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ORIGINAL ARTICLE

Are internet videos useful sources of information during global public health emergencies? A case study of YouTube videos during the 2015–16 Zika virus pandemic

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ABSTRACT

Background: Internet-videos, though popular sources of public health information, are often unverified and anecdotal. We critically evaluated YouTube videos about Zika virus available during the recent Zika pandemic.

Methods: Hundred-and-one videos were retrieved from YouTube (search term: zika virus). Based upon content, they were classified as: informative, misleading or personal experience videos. Quality and reliability of these videos were evaluated using standardized tools. The viewer interaction metrics (e.g. no. of views, shares, etc.), video characteristics (video length, etc.) and the sources of upload were also assessed; and their relationship with the type, quality and reliability of the videos analyzed.

Results: Overall, 70.3% videos were informative, while 23.8% and 5.9% videos were misleading and related to personal experiences, respectively. Although with shorter lengths ($P < 0.01$) and superior quality ($P < 0.01$), yet informative videos were viewed ($P = 0.054$), liked ($P < 0.01$) and shared ($P < 0.05$) less often than their misleading counterparts. Videos from independent users were more likely to be misleading (adjusted OR = 6.48, 95% CI: 1.69 – 24.83), of poorer ($P < 0.05$) quality and reliability than government/news agency videos.

Conclusion: A considerable chunk of the videos were misleading. They were more popular (than informative videos) and could potentially spread misinformation. Videos from trustworthy sources like university/health organizations were scarce. Curation/authentication of health information in online video platforms (like YouTube) is necessary. We discuss means to harness them as useful source of information and highlight measures to curb dissemination of misinformation during public health emergencies.

KEYWORDS
Public health; internet; social media; health communication; health information; pandemic

Introduction

On 1 February 2016, the World Health Organization (WHO) declared zika virus (ZIKV) infection as a Public Health Emergency of International Concern (PHEIC). Until then, ZIKV infection was largely considered a neglected tropical disease, thought to cause infrequent local outbreaks and sporadic cases. It was previously perceived as a non-threatening viral infection, characterized by a benign acute febrile illness with joint pain, rashes, headache, conjunctivitis and muscle ache, which generally ran a mild and self-limiting course [1–3]. In contrast to this perception, the recent 2015–16 ZIKV epidemic that started in Brazil, spread rapidly across more than 47 countries and territories, infecting an unprecedentedly large number of individuals (an estimated 500,000 to 1.5 million infected persons in Brazil alone) [1–5]. Further, epidemiological and laboratory evidence suggested that serious complications, including adverse pregnancy outcomes (*viz.* stillbirth and miscarriage), birth defects (*viz.* clubfoot, ocular defects, brain malformations including microcephaly, etc.) and neurological conditions (like Guillain-Barre syndrome) occurred as sequelae to ZIKV infection [1,6–10]. Discovered in 1947 at Zika forest, Uganda in a sentinel Rhesus monkey, ZIKV is an RNA-containing arbovirus of the family *Flaviviridae* [1,11]. It spreads in humans mainly through the bite of infected *Aedes* mosquitoes, mother-to-child transmission (intra-uterine or perinatal), sexual transmission or blood transfusion [1,3,12]. The PHEIC lasted for ~ 10 months. On 18 November 2016, WHO declared the end of PHEIC status although ZIKV was still recognized as a significant public health challenge requiring intense action [13]. As of 23 July 2017, 95 countries and territories were designated

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The supplementary data for this article is accessed here by Centre for Disease Control and Prevention (CDC), Atlanta, USA with risk of ZIKV transmission [5].

