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A Cross-National Study of Fear Appeal Messages in YouTube Trending Videos About COVID-19

Yee Man Margaret Ng[1]

Abstract

The COVID-19 pandemic has underlined the need for investigating the prevalence and nature of health communication on social media. Applying the Extended Parallel Process Model, this study analyzes the use of fear appeals in 2,152 YouTube trending videos across six countries (the United States, Brazil, Russia, Taiwan, Canada, and New Zealand) from January to May 2020. The findings reveal that, during the early stage of the outbreak, COVID-19-themed videos gained early attention in Taiwan but encountered a prolonged delay in the United States and Brazil. Specifically, COVID-19 videos featured the least in Brazil's trending list. The results from a supervised machine learning coding approach further suggest that videos' threat levels exceeded efficacy beliefs across all countries. This imbalance of threat–efficacy messages was most significant in hard-hit countries Brazil and Russia, which social media may run the risk of feeding fear to the public agenda. These findings alert content creators and social media platforms to create a threat–efficacy equilibrium, prioritizing content that promotes a sense of self- and community efficacy and increases people's belief that effective protective actions are available.

Keywords

fear appeals, efficacy, message design, YouTube trending videos, automated content analysis

[1]Department of Journalism and Institute of Communications Research, University of Illinois at Urbana-Champaign, Urbana, IL, USA

Corresponding Author:

Yee Man Margaret Ng, Department of Journalism and Institute of Communications Research, University of Illinois at Urbana-Champaign, 119 Gregory Hall, 810 Wright Street, MC-462, Urbana, IL 61801, USA.
Email: margaretnym@gmail.com

As the COVID-19 pandemic continues, people across the world are preoccupied with concerns about this contagious illness. But while the pandemic itself wreaks havoc on our daily life, another threat—an "infodemic" (World Health Organization, 2020)—is going viral on social media and has further fueled public paranoia (Merino, 2014). The overabundance of (mis)information has made it exceedingly difficult for people to make informed decisions about how to keep their families safe. The uncertainty, amplified by confusing and contradictory messages from some government officials about the threat of the virus, has triggered an array of maladaptive behaviors, such as panic buying and pursuit of quack cures.

So, how does an infodemic create panic? One theoretical explanation lies in the Extended Parallel Process Model (EPPM) developed by communication scholar Kim Witte in 1992. Witte's model predicts how individuals react when confronted with fear-inducing stimuli: When individuals are unable to determine what information is and is not true, they cannot accurately evaluate the severity and susceptibility of a threat and are less likely to take recommended actions (efficacy) to prevent disease transmission. Out of fear, people might adopt defensive reactions when they feel helpless to act (Witte & Allen, 2000). Therefore, to fight against the infodemic, journalists, public health officials, and other "gatekeepers" of information, such as social media platforms, not only need to find ways to counter misinformation but also to prioritize communication that combines threat and efficacy (Witte, 1992; Witte & Allen, 2000).

COVID-19 is unlike previous global health crises, in part because of the collective access to communication technologies. YouTube, being one of the largest social media platforms (Statista, 2020), has been an important source of news (Stocking et al., 2020) and the "primary window into the world" for young people (Perrin & Anderson, 2019; Tufekci, 2018). However, YouTube faced the challenge of regulating virus-misinformation[1] and elevating authoritative content. Considering YouTube has emerged as an essential source of health information, it is important to understand whether the platform (intentionally or inadvertently) promotes and encourages public health messages, particularly messages that strengthen personal relevance and build self-efficacy regarding pandemic interventions.

Health communication strategies about COVID-19, largely affected by health policy and public discourses, could vary from country to country. However, little has been done to examine the incidence of fear appeals on social media across countries. Thus, this study focuses on six countries: Brazil, Russia, and the United States, which during the time of writing were fueling the significant rise in coronavirus cases, plus New Zealand, Canada, and Taiwan, countries that were able to contain the virus and flatten the curve during the early stage of the pandemic. Applying the EPPM, this study (1) examines the characteristics of COVID-related trending videos on YouTube and (2) compares the extent and nature of the threat and efficacy portrayals in COVID-related videos on YouTube across six countries.

This study extends the scale and scope of an existing health communication model by investigating the prevalence and nature of threat and efficacy messages on a cross-national dataset of YouTube videos collected during the COVID-19 pandemic. From a practical perspective, this study provides insight into the nature of health messages embedded in YouTube videos in various countries. In so doing, this study provides evidence suggesting the ways in which the public would benefit from holding YouTube accountable to regulatory standards and YouTube adopting policies of further transparency.

Literature Review

COVID-19 and Fear Appeals

Designing and disseminating health communication messages (e.g., public service announcements (PSAs) or social media posts) during an unprecedented pandemic could be challenging, not to mention competing for attention among the constant stream of (mis)information. The construct of public health messages becomes extra pivotal in getting the messages across.

