YouTube marketing: how marketers' video optimization practices influence video views

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Abstract

Purpose – YouTube's vast and engaged user base makes it central to firms' digital marketing effort. With extant studies focusing on viewers' post-view engagement behavior, however, research into what motivates viewers to click on and watch YouTube videos is scarce. This study investigates the implications of marketers' video optimization practices for video views on YouTube.

Design/methodology/approach – The study employed a data set of videos (N = 4,398) gathered by scraping YouTube's trending list. Using a combination of text and sentiment analysis, the study measured four video optimization practices: information content of video titles, emotional intensity of video titles, information content of video descriptions and volume of video tags. It then analyzed the effect of these video optimization practices on video views.

Findings – The study finds that greater availability of information in video titles is negatively associated with video views, whereas intensity of negative emotional sentiment in video titles is positively associated with video views. Further, greater availability of information in video descriptions is positively associated with video views. Finally, an inverted U-shaped relationship is found between volume of video tags and video views. Up to 17 video tags can contribute to more video views; however, beyond 17 tags, the relationship turns negative.

Originality/value – This study investigates the effect of marketers' video optimization practices on video views. While extant studies mainly focus on viewers' post-view engagement behavior, such as liking, commenting on and sharing videos, this study examines video views. Similarly, extant studies investigate videos' internal content, while this study investigates elements of the video metadata.

Keywords YouTube, YouTube marketing, Video marketing, Digital marketing, Video views, YouTube views, Search engine optimization

Paper type Research paper

1. Introduction

YouTube is a vast video-sharing platform that allows users to view, like, comment on, share and upload videos (Feroz Khan and Vong, 2014; Teixeira and Kornfeld, 2015). With approximately 1.9 billion monthly visits, YouTube is the second most visited website globally. It is also the second largest search engine, behind only Google. YouTube specializes in videos, which are a highly engaging form of content. Indeed, one billion hours of video content are watched each day on YouTube and approximately 78% of Internet users watch videos weekly (Chi, 2019). To capitalize on videos' growing popularity, firms are investing in YouTube and video marketing more broadly. Today, video marketing is the fastest-growing digital marketing segment (Picard, 2019), and video ad spending has surpassed $129 billion in the USA (Enberg, 2019).

With YouTube's expanding role in firms' digital marketing mix, greater research attention is being devoted to YouTube marketing, examining its various facets including the virality of YouTube videos (Feroz Khan and Vong, 2014; Nielson-Field *et al.*, 2013; Tellis *et al.*, 2019),the advertising effectiveness of YouTube videos (Tucker, 2015; Vedula *et al.*, 2017) and their sales effects (Oh *et al.*, 2017). Although available studies have contributed to increased understanding of YouTube's marketing impact, relatively little is known about the drivers of

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video views on YouTube. Extant research has primarily investigated viewers' post-view engagement behavior, such as likes (Vedula *et al.*, 2017), comments (Dessart and Pitardi, 2019; Moldovan *et al.*, 2019; Vedula *et al.*, 2017) and shares (Oh *et al.*, 2017; Tellis *et al.*, 2019). This dearth of research on video views is surprising given that video views feed into other forms of user engagement behavior on YouTube. Viewers respond to brands by liking, commenting on and sharing videos, or forming a positive brand attitude and purchase intention, only after they have viewed videos. As video views supersede other forms of user engagement, additional research on the drivers of video views on YouTube is warranted.

Accordingly, this study aims to investigate how marketers' video optimization practices on YouTube contribute to video views. Video optimization is a set of practices that marketers implement to make their videos visible by leveraging YouTube's ranking and recommendation algorithms (Choudhari and Bhalla, 2015; Lopezosa *et al.*, 2019). Video optimization operates on two levels. First, it facilitates the discovery and indexing of videos with YouTube's search and recommendation algorithms (Lopezosa *et al.*, 2019; Zhou *et al.*, 2016). This step is important, as YouTube's algorithms must first find and index videos before they can display them to viewers (Zhou *et al.*, 2016). Second, video optimization seeks to capture viewers' interest and entice them to click on videos (Choudhari and Bhalla, 2015; Lopezosa *et al.*, 2019). This optimization goal is also critical, because viewers are typically presented with multiple videos at once, and they must decide which ones to watch (Zhou *et al.*, 2016). Therefore, algorithm discovery and indexing are insufficient to accumulate views. Viewers must also show enough interest to click on videos. This study considered three optimization practices that can contribute to video views by facilitating either algorithm discovery or viewer enticement: video titles, video descriptions and video tags. While video descriptions and video tags contribute to views by enhancing algorithm discovery and indexing, video titles – –one of the first pieces of information viewers notice about YouTube videos – –increase viewer enticement (Choudhari and Bhalla, 2015; Lopezosa *et al.*, 2019).

Drawing on customer engagement theory (Harmeling *et al.*, 2017; Pansari and Kumar, 2017) and using a large data set of YouTube videos (N = 4,398), the present study investigates how the information and emotional content of video titles, the information content of video descriptions and the volume of video tags influence video views. The findings contribute to the literature by documenting the drivers of video views on YouTube. Because of their focus on viewers' post-view engagement behavior, extant studies have not adequately addressed what motivates viewers to click on and watch YouTube videos. The current study helps fill this crucial gap. Moreover, existing studies examined videos' internal content, such as their information content (Tellis *et al.*, 2019; Moldovan *et al.*, 2019), emotional content (Nielson-Field *et al.*, 2013; Tellis *et al.*, 2019) and audio-visual features (Vedula *et al.*, 2017). The present study complemented this approach by measuring elements of the video metadata that include video titles, video descriptions and video tags.

