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THE INTERACTIVE EFFECTS OF TITLE SENTIMENT AND LENGTH ON VIDEO DISSEMINATION: OPTIMAL LENGTH AND THE DIMINISHING RETURNS OF EMOTION

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Abstract: In the highly competitive ecosystem of online video platforms, metadata elements such as titles are critical determinants of user engagement. This study uses computational communication methods to explore the interactive effects of title sentiment intensity and title length on video view counts for automotive videos on the Bilibili platform. Through hierarchical regression analysis on a large-scale dataset of 984 videos, and supported by non-parametric Generalized Additive Models (GAM) and bootstrap analysis for robustness, this research reveals two key findings: First, there is a significant inverted U-shaped relationship between title length and video views, meaning views increase with length up to a peak at approximately 26-30 characters, and then decline. Second, title length plays a negative moderating role in the relationship between sentiment intensity and views. This finding suggests that emotional language is more effective in attracting user attention in short titles, but its appeal diminishes in longer, more information-dense titles, and may even have a negative impact if perceived as "clickbait." These findings offer nuanced, data–driven strategies for content creators and digital marketers for optimizing video metadata to maximize audience engagement on competitive digital platforms.
Keywords: User engagement; Sentiment analysis; Video analytics; Title optimization; Moderation analysis; Computational communication

1 INTRODUCTION

The proliferation of online video platforms has fundamentally reshaped the landscape of media consumption and information dissemination. Platforms like YouTube, TikTok, and Bilibili have evolved into primary arenas where billions of users seek entertainment, education, and product information [1]. For high-involvement consumer goods such as automobiles, these platforms serve as a critical channel where potential buyers engage in extensive information-seeking, watching reviews, comparisons, and test-drive experiences to inform their purchasing decisions [2]. In this densely saturated media environment, the competition for user attention is ferocious. An estimated 500 hours of video are upload to YouTube every minute, creating a situation where the supply of content vastly exceeds the audience's limited attentional capacity [3].
This content overload places immense importance on the role of metadata—particularly video titles—in the initial, crucial stage of content discovery. A video's title is often the first point of contact with a potential viewer, functioning as a powerful signal that influences the decision to click and watch [4]. It must be compelling enough to stand out in a crowded feed of recommendations and search results, effectively communicating the video's content and value proposition in a fleeting moment. Consequently, understanding the specific characteristics of titles that drive viewership is a paramount concern for content creators, digital marketers, and platform algorithm designers alike.
This study focuses on Bilibili, a uniquely influential platform in the Chinese digital ecosystem. Unlike its global counterparts, Bilibili has cultivated a distinctive community culture centered around its predominantly Generation Z user base, user-generated content from creators (known as "UPs"), and its signature "bullet comments" (danmu)—a real-time, overlaying commentary system that fosters a strong sense of co-viewing and community participation [5]. This highly engaged and interactive environment makes Bilibili an ideal laboratory for studying the dynamics of content engagement [6].
Previous research has identified two primary title characteristics as key drivers of engagement: emotionality and length. Studies in communication and marketing have consistently shown that content evoking strong emotions, whether positive or negative, is more likely to be shared and consumed [7]. Simultaneously, the length of a headline or title has been shown to influence readability and cognitive load, with a general consensus that an optimal length exists, avoiding the pitfalls of being either un-informatively brief or overwhelmingly verbose [8].
However, a significant gap persists in the literature. Most studies have examined these factors in isolation, neglecting their potential interactive effects. It is plausible that the effectiveness of an emotional cue is not uniform but is contingent on the overall structure of the title, such as its length. For instance, is a strong emotional appeal equally effective in a concise, 15–

character title as it is in a descriptive, 40–character one? Furthermore, many studies assume a linear relationship, whereas the true effect could be curvilinear, featuring points of diminishing returns.

This research addresses this gap by investigating the individual, non–linear, and interactive effects of title sentiment intensity and title length on the view count of automotive videos on Bilibili. The automotive sector has chosen for its status as a high–involvement category where viewers are motivated information seekers, making title accuracy and appeal particularly salient [9]. By employing a computational approach on a large–scale dataset, this study seeks to answer the following research questions:

(1) What is the nature of the relationship between video title length and view count? Is it linear or curvilinear?

(2) What is the relationship between the emotional intensity of a video title and its view count?

(3) Does title length moderate the relationship between sentiment intensity and view count?

By answering these questions, this paper aims to provide a more nuanced and holistic understanding of video title optimization. The findings will contribute to communication theory by elucidating the complex interplay of informational and emotional cues in digital media, while also offering practical, data–driven guidelines for stakeholders in the digital content ecosystem.

2 LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 Video Titles as Information Scent

In the vast information landscape of the internet, users behave like foragers, seeking valuable content while trying to minimize effort. Information Foraging Theory (IFT) posits that users decide which content to pursue based on "information scent"—cues in their environment that signal the potential value and cost of accessing a piece of information [10]. In the context of video platforms, a video's title, along with its thumbnail, constitutes the primary information scent. A strong scent convinces the user that clicking the video will lead to relevant, useful, or entertaining content that satisfies their current information need [11].

The quality of this scent has determined by the characteristics of the title. Two fundamental components contribute to this quality: the informational content and the affective (emotional) content. The length of the title has directly related to the amount of information it can convey. A very short title may provide insufficient scent, leaving the user uncertain about the video's content. Conversely, a very long title might create an overwhelming scent, increasing cognitive load and making it difficult for the user to parse its relevance quickly [12]. This suggests that the relationship between the informational value of a title and its length is not linear. There likely exists a "sweet spot" where the title is descriptive enough to provide a strong scent without inducing cognitive friction [13]. This leads to the hypothesis of a non-linear, inverted U-shaped relationship between title length and user engagement.