In the domain of science communication, fear appeals (a.k.a "scare tactics") are a commonly used messaging approach to motivate behavior change. The EPPM contends that a persuasive message using fear appeals needs to strike a balance between two concepts: threat and efficacy (Witte, 1992; Witte & Allen, 2000). The construct of threat focuses on the severity of and susceptibility to a risk. Severity is the seriousness of the threat (e.g., "More than 100,000 Americans have died from COVID-19.") and susceptibility refers to the likelihood that the threat is going to impact them or their beloved one (e.g., "The elderly are at increased risk for COVID-19."). However, how people respond to the threat depends on the rational aspect of a message, which includes the construct of self-efficacy and response efficacy. Self-efficacy refers to the recommended measures that can address the pandemic (e.g., social distancing and handwashing); and response efficacy is information that helps increase individuals' confidence (skills, social support, and supplies) to perform the recommended behaviors (e.g., "Wearing a mask is effective in preventing the spread of COVID-19.").

An effective health-risk message is created with a balance between threat and efficacy. While individuals exhibit better memory of messages infused with fear than messages with no emotional content (Snipes et al., 1999), appeals eliciting a high level of fear but a low level of efficacy may cause people to reject the messages or even engage in fear-control strategies, such as counter-arguing or discounting the messengers (Kok et al., 2018; Witte, 1992; Witte & Allen, 2000). For example, O'Neill and Nicholson-Cole (2009) found that climate change messages using dramatic, shocking, or scary images to capture attention increase feelings of helplessness due to a lack of efficacy. In a similar vein, Droulers et al. (2017) and Gallopel-Morvan et al. (2011) found that tobacco fear appeals alone provoke avoidance reactions. Conversely, people are more likely to take preventive actions—danger-control strategies—against a threat when they perceive efficacy to act is stronger than the fear or when both efficacy and threat are high (Witte & Allen, 2000). For instance, Chen and Yang (2019) found that messages about preventing breast cancer that contain high levels of threat and efficacy can help raise women's intentions to adopt recommended practices, such as breast self-examination.

In the context of COVID-19, the word “pandemic” could be a frightening concept that makes people feel powerless, so increasing their agency is another critical strategy. To enhance individuals’ perceived self-efficacy, Abbott et al. (2020) suggested that health-risk messages offer encouragement and include “how to” information, such as teaching people how to practice social distancing in different social settings. To gain response efficacy, health-risk messages should cite positive, successful cases to convince people to agree that social distancing will work to slow the spread of COVID-19. In sum, fear appeals with feasible treatments and solutions to the problem can enhance communications and encourage compliance behaviors. Social media platforms could play a role in creating this equilibrium.

Roles of YouTube During COVID-19

Since the world was gripped by the onset of the pandemic and nearly all public gatherings were called off, Internet users have turned to social media to adapt, cope, and find community. During the pandemic, YouTube experienced a tremendous surge in viewer traffic—with overall viewing time in April 2020 doubled that of the same weeks in 2019 (Stelter, 2020). Being the second most popular website worldwide (behind only Google; YouTube is one of Google’s subsidiaries; Alexa, 2020), YouTube also has become an important source of news for many Americans (Stocking et al., 2020). However, YouTube’s affordance is a double-edged sword during outbreak responses: Its power of audio and video increases attention and improves recall than text alone, making the platform an effective tool for communicating health-risk information (Basch et al., 2017; Fung et al., 2016). Yet, its low barriers to media production and dissemination enable the rapid diffusion of misleading or inaccurate information during the pandemic (D’Souza et al., 2020; Li et al., 2020), forcing the platform to remove thousands of videos and take steps to advocate information from global and local health organizations (Benson, 2020).

Much YouTube research has focused on videos with high viewing counts (D’Souza et al., 2020; Li et al., 2020). However, YouTube maintains a regularly updated list of trending videos (https://www.youtube.com/feed/trending) that aims to “capture the breadth of what’s happening on YouTube and in the world” (YouTube, 2020). Among the many new videos on YouTube on any given day, trending videos are not necessarily the most-viewed videos overall. Instead, YouTube (2020) considers a combination of signals, such as users’ engagement (number of views, comments, and likes) and how quickly the video is generating views, to determine which videos to spotlight. Yet, the exact breakdown of the metric has never been disclosed, which leads to suspicion of manipulation and quality controls behind the door that favors traditional media outlets (Alexander, 2019). Hence, in the case that YouTube does actively influence video order, the trending list of videos, arguably, not only showcases a facet of the public agenda, but also symbolizes YouTube’s internal agenda.

Since the platform is designed to host user-generated videos and collect revenue from advertisements, social responsibilities that have arisen from the service’s popularity and the content provided by its user base might seem to be a secondary consideration. The trending list is a better alternative to study message constructs, other than videos with high viewing counts, as the list also reflects YouTube's efforts to promote or encourage public health messages. This leads to the first research question:

RQ1: To what extent do COVID-related videos appear on YouTube trending list?

