical information of experimental volunteers.

| Characteristic Category | Samples | Percentage |
|-------------------------|---------|------------|
| Sex                     |         |            |
| Male                    | 17      | 38.64%     |
| Female                  | 27      | 61.36%     |
| Age                     |         |            |
| 18-30 years old         | 22      | 38.64%     |
| Over 30 years old       | 12      | 61.36%     |
| User Type               |         |            |
| New user                | 26      | 59.09%     |
| Old user                | 18      | 40.91%     |
| Platform                |         |            |
| Toutiao                 | 25      | 56.82%     |
| NetEase News            | 6       | 13.64%     |
| Tencent News            | 4       | 9.09%      |
| Ifeng News              | 5       | 11.36%     |
| Baidu News              | 3       | 6.82%      |

3.3.2. Hypotheses Two-Four: Questionnaire Design. The questionnaire is designed and revised according to literature review and expert suggestions. The relationship between main items and corresponding variables is shown in table 3.

In this paper, the Richter scale was used to rate the five-level measurement indexes: “1” means very important and “5” means very unimportant.

Considering the purpose of the research is to investigate users' perception of information narrowing, which is a relatively difficult concept to understand, the research has certain requirements on the education level of the respondents. College students with higher education (including master’s degree, doctor’s degree, etc.) aged between 18 and 30 years old as well as institutions staff members were the main respondents. A total of 404 questionnaires were distributed, of which 378 were valid and collected, accounting for 93.5% of the total. Among the valid questionnaires, 39.4% of the respondents have a bachelor’s degree, 39.4% have a master’s or more degree, and 58.2% are aged 18-25.

4. Empirical Analysis and Discussion

4.1. The Analysis and Discussion of Hypothesis One

During the experiment, according to the designed experiment steps, after each user uploaded the news screenshots from news application, researchers inputted news information in the screenshots into the data file, manually converting the pictures to format information. Next, the topic type of each piece of news in each screenshot was marked. After the classification, 0-1 formatting and coding were conducted. Later, the original 16-dimensional coordinates of recommended news were converted into codes based on different calculation requirements. Lastly, news diversity was calculated according to formula 1 and 2. Figure 2 shows the variation trend of mean value of the three types users’ daily diversity. These users are new users, old user and full users, and the diversity was calculated by the Simpson index and Shannon-Wiener index respectively. As is demonstrated in figure, the phenomenon of information narrowing was appeared among users.

In order to further explore whether there is any difference between the content diversity on the first day and the last day, the paired two-sample analysis of the mean value are used. The original assumption of T-testing is that there is no difference before and after. The calculation results are shown in table 4. If the P value is less than 0.05, then the original assumption, the diversity of users' recommendations on the first day is different from the diversity on the last day, would be rejected. The test results in table 4 show that the diversity of full and new users’ news recommendation content gradually decrease with the passage of time, resulting in information narrowing. Therefore, hypothesis H1 is supported by the results.
Table 3. Main variables and items of the questionnaire.

| Variables                                      | Item design                                                                 | Symbol | Source                        |
|------------------------------------------------|------------------------------------------------------------------------------|--------|-------------------------------|
| The Demand for News App Services               | Vision of the APP: beautiful interface, comfortable layout, clear layout.     | Q1_1   |                               |
|                                                 | News content of the APP: good quality, short update interval and diversified display. | Q1_2   |                               |
|                                                 | Interaction of the APP: easy to use and convenient navigation.                | Q1_3   |                               |
|                                                 | Function of the APP: reading AIDS, social function, personalized subscription. | Q1_4   |                               |
|                                                 | Value added experience: brand value and high reliability                     | Q1_5   | Wang [26]; Xiao [27]           |
| The Satisfaction for News App Services          | Vision of the APP: beautiful interface, clear layout.                        | Q2_1   |                               |
|                                                 | News content of the APP: good quality, short update interval and diversified display. | Q2_2   |                               |
|                                                 | Interaction of the APP: easy to use and convenient navigation.               | Q2_3   |                               |
|                                                 | Function of the APP: reading AIDS, social function, personalized subscription. | Q2_4   |                               |
|                                                 | Value added experience: brand value and high reliability                     | Q2_5   |                               |
| Usage of the Function of Personalized Recommendation | Do you have used the function of personalized recommendation?                | Q3     |                               |
| Evaluation of the Recommended Content           | The recommended content is of interest to me.                                | Q4_1   | Liu, Zhou et al. [28]          |
|                                                 | The recommended content is correct and accurate.                             | Q4_2   |                               |
|                                                 | The recommended content is diversified and rich.                             | Q4_3   |                               |
|                                                 | The recommended content is fresh and unexpected.                            | Q4_4   |                               |
|                                                 | Overall satisfaction                                                       | Q4_5   |                               |
| Perception of Importance of Evaluation Indicators | Please rank the importance of Evaluation Indexes for recommended content.   | Q5     |                               |
| Perception of Impact on Recommendation          | The recommendation function helps me enhance interest in certain types of news information. | Q6     |                               |
|                                                 | The recommendation function helps me lengthen the usage time of the news APP.| Q7     | Gao [29]                      |
| Perception of Information Overload              | The recommended function helps me broaden the vision and discover the “new world”. | Q8     |                               |
| Perception of Information Narrowing             | Do you have the feeling of “too much information to see” when reading news on these news Apps? | Q10    |                               |
| Perception of Information Narrowing             | The recommended content is seriously homogeneous, which lessening information diversity or narrowing your access to information. | Q11    |                               |
Figure 2. Variation curves of diversity with time under different computing methods.