The remainder of the paper is structured as follows. Section 2 discusses the study's theoretical background. Section 3 reviews the relevant literature, while section 4 presents the study's hypotheses. In sections 5 and 6, the data set and the empirical model are introduced. In the remaining sections of the paper, the results and their implications are discussed.

2. Theoretical background

Customer engagement theory provided the theoretical background for this study (Harmeling *et al.*, 2017; Palmatier *et al.*, 2018; Van Doorn *et al.*, 2010).Customer engagement theory views customers as active and resourceful partners who can contribute to firms' marketing efforts beyond purchases (Harmeling *et al.*, 2018; Pansari and Kumar, 2017). With growing market digitalization, customers have become empowered and now possess crucial resources that can enhance firms' marketing effectiveness (Harmeling *et al.*, 2017; Jaakkola and Alexander, 2014; Van Doorn *et al.*, 2010). Among these customer-owned resources are knowledge resources (e.g. product know-how, customer feedback), persuasion resources (e.g. customer trust, customer influence) and network resources (e.g. customers' interpersonal ties and social networks).

Firms implement customer engagement initiatives to extract resource contributions from customers (Alvarez-Milan *et al.*, 2018; Beckers *et al.*, 2018; Harmeling *et al.*, 2017). Harmeling *et al.* (2017) defined customer engagement initiatives as "a firm's deliberate effort to motivate, empower, and measure a customer's voluntary contribution to the firm's marketing functions beyond the core, economic transaction" (p. 317). Beckers *et al.* (2018) discussed customer engagement in terms of explicit firm strategies that foster online customer participation: "for example, by asking customers to share a viral marketing campaign, to 'like' the brand on Facebook, or to engage in a firm-sponsored online community" (p. 368). Firms' implementation of customer engagement initiatives can range from viral marketing to online crowdfunding to social customer relationship management (Alvarez-Milan *et al.*, 2018; Beckers *et al.*, 2018; Harmeling *et al.*, 2017). As such, firms' deliberate effort of setting up YouTube channels and creating, sharing and optimizing videos to connect with their customers – –the subject of this study – –falls under the purview of customer engagement initiatives (Beckers *et al.*, 2018).

From the customers' perspective, customer engagement has been viewed as customers' favorable behavior toward a brand (Brodie *et al.*, 2013; Tafesse and Wien, 2018). Eigenraam *et al.* (2018) provided a comprehensive framework of customers' engagement practices that included viewing, liking and sharing online brand content; creating user-generated content, such as blog posts, product reviews and brand-related videos; and participating in brand communities. Customers participate in these practices because they find them intrinsically motivating or derive social and utilitarian values out of them (Brodie *et al.*, 2013; Eigenraam *et al.*, 2018). Since customers trust other customers' opinions more than firm-originating messages, customer engagement practices have significant implications for online brand performance (Beckers *et al.*, 2018; Srinivasan *et al.*, 2016).

On YouTube, customers have multiple options to engage with brands. They can view, like (or dislike), comment on and share YouTube videos (Dessart and Pitardi, 2019; Tellis *et al.*, 2019; Tucker, 2015; Vedula *et al.*, 2017). This study focuses on video views, as this is how the majority of customers engage with brands on YouTube (Tucker, 2015; Zhou *et al.*, 2016). Similarly, video views feed into other forms of engagement behavior on YouTube, such as liking, commenting on and sharing videos or subscribing to a YouTube channel (Feroz Khan and Vong, 2014). Customers who do not view videos are less likely to participate in these engagement behaviors. Finally, video views have strong bottom-line implications (Oh *et al.*, 2017). Exponential views lead to more audience reach, which subsequently contributes to downstream metrics in marketers' sales funnels (e.g. purchase consideration). Given the above, the focus on video views is warranted (Teixeira and Kornfeld, 2015).

3. Literature review

With YouTube's expanding role as a digital marketing platform, research on firms' YouTube marketing efforts has been accumulating in recent years. Table 1 summarizes findings from studies closely aligned to the current work by investigating the marketing implications of YouTube videos. The review excluded studies that examined viewers' motivations or those that gauged viewers' responses to experimentally manipulated videos in laboratory settings, as their findings cannot be meaningfully compared to studies of actual YouTube videos.

The review table draws out certain common themes in the literature. First, the primary subject of investigation in many of the reviewed studies is related to viewers' post-view responses. Among the dependent variables considered are video shares (Nielson-Field *et al.*,

Table 1.
Summary of relevant studies

Studies	Sample size and data source	Main independent variables	Main dependent variables
Current study	4,398 trending YouTube videos	Information content of video titles Emotional sentiment of video titles Information content of video descriptions Volume of video tags	Video views
Nielson-Field *et al.* (2013)	800 videos (400 user-generated and 400 brand-generated)	Emotional sentiment of videos (positive vs. negative emotions) Arousal level of videos (high vs. low arousal)	Video shares via Facebook
Feroz Khan and Vong (2014)	The top 100 most watched YouTube videos of all time	Total videos posted by channel Video upload date Content category	Video virality (operationalized as a composite measure of video views, favorites, likes and comments)
Tucker (2015)	396 YouTube videos shared by consumer packaged, electronics and apparel brands	Exposure to a YouTube video Total video views	Advertising persuasiveness of YouTube videos (measured through viewers' purchase intention)
Oh *et al.* (2017)	72 movie trailers shared on YouTube	Number of times movie trailers are shared on YouTube When movie trailers were shared (early or later in the life cycle of movies)	Movies' box-office revenue
Vedula *et al.* (2017)	200 YouTube videos representing multiple industries including food and beverage, clothing, consumer electronics and so on	The audio (auditory loudness, onset density and timbre centroid), visual (hue, saturation and brightness) and textual (word embeddings of the text transcription of video voice-over) features of videos	Ad effectiveness measured differently as viewers ad attitude, sentiment of YouTube comments and proportion of YouTube likes
Tellis *et al.* (2019)	345 YouTube videos uploaded by the top 100 brands	Emotional content of videos Information content of videos Commercial content of videos	Video shares via Facebook, Twitter, LinkedIn and Google+
Moldovan *et al.* (2019)	35 YouTube videos	Video informativeness Video creativity Video comments	Video views

