Science communication on YouTube: Factors that affect channel and video popularity

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Abstract

YouTube has become one of the largest websites on the internet. Among its many genres, both professional and amateur science communicators compete for audience attention. This paper provides the first overview of science communication on YouTube and examines content factors that affect the popularity of science communication videos on the site. A content analysis of 390 videos from 39 YouTube channels was conducted. Although professionally-generated content is superior in number, user-generated content was significantly more popular. Further, videos that had consistent science communicators were more popular than those without a regular communicator. This study represents an important first step to understand content factors, which increase channel and video popularity, of science communication on YouTube.

Keywords

YouTube, science communication, video, channel, popularity, content analysis, review, factors

Introduction

Science communication has traditionally been dominated by professional communicators employed directly or indirectly by the mainstream media (Valenti, 1999). With the emergence of Web 2.0, platforms such as blogs, wikis, social media, and video sharing websites have redefined the mediascape (Brossard, 2013; Minol, Spelsberg, Schulte, & Morris, 2007). Web 2.0 provides an alternative to traditional content distribution by reducing the barriers for content creators to reach an audience (Juhasz, 2009). Many Web 2.0 platforms are constructed on a participatory culture, a 'function that is most noticeably absent from most mainstream media' (Burgess & Green, 2009, p. 29). Thus, in the era of Web 2.0, viewers have shifted from being passive consumers to active participants. Science communication is now conducted not only by professional communicators, but also by scientists, interest groups, professional organisations, and passionate amateurs across numerous Web 2.0 platforms (Claussen et al., 2013; Lo, Esser, & Gordon, 2010; Nisbet & Scheufele, 2009).

YouTube is a particularly significant example of the Web 2.0 phenomenon. YouTube was founded by employees of PayPal in 2005 and has undergone spectacular growth to become one of the top websites on the internet (Burgess & Green, 2009; Alexa Internet Inc., n.d.). YouTube was founded on the user-generated content (UGC) model, whereby content was to be derived from YouTube users and consumers. However, the sale of YouTube to Google in 2006 marked the beginning of a deliberate effort by YouTube management to increase the volume of professionally-generated content (PGC); content created by corporate entities to extend the reach of commercial branding (Ackerman & Guizzo, 2011; Kim, 2012; Wasko & Erickson, 2009). PGC and "astroturf" (content created by corporate entities to mimic grassroots, or UGC) has subsequently increased over the period (Burgess & Green, 2009). The evolving demographic of content creators on YouTube has meant that amateur science communicators now compete for views with large well-funded corporations like the British Broadcasting Corporation and the Discovery Channel.

Despite the large number of content consumers on YouTube, reaching an audience is not guaranteed. Reaching an audience and achieving success is a function of how popular a channel and its videos become; as measured by the number of subscribers and views received (Burgess & Green, 2009). The popularity of any given video is a function of the video's content factors, content-agnostic factors, and YouTube's video recommendation system (Borghol, Ardon, Carlsson, Eager, & Mahanti, 2012; Figueiredo, Almeida, Benevenuto, & Gummadi, 2014). Content factors are the stylistic and informational characteristics of a video (e.g. topic, duration, or delivery style), whereas content-agnostic factors relate to characteristics external to the video (e.g. the creator's social network or video upload date and time). YouTube's recommendation system both identifies what is popular and creates what is popular in a rich-get-richer popularity scenario (Figueiredo, Benevenuto, & Almeida, 2011; Szabo &

Huberman, 2010; Zhou, Khemmarat, & Gao, 2010). That is, the recommendation system recommends popular videos to viewers, which in turn increases the popularity of those videos (Zhou et al., 2010). Although a growing body of literature has independently addressed content and content-agnostic factors of YouTube videos broadly, few studies have examined science communication videos specifically.

To fill this knowledge gap, we examined content factors of science communication videos on YouTube for their influence on video popularity. We first assessed the differences in professionally- and user-generated channels; specifically, the number of views, subscribers, age of the channel, and number of videos created. Then, within the context of PGC and UGC, we examined the impact of video length and pace and how the video was delivered; delivery being a function of the gender, style, and the continuity of the delivery person(s) between videos. This was achieved by manually coding content factors of a sample of videos and analysing the relationships against YouTube's popularity metrics. Although manually coding limits the quantity of videos that can be sampled, it was necessary to obtain much of the data required. Understanding which video content factors contribute to video popularity on YouTube and the impact of PGC on UGC, if there is any, will assist content creators to create more engaging and popular science communication content. In the next section, current research on understanding popularity on YouTube is reviewed, followed by the methods section that will detail the sampling protocols and video coding procedures. The results section follows, divided into channel and video specific sections, and finally, the results are discussed and the paper concludes by highlighting future research.

