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Early Public Responses to the Zika-Virus on YouTube: Prevalence of and Differences Between Conspiracy Theory and Informational Videos

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ABSTRACT

In this paper, we analyze the content of the most popular videos posted on YouTube in the first phase of the Zika-virus outbreak in 2016, and the user responses to those videos. More specifically, we examine the extent to which informational and conspiracy theory videos differ in terms of user activity (number of comments, shares, likes and dislikes), and the sentiment and content of the user responses. Our results show that 12 out of the 35 videos in our data set focused on conspiracy theories, but no statistical differences were found in the number of user activity and sentiment between the two types of videos. The content of the user responses shows that users respond differently to sub-topics related to Zika-virus. The implications of the results for future online health promotion campaigns are discussed.

KEYWORDS

Zika-virus; YouTube; Informational and Conspiracy Theory Videos; Topic Modeling; Semantic Networks

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1 INTRODUCTION

During the onset of a possible epidemic, the information available to the public is typically incomplete, unclear and often contested. Limited as it may be, information at hand may still install fear among the public and impact people's behavior, which in turn may affect the course of the epidemic [e.g., 11]. Media play an important role in spreading information about possible epidemics. Increasingly, this information is spread not only by media institutions but also by media users through their social media channels, which have become an important forum for disseminating health information.

As the largest video-sharing network, YouTube is a popular social media forum for sharing videos on health related topics [e.g.,

4, 7, for recent examples], and searching for health information [17]. According to recent estimates, YouTube has over 1 billion monthly users, watching a total of 6 billion hours of video per month [26]. Much of the content on YouTube is health related and recent studies have investigated content related to a wide range of health issues, such as vaccines [7, 15], anorexia [27], Ebola [4], rheumatoid arthritis [25], and tanning bed use [14]. As both a mass communication tool allowing one-to-many communications [13], and a discussion forum enabling commenting on the videos and replying to comments provided by others, YouTube adds new dimensions to health communication. Mapping the prevalence and the content of health-related videos and user responses to those videos on YouTube provides information for designing and targeting health interventions and campaigns in online settings.

The quality of health related information found on YouTube varies. Although many videos contain information that can be qualified as correct and helpful, YouTube is also known as a source of misleading and incorrect information, information that is easily accessible to YouTube users [17]. YouTube videos have been discussed as a source of misinformation on various health related issues such as vaccines [7], obesity [36], skin cancer [3], anorexia [27] and Ebola [19]. For example, in an analysis of videos related to rheumatoid arthritis, 30% was qualified as misleading, yet the audience responses (popularity, number of viewers, number of likes) did not differ between useful and misleading videos [25].

1.1 Conspiracy Theories

In addition to misinformation, YouTube videos and public responses to these videos have been linked to conspiracy theories [22]. Douglas, Sutton, and Cichocka [8, p.537] define conspiracy theories as "explanations for important events that involve secret plots by powerful and malevolent groups". Conspiracy theories have emerged online during different crises and events on a regular basis –including the moon landing, 9/11, chemtrails, and climate change science. Conspiracy theories about medical issues appear to be widespread. For example, Oliver and Wood [20] show that 63% of the American public has heard of the rumor that the US Food and Drug Administration deliberately prevents the public from getting natural cures for cancer because of pressure from drug companies. Over a third of Americans believes this to be true. The existence of conspiracy theories regarding the spread of viruses has been shown in the case of AIDS [e.g., 16], H1N1 [2] and Ebola [1].

Recently, misinformation and the presence of conspiracy theories in social media has been linked to public health. In the United

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States, lower vaccination rates were found in states where misinformation and conspiracies were more prevalent on Twitter [10]. Also, agreeing with conspiracy theories is related to a lower willingness to follow medical advice (e.g., using sunscreens or vaccines [20]).

