

Video Diffusion in User-generated Content Website: An empirical analysis of Bilibili

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Abstract— 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 marketing part. Therefore, it is necessary to identify which factor would give influence to information diffusion in User-generated content website. This research based on video user-generated content website try to find key factors to video diffusion, which provide some basis for web designers and people who use UGC as a marketing tool.

Keywords— user-generated content, information diffusion, video diffusion, new media, YouTube.

I. INTRODUCTION

With internet development, various kinds of new things have been created, based on widely application of Web 2.0 user-generated content has been developed recently. Sites like Facebook, Myspace, Twitter, YouTube are typical user-generated content website, both websites are emphasizing users' value like users' control, user's participation, users in these websites are create content and sharing with others who have some social connections with them (Alexander, 2008; Herring et al, 2005; O'Reilly, 2005).

User-generated content creating more values than people' expected, previous researchers has been focused on various of user-generated content to prove their powerful influence on media advertising, trend forecasting and provide data to understand consumers' behavior. Qian Ye (2011) proved that traveler reviews on user-generated content increase online sales of hotel; Vasant Dhar (2009) proves that music future sales influenced by number of blogs post on the related album on some user-generated content; Carmen Cox (2009) find that consumer consider user-generated content as credible information source instead website sponsored by government when they search travel information.

YouTube as the one of the biggest video sharing website in the world created huge value, users upload thousands of videos one day, some researchers have focused on YouTube to analyzed factors which influence video popularity. People researched video popularity on YouTube through user's social network (Hema, 2011; Yuping, Michelle 2012), gain insight into content popularity and traffic caused by video sharing activities (Cha et al, 2007; Cha et al, 2009) and time component of video popularity. (R. Crane, D. Sornette, 2008, Szabo. Huberman, 2010) Previous research on YouTube

website most focus on above attribute's influence on video popularity, however this paper use video's detail attribute to analysis their influence to video popularity.

Instead of YouTube, this research focus on BILIBILI website which is a video sharing website in China like YouTube but with enhanced social features, this website provides a special comment system called Danmaku comment which allow people send short comment fly from right to left on the video screen, also when people watch video, they can see Danmaku comment send by previous viewers or viewers send Danmaku comment at same time. (Fig 1)



Figure 1. Example of Danmaku platform

With analysis result, it could find which factor give positive influence to video popularity. So, for the video websites designers, they can reference this result when they built or enhance corresponding features to attract more users. Also, user-generated content website as a new marketing tool, sometimes it could create unexpected value when companies use these new media in their marketing strategy.

II. HYPOTHESIS

In Danmaku, a video has various attributes such as the number of comments, coin, follower. We categorized attributes as 3 groups. Properties that shows user's activity as active like comment which need multiple actions is "active participation" property, only one action like lick is "simple participation" property, and attribute that shows properties of video sharing and follower activity as "exogenous" property.

We expect that an aspect of video diffusion will show “S-Curve” within 30 days, same with one of the most popular innovation diffusion theory. Based on this, we divide the time window of analysis as 3 stages matching the inflection points. 1st one is the initial stage. It is a time that the increase of view number is accelerated yet. 2nd one is the increase stage. During this stage, view of video gets a constant attention, and the number of views grow rapidly. Last one is the end stage which means a period that the number of views increases slowly or rarely. We assume that in a different stage, the factor that shows a significant effect will be change.

In the initial stage, the number of followers could be non-zero number, but the sharing and other attributes could be zero. Bilibili allows individuals to subscribe to or follow other users' activities like other UGC communities such as YouTube and Twitter, and past research shows that the average network size(subscriber) had positive effect to video's popularity (Liu-Thompkins & Rogerson, 2012; Haridakis & Hanson, 2009).

According to previous researches, sharing activity also plays a non-trivial role in the number of video views (Cheng et al, 2010). As a result, we also assumed that those who were shared would watch video as interest in video waned.

TABLE 1. CATEGORIES AND ATTRIBUTES

Category	Attribute
Active participation	Forum Comment Danmaku Comment
Simple participation	Favorite Coins
Externality	Follower Sharing

- **H1:** In the initial stage, exogenous attributes will show a significant effect to video popularity.
- **H1a:** In the initial stage, the number of followers will affect significantly a video popularity.
- **H1b:** In the initial stage, the number of sharing will affect significantly a video popularity.

There are several studies that identified the effect of number of comments on views (Haridakis & Hanson, 2009; Hartwick & Barki, 2010; Chen, Gao & Rau, 2015; Wu et al, 2018). Bilibili has two kinds of comments: forum comment and Danmaku comment. Danmaku comment is a view's statements that flows on the screen. Also, video quality affect likelihood of consumption and the possibility to share the content with others (Liu-Thompkins & Rogerson, 2012). In this study, we assume coin proxies the video quality. To sum up, endogenous attributes will affect a video popularity.

- **H2:** In the increase stage, active participation and simple participation will affect significantly a video popularity.
- **H2a:** In the increase stage, the number of forum comment will affect significantly a video popularity.
- **H2b:** In the increase stage, the number of Danmaku comment will affect significantly a video popularity.

- **H2c:** In the increase stage, the number of coins will affect significantly a video popularity.
- **H2d:** In the increase stage, the number of favorite will affect significantly a video popularity.

In the end stage, also known as a mature stage, all attributes could show influence to video popularity. So, we assume that in the end stage, all video attributes show a significant effect to video popularity.

- **H3:** In the end period, both active participation, simple participation and externality attributes will affect significantly a video popularity.

