

## Research on Factors Influencing Video Popularity Based on the Three Elements of Popularity: A Case Study of Bilibili (Postprint)

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**Date:** 2023-10-08T00:00:00+00:00

### Abstract

[Purpose/Significance] This study investigates the non-content influencing factors in the formation of video popularity on the typical bullet-comment video website—Bilibili, analyzing their potential impact on video popularity from the perspectives of video attributes, creator platform attributes, and social attributes, to provide guidance for the future development of Bilibili and other related new media video website users and platforms. [Method/Process] Based on the 5W model, a video popularity formation process model is constructed, and grounded in the three elements of popularity theory, a video popularity influencing factors model is built. By scraping objective data, principal component analysis is adopted to measure popularity indicators, and multiple regression is applied for empirical research on influencing factors. [Results/Conclusion] The personal verification status, follower count, number of verifications of video creators, and video description length have significant positive impacts on video popularity; video title length has a significant negative impact on video popularity. Videos published during leisure time have overall higher popularity, while videos published during sleeping hours have overall lower popularity.

### Full Text

## Research on Influencing Factors of Video Popularity Based on the Three Elements of Popularity: A Case Study of Bilibili

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## Abstract

**[Purpose/Significance]** This study explores the non-content influencing factors of video popularity formation on the typical danmaku video website Bilibili, analyzing their potential impact on video popularity from the perspectives of video attributes, creator platform characteristics, and social attributes, to provide guidance for the future development of users and platforms on Bilibili and other related new media video websites. **[Method/Process]** Based on the 5W model, a video popularity formation process model was constructed, and a video popularity influencing factor model was built based on the three elements of popularity theory. Through crawling objective data, principal component analysis was used to measure popularity indicators, and multiple regression was employed for empirical research on influencing factors. **[Result/Conclusion]** The personal authentication, fan count, number of authentications of video creators, and video description length have significant positive effects on video popularity; video title length has a significant negative effect on video popularity. Videos released during people' s leisure time have higher overall popularity, while those released during sleep time have lower overall popularity.

**Keywords:** Bilibili website; video popularity; 5W mode; three elements of popularity; empirical analysis

## Introduction

Social media has become an important channel for meeting people' s needs for information, entertainment, and interpersonal communication. According to the 48th "Statistical Report on China' s Internet Development" released by the China Internet Network Information Center (CNNIC), as of June 2021, China' s internet user base reached 1.011 billion, with 21.75 million new users added since December 2020, and internet penetration reached 71.6%. Bilibili' s Q2 2021 financial report [1] shows that the platform' s monthly average active users reached 237.1 million, daily average active users reached 62.7 million, monthly active UPloaders (UP 主) reached 2.2 million, and monthly submissions reached 7.7 million. Professional User Generated Video (PUGV) content accounted for 91% of audience viewing time. Audiences seek high-quality videos to efficiently utilize their limited time and attention, and the asymmetric distribution of video popularity has become the norm [2]. Under platform policy mechanisms, video creators (UP 主) have equal opportunities for content creation, while audiences can asynchronously request content from unlimited choices [3]. Faced with such a large active user base, identifying popular works requires examining not only content but also platform structure to enhance video popularity—a critical concern for both creators and platforms. This study aims to address how the structural attributes of creators and videos themselves influence video popularity on video-based social platforms.

## Literature Review

Academic research defines “popularity” as the result of increased metrics driven by user information behaviors after content release [4], with video popularity reflecting this heat [5]. For video-based social platforms, scholars have used cumulative play counts to measure account communication effects [6] or adopted quantitative indicators such as likes, comments, and shares to comprehensively measure communication effects [7]. S. X. Ouyang et al. [5] note that view count is widely used in video popularity research, supplemented by metrics like comment or favorite counts. Bilibili’s diverse interaction features include not only view count as a basic popularity measure [8] but also danmaku count, likes, coin donations, favorites, forwards, comments, and creator fan counts [9]. Similar platforms like iQiyi display heat values that integrate user viewing, interaction, and sharing behaviors into a multi-dimensional evaluation system with reasonable comprehensive weights [10]. These approaches inform our popularity measurement approach. Based on literature and our research context, we define popularity as the result of increased metrics driven by user information behaviors during video viewing.