During the early stages of an epidemic, misinformation and conspiracy theories may be especially pertinent since ill-informed behavioral responses (e.g., with regard to vaccination decisions or travel plans) may contribute to spreading the disease. Media portrayals of and attention to epidemics do not always reflect the most recent science based knowledge about how, to what extent, and with which consequences epidemic spreads. "Media logic does not equate to epidemiological logic" [23, p.10], and may as such contribute to how the public understands a health crisis. Indeed, recent evidence suggests that differences in public responses to the 2009 influenza A H1N1 outbreak were partly shaped by differences in information presented by the media [23]. The gap between information about epidemics in media and information from official sources is likely to be larger in the case of social media. Contributors to social media content are less closely linked to official sources and the process of posting, commenting, and sharing lacks the scrutiny and journalistic gatekeeping of traditional media.

Indeed, several studies link social media information to the spread of conspiracy theories. In a large-scale analysis of Twitter data, Vousoughi, Roym and Aral [33] show that false news, among which conspiracy theories, spread faster, farther and deeper than true news. False news, according to their analysis, is more novel than true news, and is met more often with fear, disgust and surprise. Yet, the question is whether the results of the analysis of Vousoughi et al. [33] apply to conspiracy theories in general: as the authors note themselves, conspiracy theories can be both true or false. Del Vicario et al. [32] directly compared how conspiracy theories vs. scientific information spread on Facebook and found that both conspiracy theories and scientific information are mainly spread among people with the same information preferences. Yet, the cascade dynamics differ between the two types of information: scientific information is assimilated more quickly and has a longer lifetime, yet lifetime is not related to size. Conspiracy theories assimilate more slowly and the size of cascades related to conspiracy theories is positively related to their lifetime. Bessi et al. (2015)[5] inspected how mainstream science news and conspiracy news were consumed by over 1,2 million individuals on Facebook, and concluded that the two types of information were related to polarized communities. Zollo et al., (2015)[37] observed that sentiment of comments to conspiracy news tended to be more negative than comments to science news, as is the average sentiment of comments by users of conspiracy pages.

1.2 Social Media and the Zika-virus

In the current study, we investigate the nature of the most popular videos (informational and conspiracy theory) providing health-information on the Zika-virus in YouTube videos, and the user responses (comments and replies to the comments) to these videos. The Zika-virus was first discovered in Uganda in 1947 but remained largely unknown to the general population. This changed when an outbreak of the virus in Brazil and neighboring countries, in

early 2016, coincided with an increase in occurrences of microcephaly, a malformation of the brain which causes babies to be born with an abnormally small head. A link between the Zika-virus and microcephaly was only recently confirmed [18].

In social media, the spread of the Zika-virus was the center of much attention, especially after Zika was labelled an international health emergency by the World Health Organization on 1 February 2016 (see [12]). In an analysis of Zika related tweets, Dredze, Broniatowski, and Hilyard [9] find many references to conspiracy theories, in which microcephaly is explained as a side effect of larvicides allegedly produced by chemical company Monsanto, or as a side effect of existing vaccines.

The current paper aims to map the prevalence and popularity of videos containing Zika related conspiracy theories on YouTube during the onset of the Zika-virus crisis. We compare YouTube metrics that indicate or may affect the popularity of video's (e.g., views, likes, comments, shares). Since Zollo et al. [37] observed that sentiment of comments to conspiracy news tended to be more negative than comments to science news, as is the average sentiment of comments by users of conspiracy pages, we also compared the content and sentiment of the comments.

We analyzed the 35 most popular videos referring to the Zika-virus during the recent outbreak (December 2015 - July 2016). These 35 videos were by far most popular according to the number of views, metric that places them at the top of searches on the Zika-virus. We mapped and compared user responses to videos containing informational and conspiracy theory content and analyzed the relation between the sentiment in the comments and video popularity. Our empirical research questions are:

- (1) What type of Zika-related videos (informational vs. conspiracy) were most often viewed on YouTube?
- (2) How did the number of comments, replies, likes and shares differ across the two video types?
- (3) How did the sentiment of the user responses differ between the two video types?
- (4) How did the content of the user responses differ between the video types?

