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Master's thesis of Engineering

Video Diffusion in User-Generated Content Website – An empirical analysis of Bilibili

사용자 생성 콘텐츠 웹 사이트의 동영상 확산-Bilibili 기반으로 실증 분석

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Abstract

Video Diffusion in User-Generated Content Website – An empirical analysis of Bilibili

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User-generated content emphasis user' value, and based on the development of Web 2.0, it takes an important position whatever in information diffusion and market management part. Therefore, it is necessary to identify which factors would give influence to information diffusion in UGC.

This thesis based on a video UGC website – Bilibili, try to find influential factors during the video diffusion process. Different from previous research which mainly focuses on the social network, this thesis mainly used video characteristic data to explore effective factors to video diffusion. First, after the draw the number of views increase trend within one month, views trend in Bilibili indicates that video diffusion showed a different diffusion curve.

Then through careful analysis of each different diffusion periods, this thesis found the influential factors are different during different diffusion periods. The analysis result showed that higher interactive among users and contents could attract more people to watch the video which improves video diffusion rate, and also showed the impacts of general comment below the video and sharing activity, video quality to video diffusion.

Based on this thesis, some marginal implications also introduced such as it could provide some basis for web designers, people who use UGC as a marketing tool and users who want to be a UGC content producer.

Keywords: User-generated content, video sharing website, video diffusion, Bilibili, new media, Danmaku comment, social network.

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1. Introduction

Since the establishment of Facebook in 2008, the number of users has increased by nearly 24 times, market value has increased by nearly 71 times, YouTube monthly active users are 1.5 billion and market value reaches 800 million US dollars. Instagram, Snapchat and Wikipedia users are more than a million people [1]. With the emergence of Web 2.0, it breaks boundaries between consumer and producer, could describe it as “produsers” (Dr. Axel Bruns 2008). These types of websites, also known as User-Generated Content (UGC) websites which quickly gained a lot of popularity and value in a short period.

The unique feature of these websites is that users can easily create their accounts, then they can post contents create by themselves to the website and share it with other viewers. These kinds of features attract a large number of users, whether they are professional producers or amateurs. These sites also support a variety of social activities, such as user can choose to be friends or subscribe to other users, comment on content, collect favorite contents, or even share the contents to other websites. These user-centric concept websites which emphasizing users’ value in contrast to traditional media. Ultimately, UGC websites have changed the way consumers engage in popular culture and have had a huge impact on digital products such as media and entertainment (Andrew N. Smith 2012).

Compared with traditional media, one of the characteristics of UGC is that few users and videos have achieved great success. While in most cases, uploaders and videos are rarely viewed, only a few people could get a large number of views (Meeyong Cha et.al, 2007, 2009, Flavio Figueiredo, 2014), researchers also motivated by this phenomenon which because there is a huge difference exist on the same website. YouTube, as the biggest video sharing website, various kinds of literatures had already studied video diffusion and influential factors during the diffusion process. Previous researches most focused on the influence of uploader's social network property (Anjana Suarrla et al. 2012, Mirjam Wattenhofer et al. 2012, Yuping Liu-Thompkins et al. 2012, Hema 2010), some researchers had explored the correlations between video diffusion and video attributes like comment, rating, and favorite (Gloria Chatzopoulou et. al 2010). But no more detailed research like how and when the factors give influence to video diffusion. Therefore, the goal of this thesis was tried to analyze what factors, in case of video attribute, drive users to watch the video during the diffusion process.

In addition to the prior research which focused on YouTube, this thesis chose a Chinese video sharing website – Bilibili as research object. Similar to YouTube, users can also create their accounts and upload videos in Bilibili. Besides, social activities such as comments and favorite, etc. can also be used. Reasons that chose Bilibili as research object was that first compared to YouTube, Bilibili is smaller but more active video sharing website compare with YouTube (Adele Lu Jia 2018). Second reason was that, there is a special comment system – danmaku comment which is a timeline-synchronized user comment system. Users use this danmaku comment system could create a co-viewing experience with viewers. Viewers also could obtain extra information, get entertainments and have belongings to a group, feel strong social connections when they watch videos through this system (Yue Chen et.al, 2015, 2017). Some viewers even prefer to watch danmaku comments in the video compared to watching the video content (Yue Chen et al. 2015). Therefore, this thesis collected a large number of video attribute data from Bilibili to analyze what factors in Bilibili will affect video views and explain why this happened.

The contributions of this research are mainly concentrated on the following aspects: First, for literature, previous researches lack the specific analysis of video attribute to video diffusion, this thesis could complement this part. On the other hand, through quantify and analysis the effect of user activity like comment activity, sharing activity etc., we could understand what kind of factors or action would influence audience's choice when they choose to watch a video, and then the corresponding programs based on the analysis result could be adopt so that related people could promote favorable actions and avoid adverse actions.

