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Exploring the Cognitive and Emotional Impact of Online Climate Change Videos on Viewers

Nai-Hua Chen

Department of Information Management, Graduate Institute of Services and Technology Management, Chienkuo Technology University, Changhua City 500-94, Taiwan; nhc@ctu.edu.tw; Tel.: +886-471-111-111

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Abstract: Climate change is a significant challenge for the international community. A significant part of addressing this challenge involves informing people about climate change to try and change behavior. Organizations like Technology, Entertainment, and Design (TED) use social media as a means of disseminating information about the complexities of climate science. In this study, we investigate viewers' responses to 50 TED videos associated with climate change that are posted on YouTube. We elucidate the opinions of both speakers and viewers through sentiment analysis of 59,023 comments and negative binomial regression techniques of viewers' reactions. The most frequently mentioned keywords are emission, temperature, environment, nature, renewable energy, and economics. The top three emotions evoked by reviewer are trust, fear, and anticipation. The issue of economics is largely responsible for triggering these emotional responses.

Keywords: climate change; TED videos; hierarchical negative binomial regression; sentiment analysis

1. Introduction

Social media amplifies the ubiquitous dissemination of information over the Internet. YouTube dominates the online sharing of videos through a platform that is driven by users posting their own videos or sharing existing videos [1]. The platform actively encourages viewers to express their views on these videos. Quick and direct feedback is facilitated through buttons on the platform, while viewers can also leave more extensive thoughts and reactions in a free-response comment space below the video content [2]. A number of platforms are globally significant in sharing information through social networks. These include Facebook, YouTube, Twitter, and Instagram. YouTube is of particular significance in displaying a wide variety of user-generated video content to communicate with viewers [3].

Environmental sustainability awareness is one prerequisite for a change in environmental behavior. The use of social media has been increasing exponentially and has changed the way that people access information. Some environmental groups attempt to raise public environmental sustainability awareness through social media sites, such as YouTube [4]. Technology, Entertainment, and Design (TED) is a not-for-profit organization that records presentations from a wide range of speakers and then shares them online. The TED channel posts videos of short speeches that target "people from every discipline and culture who seek a deeper understanding of the world" [5]. A particularly topical and significant issue is climate change, as it relates to global environmental sustainability [6]. Environmental organizations create videos that are posted on social media sites. We can discern viewers' opinions on climate change by exploring their reactions to such videos.

While the goal of influencing behavior through social media sharing is important, it is unclear how the mechanism works. Few studies evaluate public perceptions of climate change through posts on social media. The present paper attempts to bridge this knowledge gap. Researchers can collect valuable information by analyzing viewers' reactions through clicks on the videos they view on social media sites. The unstructured data on social media websites (e.g., in comments under videos) can be analyzed by text mining. This approach extracts significant information about customers' perceptions of a company's services. Text mining can handle large volumes of data using such approaches as pattern identification [7].

Counting models have been variously proposed in, amongst other areas, purchase frequency [8], dental epidemiology [9], and hospital visits [10]. Count data are traditionally handled by the Poisson model, in which the variance equals the mean. Over-dispersed count data are usually treated through the use of a negative binomial model [11]. Following the rationale of this approach, we propose a hierarchical negative binomial regression model for predicting users' evaluations (the difference between like or dislike) and reactions in the semantic features (the differences in positive and negative perceptions) of TED videos posted on YouTube.

2. Related Work

2.1. Social Media and Public Engagement with Climate Change

Public engagement is an important part of combatting climate change. By identifying and changing the specifics of people's behavior, it is possible to have a positive impact on climate change. There is a clear relationship between what people think and feel—and then do—about climate change. Engagement with climate change reflects an evaluation of the response to climate change, which is comprised of cognitive (thoughts), emotional (feelings), and behavioral (actions) components [12].

Social media provides an opportunity for the some public groups to share opinions and engage with climate change issues [13]. Feygina et al. [14] found that promoting climate change through public media enhances public engagement. Cody et al. [15] used sentiment measurement (Hedonometer) to determine responses to climate change news, events, and natural disasters being shared on Twitter. Uldam and Askanius [16] studied YouTube comments relating to issues raised by the UN COP15 climate conference to understand viewers' attitudes toward politics and political engagement. Shapiro and Park [17] used network structures to make comparisons between video discussion networks, and found co-comments across multiple video discussions.

2.2. Opinion Mining

Opinions influence not only the behavior of the person expressing the opinion, but also others' decisions. Opinion leaders can serve as role models who convince their followers to respond or act [18]. Developments of information technology and associated social media networks enable opinion leaders to reach a large audience. Understanding how viewers' reactions influence others' opinions is of significant interest [19].

Opinion mining (also called sentiment analysis) is defined as the extraction of valuable knowledge from textual data [20]. Various researchers have applied opinion mining to social media data, such on Facebook and Twitter [21,22]. For example, Mostafa [23] evaluated consumers' attitudes using their sentiments (positive or negative) toward tweets about well-known brands. In a sentiment analysis, Oksanen et al. [24] elucidated viewers' emotional reactions to pro-anorexia and anti-anorexia content posted on YouTube. Öztürk and Ayvaz [25] evaluated Twitter posts about the Syrian refugee crisis using sentiment analysis. Ordinary least-squares regression models reveal that video background information is more significantly associated with positive, rather than negative, sentiments. Meire et al. [26] reported a sentiment prediction model using the leading information, lagging information, and traditional post variables of soccer teams' Facebook posts. Tudoran [27] determined consumers' opinions in a sentiment analysis of ad-blocking behavior.