Literature Review

As there are few studies that have examined science communication on YouTube the selection of content factors in this study may seem arbitrary, though this is not the case. We focus on content factors, as opposed to content-agnostic factors, as they are valuable to understanding drivers of popularity broadly and allow recommendations to be made in the creation of science communication content. Upon accepting content factors, the first evaluation is a fundamental separation of professionally-generated and user-generated channels and their videos. Expected differences in channel resources between user-generated and professionally-generated channels led us to examine content factors related to the delivery of content. For instance, a channel with large resources may be capable of employing professional creators, which undoubtedly have different skill sets and, therefore, ideas about how a YouTube video should be presented. Ultimately, the content factors selected provide a baseline for future research to build upon. Before reviewing content factors, we briefly address the primary content-agnostic factor that appears to drive video and channel popularity.

A channels social network is the primary content-agnostic factor that influences, and also confounds, video and channel popularity (Burgess & Green, 2009; Juhasz, 2009; Yoganarasimhan, 2012). Crane and Sornette (2008) postulated three categories of video (viral, quality, and junk) and found that each had a distinct view count distribution history. Figueiredo et al. (2011) similarly found that top videos (the quality category in Crane and Sornette (2008)) experience a significant burst of activity, receiving many views in a single day or week, with other videos undergoing several smaller peaks of activity. The growth of video views is linked to the rich-get-richer effect of the recommendation system (Borghol et al., 2012) and the channels social network (Yoganarasimhan, 2012). Despite these findings, social network analysis on YouTube is problematic for two reasons. Firstly, a complete social network within YouTube cannot be attained because not all channels make lists of 'friends' or 'featured channels' available; and secondly, it is not feasible to determine the social network of a channel beyond YouTube due to difficulties in connecting social networks across platforms (Yoganarasimhan, 2012). Though an analysis of the social network of science communication channels on YouTube is beyond the scope of this paper, it is clearly an important consideration in understanding channel popularity generally.

Although the popularity of a YouTube video is a function of content and content-agnostic factors, content factors appear to be the most informative for understanding broad popularity within the YouTube community. Broad popularity is meant here as popular among a wide spectrum of viewers; whereas narrow or niche popularity is only popular within a limited audience. Figueiredo et al. (2014) examined

YouTube users’ perceptions of video popularity by exposing volunteers to pairs of preselected videos. User preferences meant that in many evaluations users could not come to a consensus on which video had the best content; but, in those evaluations where users did come to a consensus, the video identified as having the preferred content was frequently more popular on YouTube (Figueiredo et al., 2014). Hence, for a video to be popular among a broad audience, the content must be broadly appealing. Therefore, understanding the content factors are vital to understanding what drives popularity broadly.

Most studies examining science communication on YouTube are directed at assessing the veracity of the information; which, depending on the topic, does appear to influence video popularity. Keelan, Pavri-Garcia, Tomlinson, and Wilson (2007) analysed 153 immunisation videos for accuracy and tone, categorised as positive, ambiguous, or negative. Positive videos were those that presented immunisation in a positive way, ambiguous content was neither for nor against, and negative content had a central theme of anti-immunisation. Keelan et al. (2007) found no errors in positive content, whereas 45% of negative content had misleading information. Despite misleading information, negative videos had higher view count and ratings than positive videos. Conversely, Sood, Sarangi, Pandey, and Murugiah (2011) analysed 199 videos on kidney stone disease and found useful videos received significantly higher views than misleading content. Still, other research has found no statistical difference in view count and ratings between useful and misleading content (Ache & Wallace, 2008; Azer, 2012; Murugiah, Vallakati, Rajput, Sood, & Challa, 2011; Pandey, Patni, Singh, Sood, & Singh, 2010).

The type of channel is of particular interest in understanding YouTube popularity. Professionally-generated channels (i.e. channels that exist to extend commercial branding) often have superior financial resources compared with user-generated channels. Financial resources can allow professionally-generated channels to increase the appeal of the channel and/or of specific videos through the creation of regular or large volumes of content and content of high production value. Hence, the UGC community has expressed concern that they will be overshadowed by PGC (Kim, 2012). Although superior resources might allow channels to employ professional video producers and presenters, it has been argued that ‘in order to operate effectively as a participant in the YouTube community, it is not possible simply to import learned conventions … from elsewhere (e.g. from professional television production)’ (Burgess & Green, 2009, p. 69). Furthermore, the popularity of YouTube content is not determined by the quantity of videos a channel uploads but by the views and engagement (YouTube, 2012). Thus, while regular content assists in engaging one’s audience (YouTube, n.d.), a channel must still host content that the YouTube community finds engaging.