This article is organized as follows. In section 2, this article showed the literature reviews and based on literature gives the hypothesis of this thesis. Section 3 introduced data and methodology used in this article. Section 4 listed the analysis results based on section 3. And the last part of section 5 presented the implications and limitations of this thesis.

2. Literature review

2.1 UGC and Bilibili.

Statistics proved the huge scale of UGC websites both in the amount of user and revenue. Researchers began to think about the impact on society both from information diffusion and economics and management.

First, in terms of information dissemination, the emergence of UGC has caused tremendous changes and evolutions in traditional media participation and communication. Research on information dissemination in UGC has been started early. Some studies indicate that UGC is a good tool for improving the interaction and participation of citizens in traditional media, and how UGC integration fits into existing news principles (David Domingo 2008, Steve Paulussen et al 2007, Deborah Soun Chung 2007). Anna Maria Jonsson (2010) examines whether UGC has achieved the problem of granting citizen democracy by comparing user engagement and content types. It was found that compared with before, through the development of UGC, some media have shown great creativity through the development of interactive with the public and other characteristics of UGC, so that the opportunities for citizen participation are greater, people can interact and can create their content in the newspaper.

In terms of economy and management, UGC has injected new vitality and marketing development methods into traditional economic management methods. Use UGC to enhance brand management by communicating with customers, provide better service so that it could achieve better value. Burmann (2009) defined this phenomenon as a User-generated brand (UGB) which means: "*the strategic and operative management of brand-related user-generated content (UGC) to achieve brand goals*" (Burmann & Arnhold, 2009, p. 66). At the same time, the potential benefits of UGB appeared in aspects of cost-effectiveness, tracking the ability of consumers, and immediate feedback on brands (Burmann 2010).

UGC websites also have a significant impact on product sales in addition to brand management (Angella J Kim 2016, Qiang Yue 2011, Tanya (Ya) Tang et al. 2014). Tanya Tang (2014) found that though classify UGC with positive and negative and found that it has an impact on product sales. Vasant Dhar (2009) verified whether comments from websites affected the sales of music by tracking and investigating data from blogs and social network websites. It was found that in addition to traditional factors, the sales volume of music is related to the number of blogs and comments related to the album. Also, Qiang Yue (2011) tested the impact of UGC on hotel online reservations through user comments, which is an e-word-of-mouth effect. And found that the value of traveler reviews has had a major impact on online sales of hotel rooms.

2.2 Video diffusion in UGC

This section through various aspects shows an overview of previous literature related to video diffusion in UGC.

Until now, UGC has a variety of expressions, and video has become one of the most important parts. YouTube, as the largest video sharing website, has been the main target of the researcher. Some researchers have conducted a holistic analysis of YouTube. Meeyong Cha (2007, 2009) analyzed and compared data in YouTube and Daum to observe users' behavior and then got different video evolution conditions in YouTube and Daum so that it could give some suggestions to website designers. Xu Cheng (2007, 2013) analyzed YouTube videos, found that regardless video's length and access mode, lifespan, rating, and comments are different with traditional video websites, and there was a strong correlation between videos, video connections showed small world network property. Flavio Figueiredo (2014) helped people better understand the dynamic development of video on YouTube. he differently grouped videos and extract the popularity trend from different groups.

A large number of scholars explore the factors that influence video diffusion in YouTube from various aspects, the most common research is analysis the influence of author's social network property to video diffusion (Anjana Suarrla et al. 2012, Mirjam Wattenhofer et al. 2012, Yuping Liu-Thompkins et al. 2012, Hema 2010), influence of external links (Suman Deb Roy et al. 2013, Haitao Li et al. 2013, Honglin Yu et al. 2014, Henrique Pinto et al. 2013), influence of video quality and comments (Zechen Wu & Eisuke

Ito 2014, Rodrigo Laiola et al. 2012, Vivian Motti & Cesar 2009, Yikun Xian et al. 2015, Mike Thelwall & Rardeep Sud 2011, Renan G. Cattelan et al. 2008, Sergiu Chelaru et al. 2014).

Among them, social networks most common property to study its influence on video diffusion. Anjana Suarrla et al. (2012) examined video uploader's position in a total network on YouTube when its video in the diffusion process. Mirjam Wattenhofer et al. (2012) compared YouTube with the traditional online social platform and found that its network nature is more like Twitter, a content-driven platform. Yuping Liu-Thompkins et al. (2012) found that from the nature of the network, the ideal network to promote video diffusion is more followers and fewer friends, which means more subscribers and fewer connections. And there was a curve relationship between subscriber network connectivity and diffusion rate, that is, medium connectivity has the highest video diffusion rate.