H1a: There is a positive linear relationship between video title length and view count.

H1b: There is a negative quadratic relationship between video title length and view count, suggesting an inverted U-shaped curve where view count increases with length up to an optimal point and then decreases.

2.2 The Role of Emotionality in Driving Engagement

The second critical component of information scent is its affective quality. Decades of research in psychology and communication have established that emotion is a powerful driver of attention, memory, and behavior [14]. Content that elicits an emotional response is more likely to been noticed, processed, and shared. This phenomenon is explained by theories such as the Elaboration Likelihood Model (ELM), which suggests that cues evoking emotion can act as powerful peripheral signals that influence attitudes and behaviors, especially when viewers are not deeply engaged in systematic processing (e.g., when scrolling through a feed) [15].

Berger & Milkman (2012) found that The New York Times articles that evoked high-arousal emotions (like awe, anger, or anxiety) were more likely to become viral [16]. Similarly, studies of social media posts have found that both positive and negative sentiment can increase engagement, often mediated by the level of emotional arousal [17].

The intensity of the emotion, rather than just its positive or negative valence, appears to be a key mechanism. A title with high emotional intensity—whether strongly positive (e.g., "The Most INCREDIBLE Car I've Ever Driven!") or strongly negative (e.g., "Why This Car is a COMPLETE Disaster!")—creates a stronger affective scent, promising a more engaging or dramatic viewing experience compared to a neutral, purely factual title (e.g., "A Review of the 2024 Model X") [18]. The distribution of sentiment scores in the dataset, which peaks at moderate levels but also shows a wide spread, suggests that creators are experimenting with varying levels of emotionality. The bivariate analysis indicates a complex, U- shaped relationship, where both very low (neutral) and very high-intensity titles perform better than moderately emotional ones. This suggested that being emotionally unambiguous, either by being purely factual or highly emotional, is a superior strategy [19].

H2: Higher emotional intensity in a video title is associated with a higher view count.

2.3 The Interaction of Length and Sentiment: A Moderation Hypothesis

The central argument of this paper is that the effects of title length and sentiment intensity are not independent. We propose that title length moderates the effect of sentiment on viewership. This hypothesis is grounded in the principles of cognitive load and signal clarity. The cognitive resources a user is willing to expend on evaluating a single video title are extremely limited. The processing of emotional cues must therefore be efficient [20].

When a title is short, it has low cognitive load. In this context, an emotional word or phrase acts as a very clear and potent signal. It is the dominant component of the information scent and can effectively capture attention. For example, in a short title like "Mind-Blowing Speed!", the emotional component is unambiguous and powerful.

However, as a title gets longer, its informational density increases. It contains more descriptive keywords, technical specifications, or contextual phrases. This increased length demands more cognitive effort from the user to read and comprehend. In this high-load context, the role of the emotional cue changes. A strong emotional term embedded in a long, descriptive title may be perceived differently. It could be seen as incongruous with the factual tone, potentially reducing the title's credibility and making it appear as "clickbait" [21]. Alternatively, the emotional signal might simply get lost amidst the other informational cues, its potency diluted. The user, already expending effort to process the title's length, may be less receptive to a strong emotional appeal. This suggests that the positive effect of sentiment intensity should weaken as title length increases, and may even become negative for very long titles [22].

This proposed mechanism is visually suggested in the binned heat-map in the present paper, which displays the actual mean view counts for different combinations of title length and sentiment score bins. For instance, within the longest title length bin (31-36), the view count does not consistently increase with sentiment, showing a much more erratic pattern compared to shorter length bins. This provides preliminary evidence for an interaction [23].

H3: Video title length negatively moderates the relationship between sentiment intensity and view count. Specifically, the positive effect of sentiment intensity on view count will be stronger for shorter titles and weaker (or even negative) for longer titles.

3 METHODOLOGY

3.1 Data Collection and Sampling

The dataset for this study was compiled from Bilibili (bilibili.com), a prominent video-sharing platform in China known for its extensive user-generated content and highly engaged community. Data collection was performed using a custom Python-based web scraping script.

The collection period spanned from July 2019 to December 31, 2024, to capture a wide range of videos over time.

The sampling process focused on videos within the automotive content category, which includes a variety of sub-topics such as vehicle reviews, test drives, model comparisons, and brand events. To ensure the sample's diversity and representativeness, videos were collected from creators of varying scales and audience levels, rather than focusing solely on top-tier influencers. This approach enhances the generalizability of the findings across the broader automotive content ecosystem on the platform.

An initial raw dataset was subjected to a data cleaning process. Videos were excluded if they met any of the following criteria: poor image quality, absence of key information (e.g., identifiable persons or vehicles), or asynchronous audio and video. After this filtering process, a final sample of N=984 videos was retained for analysis. For each video in the final dataset, key metadata were extracted, including the video title, view count, and publication date.

3.2 Measurement of Variables

3.2.1 Dependent variable: view count

The primary dependent variable, representing the reach and popularity of a video, is its total view count. As is common with online media engagement data, the raw distribution of view counts was highly right-skewed, as illustrated in Figure 1A.The mean view count (813,272) was significantly larger than the median (563,728), indicating the presence of high-performance outliers that violate the assumptions of ordinary least squares (OLS) regression. To normalize the distribution and stabilize the variance, a natural logarithmic transformation was applied (Log_View_Count = ln (View_Count)). The resulting transformed variable, shown in Figure 1B, closely approximates a normal distribution, making it suitable for parametric statistical analysis.