Extending the Scale and Scope of Fear Appeals Research

Prior research has content analyzed the use of threat and efficacy constructs in YouTube videos. For example, Paek et al. (2010) found that threat appeals are the predominant message strategy (other than humor and social appeals) for YouTube antismoking campaign videos. Likewise, Krajewski et al. (2019) found that threat messages often outweigh efficacy messages regarding global water crisis PSAs. However, the samples used in these studies were relatively small and not generalizable. For instance, Paek et al. (2010) studied 934 antismoking video clips in English and Krajewski et al.'s (2019) analysis was restricted to around a hundred videos that were short (<2 minutes) and appeared as the first 200 in the search. To a further extent, YouTube's influence is not restricted to the United States but to many other countries. YouTube's most popular channels post a substantial amount of content in languages other than English (Van et al., 2019). The inclusion of only English YouTube videos in previous COVID-19 studies (D'Souza et al., 2020; Li et al., 2020) presents a language bias and further limits research generalizability, mitigating our ability to understand COVID-19 as a global phenomenon.

Amid the pandemic, some of the world's largest economies—the United States, Brazil, and Russia—have faced relentless criticism of slow and ineffective containment of the outbreak. Since the start of the pandemic, political figures, like President Trump and President Bolsonaro in Brazil, publicly downplayed the coronavirus risk (Bump, 2020; Linvill & Warren, 2020). The conflicting statements between officials and scientists could have made the public more susceptible to rumors and misinformation about the pandemic's scale, origin, prevention, and treatment. Conversely, *The New York Times* columnist has lauded Taiwan, Canada, and New Zealand for their success in flattening the infection rates curve (Goldberg, 2020). Early in the pandemic, the Taiwanese government provided regular PSAs about cooperative strategies and built digital platforms, such as chatbot and vTaiwan, to disseminate public health information (Lin et al., 2020). Leadership in Canada and New Zealand have taken a clear stance on the severity of the virus. These countries were testaments to what early action and aggressive monitoring bring to the table when battling a pandemic. Since official responses differed greatly across countries, national public discourses and health messaging strategies on YouTube might also show significant variation.

Although YouTube is an important tool for health communication during outbreak responses (Moorhead et al., 2013), researchers' attention to the platform has been disproportionate to its influence among the general population. One reason is examining the message content of YouTube videos can be daunting. Yet, YouTube offers an open

Application Programming Interface (API), which to some extent is more generous than Twitter's—researchers can query search results from YouTube and scrape the entire history of a given channel. This study attempts to answer Rains' (2020) call to apply big data and computational techniques to extend the literature on fear appeals. Since web use is blossoming along traditional lines, defined by languages and geographies (Ng & Taneja, 2019, 2023), beyond English-speaking countries (the United States, Canada, and New Zealand), this study examines YouTube's message constructs in Taiwan (Traditional Chinese), Brazil (Portuguese), and Russia (Russian) through video transcripts. Employing a supervised machine learning method, this study analyzes phrases and topics related to fear appeals in broader scopes and scales.

On the basis of the above, this study examines how the constructs of threat and efficacy are present in YouTube videos across countries. This study proposes three other research questions:

RQ2: What are the descriptive characteristics of COVID-related videos, and how do those characteristics differ across countries?
RQ3: To what extent are threat messages and efficacy messages present in COVID-related videos, and how do those portrayals differ across countries?
RQ4: How balanced are the presence of threat messages and efficacy messages in COVID-related videos on YouTube trending lists across countries?

Methods

Data Collection

While YouTube does not provide country-level statistics at the video level or individual user level, it maintains a regularly updated list of "trending videos" for each target country. Querying YouTube's API (mostpopular/regioncode), this study collected the first 200 trending videos from the United States, Russia, Brazil, Canada, Taiwan, and New Zealand from January 1, 2020 to May 31, 2020 (5 months), four times a day. Videos that trended two or more times a day or days had their details entered in the data set multiple times. This yielded 29,904 unique videos.

To select COVID-related videos, this study first extracted videos that contained the word "COVID" in video tags, descriptions, or titles. This study then examined the top 10 frequent words that accompanied the starting word "COVID" in each country, soliciting logical variants, slang terms, and misspellings. All non-English tags (vocabulary) were translated into English using Google Translate API (via python library *googletrans*). Native speakers confirmed that these words were related to the pandemic. Previous research has showed that Google Translate and the translations of human translators ("gold standard") are comparable (de Vries et al., 2018). Through this process, Taiwanese were more likely to use the term "武漢肺炎" (Wuhan virus) and Russian used коронавирус to refer to the pandemic. Using all these relevant keywords, a search was done again and the final dataset yielded 2,788 unique COVID-related videos.

Video Metadata and Transcripts. Video metadata includes video ID, title, tags, channel name, trending date, uploaded date, assigned category, as well as popularity metrics (i.e., the number of views, likes, dislikes, and comments). Transcripts of those 2,788 videos were also collected. YouTube transcripts are either uploaded by creators or automatically generated (at the creators' request) by Google's speech recognition technology which has reported a 95% word accuracy rate for English (Protalinski, 2017). This study successfully collected transcripts from 2,152 videos (77.2%). That represented more than 80% of videos for most of the countries, except for Taiwan, where only 65.3% of the videos enabled the subtitle feature. YouTube transcripts are available as a stream of text, with no punctuations or segmentations.

Analytical Procedures

To answer RQ1 and RQ2, this study examines the following characteristics of COVID-related videos:

Proportion. To determine whether YouTube prioritized COVID information, this study calculated the percentage of COVID-related trending videos over the total number of trending videos of each country.