In addition to the impact of social network on video proliferation, Hema (2010) taken author’s social network properties as main research objective and connected with video properties to analysis the comprehensive factors which affecting video diffusion. It was concluded that the size and structure of the author’s social network has a significant impact on the spread of the uploaded video, and the factors that affect video spread changed as the upload time changes. Yuping Liu-Thompkins et al. (2012) also found that video production quality has no effect on diffusion, but user ratings have an impact on video diffusion. In terms of the nature of the uploader, the author's past success will also affect the spread of the current video, and the number of uploaded videos will also have a positive impact on video proliferation.

For other influential factors related to video diffusion, Gloria Chatzopoulou et. al (2010) found that the number of video views is correlated with comments number, ratings, and favorite number.

The commenting system as an expression of uses' sentiment, is one feature of UGC. YouTube also allows viewers to comment on videos so that viewers could express their feelings or opinions about the video when they watching. Therefore, some researchers have also studied the correlation between the number of comments and the number of views (Zechen Wu & Eisuke Ito 2014, Rodrigo Laiola et al. 2012, Vivian Motti & Cesar 2009, Yikun Xian et al. 2015, Sergiu Chelaru et al. 2014).

Because YouTube allows users to share videos with other online social websites, some researchers had also explored the relationship between sharing capabilities and video viewing. Most of these theses predicted the future video views by sharing behavior (Suman Deb Roy et al. 2013, Haitao Li et al. 2013, Honglin Yu et al. 2014, Henrique Pinto et al. 2013).

While for video quality, it is a difficult attribute to judge because everyone's preferences are different and it is difficult to meet everyone's preferences. However, some researchers also took a rating system as video quality to analysis its influence on video diffusion (Yuping Liu-Thompkins et al. 2012).

2.3 Hypotheses

Based on previous literature reviews of video diffusion, this chapter sets the hypotheses related to video attributes of this thesis.

First, for social network property, Hema (2012) proved that the size of the author's social network gave a significant effect on video diffusion. More detailly, subscriber network is an important factor which gives influence to video diffusion, more subscribers better diffusion rate (Anjana Susarla 2012, Yuping Liu-Thompkins et al. 2012).

While different from previous researches, instead of subscriber network data, subscriber in this thesis is number of followers. Apart from this, a standard for determining the size of subscribers would be compared to the average follower number. Therefore, if the follower number less than average follower number would mean video uploader has fewer followers, while if the follower number bigger than the average number it would mean video uploader has more followers.

Bottleneck phenomenon shows problems to information diffusion which also suitable on internet, only a small group of people could search the video (Hendricks and Sorenson. 2009) except uploader with a huge number of followers. Similar condition also on Bilibili, if uploader uploads a video in Bilibili, there would be a hint in homepage or system would recommend a video to followers, so followers could see the video easily thus easy to diffuse.

For comment on a video, Bilibili has two types of comment, one is Danmaku comment which is introduced above, second is general comment which most video websites adopt. General comment as an expression of emotion, in YouTube, most comments were positive and this kind of positive comment do not attract reply (Mike Thelwall & Pardeep Sud, 2011). Thus, social activities in the general comment area are not very active.

Compared with the general comment system, users preferred the real-time comment system (Rodrigo Laiola Guimaraes et.al, 2012). So, for the timeline-synchronized danmaku comment system, users were more willing to post danmaku comment compare with general comment (QunfangWu et.al, 2018). Table 1 is statistics result of general comment and damaku comment, an average number is almost 1.5 times difference in these two kinds of the comment system, also prove that viewers prefer to send danmaku comment.

Table 1: statistics of general comment and danmaku comment.

Variable	Obs	Mean	Std. Dev	Min	Max
Danmaku	129,282	44.08	349.98	0	11,022
Comment	129,282	28.37	155.21	0	5195

Number of Obs: 129,282.

People watch the video for entertainment, and danmaku comment gives co-viewing experience, enhance viewers entertainment (Yue Chen et al. 2015, 2017) and have a strong interactive among viewers (Lili Liu et.al, 2016). Paul Haridakis (2009) already proved that social interactive and co-viewing motivation significantly affected to views.

For sharing activity, Cheng et al (2010) demonstrated that in the early stage of video diffusion, views increased through sharing activity. Honglin Yu (2014) analyzed the relationship between several video views on YouTube and the video links on Twitter, found that sharing activity gave more information to video views. Haitao LI (2013) found that in late-stage video views show less correlation with external links. Bilibili also allows users to share video link to another website.

Video quality also is an important factor to video diffusion, in YouTube, there is a rating system to quantify video quality (Yuping Liu-Thompkins et al. 2012). However, do not like YouTube, instead of rating system there is a coin donation system in Bilibili. It means that if you are satisfied with the video you watched you can give coins to the video, and if a video received a lot of coins, this video would be recommended by Bilibili. And video quality does not affect video views (Yuping Liu-Thompkins, 2013), the coin is an attribute that is easy to ignore.

Based on findings from previous research and variable attributes on Bilibili, hypothesis of each variable would be as follows:

H1: General comments will significantly increase video views.

H2: Danmaku comments will significantly increase video views.

