



# Examining the Impact of User Interaction Behavior on the Effectiveness of Social Media Content Recommendation

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**Abstract.** The widespread use of social media platforms has significantly transformed the way people access information. However, social platform's recommendation algorithm influences this progress, which largely determines content available to users. This process can lead to the 'filter bubble' effect, limiting user from being exposed to different perspectives. This study investigates the bidirectional interaction between user's interaction behavior and recommendation mechanism. It focuses on how user's positive interaction (like, collect, share) and negative interaction (using 'uninterested' function) influence content filtering. A questionnaire survey was conducted to collect data on the frequency of different interaction behaviors (independent variable), perceived content recommendations (dependent variable) and social network heterogeneity (moderator variable). By conducting correlation analysis of the variables, the study confirmed the research hypothesis that positive interaction behavior increased recommendations of homogeneous content, whereas negative interactions reduced similar content recommendations. User's social network heterogeneity influences this process by negatively reduce positive interaction behavior's impact on homogeneous content recommendation. These findings indicate that more active user actions are required to shape better online environment.

**Keywords:** User interaction behavior, Social media, Filter bubble, Content recommendation, Social network heterogeneity.

## 1 Introduction

Recent years have seen the widespread adoption of mobile communication devices and the increasing importance of social platforms in people's daily life. They have become significant medium within aspects of social interaction, knowledge acquisition and entertainment. The 56th Statistical Report on Internet Development in China, published on 21st July, 2025, showed that the country's internet usage has reached new heights as of June. It stated that the number of netizens in China had reached 1.123 billion, and the Internet availability rate was 79.7% [1]. This trend has brought about a growing importance of social platforms' algorithm design, which decides the types of content available to users to a great extent. Currently, most social platforms tend to recommend

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content based on user's preference, which could create a sphere where homogeneous contents are gathered together, meanwhile probably creating the 'filter bubble' [2]. The concept of filter bubble was initially proposed by Pariser, emphasizing the intangible impact of the recommendation mechanism on social media users. It is understood as a personalization system which functions through recommendation algorithms to create a bubble based on user's preferences. [3] This mechanism functions when the information filter filters the user preference content, personalize the information received by user and isolate the user from other information. In this process, users' interactive behaviors, such as Like, Collect and selecting 'not interested', can influence the function of recommendation mechanism.

So far, there have been growing number of researches about the relationship between user's interaction behavior and social platform recommendation mechanism in academia, and some scholars have built models to conduct quantitative evaluation on it. For example, Cen et al. investigated 750 subjects' experience of a music player, separating them into multiple groups and letting them behave differently to reveal the difference of recommendation mechanism [4]. In domestic research, Zhao and Wang examined Generation Z university students' perceptions of and resistance to filter bubbles across multiple platforms. The study shows that students' resistance toward filter bubbles varies based on platform type and usage habits, which offers methodological insights for subsequent analyses [5]. However, these studies primarily focus on direct relationship between user and the algorithm, which overlooked the possible influence of user's social network heterogeneity. To fill this gap, this study will introduce the concept of social network heterogeneity as a moderator variable. On the contradictory of homogeneity, social network heterogeneity can refer to the extent of diversity of a person's online social contacts. It refers to the extent to which user's daily interactive targets are different from user themselves in terms of gender, region, age, viewpoints and so on [6]. It will argue that high social network heterogeneity has the potential to influence social platform's recommendation algorithm.

This study will investigate the two-way interaction between user's interactive behavior and recommendation mechanism and how social network heterogeneity moderates this relationship. It will conduct a questionnaire survey to collect quantitative data of user's daily social media interaction frequency; their perceived homogeneous content recommends frequency and their frequency of interacting with diverse kinds of people. The questionnaire will be distributed on 'WenJuanXing', a widely used online survey tool in China. Then it will use SPSS (version27) to conduct a correlation analysis to examine whether there exists relationship between these variables. The study aims to reveal how social media's recommendation algorithm subtly controls user's received content. It also targets to find how user's interaction behavior and social network heterogeneity play a role in the process and what users should do to reduce the filter bubble effect.

