

# ***Relationship Between Doom-scrolling and Mental Health under the Influence of Recommendation Algorithms***

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**Abstract:** Doom-scrolling is an entirely new concept in the study of mental health and has attracted considerable societal attention over the past few years. This paper is divided into two studies on the relationship between doom-scrolling and mental health: Study 1 explained how the doom-scrolling phenomenon occurs by analyzing the underlying logic of the social media personalized recommendation algorithm, while in Study 2, 15 items of the Doom-scrolling Scale were confirmed by confirmatory factor analysis. Different reliability coefficients support the scale's high reliability and prove the scale's applicability to the target group. In Study 2, it was further explained that there is a significant negative impact relationship between misfortune rolling and mental health of happiness index. The structural equation model shows a significant negative relationship between doom-scrolling and mental health. This pioneering research on doom-scrolling emphasizes the impact of this concept on both individuals and society.

**Keywords:** recommendation algorithm, social media, negative emotions, doom-scrolling, mental health

## **1. Introduction**

In the world-connect era, social media has broken the boundaries of communication and interaction, making contact between people more convenient and faster and providing users with an “immersive and companionship” virtual space. However, social media brings not only convenience but also hidden dangers.

People have been fighting the Covid-19 pandemic for the past few years, which has brought about hitherto unheard-of difficulties for every person and society in the world. Due to the pandemic's unknown nature, people are compelled to access all Covid-19 news and information via the Internet and social media. Uncertain stimuli like pandemics and epidemics undoubtedly cause people to become engrossed in uncontrollable and uncomfortable thoughts, which may be mitigated by learning the unknown. People are urged to get all the information to safeguard themselves from harm and feel in control. They are kept occupied by scrolling through their phones for extended periods in looking for other negative information and news. Continued exposure to negative social media news and news threads could manifest as “doom-scrolling,” which is characterized as a tendency to constantly search

for negative and gloomy content on social media and news feeds [1-3]. Doom-scrolling is also defined as “a habitual, immersive scanning for timely negative information on social media newsfeeds [4].”

If attempts to ease the uncomfortable thoughts inspire people to browse for negative information actively, personalized recommendation algorithms on social media will passively present certain negative information on their home page, indicating that recommendation algorithms are also an essential factor that affects the formation of doom-scrolling, thereby further affecting the mental health of people. Previous research has shown a connection between using social media and rising levels of anxiety and sadness. At the same time, the number and duration of social media used by youth groups are also significant in all age groups and are more affected by social media. There is also a large amount of research on social media recommendation mechanisms. For instance, Guo Shaofang assessed the impact of micro media news dissemination integrated with a personalized recommendation algorithm [5]. However, the number of research combining the two of them is still rather limited.

In this case, the theoretical significance of this study mainly includes the following aspects: First, different from the previous research based on trending topics and opinion leaders, the recommendation mechanism of social media platforms was at this moment chosen as the entry point to analyze the recommendation mechanism, which has been more personalized in recent years, and provides a new research perspective for emotional communication. Second, understanding the impact of the recommendation mechanism on personal emotions enables the users to be aware of “I am trapped in the negative emotional loop due to the external factors” and consequently to break the loop and leave the tide of negative emotions. Third, this study can inform social media platform operators of the shortcomings of the existing recommendation mechanism and the loss of users caused by these shortcomings. This study focused on the recommendation algorithm of social media by reading relevant research and analyzing data from the “The relationship between doom-scrolling and mental health” questionnaire using SPSS. It was expected to verify that the recommendation algorithm further deepens users’ negative emotions and that attempts are made to propose appropriate and practical solutions.

