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Effect of Title Length and Word Count on Views: Evidence from Microsoft Excel videos on YouTube

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Abstract

This study examines the influence of title length and the number of words in titles on the view counts of YouTube videos, with a focus on optimizing title characteristics to enhance viewer engagement. Using a dataset of 12,466 Microsoft Excel tutorial videos published between January 2006 and November 2023, the analysis identifies significant patterns in title characteristics that affect viewership. The results reveal a bell-shaped relationship, with both mean and median view counts peaking at specific title lengths and word counts, emphasizing the importance of striking a balance between informativeness and brevity. Furthermore, the study highlights the critical role of visual information (character count) compared to semantic information (word count) in driving video engagement. By providing actionable insights, this research offers practical, cost-efficient guidelines for creators to optimize their video titles, ultimately contributing to more effective content strategies on digital platforms.

Keywords: Video-sharing platform, Title, Viewing behaviour

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1. Introduction

Advancements in digital technology have significantly transformed the way people interact with media. Between 2006 and 2023, the media consumption time of consumers in Japan increased by 1.3 times, with the time spent on media via smartphones rising by 13.8 times [1]. A new medium that has developed alongside these changes in media interaction is the social media video sharing platform. Unlike traditional media, social media video sharing platforms allow anyone to become an information disseminator. YouTube, the central player in this domain, had an average monthly user base of 73.69 million in Japan in 2023 [2], accounting for approximately 60% of the country's population and making it a highly influential medium.

Initially, YouTube, now a colossal medium, was predominantly populated with videos aimed at entertainment purposes such as gaming, music, sports, and general entertainment. However, its usage has since diversified to include news, corporate service explanation videos, personal diaries in the form of Vlogs, and educational videos aimed at skill and knowledge acquisition. For creators and companies utilizing YouTube, attracting a larger audience to their videos is a primary objective. Under-standing the factors influencing video views has been a significant area of interest for researchers. Notably, a vast majority of total views, approximately 85%, are concentrated within a mere 3% of all channels, leaving many videos with minimal views [13]. This study, therefore, focuses on the titles of YouTube videos—an essential yet cost-effective factor influencing viewer click decisions. The objective is to elucidate the relationship between video titles and view counts, identifying the optimal title length that is neither too short nor too long,

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and to provide guidelines for creators and companies to set effective titles.

This study aims to address this gap by examining the relationship between YouTube video characteristics and viewership metrics. Specifically, we analyse the optimal title length and word count that maximize engagement. The research focuses on educational content, which is less influenced by trends and external factors, using tutorial videos related to Microsoft Office Excel, which is the most commonly used IT skill in new employee training [12], as a case study. By analysing 15,895 videos published in Japan between January 2010 and November 2023, this study evaluates how title length, view counts, and likes are correlated.

The contributions of this study are as follows:

1.Empirically identify the optimal title length and word count that maximize YouTube video viewership, revealing a bell-shaped relationship in both mean and median view counts.

2.Demonstrate the critical role of visual information (character count) over semantic information (word count) in driving engagement.

3.Provide practical, cost-efficient guidelines for creators and companies to optimize video titles, bridging the gap between content design and audience behaviour analysis.

In this research, we review existing studies on user-generated content (UGC) popularity, particularly focusing on video viewership factors on YouTube. The methodology section describes the data collection process, sampling methods, and variables analysed. The subsequent discussion section presents the study's main findings. Finally, we outline the limitations of this research and propose future directions for enhancing video engagement strategies.

2. Background

2.1. Evaluation Criteria for YouTube Content

While there is no standardized method for evaluating the popularity of YouTube videos, numerous studies have employed metrics such as total view count, daily view count, and number of likes [7,8,9,10]. The focus of evaluation varies depending on the research objective, including the popularity of the video's theme, the popularity of the video's channel, and the popularity of the video itself. This study aims to provide effective improvement methods to increase the viewership of individual videos, thus defining video popularity based on the total view count.

