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Short communication

Celebrity over science? An analysis of Lyme disease video content on YouTube

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ABSTRACT

Lyme disease has been a subject of medical controversy for several decades. In this study we looked at the availability and type of content represented in a (n = 700) selection of YouTube videos on the subject of Lyme disease. We classified video content into a small number of content areas, and studied the relationship between these content areas and 1) video views and 2) video likeability. We found very little content uploaded by government or academic institutions; the vast majority of content was uploaded by independent users. The most viewed videos tend to contain celebrity content and personal stories; videos with prevention information tend to be of less interest, and videos with science and medical information tend to be less liked. Our results suggest that important public health information on YouTube is very likely to be ignored unless it is made more appealing to modern consumers of online video content.

1. Background

User generated video content hosted by YouTube has become a popular resource for a variety of information consumers; based on YouTube's own estimates, viewers consume hundreds of millions of hours of YouTube video content each day, a large share of which is consumed by persons in the 18–49 age range. Given its large audience, YouTube has a considerable potential to share health information, however, some have suggested that it makes socially and medically deleterious content more available (Madathil et al., 2015). In research on anorexia videos on YouTube, Syed-Abdul et al. (2013) found that pro-anorexia lifestyle videos are less abundant but more popular than medically informative videos. Popular videos on cardiopulmonary resuscitation (Murugiah et al., 2011) and first aid (Butler et al., 2013) are also among the least informative, while those about chronic disease, like asthma, often advocate unproven medical treatments (Gonzalez-Estrada et al., 2015). Content relating to self-harm tends to reinforce harmful behaviours rather than recovery (Lewis et al., 2012), and obesity related video content tends to reinforce mockery, judgement and stigma (Hussin et al., 2011; Yoo and Kim, 2012).

On the other hand, YouTube content can contribute to greater awareness of a variety of health issues, and connect persons in need of social support and shared illness experiences. YouTube videos on epilepsy are thought to increase sympathy and understanding in a way that is positive and understandable to a general audience (Wong et al., 2013). YouTube is also used to share social support messages for and among people suffering from illness (Frohlich and Zmyslinski-Seelig, 2012), and could be an important tool for educating the public about health issues in other parts of the world (Basch et al., 2015). YouTube can also be used to share experiences of persons using the health care system (Myrick and Oliver, 2015). Finally, YouTube has been a useful tool in some specific areas of medical education, such as anatomy (Jaffar, 2012) and perioperative nursing (Logan, 2012).

YouTube users show preferences for some types of health-related content; videos showing personal experiences are generally more popular than videos containing information and education (Lo et al., 2010). Some health-related video content contains explicit and implicit references to conspiracy theories and anti-government sentiment, particularly with respect to medically contentious issues, such as immunization and illicit drugs (Briones et al., 2012). It is also linked to the marketing of some specific health-related products, like smokeless tobacco (Luo et al., 2014). Online content that expresses skepticism towards the medical establishment tends to focus more on developing personal narratives and building relationships rather than sharing of information (Grant et al., 2015).

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In this short communication we analyze YouTube content on Lyme disease in order to understand links between the material contained in and associated with the videos and 1) the frequency of views and 2) the likeability of videos. Lyme disease is caused by a bacterial infection spread by the bite of a tick, and can cause serious illness if left untreated. It has been a subject of medical controversy since at least the early nineties (Aronowitz, 1991), largely due to the diverse range of symptoms, the possible appearance of post-treatment effects, and the difficulty of diagnosing it in early stages of disease. Social media marketing, including YouTube, has helped increase the profile and awareness of Lyme disease among health professionals and the public (Aenishaenslin et al., 2016), however, online content often expresses a diversity of frequently conflicting viewpoints, and can be a touchstone of fierce debate. For this reason, information and awareness campaigns may be enhanced by better understanding the factors that influence the popularity of YouTube content on Lyme disease. The results of our analysis offer useful information to the public health community interested in using these online tools to reach a larger audience of information consumers.

2. Materials and methods

We used a single search phrase, “Lyme disease” (without quotes, case insensitive) within YouTube's search tool. At the time the study was conducted the total number of videos returned on this search phrase is over 150,000. We took a systematic sample by extracting information from the 700 top listed videos returned from the search. Data were extracted from this search from January to April 12, 2017. The authors collected key statistics for the 700 sampled videos: upload date, view date, uploader of video, number of video subscribers, number of times the video was viewed, number of times the video was ‘liked’, the number of times the video was ‘disliked’, and video duration in minutes based on public information associated with each video. We classified the uploader of the video into one of three categories based on the institution or individual owning the video channel: academic, government, news/entertainment and private individuals. The latter category includes individuals not obviously affiliated with academia, government or news/entertainment.