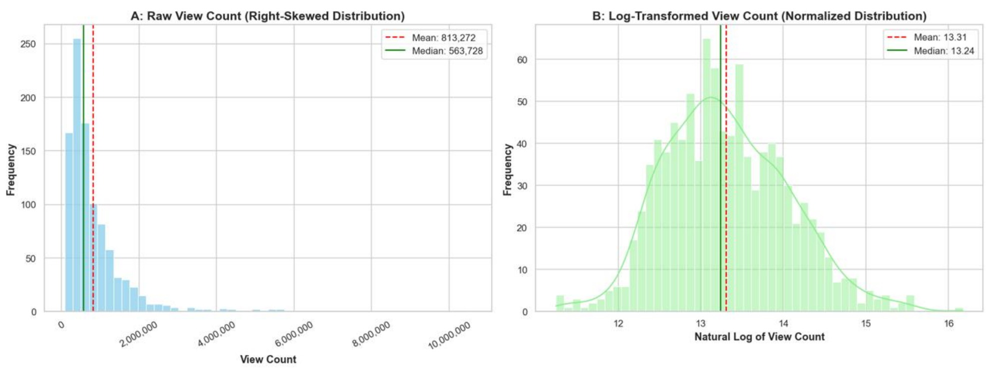

Figure 1 Distribution of View Count

3.2.2 Independent variables: title length and sentiment intensity

Title Length: This variable was measured as the total number of characters in the video's title. The distribution of title lengths, shown in Figure 2, ranged from 3 to 49 characters, with a mean of 17.94 and a median of 17.00.

Sentiment Intensity Score: The emotional intensity of each title was quantified using a sophisticated two-step process. First, a pre-trained BERT (Bidirectional Encoder Representations from Transformers) multilingual sentiment classification model was employed. This model trained on a five-star rating system, is adept at capturing both the polarity (positive/negative) and magnitude of sentiment in text. For each title, the model calculated a raw sentiment score (Sraw) by computing a weighted probability average, which was then standardized to a [0, 1] interval. On this scale, 0 represents the most negative sentiment, 1 represents the most positive, and values around 0.5 are neutral.

Second, recognizing that user engagement is often driven by the magnitude of emotion rather than its direction, the raw score was converted into an intensityscore (Sintensity). This was achieved using the formula: Sintensity=2* |Sraw-0.5|. This transformation maps titles with sentiment scores near the neutral midpoint (0.5) to intensity scores near 0, and titles with scores near the extremes (0 or 1) to intensity scores near 1. The final sentiment intensity score, therefore, ranges from 0 (completely neutral) to 1 (maximum emotional intensity). The distribution of this final score is presented in Figure 3.

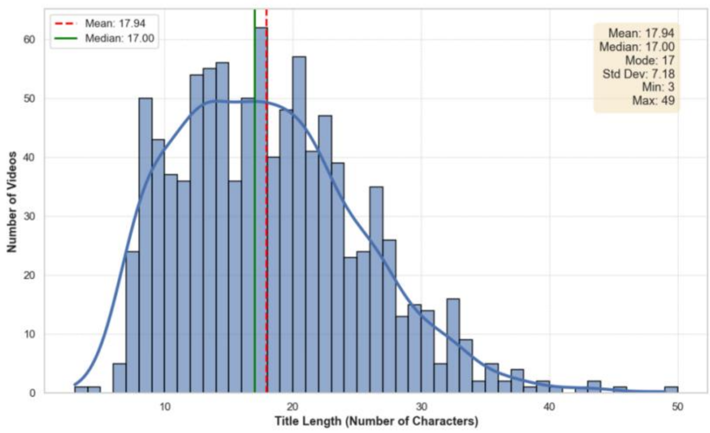

Figure 2 Distribution of Title Length

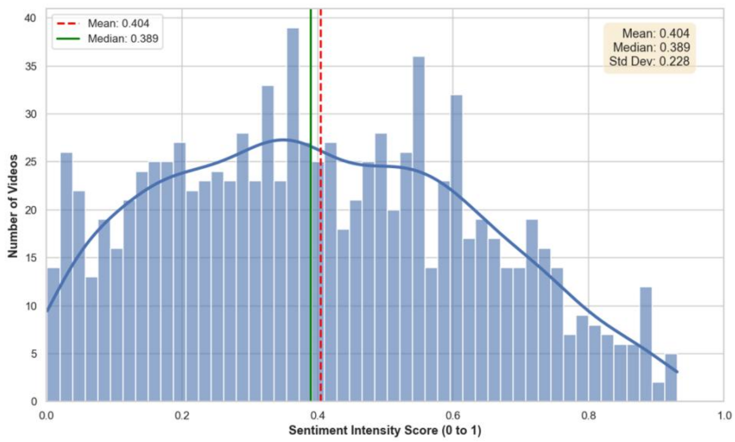

Figure 3 Distribution of Sentiment Intensity Score

3.2.3 Control variable

To account for potential temporal effects, such as platform algorithm changes or shifts in user behavior over the long data collection period, a control variable for publication date was included. Videos were categorized into two groups: those published before July 2023 ("older") and those published on or after July 2023 ("newer").

3.3 Analytical Strategy

The data analysis was conducted in three main stages. First, descriptive statistics and visualizations were used to characterize the distributions of all key variables and to conduct a preliminary exploration of the bivariate relationships. This included plotting the distribution of view counts before and after log transformation (Figure 1), the distributions of title length (Figure 2) and sentiment intensity (Figure 3), and creating binned plots to visualize the mean view counts across different strata of sentiment intensity (see Figure 4) and title length (see Figure 5).