2.2. YouTube's Recommendation System

In the context of YouTube video viewing behaviour, selections are primarily made from recommended videos within YouTube or from search results, although direct access via external social media links also exists. YouTube's algorithm, which initially prioritized view count, has evolved into a recommendation system utilizing ma-chine learning and neural networks [3]. Issues such as the display of inappropriate videos, including misinformation and extreme content, are addressed by deletion or suppression in recommendations [4]. Google has officially stated that view count, watch time, and engagement are factors influencing recommendations [3]. Existing research indicates that the inclusion of view count and watch time in the recommendation system leads to a cascade effect, whereby videos with high view counts are more likely to gain additional views, as demonstrated by Borghol et al. (2012) [5]. Choudhari et al. (2015) highlighted that higher search rankings for videos correlate with increased view counts, with factors such as video title, description, transcription, annotations (links), view count, shares, comments, and channel reliability influencing search rankings. Notably, the video title is mentioned as one of the initial pieces of information viewers notice about a YouTube video, with a significant impact on capturing viewer interest [6].

Understanding the mutual influence between YouTube's recommendation system and view counts, and identifying the factors that affect view counts, can benefit a larger number of creators.

2.3. Factors Influencing View Counts

Tafesse (2020) investigated the impact of video title information density, emotional factors, video description information density, and number of tags on YouTube video view counts. Titles with less information density were found to be more effective in increasing view counts (negative correlation) compared to titles with higher information density, whereas the length of the description showed a positive correlation. The number of tags displayed an inverse U-shaped relationship, peaking at 17 tags. Additionally, it was noted that negative emotions attract more viewer attention than positive emotions [7]. Velho et al. (2020) identified nine factors affecting daily view counts, finding that the number of likes, channel productivity, elapsed days since video posting, and video format were significant [8].

Numerous factors influencing the popularity of YouTube videos have been explored, yet a consensus has not been established. Based on existing research, we categorized the factors that effectively influence view counts into four groups:

1) Characteristics of the Account Owner. We classified four factors under the characteristics of the account owner: the number of subscribers, the frequency of video uploads, the attributes of the account owner, and the variety of themes handled by the account. Debove et al. (2021) indicated that organizational accounts have a lower success rate compared to individual accounts, meaning that organizational accounts tend to struggle in gaining views

[9]. Velho et al. (2020) defined the productivity of a channel as the number of videos published within a certain period and stated that it is a significant factor in explaining video popularity [8]. Yoo et al. (2021) found no significant relationship between the number of subscribers and the number of views [10].

2) Characteristics of the Content. We categorized the theme of the video itself, the relevance between the account and the theme, and the length of the video under the characteristics of the content. The view count significantly varies depending on the theme or genre of the video. According to YouTube's official announcement of the top 10 YouTube videos in Japan for 2023, seven were entertainment-related, while the other three were related to diet, sports, and music, with no educational videos included. Although watch time is a factor in the search algorithm, Velho et al. (2020) stated that there is no significant correlation between video popularity (daily view count) and video length [8].

3) Effects of Promotion. Figueiredo et al. (2016) demonstrated that popular videos are more likely to be shared and promoted, leading to a cascade effect resulting in higher view counts. However, the effects of PR/promotion are heavily influenced by external factors such as other social media platforms and word-of-mouth, and the quantitative impact remains unclear [11]

4)Video Information. We classified video titles, descriptions, and thumbnails under video information. This information is crucial as it is always visible to users when deciding whether to watch a video and can be controlled and improved by the upload-er. Existing research has shown a negative correlation between the information density of video titles and view counts, while a positive correlation exists between the information density of video descriptions and view counts [7].

2.4. Impact of Video Titles

Although it has been shown that a high information density in video titles can lead to information overload, causing viewers to avoid titles with excessive information and refrain from watching the videos [7,8], this study focuses on both visual and semantic information density. If the number of characters includes all types of characters such as alphabets, hiragana (a phonetic script used for native Japanese words), katakana (a phonetic script used mainly for foreign words, names, and technical terms), numbers, and symbols, the character count reflects the visual length and complexity, indicating the visual burden on viewers processing the title. On the other hand, the number of words, defined as groups of characters separated by spaces, punctuation marks, or meaningful units, reflects semantic information density and the cognitive processing required for viewers to understand the title's content.