## **2. Methods**

### **2.1. General Description**

Three research methods, including the literature survey method, questionnaire method, and data analysis method, were used in this study. Firstly, the literature survey method was used to find out the current progress of relevant research and learn from previous experience. Afterward, according to the referenced research, the logic of personalized recommendation algorithms in social media was described clearly, and the questionnaires were designed. In addition, the questionnaire method was also applied. Two scales were designed by referencing the research of “The Dark at the End of the Tunnel: Doom-scrolling on Social Media Newsfeeds” [4]. After sending questionnaires on the Internet, data involving basic information, personal social media usage, the understanding of doom-scrolling, and the mental health situation of the users were collected. Last, the data analysis method was used to tackle the data collected from the questionnaire. SPSS was used to analyze these data, verifying the efficiency of doom-scrolling, further deepening the negative emotions.

### **2.2. The Literature Survey Method**

Firstly, open the academic search engine such as CNKI and Google Scholar, and then enter the keywords to be searched, such as “recommendation algorithm,” “social media,” and “negative emotion.” Then, choose the articles with high relevance in the title, keywords, or abstract; a publication time of nearly three to five years may be preferred. Given that the literature survey aims

to gain more details of the recommendation algorithm, it is preferred to review more articles while choosing the reference research. In order to explain the recommendation algorithm logic clearly, the algorithm description part of the literature is an important part to read.

### **2.3. The Questionnaire Method**

The participant study currently includes 83 participants recruited from college students in Beijing through online surveys (additional participants in the follow-up meeting). Sharma et al. established the Doom-scrolling Scale. The 15 questions on the unidimensional scale (such as “I lose track of time when I read bad news on social media”) are assessed on a 7-point Likert scale, with one denoting “strongly disagree” and seven denoting “strongly agree.” High rankings suggest advanced doom-scrolling.

Besides, the data analysis mainly uses SPSS and Amos for analysis, and the specific research details are as follows.

## **3. Experiment Results and Analysis**

### **3.1. Experimental Basis**

Herein, the experiment was mainly divided into three parts: the first part describes the underlying logic of the social media content recommendation algorithm; the second part verifies the reliability and fitness of the Doom-scrolling Scale in the target population; and the third part justifies the hypothesis that Doom-scrolling has a significantly negative correlation with mental health.

All the data in this experiment are from the participant information obtained from the questionnaire and the data contained in each question.

### **3.2. Presentation and Description of Experimental Results**

#### **3.2.1. General Situation of Personalized Recommendation Algorithm**

With the development of technology, surfing online on social media platforms has become the norm for most people. At the same time, the push notification mechanism of the platform has also changed from the initial “what they provide, what users see” to “what users want to see, what they push.” Hence, personalized recommendation algorithms have been born as the times require and have even become the core of some social media platforms [6-8].

At present, personalized recommendation algorithms are almost used by all social media platforms, which enables the platform to make what users see more consistent with their preferences by mining their identity characteristics and content preference, thereby sorting out the content that the users like, predicting the content that they may be interested in, and push it to the users so that the user experience can be enriched and their willingness to use the platform can be enhanced.

There are now two well-liked personalized recommendation algorithms: the collaborative filtering recommendation algorithm and the content-based recommendation algorithm.

Searching for similar content based on the online interaction preferences of users is the basic logic of the content-based recommendation algorithm. The recommendation system will summarize users’ interest areas through their browsing histories and interaction records and then compare them with the content to be recommended to find similar content and recommend it to the users, as shown in Figure 1 and Figure 2.