Table 4. Results of T-testing.

| User Type     | Day 1 | Day 15 | P value (T<=t) |
|---------------|-------|--------|----------------|
| Full user     | 0.824 | 0.770  | 0.00000693     |
| New User      | 0.848 | 0.785  | 0.00000006     |
| Old User      | 0.789 | 0.749  | 0.05421315     |

It can be seen from figure 2 that the variation trend of the diversity of new and old users have a little difference. The decline trend of the diversity of new users seems to be more obvious, and the diversity of old users is generally lower. In this case, the same t-test operation both on new users and old users have been conducted and the calculation results are shown in table 4: the diversity of new users passed the T-testing, but old users did not.

4.2. The Analysis and Discussion of Hypothesis Two-Four

4.2.1. Descriptive Statistics of User Perception. Based on the descriptive statistics of users’ questionnaire data analyzed by SPSS 20.0, the degree of users’ perception of the "recommendation function helps me to reduce the information burden" is 3.18. Although the user thinks that the function of personalized recommendation has little impact on themselves, they have recognized the "information burden reduction" function of recommendation to some extent. On the other hand, the degree of users’ perception of the information overload is 3.48. And, the perceived degree of information narrowing is 3.08. Though weak, but it indicates that users have approved the homogenization problem in recommended news, limiting them to get diversified information.

4.2.2. Reliability and Validity Test. The reliability of the questionnaire was calculated by MATLAB. The overall reliability value of the questionnaire is 0.921 which passes the reliability check, and the internal consistency of each index is good. The structure validity of the questionnaire was analyzed by the cumulative variance contribution rate, KMO, and Bartlett spherical test of SPSS statistics 20.0. The KMO value of the questionnaire is 0.913, and the Sig value is 0.000 while this of each variable is less than 0.001. Through the results of reliability and validity test, it can be seen that the validity of each variable of the questionnaire is good, which is suitable for the following analysis.

4.2.3. Hypotheses Test. For hypothesis H2 that “The perception of the importance of evaluation indicators is related to the evaluation of personalized recommendation content and has a positive impact on the evaluation of personalized recommendation content”, according to the analysis data shown in table 5, the perception of the importance of the evaluation indicator is significantly related to the evaluation of recommended content, that is, the stronger the user's awareness of the importance of the indicator, the higher the score will be given with the indicator. Hypothesis H2 is supported by the results.
Table 5. Correlations of H2.

| Perception of Importance of Evaluation Indicators | Q4_1   | Q4_2   | Q4_3   | Q4_4   |
|--------------------------------------------------|--------|--------|--------|--------|
| Evaluation of the Recommended Content            |        |        |        |        |
| Q4_1                                             | .369** |        |        | .513** |
| Q4_2                                             | .359** | .493** |        | .526** |
| Q4_3                                             | .404** | .489** | .433** | .548** |
| Q4_4                                             | .378** | .480** | .454** | .529** |
| Q4_5                                             | .325** | .502** | .453** | .544** |

Notes: Symbols in the table are the same as those in table 3; ** Correlation is significant at the 0.01 level (2-tailed).

For hypothesis H3 “Evaluation of personalized recommendation content is related to the perception of the impact of the recommendation”, the correlation between the two parts is calculated. It can be seen from table 6 that there is a significant positive correlation between the evaluation of personalized recommendation content and the perception of the impact of the recommendation. The correlation coefficients in the table are all above 0.5, indicating that the correlation is relatively strong. Among them, the correlation coefficient between Q4_1 “The recommended content is of interest to me” and Q9 “recommendation function helps reduce me the information burden” is 0.719, which shows that there is a significant strong correlation between the two terms, that is, the higher the evaluation of recommendation consistent interest is, the stronger the perception of recommendation function helping user to reduce the information burden is. In addition, correlation coefficients related to information burden reduction are the highest among all coefficients, indicating that the impact of personalized recommendation may be the most significant in reducing the information burden. Hypothesis H3 is supported by the results of table 6.