Climate change is a global problem that demands universal efforts to protect the environment. In a non-computational sentiment analysis, Jost et al. [28] investigated the climate-related changes in different communities. Their results show that positive sentiments prevail over negative sentiments in terms of transitions of these communities from their current development trajectories.

3. Research Method

3.1. Sample

By inserting the keywords "climate change" and "TED" into YouTube, we retrieved 50 videos (each with more than 100 comments) posted before 14 June 2019 (Appendix A, Table A1). We collected the video contents as well as the viewer responses (likes and comments). Table 1 shows the attributes of the selected videos in each year from 2007 to 2019.

Table 1. Statistical attributes of the selected videos.

Attributes	Viewers (No.)	Likes (No.)	Dislikes (No.)	Length (Min.)	Comments (No.)	Year of Posting
max	3,185,698	81,000	3700	29:32	11,573	2019
min	26,472	279	26	03:58	107	2007
median	111,529.5	1693	250.5	14:56	500.5	2015.5

3.2. Data Processing

Social media provides a platform for information sharing about user-generated content (UGC). Content creators use context data to produce engaging content. We set speakers' dominant keywords in the TED climate change videos as our independent variable. Viewers' engagement behavior is represented by the "like" or "dislike" clicking frequency and comments [29]. Two dependent variables were evaluated. One is the difference between likes and dislikes. The other is the difference between positive and negative sentiment states (identified from comments). In terms of the antecedents of viewers' responses, the speakers' content keywords were treated as independent variables.

In the first stage of data processing, we analyzed both the speakers' narratives and viewers' comments. Our sentiment analysis model was carried out using the "tm" [30] and "Rweka" [31] packages in R. After loading the libraries, we analyzed the documents containing the sentimental terms (anger, anticipation, disgust, fear, joy, sadness, surprise, trust, negative perception, and positive perception) in order to construct word clouds of the 50 selected videos and associated comments (59,023). The "tidy text" [32] package in R includes a dataset called "sentiments", which provides several distinct lexicons (dictionaries of words assigned to sentiment categories or values).

The hierarchical negative binomial regression (NBR) was performed by using a Markov chain Monte Carlo algorithm, namely the "rhierNegbinRw" algorithm in the R package "bayesm". The parameters were optimized by using the Metropolis–Hastings algorithm, which sequentially generates random samples from a probability distribution [33]. We also evaluated the difference between the high and low sentimental states (positive and negative) of the comments in the hierarchical negative binomial regression. Figure 1 shows our data analysis framework.

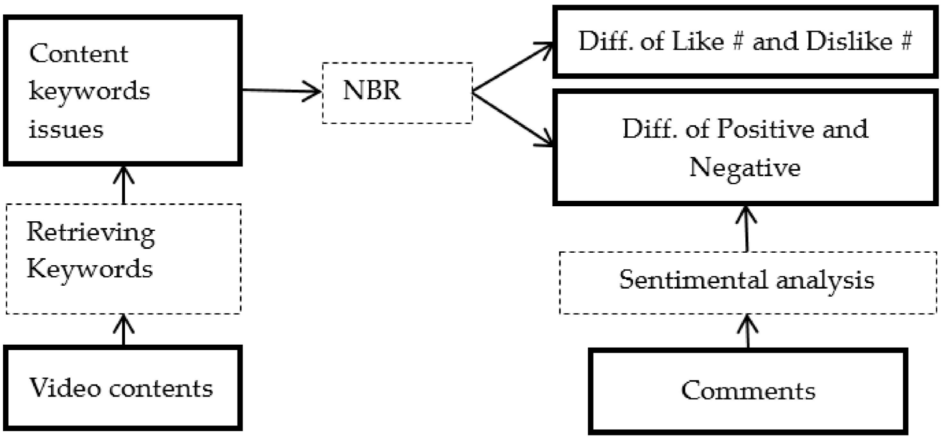

Figure 1. Data analysis framework (note: NBR: negative binomial regression).

3.3. The Hierarchical Negative Binomial Regression Model

The Poisson regression model describes a fundamental random process, in which a certain number of events occur with a certain probability within a fixed time interval. Suppose that y_i is the ith count response variable in an interval of length t_i. Its Poisson distribution is expressed as $f(y_i;\lambda_i) = \frac{(\lambda_i t_i)^{y_i} e^{-\lambda_i t_i}}{y_i!}$, $i = 0, 1, 2, \ldots$, where λ_i is the mean yi in t_i. In a time-independent Poisson distribution, t_i is set to 1.0. The Poisson model is characterized by identical values of the mean and variance. In practice, the Poisson model is useful for describing the mean, but underestimates the variance in the data. Moreover, the Poisson regression model is not suitable for all applications [34]. Over-dispersion (in which the variance exceeds the mean) biases the parameter estimates and causes failure of the conditional independence problem [35].

We propose a fully parametric method, the negative binomial distribution (NBD), as a variation of the standard Poisson regression model to account for over-dispersed count data. The traditional NBD model is a mixed Poisson–gamma model that replaces the gamma prior with a shape parameter α and a scale parameter $\frac{p}{1-p}$ on λ_i such that $y_i \sim \text{Poisson}(\lambda_i)$ and $\lambda_i \sim \text{Gamma}\left(\alpha, \frac{p}{1-p}\right)$, [36]. The probability of this distribution is given by Equation (1):

$$f(y_i|\alpha,p) = \frac{\Gamma(\alpha+y_i)}{y_i!\Gamma(\alpha)}(1-p)^{\alpha}(p)^{y_i},\ i = 0, 1, 2, \ldots, \tag{1}$$

where α is the nonnegative dispersion parameter, p is the probability parameter, and Γ is the gamma function. As α tends to infinity, the NBD approaches the Poisson distribution. The mean is $\lambda_i = \frac{\alpha p}{1-p}$ and the variance is $\sigma^2 = \frac{\alpha p}{(1-p)^2} = \lambda_i + \frac{\lambda_i^2}{\alpha}$. Because the variance is larger than the mean, it is usually favored over the Poisson distribution for modeling over-dispersed count data.

