

# Analysis on the “Douyin (TikTok) Mania” Phenomenon Based on Recommendation Algorithms

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**Abstract.** As one of the most popular short video platform, Douyin has accumulated more than half of the Chinese netizens as its daily active users. Many users spend plenty of time viewing Douyin short videos, which make Douyin addiction become a widespread phenomenon. In this paper, the author analyzes algorithm principles used in Douyin. Combining both perspectives of mass media communication and algorithm technology to explain how it effects Douyin addiction. For one thing, the recommendation algorithm caters users by fully meeting their needs. Using the hierarchical interest label tree, the user persona and the partitioned data buckets strategy to recommend more accurate and personalized contents. For another, the algorithm uses the collaborative filtering algorithm and low-cost interaction design mechanism to make traps for users. The author also finds that there is a closed-loop relationship between Douyin addiction and algorithm optimization. The algorithm principles positively effects users' continuance intention. Meanwhile, the more frequent the user uses Douyin, the more accurate the algorithm will be. If not intervened, the addiction may be severely exacerbated. So, the author comes up with a few suggestions for Douyin developers and users, trying to break the closed-loop.

## 1 Introduction

Douyin, the Chinese origin version of TikTok, is an online short video mobile application that has been launched by ByteDance in September 2016. According to their official introduction, “Douyin is a short video platform that helps users express themselves and record a good life” [1]. Most of the videos on Douyin last from 15s to 60s, both hilarious and condensed, covers a wide range of topics.

According to Mary Meeker's 2019 Internet Trends Report [2], which was one of the most highly anticipated annual reports for all the Internet related industries. It showed that Chinese Internet robust usage growth is primarily driven by Short-Form Video. Among all the short video application these days, Douyin has become the leading short video application by number of downloads and great influences all over the world. It becomes a phenomenal success that, according to ByteDance's annual data report, Douyin has already amassed 400 million DAU up to January 2020 only in China, nearly half of the Chinese netizens [3].

The most conspicuous feature that distinguishes Douyin from other similar products is that it is an algorithm-driven, content-oriented product, which means that its popularity is largely dependent on the powerful AI algorithms and content distribution strategies. In this research, the author investigates all the invention patents related to the recommendation algorithm applied by ByteDance. These patents show the unique method of ByteDance that uses the algorithm to distribute contents.

With thoroughly understanding of the algorithm principles and analyzing them in conjunction with the theory of communication, it can be explained that why Douyin can achieve such great popularity in a short time.

With the recommendation of the algorithm, each user will receive a completely personalized videos feed based on the matching between their own personalities, content labels, and the characteristics of their environment. The user passively accepts the system's personalized recommendation content without any initiative selection or search. This is a huge revolution to the way people are used to obtaining information on the Internet. This greatly alleviates the effort that people have to pay to get the information they want, and frees people from massive amounts of information. The effective information distribution strategy of contents is an essential ingredient of not only Douyin's success but also the innovative channel of information dissemination. However, while the products represented by Douyin introduced algorithm technology into the field of communication, highly personalized distribution also brought unprecedented problems and challenges. Because the content that users sees basically meets their needs and interests, and does not need to spend the cost to find them. As a result, this may lead users to watch short videos for hours and even become an addiction. This article also refers to plenty of researches in the field of computer science, new media communication, psychology and marketing strategies to analyze the principle of Douyin's recommendation algorithm and its effects.

Generally speaking, this paper discusses how Douyin's

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algorithms help it attract users and maintain user stickiness. In addition, this paper analyzes the abuse of the recommendation algorithm, as well as the association between these disadvantages and the phenomenon of “Douyin Mania” and other impacts. This research can be useful for media scholars to have a deeper understanding of the recommendation algorithm principles, and make technology and media better integrate and benefit people's lives.

## 2 The Phenomenon of “Douyin Mania”

Although a short video may be only cost 15 seconds, when users use short video app like Douyin to kill some

fragmentary time, it usually turns out that they will consume far more than 15 seconds without even noticed.

Because the only operation that the user need to do, after a video is finished, is to swipe up the screen and start the next one. It is very low-cost and simple for users of all ages.

According to Mary Meeker’s 2019 Internet Trends Report, Mobile Short Form Video has brought the main cause for users to spend more time on their smartphones. From April 2017 to April 2019, the average daily use time of Chinese Short Video Apps has grown from less than 100 million hours to 600 million hours. Among all the short video apps, Douyin headed the top of the number of Daily Active Users (DAU), leading the growth both in the number and duration of users[2].