YouTube is the most popular, freely available, easy-to-use internet-based video sharing platform. According to internet traffic estimates, as of April 2017, YouTube was the second most commonly visited website worldwide (https://www.alexa.com/topsites). The 2015–16 ZIKV pandemic and the drastic change in the perception about ZIKV infection captured a lot of public attention. This was also reflected from the Google Trends data that documented a huge rise in zika virus-related internet searches during the pandemic [14,15]. The internet has emerged as a major source of health-related information for the general public, surpassing traditional sources like television, radio, press, and lectures in many instances [16–18]. Information provided in the form of videos is especially appealing to viewers, and has been evaluated previously in relation to various health topics [19–25]. Particularly during epidemics, internet based video platforms like YouTube experience a tremendous surge in viewer traffic, attracting thousands of views [23,25]. In comparison to other epidemics in the past, the recent ZIKV-pandemic related PHEIC was of particular concern for the public because there were grave implications for maternal health as well as child health, which could affect future generations. The situation was also sensitive due to the timing of international mega-events like the 2016 Rio de Janeiro Olympic and Paralympic Games that were to be held in Brazil around that period. This triggered fears about greater spread of the disease and threat to global health [26,27], leading to speculations about even postponement or moving of the games.

Spread of misinformation during an epidemic can fuel public paranoia and panic, and hamper efforts to contain it as illustrated by previous experiences [28,29]. Although information available in internet platforms like YouTube are often of questionable veracity and have shortcomings like presentation of opinion as fact, anecdotal nature, blind authorship, and lack of source citation [21,30,31], yet such information is popular, trusted and frequently considered valid by the viewers [18]. In fact, during the recent ZIKV pandemic, it was found that the misleading posts in the popular social media platform Facebook (Facebook Inc., Menlo Park, CA, USA) were more popular than the posts dispersing accurate information about the disease [32]. Since internet-based sources offer information sharing features and social networking interfaces, there is a serious danger of dissemination of such unverified information rapidly [30].

In view of the above, it is of significance to assess the nature of health information available in internet platforms like YouTube. It is of interest to promote accurate and trustworthy information through such platforms, while discouraging the spread of misleading information, especially during global public health emergencies. The current case-study was conceived in this context, with the primary objective to evaluate if videos on ZIKV available on YouTube were useful mediums of information during the 2015–16 ZIKV pandemic. We also investigated if the viewer interaction metrics, characteristics and sources of YouTube videos varied as a function of their type, content, reliability and quality. In addition, we discuss potential mechanisms to harness YouTube as a useful medium of obtaining health information for the general public.

Methods

Search strategy and data retrieval

A search for ZIKV related videos in YouTube (https://www.youtube.com) on 1 December 2016 using the query term ‘zika virus’ returned approximately 705,000 results. Studies in the past on internet user behaviour have indicated that the probability of users to go beyond the first few pages of results from a search engine is low. Around 90% of the users of internet search engines click on results within the first 3 pages of search results, yet 79% of users search through multiple pages if they do not find what they want in the first page [19–21,33,34]. With these considerations and at the same time to ensure an adequate no. of video samples so as to carry out a methodologically feasible and statistically acceptable analysis, the first 120 videos (*i.e.* initial 6 pages of the search results, with 20 videos listed per page) were screened for the study. The videos were sorted by relevance (*i.e.* the default filter setting in YouTube) during this process. Alternate sorting options provided by YouTube such as ‘sorting by upload date’, ‘sorting by rating’, or ‘sorting by view count’ were avoided since they were likely to return a highly conservative and selected group of videos (*e.g.* the most recent videos, or the most viewed videos, etc.) during the search, thereby introducing selection bias and/or coverage bias. For back-up, uniform resource locators (URLs) of the 120 videos were saved. We documented the video characteristics like length of the videos and date of upload. Besides, viewer interaction metrics (namely no. of views, likes, dislikes, shares, and comments) was recorded for every video on the same day. Video popularity (total views received by a video divided by no. of days on YouTube since upload of the video) was also estimated as described previously [20–22]. Five videos were duplicated in part or whole, 10 videos were in languages other than English, and viewer interactive features (*e.g.* shares, comments, etc.) were disabled (by the uploaders) for 4 videos. These 19 videos were excluded and the remaining 101 videos were used for further analysis.

Video classification and sources

To address our primary objective (*i.e.* whether the YouTube videos on ZIKV were useful), all the selected videos were viewed in their entirety independently by two researchers. If the video contained scientifically correct and accurate information about ZIKV, it was marked as informative or useful. On the other hand, if the video contained erroneous and/or scientifically unproven information about ZIKV (based on currently available scientific evidence), it was marked as misleading. Further, it was observed that some videos described an individual's experience with family members/relatives/friends/neighbours suffering from ZIKV disease. Such videos were marked as personal experience videos. A review of the available literature indicated that similar non-overlapping schemes of classification were found to be suitable in the past [19–24]. There was 100% concordance between the two researchers while carrying out this classification.

