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The Influence of Contributor Experience on Content Popularity: A Content Novelty Perspective

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Short Research Paper

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Abstract: User Generated Content platforms such as YouTube are emerging as popular online communities. With tons of content generated every second worldwide, identifying factors that influence content popularity becomes an important issue. The contributor experience has been studied as a predicting factor of content popularity but its relationship with popularity is not consistent. Drawing on a dataset from Bilibili.com, we investigate the influence of contributor experience on content popularity from a perspective of novelty. Further, we investigate how this effect is moderated by different contributor identities. Our results show that contributor experience has a negative effect on content popularity, and institutional contributor identity weakens this effect while personal verification strengthens it. Our research results provide important implications for both platform operators, content contributors, and users.

Keywords: Content Popularity, Contributor Experience, Identity Verification, Novelty, User Generated Content

1. INTRODUCTION

Recent years have witnessed the prosperity of User Generated Content (UGC) platforms, on which users could create and upload content to share with other users. YouTube, one leading UGC platform worldwide, now attracts about 2 billion active users every month, uploading 500 hours of content every minute [1]. Due to the large userbase of UGC platforms, tons of content are created and shared among users. However, the attention and time that common users could spend on consuming UGC content are limited. This eventually leads to the uneven distribution of content popularities: only a small portion of content receives much attention from other users and becomes popular content on UGC platforms. Thus, a fundamental issue related to both UGC platforms and users is to identify the content that has the potential to become popular in the future [2].

Many contributors and content characteristics have been shown can help identify popular content and predict popularity. Especially, contributor experience, usually measured by how much content the contributor has contributed, is considered effective in predicting content popularity [2-3]. Previous studies show that content created by experienced contributors may be more popular, due to higher exposure brought by frequent releasing activities [4-5]. However, several recent studies also established a negative relationship between contributor experience and content popularity [6-8]. Therefore, the inconsistent results call for a detailed reexamination of the influence of contributor experience on content popularity.

Drawing on a dataset from Bilibili.com, a popular online video community in China, we investigate the influence of contributor experience from a perspective of novelty. Novelty is the perception of unique differences from others [9], which can arouse consumers' interest and thus drive content consumption [10-13]. Although experienced contributors may be more efficient and sophisticated in creating content, their rich experiences may hinder them from creating more novel content. The reason is that these experienced contributors may find it difficult to find more new ideas or they might simply become less enthusiastic and thus would just follow routines when they create new content. To the best of our knowledge, little prior literature has studied the influence of contributor experience from such a perspective of novelty.

Further, the influence of contributor experience might be further complicated by other factors. In recent years, UGC platforms, such as Twitter and Bilibili.com, start to allow contributors to receive official verification certified by the platforms to disclose their identities (certified individual or institution). Contributors with different identities may have different willingness and capabilities in creating novel content. It then follows that the influence of contributor experience on content popularities might also be differential across different types of verifications. Such a moderating effect is also worthwhile to investigate.

This paper aims to supplement relevant literature by exploring the influence of contributor experience on content popularity and how this influence is moderated by contributor identity verifications. Our results show that contributor experience is negatively associated with content popularity and this relationship is stronger for contributors with personal identity verification while weaker for institutional contributors.

2. LITERATURE REVIEW

2.1 Content popularity

Content popularity measures how popular a content is among users on the same UGC platform [2]. It is considered an important measurement and has drawn much attention from academics. Chai (2009) views popularity as an important dimension of the evaluation framework of content quality [14]. Typically, content popularity is divided into two categories: implicit and explicit popularities. Implicit popularity reflects users' attention but not necessarily appreciation about certain content. However, explicit popularity indicates users' appreciations expressed through favoring and donating to content, which has been less considered in literature [2].

Many studies have focused on identifying popular content, ranging from revealing the popularity characteristics to predictions based on features and generative models [2]. Different content and contributor characteristics are usually combined to predict the exact numbers or levels of popularity, such as the experience and social capital of contributors [2-5]. Especially, content novelty has been found to play an important role in popularity [10-13]. The reason is that novelty can bring users hedonic value and further affect their behaviors, and then increase the popularity. For example, Malik (2020) shows that novel content is preferred on YouTube by platform audiences [13]. Given the influence of novelty, the effects of some specific features on popularity may behave differently. Our research is a detailed examination and explanation of the influence of contributor experience from the perspective of novelty.

2.2 Contributor experience

Contributor experience, measured by the quantity of content the contributor has contributed, is a dimension of reputation [15]. Reputation has been studied widely in different fields, including marketing and information systems. Research have shown it can reduce uncertainty, and then promote users' willingness to pay and online purchase [16-17]. On UGC platforms such as online review communities, reputation is also shown can positively influence content performances [4-5,15,18].