## 2 Method

### 2.1 Research Design

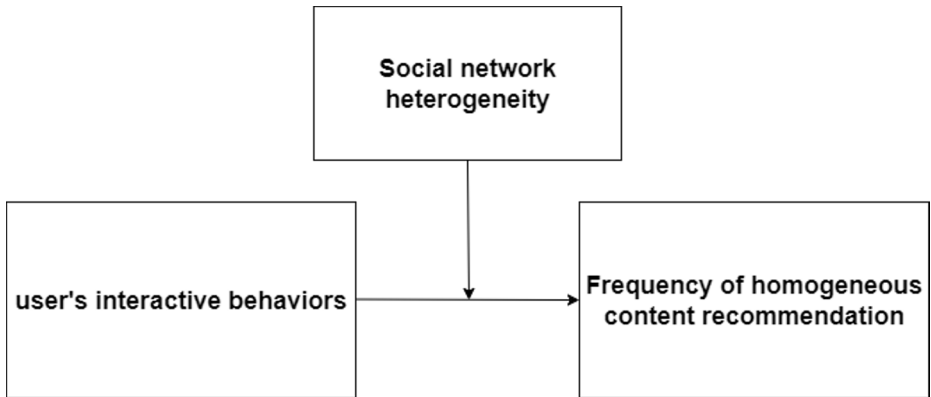


Fig. 1. The conceptual model.

This study employs a quantitative research method by conducting an online questionnaire survey, which collect respondents' self-reported data. The survey examines the relationship between user's frequency in conducting interaction behaviors (independent variable) and their perceived frequency of receiving homogeneous content (dependent variable). It also measures user's social network heterogeneity as a moderator variable. The concept model in figure 1 presents the hypothesized relationships between those variables. Firstly, user's interactive behaviors influence their perceived frequency of receiving homogeneous content [7]. Meanwhile, user's social network heterogeneity can conduct influence on this process. This is because the degree of a user's social network heterogeneity presents how frequently they interact with individuals different from themselves. The more users interact with those individuals, the more likely they are to receive diverse information and thus reduce the frequency of homogeneous content recommendations [8].

### 2.2 Research Hypothesis

This study contains three hypotheses.

H1: users' positive interaction behavior (like, collect, share) will increase the frequency of recommending homogeneous content.

H2: users' negative interaction behavior (clicking "not interested") will reduce the frequency of recommending homogeneous content.

H3: User's social network heterogeneity serves as a moderator variable influencing the independent and dependent variable. Higher social network heterogeneity reduces the effect of conducting interaction behavior on homogeneous content recommendations.

### 2.3 Data Collection

The questionnaire was distributed on a widely used online survey tool in China named ‘WenJuanXing’, and its respondent was recruited from the platform’s users through convenience sampling. A total of 357 valid responses were collected. The questionnaire contains four main parts.

Part1: Demographic variables and frequency of daily social media use

The participants were asked to report their age, gender and daily social media usage time. Responses that reported excessively low daily social media usage time were considered invalid. The questionnaire did not set any restriction on participants’ gender and it set the age range from 18 to 45. This approach helps collect responses from a more diverse social group and minimizes the potential influence that a specific gender/age group may have on the result.

Part2: Measuring user’s frequency of conducting interaction behaviors

This part assesses the frequency of users’ daily interactions on social media. It asked participants to report how often they conducted interaction behaviors over the last month. The interaction behaviors included liking, sharing, commenting and using ‘uninterested’ function. A 5-point Likert scale was used, and responses were scored accordingly [9]. For liking, collecting, and sharing, the options ‘never’, ‘rarely’, ‘occasionally’, ‘frequently’ and ‘very frequently’ were assigned 1, 2, 3, 4 and 5 points. Using ‘uninterested’ function was reverse-scored.

Part3: Measuring user’s perceived frequency of homogeneous content recommendation

This part assesses user’s frequency of receiving homogeneous content recommendations over the last month. Questions regarding the frequency of receiving news reports regarding ‘global warming is fake news’ and ‘traditional Chinese medicine heals all diseases’ were presented on a 5-point scale from 1 = never to 5 = almost every day [10].

Part4: Measuring user’s social network heterogeneity

This part assesses the frequency of user’s interactions with individuals who are different from themselves in terms of social identity and viewpoints. It applied a 5-point Likert scale and asked questions like ‘How often do you talk about political issues on social media with people of different gender/nationality/region/viewpoint?’ The answers were scored from 1= never to 5= very frequently [11].

### 2.4 Data Analysis

The study applied SPSS (version 27) to analyze collected data. Firstly, it employed a bivariate correlation analysis to examine the relationship between the frequency of users’ interaction behavior and their perceived frequency of receiving homogeneous content. Subsequently, it conducted a hierarchical regression analysis to test the moderating effect of user’s social network heterogeneity.