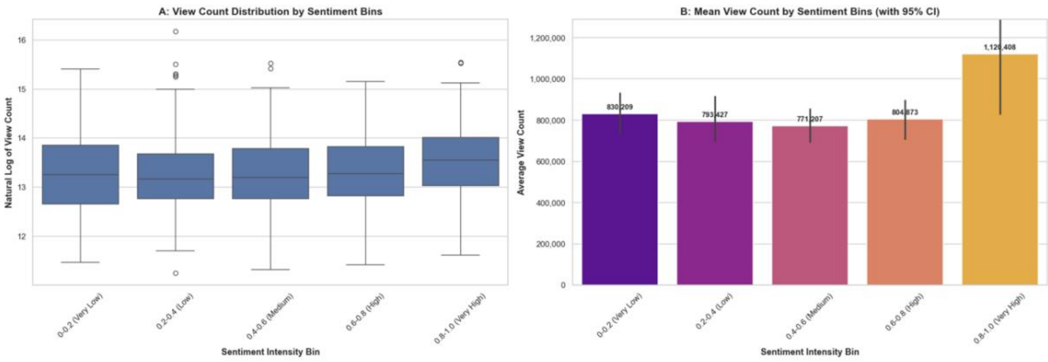

Figure 4 View Count Analysis by Binned Sentiment Intensity

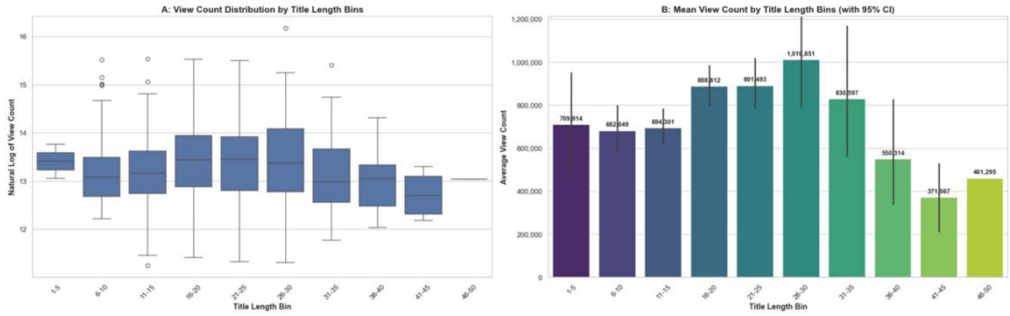

Figure 5 View Count Analysis by Binned Title Length

Second, to formally test the hypotheses, a hierarchical OLS regression analysis was performed on the log–transformed view count. This approach allows for a systematic assessment of the explanatory power added by each set of variables. Four nested models were specified:

- Model A: Included only the sentiment variable (Log_View_Count ~ Sentiment +Sentiment_sq).
- Model B: Included only the length variables (Log_View_Count ~ Length + Length_sq).
- Model C (Main Effects Model): Included all main effect terms (Log_View_Count ~ Sentiment + Sentiment_sq + Length + Length_sq).
- Model D (Interaction Model): Included all main effects plus the interaction term to test the moderation hypothesis (Log_View_Count ~ Sentiment + Sentiment_sq + Length + Length_sq + Sentiment * Length).

The quadratic terms (Sentiment_sq and Length_sq) were included to model the hypothesized non–linear relationships. Model fit was compared across the hierarchy using the Adjusted R^2 statistic.

Third, to ensure the robustness and validity of the findings from the primary regression analysis, two additional analyses were conducted. A non–parametric Generalized Additive Model (GAM) was fitted to visualize the interaction surface without the constraints of a pre–specified functional form. Furthermore, a bootstrap analysis (500 resamples) was performed on the interaction coefficient from Model D to assess its stability and to compute a robust 95% confidence interval.

4 RESULTS

4.1 Descriptive Statistics

The final dataset comprised 984 videos. The primary dependent variable, view count, exhibited a wide range, with a mean of 813,272 and a standard deviation of 798,253. As shown in Figure 1, the log–transformed view count was normally distributed with a mean of 13.31 and a standard deviation of 0.747. The independent variables also showed considerable variation. The title sentiment intensity score had a mean of 0.404 (SD = 0.228). The title length ranged from 3 to 49 characters, with a mean of 17.94 (SD = 7.18). The distributions of sentiment and length are visualized in Figure 2 and Figure 3, respectively.

4.2 Bivariate Analysis

Preliminary analysis of the relationships between the independent variables and view count was conducted by grouping the data into bins. Figure 4 shows the average view count across five sentiment intensity bins. A U–shaped or J–shaped pattern is observable. The lowest average view count was found in the medium sentiment bin (0.4–0.6), while the highest average was in the very high sentiment bin (0.8–1.0), which had a mean view count of 1,120,408. This suggests that both emotionally neutral and highly charged titles outperform moderately emotional ones.

Figure 5 displays the average view count across ten title length bins, revealing a clear inverted U–shaped relationship. Viewership increases with title length, peaks in the 26–30 character bin with a mean of 1,010,851 views, and then declines steadily for longer titles. The lowest performance was observed in the 41–45 character bin. This provides strong initial support for H1b, positing a curvilinear effect of title length.