H3: Sharing activity will significantly increase video views.

H4: Coins will significantly increase video views.

3 Data and Methodology.

This section includes two parts, 3.1 introduced and explain the data used in this thesis. 3.2 presented the methodology used in this thesis.

3.1 Data

To generate data of this thesis, video data was collected by 5,000 videos uploaded by 21/08/2018 in Bilibili and monitored these videos for 30 days so it ends with 19/09/2018, and the interval to observe changes in each data is 24-hours. During the data crawled process, some videos were deleted because of copyright or other reason. But generally, the crawler process is smooth, in the end, a panel data was formed by 4366 videos in one month.

Here two kinds of data were crawled, one is video attribute data which included some basic information about videos in bilibili, another kind of data is related to video author also named uploader which means users in bilibili who will upload videos.

Video attribute data:

Like YouTube, almost all videos in Bilibili are public, in general users in Bilibili usually upload thousands of videos one day and other users in Bilibili can get a list of the latest uploaded videos by the latest uploaded video category. Also, bilibili provides a few methods for a user to interact with other viewers and uploader. Like other video sharing websites, when users watch a video they can send short danmaku comment or long general comment to express their opinion and their felling, or they can donate coins if they think this video quality is good, and if they are interested in the video they can collect the video through click favorite button so that the video will collect in their account and convenient to review, apart from this, if users want to share or recommend this video to other people, bilibili also has sharing function which provide video links for user to share.

Uploader data:

Uploader means people who produce videos in Bilibili, the video could take or edit by themselves. Uploader data mainly include two kinds of data, one is the number of followers/subscribers, the other one is the number of submissions, this number counts how many videos uploaded by the uploader from the past.

Table 2: Description of each data variable.

Variable	Description
Views ($V_{i,t}$)	The total number of views that video *i* have received in time *t* since its launch.
Danmaku ($Dmk_{i,t}$)	The total number of danmaku comments that video *i* have received in time *t* since its launch.
Coins ($C_{i,t}$)	The total number of coins that video *i* have received in time *t* since its launch.
Comment ($Cmt_{i,t}$)	The total number of general long comments that video *i* have received in time *t* since its launch.
Sharing ($S_{i,t}$)	The total number of links that video *i* have shared to another website in time *t* since its launch.
Follower ($Fol_{i,t}$)	The total number of followers that video *i* 's uploader has received in time *t* since it uploads a video.
Submission (Sub_i)	Total number of videos that video *i* 's uploader has uploaded.

Apart from total data of each variable collected, because we need to observe effect features during the diffusion process, a dynamic model for video diffusion was defined in this thesis because it can help us better to understand and find effective factors during the video growth process. Table 3 showed the description and how it calculated by.

Table 3: Description of daily variables.

Variable	Description
Daily Views ($v_{i,t}$)	Number of new views that video *i* receives during time period *t*. $v_{i,t} = V_{i,t} – V_{i,t-1}$
Daily Danmaku ($ddmk_{i,t}$)	Number of new danmaku comment that video *i* receives during time period *t*. $ddmk_{i,t} = Dmk_{i,t} – Dmk_{i,t-1}$
Daily Coins ($dc_{i,t}$)	Number of new coinss that video *i* receives during time period *t*. $dc_{i,t} = C_{i,t} – C_{i,t-1}$
Daily Comment ($dcmt_{i,t}$)	Number of new views that video *i* receives during time period *t*. $dcmt_{i,t} = Cmt_{i,t} -Cmt_{i,t-1}$
Daily Sharing ($ds_{i,t}$)	Number of new views that video *i* receives during time period *t*. $ds_{i,t} = S_{i,t} – S_{i,t-1}$

3.2 Methodology.

Previous researchers use the number of views as a witness and basis for video diffusion, this thesis also uses views as the standard for video diffusion. More views, the more people watching this video, indicating that video spreads widely.

Gloria Chatzopoulou et. al (2010) found that video views were correlated with other video features like video comments, sharing activity and ratings. So, this thesis used video characteristics to find which factor would give influence to a video view. Apart from this, video i's view in *t* was depending on the past views the video received so lagged views also analyzed here.

Uploader in this thesis only means the number of followers and defined as a dummy variable to observe some followers' influence on video diffusion. The average number of followers was 7655, so if follower number less than the average number, define it to 0, if follower number bigger than 7655, define it to 1.

Views modeled as follows:

$$y_{i,t} = \ln (v_{i,t}).$$

$$y_{i,t} = \sum_{n=1}^{n} \alpha y_{i,t-n} + D_1 X_{i,t-1} + D_0 X_{i,t-1} + \varepsilon_i.$$

Here $v_{i,t}$ means video i's daily views in t time, $y_{i,t-n}$ means lagged daily views, $X_{i,t-1}$ was a daily data set which includes daily danmaku comments, daily general comments, daily coins, and daily sharing data. ε_i was a mean-zero error term.