### China Short-Form Video = Driving Incremental Mobile Time Spent Growth

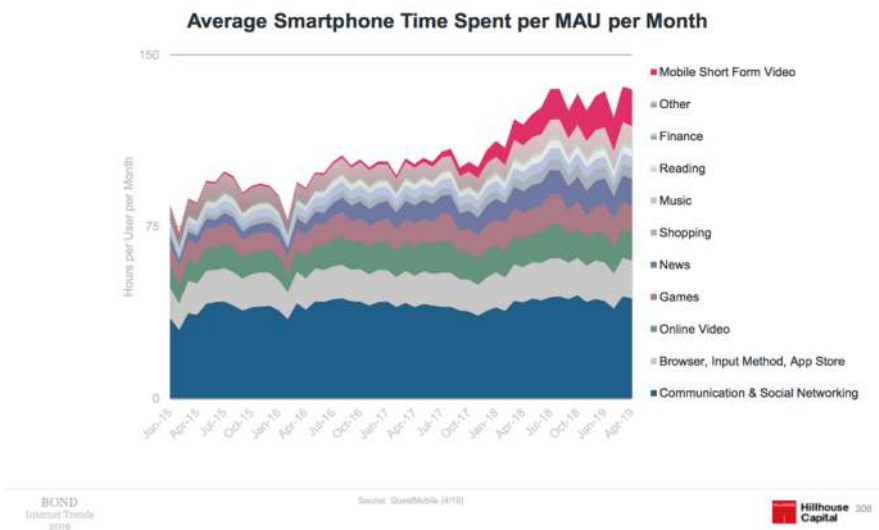


Fig1. Average Smartphone Time Spent per MAU per Month from 2019 Internet Trends Report [2].

### China Short-Form Video = Leading User + Usage Growth Across All App Categories

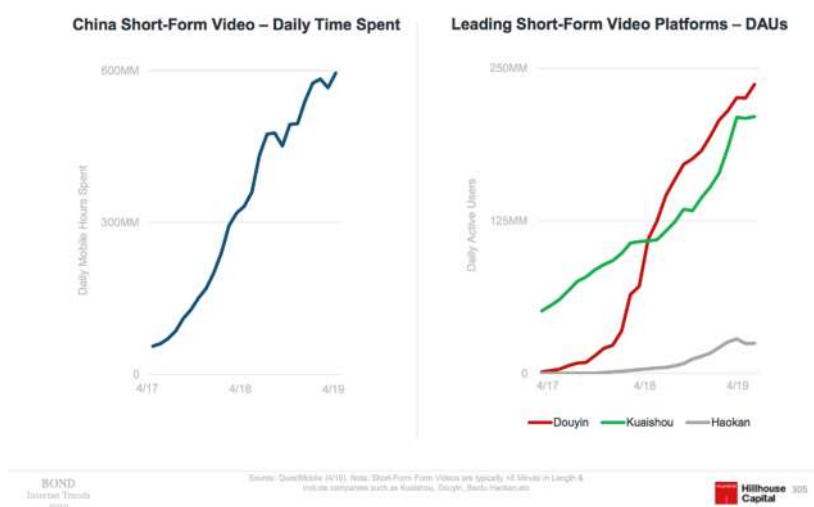


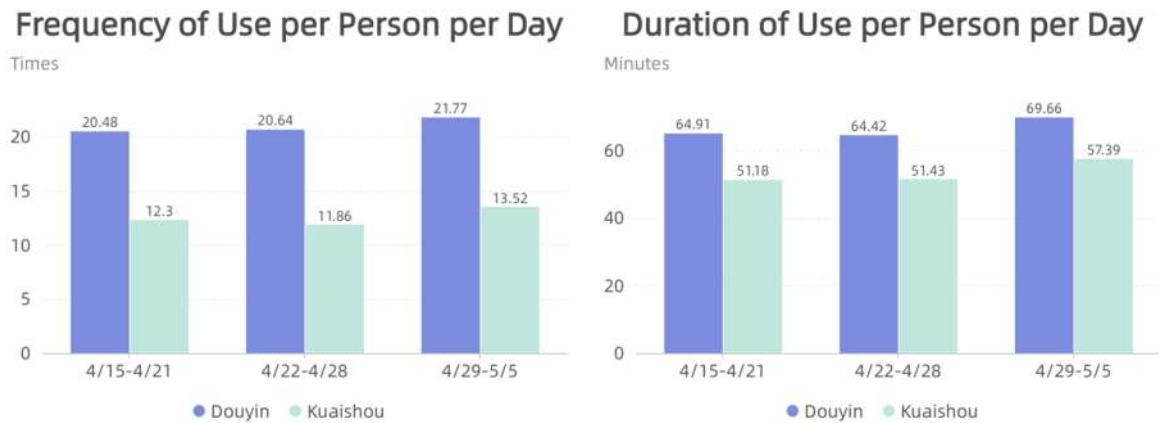
Fig2. China Short-Form Video Daily Time Spent & Leading Platforms from 2019 Internet Trends Report [2].

Statistics from BigData-Research also showed that short videos have been considered high-frequency applications, with 41.3% of users using multiple times a

day and 56.9% of users using more than 60 minutes per day [4]. Douyin, as one of the most popular short video platform in China today, is even higher than this overall

average. According to data from China Securities, the average daily usage of Douyin users can reach more than

21 times a day and almost 60 minutes [5].



**Fig3.** The Usage of Douyin and Kuaishou [5].

Therefore, there are some critics think Douyin is a “Time Black Hole” that caused people’s addiction to browsing short videos. It kills people’s time, distracts people’s attention, and makes it difficult for them to concentrate on serious things. Users seem to be caught into a vortex of entertainment.

Douyin has been so compelling that in April 2018, developers were forced to add an “anti-addiction” notification. After 120 minutes of continuous use by the user, the system will automatically lock, and the user needs to re-enter the password to continue using. This Douyin addiction, which also sort of “Douyin Mania”, has become the status quo for many Chinese people.

mostly controlled by the audience, as it is the user who has the choice to stay or leave an application. Study lead by Cao Huanhuan, a senior algorithm architect of ByteDance, shows that there is a clear correlation between user satisfaction and user continuance intention. Their result also finds out that satisfaction is the most significant among all the variables affecting intention of usage continuance [6]. Therefore, the success of the Douyin recommendation algorithm hinges on it complete satisfaction with of users’ needs.