4.3 Hierarchical Regression Analysis

To formally test the hypotheses, a hierarchical OLS regression was performed. The progression of model fit is visualized in Figure 6A. Model A (sentiment only) explained very little variance (Adj. R^2=0.0030). Model B (length only) provided a substantial improvement (Adj. R^2=0.0164). The main effects model (Model C) offered a slight improvement over Model B (Adj. R^2=0.0181). The final interaction model (Model D) yielded the best fit, with an Adjusted R^2 of 0.0220. The statistically significant increase in explanatory power from Model C to Model D underscores the importance of the interaction term.

The detailed results for the final model (Model D) are visualized in the coefficient plot in Figure 6B. The key findings are as follows:

(1) Title Length: The linear term for ‘Length’ was positive and highly significant (β=0.0660, p<0.001), while the quadratic term ‘Length_sq’ was negative and highly significant (β=-0.0012, p<0.001). This pair of coefficients provides strong statistical confirmation for the inverted U-shaped relationship hypothesized in H1b.

(2) Sentiment Intensity: In the final model, the main effects for ‘Sentiment’ (β=0.2499, p=0.524) and ‘Sentiment_sq’ (β= 0.5976, p=0.169) were not statistically significant. This suggests that, after accounting for title length and the interaction effect, sentiment does not have a simple, direct impact on view count, lending indirect support to the moderation hypothesis.

(3) Interaction Effect: Crucially, the interaction term ‘Sentiment_Length’ was negative and statistically significant (β =-0.0325, p=0.027). This result supports H3, indicating that title length negatively moderates the effect of sentiment intensity on log-transformed view count.

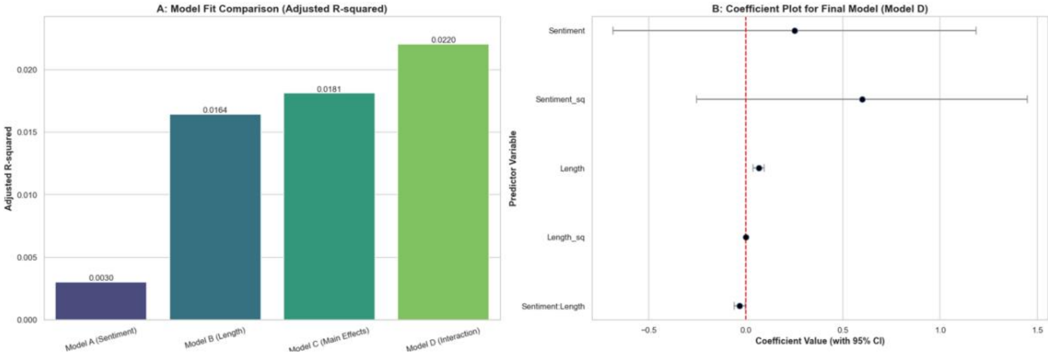

Figure 6 View Count Analysis by Binned Title Length

4.4 Visualization of the Interaction Effect

The nature of the significant interaction effect is detailed in the visualizations presented in Figure 7. The Conditional Effects Plot (Panel B) is key to interpretation. It displays the predicted relationship between sentiment score and view count at three different levels of title length (short, medium, and long). For short titles (e.g., ~10.8 characters), the slope is positive and steep, indicating that higher sentiment strongly predicts higher viewership. For medium-length titles (e.g., ~18.0 characters), the positive slope is weaker. For long titles (e.g., ~26.8 characters), the slope becomes slightly negative. This plot vividly illustrates the moderating role of title length. The Interaction Heatmap (Panel C) visualizes the model's predictions across the entire continuous range of both variables, confirming the interaction.

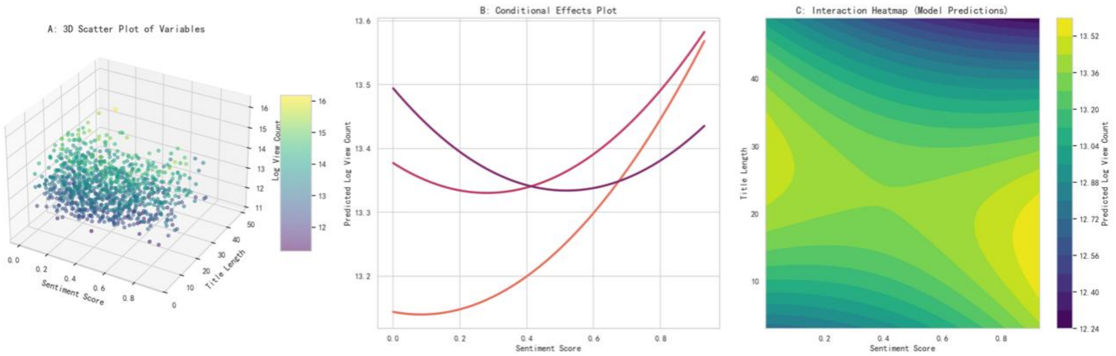

Figure 7 Interaction Visualizations

5 ROBUSTNESS CHECKS

To ensure the reliability of the regression results, two additional analyses conducted. Further diagnostic plots for the sentiment variable and model residuals are provide in Figure 8, showing acceptable patterns for the regression assumptions. The 2D density analyses in Figure 9(Hexbin Plot) and Figure 10(Binned Heatmap) provide a non–parametric view of the data, revealing the actual concentrations of high–viewership videos and supporting the patterns identified by the regression model.