4. Results

4.1. Speaker Content Text Analysis

A word cloud was used to represent the keywords drawn from the video captions (Figure 2). The results show speakers persuading viewers to take an action immediately. The top 10 noun keywords appearing in the speakers' contents are climate, people, word, energy, carbon, warming, plant, emissions, atmosphere, and water. We further use the n-gram, a computational linguistics tool, to evaluate contiguous sequence text as n terms (Figures 3 and 4). The results of bigrams and trigrams show that sea level, global warming, carbon dioxide, fossil fuels, solar panels, and greenhouse gas/gases are most frequently mentioned by speakers. Figure 5 shows the linkages among the speakers' keywords. For example, the word *climate* usually accompanies the words *change*, *scientist*, and *system*, while the word *emissions* is commonly mentioned with *carbon*, *dioxide*, and *gas*. The word *gas* links with greenhouse. The word *ice* associates with *sea*, *level*, and *sheet*. The common keyword analysis shows that speakers' issues cluster around the topics of emission, *temperature*, *environment*, *nature, renewable energy*, and *economics* (Table 2). Out of the 50 selected videos, the most mentioned topic relates to emissions. The correlation plot, according to the Pearson correlation coefficient, shows that speakers' contents containing the "emission" issue were usually discussed with the "nature" and "renewable energy" issues (Figure 6).

Figure 2. Word cloud relating to the contents of the 50 videos.

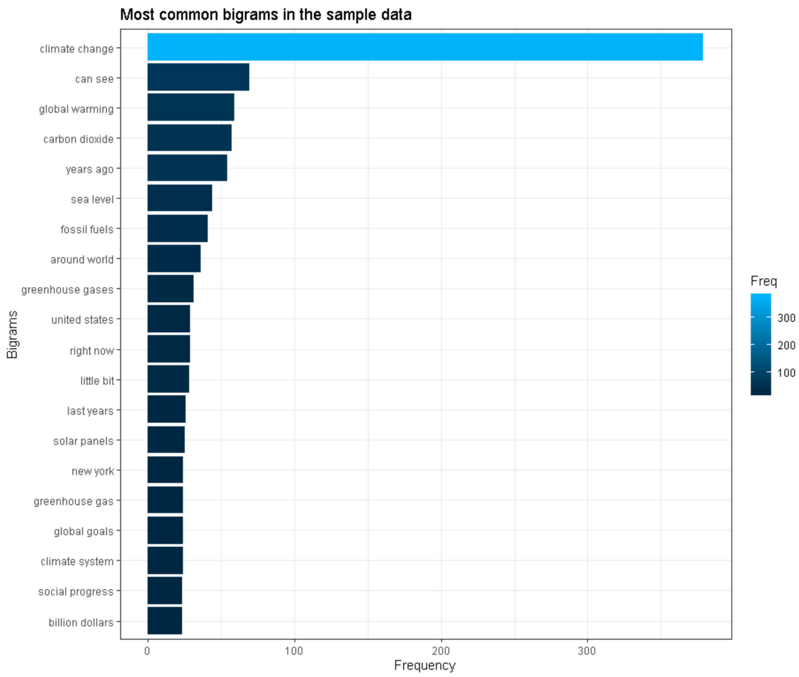

Figure 3. The most common bigrams in the sample data.

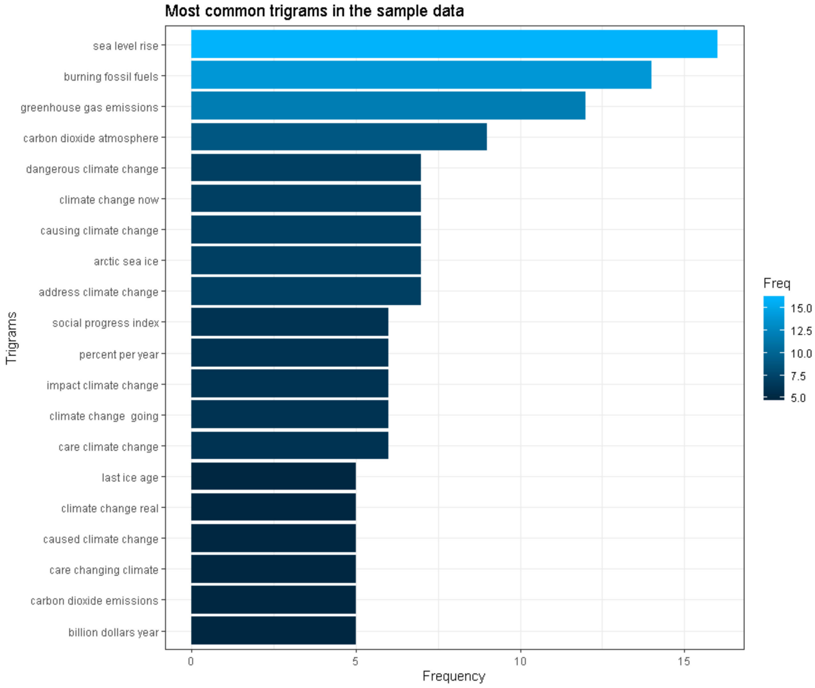

Figure 4. The most common trigrams in the sample data.