Control variable:

Video diffusion trend in Bilibili.

To better understand the diffusion trend in Bilibili, Figure 1 shows the growth trend of the total video views in one month and daily views changed condition in this month.

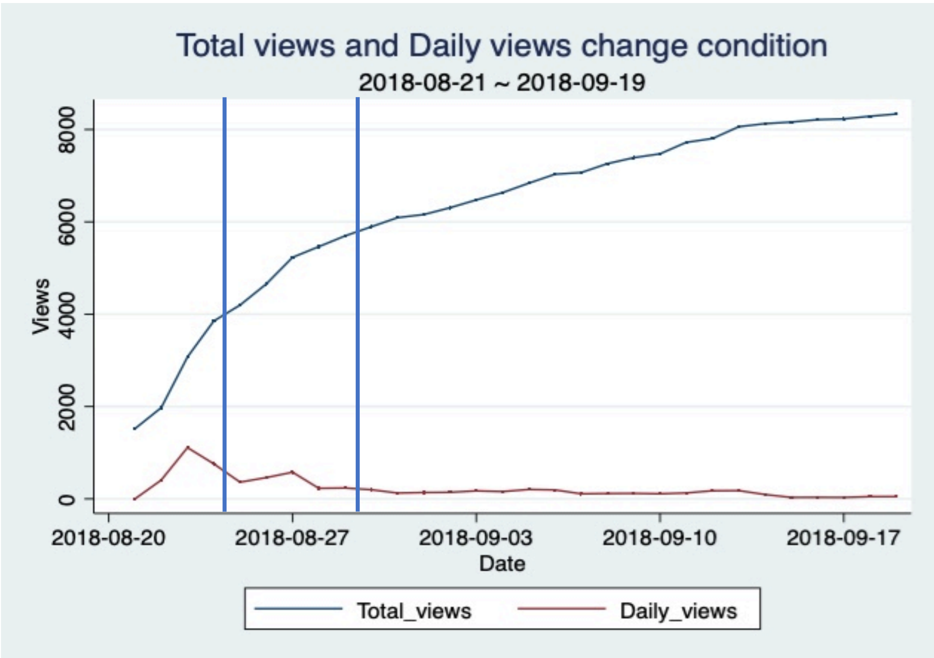

Figure 1: Total views in one month and daily views changed condition.

In Figure 1 the blue line is the total average number of views within one-month, the red line is daily views changed condition. According to the red line shown in Figure 1, there were two peak-time for Bilibili video increase trend.

The first peak time was 23 August, thus the initial period was around 21 August and 23 August, in this period daily views showed an increasing trend, total views thus increase with a quick speed.

And second peak-time was 28 August, so the decrease period was from 24 August end with 28 August. In this period, daily views number was decreased, as a result, a total number of views increased with a slow speed.

The last period was a steady period which from 29 August ends with 19 September, daily views kept at a steady level and total views increased with a steady speed.

4. Analysis results and Conclusion.

This chapter is organized as follows. Section 4.1 showed a test result based on the above research model. Section 4.2 presented conclusion through the different period and different characteristics help us to better understand each variable's effect.

4.1 Analysis result.

Based on the research model set on the above chapter and data used in this research, the analysis result shown in table 4. Because data collected is panel data, so first Hausman test was used to test which model is much more suitable to data in this thesis. The result of the Hausman test proves that the fixed effect model is suitable for the data.

Table 4: Analyze result

Dependent variable: Log daily views	Initial period		Decrease period		Steady period.	
Follower	Less Follower	More Follower	Less Follower	More Follower	Less Follower	More Follower
Logged Daily variable (t-1)	0.268***	0.113***	-0.162***	-0.405***	0.239***	0.073***
Logged Daily variable (t-2))					0.131***	0.102***
Logged Daily variable (t-3)					0.016	0.069***
Logged Daily variable (t-4)					-0.002	-0.010
Lagged daily comment (t-1)	-0.286***	-0.003	0.101*	0.117	0.304***	0.456***
Lagged daily danmaku comment (t-1)	-0.098	-0.190	0.079	0.383***	0.305***	0.413***
Lagged daily sharing (t-1)	0.050	-0.228	0.145	0.053	0.270***	0.060
Lagged daily coins (t-1)	-0.007	0.337**	0.049	0.097	0.277***	0.224***

* P < 0.05

** P < 0.01

*** P < 0.001

4.2 Conclusion

4.2.1 Conclusion of daily views.

Because there is a short time interval in increase period and decrease period, so only one day lagged daily views used in these two periods. And first we explained analysis result with video attributes separately which were similar to the hypotheses set in section 2.

First, in the first initial period which was daily views increased every day and total views increase with a quick speed. Through the analysis result, we can observe that no matter how many followers, lagged daily views show a significant and positive effect on video view.