## 3 Results

### 3.1 Questionnaire Survey Data

A total of 357 valid responses were collected and verified. The result shows that males accounted for 48.9% of the respondents and females accounted for 51.1% of it. In terms of age distribution, 69.55% of the respondents were aged from 18 to 25, 26.25% were aged 26-35 and 4.2% were aged 36-45.

Concerning the score of user's positive interaction behavior, the mean score was 10.46, the median was 10.63 and standard deviation was 3.14. For the score of user's negative interaction behavior, the mean score was 3.02, the median was 2.79 and the standard deviation was 1.15. User's perceived frequency of homogeneous content recommendations had a mean score of 3.58 and a standard deviation of 1.75. User's social network heterogeneity had a mean score of 11.3 and a standard deviation of 2.99.

The result shows that respondents tend to have high frequency in conducting interaction behaviors on social media. They also present low frequency of receiving homogeneous contents and relatively high frequency in interacting with diverse people.

### 3.2 Correlation Analysis Result

In order to examine the bivariate relationships between interaction behaviors and homogeneous content recommendation, Spearman's rho correlation analysis was conducted. Table 1 represented the result of the correlation analysis.

Relationship between positive interaction behavior and homogeneous content recommendation: Table 1 showed that there was a significant positive correlation ( $r=0.679$ ,  $p < 0.01$ ). This means higher frequency of conducting positive interaction behavior can lead to greater homogeneous content recommendation.

Relationship between negative interaction behavior and homogeneous content recommendation: Table 1 showed that there was a significant negative correlation ( $r= -0.535$ ,  $p < 0.01$ ). This means higher frequency of conducting negative interaction behavior can lead to a decrease in homogeneous content recommendation.

The result showed that both positive and negative behavior have impact on the frequency of homogeneous content recommendation. It also showed that all variables were statistically significant at the 0.01 level (2-tailed). (model 2) to test the moderating effect. In terms of model explanatory power, model 1 could explain 62.5% of the variance in perceived homogeneous content ( $R^2 = 0.625$ ). After introducing the interaction terms, the  $R^2$  of model 2 increased to 0.630, and significance change was  $0.032 < 0.05$ . This shows that the introduction of interaction terms can significantly increase model explanatory power, which proves it effective to include heterogeneity as a moderator variable.

According to Table 2, the unstandardized coefficient B of term positive heterogeneity was -0.020, the standardized coefficient Beta was -0.591. The significance level was  $0.006 < 0.01$ , which indicates that heterogeneity has a negative moderating effect on the relationship between positive interaction behavior and homogeneous content. This means the higher degree of heterogeneity one has; the weaker influence positive

interaction behaviors will have on homogeneous content recommendation. In contrast, the significance level corresponding to the term negative\*heterogeneity was 0.637 > 0.05, indicating that heterogeneity has no significant moderating effect on the relationship between user’s negative interaction behavior and homogeneous content recommendation.

**Table 1.** Relationship between independent and dependent variables

Correlations					
			positive_interaction	negative_interaction	homogeneous_content
Spearman's rho	positive_interaction	Correlation Coefficient	1.000	-.234**	.679**
		Sig. (2-tailed)	.	.000	.000
		N	357	357	357
negative_interaction		Correlation Coefficient	-.234**	1.000	-.535**
		Sig. (2-tailed)	<.001	.	<.001
		N	357	357	357
homogeneous_content		Correlation Coefficient	.679**	-.535**	1.000
		Sig. (2-tailed)	<.001	<.001	.
		N	357	357	357

\*\* . Correlation is significant at the 0.01 level (2-tailed).

**Table 2.** Heterogeneity as moderator variable on user interaction and content recommendation

Coefficients						
	Model	Unstandardized Coefficients		Standardized Coefficients		Sig.
		B	Std. Error	Beta	t	
1	(Constant)	1.896	.316		6.009	<.001
	positive_interaction	.299	.020	.536	14.954	<.001
	negative_interaction	-.670	.051	-.439	-13.122	<.001
	heterogeneity	.051	.021	.087	2.486	.013
2	(Constant)	3.215	.958		3.356	<.001
	positive_interaction	.045	.062	.081	.720	.471
	negative_interaction	-.592	.188	-.392	-3.149	.002
	heterogeneity	-.038	.075	-.065	-.510	.610
	positive*heterogeneity	-.020	.007	-.591	-2.850	.006
	negative*heterogeneity	-.008	.016	-.073	-.472	.637

### 3.3 Comparison with Hypotheses

The result of the analysis indicates that there exists a relationship between user’s interaction behaviors and their perceived frequency of homogeneous content recommendation. It also shows that user’s social network heterogeneity acts as a moderator variable between them.