The sources of the uploaded videos were identified from the concerned YouTube pages. These sources were grouped into the following mutually exclusive subtypes during analysis: news agency (*e.g.* CNN, BBC, Reuters, etc.), government agency or inter-governmental bodies (*e.g.* White House, WHO, CDC, etc.), for-profit commercial company (*e.g.* Good Knight mosquito repellent, etc.), health information websites (*e.g.* Dr. Oz Show, MedRition.com, etc.), university/hospital channels (*e.g.* John Hopkins University, etc.), independent users (*e.g.* homemade videos, sources without clear affiliation like Dark5.tv, etc.), and internet-based video channels (*e.g.* Journeyman.tv, SciShow, WatchMojo.com, etc.).

Evaluation of video reliability, quality and content

The reliability of the information present in the videos was graded using a score-based scale adapted from the DISCERN tool [19–21,35]. This scale consisted of 5 questions (*Supplementary Table 1*), which could be answered by either a 'Yes' or a 'No' response. The 'Yes' responses were desirable and indicated good reliability, with every 'Yes' response fetching 1 point. In contrast, a 'No' response indicated poor reliability and garnered 0 point each. Thus, a cumulative reliability score between 0 (*i.e.* lowest possible score, indicating least reliability) and 5 (*i.e.* best possible score, indicating highest reliability) was possible for every video.

As reported previously [19–21,36], the quality of the videos was assessed by the Global Quality Scale (GQS). It allowed a mechanism for rating the overall quality of each video (possible range: 1 to 5, with 1 indicating poor quality and 5 indicating excellent quality) (*Supplementary Table 2*). Accordingly, two reviewers initially marked each video between 1 and 5 independently, depending upon the quality of information contained therein and how useful they considered it for a user as per their assessment. Thereafter, the final score was assigned by consensus.

For the content of the videos, it was examined if they addressed three different aspects of ZIKV infection, namely epidemiology, clinical features and complications, and prevention and management.

Data analysis

The categorical information was summarized by counts and percentages along with 95% confidence intervals (CIs). The quantitative variables were expressed as median (with range). Comparisons between the informative and misleading videos were carried out using the non-parametric Mann-Whitney U test. Further, taking government and news agency videos as reference, we estimated odds ratio (ORs) with 95% CIs to test if the video source was an independent predictor for a video being misleading or informative. These estimates were further adjusted by multiple logistic regression to account for the influence of other video attributes, such as video length, and number of views and shares received. Finally, amongst the informative videos also, a source-wise comparison of the viewer interaction metrics and video characteristics was conducted using Kruskal-Wallis test. All calculations were performed using SPSS 22.0 (SPSS Inc., Chicago, USA) at two-sided alpha 0.05.

Results and observations

The 101 videos attracted 8,769,304 views (range: 139 – 719,768), 118,049 likes (range: 0 – 15,844), 5330 dislikes (range: 0 – 542), and 27,940 comments (range: 0 – 2367) cumulatively (Table 1). They were shared total 41,077 times (range: 0 – 3446). The time period since the videos were uploaded ranged from 186 to 486 days, whereas the video runtimes ranged from 0.23 to 38.92 minutes.

The videos notched a median reliability score of 2 (range: 0 – 5) (Table 1). The maximum and minimum numbers of 'Yes' responses for reliability were recorded with the first (61.39%) and the fifth (27.72%) questions of the DISCERN tool respectively. The net score of 0 (indicating the least reliable videos) was satisfied by 18 (17.82%) videos, while the best cumulative score of 5 (indicating the most reliable videos) was satisfied by 6 (5.94%) videos. In respect of quality, the median GQS score of the videos was 2 (range: 1 – 5). The net score of 5 (indicating best quality) was received by 4 (3.96%) videos. Content-wise evaluation revealed that nearly

Table 1. Summary characteristics of the videos (N = 101).