Superior resources of a channel may give it an advantage through advertising. YouTube’s video recommendation system uses the engagement metrics, or popularity metrics, to recommend videos to other viewers. These can be manipulated as numerous websites sell fake views, comments, likes, and subscriptions for YouTube channels and videos (Hoffberger, 2013). While YouTube has responded by continually policing the artificial inflation of popularity metrics, which in the past has led to the removal of views and videos, it appears to be an ongoing problem (Pfeiffenberger, 2014). Regardless of illegitimate forms of advertising, channels can purchase legitimate advertising. Google advertising can be purchased to increase views and engagement on videos and channels, thereby giving well funded channels a competitive advantage.

In an information rich world, the limiting factor in consuming content is the consumers’ attention (Davenport & Beck, 2001). It logically follows therefore that short videos and/or fast paced videos which give the illusion of being short, might be more engaging than long or slow paced videos (Grabowicz, 2014). Although the length of science communication videos have not been reviewed explicitly in the primary literature, several media companies have analysed YouTube video length more generally. The Pew Research Center (2012) reviewed the most viewed YouTube videos between January 2011 and March 2012 and found ~50% were less than two minutes and ~82% were less than five minutes; and Ruedlinger (2012) claims video length was inversely correlated with capturing and holding viewer attention in business videos.

Nevertheless, these findings may be indicative of sampling bias given that the average length of YouTube videos was found to be 4.4 minutes (Lella, 2014). That is, if the majority of videos are short, then it is likely that most popular videos are short.

Although the evidence is weak, there is some suggestion that UGC is more popular than PGC. Lorenc et al. (2013) reviewed the top 241 most subscribed channels and found ~68% were from user-generated channels, and of the genres represented (comedy n = 83, music n = 79, gaming n = 36, fashion/ beauty n =14, other n = 29) only the music genre had more professional-generated than user-generated channels. In the context of science communication, Lo et al. (2010) reviewed videos on epilepsy and found that UGC content had more views, ratings, and comments than PGC, and noted that comments on UGC attempted to engage with the videos' creator and other viewers, whereas comments on PGC did not. However, little weight can be afforded either of these findings as Lorenc et al. (2013) has not undergone peer-review; and Lo et al. (2010) examined only 10 videos that included only two professionally-generated. Hence, this study makes a significant contribution to the science communication literature by examining science communication on YouTube more thoroughly.

Method

Video procurement

To achieve the aims of this paper, it was calculated that a minimum sample of 385 videos was required. To limit bias induced by channels with large numbers of videos, a clustered random sampling approach was used. In December 2013, YouTube channels were randomly sampled in 50 channel blocks from the top 1000 channels from the SocialBlade (2013) categories of 'Education' and 'Science & Technology'. Videos were then randomly sampled from each channel and reviewed for inclusion. Videos in English, at least 180 days old, and could be defined as science communication (in the context of this study, see definition below) were retained until 10 videos per channel were identified, resulting in a total of 39 YouTube channels included in the dataset. Clone-videos and channels principally composed of reposted content from other creators were excluded from the dataset.

Science communication

Science communication in practice is considerably broad, often attracting equally broad definitions in the academic literature (*sensu,* Bryant, 2003; Gilbert & Stocklmayer, 2013). In this study, 'science' was taken as any topic that would be categorised in one of the Scopus science subject areas of physical, life, health, or social sciences, excluding the topic of 'Arts and Humanities' (Elsevier, 2014). The tone of communication of these topics can also be quite broad. Hence, ‘science communication’ in this study was taken to be any video that might be seen as a form of science journalism that is not overtly didactic or instructional, while also not being principally focused on entertainment. Defining science communication in this way was necessary because of the different reasons that one watches YouTube (Burgess & Green, 2009). Although this is somewhat subjective, consistency was maintained as a single author (DJW) reviewed all material for inclusion.

Data coding

The collection of channel data, video popularity metrics, and video content factors of the identified YouTube videos began in January 2014. Data was obtained on videos and channels using both automated (Zdravkovic, 2013) and manual coding procedures. The following data were coded for each channel:

(a) Channel age, as measured from the first upload event;

(b) Number of videos at time of video procurement;

(c) Channel views at time of video procurement;

(d) Channel subscriptions at time of video procurement; and,

(e) Channel type, coded as professionally-generated content (PGC) for channels named after corporate entities or as user-generated content (UGC) for channels that are YouTube derived.