2013; Tellis *et al.*, 2019), video virality (Feroz Khan and Vong, 2014), advertising persuasiveness (Tucker, 2015), advertising effectiveness (Vedula *et al.*, 2017) and product sales (Oh *et al.*, 2017). Only two studies considered video views as a dependent variable (Feroz Khan and Vong, 2014; Moldovan *et al.*, 2019). In Feroz Khan and Vong (2014), video views were summed with video likes, comments and shares to create a composite measure of video virality, whereas in Moldovan *et al.* (2019), the video sample is too small ($N = 35$) to draw any meaningful conclusion.

Second, the reviewed studies primarily examined videos' internal content, including their emotional sentiment (Moldovan *et al.*, 2019; Nielson-Field *et al.*, 2013; Tellis *et al.*, 2019), arousal level (Nielson-Field *et al.*, 2013; Tellis *et al.*, 2019), information content (Moldovan *et al.*, 2019; Tellis *et al.*, 2019), advertising persuasion (Tucker, 2015) and audiovisual features (Vedula *et al.*, 2017). This focus on videos' internal content means that elements of the video metadata, such as video titles, video descriptions, video tags and a host of other video-level features, including channel characteristics and timing of video uploads, have not been adequately studied.

Third, in terms of key findings, Nielson-Field *et al.* (2013) and Tellis *et al.* (2019) found that videos conveying positive and high-arousal content are associated with higher video shares. In addition, Tellis *et al.* (2019) found that videos conveying factual product information and those prominently displaying brand messages are associated with fewer video shares. Feroz Khan and Vong (2014) found a significant positive effect of the number of videos posted by a YouTube channel and the content category and age of videos on video virality. Tucker (2015) found that YouTube videos with a high number of views are generally perceived as having lower advertising persuasiveness, when advertising persuasiveness is measured in terms of viewers' intentions to buy the advertised products. Oh *et al.* (2017) found that the volume of shares that movie trailers received on YouTube positively predicts next-day movie sales. Vedula *et al.* (2017) found that the visual features early segments and the audio features of middle and final segments, where presumably the core message of videos is presented, and which positively predicts ad effectiveness. The researchers also found that the video voice-over explains ad effectiveness more than audiovisual features. Finally, Moldovan *et al.* (2019) found that videos combining greater creativity with factual information are associated with more views.

As evident from Table 1, the current work contributes to the literature by examining video views as opposed to viewers' post-view responses, by focusing on elements of the video metadata as opposed to their internal content, and finally by employing a larger and more representative sample of YouTube videos than has been used in extant research.

4. Hypotheses

Drawing on the theoretical background and literature review presented in the preceding sections, the conceptual framework shown in Figure 1 is developed. The subsequent section elaborates on proposed relationships.

4.1 Video titles

Video titles are the headlines that marketers ascribe to their videos. Because video titles are one of the first pieces of information viewers notice about YouTube videos, they significantly shape viewers' video choices. Video titles serve two functions: offering information and sparking viewers' interest (Lopezosa *et al.*, 2019).

4.1.1 Video titles: information content. The first function of video titles is to inform viewers and YouTube's search and recommendation algorithms about videos' content. Because video titles are used by both viewers and YouTube's algorithms, predicting their effects on video views is far from straightforward.

To enhance their effects on viewers, video titles may only need to contain essential details. Incorporating too much information may increase a title's complexity, thereby making it less effective at informing viewers by possibly causing information overload. Information overload is especially pertinent in digital platforms, such as YouTube, that are characterized by vast information availability (Gomez-Rodriguez *et al.*, 2014; Roetzel, 2018). For example, when viewers search for a video, they are typically presented with a range of choices and need to review titles and other supplementary details, such as channel information and video thumbnails, to select a suitable video (Vedula *et al.*, 2017; Zhou *et al.*, 2016). Given the number of choices they face, viewers may lack the time and cognitive resources to process dense titles

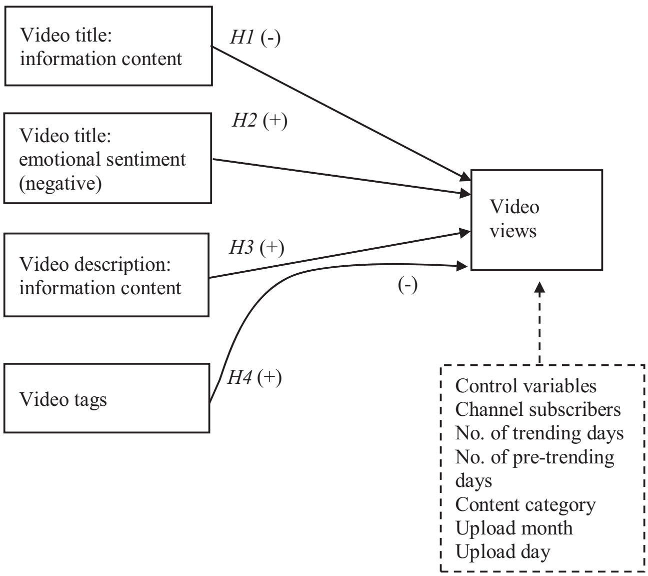

Figure 1.
Proposed model

and may therefore click on videos with concise titles instead. In contrast, greater availability of information in video titles might enhance their effects on YouTube's search and recommendation algorithms. Unlike humans, algorithms thrive on vast data availability (Jordan and Mitchell, 2015). As such, titles rich in information might enable YouTube's algorithms to better discover, index and categorize videos (Zhou *et al.*, 2016).