### 3 The Recommendation Algorithm principles which lead to Douyin Mania

Comparing the differences between ByteDance’s products and traditional Internet giants’ products, it is not difficult to find that the kernel of its success is at the technical level. Although is a commercial corporation, Bytedance (Douyin’s parent company) is very enthusiastic about artificial intelligence. They even established an AI Lab in 2016, whose main research focus has been the development of innovative technologies that serve the purposes of ByteDance’s content platforms.

In that context, Douyin, as a product of Bytedance, could gain such a great popularity in a short period must has a close relationship with their powerful intelligent algorithm behind it.

The main purpose of the recommendation algorithm is to enable users to obtain personalized content that they are interested in, without initiative searching. It is aimed to improve users’ satisfaction and dependence on Douyin, which can be divided into the following two aspects: how the algorithm caters to the audience and how the algorithm traps the audience.

#### 3.1.1 “Full Coverage of Users interest”: A Global Interest Exploration Recommendation Method

“In the era of short videos, the creative forms and genres of short videos are extensive, and any details of life can be used as materials for creative expression”, according to the 2019 Creator Ecology Report officially released by Douyin [7]. There are miscellaneous content materials on Douyin that could have covered all area of interests, including but not limited to mini self-made sitcoms, current news, vlog (video log), education, special skills and so on. For such a huge content materials on Douyin platform to accurately match the corresponding audience, a sophisticated and logical labels classification method is the foundation.



**Fig4.** Popular Topics in Douyin.

ByteDance applied for an invention patent entitled “A Global Interest Discovery Recommendation Method and Device” [8]. This patent clarified how they systematically categorize a large number of contents to better fit the interests of users. According to the patent, they build a global algorithm to “construct a hierarchical interest label

#### 3.1 The Algorithm Caters to Expectations of Users by Fully Meeting Needs

In any mass communication process, the initiative is

set based on the theme of contents, and calculated the relevant degree of each interest label in the set" [8].

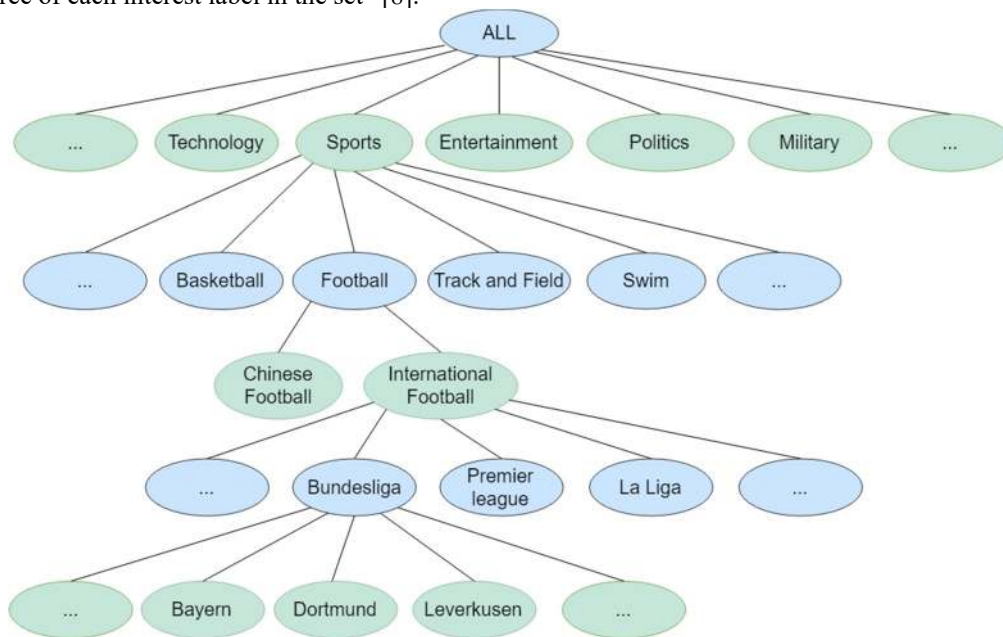


Fig5. The Hierarchical Interest Label Tree.

The implementation of this method is to build the interest label set as an interest label system tree diagram. The tree diagram can clearly show the inclusion and hierarchical relationship between the data. In this hierarchical label classification tree, the root node is all the content of Douyin. The meta-classifiers in the first layer below are some general category like Sports, Technology, Entertainment, etc. Suppose there is a parent node (meaning a node who has branch) represent sports, then its child nodes mean more detailed classifications in the field of sports, such as basketball, football, swim. Each branch can be further refined into narrower and specific domain. Douyin also encourages creators to specialize in only one domain, instead of pursuing broad coverage of the content. As to the recommendation algorithm, such content can be more accurately recommended to the users who need it, and increase the valid audience.

### 3.1.2 The Algorithm Knows You Better: Draw User Persona

In order to better match the content with the user, the algorithm also needs to understand the user well, that is, to draw user's persona. It means sorting the user's information and labeling the user to achieve accurate content recommendations [9]. According to the algorithm principle promulgated by ByteDance, they basically use user's interest characteristics, identity characteristics, and behavior characteristics to describe a user [10].