Existing popularity research focuses on three platforms: WeChat Official Accounts, Weibo, and online video platforms. WeChat studies have analyzed information communication components using the 5W model [4], constructed network structures [11], and examined correlations between communication heat and themes, posting times, and title features [12]. Other research has quantified title keyword popularity and semantic decomposition [13] or identified five factors (title, content, timing, data analysis, secondary forwarders) through questionnaire data [13]. Weibo and video platform research has adopted audience perspectives, measuring heat through browsing, forwarding, and commenting behaviors [14] and using uses and gratifications theory to analyze significant factors [14]. Given the high correlation between video play counts and user engagement [6], most studies use play count as a heat measure while exploring user participation impacts from different dimensions [15-16]. Considering danmaku features, scholars have examined how danmaku quantity and emotional intensity affect play counts, favorites, and coin donations [8], while also investigating moderating effects of creator fan counts and submission numbers. Most video platform research focuses on popularity evolution and prediction, including Bilibili user-generated content popularity analysis [3], YouTube popularity evolution modeling [17], long-term popularity prediction through perceptual regression models [18], and Youku popularity pattern studies [5].

In summary, video platform research concentrates on popularity prediction and questionnaire-based audience behavior analysis, but lacks comprehensive popularity measurement and objective factor identification from creator and video structure perspectives. This study addresses these gaps by using objective data to analyze structural attribute impacts on video popularity from creator and video perspectives, enriching related research and providing practical guidance for creators and Bilibili’s operations.

## Theoretical Framework and Research Hypotheses

### 2.1 5W Model and Three Elements of Popularity

Lasswell's 1948 5W model identifies five communication components: communicator (who), information (what), medium (which), audience (whom), and effect (what effect) [4]. Xing Yuqing et al. [19] similarly propose that information communication involves four elements (source, destination, channel, information), with effects influenced by communicator, audience, medium, and environment. The 5W model applies to Bilibili's information communication process.

Malcolm Gladwell's three elements of popularity theory comprises: key persons, environmental power, and content stickiness. Key persons are small groups influencing larger populations, conceptualized as "mavens" (information providers), "connectors" (information disseminators), and "salesmen" (persuaders). Information communication is affected by internal and external environments. Content stickiness refers to information characteristics that guide audience participation. This theory has been applied to Weibo research [20-21], making it suitable for Bilibili analysis. Based on these studies and platform features, we can identify quantifiable influencing factors at each level.

### 2.2 Research Model and Hypotheses

Drawing on the 5W model, Bilibili's video information communication process involves five elements: video creator (who), video and creator information (what), Bilibili platform (which), video audience (whom), and popularity (what effect). We constructed a Bilibili video popularity formation process model [Figure 1: see original paper]. Integrating the three elements theory, we identified platform structural factors affecting video popularity, analyzing creator attributes and video attributes.

#### Key Persons and Video Popularity

Creator characteristics were categorized into personal, social, and platform attributes. Personal attributes (nickname, profile description length, submission count, following count) serve as control variables to isolate platform-based heat effects.

Regarding social attributes, fan count directly represents a creator's social recognition. Cong Ting et al. [23] demonstrated significant positive correlations between fan counts and likes, while Weibo research shows each 10,000-fan increase yields eight additional forwards [20]. More fans increase engagement behaviors, substantially boosting video popularity. Therefore:

*H1a: Creator fan count has a significant positive effect on video popularity.*

Regarding platform attributes, Bilibili's incentive mechanisms strengthen creator-audience interaction through identity verification and membership systems [24]. Verification benefits include authoritative badges and prioritized search exposure. Research shows source credibility significantly affects

communication processes [25-26], with verification status influencing user attention and communication effects. Higher credibility increases acceptance and dissemination likelihood. Membership privileges provide access to premium content, enhancing creative quality and inspiration, while personalized space customization attracts attention [27]. Therefore:

*H1b: Creator membership status has a significant positive effect on video popularity.*

*H1c: Creator personal authentication has a significant positive effect on video popularity.*

*H1d: Number of creator authentications has a significant positive effect on video popularity.*

### **Environmental Power and Video Popularity**

Online content attention exhibits cumulative effects, with article lifespans following lognormal distributions [28], peaking within six hours post-publication and decaying rapidly after 24 hours. Videos published over three months before data collection were assumed to have stable metrics for reliability [27]. Environmental power factors include daily posting time and days since publication. Human activity divides into three states: working, leisure, and sleeping [20], with content posted during commutes, after work, and before bedtime gaining higher visibility [11]. Therefore:

*H2a: Videos posted during leisure time have higher overall popularity.*

*H2b: Videos posted during sleep time have lower overall popularity.*

### **Content Stickiness and Video Popularity**

Content stickiness factors primarily involve video attributes: title, tags, description, and duration. Titles provide direct information output and content distillation; longer titles increase audience aversion. Tags enable precise, multi-dimensional content marking, facilitating automatic categorization and search exposure [29]. Descriptions clarify video elements (background music, sources, creator outfits), with longer descriptions indicating higher creator knowledge quality [30]. Given information overload and scarce audience attention, video content must capture users quickly [31], while excessive duration inefficiently utilizes fragmented time. Therefore:

*H3a: Video title length has a significant negative effect on video popularity.*

*H3b: Number of video tags has a significant positive effect on video popularity.*

*H3c: Video description length has a significant positive effect on video popularity.*

*H3d: Video duration has a significant negative effect on video popularity.*

The overall model incorporates creator platform attributes, social attributes, and video attributes as independent variables, life states as grouping variables, and creator personal attributes as controls [Figure 2: see original paper].

## Empirical Study of BiliBili Video Popularity

### 3.1 Research Methods and Variable Definitions

This study used SPSS 25 and Stata 15.1. First, principal component analysis measured video popularity through audience behavior indicators. Second, multiple regression analyzed influencing factors. Finally, grouping regression by posting period was conducted with descriptive and correlation analyses. Variable measurements are detailed in Table 1. Posting periods were categorized as: working state (8:00-12:00, 14:00-18:00) = 1; leisure state (12:00-14:00, 18:00-24:00) = 2; sleep state (24:00-8:00) = 3.

### 3.2 Sample Selection and Data Sources

BiliBili's large user base, strong interactivity, and high long-term retention rates make it highly valuable for research. Video content itself affects popularity [32], so to ensure generalizability, we crawled page information across all 18 video zones. Following W. Guan [33] and Yang Deqing et al. [34], we filtered videos published over three months before collection (December 11-22, 2020) and excluded official accounts to avoid holiday/event biases [27]. After removing invalid and missing values, 5,200 valid data entries were obtained.

### 3.3 Video Popularity Measurement

BiliBili's "one-click triple support" (like, coin, favorite) incentivizes creators and significantly impacts recommendations and popularity. Based on previous research and comprehensiveness considerations, we used principal component analysis on seven audience behavior indicators: views, danmaku, likes, coins, collections, forwards, and comments. After standardization, KMO (0.820 > 0.8) and Bartlett's test ( $P < 0.05$ ) confirmed suitability. Initial analysis extracted one component (eigenvalue = 4.995, variance = 71.358%). To better capture dimensions, we specified three components (eigenvalues: 4.995, 0.686, 0.592; cumulative variance = 89.616%; weighted variances: 79.63%, 10.93%, 9.44%). Factor loadings are shown in Table 2, with linear combination coefficients and weights in Table 3, yielding the popularity formula:

$$\text{Popularity} = 0.146 \text{Views} + 0.173 \text{Danmu} + 0.131 \text{Likes} + 0.118 \text{Coins} + 0.133 \text{Collections} + 0.130 \text{Forwards} + 0.130 \text{Comments}$$

### 3.4 Descriptive Statistics and Correlation Analysis

Descriptive statistics (Table 4) and grouping by posting period (Table 5) reveal that working-state uploads show the greatest variation, leisure-state uploads are most numerous with highest popularity, and sleep-state uploads are least numerous with lowest popularity, supporting H2a and H2b. Correlation analysis (Table 6) examined relationships among variables, with VIFs (<10) confirming no multicollinearity.