Date of the First Video. To estimate how early COVID information gained public attention, this study tracked the date when the first video COVID-related video appeared in the YouTube's trending list of each country.

Video Category. This study further analyzed the category (genre) assignments of each trending video. YouTube allows creators to sort their channels and videos into one of the 32 categories, such as Music, Sports, News & Politics, Education, and Science & Technology. Although channels and videos can be labeled independently of each other, for example, the creator of an Entertainment channel might upload a video and label the video as Comedy, three-fourths of the channels have the same category assigned to 80% of their videos (Bärtl, 2018). I examined which categories were predominantly represented for each country.

Human Labeling and Automated Content Analysis

Previous studies (Emery et al., 2014; Krajewski et al., 2019) considered a message containing a threat or an efficacy construct even when the reelevated themes/words just appeared once. A binary 0–1 (no–yes) coding system may work well for short communication, such as tweets or news headlines, to indicate a construct presence. However, YouTube videos are usually a much longer form of communication. To answer RQ3 and RQ4, this study split each transcript into segments of 40 words (~200 characters, a similar length of a tweet) (N=230,438 segments) to calculate four *construct density scores* (i.e., severity, susceptibility, self-efficacy, and response efficacy).

Each density score was estimated based on a summation of the number of a construct appearance, divided by the number of segments of a transcript.

To address the issue of language specificity, four coders, who were proficient in English and were naïve speakers of one of the following languages—Traditional Chinese, Portuguese, or Russian—took part in the content analysis. This study further employed Google Translate to convert non-English transcripts to English as a cross-check of coding. A 0–1 (no–yes) coding system was used to identify the presence or absence of one of the constructs: severity, susceptibility, self-efficacy, or response efficacy, respectively. Therefore, a segment could have multiple constructs. Consistent with Witte (1992), the EPPM constructs were operationalized as indicated below:

Severity. Severity was defined as the magnitude or seriousness of COVID-19. Videos were coded to indicate whether they referenced (1) the magnitude of COVID (e.g., widespread/pandemic/mortality rate), (2) the seriousness of illness (e.g., death/hospitalization/symptoms/implications), or (3) concerns about mutation or resistance.

Susceptibility. Susceptibility was defined as any references to individuals or groups at higher risk for severe COVID-19. Videos were coded to indicate whether they referenced (1) risk for severe illness increases with age; (2) older adults at increased risk with those aged 85 or older are at the greatest risk; (3) those of any age with certain underlying medical conditions are at increased risk, or (4) other risk factors (pregnancy and other sociodemographic factors, etc.).

Self-Efficacy. Self-efficacy was operationalized whether the video mentioned any (1) individual-level (e.g., covering cough, vaccinations) and societal-level behaviors (e.g., closings, quarantines) recommended by the Centers for Disease Control and Prevention (see also Bandura, 1998); (2) "how to" information for protection measures, (3) words of encouragement, or (4) instructions/links to other health resources (e.g., websites, phone number) for updates.

Response Efficacy. Response efficacy was assessed whether (1) the videos discussed recommended actions were effective or not, (2) mentioned the number of those who recovered from the virus, or (3) about individuals who had triumphed over the virus and their stories.

Table 1 presents the codebook and sample messages.

Coders received training that consisted of watching COVID-related YouTube videos, and meeting as a group to review, discuss, and refine coding criteria. Questions about and discrepancies with the coding criteria were resolved by consensus. To calculate the intercoder reliability, each coder hand-labeled a random sample of 1,000 (original or translated) English segments and another 1,000 segments of their language. Intercoder reliability was found to be acceptably high between coders (Kappa = .82 for Chinese transcripts; .86 for Portuguese; .84 for Russian; Landis & Koch, 1977), reassuring a decent performance of YouTube auto-translation (De Vries et al., 2018; Windsor et al., 2019). After reaching a satisfactory level of reliability, the

Table 1. Theoretical Constructs and Sample Messages from YouTube Video Transcripts.

Constructs	Operational definitions	Examples
Severity	Videos referencing • Magnitude of COVID-19 • Seriousness of illness • Concerns about mutation or resistance	". . .if we do nothing calls it will be a catastrophe 30 50 60 percent of the population could contract the virus and so many people would need we want to avoid those worst-case scenarios"
Susceptibility	Videos referencing key CDC susceptibility statements: • Risk for severe illness increases with age • Older adults at increased risk with those aged 85 or older are at the greatest risk • Those of any age with certain underlying medical conditions are at increased risk • Other potential risk factors (pregnancy, sociodemographic factors, and environmental factors, etc.)	". . .over 65 years old and citizens suffering from chronic diseases such as diabetes mellitus bronchial asthma cancer diseases as well as those who have suffered a heart attack or stroke are obliged to observe the home regime"
Self-efficacy	Videos referencing • Individual behaviors recommended by the CDC (e.g., covering cough, vaccine) • Coordinated/societal-level behaviors (e.g., closings, quarantines) • "How to" information for protection measures • Words of encouragement • Instructions/links to other health resources	"Avoid long walks and crowded places. Keep a social distance of 2 meters. Take care of yourself and your loved ones"
Response efficacy	Videos referencing • Discussion whether recommended actions were effective or not • Mentioned the number of those who recovered from the virus • Individuals who had triumphed over the virus and their stories	"the contact tracing and quarantine and the public health measures are very effective at bringing the outbreak under control that can dramatically reduce the number of cases"

CDC = Centers for Disease Control and Prevention.

coders all together analyzed a random sample of 12,000 segments (5.21% of the total). These human-coded segments were then used as input for a supervised machine learning procedure to predict whether the remaining segments contained the constructs.