When users first log in to Douyin, they can choose to log in through a third-party social account. This allows the algorithm model to mine existing user information and historical social behavior on external data to analyze user habits more quickly. However, not all users will choose this login method, so the understanding of users must be mainly based on user usage on Douyin. Basic identity information, such as gender, age, location and occupation,

can be predicted by models. For example, the resident location comes from the user's authorized access to the location information. Based on the location information, the resident point is obtained through traditional clustering methods [10]. That means counts the user's location information data collection in a form similar to a scatter plot, and takes the center of the cluster is used as the resident location. Combining the resident point with other information can infer the user's work place, business trip place, and travel place [10]. The aggregation of these user tags into environmental features will be very helpful for recommendations.

The user's interest characteristics refer to the categories, creators, specific labels that they are interested in. Users with similar interests will form User Clustering and share each other's interest characteristics. In addition, the model also needs to learn the behavior characteristics of the user, such as when the user tends to use Douyin, how long and how often. This information will also help the algorithm fit better. For instance, if the user's habit of using Douyin is high frequency but each time is very short, then the algorithm may consider to recommend videos with shorter duration.

Time-effectiveness is essential for the recommendation algorithm because people's needs are changing at all the time. Douyin uses a stream computing method to dynamically process most of user profiles. As long as there are user actions, the algorithm will update the labels. For user profiles that are not sensitive to timeliness, traditional batch computing with non-real-time and high-latency features is used. This mixed use of stream computing and batch computing requires only dozens of machines to support the interest model update of tens of millions of users every day. The features update can basically be done in real time. After the user make a judgment on whether like or dislike the current video and swipe to the next one, the algorithm already has a new

portrait of the user. This means that the longer the user uses Douyin, the more the algorithm will understand the user.

### 3.1.3 Efficient Information Distribution: Matching Strategy

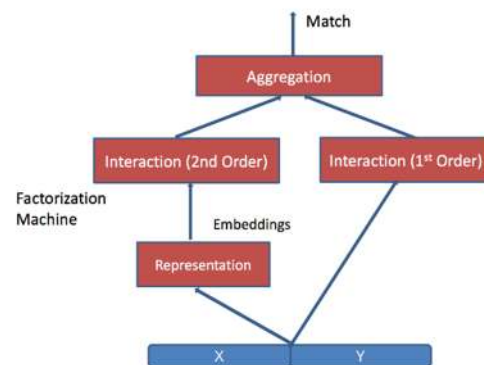
“Under the de-medialization trend in the digital media era, users are no longer just passive receivers and consumers of information, but also active senders and producers. The situation where one person decorates two corners greatly increases the amount of information. [11]” The content distribution efficiency of manual editors can no longer meet the rapidly changing content output. Efficient and high-quality extraction of the information has become a necessary requirement, which happens to be the core goal of Douyin algorithms. They do not rely on social relationships or require the user to have any initiative searching operations, which greatly reduces the cost for users to obtain information. The above two steps make the algorithm understand the user and the content more and more. The next step is to solve the most important matching problem.

Most recommendation systems divide the matching problem into two parts: recommendation recalling and recommendation ranking. The recommendation recalling is to retrieve candidate sets that meet users interests in all content sets, and then screens out a suitable number of candidate lists. There is a huge amount of content on the Douyin, that the recommendation system cannot calculate all the correlation between the contents and users. Therefore, it is necessary to design some recalling strategies, and filter out a thousand-level content library from the massive content each time it is recommended. Inversion is one of the main ideas, which is to positioning content based on certain attributes of the content, such as genres, topics, and popularity, rather than based on the order of content records. This method can quickly truncate massive content sets based on user interest tags, and efficiently filter a small portion of content from a large content library.

The recommendation ranking is based on the combination of metrics from different dimensions. All the metrics will be combined to score the content on the recommendation candidate list, and then determine the order of recommendations.

In Douyin recommendation algorithm model, multiple machine learning algorithms are used in combination to seek higher performance. The key to all machine learning algorithms is that it can learn sophisticated feature interactions behind user behaviors. “Most feature interactions are hidden in data and difficult to identify a rule. (for instance, the classic association rule “diaper and beer” is mined from data, instead of discovering by experts), which can only be captured automatically by machine learning. Even for easy-to-understand interactions, it seems unlikely for experts to model them exhaustively, especially when the number of features is large.” [12]

## Typical Architecture for Recommendation



**Fig6.** Typical Architecture for Recommendation [13].

The typical architecture for recommendation algorithm start with receiving a set of inputs characteristics  $X, Y$  from the content and the user. As the input data are huge, these inputs need to be compressed. In the embedding level where inputs are generated to lower dimensions feature vectors that make it easier to calculate. After that, the classifiers obtain characteristics about the content and the user, train it separately. The final fusion result comes from the aggregation of several training models, which may have different weights for each feature that make the matching result more reliable.