However, several previous studies have also revealed the negative effect of contributor experience. For instance, Khan (2014) shows that the total number of videos posted by a user has a negative effect on virality [6]. Similarly, Tafesse (2020) reveals the negative effect of the amount of content created by a contributor on his/her follower engagement, and this effect is due to the low level of perceived novelty [7]. Such findings call for a reexamination of the effect of contributor experience. Therefore, our research reexamines the role of contributor experience in content popularity in an attempt to reconcile the conflicts. To the best of our knowledge, we are the first to explore the moderating impact of contributor identity on this effect.

3. HYPOTHESES DEVELOPMENT

3.1 Contributor experience

According to the elaboration likelihood model [19], contributor experience can influence content popularity via both peripheral and central routes. Under the peripheral route, users rely on simple decision cues such as the credibility of the message sources and make a less cognitive effort [20]. Experience is a simple and heuristic clue to contributor reputation. Thus, drawn from the peripheral route, users tend to prefer content created by experienced contributors more. It suggests that rich experience can have a positive effect on popularity.

The central route commands users to think about issue-related information critically and focus on the messages themselves [20]. For contributor experience, this route involves the novelty of content——the perception of unique differences from others [9]. Users are exposed to massive and similar content on UGC platforms and may suffer from the information overload problem. Content with high novelty, in this situation, can distinguish itself from other content and draw users' attention [10]. Empirical results confirm that novel content on YouTube is preferred by platform audiences [13]. However, content contributing is a productive and creative process, contributors who have created a large quantity of content may not necessarily be novel and creative [21]. Instead, these contributors may find it difficult to make novel ideas or they may be less enthusiastic when creating new content. Given this, the central route suggests that a rich creating experience can weaken the perceived novelty of contributors' content, thus may decrease other users' engagement and appreciation [7].

The elaboration likelihood model indicates that attitudes formed via central-route processes are higher and more influential than that via peripheral-route [19]. Thus, we propose that in our research context, the negative effect caused by contributor experience dominates and hypothesize as follows:

H1: Contributor experience is negatively associated with content popularity.

3.2 Contributor identity

Content created by contributors can entertain audiences and bring them value. According to the social exchange theory [22], users will pay back in exchange for contributors' efforts by clicking the "like" button, giving a virtual donation, and so on. This user feedback and rewards are measures of content popularity in the community. However, contributors' identify may have different effects on users' intention to reward. If the contributor is an organization, then uploading content is considered a kind of marketing behavior that may lead to benefits in any form. Social exchange theory indicates that users intend not to reward when the contributors' behavior is not a cost but a gain for themselves [23]. Accordingly, users will have less incentive to reward institutional contributors, compared to unverified contributors. On the contrary, personal identity verification usually links to higher levels of historical contributing efforts, more knowledge in a particular field, and a higher number of followers in the community. Thus, it reflects the reputation and professionalism of the contributor, and their efforts are easier to be acknowledged by other users. As a returned favor, users may reward more.

In light of the above arguments, we hypothesize as follows:

H2a: Content produced by contributors with institutional identity verification is less popular than content produced by unverified contributors.

H2b: Content produced by contributors with personal identity verification is more popular than content produced by unverified contributors.

As previously argued, contributor experience influences content popularity through perceived novelty. However, the perceived novelty might be different for content created by contributors with different identities.

On the one hand, institutional contributors, such as governments, media, and enterprises, may have more resources and capabilities in creating content. Usually, they have a professional group to maintain the account, produce content and monitor users' responses. For these institutional users, keeping creativity and productivity can be easier than common personal contributors. Thus, we propose the following hypothesis:

H3a: The negative association between contributor experience and content popularity is weaker for contributors with institutional identity verification.

However, personal identity contributors can play a role in the opposite direction. As mentioned above, contributors with personal verification usually have rich experiences in a specific field. Their success often induces them to repeat what has worked well in the past [24-25], which will reduce innovative behavior. They will choose to exploit mature experience but not explore in other directions. As a result, richer experiences of these contributors may reduce content novelty even in a higher magnitude. Thus, we propose as follows:

H3b: The negative association between contributor experience and content popularity is stronger for contributors with personal identity verification.

The theoretical framework of our research is shown as follows.