During the supervised machine learning procedure, the 12,000 human-coded segments were randomly split into training sets (three-fourths of data) and testing sets (one-fourth). Both sets were stratified and included the same ratio of threat and efficacy. Segments were preprocessed as a list of weighted words ("the bag-of-words" approach). Rare words were assigned a greater weight and assumed to carry a higher discriminatory power. Gradient Boosting Classifier[2,3] (Schapire & Freund, 2012) was used to classify each transcript segment and subsequently automatically classify the larger dataset of transcripts for EPPM constructs. After the classification, segments were reassembled into original transcripts and returned the density scores.

To answer RQ4, this study followed Witte's additive approach (1996) and curated a threat–efficacy index to represent the balance between threat and efficacy message in each video. Severity items were summed with susceptibility items, and then subtracted from the summation of self- and response efficacy (no interaction between the two is proposed).

Considering the heterogeneity of the variances, Welch's analyses of variance (ANOVAs) on four density scores were performed. When results were significant, this study used Games-Howell post-hoc tests (Games et al., 1981), an improved version of Tukey's post-hoc tests for unequal group sizes and unequal variances, to assess pairwise differences.

Results

RQ1 asked to what extent do COVID-related videos appear on YouTube trending lists. Results showed that, during the 5-month period, New Zealand had the most COVID-related video on its trending list (7.1%), followed by Russia (6.1%). Conversely, Brazil had the least portion of COVID-related videos (2.4%) on its trending list.

RQ2 asked what are the descriptive characteristics of COVID-related videos, and how those characteristics differ across countries. Results showed that COVID-related videos first appeared in Taiwan's trending list on January 1, 2020. However, it took another 3 weeks, until January 22, for videos to be spotlighted on Russia's and New Zealand's lists. Brazil was the last country to have COVID-related videos on its trending list (January 28). Regarding video categories, News & Politics was the dominant category for all countries, except for Brazil, where Entertainment was the dominant category. While the portion of the News & Politics videos was close to 80% in Taiwan, Brazil just had only one-fifth of the COVID-related videos from News and Politics. Other common categories included Education, People & Blogs, and Comedy. Table 2 presents the details.

RQ3 asked to what extent are threat and efficacy messages present in COVID-related videos, and how do those portrayals differ across countries. Welch's ANOVAs revealed significant differences for all construct density across countries: severity

Table 2. General Descriptions of COVID-Related Videos for Seven Countries.

Countries	No. of observations (unique) [% out of all trending videos]	Major video categories	First appeared on	Title of the first video
Taiwan	4,099 (555) [4.5%]	News & Politics (79.2%) People & Blogs (9.4%) Music (4.5%)	01 January	武漢染SARS. . .台商大本營恐淪陷？兩岸全面警戒！SARS現蹤武漢！毛寶漲停、康那香逾半根停板！-【這！不是新聞 精華篇】20191231-4 / *這!不是新聞* [Wuhan suffers from SARS. . .Taiwan business base camp may fall? Fully alert across the strait! SARS is now in Wuhan! Maobao daily limit, Kang Naxiang more than half of the limit! / This! Not news, essence 20191231-4]/*This! Not news*
New Zealand	6,770 (432) [7.1%]	News & Politics (67.4%) Comedy (10.6%) Entertainment (8.2%)	22 January	24 Oras Express: January 21, 2020/ *GMA News*
Russia	5,222 (1344) [6.1%]	News & Politics (47.1%) People & Blogs (14.9%) Entertainment (7.6%)	22 January	Минск переключается, Миллиарды пенсионеров, Китайский вирус // Галопом по Европам #140/ *Константин Сёмин* [Minsk switches, Billions of pensioners, Chinese virus // Gallop across Europe # 140/ *Konstantin Semin*]
Canada	5,874 (364) [5.7%]	News & Politics (65.4%) Education (8.4%) Entertainment (7.3%)	25 January	China puts millions under lockdown to contain coronavirus /DW News
The United States	5,476 (322) [5.5%]	News & Politics (63.5%) Education (9.1%) Entertainment (8.3%)	26 January	Coronavirus spread is "accelerating" says China as death toll rises to 41/ *Channel 4 News*
Brazil	2,463 (125) [2.4%]	Entertainment (22.0%) News & Politics (20.9%) Music (16.2%)	28 January	O CORONAVÍRUS e a POLÊMICA de Cyberpunk 2077/ *Gameplayrj* [THE CORONAVIRUS AND THE POLITICS OF Cyberpunk 2077// *Gameplayrj*]

($F=51.01$, $p<.001$), susceptibility ($F=13.23$, $p<.001$), self-efficacy ($F=8.89$, $p<.001$), and response-efficacy constructs ($F=16.18$, $p<.001$).