The following popularity metrics were extracted for all videos simultaneously:

(a) Video view count;

(b) Number of comments on the video;

(c) Number of subscriptions driven from the video;

(d) Number of times the video was shared;

(e) Total number of ratings.

Each video was reviewed manually and the following content factors coded.

1. Video length (seconds) taken as the complete video duration.
2. Pace of content delivery (words per minute) calculated from the video and YouTube's automatic transcript feature. Although this feature does not record each word accurately, it does capture the number of words accurately (unpublished data).
3. Communicator continuity (binary) identified whether a channel had a continuous science communicator or communicators who delivered content. Channels were initially classified into three categories of mostly continuous, >66% of videos had the same communicator; mostly non-continuous, >66% of videos did not have the same communicator; and mixed. In the final dataset this was collapsed to a binary classification as no "mixed" channels were identified.
4. Gender (male, female, both, or no-gender) of the person or persons delivering the science content.

5. Video style was coded as one of six styles identified while reviewing the dataset. Vlog: an iconic YouTube video style where the presenter delivers content by talking directly to the camera. Hosted: stylistically similar to the vlog where the communicator presents the information; however, other people such as members of the public or interviewees are also part of the video content. Interview: videos where the person delivering content is being interviewed by a person off camera who is often the video creator. Presentation: the presenter is presenting information to an audience and not the camera specifically. Voice over visuals: videos where someone talks over animated or static visuals. Text over visuals: similar to voice over visual, but with text in place of the voice.

Statistical Analysis

All statistical analysis was carried out in the R statistical package version 3.0.2 (Cran Team, 2014). Provided assumptions held and data transformations were suitable, parametric tests were used, otherwise non-parametric tests. Welch's t-test was used in place of Student's t-test where unequal variance was identified using Levene's test for homogeneity of variance. An alpha of 0.05 was used for significance in all tests. Effect sizes and correlations were described according to Cohen (1988) and Evans (1996).

Results

Channel Results

A total of 411 YouTube channels were sampled to obtain the 39 science communication channels required. These consisted of 21 professionally-generated and 18 user-generated channels. The age of professionally-generated channels (M = 1220 days, SD = 864) was not significantly different from user-generated channels (M = 1263 days, SD = 679; Student's $t(37) = 0.17$, $p = 0.87$, Cohen's $d = 0.05$). Professionally-generated channels had significantly more videos than user-generated channels (Welch's $t(34.5) = 1.73$, $p = 0.04$, Cohen's $d = 0.55$; Figure 1(a)). Professionally-generated and user-generated channels both had highly positively skewed distributions of subscriptions and channel views (Figure 1(b) and (c)). Hence, half of professionally-generated and user-generated channels had less than ~1.8×10^6 and ~4.6×10^7 channel views (respectively), and less than 26,533 and 366,805 subscriptions (respectively). Channel type had a large effect on subscriptions and channel views; user-generated channels had significantly more subscriptions (Welch's $t(33.4) = 4.90$, $p < 0.01$, Cohen's $d = 1.55$) and channels views (Student's $t(37) = 3.38$, $p < 0.01$, Cohen's $d = 1.09$) than professionally-generated channels.