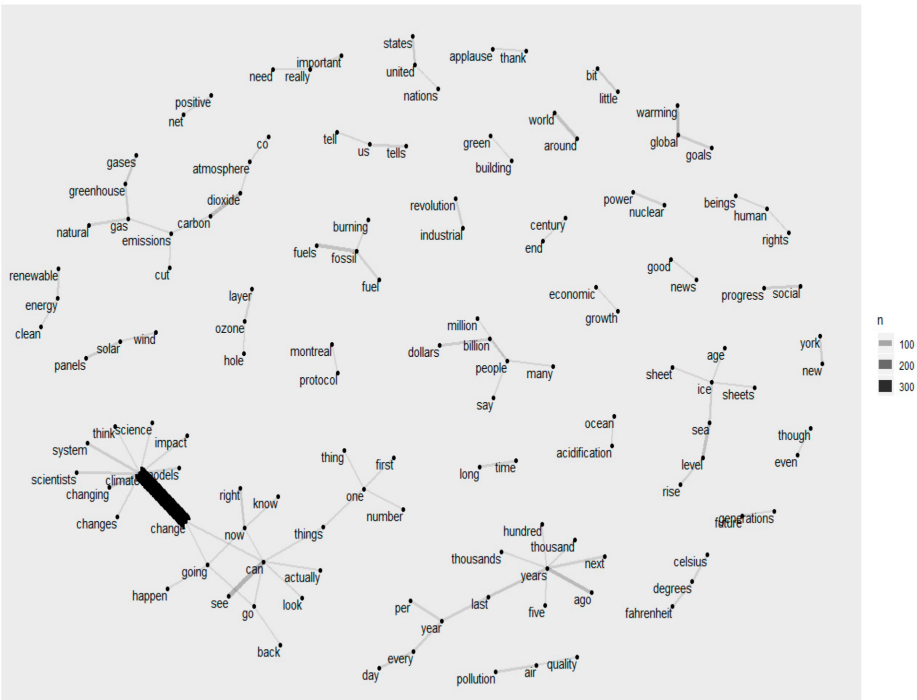

Figure 5. Word network plot of speakers' contents using words occurring more than 10 times.

Table 2. Speakers' content issues and their correlated keywords.

Issues	Keywords	No. of Video Appearances (N = 50)
1. emission	carbon/dioxide/gas(es)/fossil/fuel(s)	31
2. temperature	(global) warming	22
3. environment	sea level/ice sheet(s)	21
4. nature	animal/species/plants	18
5. renewable energy	wind/solar/nuclear	14
6. economics	economics	10

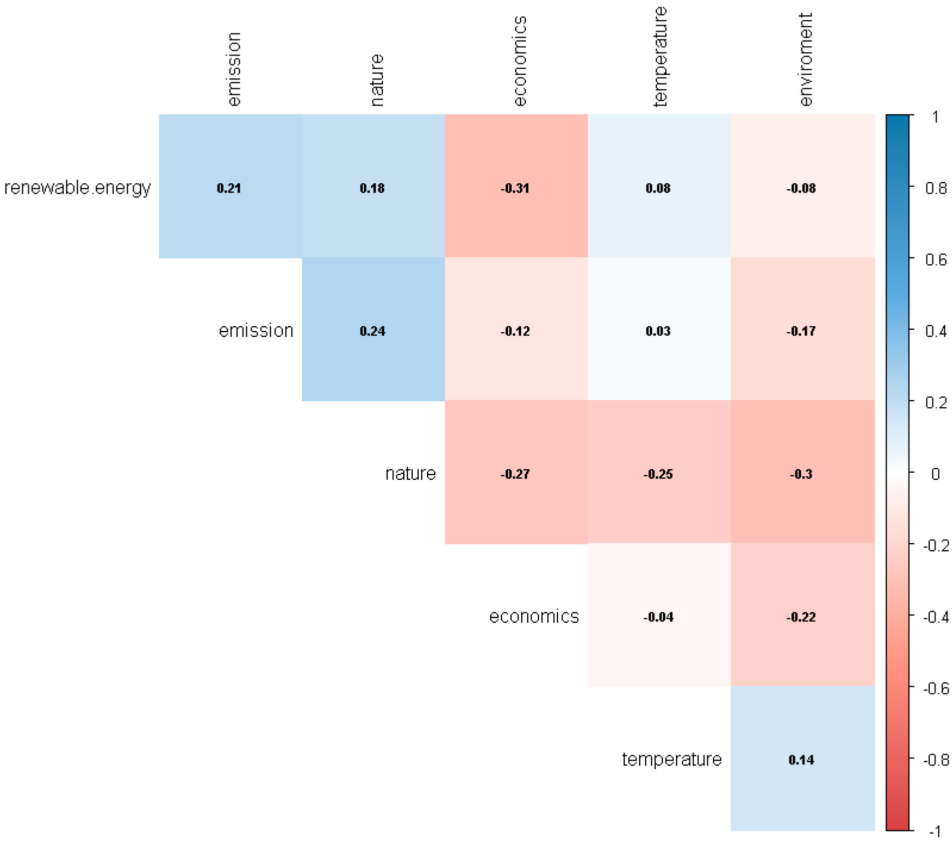

Figure 6. The correlation plot of hot topics.

4.2. Viewer Sentiment Response

Figure 7 shows the sentimental state of the comments in terms of anger, anticipation, disgust, fear, joy, sadness, surprise, and trust. The sentiment analysis of the viewers' complete comments reveals an overall positive attitude toward video contents relating to climate change (Figure 8). Trust, fear, and anticipation are the top three emotions that viewers express (Figure 7 and Table 3). The circus plots in Figures 9 and 10 relate the sentiment data to the speakers' issues. Users refer to trust, fear, and anticipation more frequently for all issues (Appendix A, Table A2). The emotional comments of trust, fear, and anticipation were related to the emission and nature issues. All comments relate more to positive than negative emotions. The top three elements recalled by viewers are nature, renewable energy, and emission (Appendix A, Table A3).