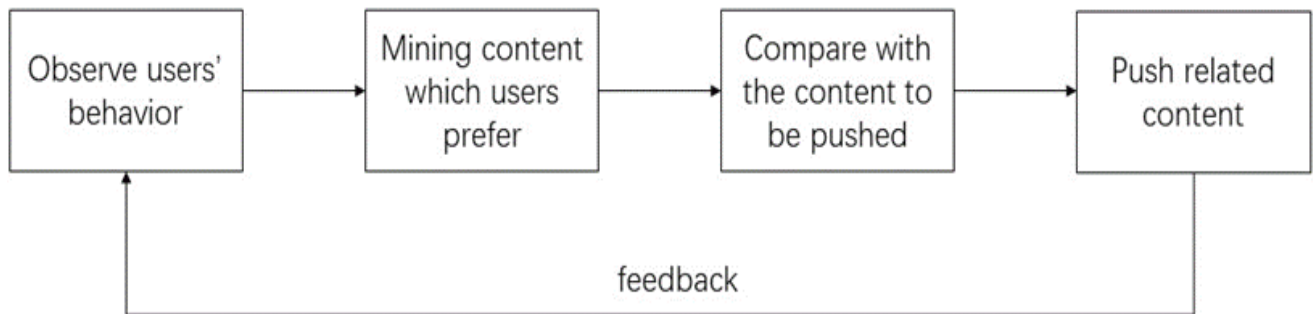


Figure 1: Basic logics of content-based recommendation algorithm.

The collaborative filtering recommendation algorithm is to recommend from the perspective of users. First, user preferences are summarized through their behavior records, and then users with similar preferences can be found. For example, the users who often interact with the same content or the same blogger can be classified as those with similar preferences. Afterward, the recommendation system will push these contents to users sharing similar preferences.

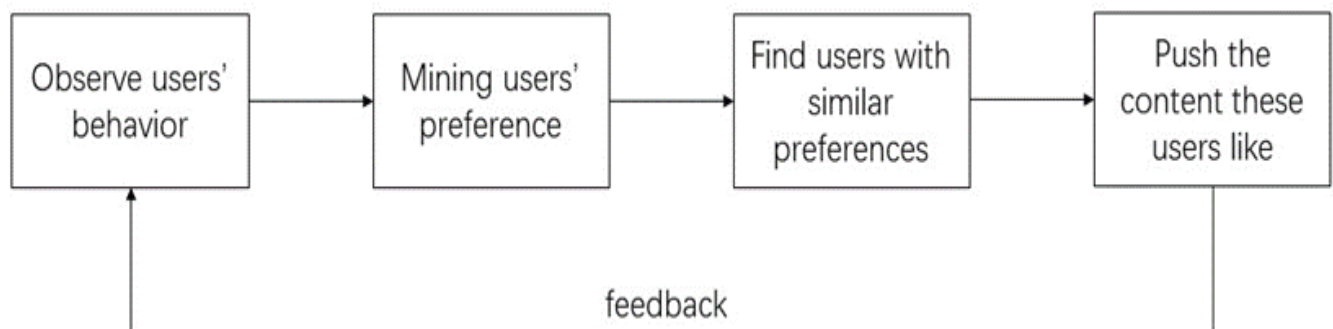


Figure 2: Basic logics of collaborative filtering recommendation algorithm.

### 3.2.2. The Reference Significance of Retrieval Algorithms for Recommendation Algorithms

Semantic analysis is also useful for personalized recommendation algorithms to understand users' interests. Recently, researchers have been studying new algorithms to optimize the relevance of retrieval continuously. The recommendation algorithms can be seen as a retrieval system that implicitly inputs user preferences and user behaviors such as likes and comments can be seen as an input process. The recommendation algorithm retrieves these implicit inputs. Therefore, the personalized recommendation algorithm does not fundamentally differ from the retrieval system in principle. Because retrieval has similarities with recommendation-semantic analysis, the research on retrieval algorithms also has reference points for the research on recommendation algorithms.