The results showed that Russia's severity density ($M=0.047$) was significantly higher than that of the United States ($M=039$), Canada ($M=0.035$), Taiwan ($M=0.035$), and New Zealand ($M=0.033$). In turn, Brazil ($M=0.044$) and the United States were significantly higher than that of New Zealand. In the same vein, Russia's videos had the highest susceptibility density ($M=0.010$), followed closely by Brazil's ($M=0.010$). Russia's susceptibility density was significantly higher than that of the United States ($M=0.008$), Taiwan ($M=0.008$), and New Zealand ($M=0.007$). The susceptibility density scores of Brazil and Canada ($M=0.009$) were higher than that of New Zealand. For self-efficacy, New Zealand's density score ($M=0.016$) was significantly lower than that of Canada ($M=0.023$), the United States ($M=0.021$), and Russia ($M=0.020$). For response efficacy, the US's score was significantly higher than that of Brazil's ($M=0.005$), New Zealand's ($M=0.004$), and Russia's ($M=0.003$). Canada ($M=0.004$) was significantly higher than that of Brazil and Russia. Figure 1 is a box-plot visualization to compare density scores across countries (Ng, 2022).

RQ4 asked how balanced threat messages and efficacy messages in COVID-related videos on YouTube trending lists across countries are. Considering all countries, efficacy density scores (summation of self-efficacy and response efficacy) ($M=0.022$, $SD=0.011$) were significantly lower than threat density scores (summation of severity and susceptibility) ($M=0.050$, $SD=0.020$), $t(2{,}189)=61.644$, $p<.002$. There was also a significant discrepancy among countries regarding their differences between threat and efficacy ($F=43.15$, $p<.001$), with Russia ($M=0.034$) and Brazil ($M=0.032$) showing a significantly higher threat–efficacy imbalance than the rest of the countries studied.

Table 3 presents the Games-Howell post-hoc analysis.

Discussion

Drawing upon the EPPM (Witte, 1992; Witte & Allen, 2000), this study examined the characteristics of COVID-related videos on YouTube and assessed the extent threat and efficacy messages are present in COVID-related videos across six countries. Using automated content analysis, this study analyzed the transcripts of 2,152 YouTube trending videos. Results reveal that YouTube neither proactively promotes COVID-19 videos over other topics nor prioritizes communication that combines threat and efficacy. This claim is particularly obvious when examining trending videos of some of the worst-hit countries by coronavirus.

General Video Characteristics

Even as the first sign of COVID-19 emerged from Wuhan, China in late 2019, much of the world remained in an information vacuum. Yet, Taiwan was the exception. As a close neighbor of mainland China, Taiwan was expected to have one of the highest

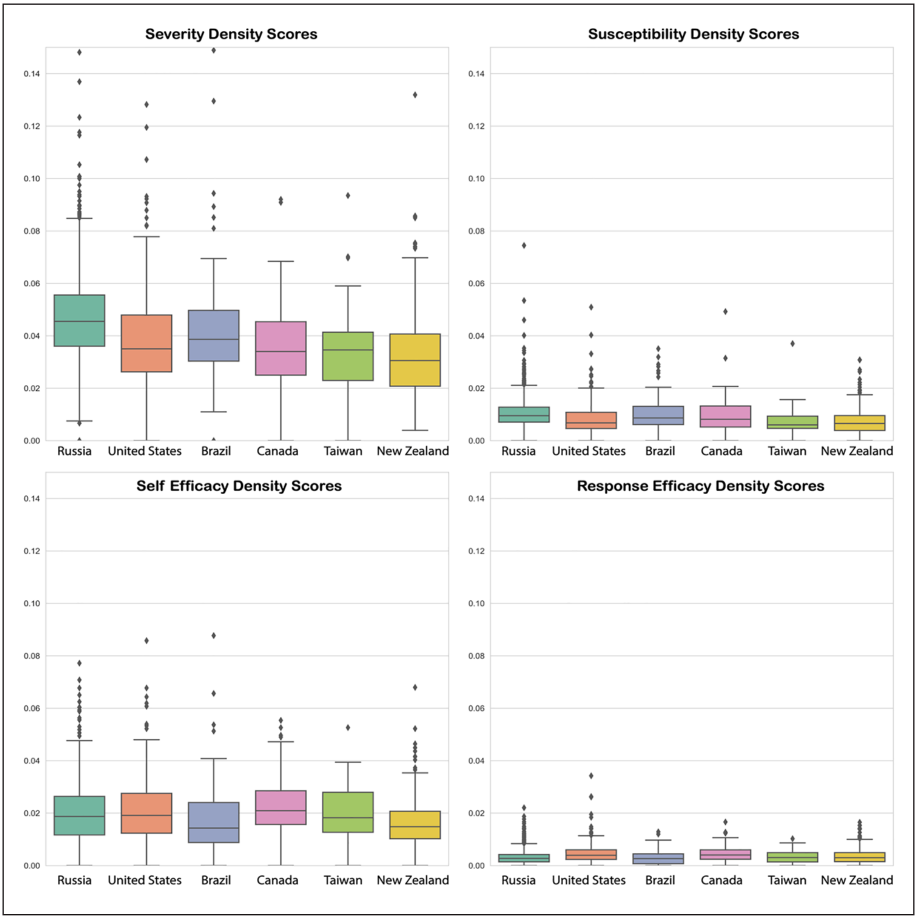

Figure 1. Construct density scores across six countries.