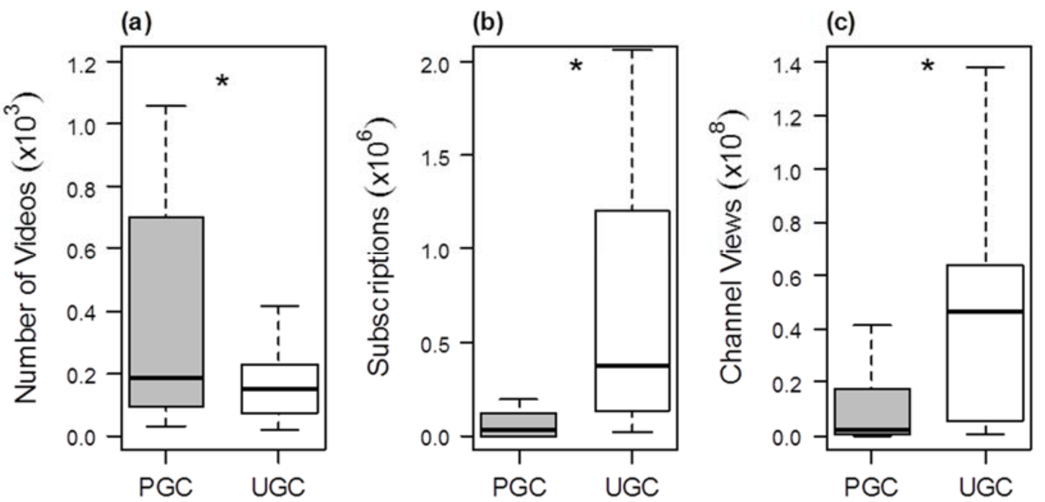

Figure 1. The number of videos (a), subscriptions (b), and channel views (c) of professionally-generated (PGC) and user-generated (UGC) YouTube science channels. Asterisks indicate a significant ($p < 0.05$) difference between PGC and UGC.

Pearson's product moment correlation was used to examine the relationships between channel data and popularity metrics. Both professionally-generated and user-generated channels exhibited similar relationships between channel data and popularity metrics; hence, channel type (i.e. UGC or PGC) was not considered in the correlations. Channel views were very strong positively correlated with subscriptions ($t(37) = 15.7$, $p < 0.01$, $r = 0.93$), and moderate positively correlated with the number of videos on a channel ($t(37) = 2.8$, $p < 0.01$, $r = 0.42$). However, by controlling for subscriptions and uploads, views per subscription was not correlated with subscriptions ($t(37) = 1.92$, $p = 0.06$, $r = -0.30$), and no correlation was found between views per video and number of videos ($t(37) = 0.80$, $p = 0.43$, $r = -0.13$). Number of videos was moderate positively correlated with the age of a channel ($t(37) = 4.2$, $p < 0.01$, $r = 0.57$); but, after controlling for channel age no correlation was found between the age and the number of videos uploaded daily ($t(37) = 0.11$, $p = 0.92$, $r = -0.07$). Interestingly, neither channel views nor subscriptions were correlated with the age of the channel ($t(37) = 1.32$, $p = 0.19$, $r = 0.21$; $t(37) = 0.01$, $p = 0.99$, $r = 0.00$; respectively), and channel subscriptions were not correlated with the number of videos on a channel ($t(37) = 0.89$, $p = 0.38$, $r = 0.14$).

Video Results: Popularity Metrics

Ten videos from each channel were acquired resulting in a final dataset of 210 videos of PGC and 180 videos of UGC. Similar to channel age, video age was approximately normally distributed (*M* = 752 days, *SD* = 540), and there was no significant video age difference between PGC and UGC (Student's $t(387) = 0.54$, $p = 0.59$, Cohen's $d = 0.06$). All video popularity metrics (i.e. views, comments, subscriptions driven, number of shares, and total ratings) were found to be highly positively skewed (skew > 4.6, kurtosis > 24.8). Furthermore, Spearman's rank-order correlation showed that all popularity metrics were very strong positively correlated to one another, which differed little between channel type (all relationships $\rho > 0.88$ and $p < 0.01$). Hence, only video views were considered further as the dependent variable.

Considering popularity metrics in terms of engagement revealed that engagement activity differed between popularity metrics, and that PGC and UGC were engaged with differently. Engagement refers to the number of views received per event of another metric. A one-way between subjects ANOVA (followed by Tukey's Post Hoc test) was conducted without video type as a function. All engagement metrics had significantly different views per engagement event ($F(3, N = 647) = 467$, $p < 0.01$, $\eta^2 = 0.52$; Figure 2). That is, views per rating event were significantly lower than per subscription driven; views per subscription driven were significantly lower than per comment received; and views per comment were significantly lower than per share event. Whether a video was professionally-generated or user-generated had no effect on the number of views received per subscription driven (Welch's $t(199) = 0.26$, $p = 0.80$, Cohen's $d = 0.03$) or comment received (Student's $t(345) = 1.53$, $p = 0.13$, Cohen's $d = 0.16$). However, UGC had significantly fewer views than PGC per rating received (Student's $t(372) = 5.30$, $p < 0.01$, Cohen's $d = 0.55$); and PGC had significantly fewer views than UGC per share event (Welch's $t(206) = 4.90$, $p < 0.01$, Cohen's $d = 0.63$; Figure 2). Thus, for the same number of views UGC would receive significantly more ratings, but PGC would be shared significantly more.