For instance, if visual information density alone influences viewer behaviour, a name with more characters like "Amsterdam" would be less likely to be clicked com-pared to a shorter name like "Lima." However, excluding differences in the city's attractiveness or the number of people interested in it, it is not intuitive to assume that the number of characters alone would impact click-through rates.

Furthermore, if information overload is the main factor, there should be an optimal amount of information that viewers can process, suggesting a non-linear relationship where titles with moderate information density are more likely to be clicked.

Based on this, the following hypotheses are derived:

- H1: The more characters in a YouTube video title, the lower the view count (in-formation overload).
- H2: Within a certain threshold, the more characters in a YouTube video title, the higher the view count (information insufficiency).
- H3: The more words in a YouTube video title, the lower the view count (information overload).
- H4: Within a certain threshold, the more words in a YouTube video title, the high-er the view count (information insufficiency).

3. Methodology

3.1. Data Collection

We targeted videos published on YouTube between January 2010 and November 2023. Using the official YouTube Data API provided by Google, we retrieved videos linked to channels that exactly matched the keyword “Excel”. Additionally, we restricted our dataset to videos with titles and descriptions written in Japanese. The determination of Japanese was based on the presence of "hiragana" and "katakana," which are unique to the Japanese language. Only videos containing these characters were included.

The breakdown of the videos is shown in Table 1.

Table 1. Sampled videos

Japanese Characters	Presence of Kanji	Count
Present	Not Applicable	41,943
Absent	Present	1,061
Absent	Absent	58,900

Videos that contained only kanji, which are characters of Chinese origin also used in Japanese, were predominantly videos in Chinese and were excluded from this analysis.

3.2. Data Cleaning

In keyword-based search algorithms, irrelevant channels and videos, such as those related to the cosmetic brand "Excel" or the Japanese major café chain "Excelsior," often appear in the results instead of videos about Microsoft Excel software. To address this issue, we employed Non-negative Matrix Factorization (NMF) for topic modeling, classifying video content into five distinct topics.

During this classification process, we identified two topics with a high concentration of Microsoft Excel-related content and functions. Videos were classified as Excel-related if their probability distribution across these two topics exceeded a threshold of 0.3.

Moreover, YouTube videos include two formats: vertical, short-form videos for smartphones (Shorts) with a maximum duration of 60 seconds that appear in a scrollable feed, and traditional horizontal videos, which viewers click to watch. As the official API does not provide a feature to distinguish Shorts, we used the hashtag "#shorts" to exclude such videos.

Consequently, we obtained a dataset of 12,466 Excel-related, traditional videos.

We normalized the text information from the channel descriptions and video descriptions for analysis.

3.3. Verification

Due to the tendency of a small number of videos to accumulate a disproportionately high number of views while the majority garner relatively few, a logarithmic trans-formation was applied to the view counts. This transformation aims to mitigate the impact of extreme values on the analysis results.

For the log-transformed view counts, referred to as "log views," the normality assumption was tested using the Shapiro-Wilk test. The results indicated that the dataset does not follow a normal distribution (p-value < 0.000).

The videos were categorized into seven groups based on title length and another set of seven groups based on the number of words in the title. The objective was to investigate whether there were significant differences in view counts among these groups.

Initially, the distributions of view counts across the groups were visualized using box plots. Given that the data did not conform to a normal distribution, a non-parametric approach, specifically the Kruskal-Wallis H test, was employed to examine overall differences among the groups. Subsequently, pairwise comparisons were conducted using the Pairwise Wilcoxon Rank Sum Tests.

Detailed descriptions of each group are presented in Tables 2 and 3.