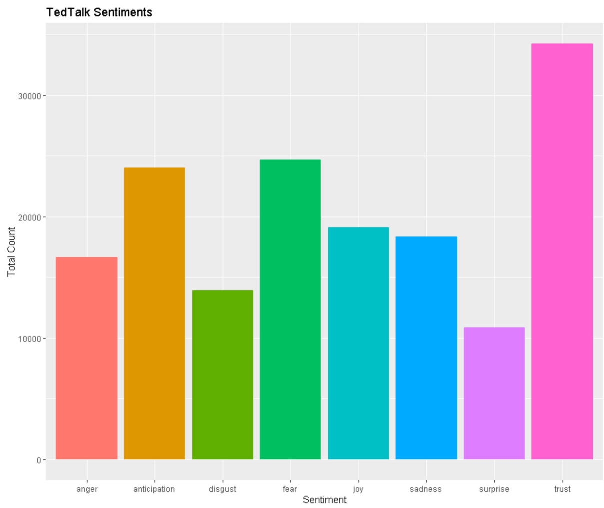

Figure 7. The emotional sentiment scores of the viewers' comments.

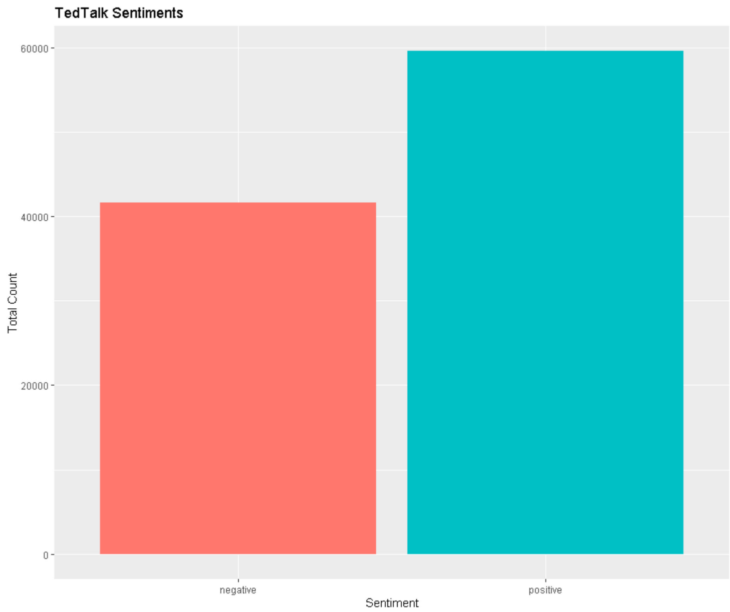

Figure 8. Positive and negative sentiment scores relating to viewers' comments.

Table 3. Sentiment analysis scores summed over all selected videos.

Sentiment	Count	Rank
trust	34,237	1
fear	24,677	2
anticipation	24,019	3
joy	19,104	4
sadness	18,346	5
anger	16,645	6
disgust	13,916	7
surprise	10,867	8
positive	59,555	1
negative	41,614	2

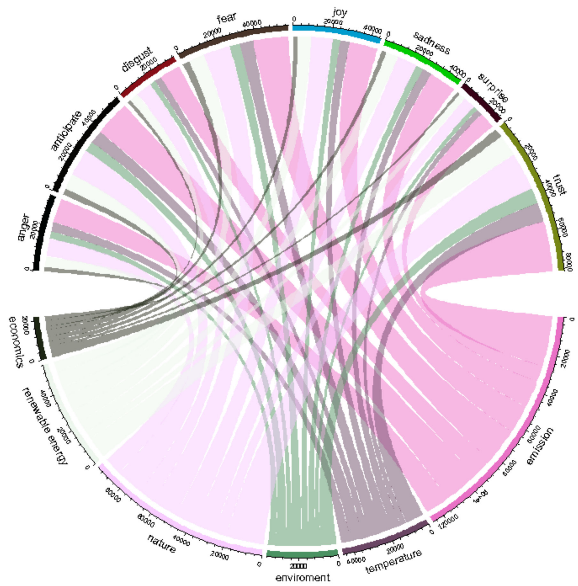

Figure 9. Circus plot of sentiments in video comments versus issues.

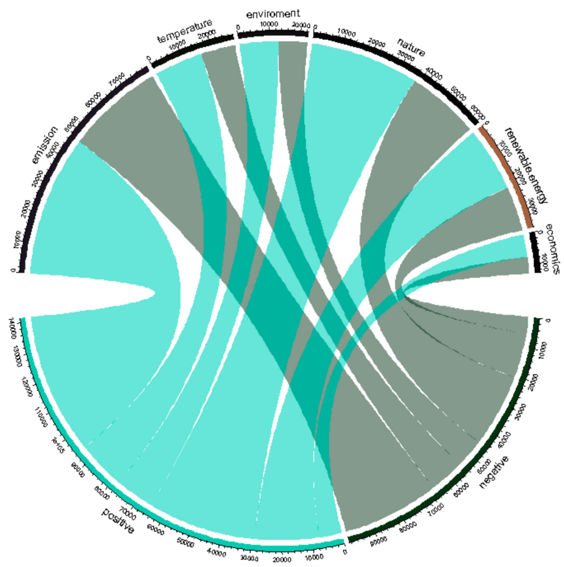

Figure 10. Circus plot of positive and negative sentiments versus issues.