Take A Neural Corpus Indexer for Document Retrieval as an example [9]. It proposed a sequence-to-sequence neural network model, with a query as input and the most relevant document identifier (docid) as output, which puts documents and other information in the network. The research is mainly

divided into three parts to explain the NCI algorithm. Firstly, it used the hierarchical k-means algorithm to classify documents into k clusters, then encoded each level and each cluster to generate the docid of every query. Clustering groups documents based on content similarity to put similar documents into one category. Some information can be found from the encoding if encoded according to category and hierarchy. So that targeted searches can be carried out to improve the efficiency of information retrieval. Secondly, it used two kinds of methods to generate a document query. The third part is to improve the encoder and decoder parts. Adding a comparative learning component to the decoder makes the algorithm more stable. The recall is a vital evaluation indicator of retrieval algorithms, which is the proportion of relevant records retrieved from the system relative to the total number of relevant records. The higher the recall, the more relevant the retrieval results returned to the user, and it also fits the user's needs. Thus, if the retrieval algorithm is optimized, the ultimate goal is to improve the recall. After training and testing, the research finds that compared to the previous methods, the recall performance has improved.

Given that most mainstream recommendation and retrieval methods currently follow the principles of the above methods, the returned results will have a high recall, which means high content similarities. Therefore, it has a high rate of deepening the doom-scrolling phenomenon.

### **3.2.3. Effect of the Personalized Recommendation Algorithm on Further Deepening Negative Emotions**

The logic of the content-based recommendation algorithm is to identify the content users have browsed and interacted with as the content they like and desire to see again. Hence, the recommendation algorithm will regard it as the content users like and push similar content regardless of the user's emotional attitude.

Based on this deduction, it can be understood by analogy that while users are browsing social media, they see some contents that arouse their negative emotions and then make interactions, such as expressing their own opinions, when the behavior of browsing and commenting will be judged as the users like this content by the recommendation algorithm. The relevant content will continue to be pushed. Users receive many such content, which can be expected to deepen their negative emotions further.

There is an example that can clarify this hypothetical situation. At the beginning of 2023, many people were infected with COVID-19 all over China, but not all of them were treated with medicine or knew how to relieve some symptoms. People would then search Little Red Book for how to buy medicine and ask for treating COVID-19 symptoms with anxiety or other negative emotions. At this time, the personalized recommendation algorithm of Little Red Book may determine that users are interested in the content of "COVID-19" and recommend relevant content based on the browsing and comments they follow. Among these relevant contents, posts that described various strange symptoms or sufferings after being positive and outputting negative emotions occupied a certain proportion. This proves that the personalized recommendation mechanism can further deepen users' negative emotions.

### 3.3. Research on the Relationship Between Doom-scrolling and Mental Health

#### 3.3.1.Descriptive Statistics

Table 1: Sample characteristic distribution description.

Variable	Option	Frequency	Percentage	
Gender	male	19	22.9	23%
	female	64	77.1	77%
Grade	PhD or above	6	7.2	7%
	Undergraduate sophomore year	9	10.8	11%
	Undergraduate third year	14	16.9	17%
	Undergraduate Senior	22	26.5	27%
	Undergraduate freshman year	3	3.6	4%
	Master's degree in progress	29	34.9	35%
Duration of social media usage	10	5	6	6%
	13	1	1.2	1%
	14	1	1.2	1%
	2	13	15.7	16%
	3	15	18.1	18%
	4	11	13.3	13%
	5	7	8.4	8%
	6	11	13.3	13%
	7	8	9.6	10%
	8	9	10.8	11%
	9	2	2.4	2%
Number of social media usage	13	1	1.2	1%
	14	2	2.4	2%
	2	2	2.4	2%
	3	14	16.9	17%
	4	22	26.5	27%
	5	16	19.3	19%
	6	13	15.7	16%
	7	5	6	6%
	8	7	8.4	8%
	9	1	1.2	1%
Q1	No	1	1.2	1%
	Yes	82	98.8	99%
Q2	No	4	4.8	5%
	Yes	79	95.2	95%

#### 3.3.2.Reliability Analysis

Table 1 describes the sample characteristic distribution description. In this study, the main factors were measured using a scale. Inspecting the data quality of the measurement results is an important prerequisite to ensure the significance of subsequent analysis. Firstly, the internal consistency of each dimension was analyzed by the reliability test of the Cronbach coefficient. The value range of the Cronbach coefficient is 0-1, with a higher value of the test result coefficient indicating higher

reliability. Generally, the reliability coefficient is less than 0.6. In that case, it is considered that the reliability is not credible, so it is necessary to redesign the questionnaire or try to collect data again and analyze it again.