2 DATA & METHODS

Using the number of views as an indicator of popularity and the search string "Zika-virus", we collected all the English language videos with at least 40,000 views on July 11, 2016, which resulted in a data set containing 35 videos. YouTube considers the number of views as the fundamental parameter of video popularity. Hence, collecting videos with the highest number of views, for our given search string, allows us to capture those videos that would be listed first by search engines (or the search function within YouTube). The upload dates for the 35 videos in our set range between December 30, 2015 and March 30, 2016.

For each of the 35 videos in our data set user responses were collected using the Netvizz YouTube Data Tool [24]. In total, 28795 user responses were collected, representing both comments (12584) and replies to comments (16211). Once collected, the user responses

were cleaned prior to analysis. More specifically, noise-words, punctuation, and numbers were removed, and all words were lower-cased and stemmed (i.e., reducing inflected words to their word stem, such as plurals converted to singular forms).

We use a mixed methods approach to analyze both the videos and the user responses to these videos. In the following sub-sections we provide details on the different types of analysis used in this paper.

2.1 Categorization of video content

First, we employed content analysis to determine the main topic and type of information source used in each video. This analysis was based on close watching the sample of videos, and coding the video as either disseminating informational or conspiracy theory content. Furthermore, to explore relationships between the different popularity metrics for our data set, we use correlation and regression analysis based on the number of shares, comments, replies, likes, and dislikes between the two types of videos (i.e., information vs. conspiracy theories videos).

2.2 Analysis of comments and replies

We compared the content of the user responses to the two video types (informational and conspiracy theory) using topic modeling and semantic network analysis. For topic modeling, latent Dirichlet allocation (LDA), as implemented in the MALLET, was applied to the user responses content [6]. Topic models identify, extract, and characterize the various (latent) topics contained by collections of texts, such as YouTube user comments. More specifically, topics are automatically identified based on word co-occurrence patterns across a corpus of text documents, where a cluster of words that co-occur frequently across a number of documents constitute a topic. Based on the assumption that text documents are collections of multiple topics, where a topic represents a probability distribution over words, topic models connect words that are often used together. In this study each user response (i.e., comment and/or reply) was considered a distinct text document.

We compared the results of the LDA topic model with semantic network visualizations. Automated semantic network methods were used to visualize the co-occurrence patterns across the user responses as our cases, and the words as the variables. These semantic networks visualize clusters of concepts that co-occur across comments and replies to the videos [21]. The more often these concepts co-occur, the stronger the link between them in the resulting network [35]. A semantic network has been generated for all the user responses to the two types of videos (informational and conspiracy theory videos) using VOSviewer [29].

In order to examine sentiment in the user responses for the videos in our dataset, we used SentiStrength [28]. The SentiStrength opinion-mining algorithm is designed to extract positive and negative emotion from sentences, and was specifically developed to account for the grammar and spelling style often used in social media. The software uses a dual positive/negative sentiment strength scoring system to output a positive sentiment score from 1 to 5 and a negative score from -1 to -5 for each comment. A comment with a score of 5/-1 is to be interpreted as strongly marked by positive

Table 1: Descriptive statistics of video metrics

	Informational (n=23)		Conspiracy(n=12)	
	M	SD	M	SD
Views	205.097	211.859	159.224	163.452
Top Level Comments	404	367	274	293
Replies	517	473	361	359
Likes	3340	4417	1627	1981
Dislikes	122	109	102	151
Shares	109	833	689	630

sentiment, and one yielding 1/-5 is primarily negative in regards to sentiment content.

3 RESULTS

3.1 Informational vs. conspiracy theory videos

Most of the videos (23 out of 35) were categorized as informational videos, of which nine were delivering science-based information and fourteen circulating news media broadcasts on the topic. Informational videos provided, in general, facts about the origin, spreading, and consequences of the Zika-virus, or updates about the outbreak. Twelve of the videos collected presented conspiracy theory videos, either listing different alternative explanations for the epidemics of the Zika-virus (2 videos), or naming particular organizations and actors responsible for the Zika-virus. These videos attributed the virus to Bill Gates (4 videos), the Rockefeller foundation (2 videos) or Monsanto (2 videos), often linked to, for example argumentation that genetically modified (GMO) mosquitos cause the Zika-virus (5 videos), and that the virus is used as a bio-weapon (3 videos) for world depopulation. In addition, one video argued that the ban on DDT has caused a rise in the number of mosquitos, leading to the spread of the Zika-virus. In two videos the link between the Zika-virus and microcephaly was contested.