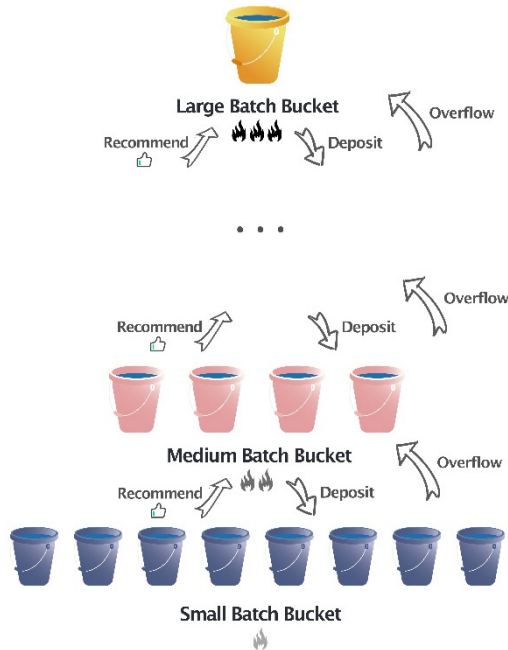
The continuously updated data set of the platform can be divided into two parts, the training set and the test set. The training set includes not only the input features, but also the real accuracy of the matching result, which calculated by subsequent user’s feedback. To train the model, the predicted result output is compared to the real result and the cost is the difference of the two. The smaller the cost is, the more accurate the model is. Improving the accuracy is the significance of training. The point of training is to make the cost as small as possible through millions of training examples. To do this, the model updates the features’ weights step by step, until the prediction closely matches the correct output. Once trained well, a training model has the potential to make accurate predictions each time. The model will then be used in the test set to recommend the content to users. The recommendation algorithm model is always learning, even if the model is already put in use. Online training is based on the latest samples to update model parameters in real time.

As the result, it ensures the algorithm to follow up with changes in users’ needs at any time and make adjustments in a timely manner.

Based on the elaborate division of content and user groups, combined with the precise and intelligent matching, users will always be in a mood of entertainment that satisfied by the recommendation content. This allows users to immerse themselves in short videos of Douyin one after another. And because most of the recommended content can hit the user’s needs, the curiosity and expectation for the next video will be magnified. The next one, just like Pandora's box, keeps attracting users, so that they cannot leave this application.

### 3.1.4 Finding the Emotional Resonance: Partitioned Data Buckets

The author of the “data pool marketing” theory, Yang Fei, defined the concept of the data pool in his book: “The key to the data pool is to get more data through the continuous operation of the original data.”[14] This theory is reflected in the algorithmic logic of Douyin. In order to seek a wider audience resonance, Douyin uses the method of partitioned data buckets to launch new content.



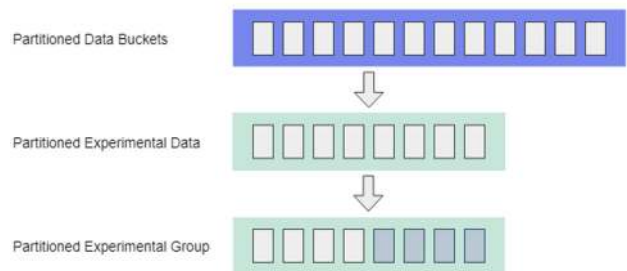
**Fig7.** The Partitioned Data Bucket System of Douyin.

The platform divides users into several small batch buckets according to a certain randomness (such as a group with the same user’s ID tail number). When the platform launches new content, it will first use one of the small batch buckets to test the content recommendation effect. The four-basic metrics are the number of views, likes, replays, shares and completion rates, each of them have different weights. When the comprehensive score of these evaluation indicators reaches a specified value, it means that this short video has the potential to be a popular video. Then this video overflows into a medium batch bucket to do the test again. The content of different size of the buckets will get different level of views. The recommended content is filtered by layers to ensure the quality. The top-performing video will be continuously overflowed all the way up to the large batch bucket or even the whole platform.

The basis of these explosive content is the emotional resonance that is sought in the expanding scope of testing. This can be an effective way to evaluate content. Due to the huge amount of content on the Douyin platform, multi-layer screening is a very reasonable method to guarantee the quality of the content. After all, only if the content is good, can Douyin retain users.

Moreover, according to Cao Huanhuan’s report [10], Douyin also uses a combination of partitioned data buckets and A / B Test to test whether the newly launched recommendation strategy is effective.

### Principle of A/B Test System



**Fig8.** Principle of A/B Test System [10].

This is actually similar to the test and recommendation of content. First, all users are divided in to several small batch buckets, and then one of the small batch bucket is extracted and 50% of it is labeled as the experimental group. A / B Test uses quantitative methods to verify the feasibility and effectiveness of the strategy. For example, start an experiment with 10% data, of which 5% is the experimental group with a new strategy and another 5% is the baseline with the old strategy. In the same time interval, under the same test environment, and with the same user group (no obvious attribute difference), compare the relevant data of the two groups. In that way, they can test the performance of the new strategy. It can be very important for a product to optimization.

### 3.1.5 “Everyone Can Be Famous”: The Decentralization

Douyin dilutes the significance of social connection between acquaintances, friends, and families in the real world through decentralization. On the contrary, it makes all users of the entire platform can be easily linked to each other that forms a whole connection system all together. The algorithm is the engine of what users of Douyin see, not their circle of friends. Users are not bound by the narrow circle of their actual life. Instead, users can focus on anything they might be interested in.