In this analysis, the results of reliability analysis in Table 2 show that the two dimensions of doom-scrolling and WEM-WBS are in the range of 0.8-1 in general, indicating the good consistency and the acceptable reliability of the scale used in this study.

Table 2: Reliability Analysis.

Variable	Cronbach's alpha	Item
Doom-scrolling	0.963	15
WEM-WBS	0.888	14

### 3.3.3. Validity Analysis

According to the model fitness results in Table 3, CMIN/DF=2.036, in the range of 1-4, and the other IFI and CFI results have reached the excellent level of more than 0.9. Therefore, combining the results of this analysis, it can be concluded that the doom-scrolling model has a good fitness.

Table 3: Model fitness test.

Statistical inspection index	CMIN/DF	IFI	CFI
Critical value	<3	>0.9	>0.9
Measurement model	2.036	0.918	0.917

### 3.3.4. Dimensional Convergence Validity and Combined Reliability Test

The convergence validity AVE and combination reliability CR of each scale dimension were further examined under the assumption that the CFA model of the doom-scrolling scale had good fitness. The test process calculated the standardized factor load of each measurement item on each dimension through the established CFA model and the convergence validity value and combined reliability value through the calculation formula. According to the standard, AVE>0.5, CR>0.7, proving the scale's good convergence validity and combined reliability, as shown in Table 4.

Table 4: Dimensional Convergence Validity and Combined Reliability Test.

Path relationship			Estimate	AVE	CR
a	<---	Doom-scrolling	0.794	0.6413	0.9637
b	<---	Doom-scrolling	0.724		
c	<---	Doom-scrolling	0.734		
d	<---	Doom-scrolling	0.824		
e	<---	Doom-scrolling	0.872		
f	<---	Doom-scrolling	0.682		
g	<---	Doom-scrolling	0.773		
h	<---	Doom-scrolling	0.79		
i	<---	Doom-scrolling	0.859		
j	<---	Doom-scrolling	0.893		
k	<---	Doom-scrolling	0.623		
l	<---	Doom-scrolling	0.849		



Table 4: (continued).

m	<---	Doom-scrolling	0.76		
n	<---	Doom-scrolling	0.893		
o	<---	Doom-scrolling	0.884		

### 3.3.5. Confirmatory Factor Analysis of WEM-WBS Scale

The Warwick-Edinburgh Mental Well-being Scale (WEM-WBS) was prepared by Tennant et al. in 2006, which has been proven suitable for assessing positive mental health and has good reliability and validity among students. The main feature of WEM-WBS is that it consists of 14 items, which are brief and easy to operate. They also integrate three aspects of positive emotion, positive psychological function, and interpersonal satisfaction that reflect mental health. The used Chinese version of WEM-WBS was conducted [10]. The single-dimensional structure of the Chinese version of WEM-WBS shows an acceptable fitting index: GFI=0.845; CFI = 0.885; NFI = 0.872. Meanwhile, the reasonable validity of the Chinese version of the scale among middle school students and urban residents has also been confirmed [11].

### 3.3.6. Description Statistics

Table 5 presents the descriptive statistical analysis results and normality tests of the factors used in this study. According to the results of the descriptive statistical analysis, except for individual variables, the mean value of each variable is in the range of 3-4. Among the scoring methods of the scale, the doom-scrolling scale is 1-7 positive score, and the WEM-WBS scale is 1-5 positive score, indicating that the study object group is at the middle level in the relationship between doom-scrolling and mental health.

