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Political and human intervention topics shape the diffusion of climate change denial online

Keywords: Climate Denial, Climate Change, Social Media, Diffusion, Big Data

Extended Abstract

The diffusion of climate change denial online is a significant problem that poses a threat to both the environment and public awareness [1]. However, it is currently unclear whether specific message factors are highly associated with the diffusion of climate denial online. This knowledge gap is concerning, as it limits scholars and policymakers' ability to understand the dynamics of climate-denying content online, which can impede efforts to address the ongoing crisis and create more effective climate change communication strategies [2]. Furthermore, this lack of clarity increases the difficulty of identifying and mitigating misinformation related to climate change [9]. This study aims to fill this gap by answering the question: *what message factors are associated with increased diffusion of climate change denial online?*

In this study, we leveraged a dataset of 7 million climate-change related tweets [3] and then extracted their functional [7], user-level, emotional [4], and topic framing [6] features to model retweet count using a negative binomial regression [8]. We evaluate the relationship between these features and the diffusion of both climate affirming tweets, and climate denying tweets.

To interpret our results, we introduce a means-based effect threshold. This approach is particularly advantageous, in cases such as this, when the scale of data makes every coefficient statistically significant. The method's output (Δ **retweets** in Table 2) can be interpreted as the average change in the number of retweets for either doubling a variable's value (for strictly positive variables) or changing from false to true (for boolean variables). We choose the threshold of $|\mathbf{\Delta retweets}| > 1$ for a meaningful effect. For these meaningful effects, we report the exponential of the coefficient (e^{β}) as a multiplier [5].

The results reveal that tweets about human intervention (e.g. calls to action) and politics (e.g. tweets about politicians) were associated with the greatest diffusion of climate change denial, predicting an 82% and 66% increase in retweet count, respectively. Additionally, the presence of visual media predicted a larger increase in diffusion for climate denial tweets (201% increase) than for climate change affirming tweets (76%). Finally, we find that climate change affirming tweets about climate awareness events (e.g. international polar bear day) diffuse more (150%).

Our findings shed light on the specific topics and message factors that are most strongly associated with the diffusion of climate change denial online. These findings are significant because they help policymakers and scholars better understand diffusion factors for climate-denying content online, which can inform more effective communication strategies and help combat the spread of climate denial and misinformation. The study also introduces a new approach for interpreting model outputs, which could have broader implications for interpreting large-scale social media data. Overall, the study underscores the urgency of addressing the diffusion of climate change denial online and highlights the need for ongoing research to counter this threat.

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Topic Name in Effrosynidis et al [3]	Shorthand
Global stance	global
Significance of Pollution Awareness Events	awareness
Importance of Human Intervantion	intervention
Politics	politics
Undefined / One Word Hashtags	undefined
Seriousness of Gas Emissions	emissions
Donald Trump versus Science	trump
Weather Extremes	weather
Ideological Positions on Global Warming	ideology
Impact of Resource Overconsumption	consumption