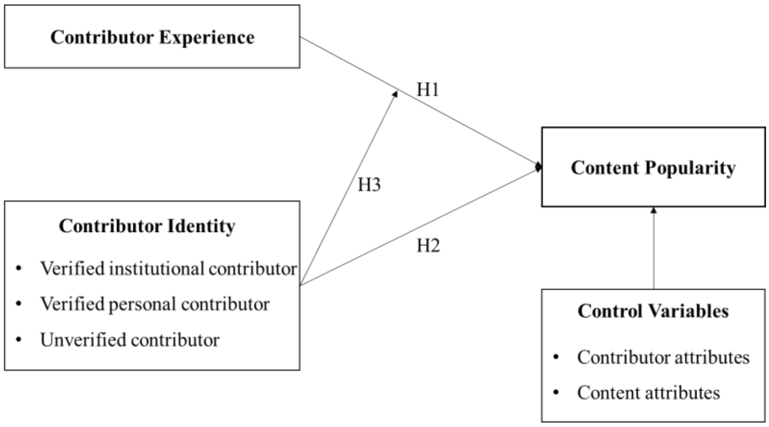

Figure 1. Research model

4. RESEARCH METHODOLOGY

4.1 Data collection

Bilibili.com is a leading online video community in Chinese. Well-known individual contributors ("web celebrities") can receive a personal verification while institutional contributors can receive an institutional verification. A lightning icon will be added to profiles of those verified accounts. Further, "Coin" is a limited resource in Bilibili.com and users can express their appreciation and support for videos by giving coins to them, as a kind of virtual donation. Therefore, the number of coins received can measure the explicit popularity of videos. In addition, every video in Bilibili.com has a unique district tag that indicates the topic of the video. We collected all videos published with the district tag "Playing Music" from July 1st to August 31 in 2021. Then, all contributors of these videos are extracted and we randomly chose 1,000 from them and obtain all their contribution history.

On Bilibili.com, videos are categorized into original videos (created by contributors) and reprinted videos (not created but reprinted by contributors). The mechanism of virtual donation in Bilibili.com is different for those two types of videos. To avoid the confounding influence of different mechanisms, we focus on content popularity of original videos in this study. Since users may have different tendencies to reward for videos with different topics and district tags, we only keep videos related to music from all contributors' contribution history. This leaves us with a sample containing 18,850 videos. Variables are explained as follows.

4.2 Measurements and model

To test hypotheses H1, H2a and H2b, we examine the following:

$$\begin{aligned} Ln\ Content\ Popularity\ &= \alpha + \beta_1 Ln\ Contributor\ Experience_{ij} \\ &+\beta_2 Institutional\ Verification_i + \beta_3 Personal\ Verification_i \\ &+\gamma Control\ Variables + \varepsilon \end{aligned} \tag{1}$$

where $Content\ Popularity_{ij}$ is measured by the number of coins received by contributor i's video j, $Contributor\ Experience_{ij}$ is measured by the number of videos contributor i has uploaded at the time when video j is published. The larger this number is, the more creating experiences the contributor has when creating and publishing the video. Thus, H1 is tested by β_1. $Institutional\ Verification_i$ and $Personal\ Verification_i$

are two dummy variables to indicate whether the contributor is a verified institutional account, verified personal account or personal user without verification. The estimation of β_2 and β_3 thus can test hypothesis H2a and H2b. A logarithmic transformation is applied to variables $Content\ Popularity_{ij}$ and $Contributor\ Experience_{ij}$ because of their skewed frequency distributions.

To test H3a and H3b, we examine:

$$\begin{aligned} Ln\ Content\ Popularity_{ij} &= \alpha + \beta_1 Ln\ Contributor\ Experience_{ij} \\ &+\beta_2 Institutional\ Verification_i + \beta_3 Personal\ Verification_i \\ &+\beta_4 Institutional\ Verification_i \\ &\qquad * Ln\ Contributor\ Experience_{ij} \\ &+\beta_5 Personal\ Verification_i * Ln\ Contributor\ Experience_{ij} \\ &+\gamma Control\ Variables + \varepsilon \end{aligned} \quad (2)$$

where β_4 and β_5 are the coefficients of the interaction terms between contributor experience and identity verification, used to test H3a and H3b respectively.

Following the approach adopted in related prior studies [6-7], we choose some relevant contributor characteristics as control variables, such as the $Number\ of\ Followers$ and $Number\ of\ Followees$(who the contributor follows), and the $Contributor\ Level$ (an integer between 0 and 6, measuring how active a contributor is). Video characteristics are also controlled, including the $Video\ Length$ (in seconds) and $Description\ Length$, $Video\ Age$ (measured by the duration since published till 10th December). Whether the video is coauthored by other contributors is also included to control the influence of multiple authors by the variable $Cooperation$. $Number\ of\ View$ is used as the proxy of content quality and can also eliminate the influence of platform's traffic distribution mechanism. All control variables except $Contributor\ Level$ and $Cooperation$ are taken logarithms as well.

5. RESULTS

5.1 Descriptive statistics

Table 1 reports the descriptive statistics. The variances of most variables are larger than the mean, and their skewness are all greater than 0, indicating a right skewed distribution, supporting our logarithmic operation above.