Characteristic/Parameter	Total count	Median (range)† or % (95% CI)‡
Video metrics		
No. of views	8,769,304	24,124 (139 – 719,768)†
Likes	118,049	171 (0 – 15,844)†
Dislikes	5330	14 (0 – 542)†
Shares	41,077	166 (0 – 3446)†
Comments	27,940	95 (0 – 2367)†
No. of days in YouTube	–	299 (186 – 486)†
Popularity	–	79.18 (0.74 – 2617.6)†
Video length (minutes)	664.32	4.00 (0.23 – 38.92)†
Video type		
Informative	71	70.3 (60.8 – 78.3)‡
Misleading	24	23.8 (16.5 – 32.9)‡
Personal experience	6	5.9 (2.8 – 12.4)‡
Reliability score of the videos (DISCERN tool)*	–	2 (0–5)†
Aims clear and achieved?	62	61.39 (51.64 – 70.3)‡
Reliable sources of information?	58	57.43 (47.69 – 66.62)‡
Balanced and unbiased?	30	29.7 (21.67 – 39.22)‡
Additional sources of information for reference?	28	27.72 (19.93 – 37.15)‡
Areas of uncertainty mentioned?	25	24.75 (17.37 – 33.99)‡
Videos with total score 0	18	17.82 (11.58 – 26.42)‡
Videos with total score 1	23	22.77 (15.68 – 31.86)‡
Videos with total score 2	23	22.77 (15.68 – 31.86)‡
Videos with total score 3	19	18.81 (12.39 – 27.52)‡
Videos with total score 4	12	11.88 (6.93 – 19.63)‡
Videos with total score 5	6	5.94 (2.75 – 12.36)‡
Content (domains addressed)		
Epidemiology	60	59.41 (49.66 – 68.47)‡
Clinical features & Complications	64	63.37 (53.64 – 72.11)‡
Management & Prevention	41	40.59 (31.53 – 50.34)‡
None of the 3 domains addressed	14	13.86 (8.44 – 21.93)‡
All 3 domains addressed	4	3.96 (1.55 – 9.74)‡
Quality score of the videos (GQS tool)**	–	2 (1 – 5)†
Videos with score 1	24	23.76 (16.52 – 32.93)‡
Videos with score 2	34	33.66 (25.2 – 43.33)‡
Videos with score 3	25	24.75 (17.37 – 33.99)‡
Videos with score 4	14	13.86 (8.44 – 21.93)‡
Videos with score 5	4	3.96 (1.55 – 9.74)‡

Abbreviations: GQS, Global Quality Scale. *Refer supplementary Table 1 and **refer supplementary Table 2.

Table 2. Source-wise distribution of different video types.

Video source	Total videos (N = 101)	Video type: Informative	Misleading	Personal experience
Government agency	4 (3.96)	4 (100)	0	0
News agency	40 (39.60)	31 (77.5)	7 (17.5)	2 (5)
Profit companies	1 (0.99)	1 (100)	0	0
Independent users	31 (30.69)	15 (48.39)	14 (45.16)	2 (6.45)
Health information websites	7 (6.93)	7 (100)	0	0
University channels	1 (0.99)	1 (100)	0	0
Internet based video channels	17 (16.83)	12 (70.59)	3 (17.65)	2 (11.77)

Values expressed as count (%).

Table 3. Comparison of characteristics between informative and misleading videos.

Characteristics	Informative videos (n = 71)	Misleading videos (n = 24)	*P*-value
Views	16,176 (139 – 719,768)	30,632 (1531 – 527,909)	0.054
Likes	124 (0 – 15,844)	429 (14 – 6722)	< 0.05
Dislikes	9 (0 – 440)	28 (2 – 542)	< 0.01
Shares	107 (0 – 2626)	244.5 (0 – 3446)	< 0.05
Comments	46 (0 – 1743)	203 (8 – 2367)	< 0.05
Days in YouTube	299 (186 – 394)	302 (199 – 486)	0.196
Median popularity	57.48 (0.74 – 2617.6)	97.17 (5.05 – 1969.8)	0.066
Video length, min	2.57 (0.23 – 38.92)	6.37 (1.45 – 25.77)	< 0.01
GQS	3 (1 – 5)	1 (1 – 3)	< 0.01

Abbreviations: GQS, Global Quality Scale. Comparisons between informative and misleading videos were done by Mann-Whitney U test.