3.1.1 User activity. Table 1 presents the means and standard deviations of the main YouTube metrics for both types of videos. The means of all metrics appear higher for informational videos, but there are substantial differences between the videos, as is indicated by the high standard deviations. In order to test for differences between the metrics of informational and conspiracy theory videos, we applied negative binomial regression analysis, using the MASS package that is available in R [30]. Negative binomial regression analysis is suited for analyzing count data with high dispersion, i.e. variances that exceed the mean [31], which is the case in the YouTube metrics we report. The analyses revealed no significant differences ($p < .05$). Since the different metrics are strongly correlated (see Table 2 for the Spearman correlations), we repeated the analyses but this time added the number of views as a covariate. Again, no significant differences in terms of likes, dislikes, shares, number of top level comments, and replies were found.

In terms of the activity levels of unique users, the number of unique users (11498) generating a total of 20745 user responses to the 23 informational videos was almost three times larger than the number of unique users (4356) generating 8050 responses to the 12 conspiracy videos. To assess the levels of user activity in terms of responses (i.e., comments and replies) per video type, we conduct a

Table 2: Spearman Correlations between the video metrics

	Views	All Comments	Top Level Comments	Replies	Likes	Dislikes	Shares
Views	–						
All Comments	0.692***	–					
Top Level Comments	0.721***	0.967***	–				
Replies	0.669***	0.981***	0.926 ***	–			
Likes	0.696***	0.874***	0.915 ***	0.854***	–		
Dislikes	0.670***	0.914***	0.903 ***	0.884***	0.784***	–	
Shares	0.396*	0.455**	0.522 **	0.380*	0.549**	0.453**	–

* $p < .05$, ** $p < .01$, *** $p < .001$ (two-tailed)

t – test comparing the ratio of number of responses per video to the number of video views. While there are fewer responses (per view) in the informational videos ($M_{\text{informational}} = 0.0048$; $M_{\text{conspiracy}} = 0.0056$), the difference in means is insignificant ($t(29.1) = 0.70$; $p > .05$). Similarly, while there are fewer unique commenters per view in the informational videos ($M_{\text{informational}} = 0.0027$; $M_{\text{conspiracy}} = 0.0033$), the ratio does not vary significantly across video types ($t(27.4) = 1.05$; $p > .05$).

We also conducted a Negative Binomial Regression subtracting 1 from the dependent variable of the number of responses per unique user, thus testing the extent to which video type influences users to issue more than one response, controlling for the total number of responses per video. The effect of the informational videos is insignificant ($b = 0.07$; $p > .05$). Interestingly, though, the total number of responses for each of the video types predicts against additional responding per unique user ($b = -1.0 \times 10^{-4}$; $p < .001$).

Thus, we find no significant differences between informational and conspiracy theory videos when assessing user activity in terms of responses per view and unique users per view. We also find that the video type does not influence whether users issue more than one response. However, we do find that neither type of videos promotes additional responding per unique user, showing low engagement of YouTube users viewing Zika-virus related content.

3.2 Content of user responses

3.2.1 Sentiment analysis. All user responses were coded for sentiment in order to establish whether the sentiment differs between informational and conspiracy theory videos. In the sentiment analysis, most responses, fall within the zone of 1/-1 (31.78%), which indicates that such comments are not very affective in the case of Zika on YouTube. In the comments to the informational videos, only 0.05% of comments were maximum positive (score 5/-1), and only 0.50% of comments were maximum negative (score -5/1). As examples of highly positive (5/-1) and highly negative (-5/1) by the SentiStrength opinion mining algorithm:

Highly positive: “I fucking love Canada... Just cold enough to keep the bugs out”

Highly negative: “I fucking hate mosquitos so much. Make these fucking cancers on the earth extinct. Put all funding to making these little fucks a sentence in a history book.”