virus caseloads. However, this study found that Taiwan had the first COVID-related videos hit its YouTube trending tab on January 1—much earlier than when the country recorded its first coronavirus case on January 21. Early public attention to the virus contributed to Taiwan's success in the battle against COVID-19 as there was more time for citizens to anticipate disease prevention measures and digest related health information. On the contrary, that information vacuum seems to last much longer in the United States and Brazil than in other parts of the world. The first COVID-related video only appeared on the US trending list on January 26 and Brazil's on January 28. Although the United States confirmed its first COVID-19 case on January 20, YouTube did not capture the instance in its trending list. The delay shows a lack of public interest in COVID-19 in the United States during the early containment and mitigation

Table 3. Games-Howell Multiple Comparisons for Different Countries on Threat and Efficacy Portrayals.

		Severity		Susceptibility		Self-efficacy		Response efficacy		Threat–efficacy	
(I) Country	*(J)* Country	*MD (I−J)*	*SE*	*MD (I−J)*	*SE*	*MD (I−J)*	*SE*	*MD (I−J)*	*SE*	*MD (I−J)*	*SE*
Russia	United States	0.008***	0.001	0.002***	0.000	−0.001	0.001	−0.002***	0.000	0.012***	0.001
	Brazil	0.003	0.003	0.000	0.001	0.002	0.001	0.000	0.000	0.002	0.002
	Canada	0.011***	0.002	0.001	0.001	−0.003	0.001	−0.001***	0.000	0.016***	0.001
	Taiwan	0.011**	0.003	0.003*	0.001	0.000	0.002	−0.000	0.000	0.015***	0.002
	New Zealand	0.014***	0.001	0.003***	0.000	0.004***	0.001	0.001	0.000	0.014***	0.001
United States	Brazil	−0.005	0.003	−0.002	0.001	0.002	0.002	0.002***	0.000	−0.011*	0.002
	Canada	0.003	0.002	−0.001	0.001	−0.002	0.001	0.000	0.000	0.004	0.002
	Taiwan	0.003	0.003	0.001	0.001	0.001	0.002	0.001	0.000	0.002	0.002
	New Zealand	0.006*	0.002	0.001	0.001	0.004***	0.001	0.001*	0.000	0.001	0.001
Brazil	Canada	0.008	0.003	0.001	0.001	−0.004	0.002	−0.001**	0.000	0.015***	0.002
	Taiwan	0.008	0.004	0.003	0.001	0.002	0.002	−0.000	0.001	0.013*	0.003
	New Zealand	0.011**	0.003	0.003*	0.001	0.002	0.002	−0.001	0.000	0.012**	0.002
Canada	Taiwan	0.000	0.003	0.002	0.001	0.002	0.002	0.001	0.001	−0.001	0.003
	New Zealand	0.002	0.002	0.002*	0.001	0.006***	0.001	0.001	0.000	−0.003	0.001
Taiwan	New Zealand	0.002	0.003	0.000	0.001	0.004	0.002	−0.000	0.000	−0.001	0.002

Note. MD = difference in mean; *SE* = standard error.
*$p < .05$. **$p < .01$. ***$p < .001$.

periods; results are consistent with another analysis that is based on Google Trends data (Husain et al., 2020).

Since the outbreak, COVID-related videos have appeared on countries' trending lists in various proportions, ranging from 2.4% in Brazil to 7.1% in New Zealand. The proportions were relatively small, considering the crisis hit hard in some of the countries studied. The small proportions could imply that COVID-related information was primarily missing from the public agenda or YouTube did not take an active role to prioritize COVID-related information over other topics. To tell a complete story, this study further investigated the categories (genres) to which those trending videos belonged. These patterns, to some degree, hint at the purposes and narratives of the videos. Among countries investigated, Brazil had the smallest proportion of COVID-related videos (20.9%) from News & Politics, but with more of its trending videos being from the Entertainment category (22.9%). Without any close examination of the video content, it is unfair to say videos labeled as News & Politics convey better health information than Entertainment videos. However, the category proportion is one way to reflect what information sources—whether they are more fact-based or opinionated—people relied on to understand the pandemic. Particularly, research shows that people who watch more soft news are relatively more cynical about politics than people who watch more hard news (Boukes & Boomgaarden, 2015). The distrust may vary people's perceptions and motives to follow recommended actions.

Threat Levels Exceed Efficacy Beliefs

Consistent with previous research (Krajewski et al., 2019; Paek et al., 2010), this study found that threat messages are more prevalent than efficacy messages on YouTube videos, running the risk of feeding fear to the public agenda. Although people are able to recall messages with fear appeals better (Snipes et al., 1999), videos that employ the language of threat without providing logic may foster the very individualism and competitiveness that could turn sensible behaviors into maladaptive reactions, such as panic buying (Olson, 1995; Witte, 1992). Yet, there are several plausible reasons to explain the imbalance. First, during the early stage of an outbreak, what is known is usually fear-inducing (e.g., deadly diseases, serious complications); what is unknown, such as why certain people show no symptoms or whether vaccination is an effective cure, leaves little sense of efficacy. At the early stage, video creators could only explain what could be done to minimize risks to increase the efficacy of a video.