Second for the decreased period, daily views decreased and total views increase at a low speed. In this stage, whatever how many followers lagged daily views do not increase video views.

In the last period, the number of daily views remained at a relatively low and steady state, and the total number of views also increased at a very low speed. At this stage, we can see that the number of the first two lagged daily views (t-1, t-2) have a positive and effective impact on the number of views, which means that any specific day is significant effect by the views from previous days. While there is a slight difference between groups with a large number of followers and groups with a small number of followers for people, for video uploader with fewer followers the effective lagged daily views are last two days but for video uploader with more followers, the effective lagged daily views are last three days which prove that video uploader with more followers the lagged views' influence keep quite long compare with uploader with few followers.

4.2.2 Conclusion of video attributes.

Except daily variables, video attributes also gave influence to video views, and the result of hypotheses showed in next tables.

Table 5: Result of hypothesis

Results	Initial period		Decrease period		Steady period	
Follower	Less Follower	More Follower	Less Follower	More Follower	Less Follower	More Follower
General Comment	Reject	Reject	Support	Reject	Support	Support
Danmaku Comment	reject	Reject	Reject	Support	Support	Support
Sharing Activity	Reject	Reject	Reject	Reject	Support	Reject
Coins	Reject	Support	Reject	Reject	Support	Support

For general comment, in the initial period H1 was rejected which means in this period general comment do not significant effect video views whether follower is less or more. It may happen because it is still short period after video upload, viewers not willing to post general comment in this period.

In decrease period, general comment does not increase video views when uploader have more follower, this may be because the amount of general comment accumulated is still enough to make user active to watch video to post comments. While after a long-time accumulation, number of general comment increase, other viewers also more willing express themselves through this way that why H1 supported in steady stage.

For danmaku comment, in the initial period results showed that whatever uploader have less or more follower, danmaku comment do not affect video views, reasons for this phenomenon may similar with general comment, it still a short time since video upload, so fewer viewers post danmaku comment, and when people watch danmaku videos, some of them prefer wait for a time when the number of danmaku comment increase.

In the deceased period, danmaku comment number do not increase video views when uploader have less followers which proved danmaku comment post speed is quite slow in this group. While this condition is contrast when uploader have more followers, reason may be because that uploader with more followers, danmaku comments start to show significant effect to video views. H2 supported at this time may be means viewer start to post danmaku comment and viewers also chose videos based on danmaku comment received in past time.

H2 supported in steady stage, damaku comment number were significant both followers more less, because after a long time since video uploaded, video received enough danmaku comment number, videos become active so that more people willing to post danmaku comment and attract viewer more than before.

For sharing activities, analysis result partially rejected H3, indicted that sharing activity in the initial period and decrease period do not always increase video views. According to the result above, sharing activity only do significant effect during the steady stage when follower is less. During the initial period and decrease period, H3 was rejected whether follower is less or more.

There may be two reasons, first is people from other website need time to find correspondent video, so there is a time difference between video views and sharing activities, second may be because that video popular in Bilibili do not mean it also popular in other website, so that is why sharing activity show significant in the steady stage. This result does not strange as Bin Nie (2014) found that video's popularity does not affect popularity on another website.

Analysis result of coins in the initial stage show that coins do not increase video views in initial period when uploader have less follower. Reason for this phenomenon because that, in general condition uploader with less follower would receive less coins.

Through hypotheses result, H4 rejected. Coins do not increase video views in decrease period whether uploader have less or more follower which means coins are not effective after videos has been uploaded for a while.

During the stable stage, like other attributes, after a long-time accumulation number of coins increased and it start to significant effect video views. According to the system rules of Bilibili, Once the video receives a lot of coins and reaches the standard number set by Bilibili, this video could recommend by Bilibili and attract more viewers. So that is why in the stable stage, coins showed a significant effect to video views even uploader have less follower.

5. Implications and limitations

5.1 Implications

Implications to literature: prior research has deeply explored the role of social network on video diffusion (Anjana Suarrla et al. 2012, Mirjam Wattenhofer et al. 2012, Yuping Liu-Thompkins et al. 2012, Hema 2010), and external links to other websites (Suman Deb Roy et al. 2013, Haitao Li et al. 2013, Honglin Yu et al. 2014, Henrique Pinto et al. 2013) on UGC. The focus of this research is on the impact of video characteristics on video diffusion, which not only impacts what factors induce video success but also analyzed detail influence during the different diffusion process. Previous literature on video diffusion highlights the part video characteristics' importance such as social network, link or comment. In additional to diffusion trends almost literature through the total scale of video views.

The result in this thesis demonstrated that video characteristics impact on video diffusion, but not always, the impacts and influence factor changed during the diffusion process. This kind of changes could be reference by three kinds of people.