Table 3: Mean sentiment scores of informational vs. conspiracy theory YouTube videos.

	Informational ($n = 23$)		Conspiracy ($n = 12$)	
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Positive sentiment	1.61	0.148	1.70	0.170
Negative sentiment	1.91	0.271	2.03	0.165

In order to establish whether the means of the sentiment scores differ between informational and conspiracy theory videos, the mean aggregate positive and negative sentiment scores were compared using a Mann-Whitney U t-test, which is fit for handling non-normal data (Table 3). None of the means were significantly different from each other (at $p < .05$), although the difference in positive sentiment scores almost reached conventional levels of significance ($p = .079$), suggesting that positive sentiment is lower among conspiracy theory videos. Since the sentiment scores are nested in videos, we calculated the intraclass correlation coefficient (ICC), a measure of how much of the total variance can be attributed to differences between videos. The ICCs for negative and positive sentiment are between .02 and .03, indicating that differences between videos do not account for much of the variance in the sentiment of the comments. Also, for both negative and positive sentiment, the estimated variance that can be attributed to differences between videos (τ_{00}) is lower than its corresponding standard deviation (positive sentiment: $\tau_{00} = .0168$, $SD = .1295$; negative sentiment: $\tau_{00} = .0314$, $SD = .1773$), another indication that the variance attributed to difference between videos is negligible.

3.2.2 LDA Topic Models. When fitting the LDA topic model to a collection of text documents, the analyst needs to specify the number of topics to be identified. This selection generally implies exploration of different solutions to achieving the best fit. Based on the weight values presented in the tables below, we choose four topics to be detected, running the algorithm for 3000 iterations with the $\sum \alpha = 5$. In Tables 4 and 5 we present the four topics identified for each of the video types and the top ten words belonging to each topic. The weight value for each topic represents the prominence of each topic across the collection of document. We also provide a label for each topic summarizing their content.

The results of the topic modeling show that the user responses to the two types of videos contain similarities as well as differences

(see Tables 4 and 5). While both types of videos elicit topics related to the causes of the Zika-virus and affected stakeholders, we also note unique topics for each type of videos. Informational videos user responses discuss the consequences of the virus, while the conspiracy theory videos user responses also focus on the stakeholders responsible for the outbreak.

To further visualize the differences in content between the 20745 user responses to the 23 informational videos, and the 8050 responses to the 12 conspiracy videos, we visualized semantic maps of the co-occurring concepts (i.e., words and phrases) for each video type. In Figures 1a and 1b, concepts are the nodes (i.e., N) and co-occurrences of these concepts are represented by links (i.e., E).

In informational videos, the user responses focus on discussions surrounding man, woman, government, God, world, and Africa (red cluster), rights, abort, fetuses (yellow cluster), the causes of the outbreak; water, and virus mutation (green cluster), and to a lesser extent research, university (blue cluster) (Figure 1a). In the conspiracy video responses, Monsanto, government, Brazil and GMOs are mentioned (red cluster), while the problem is discussed in terms of pesticide, larvae and chemicals (green cluster). We also note an additional cluster in which the purpose of the Zika-virus is discussed in terms of control, life, and truth (blue cluster) as well as religion-linked words on man, woman, God and Bible (yellow cluster) (Figure 1b).

Taken together, the topic modeling and the semantic network analysis show that whereas the responses to informational videos discuss clusters around the causes and consequences of the Zika-virus, responses to conspiracy theory videos revolve around the Zika-virus as a means to population control and allocating responsibility for the spread of the virus to various organizations and actors.