Table 2. Grouping by number of title characters

Group	Condition	Size
Group A	Length is 9 characters or less	72
Group B	Length is between 10 and 19 characters	1,552
Group C	Length is between 20 and 29 characters	5,764
Group D	Length is between 30 and 39 characters	6,844
Group E	Length is between 40 and 49 characters	4,952
Group F	Length is between 50 and 59 characters	2,892
Group G	Length is 60 characters or more	2,856

Table 3. Grouping by number of title words

Group	Condition	Size
Group H	Title is 4 words or less	73
Group I	Title is between 5 and 9 words	1,149
Group J	Title is between 10 and 14 words	3,133
Group K	Title is between 15 and 19 words	3,296
Group L	Title is between 20 and 24 words	2,375
Group M	Title is between 25 and 29 words	1,317
Group N	Title is 30 words or more	1,123

4. Results and Discussion

4.1. Analysis of Title Length

Descriptive Statistics. The analysis of descriptive statistics for each group reveals distinct trends in view counts relative to title length. Both the mean and median view counts exhibit a notable pattern, peaking at Group E and forming a bell-shaped distribution across the groups. Additionally, Groups E and G show an increase in the number of outliers, indicating a broader range of performance outcomes.

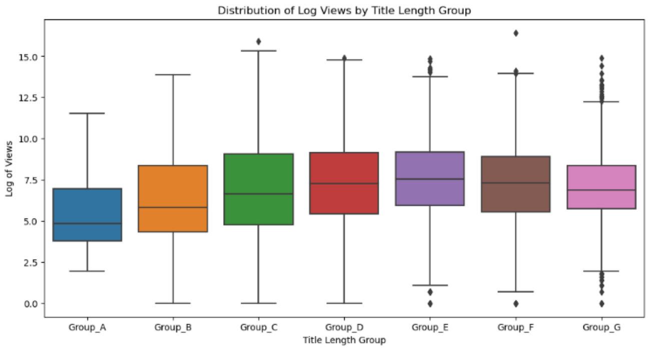

Figure 1. Distribution of Log Views by Title Length Group

Overall Group Validation. To verify the significance of these results, the Kruskal-Wallis H test was employed. The Kruskal-Wallis H test, a non-parametric method for testing whether samples originate from the same distribution, confirmed significant differences in view counts among the groups (p-value < 0.000). This finding suggests that title length has a statistically significant impact on video view counts. To further explore these differences, pairwise comparisons were conducted using the Pairwise Wilcoxon Rank Sum Tests, which revealed specific group pairs with significant differences in view counts.

Group Comparisons. The Pairwise Wilcoxon Rank Sum Tests revealed significant differences between most group pairs. Comparisons that did not show significant differences were between Group A and Group B (p-value = 0.096) and between Group D and F (p-value = 0.52). These results highlight the critical role of title length in influencing video view counts, with an optimal range identified around the lengths represented by Group E. However, the presence of numerous outliers in Groups E and G suggests that while longer titles generally attract more views, they also result in a wider range of performance outcomes.

These results support H2, but H1 remains open to debate. Titles that fall within the optimal length range (Group E) indeed attract the highest view counts. This suggests that titles with sufficient information, but not excessive length are most effective in engaging viewers. Conversely, the reduction in view counts due to information overload is partial; while there is a tendency for view counts to decrease when the title length is excessively long, this trend is not observed between 40-59 characters (Group E and F), indicating a broader acceptable range.