First, is for website designers, they want to improve video diffusion so that they can improve the influence of website and success whatever in the scale of users or website revenue. In order to achieve this goal, it needs to find positive factors. For example, compared to other characteristics, danmaku comment system has shown a strong and positive influence on views during the video diffusion process. Which means that users are willing to interact with another user. While at the same time influence of general comment is weaker, indicate that even it also is an interactive method, users prefer real-time, easy to input method to communicate with others. Based on the success of Bilibili, another video website in China like Youku, iqiyi also adopt this comment system to improve users' activity.

Second is for the market manager who wants to use UGC as their new marketing tool. For market managers, it is most important for them to find a video could spread widely so that it can achieve the advertisement value. For now, most managers refer to the number of followers to determine the video diffusion level. While uploader with more followers do help to video diffusion, but not absolutely. Except for the diffusion rate, the manager also needs to consider the viewers' feeling. For this aspect, it could reference the number of coins, if an uploader always received a lot of coins which means viewers satisfy the uploader's video, even diffusion rate is not good as uploader with a huge number of followers, this kind of people may show better advertisement effect. Except this, the can use different policies to spread content to improve the influence of their advertisements during the diffusion process because the impact factor changed, thus, could achieve the highest profit.

And the last group is users who want to become a content producer. Nobody could have a huge number of followers since the start, this research is suitable for them. Based on this research they can choose different video factor to promote content diffusion with a different number of followers at a different stage. For example, if people only have a few followers, the significant factor was the general comment in the early days after video upload while the video quality is not as important as we think. So, based on this condition, people could post some controversial videos at first to attract views and then as time goes on it may be a success.

5.2 Limitations.

Of course, this research has limitations, and it can also be studied as a subject in the future. First of all, this thesis has data limitations, because the Bilibili can only access the first five pages of follower, therefore, we have no way to get the total social network data of the uploader, can only get the scale data of the followers.

Second, we analyze the data from a whole view analysis. The collected data is not classified by category, actually, there are different categories in Bilibili, which included music, movies, and games, etc. In fact, different categories would have different diffusion process and the influence may also different, the research could be done as a project in the future.

Finally, the limitation is the scope limit of Bilibili, because Bilibili is just a video sharing website based on the Chinese market, although its danmuku comment is very special characteristic, it is also very likely that because of the cultural reason that people prefer to use the danmaku comment system. We don't know what happened if the danmaku comment system spreads across the world, or what will be different if the same system would adopt by YouTube.

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[1] Data source:

Statista. Facebook's annual revenue from 2009 to 2018, by segment (in million U.S. dollars) https://www.statista.com/statistics/267031/facebooks-annual-revenue-by-segment/
Statistia: YouTube. https://www.statista.com/topics/2019/youtube/
Business insider. https://www.businessinsider.com/millennials-skip-youtube-ads-and-thats-ok-2017-1?r=UK

Source: User-generated content - Statistics & Facts.
https://www.statista.com/topics/1716/user-generated-content/

Appendix:

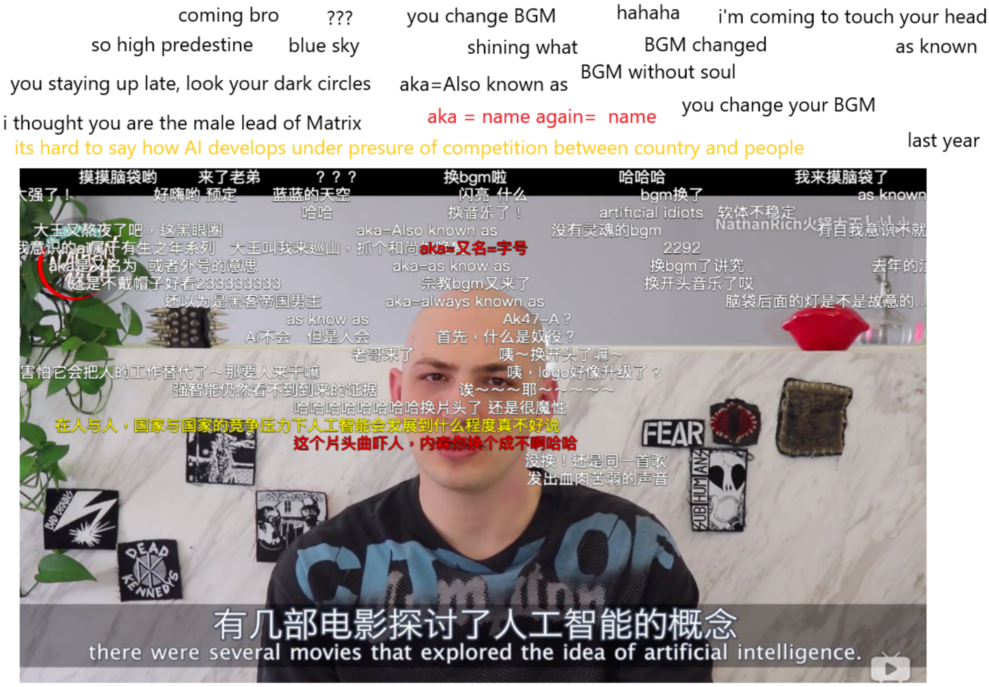

Figure 1: Example of danmaku comment.