At the same time, the high degree of decentralization of Douyin satisfies the desire that “everyone wants to be famous”. Decentralization fulfills Marshall McLuhan’s prediction that “Centers Everywhere, margins Nowhere” [15]. The development of the Internet itself is an irreversible “decentralization”. In the process, people are transferring the power of “Selecting Content” from traditional manual “Gate Keeper” to AI and algorithms, but it can also be argued that, to each user themselves. The public is paying more and more attention to their right of expression, and ordinary people are beginning to speak out, showing their own life.

Douyin’s algorithm recommendation mechanism is based on the principle of decentralization. For ordinary users, it is a good opportunity to stand out. Unlike some “centralized” social media, they encourage fresh users to produce content instead of focusing the main traffic on celebrities and hotspots [16]. The content is the most important factor for the algorithm to decide whether to distribute it, rather than creator’s identity, use-age or social status. Therefore, everyone has the possibility to become popular overnight.

### 3.2 The Algorithm is Making Traps for Users: The Recommendation Algorithm Pushes Users Addicted to Douyin

#### 3.2.1 Algorithm Finds Your Unknown Part: Collaborative Filtering Algorithm

Joseph Luft and Harrington Ingram, two famous American social psychologists, came up with “the Johari Window” theory [17]. Their theory believes that people's cognition consists of four areas. Among them, the unknown area refers to the part that not known to self or others, which is difficult to be observed. However, Douyin’s collaborative filtering algorithm may inadvertently help users discover their latent interests, which can also be a trap for them to spend more time on Douyin.

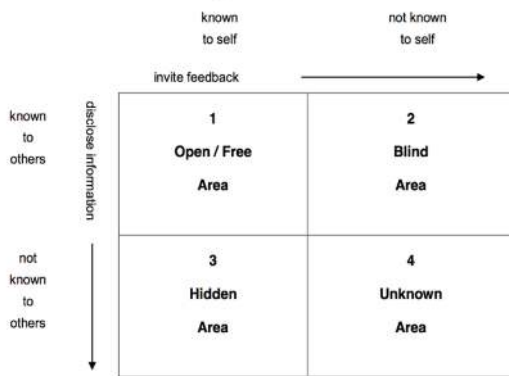


Fig9. The Johari Window [17].

Collaborative filtering algorithm mainly includes user-based filtering and item-based filtering. Their common principle is to identify similarities from data mining (user portraits and content labels), and expand more possibilities based on the similarity of some features.

As for the item-based filtering, it based on similarities and correlation between contents. ByteDance invented their own patent to protect their rights on how to compute the correlation between labels and how to exploit users potentially interests [8]. First, the model will set a threshold value of correlation between two different labels according to the shortest distance between them. Then they collect each user’s all known interest labels. It can be a set like the following hierarchical union set of the global hierarchical label tree.

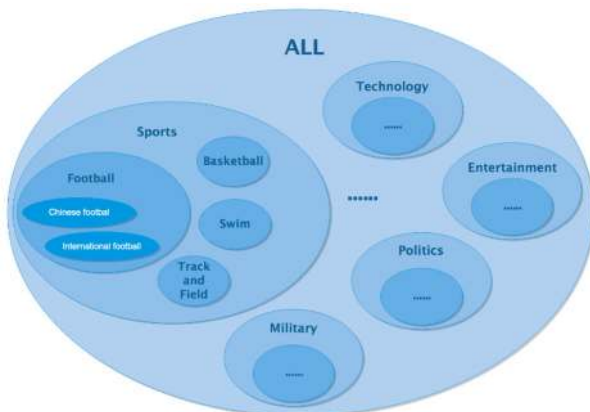


Fig10. The Hierarchical Union Set.

$$\text{rel}(t1, t2) = 2 * N(t1, t2) / (N(t1) + N(t2)) \quad (1)$$

“In this formula,  $N(t1, t2)$  means the number of times that both the interest label  $t1$  and  $t2$  appear in a user’s interest union set. And  $N(t1)$  is the users amount that only label  $t1$  is in the interest union set. Similarly,  $N(t2)$  means the users amount that only label  $t2$  is in the interest union set.” [8] The equation shows that the more users like  $t1$  and  $t2$  at the same time, and the fewer users only like  $t1$  or  $t2$ , the higher the correlation between  $t1$  and  $t2$ . If the correlation is less than the threshold value, it means that contents of these two labels are considered completely irrelevant and would not be recommended.

After having the correlation between different labels, the model also defines a priority score for user  $u$  to explore the interest tags  $t$ :

$$\text{score}(u, t) = w1 * \text{hot}(t) + w2 * \text{rel}(t, Tu) - w3 * \text{freq}(t) \quad (2)$$

“In this formula, not only the correlation between tags ( $w2 * \text{rel}(t, Tu)$ ) is considered, the equation also adds a certain percentage of the popularity of the tag ( $w1 * \text{hot}(t)$ ), and subtract the degree of label  $t$  has been explored ( $w3 * \text{freq}(t)$ ).”[8] It is aimed to provide fresher field of content to the user and explore their interests on a larger scale. So, the recommendation algorithm will not only recommend to user the content and topic that they are exactly interested in or concerned about, but also something fresh and unexpected. In that case, Douyin will not easily lose the user who is querulous about the singularity of contents.