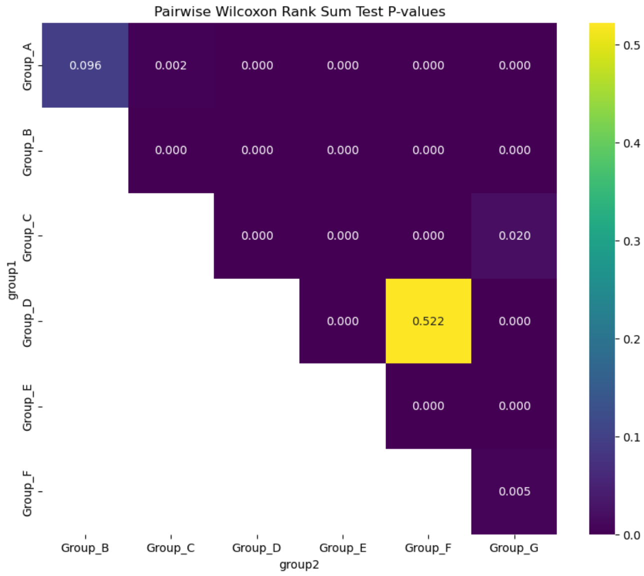

Figure 2. Pairwise Wilcoxon Rank Sum Test with Title Length Group

4.2. Analysis of the Number of Words in Titles

Descriptive Statistics. The analysis of descriptive statistics based on the number of words in titles, similar to the title length analysis, reveals that both the mean and median view counts peak at Group L, forming a bell-shaped distribution across the groups. Furthermore, Groups L and N exhibit an increased number of outliers, indicating a broader range of performance outcomes.

Overall Group Validation. The Kruskal-Wallis H test also confirmed significant differences in view counts among the groups (p-value < 0.000), showing results similar to those observed with title length.

Group Comparisons. The Pairwise Wilcoxon Rank Sum Tests revealed results largely consistent with the analysis based on title length, showing significant differences between most group pairs. Comparisons that did not show significant differences were between Group H and I (p-value = 0.211), Group K and M (p-value = 0.838), and Group L and M (p-value = 0.204). These results indicate that optimizing the number of words in video titles is as effective in enhancing viewer engagement as optimizing title length. These findings support H4, which suggests that within a certain threshold, more words in a YouTube video title led to higher view counts due to information sufficiency. The optimal range of word count appears to be around the levels represented by Group L. However, H3, which posits that more words in a title decrease view counts due to information overload, remains open to debate. The presence of numerous outliers in Groups L, M, and N, as well as the lack of clear differences in view counts among Groups K, L, and M, suggest that the impact of word count on viewership may vary.

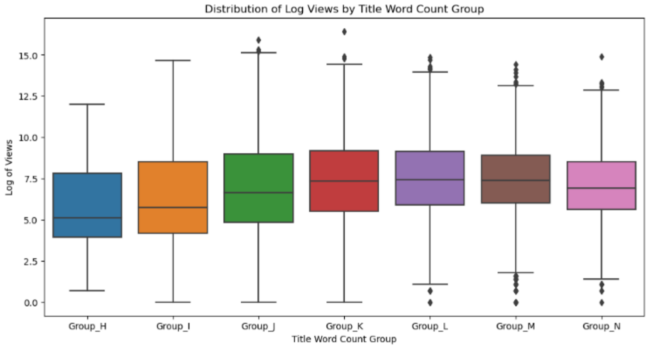

Figure 3. Distribution of Log Views by Title Word Count Group

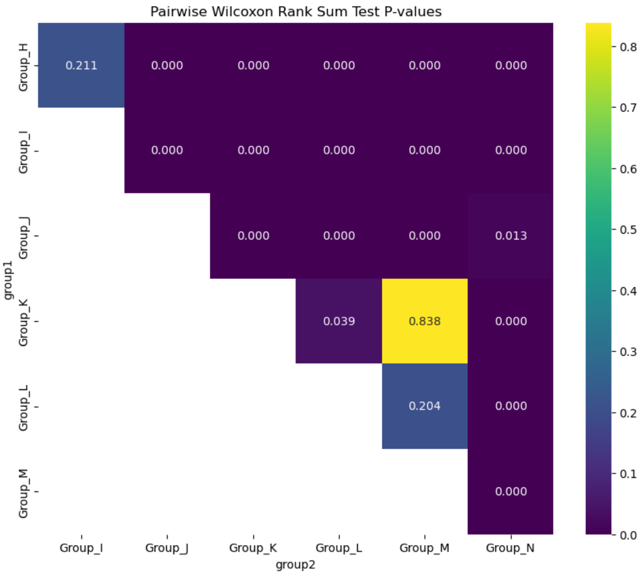

Figure 4. Pairwise Wilcoxon Rank Sum Test with Title Word Count Group

4.3. Discussion

This study aimed to address the challenge of improving video engagement through cost-efficient title optimization. By analysing the impact of title length and word count on viewership, the findings provide actionable guidelines for creating effective video titles. These insights contribute to a more balanced and equitable content ecosystem on YouTube, addressing the current disparity in video exposure.