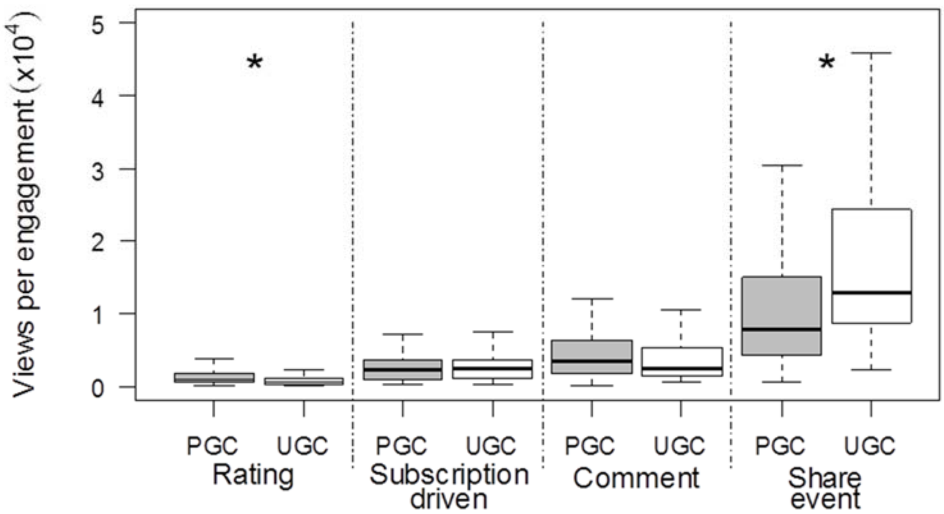

Figure 2. Number of views of professionally-generated (PGC) and user-generated (UGC) YouTube science videos per engagement event. Asterisks indicate a significant ($p < 0.05$) difference between PGC and UGC.

Video Results: Content factors

Professionally-generated content and UGC differed in several, but not all, of the content factors measured. A chi-square test was used to examine the proportions of PGC and UGC that contained a regular science communicator. UGC had a significantly higher proportion of videos (~56%, n = 100) with regular communicators than PGC (~37%, n = 77; $\chi^2(1, N = 390) = 13.95$, $p < 0.01$). A binomial exact test was used to evaluate whether science communicators were equally represented by both genders. The test showed males were in a significantly greater proportion of both PGC ($p < 0.01$) and UGC ($p < 0.01$; Figure 3(a)). There was no null hypothesis to test the proportion of delivery styles employed in PGC and UGC; still, Figure 3(b) shows that PGC was marginally more varied UGC. The rapidity with which content was delivered, as measured in words per minute, was significantly quicker in UGC (M = 169, SD = 32) than PGC (M = 153, SD = 27; Student's $t(338) = 5.10$, $p < 0.01$, Cohen's $d = 0.55$). Despite the difference in pace there was no significant difference in the length of PGC (Mdn = 196 s, range 19–4996 s) and UGC (M = 333 s, SD = 196 s; Welch's $t(355) = 0.37$, $p = 0.71$, Cohen's $d = 0.04$).

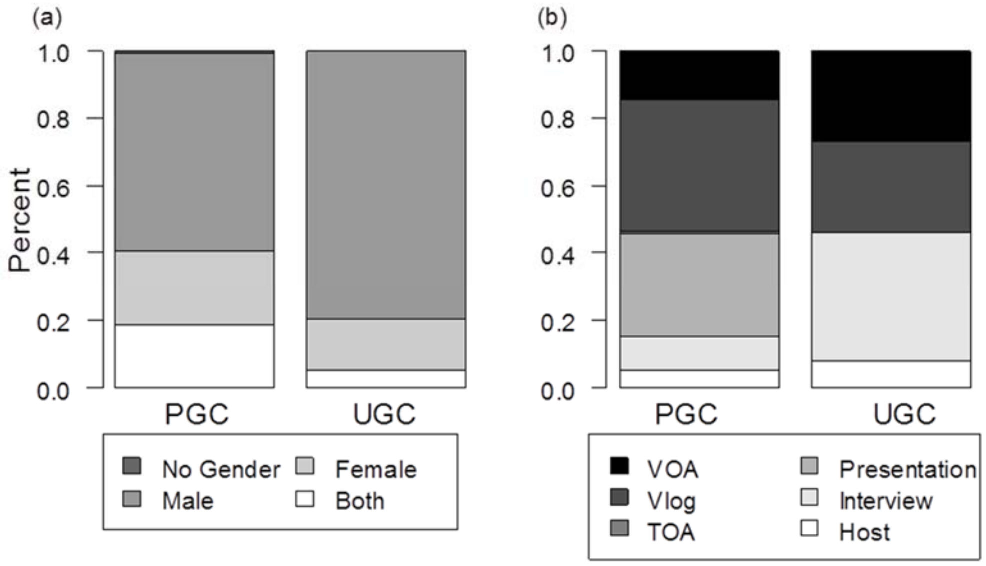

Figure 3. Gender representation (a) and deliver style (b) of professionally-generated (PGC) and user-generated (UGC) YouTube science videos.