Table 6. Correlations of H3.

| Perception of Impact on Recommendation | Q6   | Q7   | Q8   | Q9   |
|----------------------------------------|------|------|------|------|
| Evaluation of the Recommended Content   |      |      |      |      |
| Q4_1                                   | .576** | .613** | .605** | .719** |
| Q4_2                                   | .553** | .585** | .567** | .694** |
| Q4_3                                   | .556** | .595** | .571** | .672** |
| Q4_4                                   | .571** | .614** | .612** | .690** |
| Q4_5                                   | .583** | .639** | .621** | .726** |

Notes: Symbols in the table are the same as those in table 3; **Correlation is significant at the 0.01 level (2-tailed).

For hypothesis H4 “Evaluation of personalized recommendation content, the perception of the impact of the recommendation and the perception of information narrowing are correlated”, as the test shown in table 7, it can be seen that all the correlation coefficient values are small, almost less than 0.3, indicating that the correlation between recommendation content evaluation and perception of the impact of the recommendation is weak that they are almost irrelevant. Hypothesis H4 is not supported by the results. This hypothesis was put forward because the information overload is resulted from an overwhelm amount of news for users read, while the information narrowing is resulted from news homogeneity. Therefore, it is assumed that users’ evaluation of news content and recommendation is related to their perception of information narrowing. However, this is not supported by the result, probably because users’ perception of information overload and narrowing is relatively independent, which is not related to their satisfaction with recommended news nor the impact of recommendations.
Table 7. Correlations of H4.

| Evaluation of the Recommended Content | Perception of Information Overload | Perception of Information Narrowing |
|---------------------------------------|-----------------------------------|-------------------------------------|
| Q4_1                                  | .190**                            | .074                               |
| Q4_2                                  | .183**                            | .061                               |
| Q4_3                                  | .220**                            | .040                               |
| Q4_4                                  | .188**                            | .041                               |
| Q4_5                                  | .132*                             | .079                               |
| Perception of Impact on Recommendation|                                   |                                     |
| Q6                                    | .028                              | .146**                             |
| Q7                                    | .119*                             | .231**                             |
| Q8                                    | .036                              | .082                               |
| Q9                                    | .262**                            | .179**                             |
| Perception of Information Overload    | Q10                               | 1                                  |
|                                       |                                   | .197**                             |

Notes: Symbols in the table are the same as those in table 3; *Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.01 level (2-tailed).

To summarize, H1, H2 and H3 are supported by the results, while H4 is not. Based on the difference between the T-testing results of new and old users, this paper puts forward an inference: the process of new users becoming old users is accompanied by information narrowing, while the daily recommended news of old users had already been the result of “information narrowing”.

5. Conclusion

5.1. Conclusions and Suggestions

Based on the literature of information narrowing and personalized recommendation, the research was carried out by two research methods, experimental tracking method and questionnaire survey, under the actual application situation of personalized recommendation. The experimental tracking method verifies that information narrowing does exist in the context of personalized recommendation, which enhances users’ understanding of personalized recommendation services and raises improvement directions for similar product service providers. The results of statistical analysis and hypothesis test of questionnaire survey show that under the condition of low diversity and richness of news recommendation, users’ perception of information narrowing is not strong, but they have a distinct perception of information overload, that is, compared with the breadth of information, users’ information demands are more inclined to whether the recommended content conforms to their own preferences.

The suggestions for preventing from the negative effects of information narrowing should be carried out from two aspects [30]: one is the information transmission technology improvement, which means in the use of personalized recommendation algorithm, the enterprises should not only focus the recommended precision indicators, but also focus more on the improvement of diversity and novelty of the two indicators, or provide multi-mode for users to select and reduce the strength of recommendation guidance. The other is that in terms of the information audience, users should enhance their awareness of information narrowing, jump out of the cognitive comfort zone, and increase reading and browsing, trying to get information from multiple channels, and thus reach out to different perspectives as comprehensively as possible.
5.2. Deficiencies and Prospects
The duration of the experiment, the number of subjects and the number of news are not sufficient, and the efficiency of labeling data manually in this research is low. It is difficult to measure information narrowing. In future research, exploring quantitative methods from the perspective of informatics should be considered. With the development of personalized recommendation research and application, we hope that the social impact of personalized recommendation will attract more scholars’ attention.

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