Practical Implications. These findings have several practical implications for content creators and marketers on video platforms:

1. *Optimal Title Length.* Titles that are too short or too long tend to perform less well compared to those within an optimal length range. For maximum viewer engagement, title lengths should be carefully crafted to fall within the effective range identified (Group E).

2. *Optimal Number of Words.* Similarly, the number of words in a title plays a crucial role in attracting viewers. Titles with an optimal number of words (as represented by Group L) are more likely to achieve higher view counts. This balance helps to ensure that titles are informative yet concise, capturing viewer interest without overwhelming them.

3. *Handling Variability.* The presence of outliers in both title length and word count analyses suggests that while longer and wordier titles can attract more views, they also introduce greater variability. Content creators should be mindful of this variability and consider testing different title lengths and word counts to find the optimal balance for their specific audience.

4. *Visual Information and Semantic Information.* Both types of information showed a tendency for view counts to decrease due to information overload, but this trend was more pronounced with visual information. When crafting titles, a more sensitive approach to character count might yield better performance.

5. *Data-Driven Optimization.* The use of non-parametric tests such as the Kruskal-Wallis H test and Pairwise Wilcoxon Rank Sum Tests provides robust evidence of the impact of title characteristics on view counts. Content creators are encouraged to leverage data-driven approaches to optimize their titles, ensuring that they align with the identified optimal ranges to maximize engagement.

5. Conclusion

On video platforms such as YouTube, gaining popularity, i.e., increasing view counts, is a common goal for creators and content providers. However, effective methods for significantly increasing view counts have not been established. This study focused on factors that require low costs to improve and are controllable by the creators, specifically examining the impact of the number of characters and words in titles on view counts. The findings indicated that the visual information conveyed by character count significantly affects view counts, while the impact of the semantic information conveyed by word count is limited. This suggests that keeping the character count within an appropriate range is an effective strategy for creating more engaging titles.

Contributions. This study provides three contributions:
1.Empirical evidence supporting the impact of title characteristics (length and word count) on video engagement.
2.Practical insights into cost-efficient strategies for optimizing YouTube titles.
3.A foundation for future studies exploring user-generated content (UGC) on digital platforms.

Limitations. This study has several limitations.

1. Language Dependency. The results are limited to Japanese, making generalization difficult. Therefore, expansion to other languages and countries is necessary. Particularly, Japanese allows for diverse expressions using kanji, hiragana, katakana, and sometimes the alphabet, which can affect the character count.

2. Specific Content. The results are specific to Microsoft Excel-related videos. While Microsoft Excel is a common tool that many workers need to learn, making educational content on it relatively likely to gain higher view counts, other more specialized subjects may not yield similar results. As Google's official search algorithm indicates, view counts and watch time influence recommendations, which might not be the case for more niche topics.

3. Unexamined Factors. The study did not examine the impact of other factors beyond title length. Factors such as the characteristics of the account owner, content features, and PR/promotion interactions and their influence were not discussed.

Additionally, the influence of information contained in the title, specific keywords, and thumbnails on view counts and their interactions were not considered.

Future Directions. Future research should address the limitations of this study by expanding its scope to different languages and regions, allowing for a cross-cultural comparison of title optimization strategies. Furthermore, it is essential to investigate the interplay between title characteristics and other critical factors, such as thumbnail design, keywords, and audience demographics, to gain a holistic understanding of video engagement determinants. Another important direction is the development of automated tools that utilize machine learning to assist creators in crafting and optimizing video titles. By building on these foundations, future studies can contribute to the establishment of comprehensive guidelines that empower creators to enhance video engagement more effectively on digital platforms.

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