III. DATA AND METHODOLOGY

The present study uses data of Bilibili website using web crawling. The dataset is collected daily and includes both video attributes which are uploaded within one month and the attributes of its uploaders. The video attribute includes comment, Danmaku comment, coins, favorite, sharing activity and number of views, and the uploader attributes involves number of total views, the number of followers and previous video submission. We collected data of 4230 videos and 3,472 uploaders during 30 days and missing values were eliminated from the dataset. The basic statistics of our data are shown in table 1.

TABLE 2. STATISTICS SUMMARY OF DATASET

Observation = 128900 video = 4230, uploader = 3472		Mean	Std dev.	Max.	min.
Video attribute	Views	6157.00	64302.99	36950000	0
	Danmaku comment	42.56	342.09	110000	0
	Coins	118.85	2029.60	122000	0
	Comment	88.69	1432.63	4700000	0
	Favorite	135.11	1684.62	104000	0
	Sharing	28.34	473.73	28000	2
Uploader attribute	Follower	5259.83	30794.12 1	913000	0
	Submission	100.11	168.65	980	1
	Total view	1136229. 00	4400235. 00	0	0

Before analysis, we divided the data into the initial period, increase period and the end period. The initial period is early stage of content where upload within a short time.

The increase period is second stage where the number of view increase rapidly, and the end period refers that the growth of view is saturated. In the present study, we assumed that 0-4th (5days) is considered as initial period, 5th – 24th (20 days) as increase period and end period is 25th -29th (5days).

To analyse the effect of the video attribute on the number of views, we will conduct fixed effect panel regression. Fixed effect model assumes that there would be correlations between the constant and independent variables. Because our assumption that the uploader attributes influence to the video attributes and the number of views can be supported, only video attributes are included in the independent variable, and

the uploader's attributes are considered as fixed effect of each video.

$$view_{i,t} = \alpha_i + \beta_i^{video} x_{i,t} + \varepsilon_i$$

From this analysis, we expect to give meaningful implications to the online video platforms. First, the present study will provide the effective way to diffuse video content on web platform. Also, we can give an answer to what kind of attributes are efficient to diffuse the video content on the online platform.

IV. ANALYSIS RESULT

With data crawling from Bilibili, video diffusion tends shown as Figure 2. As we assumed before, video diffusion trend shown as a "S-Curve", which means it have initial period, increase period and end period.

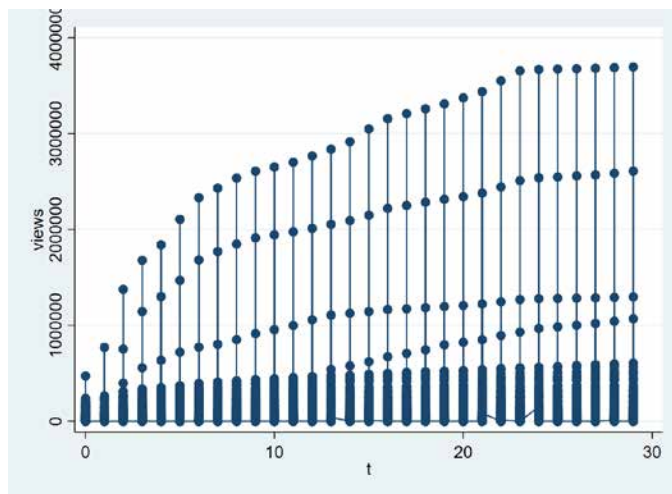


Figure 2. Video views increase trend in Bilibili

According to video diffusion trend, we divided data into three groups, also through Hausman test, fixed effect model is suitable in this paper.

Model 1						
	Active participation		Simple participation		Externality	
Time	dmk comment	comment	coins	favorite	sharing	follower
0-4d	0.153***	0.407***	0.137**	0.656***	-0.05	0.178***
5-24d	0.143***	0.187***	0.146***	0.529***	0.104***	0.227***
25-29d	0.103***	0.059*	0.078***	0.248***	0.105***	0.171***
0-29d	0.113***	0.341***	0.170***	0.638***	0.102***	0.294***

* p < 0.05 **p < 0.01 ***p < 0.001.

Figure 3. Data analysis result

Figure 3 shows the analysis result. In the initial period, follower shows a significant effect to views which means H1a supported, while sharing activity shows a negative and non-significant effect to video diffusion which means H1b is reject.

In the increase period (5th – 24th), both active participation, simple participation showed a significant effect to video diffusion, as a result, H2a, H2b, H2c, H2d are supported.

Both active participation, simple participation and externality show a positive and significant effect to video diffusion in the end period (25th – 29th) which means H3 is supported.

Consider video attribute, most attributes show a positive and significant effect to video diffusion in video upload period, users watch videos through number of danmaku comment, forum comment, number of coins and number of favorite in the website, outside of website people watch videos through links from Bilibili.

In the aspect of uploader attribute, uploader with more follower always gain more views than uploader with less follower, that's why at the initial period, follower shows a positive and significant effect to views. At the same time, after users watch the video, some people may become a follower of the uploader, and then give influence to views that's why follower always give significant effect to views.

V. CONCLUSION

In this article, we conducted an analysis on a user-generated content (UGC) website – Bilibili, with enhanced social features. Based on statistics for more than 4 thousand new upload videos in 30 days, we give the result of influential factors to video diffusion which is much more detail than previous study and could apply our findings to different aspect.

Among our results, we find that users' participation, both active participation or simple participation show positive influence to video diffusion. So different people, for example video website designers, they can create new patterns to promote users' participation like danmaku comment system in Bilibili to promote communication within users. For market manager, in order to expend video influence not only they can find uploaders with huge number of follower but also could send comment to video or donate coins or make people click favorite of the video which make video "active".

While due to the limitation of Bilibili, we can just get the number of followers, not the network of Bilibili user, which also is the limitation of this paper. So, in future research, we can research the impact of user's social network on video diffusion in Bilibili.

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