Here, the negative effects of longer titles on humans are anticipated to outweigh their positive effects on algorithms. First, YouTube's algorithms can make up for lack of details in shorter titles from other sources, such as video descriptions, video tags and channel information (Zhou *et al.*, 2016). Second, algorithms can only recommend relevant choices as per set criteria; humans still have the final say regarding which videos to click on and watch. Therefore, the following hypothesis is proposed:

H1. Video titles with greater information content will be negatively associated with video views.

4.1.2 Video titles: emotional sentiment. The second function of video titles involves capturing viewers' attention and sparking their interest in videos. This function is essentially emotional, suggesting that video titles need to appeal to viewers' emotional needs and motivate them to click on videos (Lopezosa *et al.*, 2019). This observation suggests that the emotional sentiment of video titles can be a crucial factor in enhancing video views.

Research on online content virality (social sharing) suggests that content with positive valence is more likely to go viral than that with negative valence (Berger and Milkman, 2012; Tellis *et al.*, 2019). Yet, viewing and sharing online content each involves fundamentally distinct evaluation contexts. While viewing is often performed in private, sharing is essentially a social process, and considerations such as self-image enhancement and social acceptance figure centrally in users' decisions to share online content (Tellis *et al.*, 2019).

Viewers might be inclined to share positive videos to bolster their self-image and social acceptance; however, during private viewing, they may show greater enthusiasm for videos with negative valence. This hypothesis can be explained through people's negativity bias (Baumeister *et al.*, 2001). Findings from psychology have consistently showed that negative information has a greater impact on people's attention and evaluation processes (Baumeister *et al.*, 2001; Smith *et al.*, 2003). People are automatically drawn to negative information more strongly than they are to positive information, even when the information is of equal weight (Baumeister *et al.*, 2001; Pratto and John, 1991). While part of this negativity bias is evolutionary, part of it is related to the fact that the brain systems responsible for evaluating negative stimuli are more responsive than those responsible for evaluating positive stimuli (Pratto and John, 1991; Smith *et al.*, 2003). Although it could be argued that positively valenced titles can foster video views through social sharing, not all recipients attend to shared content. In fact, social shares do not seem to be a major source of video views in a YouTube context (Zhou *et al.*, 2016). Therefore, a positive association is hypothesized between negative emotional sentiment in video titles and video views:

H2. Video titles with negative emotional sentiment will be positively associated with video views.

4.2 Video descriptions

Video descriptions are textual explanations that offer details and context to YouTube videos including the videos' theme and purpose, and where, when and how they were created (Choudhari and Bhalla, 2015; Lopezosa *et al.*, 2019). Video descriptions also typically contain relevant keyword tags. Together, the details in video descriptions assist YouTube's search and recommendation algorithms in discovering, indexing and accurately categorizing YouTube videos (Choudhari and Bhalla, 2015; Lopezosa *et al.*, 2019; Zhou *et al.*, 2016).

Although both video titles and video descriptions play important optimization roles, their roles differ slightly. As previously discussed, video titles serve both informational and emotional functions, whereas video descriptions appear to mainly serve informational function. This could be inferred from the distinct policies that YouTube applies to these video metadata. For instance, external links can be added to video descriptions, but not to titles (Choudhari and Bhalla, 2015; Feroz Khan and Vong, 2014). Similarly, video descriptions are allowed a maximum length of 5,000 characters, whereas titles are limited to 100 characters. Finally, descriptions are shown underneath videos (on desktops/laptops) or beside videos, just underneath video titles (on mobile). These features underscore the informational purpose of video descriptions, while their role in viewer enticement appears to be limited. Therefore, the information content of video description is considered here, and greater availability of information in video descriptions is anticipated to contribute to more video views.

Video descriptions rich in information offer more context and can readily accommodate several keywords, which facilitates video discovery and indexing by YouTube's algorithms, thereby boosting video views (Zhou *et al.*, 2016). Descriptions rich in information might also signal the domain authority of YouTube channels, which might subsequently improve a video's ranking in search results. Therefore, the following hypothesis is proposed:

H3. Video descriptions with greater information content will be positively associated with video views.

4.3 Video tags

Video tags are a collection of keywords that marketers include in their YouTube videos (Choudhari and Bhalla, 2015; Lopezosa *et al.*, 2019). Video tags are created as a series of comma-delimited keywords and phrases that viewers are thought to use when searching for videos. Their format makes it expedient to match video tags with viewers' search keywords and phrases (Choudhari and Bhalla, 2015). Moreover, the constraints placed on video titles and video descriptions mean that not all relevant keywords and phrases can be meaningfully incorporated into these video metadata. Such keywords are often reserved for video tags.

In creating video tags, the best practice is to cover all possible search keywords and phrases viewers might use when searching for videos (Lopezosa *et al.*, 2019). A close match between viewers' keywords and marketer-created video tags increases the likelihood of videos appearing in viewers' search results, thereby boosting video views (Zhou *et al.*, 2016).

Notably, YouTube does not limit the number of tags for videos, which raises the question: does creating video tags ad infinitum lead to more video views? Industry experts advise only creating relevant keywords and phrases and caution against applying unrelated keywords, since videos with irrelevant keywords could be flagged as spam (Choudhari and Bhalla, 2015). Practitioners' wisdom thus suggests that using more video tags can lead to more video views, but only up to a certain optimum level. When the volume of video tags exceeds this optimum level, more tags might lead to fewer video views by prompting YouTube's algorithms to flag those videos as spam and penalize the channels for their improper conduct (Choudhari and Bhalla, 2015). To capture this potentially curvilinear relationship, an inverted U-shaped relationship between video tags and video views is proposed:

H4. The relationship between video tags and video views will be inverted U-shaped.