### 3.5 Multiple Linear Regression Analysis

White' s test ( $\text{Prob} > \chi^2 = 0.4583 > 0.05$ ) accepted homoscedasticity. Regression results are shown in Table 7 .

#### Model Interpretation:

1. **Creator Social Attributes:** Fan count (Fans) showed positive coefficients (0.158, 0.164, 0.164) with significance  $< 0.01$  across models, supporting H1a.
2. **Creator Platform Attributes:**
  - Membership status (Im) showed negative but non-significant coefficients, rejecting H1b (likely due to low membership barriers).
  - Personal authentication (Ipi) showed positive coefficients (0.089, 0.055, 0.125), significant in Models 1 and 3 ( $< 0.01$ ) but not Model 2 (0.222), partially supporting H1c (effective during leisure but not working states).
  - Authentication count (Pcm) showed positive coefficients (0.221, 0.221, 0.209) with significance  $< 0.01$ , supporting H1d.
3. **Video Attributes:**
  - Title length (Titlel) showed negative coefficients (-0.280, -0.245, -0.301) with significance  $< 0.01$ , supporting H3a.
  - Tag count (Vln) showed negative coefficients (-0.052, -0.056, -0.050) with significance  $< 0.01$ , rejecting H3b (likely due to tag abuse).
  - Description length (Vil) showed positive coefficients (0.039, 0.049, 0.036) with significance  $< 0.05$ , supporting H3c.
  - Duration showed mixed, non-significant coefficients, rejecting H3d (audiences can adjust playback speed).

Model 4 (sleep state) showed only title length significantly affected popularity (-0.333,  $P < 0.01$ ), consistent with reduced creator activity and audience engagement during sleep hours, further validating H2b.

## Research Conclusions and Implications

### 4.1 Conclusions

Based on the three elements of popularity theory, this study examined BiliBili video popularity from key persons, environmental power, and content stickiness perspectives. The robust models reveal:

1. **User routines dominate popularity:** Similar to Fang Jing and Wang Di' s findings, but with clearer time-state divisions, showing posting time differences substantially impact popularity.
2. **Creator social influence significantly affects popularity:** Consistent with Liu Xingjun and Zhao Rongying, creators with more fans generate greater engagement across platforms.

3. **Creator authority attracts attention:** Aligning with S. W. Sussman and Sun Tingting, comprehensive identity features enable audiences to infer source credibility, influencing popularity.
4. **Optimal video structure planning enhances popularity:** Appropriate title length, clear tags, and explanatory descriptions guide audience information processing. This expands research on user participation, video popularity, and video structure, offering practical insights for creators and platforms.

## 4.2 Recommendations and Future Research

**Recommendations:** 1. **Optimize posting timing:** Considering review delays, creators should post during audience leisure times to align with daily routines and maximize popularity. 2. **Enhance self-presentation:** Creators should actively display authoritative identities through effective personal authentication to build trust and recognition. 3. **Rationalize video structure:** Use tags judiciously for traffic attraction; set concise titles for fragmented-time audiences; summarize video content in descriptions to attract viewers.

**Limitations:** This study used objective data, neglecting subjective user emotions in comments/danmaku and external factors like cultural atmosphere or IT environment. Demographic data and weekend effects were not controlled, though research shows weekend uploads exceed weekday volumes [3], potentially causing bias. Future research should address these limitations through qualitative sentiment analysis and more comprehensive data collection.

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**Author Contributions:** Ji Haixiang: conceptualization, literature review, data collection and analysis, writing-original draft; Ren Nan: supervision, methodology, writing-review and editing.

*Note: Figure translations are in progress. See original paper for figures.*

*Source: ChinaXiv –Machine translation. Verify with original.*