40% videos (95% CI: 31.53 – 50.34%) provided information on prevention and management of ZIKV, whereas information on the epidemiology and clinical features/complications of the disease were included in 59.41% (95% CI: 49.66 – 68.47%) and 63.37% (95% CI: 53.64 – 72.11%) videos, respectively (Table 1). Only 4 videos (3.96%, 95% CI: 1.55 – 9.74%) provided comprehensive information with respect to all the three domains.

Altogether, 71 videos (70.3%, 95% CI: 60.8 – 70.3%) were deemed informative; whereas 24 videos (23.8%, 95% CI: 16.5 – 32.9%) were categorized as misleading (Table 1). Six videos (5.9%, 95% CI: 2.8 – 12.4%) were related to personal experience. Overall, most (39.6%) of the videos were traced to news agencies (Table 2). Independent users (30.69%) and internet based video channels (16.83%) were the other major sources. All the videos uploaded by government agencies, university channels, and health information websites in the current study sample were informative; but they constituted only a minor proportion (3.96%, 0.99% and 6.93% respectively) of the total videos (Table 2).

Significant differences were observed between the informative and the misleading videos with respect to video characteristics and viewer interaction metrics (Table 3). The informative videos were shorter ($P < 0.01$) than the misleading videos. Quality-wise as well, the informative videos had scores (GQS median: 3, range: 1 – 5), which were significantly superior ($P < 0.01$) in comparison to that of the misleading videos (GQS median: 1, range: 1 – 3). In spite of that, the misleading videos were more likely to be shared ($P < 0.05$), liked ($P < 0.01$) and commented upon ($P < 0.05$) than the informative videos. The misleading videos were also disliked more ($P < 0.01$) than their informative counterparts.

Videos uploaded by independent users were significantly more likely (OR = 4.67, 95% CI: 1.57 – 13.89, $P < 0.01$) to be misleading as compared to the videos uploaded by government agencies and news channels (Table 4). This association persisted (adjusted OR = 6.48, 95% CI: 1.69 – 24.83, $P < 0.01$) even after controlling for covariates (*viz.* number of views, shares, and video length).

Amongst only informative videos also, there was considerable variation in quality, reliability, and viewer

Table 4. Likelihood of videos being misleading according to source.

Source of videos	Misleading Videos	Informative videos	Crude OR (95% CI)	Adjusted OR (95% CI)
News agency/ Government agency	7	35	reference	reference
Independent	14	15	4.67 (1.57 – 13.89)	6.48 (1.69 – 24.83)
Internet based video channels	3	12	1.25 (0.28 – 5.62)	-
Health information websites	0	7	0.32 (0.02 – 6.15)	-

Abbreviations: OR, odds ratio; CI, confidence interval.

interaction metrics according to the source (Table 5). News agencies (43.66%) were the single largest source of informative videos, with median reliability score (DISCERN) and median quality score (GQS) of 2 each. The independent sources, which constituted 21.13% of the informative videos, displayed the highest proportion of viewer interaction metrics (contributing to 43.3% views, 48.52% likes, 46.12% dislikes, and 35.78% shares garnered by informative videos). Their median GQS and median reliability scores were 3 each. The best scores for quality and reliability were secured by the videos from health information websites (median GQS 4, median reliability 3) and government agencies (median GQS 3.5, median reliability 3.5). However, these two sources contributed to only 9.86% and 5.63% of the informative videos, respectively.

Discussion

We found that nearly one-fourth of the YouTube videos in our study sample contained misleading information about ZIKV. The proportion of videos containing misleading health information in YouTube has been found to be sizeable in the past as well – 16.2% during H1N1 influenza pandemic [22], 16.7% on Sjogren's syndrome [20], 18.1% on kidney stones [24], 20.7% on West Nile virus infection [25], 30.4% on rheumatoid arthritis [21], and 33% on hypertension [19]. When a query term is entered in YouTube with the default setting of 'sorting by relevance', the YouTube search engine algorithm returns the results by measures of relevance after matching the metadata (such as title, short video description, keywords and tags/annotations that are needed to be furnished at the time of uploading) of the available videos with the query term searched for. The worrisome aspect for public health information/communication in general is that even after being 'sorted by relevance'; a sizeable percentage of YouTube videos are misleading and inadequate. The huge viewership of the YouTube videos in our sample and the fact that majority of them were informative (~ 70%) is surely heartening, but there are several important areas of concern.