The principle of user-based collaborative filtering is similar. It's just that it will be more complicated in calculation, because the model has more dimensions of data to describe a user than content. To make it easier to understand, according to Paul Resnick and his group, the user-based filtering means “helping people make choices based on the opinions of other people [18]”. People with certain similar characteristics may somehow share similar taste, so that the algorithm can find users with some similar characteristics, and cross-recommends their respective areas of interest to expand the user's area of interest as much as possible.

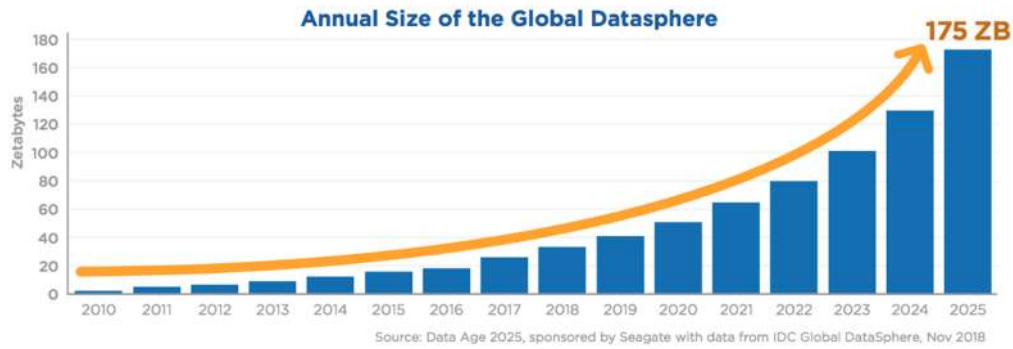
Since recommendation algorithms, especially collaborative filtering algorithms, have been involved in the media. The academic community has been concerned that “they increase ideological segregation” [19].

However, according to the above algorithm logic of Douyin, it can be concluded that the collaborative filtering algorithm is not filtering out information for the user, but actually expanding the range of content that the user can access. Admittedly, there’s no denying that the problem of “Filter Bubbles” and “Information Cocoons” exist, but the author considers that these phenomena are not actually caused by recommended algorithms.

In 2016, Oxford researcher Seth Flaxman and his team addressed the issue by “examining web browsing histories for 50,000 US-located users who regularly read online news. They found that, somewhat counterintuitively, social networks and search engines are associated with an increase in an individual’s exposure to material from his or her less preferred side of the political spectrum. [19]” This study shows that people's actual media consumption is more diverse than they afraid. In fact, the dimensions of

the input features that algorithm training relies on are much larger than people think. And the flexibility of the model is also far beyond our imagination. Collaborative

filtering is not as simple as finding common points among people, but is constantly superimposing more potential interest areas by calculating from local similarity.



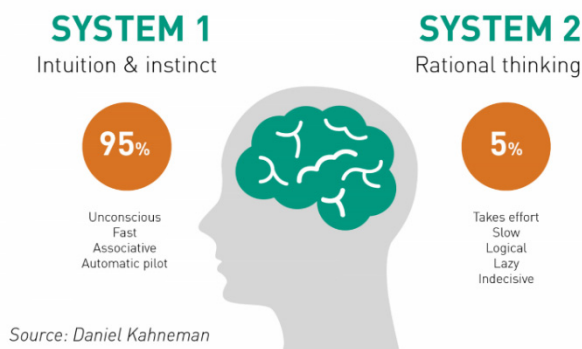
**Fig11.** Annual Size of the Global Datasphere [20].

Besides, according to IDC’s report, the expansion in the size of the Global Datasphere is explosive and will be a never-ending [20]. The fact is that people cannot face such a large amount of information and rely entirely on humans to process them. The use of algorithms may be the only way to keep the information distribution speed up to the information production speed.

What needs to be more careful is that among the overloaded information may lead to FOMO—fear of missing out. “FOMO is considered a form of social anxiety—a compulsive concern that one might miss an opportunity for social interaction, a novel experience, or some other satisfying event, often aroused by posts seen on social media sites.[21]” Users are satisfied and adapted with the recommended content of Douyin, and may always be curious about whether the next video is more attractive. They are afraid to miss the unknown part that it turns out to be endless browsing of the recommendations feed and eventually become addictive to it.

### 3.2.2 Low-cost Interaction Design and Decision-making Mechanism

The Nobel laureate Daniel Kahneman, wrote a book titled “Thinking, Fast and Slow”.[22] In his book, he believes that there are two systems in the brain. “System 1” is unconscious fast thinking, and “System 2” is consciously slow thinking, which will be activated only when “System 1” cannot solve the problem. “System 2” requires concentration for a period of time and consumes more energy of the human body. It explains the inertia of the human brain.



**Fig12.** System 1 and System2 in our Brain [22].

Communication scholar Wilbur Schramm came up with a mathematical formula trying to explain how this inertia affects people's choice of media [23]:

possible rewards ÷ effort required = probability of choice (3)

It means that the greater the probability of meeting the need, the lower the degree of effort, and the higher the probability of choosing a certain channel to receive information. Every time a user makes a choice, they have to think about it. The process is painful[24] for them. The recommendation algorithms of other software often give users more choices. They recommend you things you might like, but these contents will play the role of an additional option. However, what Douyin seeks is to put the user in the state of extreme passive acceptance, making the recommendation as the only option.