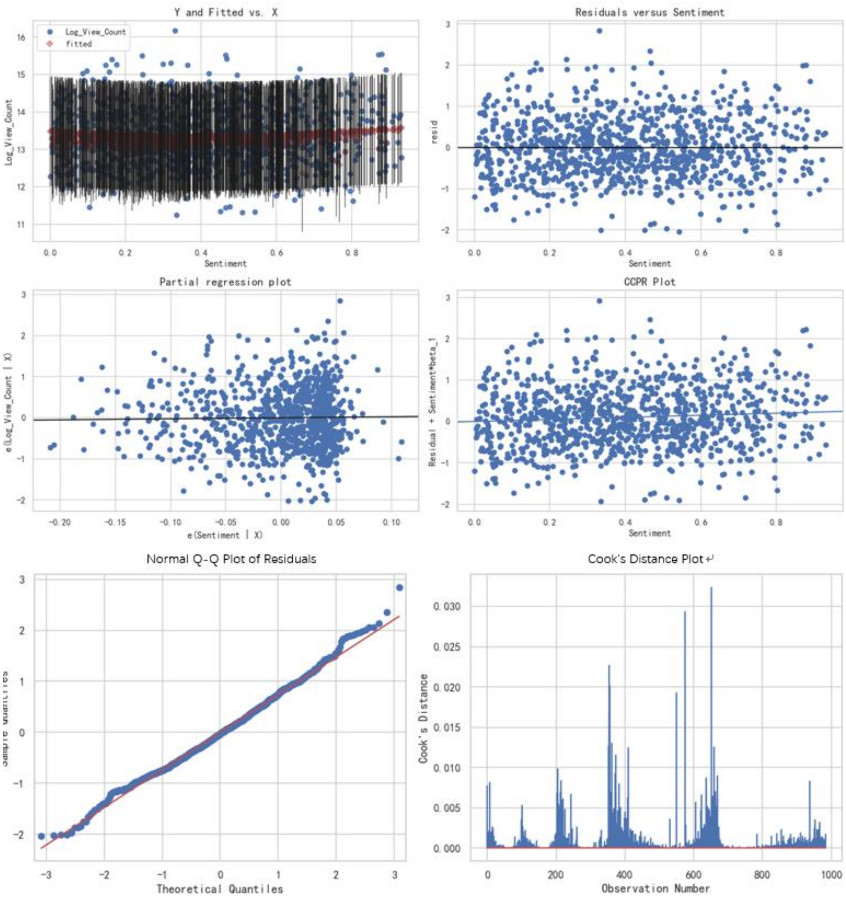

Figure 8 Diagnostic Plots for Sentiment Variable 2D Density Analysis

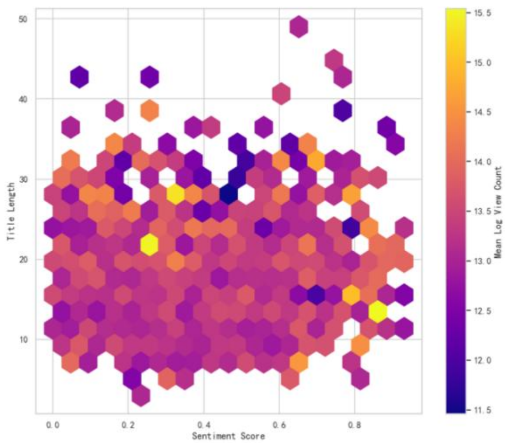

Figure 9 2D Density Analysis (Hexbin Plot)

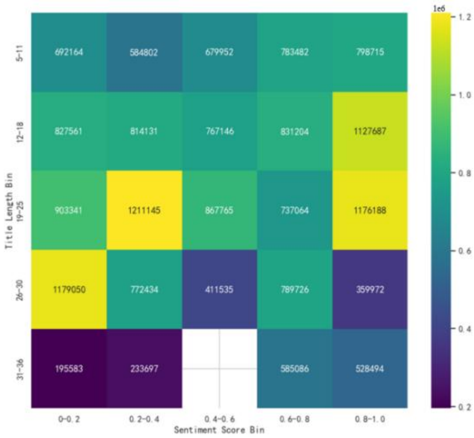

Figure 10 Binned Coupling Analysis (2D Binned Heatmap)

5.1 Non-Parametric Validation with Generalized Additive Model (GAM)

The OLS regression model assumes a specific functional form. To relax this assumption, a Generalized Additive Model (GAM) was fitted. Figure 11 presents the interaction surface plot from the GAM analysis. The GAM plot reveals a complex interaction surface that, while more flexible, corroborates the primary finding from the regression model. It shows that the effect of sentiment on viewership is not uniform across all title lengths. The general pattern observed in the GAM surface is consistent with the interaction found in Model D, lending non–parametric support to our conclusions.

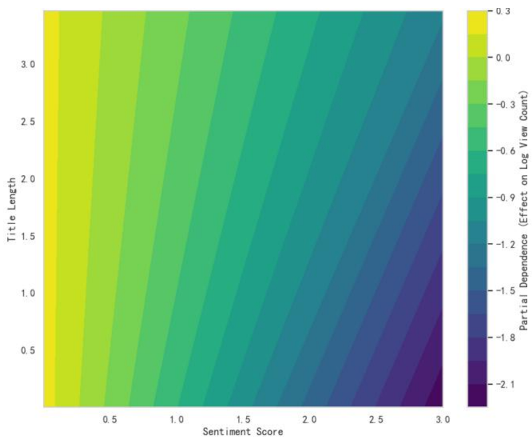

Figure 11 GAM Interaction Surface

5.2 Bootstrap Analysis of the Interaction Coefficient

To assess the stability of the estimated interaction coefficient, a bootstrap analysis was performed (500 resamples). Figure 12 displays the bootstrap distribution of the Sentiment*Length, interaction coefficient. The distribution is approximately normal. Most importantly, the 95% confidence interval derived from the bootstrap distribution is [–0.064, –0.003]. As this interval does not contain zero, we can confidently conclude that the negative interaction effect is statistically significant and robust. This analysis strongly reinforces the central finding of the study.