Video views indicate the number of viewers that have watched at least part of a video, but say little about the impact of videos on users. The number of minutes watched per view may be a superior metric for engagement with content, but this is not generally available to anyone other than the video uploader. We propose using the views, likes and dislikes for each video to calculate an alternative metric, the ‘likeability index’, as

$$I = (\alpha L - D)/\alpha * V \times 100, \quad (1)$$

where L is the number of video likes, D is the number of video dislikes and V is the number of video views. The index is bounded between $-100/\alpha$ and $+100$, and we use it to measure viewer attitudes towards videos, with larger positive values indicating greater likeability due to positive user engagement (clicking the ‘Like’ button) and with values approach $-100/\alpha$ indicating less likeability (clicking the ‘Dislike’ button). The index is correlated to the ratio of likes to views for a video, but also adjusts the likeability of videos based on the number of dislikes. The constant, α, helps account for the relative importance of likes and dislikes of a video, and the possibility that many dislikes on YouTube are the result of conflict provoking (‘trolling’) behaviour rather than substantive dislike of content (McCosker, 2014). For this research, we set $\alpha = 20$, a value equal to the average ratio of likes to dislikes found in the sample.

For every video 10 minutes in length or under ($n = 469$), one of the study authors (RT) classified each video into non-exclusive categories based on their content: science/medical, personal experience, celebrity, prevention and symptoms. Each category was classified as “Yes” or “No” depending on RT's assessment of the content. In order to test the rigour of the classification method, the other study authors (NY and SS) made a blind classification of a random sample of 30 videos. We compared the inter-rater reliability between the classifications using Fleiss' Kappa, which allows comparison between multiple raters. The overall agreement between raters was moderate ($\kappa = 0.466$, $p < 0.001$), although the agreement was notably lower for the science/medical and symptom categories at 0.217 ($p = 0.045$) and 0.159 ($p = 0.155$), respectively. To address this, we extracted the transcripts from the videos for which text was publicly available ($n = 349$) and searched for the frequencies of terms related to science/medicine and symptoms within this subset. We then updated the original classification of videos for these two content areas in the following manner. If the rater's classification was “No” and the frequency of term use was above the 75th percentile, the video was re-classified as “Yes” for the given category. If the rater's classification was “Yes” and the frequency of term use was below the 25th percentile, the video was re-classified as “No” for the given category.

We summarize simple descriptive statistics for all data. We also modelled 1) the log of total video views and 2) the likeability index as a linear function of the content areas and other video characteristics. This analysis is restricted to videos under 10 min in length. The purpose of the model is to identify associations between the classified video content and both the views and the likeability of the videos, and to generate scenario models for understanding how video and uploader attributes influence views and likeability. All data processing and analysis was performed using the R language. The working data set is available from the authors.

3. Results

The sample of 700 videos had a total of 148 viewing hours available with a total of 12,767,635 views. Summary statistics are presented in Table 1. Table 2 has the frequencies, views, minutes of content, and an estimated hours viewed within each content area and by uploader. For all video content areas except for celebrity, the frequency of content (as a percentage of all videos) is greater than the frequency of views (as a percentage of all views). When combined, academic and government uploaders are responsible for less than 2% of the video content in our sample.

The results of our models are presented in Table 3. Based on the adjusted R^2, the models explain a modest share of the variability in both the log of video views (0.38) and likeability (0.21). The length of time since upload is positively associated with views, and negatively associated with likeability. Uploaders with more subscribers tend to get more video views, though the relationship does not appear to be linear. Celebrity content is strongly associated with the log of video views, with celebrity content having more than double the average number of views as a videos without celebrity content, all else being equal. Personal content is also positively associated with more video views, and prevention-related content is associated with fewer views.

The content categories show different associations with likeability compared to video views. Celebrity videos show a negative and weak association with likeability, and prevention content shows a similarly weak but positive association with likeability. The type of content uploader is strongly associated with likeability; private individual uploaders have higher likeability than academic, government, and media uploaders.

For illustrative purposes, we compare the views and likeability predicted by these models for two scenarios. Predictions involve