Data source:Bilibili. https://www.bilibili.com/video/av46784531

Table1: Statistics of original data.

Variable	Obs	Mean	Std. Dev	Min	Max
Views	129,282	6,307.78	63,947.57	0	3,695,000
Danmaku	129,282	44.08	349.98	0	11,022
Coins	129,282	117.77	2,019.51	0	122,000
Favorite	129,282	136.80	1,685.13	0	104,000
Comment	129,282	28.37	155.21	0	5195
Sharing	129,282	28.93	473.62	0	28,000
Follower	129,282	7,655.37	63,340.84	0	2,068,000
Submission	129,282	127.52	226.60	1	999

Table 2: Correlation between original number.

	Views	Danmaku	Coins	Favorite	Comment	Sharing	Follower	Submissi
Views	1.000							
Danmaku	0.733	1.000						
Coins	0.579	0.605	1.000					
Favorite	0.746	0.682	0.899	1.000				
Comment	0.729	0.696	0.488	0.523	1.000			
Sharing	0.663	0.646	0.947	0.925	0.6112	1.000		
Follower	0.228	0.286	0.143	0.106	0.3572	0.141	1.000	
Submission	0.020	0.028	-0.004	-0.002	0.044	-0.003	0.198	1.000

Table 3: Statistics of daily data.

Variable	Obs	Mean	Std. Dev	Min	Max
Daily Views	129,282	224.15	3882.62	0	604,000
Daily Danmaku	129,282	1.2	21.55	0	2,279
Daily Coins	129,282	3.63	147.21	0	28,000
Daily Comment	129,282	0.622	9.76	0	1317
Daily Sharing	129,282	1.03	34.52	0	4934

Table 4: Correlation between daily variables.

	Daily Views	Daily Danmaku	Daily Coins	Daily Comment	Daily Sharing
Daily Views	1.000				
Daily Danmaku	0.717	1.000			
Daily Coins	0.572	0.612	1.000		
Daily Comment	0.635	0.568	0.438	1.000	
Daily Sharing	0.632	0.620	0.886	0.532	1.000

```
hausman fe re, constant sigmamore

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |       fe           re         Difference          S.E.
-------------+----------------------------------------------------------------
      lnddmk |    .774555     .7926409       -.0180859        .0013918
    lndcoins |   .4703593     .4784674       -.0081081         .001523
    favorite |   .0001434      .000121        .0000224        3.12e-06
      lndcmt |   .7558243      .768219       -.0123947        .0013377
     lndshar |   .1248563     .1018396        .0230167        .0031635
       _cons |   1.211132     1.212879       -.0017464               .
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =      749.06
                Prob>chi2 =      0.0000
                (V_b-V_B is not positive definite)
```

Figure 2: result of Hausman test.

국문초록

사용자 생성 콘텐츠 웹 사이트의 동영상 확산-Bilibili 기반으로 실증 분석

Video Diffusion in User-Generated Content Website – An empirical analysis of Bilibili

리얀

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사용자 생성 콘텐츠 (UGC) 사용자의 가치를 강조하며 Web 2.0 의 개발을 기반으로 정보 확산 및 시장 관리에 중요한 역할을 가지고있다. 따라서 UGC 웹 사이트에서 어떤 요소가 정보 확산에 영향을 미칠 것인지를 식별하는 것이 필요하다.

이 논문은 Bilibili 웹 사이트 기반으로, 비디오 확산 과정에서 영향력있는 요인을 찾아 보려고한다. 주로 소셜 네트워크에 초점을 맞춘 선행 문헌와는 달리, 이 논문에서는 주로 비디오 특성 데이터를 사용하여 비디오 확산에 효과적인 요소를 탐구했다. 첫째, 1 개월 이내에 비디오 조회수 증가 추세 파악했고 비디오 확산에는 세 가지 단계가 있다. 둘째, 각 단계에서 비디오 확산에 미치는 요인이 무엇인지 분석했다.

분석결과 보면 사용자와 콘텐츠의 상호 작용이 높을수록 더 많은 사람들이 동영상을 볼 수 있어 동영상 확산 속도가 향상 될 수 있음을 보여주었다.

이 논문을 바탕으로 웹 디자이너, UGC 를 마케팅 도구로 사용하는 사람들 및 UGC 콘텐츠 제작자가되기를 원하는 사용자에게 기본적인 근거를 제공 할 수 있다는 점과 같은 몇 가지 중요한 함의가 소개되었다.

주요어: 사용자 생성 콘텐츠 (UGC), 비디오 공유 웹 사이트, 비디오 확산, 뉴 미디어, Danmaku, 소셜 네트워크.

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