First, there were considerable shortcomings in the existing quality, reliability and content of the videos. The perfect scores for reliability and quality were achieved by a handful of videos (~ 6% and ~ 4%, respectively). The findings that only ~ 30% videos had presented the information in a balanced and

Table 5. Analysis of informative videos (N = 71) according to source.

Parameter	News agency	Government Agency	Independent	Health information Website	Internet video channels	*P* Value
Views	6487 (349 – 510,808)	17,272 (355 – 26,098)	50,584 (139 – 719,768)	12,163 (1413 – 58,782)	42,284 (743 – 526,719)	0.11
Likes	36 (0 – 5000)	54 (14 – 138)	663 (0 – 15,844)	170 (22 – 2127)	273 (6 – 14,000)	< 0.01
Dislikes	8 (0 – 196)	2 (1 – 31)	21 (0 – 440)	3 (0 – 83)	12 (0 – 159)	0.1
Shares	40 (0 – 2626)	93.5 (5 – 455)	340 (1 – 2574)	130 (0 – 1184)	193 (0 – 2450)	< 0.05
Comments	34 (0 – 1164)	8 (1 – 95)	100 (0 – 1743)	41 (1 – 473)	164 (1 – 958)	< 0.05
Days in YouTube	302 (186 – 319)	201.5 (188 – 394)	295 (187 – 336)	293 (193 – 307)	304 (187 – 322)	0.75
Popularity	32.48 (1.43 – 1669.3)	72.4 (1.89 – 92.39)	174.1 (0.74 – 2617.6)	39.62 (5.16 – 216.91)	134.26 (3.95 – 1761.6)	0.11
Video length, min	2.08 (0.23 – 38.92)	3.16 (0.98 – 9.87)	5.72 (0.75 – 37.25)	6.93 (2.7 – 27.65)	1.52 (0.87 – 6.05)	< 0.01
GQS	2 (1 – 4)	3.5 (2 – 5)	3 (2 – 4)	4 (2 – 5)	2 (1 – 4)	< 0.05
No. of videos (% total)	31 (43.66)	4 (5.63)	15 (21.13)	7 (9.86)	12 (16.9)	–
Total views (% total)	1,178,117 (20.82)	60,997 (1.08)	2,450,853 (43.3)	144,702 (2.56)	1,372,955 (24.28)	–
Total likes (% total)	9447 (11.2)	260 (0.31)	40,924 (48.52)	3857 (4.57)	29,837 (35.37)	–
Total dislikes (% total)	639 (24.29)	36 (1.37)	1213 (46.12)	136 (5.17)	602 (22.89)	–
Total shares (% total)	6032 (26.08)	647 (2.79)	8276 (35.78)	2201 (9.52)	5852 (25.29)	–
Reliability score	2 (0 – 5)	3.5 (2 – 4)	3 (0 – 5)	3 (1 – 5)	2 (0 – 4)	< 0.05
Aims clear and achieved?	24 (77.42)	4 (100)	13 (86.67)	7 (100)	7 (58.33)	–
Reliable information source?	20 (64.52)	4 (100)	11 (73.33)	4 (57.14)	7 (58.33)	–
Balanced and unbiased?	6 (19.36)	2 (50)	10 (66.67)	5 (71.43)	4 (33.33)	–
Additional references?	5 (16.13)	1 (25)	7 (46.67)	4 (57.14)	3 (25)	–
Uncertain areas mentioned?	6 (19.36)	2 (50)	5 (33.33)	1 (14.29)	4 (33.33)	–

Abbreviations: GQS, Global Quality Scale. Values expressed as median (range) or count (%). Comparisons of parameters across different types of sources were performed by Kruskal-Wallis test. Two videos (academic institution/university = 1, for-profit company = 1) were not included in the analysis due to the very small sample size.

unbiased manner, and only ~ 57% videos had used reliable sources of information (DISCERN) are worrying. Similarly, more than 50% videos were of poor quality and either had no (GQS score 1) or limited use (GQS score 2) to the viewers. Besides, most videos lacked a comprehensive content. Nearly 60% videos did not provide any information on prevention and/or management of ZIKV disease. Only ~ 4% videos provided information pertaining to all the three examined domains, namely epidemiology, clinical presentation/complications, and management/prevention of ZIKV disease.