4.3. Negative Binomial Regression Model

A negative binomial regression model simulates hierarchically. The estimates emerge after 1000 iterations. There are seven words from the climate change videos that lead viewers to click either like or dislike. The associated sentimental reactions (the difference between positive and negative) were simulated in the R package bayesm.

We inferred the posterior parameters from the average values of the final 20% of the 1000 iterations. The retrieved keyword issue data were expressed in binary form (1 = appeared and 0 = did not appear). Table 4 shows the effects of the difference between the like and the dislike frequencies as the predictors, and Figure 11 presents the same analysis in boxplots. The top three keyword topics that influenced the like frequencies are economics ($e^{\beta} = e^{4.737} = 114.1$), environment ($e^{\beta} = e^{3.719} = 41.2$), and temperature ($e^{\beta} = e^{3.638} = 38.0$) (Table 4 and Figure 11).

Table 4. The 95% confidence intervals of the influential parameters (β_j) of the difference between like and dislike (n = 50).

Parameter	Mean	Rank	S.D.	Confidence Interval
1. emission	3.819	5	0.091	(3.794, 3.844)
2. temperature	5.075	3	0.106	(5.046, 5.104)
3. environment	4.924	4	0.099	(4.897, 4951)
4. nature	6.196	2	0.126	(6.161, 6.231)
5. renewable energy	3.225	6	0.157	(3.181, 3.269)
6. economics	7.137	1	0.140	(7.098, 7.176)

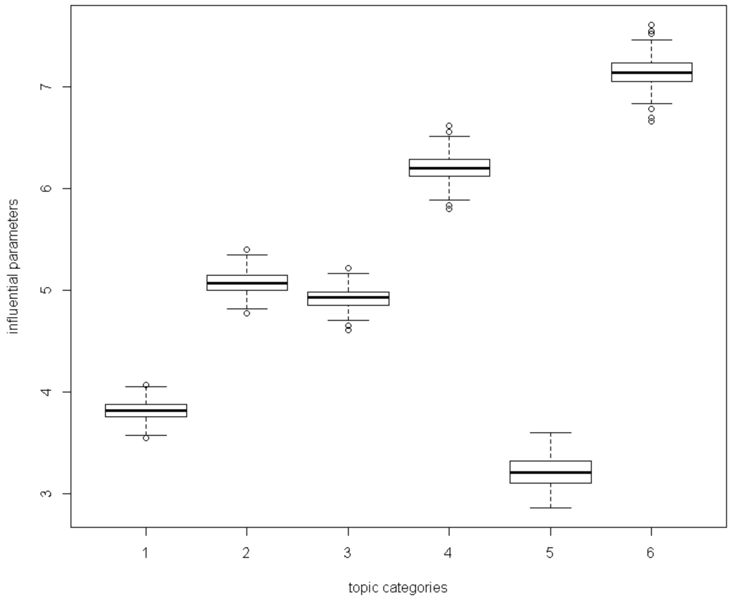

Figure 11. Boxplot of the influential parameters (β_j) of the difference between likes and dislikes on climate change videos (note: 1 = emission; 2 = temperature; 3 = environment; 4 = nature; 5 = renewable energy; 6 = economics).

Based on the sentiment responses (positive or negative), the dependent variable is defined as the difference between the positive and negative values (i.e., positive value–negative value). The same hierarchical NBR simulation was used to predict the keywords in the speakers' content. The top three keyword topics that influenced the like frequencies are economics ($e^{\beta} = e^{4.737} = 114.1$), environment ($e^{\beta} = e^{3.719} = 41.2$), and temperature ($e^{\beta} = e^{3.638} = 38.0$) (Table 5 and Figure 12).

Table 5. The 95% confidence intervals of the influential parameters (β_j) of the difference between like and dislike (n = 50).

Parameter	Mean	Rank	S.D.	Confidence Interval
1. emission	2.611	6	0.074	(2.590, 2.632)
2. temperature	3.638	3	0.082	(3.615, 3.661)
3. environment	3.719	2	0.084	(3.696, 3.742)
4. nature	3.613	4	0.076	(3.592, 3.634)
5. renewable energy	3.002	5	0.174	(2.954, 3.050)
6. economics	4.737	1	0.107	(4.707, 4.767)

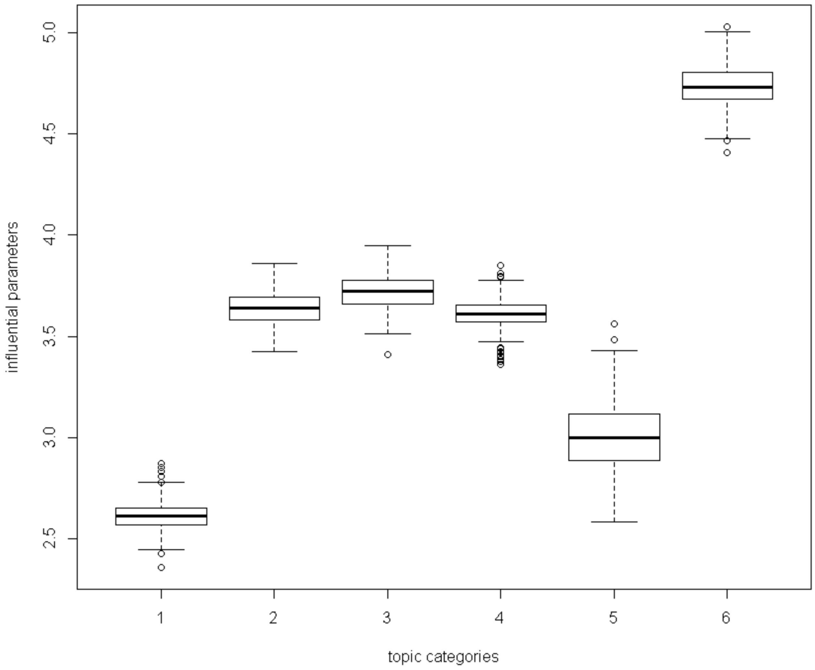

Figure 12. Boxplot of the influential parameters (β_j) of the difference between positive and negative likes on climate change videos (note: 1 = emission; 2 = temperature; 3 = environment; 4 = nature; 5 = renewable energy; 6 = economics).