Although YouTube content showed a low efficacy score, it is important to note that YouTube includes other design features to foster self-efficacy. For example, YouTube provided other visual cues, such as embedding the hyperlink of the CDC website below the video window, to direct people to the latest information about COVID-19. These design features also helped increase individuals' confidence to take action.

Threat–efficacy Imbalance in "Hard-hit" Countries

The "hard-hit" nations of Brazil and Russia showed a significantly higher threat–efficacy imbalance than the rest of the countries studied. The larger imbalance might attribute to government leaderships' slow and muddled responses to contain the spread of the virus. These countries experienced a disturbing surge of infections (increased fear) and a lack of coherent and effective responses (low efficacy). Therefore, the public agenda followed and was less likely to include what are considered as recommended actions in news and videos. In the United States, although Trump's administration showed a lack of national coordination, its own top disease expert, Dr. Anthony Fauci, has grown increasingly vocal in his concerns about the national surge in coronavirus cases and made constant media appearances to correct any false statements made by Trump. The CDC has also advised Americans since April to use face coverings in public, calling masks as "one of the most powerful weapons we have to slow and stop the spread of the virus." Therefore, people in the United States were able to expose to health information from various authorities and may be able to correct any misperceptions about COVID-19 and be more certain of what health actions should be taken.

Limitations

There are several reasons for caution when interpreting data from this study. First, the measurement of threat and efficacy has been a long-discussed issue and does not have a finite answer (e.g., Weinstein, 2000). This study followed Witte's (1996) additive model to estimate the index of threat–efficacy balance. However, Witte also cautioned that threat perceptions need to reach a certain threshold before people become motivated to consider a health-protective action. Yet, this threshold has never been specified. Furthermore, the likelihood and valence of disease severity items are quite different (Fishbein et al., 2001). For example, the risk of death or job loss brings different threat arousal to different individuals. However, this study treated all severity items same weight when I quantified the threat scores. Future studies should pay close attention to assessing the measurement issues.

Second, for analytical purposes, this study reduced videos to forms of text and metadata, which might lead to a loss of valuable communicative features. YouTube is multimodal—its visual imagery, soundtracks (tones and sounds), and transcripts can be distinctly analyzed. For videos about COVID-19, fear appeal messages could use tactics such as showing explicit pictures of individuals who have died from the virus; user comments and advertisements that appear on the same page as the video may be analyzed as well. Yet, the current computational approach offers a board overview of a large video corpus before drilling down for a targeted, multimodal examination.

Conclusion

Slowing COVID-19 viral transmission requires significant shifts in behavior. It is known that fear appeals have an impact on health compliance. However, an effective fear-inducing message needs to strike a balance between threat and efficacy (Witte & Allen, 2000). The results of this study showed that COVID-related videos' threat levels exceeded their levels of efficacy for all six countries studied. The imbalance of threat–efficacy messages was most significant in some of the hard-hit countries, such as Brazil and Russia, during the early stage of the pandemic. These findings alert content creators and social media platforms to create a threat–efficacy equilibrium, prioritizing content that promotes a sense of self- and community efficacy and increases people's belief that effective protective actions are available. The world needs to discover calm amid the coronavirus chaos.

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Notes

1. A joint industry statement on COVID-19 from Microsoft, Facebook, Google, LinkedIn, Reddit, Twitter, and YouTube: https://twitter.com/Microsoft/status/1239703041109942272/photo/1
2. Three popular classifiers: Random Forest (Breiman, 2001), Logistic Regression (Cox, 1958), and Gradient Boosting Classifier (Schapire & Freund, 2012) were used to classify each transcript segment. To evaluate model performance, a 10-fold cross-validation was conducted to assess how well the training model generalized to the testing data set. Cross-validation helps avoid overfitting. Gradient Boosting Classifier achieved the best precision (.85), recall (.83), F1-score (.85), and accuracy (.87).
3. Gradient boosting machines are a family of powerful machine learning techniques that have shown considerable success in a wide range of practical applications. In gradient boosting, the model consecutively minimizes the loss of the model by adding weak learners using a gradient descent-like procedure.

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Author Biography

Yee Man Margaret Ng (Ph.D., University of Texas) is an Assistant Professor in the Department of Journalism and Department of Computer Science (faculty affiliate) at The University of Illinois Urbana–Champaign. Her research examines technology use, social media, and information diffusion using large-scale, unstructured data and computational methods. Particularly, she explores three distinctive yet interrelated components of the web: user behavior, embedded structures, and content framing. She was an Infodemics Researcher with United Nations Global Pulse, an innovation initiative of the UN Secretary-General to harness big data and emerging communication technologies for sustainable development and humanitarian action. Before earning a PhD, she worked as a news artist at *National Geographic Magazine* and *The Seattle Times* and a data reporter for The Center for Public Integrity. During her doctoral study, she was an advanced analytics intern at Pew Research Center's Data Labs.