The second area of concern was the wide appeal and popularity generated by the misleading videos. Although such videos had poor quality and less reliability than the informative videos, yet they elicited remarkably greater viewer traffic and interactions (*viz*. views, likes, shares and comments) than the latter. It is true that misleading videos also received more dislikes than informative videos. But, the overall data indicates that a substantial number of viewers were possibly unable to judge the quality and authenticity of ZIKV-related information available in YouTube. Such a tendency was recently observed with Facebook posts regarding ZIKV [32]. Similar to our findings, misleading YouTube videos during the 2009 H1NI swine influenza pandemic were also found to attract greater viewer traffic in comparison to the useful videos [22]. Similarly, YouTube videos classified as useful received significantly lower number of views than the ones classified as misleading during the 2012 West Nile virus outbreak in the United States [25] and during the 2014 Ebola Haemorrhagic Fever epidemic [23] too. In contrast, analysis of YouTube videos related to chronic conditions (e.g. rheumatoid arthritis, hypertension, kidney stones, etc.) [19,21,24], or relatively uncommon diseases (e.g. Sjogren's syndrome) [20] suggest that the viewer engagement between misleading videos and informative videos is usually comparable or more favourable for the latter during non-epidemic situations. It is possible that the general public is more vulnerable to misinformation, especially during epidemics/pandemics when the effects are more acute. The misleading YouTube videos in our study mostly subscribed to various conspiracy theories, which ranged from calling ZIKV a genetically engineered bioweapon for mass depopulation and genocide to blaming vaccines (tetanus, diphtheria and pertussis) received mandatorily since 2014 by pregnant Brazilian women for the rising cases of microcephaly (Supplementary Table 3). Such rumour-mongering and dissemination of unfounded and misleading information may be detrimental to public health interests and seriously impair efforts to contain contagions. The recent experience of banning the larvicide pyriproxifen (due to unverified claims that it causes microcephaly) to control mosquito populations and curtail ZIKV spread in South America highlights such a possibility [32,37,38].

Third, the source of the YouTube videos was an important determinant of whether they were informative or misleading. Videos uploaded by independent users were at greater odds of being misleading than government/news agency videos (considered as reference). Even among the informative videos alone, source was a crucial factor. There was considerable variation in quality and reliability scores of the informative videos depending upon the source. Those uploaded by government agencies and health information websites had superior quality and reliability. However, such videos together accounted for just ~ 15% of the informative videos and catered to only a small fraction (< 4%) of the viewership. In fact, only one video was present from universities and academic institutions, which are generally regarded as trustworthy and factual sources of information. This lone video was comprehensive in content (addressed all the 3 examined domains of ZIKV infection) and fared well in quality (GQS score 4) and reliability (4 'Yes' answers to the 5 DISCERN questions) scales, but had received a modest number of only 852 views, 7 likes and 16 shares. The above phenomenon portrays a dual problem: (i) underrepresentation and lesser availability of ZIKV videos in YouTube from trustworthy sources which had good reliability, quality and content, and (ii) under-utilization of whatever good and trustworthy video resources on ZIKV are available in YouTube.

YouTube videos are powerful and inexpensive media to reach out to a large number of people during epidemics and PHEICs like ZIKV infection. With a rise in digital literacy and proliferation of communication and information technology, the number of people utilizing internet based platforms like YouTube for medical information may be expected to increase manifold. However, the full potential of this medium may be realized only by addressing the aforementioned challenges. Unless some curation and authentication of YouTube videos is practised, they may cause more harm than good.