4 DISCUSSION AND CONCLUSION

In conclusion, most of the videos that were analyzed in this article, provided informational content on the Zika-virus, whereas twelve out of the sample of 35 videos contained conspiracy theory content. Surprisingly, our results on user activity showed no statistically significant differences across the video types. However, the difference between mean shares to informational and to conspiracy videos, albeit not significant, is in line with the results by Vosoughi, Roy and Aral [33] on fake news spreading faster, and gaining more emotional responses than true news. These results are also in line with earlier research into misinformation in social media, in particular on that audience responses (popularity, number of viewers, number of likes) do not differ between useful and misleading videos, as also found by Singh et al., (2012)[25] in their study on videos on rheumatoid arthritis. This shows that YouTube users respond in similar ways, in terms of views, shares and likes, to videos containing informational and conspiracy theory content. For health care organizations, this result is striking as it indicates that both informational and conspiracy theory content spread online in similar ways. To counter the spread of misinformation, the monitoring of the content posted on YouTube deserves more attention by health organizations. In addition, we found no differences in the sentiment of the user responses to the two video types. Responses to both

informational and conspiracy theory videos were slightly negative, on average. This result contradicts Vosoughi, Roy and Aral [33] who found false news to trigger more negative sentiments than true news.

In terms of user (posting) activity, the only significant result we find is that neither of the two types of video content promotes additional responding per unique user. Hence, regardless of the type of video users watch, they are not likely to engage in conversations. The low engagement of YouTube users viewing Zika-virus related content is an important finding, showing that these users express their opinion in their responses without further participating in conversations. For health organizations, this finding indicates a need for careful consideration of the type of content they make available through social media platforms in order to engage users in conversations, both as a way of disseminating accurate information and as a way of addressing or debunking conspiracy theories.

Finally, our results on the content of the user responses show that comments to the two different types of videos (*informational*, *conspiracy theory*) discuss the Zika-virus using different framings: (1) Comments to *informational videos* discuss the Zika-virus as a problem for babies and pregnant women in Brazil; (2) Comments to *conspiracy theory videos*, in turn, frame the Zika-virus as a targeted means to population control and as a consequence of a larvicide produced by the chemical company Monsanto, similar to the findings on Zika-related tweets by Dredze, Broniatowski and Hilyard [9]. Two videos contest the link that Zika-virus is causing microcephaly in newborns. The extent to which the responses to both types of video overlapped requires further research into the content of the responses, for example, via a quantitative content analysis of both the videos and the related responses.

In conclusion, our findings have implications for health organizations designing online campaigns. As studies have confirmed, the influence of viewer comments on other audience members' perceptions of health-related YouTube content [34], understanding the various types of contestation present in YouTube video user responses on the Zika-virus is important for future online health promotion campaigns. Online health interventions can be targeted on the most active social media users, who can be identified using user activity information, and in particular the most active users promoting misleading information. Also, careful consideration of the type of information online health promotion campaigns make available to users is needed, to ensure participation and involvement in conversations. In addition, understanding the differences in the content of user responses to different video types can help in uncovering the most frequent topics related to conspiracy theories for intervention purposes. Such practices would help prevent an increase in deep-rooted conspiracy beliefs, which in turn may affect health choices and behavior.

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Table 4: Topics of informational videos user responses

Topic	Weight	Words representing the topic
Affected stakeholders	0.731	virus, Zika, people, baby, pregnant, brazil, Ebola, year, spread, mosquito
Consequences of Zika	0.474	people, fuck, life, kill, abortion, country, comment, baby, world, stupid
Geographic and politics of Zika	0.376	live, mosquito, fuck, Canada, plague, zika, virus, video, Florida, Trump
Causes of Zika	0.339	mosquito, human, population, world, kill, people, control, virus, nature, food

Table 5: Topics of conspiracy videos user responses

Topic	Weight	Topic Members
Causes of Zika	0.876	people, world, population, control, kill, live, human, year, country, government
Everyday considerations	0.579	video, fuck, time, love, people, good, dark, truth, watch, word
Affected stakeholders	0.473	zika, virus, mosquito, brazil, microcephaly, case, vaccine, baby, woman, spread
Responsible stakeholders	0.465	Monsanto, fact, video, people, company, chemical, science, claim, prove, evidence

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