Of the content factors measured, only communicator continuity, pace of delivery, and (marginally) gender appeared to impact upon video views. Videos with a regular communicator, in both video types, had significantly more views than videos without a regular presenter (UGC, Student's $t(178) = 9.03$, $p < 0.01$, Cohen's $d = 1.35$; PGC, Welch's $t(192) = 3.90$, $p < 0.01$, Cohen's $d = 0.54$; Figure 4). Furthermore, the effect of a regular communicator was larger for views of UGC than PGC. Using a one-way ANOVA gender was not found to be significant for views of UGC ($F(2, N = 177) = 2.53$, $p = 0.08$), whereas it was significant for PGC ($F(2, N = 206) = 2.95$, $p = 0.03$, $\eta^2 = 0.04$). Tukey's post-hoc test indicated that male-only PGC was viewed significantly more than PGC with both genders present; although this was a small effect. Pearson's product-moment correlation was used to examine the impact of pace and video length on video views. Pace was found to be weak positively correlated with views in both UGC ($t(160) = 2.60$, $p < 0.01$, $r = 0.21$) and PGC ($t(171) = 3.40$, $p < 0.01$, $r = 0.25$); but, interestingly, no correlation was identified between views and video length ($t(388) = 0.69$, $p = 0.49$, $r = -0.03$). Delivery style could not be analysed for its impact upon views as a number of channels were found to use only one style for their delivery.

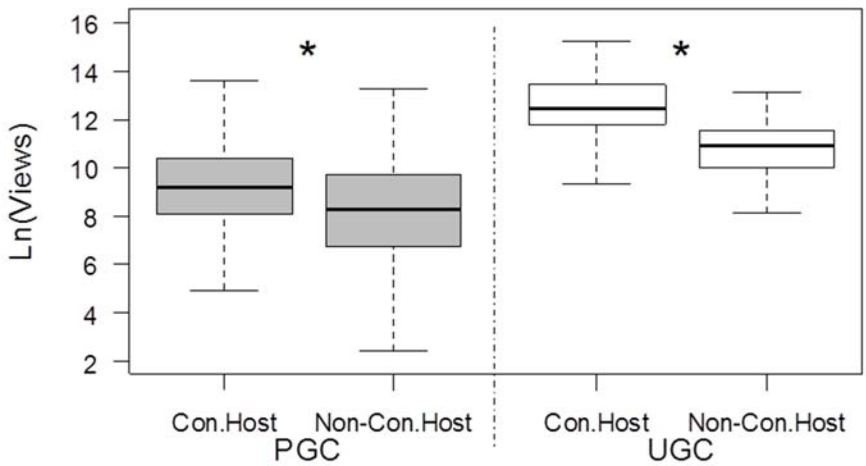

Figure 4. Views (natural log) of professionally-generated (PGC) and user-generated (UGC) YouTube science videos as a function of communicator continuity. Asterisks indicate a significant ($p < 0.05$) difference between videos with a continuous host (Con.Host) and non-continuous host (Non-Con.Host).

Discussion

In this study 390 science communication videos, from 21 professionally-generated and 18 user-generated YouTube channels, were examined to identify content related factors that influenced popularity. We identified three factors that contribute to popularity. First, although PGC is more numerous than UGC, UGC is far more popular in the science communication genre. Therefore, whether a channel is an overtly professionally-generated channel or one that appears to be YouTube derived (UGC) is the largest correlate of popularity. Second, whether a channel had a regular communicator to deliver content greatly impacted on video views. Third, for both PGC and UGC, videos that delivered information more rapidly had more views than slower paced videos. Several results from this study, namely the effect of video length on popularity and the rates of engagement with videos, disagree with findings from prior work (Chatzopoulou, Sheng, & Faloutsos, 2010). Still, we make several recommendations that may increase the popularity of science communication videos on YouTube, and we identify future research directions to expand upon this work.