Besides, in the case of an absolute value of skewness coefficient within 3 and the absolute value of kurtosis coefficient within 8, the data are considered to meet the requirements of approximate normal distribution, indicating that the data of each measurement item in this study meet the normal distribution.

Table 5: Normality test results of descriptive statistics and measurement items in each dimension.

	Items	M	SD	Skewness	Kurtosis	M'	D'
Doom-scrolling	L1	3.61	1.545	0.105	-1.049	3.61	1.68
	L2	4.11	1.645	-0.346	-0.799		
	L3	4.08	1.602	-0.378	-0.977		
	L4	3.02	1.739	0.632	-0.505		
	L5	3.55	1.602	0.164	-0.754		
	L6	3.04	1.663	0.414	-0.893		
	L7	3.14	1.69	0.28	-0.972		
	L8	3.96	1.804	-0.404	-1.154		
	L9	3.77	1.857	-0.066	-1.14		
	L10	3.61	1.545	0.004	-1.183		
	L11	3.98	1.638	-0.063	-0.966		
	L12	2.93	1.56	0.616	-0.357		
	L13	4.14	1.754	-0.476	-0.976		
	L14	3.66	1.843	0.166	-1.115		
	L15	3.54	1.699	0.109	-0.907		



Table 5: (continued).

WEM-WBS	Q1	3.42	0.977	0.024	-0.982	3.42	0.88
	Q2	3.67	0.925	-0.341	-0.226		
	Q3	3.11	0.963	0.366	-0.911		
	Q4	3.41	1.036	-0.359	-0.755		
	Q5	3.11	0.963	0.282	-0.688		
	Q6	3.52	0.651	-1.021	1.698		
	Q7	3.28	0.801	0.036	-0.545		
	Q8	3.28	0.888	-0.045	-0.42		
	Q9	3.39	0.973	-0.279	-0.792		
	Q10	2.99	0.994	0.101	-0.889		
	Q11	3.77	0.77	-0.727	1.402		
	Q12	3.65	0.818	-0.638	0.653		
	Q13	3.83	0.838	-0.815	1.034		
	Q14	3.48	0.739	0.064	-0.235		

Correlation analysis. In this analysis, exploratory analysis was carried out through the correlation between the two variables through the Person correlation analysis. According to the analysis results, there is a significant correlation between these two variables, and the results of correlation coefficient reveal that Doom-scrolling has a negative correlation with mental health ( $r=-.359$ ), as shown in Table 6.

Table 6: Pearson coefficient correlation analysis results between dimensions.

Dimensions	Doom-scrolling	WEM-WBS
Doom-scrolling	1	-.359**
WEM-WBS	-.359**	1

\*\*At 0.01 level (double tail), the correlation is significant.

Structural equation model. The results of path relationship hypothesis of the SEM model were tested for influencing factors of mental health. According to the analysis results in Table 7, in the path hypothesis test of this study, doom-scrolling has significantly negative effects on mental health ( $\beta=0.275$ ,  $P<0.001$ ), indicating the validity of the assumption.

Table 7: SEM path relationship test results of mental health influencing factors.

Path relationship			Estimate	S.E.	C.R.	P
He	<---	Doo	-0.437	0.099	-4.395	***

#### 4. Conclusion

Doom-scrolling Scale is considered to be a reliable and effective measurement tool among the youth groups in Beijing. In addition, cross-sectional analysis shows that doom-scrolling may significantly negatively affect mental health. Finally, further longitudinal and experimental research is still required to confirm the relationship between the characteristics in this study and the idea of doom-scrolling. However, this study is also subject to some limitations. First, the research's data were gathered through self-reported questionnaires, which could lead to some personal inaccuracies. Second, inferring causal relationships from the study's cross-sectional approach is challenging. Therefore, further experimental and long-term research is required to investigate this causal-effect

link. To do this analysis again, the sample size for this study needs also be expanded to a suitable level. In an independent study on the sample, a relatively new concept of “doom-scrolling” was investigated.

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