5. Methodology

5.1 The data set

The data for this study originated from Kaggle.com, which is an online hub for data scientists where they publish their data, discuss solutions to problems and compete (for a reward) to solve some of the most vexing data science problems faced by external organizations. The data under consideration here comprised 4,548 videos that were featured on YouTube's top 200 trending list in the USA between November 14, 2017, and March 5, 2018. An automated crawler was deployed to scrape details from the trending list on a daily basis for the length of the data collection period. Since the crawler gathered data daily, videos that trended for two or more days had their details entered in the data set multiple times. These duplicate entries were removed, except for the details captured on the last trending day. Accordingly, the 4,548 videos included in the data set all represent unique YouTube videos.

According to YouTube, trending videos are those that attracted broad interest within a few days of appearing on YouTube (YouTube Help Center, 2019). They allow viewers to discover videos other viewers find interesting in the platform, and YouTube considers various factors to surface these videos. Importantly, YouTube's trending videos are updated approximately every 15 min, and with each update, videos may move up or down or remain unchanged. Therefore, when tracked for an extended period, YouTube's trending list can yield a variety of YouTube videos.

The current data set contains a range of details, including video ID, category ID, publish date, number of trending days, number of likes, number of dislikes, title, descriptions, tags (both the actual tags and their volume count) and number of channel subscribers. The data set is also quite representative, where nearly all of YouTube's video categories are present in the data set (see Figure 2). The majority of the videos in the data set (97%) were uploaded to YouTube in November, December (2017), January and February (2018). To avoid a skewed distribution of upload month, videos published beyond these four months (N = 149) were removed, leaving 4,398 videos in the final sample.

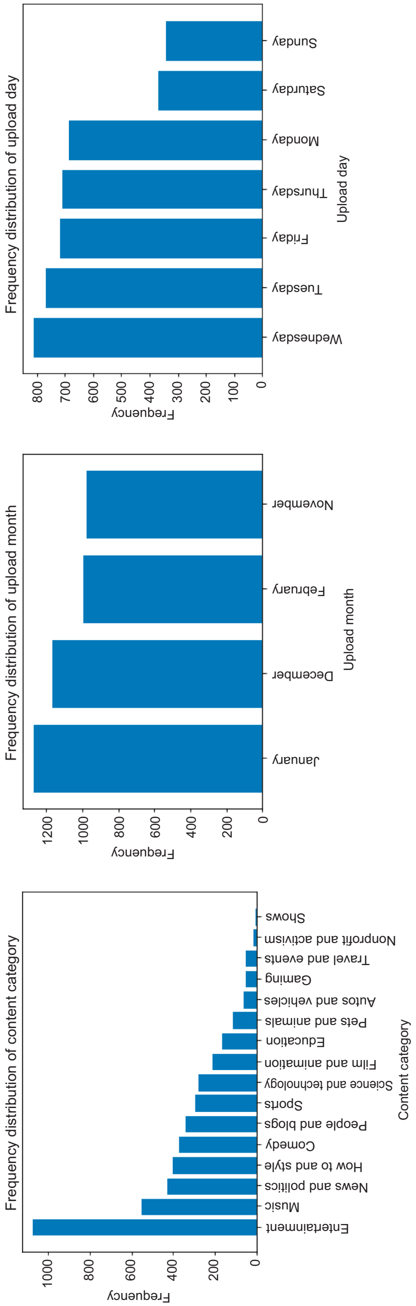

Figure 2.
Frequency distribution
of categorical variables

5.2 Operationalization of study variables

The original data set was presented in a preprocessed format, with most of the column values expressed in numerical values. However, additional preprocessing was performed using Python's pandas library (version 3.7.3) to construct and operationalize some of the study's variables.

First, simple Python codes were executed to count and assign the number of characters in video titles and video descriptions to newly created "title count" and "description count" columns. Thus, these two columns operationalized the information content of video titles and the information content of video descriptions, respectively. The character count of online content has been used to measure information content in prior research (Liu *et al.*, 2012).

Second, Valence Aware Dictionary and sEntiment Reasoner (VADER) was utilized to measure the emotional sentiment of video titles (Hutto and Gilbert, 2014). VADER consists of more than 10,000 lexical features (e.g. words, emoticons, punctuation, capitalization, slang, acronyms and initialisms) commonly found in online content. These lexical features are pre-labeled into positive, negative and neutral emotional valence and are assigned corresponding sentiment intensity scores based on results from human coders. VADER's sentiment intensity scores range from 0 (neutral sentiment) to 1 (extreme negative or extreme positive sentiment). VADER assigns aggregate sentiment scores to a given text item, such as a tweet or a video title, that add up to one (e.g. negative = 0.364, neutral = 0, positive = 0.636). VADER was adopted because it is specifically attuned to emotions expressed on social media and is a highly accurate sentiment classifier (Hutto and Gilbert, 2014).

Third, the category ID column in the original data set was used to dummy code videos' content categories. About 16 content categories were identified (see Figure 2) and dummy coded with the entertainment category as the reference, which is the largest video category in the data set.