5. Discussion and Conclusions

Climate change involves global warming. Many studies in the literature have discussed the related topics [37]. The increase of Internet users is an opportunity to change public environmental sustainability awareness globally. However, the research dealing with social media data is still very limited.

The sentiment analysis revealed that viewers of climate change videos trust the contents. This points towards TED acting as a powerful tool for the global dissemination of knowledge related to climate change.

There is little research on the association between video contents and viewers' reactions. Our research has significant implications for understanding the relationship between speakers and reviewers of TED videos. The keywords in the speakers' contents reveal current trends in climate change. The results show that emissions are a dominant issue in TED videos. Although people need power for convenience and economic growth, there is a demand for the development of carbon-free technology. Therefore, the development of green technologies must be balanced with this demand for power. Since water is an essential element for life, we are duty-bound to reduce our atmospheric carbon emissions in order to prevent particulate adsorption into our water supply. Climate change increases the Earth's temperature and thus changes global ecosystems. To avoid this imminent threat, governments worldwide must coordinate their energy policies.

The United Nations Framework Convention on Climate Change (UNFCCC) identifies two principal strategies for managing climate change risks—mitigation and adaptation [38]. Learning how to adapt to and mitigate the risk of climate change includes such approaches as renewable energy or developing green technologies [39]. The keyword results for the content show that TED videos focus predominantly on mitigation. Further studies could consider how to provide information on the different facets of adaptation to a changing climate.

Overall, positive emotions are higher than negative emotions with respect to the videos' contents. The results indicate that while reviewers fear the effects of the climate change, they anticipate steps to mitigate this problem.

The results of the hierarchical negative binomial regression (NBD) indicate viewers' concerns about climate change issues. The first dependent variable (the difference between likes and dislikes) represents reviewers' thoughts (cognition). The second dependent variable is the difference between the viewers' positive and negative feelings (emotion). Most of the cognitive responses relate to economics and nature. The majority of emotional responses are associated with economics and the environment. Stern [40] discussed the effect of global warming on the world economy. An early reaction of public policy to avoid climate change impacts is more important than doing nothing. Every individual can contribute to avoiding climate change.

This research provides a tool for measuring the performances of TED videos relating to climate change that are posted on YouTube. In previous social media studies, researchers focused on viewers' opinions [23–25]. However, the media content is also one important issue affecting viewers' engagement [41]. We evaluate both the speakers' content and reviewers' reactions. The patterns in the speakers' content were deduced by keyword-retrieval techniques, while the viewers' comments were analyzed using a sentiment analysis. The NBD simulates the relationship between speakers' content and viewers' responses (numbers of likes and dislikes as well as the sentiment analysis scores). Using this model, climate change experts could refine the contents of their presentations to target a specific audience of viewers.

6. Limitations and Further Work

The explosion of social media sites, such as Facebook and Twitter, has great potential in the dissemination of sustainability awareness [42]. This study only considered YouTube viewers. Different social media users' responses toward climate change issues could also be evaluated in further work.

Climate change is a global matter. People with different cultures have different opinions. The sample only collected English-speaking videos from TED. A cross-cultural evaluation across various social media sites is suggested [13]. It would be useful to compare the opinions of people in different countries or generations towards engagement with climate change problems.

Numerous studies have confirmed that behavioral change may be caused by activities with the objective of raising awareness [5,43]. This suggests that further research could evaluate how reviewers take responsibility for the effects of climate change after watching videos.

The NBD model was implemented in evaluating the count data in this research. Another variant of regression, such as multiple linear regression analysis [44], could be used for continuous dependent variables. The application of the Internet of Things IoT technique for website interaction evaluation is a further trend [45,46]. The use of eye-tracking techniques or facial recognition for understanding viewers' reactions and content comprehension can be implemented in further research.

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Conflicts of Interest: The author declares no conflict of interest.

Appendix A

Table A1. List of the analyzed videos.