H1: users' positive interaction behavior (like, collect, share) will increase the frequency of recommending homogeneous content. The correlation analysis proved this hypothesis. The more users conduct positive interaction behaviors, the more frequently they tend to receive homogeneous contents.

H2: users' negative interaction behavior (clicking 'not interested') will decrease the frequency of recommending homogeneous content. The correlation analysis proved this hypothesis. The more users conduct negative interaction behaviors, the less frequently they tend to receive homogeneous contents.

H3: User's social network heterogeneity serves as a moderator variable influencing the independent and dependent variable. Higher social network heterogeneity reduces the effect of conducting interaction behavior on homogeneous content recommendations. The analysis proved this hypothesis as partly true. User's social network heterogeneity can be a moderator variable on the independent and dependent variables, and high degree of social network heterogeneity reduces the effect of positive interaction behavior on homogeneous content recommendation. However, it does not take effect in term of negative interaction behaviors. No matter how high or low one's social network heterogeneity is, it will not influence the effect of their negative interaction behavior on homogeneous content recommendation.

## 4 Discussion

The result did not align with H3 as the heterogeneity had no effect on moderating the relationship between negative interaction behavior and homogeneous content recommendation. This may be because compared to positive interaction behaviors, negative interaction behaviors serve as a stronger and more direct signal of user's preference [12]. Consequently, the recommendation algorithm may tend to distribute a higher weight to negative interaction behaviors when recommending contents. This enables negative interaction behaviors powerful in the process of shaping recommended contents, which reduces the moderating effect of user's social network heterogeneity [13].

Despite the unexpected result, other results have confirmed the hypotheses. This indicates that users can actively conduct positive and negative interaction behaviors to influence effect of recommendation mechanism. As most of the netizens fail to consciously regulate their received content, the awareness of resisting recommendation mechanism should be widely propagated as a warning. Users should expand their social circle to reach more diverse perspectives as well. Furthermore, designers of the platform recommendation algorithms should improve the logic of the algorithm, enabling it to effectively filter premium content rather than homogeneous content. These initiatives can be helpful in elevating the quality of online content and boosting user's information literacy. What is more, it can help reduce the negative influence of the filter bubble effect.

However, this study has several limitations. Firstly, the sample size is relatively small due to constraints in research scale, which might affect the generalizability of the findings. Secondly, the survey relied too much on self-reported data from questionnaires, rendering the further result possibly less credible. This is because respondents

may not answer the questions honestly due to their wishes to meet social expectations. Thirdly, the simplified scoring method, merely separate users' behavior into three categories and giving them 1-5 scores, could oversimplify complex cognitive process. To refine the research method, more samples are needed to be collected and conducting long-term longitudinal survey is necessary to ensure the credibility of collected data. Furthermore, more scientific quantitative methods are required to analyze the survey data.

## 5 Conclusion

In conclusion, this essay has verified that user's interaction behavior has great influence on content recommendation, and their social network heterogeneity can partly moderate this process. Specifically, positive interactions, for instance, 'like', 'collect' and 'share' reinforce the recommendation mechanism's tendency to recommend homogeneous content. Conversely, negative interactions like using the 'uninterested' button reduces recurrence of those uninterested contents. These findings validate the research hypothesis and reveal the two-way relationship between user's interaction behavior and the filter algorithm. This result is predictable because of the fundamental design of those recommendation mechanisms, which tend to meet user's preference. This tendency intensifies the filter bubble effect, preventing users from contacting diverse information. As users keep receiving homogeneous information, which could be false information, they are more likely to form misperceptions of the society.

Through questionnaire survey and data analysis, this study has proved that users can actively influence platform's content recommendation by performing interaction behaviors. For users, this result reminds them of the importance to consciously filter received social media content to avoid the narrowing of information perspective.

However, this study has limitations as it relied heavily on self-reported data and simply collected data from online website. These factors could reduce the reliability of research result. Future investigations can conduct long-term longitudinal survey on specific social groups to ensure data credibility. Researchers can also conduct experiments to reach further conclusions.

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