Fourth, the publish date column in the original data set (i.e. the videos' timestamp) was used to construct three variables: upload month, upload day and number of pre-trending days. Upload month captured the videos' upload month and took one of four values: November, December, January or February. It was dummy coded with January as the reference category, which has the most video uploads. Upload day captured the videos' upload day and was dummy coded with Wednesday as the reference category, which has the most video uploads. Finally, number of pre-trending days measured how many days it took videos to appear in YouTube's trending list. It was operationalized by subtracting the initial upload date of videos from their first trending date. Longer pre-trending days can cause videos to lose their freshness by the time they appeared in trending list, which might subsequently hurt their view counts relative to videos that appeared in trending list immediately after being uploaded. Table 2 summarizes the study variables and their operationalization.

5.3 Model specification

To investigate the effects of video optimization practices on video views, the regression model shown in equation (1) was developed. The video views variable was log-transformed to account for skewness in the data and normalize the residuals. Guided by the conceptual framework, the regression model incorporated the information content of video titles, the emotional sentiment of video titles, the information content of video descriptions, the volume of video tags and the volume of video tags squared (to test for the curvilinear effect):

Study variables	Operationalization
Dependent variable	
Video views	The number of times videos have been viewed on YouTube
Hypothesized variables	
Video title: information content	The character count of video titles
Video title: emotional sentiment (negative)	The intensity of negative emotional sentiment in video titles measured using the VADER sentiment analyzer. Scores range between 0 and 1
Video title: emotional sentiment (positive)	The intensity of positive emotional sentiment in video titles measured using the VADER sentiment analyzer. Scores range between 0 and 1
Video description: information content	The character count of video descriptions
Video tags	The volume of tags created for videos
Control variables	
Channel subscribers	The number of users subscribed to the YouTube channel to which videos are uploaded
Number of trending days	The number of days videos have been trending on YouTube
Number of pre-trending days	The number of days it took videos to appear in YouTube's trending list since their initial upload date
Content category	The content category of videos (e.g. entertainment, music, news and politics, science and technology), dummy coded with the entertainment category as the reference, which is the largest content category
Upload month	The month in which videos were uploaded to YouTube, which ranged from November to February, and was dummy coded with January as a reference (January has the most uploads)
Upload day	Day of the week in which videos were uploaded to YouTube, which ranged from Monday to Sunday, and was dummy coded with Wednesday as a reference (Wednesday has the most uploads)

Table 2. Summary of variables and their operationalization

$$\begin{aligned}\ln(\text{Views}_i) = {} & \alpha + \beta_1 \text{Title\_information}_i \\ & + \beta_2 \text{Title\_emotions\_negative}_i \\ & + \beta_3 \text{Title\_emotions\_positive}_i \\ & + \beta_4 \text{Description\_information}_i \\ & + \beta_5 \text{Video\_tags}_i \\ & + \beta_6 \text{Video\_tags}_i^2 \\ & + \beta_j \text{Control\_variables}_{ij} + \varepsilon_i\end{aligned} \tag{1}$$

where $\beta_1, \beta_2, \ldots \beta_6$ are the parameter estimates for the main explanatory variables, α is the intercept, ε_i is the error term and β_j is the parameter estimate for the jth control variable. The model included several video-level characteristics as control variables, including number of channel subscribers, number of trending days, number of pre-trending days, content category (dummy coded), upload month (dummy coded) and upload day (dummy coded). Further, equation (1) implies that a one-unit change in each explanatory variable is associated with a (100 $\times$ β)% change in video views, keeping all other explanatory variables constant. Figure 2 and Table 3 reports the frequency distributions and descriptive statistics of the study variables.

Table 3.
Descriptive statistics and pair-wise correlations

Study variables	Mean	St. dev.	Max	Min	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Video views	1,288, 558	4,586,915	149,376,100	559	1								
(2) Video title: information content	50.15	19.56	100	4	−0.043***	1							
(3) Video title: emotional sentiment (negative)	0.07	0.14	0.8	0	0.020	0.022	1						
(4) Video title: emotional sentiment (positive)	0.1	0.17	1	0	0.004	−0.009	−0.14***	1					
(5) Video description: information content	961.8	829.9	5,063	1	−0.006	0.076***	0.015	0.044***	1				
(6) Video tags	19.3	12.4	69	0	0.009	0.140***	−0.002	0.027	0.380***	1			
(7) Channel subscribers	3,183,695	4,837,699	28,676,940	0	0.273***	−0.069***	−0.009	0.028	0.105***	0.246***	1		
(8) Number of trending days	4.9	2.61	14	1	0.191***	−0.060***	0.015	0.029	0.008	−0.055***	−0.018	1	
(9) Number of pre-trending days	7.7	112.08	2,932	0	−0.079***	−0.033***	−0.011	−0.02	−0.043***	−0.044***	−0.041***	−0.037***	1

Note(s): ***<0.01

6. Hypotheses testing

To test the proposed hypotheses, equation (1) was estimated using OLS regression. Regression diagnostics indicated that the estimated model was well behaved. The residuals were normally distributed with $\mu = 0$ and $\sigma^2 = 1$. The predictor variables had zero correlations with the residuals. Multicollinearity was not an issue either. With the exception of the first- and second-order terms for video tags, the variance inflation factors ranged between 1.01 and 1.60. White's heteroskedastic consistent standard errors are reported to correct for heteroskedasticity (White, 1980). Model estimation results are reported in Table 4. The overall model was statistically significant ($F = 39.52$, $p < 0.000$), explaining 34% of the variance in video views.