The “immersive experience” interactive design of Douyin, where users just need to continuously sliding up, and the setting of full-screen auto play are all trying to avoid giving users more options to bother them. They are not making choices, but just judgments. After coming to the recommendation page, Douyin automatically play the recommended video. If the user doesn’t like the current one, he/she can just swipe up and switch to another one, which saves the cost of exit. When the user browses Douyin recommendation feed, the user only needs to keep the brain in System 1, that consumes less energy and works unintentionally. The using cost of Douyin is very low and the interaction is simple. For the above reasons, the probability of constantly using Douyin highly increase.

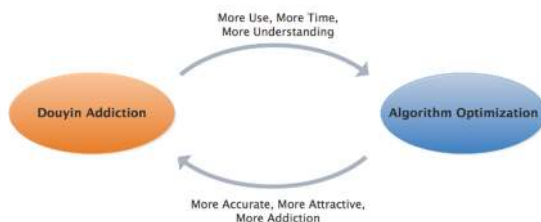
## 4 Further Discussion: The Outlet of Closed-Loop Relationship Between Douyin Addiction and Algorithm Optimization

Through the analysis of the previous section, it is indicated that the recommendation algorithm principles, more or less, positively effects the user's addiction to Douyin. However, it's not just the algorithm that is impacting the user. The user is also impacting algorithm because people are always the biggest variable in the recommendation model.



As the 2019 internet trend report goes, “The data-driven world will be always on, always tracking, always monitoring, always listening and always watching, because it will be always learning”[2]. At the same time, it also shows that the intelligence, accuracy, and other performances of the recommendation algorithm still have huge potential. In other words, the more frequent and longer the user uses Douyin, the more accurate the algorithm will be.

The influence between the algorithm and the user is bilateral. On the one hand, the algorithm decides what the user can see. On the other hand, the algorithm also largely depends on the users’ behavior to train and optimize the model. The recommendation algorithm makes users more and more addicted to Douyin. Then the more users addicted to it, the better algorithm knows what and how to recommend. If things continue in this way, the addiction may be aggravated and it can be more difficult for the users to control themselves. It suggests that there is a closed-loop relationship between Douyin addiction and algorithm optimization. This direct interaction is reaping the market and users’ time in a spiral upward tendency, which deserves serious attention. Today, under the background of the recommendation algorithm still feeds a certain proportion of mismatching-contents. The phenomenon of Douyin Mania is already generally existing. What if the model of the recommendation algorithm is far more accurate than today, that almost every short video users view can be attractive, how much time are people going to spend on it?



**Fig13.** Closed-loop relationship

The original intention of the recommendation algorithm is to improve the efficiency of information distribution, that is, to save users time from selecting information. However, with the continuous improvement of it, people save time through accurate recommendation methods, but actually spending more time watching passively received contents. It seems that the recommendation algorithm conversely causes people to be more lazy and unwilling to actively explore the world. It is unreliable to completely rely on users self-control to solve this problem. In order to break the deadlock and find an outlet, Douyin’s developers and users could work on the following areas.

For users, they need to face up to the power of the algorithm and fully understand its operation mechanism. Users should not oversimplify the algorithm. The algorithm does not just monotonously recommend what they like to users, as many people think. The input of the model has a very high dimension and can expand its area of interest based on different combinations. Besides, users should also be rational and alert to algorithms. The results of machine learning do not mean that it really

“understands” people’s mind. They use powerful computing capability to find the law in multiple trainings and output content based on it. Users need to continuously improve their new media literacy and critical thinking ability so that they will not completely control by algorithms.

In fact, Douyin has revealed the algorithm logic of its recommendation system to the public, and even released official reports to guide creators on how to run a Douyin account. They want the creators know how good content works to stimulate them to create better works. And help users to train their own recommendation persona. For example, when using Douyin, users can consciously evaluate the quality of content by feedback on the four basic metrics of short video. This timely and authentic feedback may not alleviate the addiction itself, but it helps users to receive higher quality content during the time of using Douyin.

For Douyin’s developers, perhaps in the future algorithm optimization, their focus should shift from how to increase user stickiness to how to expand more users. Meanwhile, they should pay more attention to how to incorporate more environmental variables into the algorithm. For instance, during big chunks of rest time at noon and night, maybe they can gradually decrease the accuracy of their recommendations to give users an “excuse” to leave. Besides, on Douyin’s anti-addiction system, more stringent reminders can be taken for users who frequently exceed the recommended duration.

In Douyin’s product design team, they should introduce more interdisciplinary talents, who are familiar with both technology and media communication. If there is no longer the directly “gatekeeper” of the mass content, then maybe Douyin can increase the “gatekeeper” of their recommendation system. This can also enhance the efficiency of guaranteeing the appropriateness of the content.

## 5 Conclusion

In this paper, the author analyzes principles used in Douyin recommendation algorithm. Trying to Combine the two perspectives of algorithm technology and communication to explain how the recommendation algorithm effects the widely existing phenomenon of Douyin Mania. It is undeniable that ByteDance has top quality algorithms. They even have their own powerful AI Lab, which dedicated to promoting the development of algorithms in the field of information dissemination. However, if Douyin wants to achieve sustainable development, then it cannot be an application that generally causes people to indulge in it.

On the balance between technological optimization and value orientation, Douyin still has a long way to go.

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