We believe that an integrated two-pronged approach of promoting good and informative videos on one hand, and deterring the spread and influence of misleading videos on the other hand is desirable. Health organizations, reputed hospitals and universities may play a more proactive role and should have a larger presence and visibility in online video platforms like YouTube for greater public health communication and education during health emergencies. A recent study by Basch *et al*. also recommended greater presence of public health agencies in YouTube [39]. Medical experts, researchers, patient support groups, etc. might be motivated to carry out peer review of the video content [20,40]. It would be further convenient for the lay public if such reputable organizations or regulatory bodies or peer groups flagged existing videos with misleading content and debunked them, and recommended/endorsed the informative ones [30]. Introduction of quality filters in the YouTube video search engine could also be of aid. Recently, Athanasopoulou *et al*. suggested modification of the ranking search algorithm in YouTube such that informative videos from trustworthy sources are featured first in the search results when a relevant medical key-term is entered in the YouTube's search engine [41]. This is an attractive solution because videos displayed in the initial pages of the search result are more likely to be viewed. For countering misleading health information in YouTube, one may resort to a combination of strategies that have been tried in other fields. For example, pre-emptive inoculation messages can prepare people for potential misinformation during public health emergencies by exposing some of the logical fallacies in misleading communications prior to the exposure. The rationale is based on 'the inoculation theory', wherein pre-exposure by inoculating logical explanations can help people to recognize misinformation/flawed arguments and reject them as deceiving [42,43]. Such inoculation messages have dual components – an explicit warning of an impending threat and an explanation/argument exposing the forthcoming fallacy. Thus, government agencies and health organizations can play a proactive role during outbreaks and public health emergencies by issuing prior warnings about possible unscrupulous attempts to promote misconception/hoaxes and provide the viewers with relevant health information and counter-arguments to immediately dismiss misinformation, if they come across any. Besides, messages highlighting the potential negative outcomes of misinformation may be used as interventions against misleading videos [44]. Such interventions, based on 'the social-cognitive theory', are focussed on the outcome expectations of the viewers and their subsequent behaviour. This may lead to the viewers 'liking' and 'sharing' misleading videos to a lesser extent [44]. In a similar manner, government agencies and health organizations should try to spread awareness among the public and emphasize upon aspects like cautious use of feelings, and the need of evidence and rigorous assessment by knowledgeable specialists while processing online health information [45]. This would cultivate robust epistemic belief amongst the masses which is stated to be an effective guard against the spread and influence of misinformation [45–47]. Epistemic beliefs encompass perceptions in relation to the nature of knowledge (what is knowledge and how is it conceptualized) and the process of acquiring the knowledge (where does the knowledge come from) [45,46]. According to the epistemology framework, epistemologically naive individuals consider knowledge to be relatively rigid and easy to acquire. They are more prone to share online health-related rumours/misinformation. On the other hand, epistemologically robust individuals are generally more vigilant in processing online health related information. They reject claims, justify accuracy and rely on evidences for validating the authenticity of the available source and knowledge [46,47]. It may also be noted that simple debunking of misinformation and providing corrective information may be inadequate or even trigger backfire effects (*viz*. entrenching the belief in misinformation rather than reducing it) [48]. Therefore, continued debiasing as well as behavioural interventions involving choice architectures should be explored [48]. Efforts based on principles of cognitive psychology which attempt to explain human behaviour by understanding thought processes, are essential to effectively counter misleading information disseminated through YouTube during public health crises like ZIKV.

For future research, it is desirable to capture how viewer traffic of YouTube videos changes with time over the entire period of a public health emergency (*e.g*. pre-outbreak, outbreak and post-outbreak). Such longitudinal data may offer valuable insights into the trends in viewer interest/engagement and the timing about the appearance of misleading information, such that necessary precautions/interventions may be undertaken in the most appropriate periods. As the current study was cross-sectional in nature, such analyses were beyond its scope. Another limitation of the current study was the inability to evaluate non-English videos. This was because none of the researchers were proficient in these languages. We were also limited by the unavailability of information about the viewers of the videos. Viewer information (e.g. demographics) would have been useful in appreciating additional patterns such as which section of the general population was likely to interact/react (*e.g*. like, share, dislike, etc.) in a particular manner to a particular category of videos. Lastly, videos from only one internet based video platform (*i.e*. YouTube) were encompassed in this case study. Therefore, the internal validity of the study is high. Nonetheless, it will be interesting to examine the scenario in other less popular video websites and observe if the findings are applicable for them as well.

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