Study variables	Video views (main model) *B*	Std. error	*Z*-values	Video likes (robustness check) *β*	Std. error	*Z*-values
Hypothesized effects						
Video title: information content	−0.002**	0.001	−1.94	−0.009***	0.002	−5.646
Video title: emotional sentiment (negative)	0.570***	0.173	3.289	0.611***	0.207	2.95
Video title: emotional sentiment (positive)	0.164n.s.	0.129	1.27	0.221n.s.	0.157	1.403
Video description: information content	0.000***	0.000	3.163	0.000***	0.000	7.753
Video tags	0.033***	0.006	5.121	0.051***	0.008	6.296
Video tags squared	−0.001***	0.000	−3.985	−0.001***	0.000	−5.105
Control effects						
Channel subscribers	0.000***	0.000	27.018	0.000***	0.000	28.452
Number of trending days	0.257***	0.009	27.749	0.270***	0.011	23.694
Number of pre-trending days	−0.001***	0.000	−3.398	−0.002***	0.000	−6.26
Content category (reference: Entertainment)						
Comedy	–	–	–	0.408***	0.104	3.926
Education	−0.291***	0.096	−3.029	–	–	–
Film and animation	0.271**	0.12	2.261	0.285**	0.143	1.992
Gaming	–	–	–	0.639***	0.251	2.549
How to and style	−0.235***	0.081	−2.917	0.484***	0.092	5.252
Music	0.483***	0.084	5.766	1.199***	0.105	11.383
News and politics	−0.696***	0.098	−7.093	−1.169***	0.113	−10.308
People and blogs	–	–	–	0.354***	0.129	2.741
Shows	−1.538***	0.147	−10.452	−1.279***	0.11	−11.619
Sports	–	–	–	−0.628***	0.129	−4.874
Upload month (reference: January)						
November	−0.177***	0.066	−2.687	–	–	–
December	−0.415***	0.062	−6.695	−0.322***	0.075	−4.278
Upload day (reference: Wednesday)						
Friday	–	–	–	0.191**	0.095	2.020
Sunday	0.353***	0.093	3.797	0.236**	0.108	2.178
Intercept	10.648***	0.133	80.319	6.364***	0.164	38.709
Model summary	$R^2 = 34\%, F = 39.52$***			$R^2 = 39\%, F = 67.75$***		

Note(s): To conserve space, only statistically significant dummy categories are reported
n.s. = not significant; **$p < 0.05$; ***$p < 0.001$

Table 4.
Estimation results

6.1 Hypothesized effects

Consistent with H1, greater availability of information in video titles is negatively associated with video views ($\beta_1 = -0.002$, $p < 0.05$). Specifically, a one-unit increase in a video title's character count is associated with a 0.2% decrease in video views. Consistent with H2, the intensity of negative emotional sentiment in video titles is positively associated with video views ($\beta_2 = 0.57$, $p < 0.01$). A one-unit increase in the intensity of negative emotional sentiment in video titles is associated with a 57% increase in video views. In contrast, greater positive emotional sentiment in video titles has no statistically significant relationship with video views ($\beta_3 = 0.164$, $p = 0.199$). Consistent with H3, greater availability of information in video descriptions is positively associated with video views ($\beta_4 = 0.0001$, $p < 0.01$). Specifically, a one-unit increase in the character count of video descriptions is associated with a 0.01% increase in video views. Finally, H4 is supported, as the linear term for video tags is positively statistically significant ($\beta_5 = 0.033$, $p < 0.01$), whereas the squared term is negatively statistically significant ($\beta_6 = -0.001$, $p < 0.01$). The turning point occurs at around 17 video tags [1]. Thus, adding up to 17 video tags is positively associated with video views; however, beyond that, adding more video tags is negatively associated with video views.

6.2 Control effects

The control variables also offer additional insight. Number of subscribers ($\beta = 0.000$, $p < 0.01$) and number of trending days ($\beta = 0.257$, $p < 0.01$) are positively associated with video views, while number of pre-trending trending ($\beta = -0.001$, $p < 0.01$) is negatively associated with video views. Regarding content category, videos in the film and animation ($\beta = 0.271$, $p < 0.05$) and music categories ($\beta = 0.483$, $p < 0.01$) received more views than videos in the entertainment category (reference category). Contrastingly, videos in the education ($\beta = -0.291 p < 0.01$), how to and style ($\beta = -0.235$, $p < 0.01$), news and politics ($\beta = -0.696$, $p < 0.01$) and shows categories ($\beta = -1.538$, $p < 0.01$) received fewer views than videos in the entertainment category. With respect to upload month, videos uploaded in November ($\beta = -0.177$, $p < 0.01$) and December ($\beta = -0.415$, $p < 0.01$) received fewer views than those uploaded in January (the reference category). Finally, in terms of upload day, Sunday was the only statistically significant dummy ($\beta = 0.353$, $p < 0.01$), suggesting that videos uploaded on Sundays received more views than those uploaded on Wednesdays (reference category).

6.3 Robustness checks

To check the robustness of the findings from the views model, an alternative model was tested, in which the log of video likes replaced the log of video views as the dependent variable in equation (1). Video likes is an important form of customer engagement that captures viewers' affective responses to videos (i.e. whether they enjoyed watching a video or not). The results from the views model were replicated in the likes model (see Table 4). The few discrepancies noted were related to the dummy variables for content category. In the likes model, videos in the comedy; gaming; how to and style; and people and blogs categories received more likes than videos in the entertainment category, while those in the sports category received fewer likes. Apart from these discrepancies, the likes model fully replicated the main effects from the views model, thereby offering evidence of the robustness of the proposed model to alternative specifications of the outcome variable.

7. Discussion

This study examined implications of marketers' video optimization practices for video views on YouTube. The study tested a regression model in which elements of the video metadata, including video titles, video descriptions, video tags and a host of other video-level characteristics, are used to predict video views. Estimation of the regression model on a large data set of YouTube videos (N = 4,398) generated several useful insights.