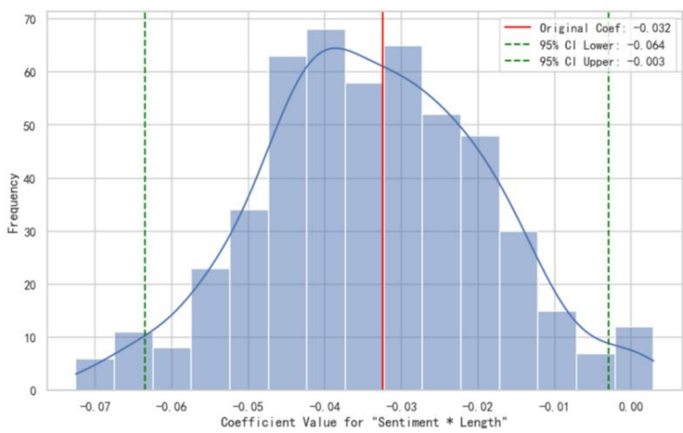

Figure 12 Bootstrap Distribution of the Interaction Coefficient

6 DISSCUSSION

6.1 Summary of Key Findings

This study set out to dissect the complex, interactive relationship between video title sentiment and length in predicting viewership on the Bilibili platform. The results from our hierarchical regression, supported by robust visualization and validation techniques, offer a nuanced perspective that advances both communication theory and practical content strategy.
The investigation yielded two primary findings. First, we confirmed a significant inverted U – shaped relationship between title length and view count. Viewership tends to increase as titles become more descriptive, but only up to an optimal point of approximately 26–30 characters, after which performance declines. This suggests a trade–off between providing sufficient information scent and imposing excessive cognitive load.
The second and more novel finding is the significant moderating role of title length on the effect of sentiment intensity. Our analysis revealed a negative interaction, meaning the positive impact of a strong emotional hook on attracting viewers is most potent in shorter titles. As titles grow longer and more informationally dense, the effectiveness of this emotional appeal diminishes and can even become detrimental. This interaction is the core contribution of our paper, highlighting that the "rules" for using emotional language in titles are not universal but are conditional on other structural characteristics of the title.

6.2 Theoretical Implications

These findings have important implications for communication theories applied to digital media. They enrich Information Foraging Theory (IFT) by demonstrating that "information scent" is not a simple sum of its parts. Rather, different cues within the scent—in this case, informational cues (length) and affective cues (sentiment)—interact with each other. A strong affective cue can enhance a weak informational signal (a short title) but may conflict with or be diluted by a strong informational signal (a long title). This suggests that the cognitive calculus users perform when evaluating content is interactive and context–dependent.
The results also resonate with the Elaboration Likelihood Model (ELM). The interaction can be interpreted through the lens of central versus peripheral processing. A short, emotional title may function primarily as a peripheral cue, quickly capturing attention and prompting a click with minimal cognitive effort. A long, descriptive title invites more central, systematic processing, where the user evaluates its informational relevance. In this mode, a strong emotional plea might be perceived as a persuasive tactic rather than a genuine signal of content quality, leading to skepticism or dismissal. Our study suggests that the effectiveness of a peripheral cue (emotion) is attenuated when the message format encourages more central processing (length).

6.3 Practical Implications

The conclusions of this research offer direct, actionable insights for a range of stakeholders in the online video ecosystem:
(1) For Content Creators and Digital Marketers: The findings provide a data–driven guide for title optimization. The simple advice to "be more emotional" is insufficient. Instead, a more nuanced strategy is required:
1. Optimal Length: Aim for titles in the 26–30 character range, as this appears to be the "sweet spot" for maximizing average views in the automotive category.
2. Conditional Emotionality: If a short, punchy title is desired, incorporating strong emotional language is an effective strategy to make it stand out. If a longer, more descriptive title is necessary to convey complex information, it may be wiser to adopt a more neutral, factual tone to maintain credibility and clarity.
3. Avoid Extremes: Very long titles (>40 characters) consistently underperform and should generally be avoided.
(2) For Platform Algorithm Designers: Recommendation and search algorithms could be refined to account for these interaction effects. Instead of simply up–ranking content with high–sentiment titles, algorithms could learn to weigh sentiment differently based on title length and other features. Recognizing that the "ideal" title is contextual could lead to more accurate predictions of user engagement and better content recommendations.

6.4 Limitations and Future Research

While this study provides valuable insights, several limitations must be acknowledged. First, the data is correlational, and therefore we cannot make definitive causal claims. While we have identified strong associations, experimental studies (e.g., A/B testing different title versions for the same video) would be necessary to establish causality.
Second, our findings are specific to one content genre (automotive) on a single platform (Bilibili). The optimal title length and the nature of the sentiment-length interaction may differ across other content categories (e.g., entertainment, education) and other platforms with different user demographics and interface designs. Future research should seek to replicate these findings in different contexts to assess their generalizability.
Third, this study focused exclusively on the title. A video's success is determined by a multitude of factors, including the thumbnail image, video tags, creator reputation, and the actual quality of the content. Future studies should aim to incorporate these variables into more comprehensive predictive models. For instance, analyzing the congruence between the emotion conveyed in the title and the emotion conveyed in the thumbnail could yield further insights.