Table 1: Summary of Data

variable	description	value range	stats (transformed)
retweets	# of retweets	[0,inf)	μ: 1.82 (.25), σ: 118 (.64) min: 0 (0), max: 149,655 (11.92)
stance*	BERT classifier for believer, neutral, denier, trained on 35,000 tweets	{0, .5, 1}	μ: 0.23, σ: 0.33 min: 0, max: 1
user variables			
log(followers + 1)	# of followers of user	[0,inf)	μ: 45,286 (7.00), σ: 889,955 (2.35) min: 0 (0), max: 133,332,797 (18.71)
log(friends + 1)	# of friends of user (i.e. people they follow)	[0,inf)	μ: 4,9655 (6.52), σ: 21,037 (2.16) min: 0 (0), max: 2,290,952 (14.64)
log(frequency + 1)	tweets per day over lifetime of account	[0,inf)	μ: 21.37 (1.98), σ: 97.41 (1.39) min: 0 (0), max: 91,825 (11.43)
log(favorites + 1)	favorites over lifetime of account	[0,inf)	μ: 20,924 (6.93), σ: 59,971 (3.53) min: 0 (0), max: 2,151,487 (14.58)
verified	whether the user was verified	{0, 1}	μ: 0.06
functional content variables			
log(text length + 1)	text length in characters	[0,inf)	μ: 139.31 (4.85), σ: 69.69 (.43) min: 1 (.69), max: 1025 (6.93)
hashtags	tweet has >= 1 hashtag	{0, 1}	μ: 0.40
mentions	tweet has >= 1 mention	{0, 1}	μ: 0.38
urls	tweet has >= 1 url	{0, 1}	μ: 0.49
media	tweet has >= 1 visual media attachment	{0, 1}	μ: 0.15
sensitive	tweet was labeled by user as sensitive	{0, 1}	μ: 0.00
emotive content variables			
sentiment*	avg. sentiment score of pre-trained VADER, TextBlob, RNN, and BERT models	(-1,1)	μ: 0.03, σ: 0.44 min: -0.99, max: 0.99
aggressive*	BERT classifier for aggressive/not aggressive, trained on 9,000 tweets	{0, 1}	μ: 0.33
framing variables			
topic*	LDA topic-modeling with k=10, transformed to 9 dummy variables with value range {0,1} (dropping “undefined” to avoid multicollinearity)	{’awareness’, ’consumption’, ’emissions’, ’global’, ’ideology’, ’intervention’, ’politics’, ’trump’, ’undefined’, ’weather’}	awareness: 2% consumption: 3% emissions: 7% global: 25% ideology 4% intervention: 15% politics: 9% trump: 7% undefined: 11% weather: 19%

*refer to Effrosynidis et al [3] for more details

Table 2: Full Negative Binomial Regression Results Table

	All Tweets		Believers		Deniers	
	n=7,641,399		n=4,875,105		n=702,431	
variable	β	Δ retweets	β	Δ retweets	β	Δ retweets
constant	-9.0012*		-8.9358*		-9.8466*	
user variables						
log(followers + 1)	0.7016*	0.73	0.7205*	0.77	0.6729*	.65
log(friends + 1)	-0.2039*	-0.79	-0.1959*	-0.78	-0.1437*	-0.73
log(frequency + 1)	-0.6279*	**-1.15**	-0.7086*	**-1.20**	-0.3826*	-0.96
log(favorites + 1)	0.1902*	-0.29	0.1904*	-0.29	0.1232*	-0.39
verified	0.2361*	0.22	0.2392*	0.23	0.4240*	0.44
functional content variables						
log(text length + 1)	0.8395*	**1.10**	0.8411*	**1.11**	0.7831*	0.94
hashtags	0.2241*	0.46	0.1687*	0.33	0.3667*	0.80
mentions	-0.4701*	-0.84	-0.4127*	-0.76	-0.4663*	-0.83
urls	-0.2404*	-0.39	-0.3409*	-0.53	0.3215*	0.69
media	0.6698*	**1.29**	0.5679*	**1.04**	1.1011*	**2.72**
sensitive	-0.2497*	-0.40	-0.2508*	-0.41	-0.4379*	-0.65
emotive content variables						
sentiment	-0.2863*	-0.45	-0.3260*	-0.51	-0.1119*	-0.19
aggressive	0.2714*	0.48	0.2564*	0.45	0.2390*	0.42
framing variables						
awareness	0.8686*	**2.47**	0.9168*	**2.68**	0.3237*	0.68
consumption	0.4077*	0.91	0.1983*	0.40	0.3811*	0.84
emissions	0.1782*	0.36	0.1843*	0.37	0.3130*	0.68
global	0.2536*	0.50	0.1571*	0.30	0.3990*	0.86
ideology	0.0667*	0.13	0.0262*	0.05	0.3470*	0.76
intervention	0.3125*	0.63	0.2749*	0.54	0.5969*	**1.40**
politics	0.3158*	0.64	0.3201*	0.65	0.5085*	**1.15**
trump	0.2196*	0.45	0.2339*	0.48	0.3524*	0.77
weather	0.0950*	0.20	0.1252*	0.27	0.3000*	0.71
stance	-0.4769*	-0.69				-0.70
alpha (dispersion)	5.7397*		5.1291*		7.1313*	

* $p < .001$