First, the study finds that video titles with less information are more effective in generating video views than titles with more information. This result can be explained through information overload theory (Toffler, 1984). Information overload occurs when the amount of information people are exposed to exceeds their capacity to effectively process it (Roetzel, 2018). Research shows that people routinely experience information overload on social media (Gomez-Rodriguez *et al.*, 2014). One manner by which social media users attempt to resolve this issue is by filtering dense information that taxes their time and processing capacity (Roetzel, 2018). This dynamic appeared to be at play in the current study. To the extent that denser video titles demand viewers to expend more time and effort to read and understand them, they may avoid such titles, thereby reducing their likelihood of clicking on videos with longer titles.

Second, the study finds that the intensity of negative emotions in video titles is positively associated with video views, whereas the intensity of positive emotions has no statistically significant association with video views. This result suggests that negative emotions in video titles attract viewers' attention more than positive emotions, thereby contradicting prior findings that positive content is more likely to spread online (Berger and Milkman, 2012; Tellis *et al.*, 2019). However, past studies investigated social shares, a concept in which people publicly share content online. The present study investigated video views, which often occur in private (e.g. people typically watch YouTube videos on their mobile devices). Therefore, the social dynamics that drive online content sharing, such as image building and social acceptance, are largely muted in video views, thereby encouraging people to watch videos with negative emotions. Greater interest in these videos can be explained through negativity bias, which makes people pay greater attention to negative than positive information (Baumeister *et al.*, 2001; Smith *et al.*, 2003).

Third, the study finds that greater availability of information in video descriptions is positively associated with video views. Video descriptions mainly serve indexing purposes, whereby YouTube's algorithms scan the details provided in video descriptions to index and categorize videos and show them to viewers (Choudhari and Bhalla, 2015; Zhou *et al.*, 2016). YouTube's algorithms might also use the content of video descriptions to infer the domain expertise of YouTube channels and rank videos higher in viewers' search results (Feroz Khan and Vong, 2014). Overall, the findings suggest that informative descriptions offer additional opportunities for video optimization.

Finally, the study finds an inverted U-shaped relationship between video tags and video views. Video tags are marketer-created keywords that reflect the search words and phrases that viewers use to find videos on YouTube (Choudhari and Bhalla, 2015; Lopezosa *et al.*, 2019). As the findings indicate, video tags are most effective when used in moderation. Specifically, applying up to 17 video tags to YouTube videos is associated with more video views; however, adding more than 17 video tags is counterproductive. When numerous video tags are used together, some of the tags end up being unrelated to the content of the video, thereby prompting YouTube's algorithms to flag the video in question as spam, which eventually harms its views count.

Collectively, the findings reveal how marketers' video optimization practices are associated with video views, thereby contributing to the limited but growing literature on YouTube marketing (Tellis *et al.*, 2019; Tucker, 2015). Whereas existing studies primarily investigated viewers' post-view responses, such as their liking, commenting and sharing behaviors (Moldovan *et al.*, 2019; Tellis *et al.*, 2019; Vedula *et al.*, 2017), this study focused on their viewing behavior. Since video views feed into all other forms of user engagement behavior on YouTube, the study's focus on video views constitutes an important addition to the literature. Moreover, extant studies have primarily examined videos' internal content, such as their emotional sentiment (Nielson-Field *et al.*, 2013; Tellis *et al.*, 2019), advertising persuasiveness (Tucker, 2015) and audiovisual features (Vedula *et al.*, 2017). This study complements extant studies by considering key elements of the video metadata and offering refined insights about their association with video views.

8. Managerial and research implications

The findings offer useful managerial implications regarding best optimization practices for YouTube videos. First, marketers need to keep their video titles as concise as possible, which helps to inform viewers about their videos while not demanding too much of their time and cognitive resources. Second, marketers may want to frame their video titles negatively. The findings show that video titles displaying negative emotions had more video views than those displaying positive emotions. Negative titles appeared to be more powerful in sparking viewers' interest in videos. Third, marketers need to craft detailed video descriptions that provide adequate information and context and incorporate relevant keywords. Finally, marketers should focus only on those keywords that fit the content of their videos. Adding keywords just for the sake of it, or simply because YouTube does not put a cap on the maximum number of keywords, can be counterproductive. In conclusion, the findings demonstrate the value of video optimization practices in driving views on YouTube, and marketers need to spend time and effort to properly optimize their videos.

In terms of future research, the findings point to multiple avenues. First, the study considered numerical aspects of the video metadata, such as character count. However, numerical measures may not capture the full picture. For instance, a title that contains few words could be perceived as less informative by viewers if those words are unfamiliar to them or have peculiar interpretations. Therefore, conceptual and measurement approaches that appreciate the qualitative nuances of the video metadata would offer a useful complement to the computational approach. Second, the study presented aggregate results without differentiating between content categories. However, the drivers of video views might differ as a function of video category (Lopezosa *et al.*, 2019). For instance, video titles may need to be more informative and, therefore, longer for utilitarian videos (e.g. news, politics and educational) than for hedonic videos (e.g. music videos and films). Thus, future research may want to examine optimization practices for different video categories. A similar approach could be devised for channel subscribers. Videos released by highly popular YouTube channels may not need to be optimized as scrupulously as videos released by smaller YouTube channels. In other words, channel size might moderate the relationship between marketers' optimization practices and video views (Feroz Khan and Vong, 2014). Finally, it should be noted that the data set used in this study may not be representative of videos shared on YouTube by mainstream business establishments. The average number of subscribers and trending indicators suggests that the creators behind the videos in the data set are highly experienced YouTube marketers. This aspect of the data set must be considered when interpreting the findings.

Note

1. The turning point in a polynomial regression is derived by taking the first derivative of equation (1) and setting it to zero, which gives $\beta_5/2\beta_6$.

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