Finally, while we controlled for the publication period, the exact time node for collecting view count data was not specified in the original dataset description. Future work should standardize this metric (e.g., view count at 7 days or 30 days post-publication) to ensure perfect comparability across all videos.

7 CONCLUSION

In the relentless battle for audience attention on digital platforms, a video's title serves as its essential opening gambit. This study demonstrates that crafting the perfect title is an exercise in managing a delicate balance between informational clarity and emotional appeal. Our analysis of 968 automotive videos from Bilibili reveals a distinct inverted U-shaped relationship between title length and viewership, pinpointing an optimal range of 26-30 characters that yielded the highest average of over 1 million views. Crucially, we moved beyond simple main effects to uncover a significant negative interaction (\beta = -0.0325) between title length and sentiment intensity. This finding indicates that the effectiveness of an emotional appeal is not universal. High emotional intensity, while capable of generating the highest average viewership (over 1.1 million views in the highest sentiment category), is most beneficial in shorter titles. As titles become longer and more descriptive, the positive impact of sentiment diminishes and can even become detrimental, a pattern confirmed by our conditional effects analysis. This research, validated through non-parametric models and bootstrap analysis, provides a robust, empirical foundation for understanding the complex dynamics of user engagement with video metadata. It moves the conversation from what works (e.g., emotion, length) to when and how these elements work together, offering a more sophisticated framework for content optimization in the digital age.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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REFERENCES

[1] Mishra A. The Rise of Short-Form Video: A Digital Revolution. International Journal of Research Publication and Reviews, 2025, 6(6): 1-5.
[2] Chaudhari P. To Study the Influence of Digital Platforms on Consumer Behavior in the Indian Automobile Industry. International Journal of Research Publication and Reviews, 2025, 6(5): 1-7.
[3] Charle Agency. 32 YouTube Statistics 2025: Key Insights & Trends You Need to Know. 2025.
[4] Erdogmuş N, Esen E. The Influence of Video Format on Engagement and Performance in Online Learning. Brain Sciences, 2021, 11(2): 128.
[5] Guo W, Chen X. The Impact of Bilibili on Gen Z's Cohort Identity and Aesthetic Resonance. In: Proceedings of the 2023 International Conference on Human-Computer Interaction, 2023: 143-150.
[6] Chen Z, He Q, Mao Z, et al. Governing Generation Z in China: Bilibili, bidirectional mediation, and technological politics. The Information Society, 2023, 39(2): 82-94.
[7] Alamäki A, Dirin A, Huotari ML, et al. Expanding knowledge on emotional dynamics and viewer engagement in travel vlogs: An automated content analysis approach. Journal of Hospitality and Tourism Management, 2024, 60: 220-230.
[8] Prinz-Weiß A, Grünewald K, Nottelmann L, et al. Caption it! The impact of headings on learning from texts. Applied Cognitive Psychology, 2023, 37(5): 1041-1052.
[9] Al-Wreikat A, Bin Kadir Shahar H, Abu Seman N, et al. The impact of social media influencers on customers' perceived values, attitudes and purchase intentions in the fashion apparel industry: moderating effect of brand reputation. Journal of Business and Socio-economic Development, 2025.
[10] Chen X, Zhang X. Exploring Prototypicality Adherence Effects on User Engagement in Video Recommender Systems. Electronic Commerce Research and Applications, 2024, 65: 101400.
[11] Liu Y, Zhang L, Chen X. Developers' information seeking in Question & Answer websites through a gender lens. Information and Software Technology, 2024, 171: 107429.
[12] Kim J, Yang X. The effect of subtitle format on cognitive load and comprehension. Technology, Pedagogy and Education, 2024: 1-18.13.
[13] Chen Y. Impacts of titles on user engagement in short video platforms. Master's thesis, Singapore Management University, 2023.
[14] Tyng CM, Amin HU, Saad MNM, et al. The Influences of Emotion on Learning and Memory. Frontiers in Psychology, 2017, 8: 1454.
[15] Kitchen PJ, Kerr G, Schultz DE, et al. A meta -analysis of the elaboration likelihood model in the electronic word of mouth literature. International Journal of Consumer Studies, 2022, 46(5): 1880-1900.
[16] Berger J, Milkman KL. What Makes Online Content Viral? Journal of Marketing Research, 2012, 49(2): 192-205.

[17] Hasell A, Weeks BE. Engagement in Emotional News on Social Media: Intensity and Type of Emotions. Journalism & Mass Communication Quarterly, 2020, 99(1): 95-117.
[18] Kim J, Yang X. Less is more: Engagement with the content of social media influencers. Journal of Business Research, 2024, 172: 114830.
[19] Hasell A, Weeks BE. Engagement in Emotional News on Social Media: Intensity and Type of Emotions. Journalism & Mass Communication Quarterly, 2020, 99(1): 95-117.
[20] Skulmowski A, Rey GD. Understanding Cognitive Load in Digital and Online Learning: A New Perspective on Extraneous Cognitive Load. Educational Psychology Review, 2021, 34(1): 171-196.
[21] Pal A, Chua AY, Goh DH-L, et al. Click me… ! The influence of clickbait on user engagement in social media and the moderating role of digital literacy. PLoS ONE, 2022, 17(6): e0266743.
[22] Kuiken J, Schuth A, Spitters M, et al. The impact of advertisement disclosure on consumer engagement in short video advertising. Behaviour & Information Technology, 2025: 1-15.
[23] Lee J, Hong IB. Predicting video views through a sentiment analysis of titles and thumbnails. Journal of Business Research, 2024, 174: 114971.