Despite the concerns of Kim (2012), this research highlights that user-generated science communication need not fear PGC monopolising audience attention. The superior financial resources of professionally-created channels and (likely) formal technical training of PGC creators do not lead to science communication videos or channels that are more popular with the YouTube community. This result can be explained by how content consumers identify trusted sources. Among the key factors used by consumers to identify trusted sources of information on Web 2.0 are communicator expertise, experience, impartiality, affinity, and a source being trusted within a content consumer's social network (Borgatti & Cross, 2003; Heath, Motta, & Petre, 2007). These factors also support why communicator continuity increased video views. Making a connection with the audience is logically more direct if there is continuity throughout a series of videos; in short, a regular communicator adds to the authenticity of a channel (Burgess & Green, 2009). Thus, the success of UGC can be explained by user-created channels fostering meaningful connections with the viewer base, and the increased success of UGC with a regular science communicator merely compounds the effect.

It is logical that the pace of content delivery needs to suit the medium of communication. To get your message across when public speaking, instructional tips often repeat the dictum that one should not speak too quickly or too slowly, while averaging between 100–150 words per minute (Sudha, 2010). Comprehension studies for instance have found that students benefit from receiving content at lower than average speaking rates (~190 words per minute; Weinstein & Griffiths, 1992). The main reason why public speakers should ensure they are not talking too quickly is because of the transitory nature of the medium. It is not possible to replay something if it is missed. In contrast however, faster rates of speech are considered to improve the persuasiveness of arguments and increases audience focus (Chambers, 2001; Miller, Maruyama, Beaber, & Valone, 1976; Smith & Shaffer, 1995). However, these are competing outcomes. Slower rates of delivery may improve comprehension, whereas greater rates may increase engagement and interest. In the YouTube context comprehension may not be affected as YouTube videos can easily be replayed as necessary. Thus, these results support the point that higher rates of content delivery do increase views; but, future research should examine whether comprehension of the message deteriorates.

For the most part, the gender of the science communicator was not found to influence views; however, in terms of representation, science communicators, especially in UGC, were often male. Jenkins, Purushotma, Weigel, Clinton, & Robinson (2009) defines a participatory culture as one with relatively low barriers to entry, where people are supported and encouraged to create and share content, and where participants feel a degree of social cohesion with other participants. YouTube is therefore often described as a participatory culture and we would nominally expect that creators represent the demographics of the community (Chau, 2010). While it appears that YouTube has relatively the same amount of male and female viewers (Chau, 2010), Abisheva, Garimella, Garcia, and Weber (2013) identified clustering in different subjects on YouTube; for example, sports had more male viewers while entertainment had more female viewers. Thus, the lack of female science communicators may be symptomatic of a lack of female viewers. Alternatively, female science communicators simply may choose not to make content. Molyneaux and O'Donnell (2008) in fact, identified that females did create and consume fewer vlogs than males, despite having the same technical skills and feeling just as much a part of the YouTube community as their male counterparts. To explore the gender gap in the creation of science communication content, future research should explore qualitative approaches.

Two findings in this study conflict with prior research: video length; and, engagement rates. First, longer videos intuitively seem that they would be less popular than shorter videos (Davenport & Beck, 2001); a point expressed by content creators and even YouTube (n.d.). This study does not support this claim. Content creators however, should not assume any video length is appropriate; further research on video length of YouTube science videos is needed and we recommend that this should occur on few channels with variability in video length to control for channel affects. Second, we found that for the same number of views, UGC would receive more ratings than PGC. In contrast Chatzopoulou et al. (2010) found that videos with higher views had relatively fewer ratings, comments, and favourites. Their explanation was that videos with more views elicit a ‘less acute reaction’ (Chatzopoulou et al., 2010, p. 2). This hypothesis might explain why we found that PGC was shared more than UGC. Our contrary finding of relatively higher ratings may simply be an idiosyncrasy of science communication; nevertheless, it alludes to how UGC becomes more popular. Given ratings were received significantly more than other engagement metrics, given UGC received significantly more ratings, and given YouTube’s video recommendation systems incorporate such engagement metrics, UGC may become more popular by simply being recommended more often.

With the abundance of information in the modern era, understanding how to capture audience attention is paramount to having one’s message heard. On YouTube specifically, long-term success requires understanding what factors contribute to the growth of video and channel popularity (Burgess & Green, 2009). It is important to recognise that analysis in this study was correlative, and causation cannot necessarily be inferred from these results. Still, this study highlights several factors that appear to contribute to popularity. Science communicators on YouTube need to have a face and they must engage with the community. The biggest mistake that content creators can make is in viewing YouTube as merely a video hosting platform, rather than a participatory community. As this study describes some of the characteristics of science communication on YouTube, it provides a foundation for future research. We urge continued research of science communication on YouTube as we cannot assume that broad YouTube trends identified elsewhere apply to the science communication genre.

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