Table 1. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Content Popularity	18850	187.501	3075.917	0	245185
Contributor Experience	18850	186.733	323.839	1	8720
Institutional Verification	18850	.028	.166	0	1
Personal Verification	18850	.047	.211	0	1
Contributor Level	18850	4.218	1.387	0	6
Number of Followers	18850	23247.631	126700.9	0	1620350
Number of Followees	18850	182.194	314.753	0	2000
Number of View	18850	7586.97	89747.293	0	4862418
Video Length	18850	286.813	3932.377	4	404329
Description Length	18850	47.027	104.599	0	1866
Video Age	18850	9636.928	9217.433	.143	71734.43
Cooperation	18850	.009	.097	0	1

5.2 Regression analysis results

First, we conduct the multiple collinearity test of each variable and the results are shown in Table 2. All the variance inflation factors (VIF) are less than 10, indicating there is no multiple collinearity in our model.

Table 2. Test for multicollinearity

Variable	VIF	1/VIF
Ln Number of Followers	4.720	0.212
Ln Number of View	2.720	0.368
Ln Contributor Experience	2.320	0.431
Contributor Level	2.320	0.432
Ln Number of Followees	1.570	0.635
Personal Verification	1.380	0.725
Ln Video Age	1.290	0.777
Ln Description Length	1.190	0.838
Ln Video Length	1.160	0.864
Institutional Verification	1.120	0.892
Cooperation	1.070	0.933
Mean VIF	1.900	

Results of the OLS regression with clustered standard errors are shown in Table 3. Model 1 is the baseline model involving only control variables. Model 2 adds the main effect of contributor experience and Model 3 adds all main effects including identity verification, used to test H1-H2, based on Eq.(1). Model 4 involves all the variables including the interaction effects and is used to test H3, based on Eq.(2).

The results of Model 2(β_1=-0.161, p=0.000) and Model 3(β_1=-0.160, p=0.000) show that contributor experience has a significantly negative effect on content popularity. H1 is strongly supported. This suggests that the negative effect of diminishing novelty outweighs the positive effect of contributor experience, and users are less motivated to reward as a result.

Institutional verification is shown can negatively influence content popularity ($\beta_2 = -0.643$, p=0.087), indicating that users have lower willingness to reward verified institutional contributors. H2a is supported. However, H2b is not supported ($\beta_3 = 0.182$, p=0.687), indicating the difference in content popularity is not significant between verified personal contributors and unverified contributors. It shows that users may have similar willingness to reward personal contributors, whether they are verified or not.

The results of Model 4 show that institutional verification (β_4=0.311, p=0.022) can mitigate the negative effect of contributor experience on content popularity, while personal verification (β_5=-0.393, p=0.000) can strengthen such negative effect. H3a and H3b are all supported.

Table 3. Regression analysis results

Variable	Model 1	Model2	Model 3	Model 4
Ln Contributor Experience		-0.161***	-0.160***	-0.154***
Institutional Verification			-0.643*	-2.184***
Personal Verification			0.182	2.237***
Institutional Verification*Ln Contributor Experience				0.311**
Personal Verification*Ln Contributor Experience				-0.393***
Constant	-2.465***	-1.414***	-1.437***	-1.470***
Observations	18,850	18,850	18,850	18,850
R-squared	0.791	0.800	0.803	0.808

*** p<0.01, ** p<0.05, * p<0.1

6. CONCLUSIONS

UGC platforms are becoming more and more popular. Due to the overwhelming volume of content created, identifying potential popular content is an important issue but has not been studied sufficiently. This paper studies how contributor experience influences content popularity from a perspective of content novelty. Further, one notable mechanism worthy of examination is the contributor identity verification on UGC platforms, which may moderate the influence of contributor experience. Drawing on a dataset from Bilibili.com, we show that contributor experience has a negative effect on content popularity and this effect is stronger for contributors with personal identity verification, weaker for institutional contributors. Our research has the following two aspects of implications.

This research has certain theoretical significance. This paper is a supplement to the research on content popularity. It provides a new, important perspective of the negative effect of contributor experience on content popularity. Contributor experience can reduce content popularity due to decreased content novelty. Such effect is also shown to be differential for contributors with different identities.

Our research also has practical implications for both the platforms and content contributors. UGC platforms can take steps to encourage contributors to produce innovative content, instead of focusing on creating a higher amount of content. Content contributors with different identities should also be aware of the negative effect of larger contribution history to keep viewers' interests.

Inevitably, our research has serval limitations. First, the dataset is cross-sectional, and it may not be able to observe the dynamic information of content. Secondly, we only use the number of coins to measure explicit popularity. Other measurements might be used to see if the results are consistent. At last, our sample is obtained from the "Play music" district on bilibili.com and thus the content mainly serves a leisure purpose. Future research can extend this research by examining content with an educational purpose.

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