Case	Title	Year	Speaker	Viewers	Comments (No.)
1	Why Climate Change Is a Threat to Human Rights	2015	Mary Robinson	76,874	360
2	How to green the world's deserts and reverse climate change	2013	Allan Savory	3,185,698	11,573
3	Innovating to zero!	2010	Bill Gates	2,133,376	4800
4	School strike for climate—save the world by changing the rules	2018	Greta Thunberg	1,400,488	3980
5	Why renewables can't save the planet	2019	Michael Shellenberger	954,927	8592
6	How We Can Make the World a Better Place by 2030	2015	Michael Green	601,969	621
7	Climate change: Earth's giant of Tetris	2014	Joss Fong	468,836	378
8	The reality of climate change	2014	David Puttnam	441,425	2826
9	Can wildlife adapt to climate change?	2016	Erin Eastwood	396,526	460
10	Why I don't care about 'Climate Change	2014	David Saddington	380,398	1338
11	How will we survive when the population hits 10 billion?	2018	Charles C. Mann	598,652	2874
12	Why I must speak out about climate change	2012	James Hansen	261,191	2596
13	A simple and smart way to fix climate change	2014	Dan Miller	242,889	1371
14	Global priorities bigger than climate change	2007	Bjorn Lomborg	240,437	842
15	The case for optimism on climate change	2016	Al Gore	229,014	1047
16	Can we stop climate change by removing CO_2 from the air?	2017	Tim Kruger	185,667	1245
17	A Creative Approach To Climate Change	2017	Finnegan Harries	159,141	142
18	Demystifying Three Climate Lies—The Road to Decarbonization	2016	Thomas Stocker	154,411	878
19	Climate Change: Fact And Fiction	2011	Bruce Wielicki	150,376	551
20	The inside story of the Paris climate agreement	2016	Christiana Figueres	125,951	415
21	The emergent patterns of climate change	2014	Gavin Schmidt	125,483	351
22	Cloudy climate change: How clouds affect Earth's temperature	2014	Jasper Kirkby	123,188	141
23	Cows, Carbon, and Climate	2016	Joel Salatin	121,806	247
24	How China is (and isn't) fighting pollution and climate change	2018	Angel Hsu	113,811	635
25	Why the Arctic is climate change's canary in the coal mine	2015	William Chapman	113,288	117
26	A climate solution where all sides can win	2017	Ted Halstead	109,771	688
27	We need nuclear power to solve climate change	2016	Joe Lassiter	107,128	1127
28	Climate Change Is Happening. Here's How We Adapt	2015	Alice Bows-Larkin	102,467	589
29	The most important thing you can do to fight climate change: talk about it	2019	Katharine Hayhoe	96,102	679
30	Can we solve global warming? Lessons from how we protected the ozone layer	2019	Sean Davis	78,414	514
31	How empowering women and girls can help stop global warming	2019	Katharine Wilkinson	73,875	216

Table A1. *Cont.*

Case	Title	Year	Speaker	Viewers	Comments (No.)
32	A surprising idea for "solving" climate change	2017	David Keith	72,438	426
33	The state of the climate—and what we might do about it	2014	Nicholas Stern	71,251	107
34	Forget climate Apocalypse. There's hope for our warming planet	2016	Jelmer Mommers	131,367	607
35	Slaying the "zombies" of climate science	2013	Dr. Marshall Shepherd	64,425	779
36	What if climate change is real?	2015	Katharine Hayhoe	62,750	462
37	A provocative way to finance the fight against climate change	2016	Michael Metcalfe	59,296	487
38	The three myths of climate change	2017	Linda Mortsch	50,069	151
39	How pollution is changing the ocean's chemistry	2017	Triona Joanne Chory	81,203	312
40	How supercharged plants could slow climate change	2019	Joanne Chory	40,387	450
41	Let's prepare for our new climate	2012	Vicki Arroyo	76,056	355
42	Climate Change Is Simple	2012	David Roberts	73,124	331
43	Volcanoes: A Forge for Climate Change	2015	Peter Ward	32,428	108
44	How the military fights climate change	2017	David Titley	57,250	153
45	Can clouds buy us more time to solve climate change?	2017	Kate Marvel	55,058	291
46	The Personal Responsibility Vortex	2012	Bret Weinstein	51,831	149
47	Climate Change: Simple, Serious, Solvable	2018	James Rae	26,472	145
48	My Country Will Be Underwater Soon—Unless We Work Together	2015	Anote Tong	42,268	223
49	Climate Change: Why you should be angry and why anger isn't enough	2013	John Ashton	37,698	738
50	A Look Into Our Climate: Past To Present To Future	2011	Michael Mann	37,623	556

Table A2. Results of the sentiment analysis.

Sentiment / Issues	Anger (Odds Ratio)	Anticipate (Odds Ratio)	Disgust (Odds Ratio)	Fear (Odds Ratio)	Joy (Odds Ratio)	Sadness (Odds Ratio)	Surprise (Odds Ratio)	Trust (Odds Ratio)
emission	12,897 (0.482)	18,838 (0.704)	11,055 (0.413)	18,785 (0.702)	15,014 (0.561)	14,267 (0.533)	8521 (0.381)	26,772 (1.000)
temperature	4957 (0.497)	6870 (0.689)	3708 (0.372)	7067 (0.709)	5070 (0.508)	4940 (0.495)	3116 (0.313)	9971 (1.000)
environment	3836 (0.468)	5468 (0.667)	2964 (0.361)	5520 (0.673)	3853 (0.470)	3868 (0.472)	2467 (0.301)	8203 (1.000)
nature	9492 (0.472)	14,299 (0.712)	8393 (0.418)	14,257 (0.709)	11,463 (0.570)	10,784 (0.537)	6350 (0.316)	20,095 (1.000)
renewable energy	5701 (0.496)	8387 (0.730)	4954 (0.431)	8474 (0.738)	6914 (0.602)	6627 (0.577)	3734 (0.325)	11,486 (1.000)
economics	2340 (0.491)	3243 (0.680)	1726 (0.362)	3513 (0.737)	2576 (0.540)	2406 (0.505)	1500 (0.315)	4768 (1.000)

Table A3. Results of the positive and negative sentiment analysis.

Sentiment / Issues	Negative (Odds Ratio)	Positive (Odds Ratio)
emission	32,557 (0.690)	47,158 (1)
temperature	11,606 (0.717)	16,176 (1)
environment	9654 (0.745)	12,966 (1)
nature	24,498 (0.676)	36,243 (1)
renewable energy	14,886 (0.695)	21,432 (1)
economics	5579 (0.741)	7533 (1)

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