What Makes a Climate Change Denier Popular? Exploring Networked Social Influence in a Disinformation Spreader Group

Aimei Yang
University of Southern California
aimei.yang@usc.edu

Abstract

This study examines the networked social influence within a climate change deniers' network. Focusing on social-mediated information sharing networks, the research addresses two key questions: 1) who are the top influencers within the climate change denial community? And 2) what mechanisms contribute to the levels of influence among deniers? Using a machine-learning based algorithm, the study quantify levels of social influence for all members of a climate change denial network over a decade. The findings reveal that a core group of deniers maintains significant influence by spreading disinformation related to social and economic consequences of environmental policies, attacking opposition, and questioning climate change science. Among the four types of deniers, conservative media outlets have the most influence.

Keywords: disinformation networks, climate change denial, networked social influence, machine learning

1. Introduction

Disinformation includes "all forms of false, inaccurate, or misleading information designed, presented, and promoted to intentionally cause harm or for profit" (Kapantai et al., 2021, p. 1301). Unlike misinformation, which refers to inaccurate information shared without the intention to harm (Wardle & Derakhshan, 2017), a defining feature of disinformation is the strategic manipulation and coordination behind disinformation campaigns (HLEG, 2018). Such coordination forms powerful networks that are capable of causing dire consequences, undermining democracy, threatening national security and public safety, and jeopardizing the survival of future generations.

There is no better example of such disinformation networks and their grim consequences than the networks of climate change deniers. Climate change deniers are disinformation spreaders because they purposively spread misleading information that is inconsistent with the scientific consensus about the reality and consequences of climate change. According to a recent report from the Intergovernmental Panel on Climate Change (IPCC, 2022) , "vested economic and political interests have organized and financed disinformation and contrarian climate change communication", deliberately undermining science and contributing to "misperceptions of the scientific consensus, uncertainty, disregarded risk and urgency, and dissent" (¶5). The IPCC report calls for urgent actions to prevent mounting loss of life, biodiversity, and infrastructure. Many of these losses have already become realities that millions around the world struggle with on a daily basis.

Gaining an in-depth understanding of the operation of climate change deniers' networks is key to combating their harmful influence. Networked social influence is an essential mechanism in the operation of coordinated networks (Bignami-Van Assche, 2005; Friedkin, 1998; 2001). Networked social influence refers to how networked members influence each other's opinions, behaviors, and performance outcomes (Aral & Walker, 2012). Studying networked social influence allow us to explore who are the most influential actors among climate change deniers, and what mechanisms allow these actors to be influential.

In this study I apply an innovative algorithm based on machine-learning (Williams et al., 2022) to quantify the level of networked influence among network members. My analysis reveals several major findings. First, a core group of deniers remains highly influential over the decades. Second, further analysis showed that when deniers share disinformation focusing on the social and economic harm of environmental policies, attacking oppositions, and questioning climate change science, such topics help boost deniers' influence level. Among the four types of deniers (i.e., conservative think tanks, conservative

URI: https://hdl.handle.net/10125/106724
978-0-9981331-7-1

foundations, trade groups/industry front groups, and conservative media outlets), conservative media outlets are significantly more influential than any other types. Theoretical and practical implications are also discussed.

2. Disinformation Networks and Networked Social Influence

Disinformation could affect the public' s perceptions about important issues, such as climate change, the effectiveness of vaccines, and election integrity, and severely harm public health, threaten public security, and undermine processes that are fundamental to democracy (Marwick & Lewis, 2017). Although terms such as fake news, disinformation, and misinformation have attracted considerable public attention since political events such as Brexit and Russia's alleged interference in the 2016 U.S. elections (Elswah & Howard, 2020; Wagnsson, 2022), disinformation is not a modern phenomenon, and it is much more widespread than political campaigns and elections. Studies have found that a range of disinformation spreaders, such as governments (Lu & Pan, 2021), special interest groups and fringe groups (Krafft & Donovan, 2020), politicians and political groups (Vargo et al., 2018), and companies (Lewandowsky, 2021), have engaged in disinformation campaigns for various purposes.

2.1. Networked Social Influence in Coordinated Networks

A fundamental process for coordinating and sustaining stable networks is social influence (Friedkin, 1998). In coalitions, the process of social influence helps members create shared goals and visions, coordinate members' behaviors, foster group cohesion, and thereby contribute to network stability. Social influence that occurs within social networks is referred to as networked social influence (Aral & Walker, 2012; Belanche et al., 2021). Research on networked social influence typically focuses either on network compositions (such as embeddedness, tie strength, and relationship heterogeneity) that facilitate or constrain the adoption and changes of opinions and behaviors (Aral et al., 2009), or on the identification of network influencers (Aral & Walker, 2012; Belanche et al., 2021).

This study falls into the latter stream of research and aims to identify prominent networked influencers who exert considerable influence on other climate change deniers. It also seeks to understand the mechanisms that enable them to be influential. I focus on prominent influencers because in a disinformation network, they may function as coalition leaders, setting the tone or inspiring actions for other disinformation spreaders (Kwanda & Lin, 2020). In other words, they are the most harmful and dangerous actors deserving close monitoring. Moreover, identifying and removing such actors can be particularly effective in destabilizing disinformation networks and countering their harm.

To identify prominent influencers, I employed an innovative algorithm that quantifies each actor's influence on other members' ability to achieve a higher rate of engagement on Facebook when sharing climate-related disinformation. Williams et al. (2021) developed the 'social value' (SV) algorithm, which serves as an equivalent of an over-time experiment within a network. Essentially, the algorithm examines whether the behaviors of others differ when a particular actor of interest is present. By observing the network over time, with cases where the actor is present and cases where they are not, I can compare the two sets of observations and infer the extent to which others' behaviors are influenced by that actor.

This approach differs from influencer studies that identify influencers based solely on their followership or social media usage patterns (Harrigan et al., 2021). The flaw in classifying influencers solely by their followers or usage patterns is that it merely identifies individuals with the potential to disseminate information on a large scale, without truly measuring their influence. However, years of media effect research have shown that a significant gap exists between message exposure and actual behavioral changes (Valkenburg et al., 2016). In contrast, the current approach identifies influencers as people whose presence in a social network has an empirically observable impact on others' behavior. Therefore, it represents a much better and more accurate approach to capturing influence.

When applying the SV algorithm in this context, I utilize observed communication outcomes (e.g., total engagement) demonstrated by an actor at one time period to compute the expected communication outcomes for that same actor in the subsequent time period. These projected values are then compared to the actual data based on observations, and the discrepancies are recorded as errors. The next step involves calculating the impact of networked influence on the actor's communication outcomes and adjusting the predictions accordingly using these values. At the heart of the estimation of networked social influence lies a machine learning model that estimates the effect of various factors on the variable of interest. One can anticipate a systematic decrease in errors for a significant portion of the population. Through these steps, the model enables us to precisely quantify the level of influence that each actor has on others within the network, thus identifying actors with high levels of networked influence. I also record the networked social influence levels of each actor and utilize it as the dependent variable to further examine the mechanisms that contribute to the varying ability of actors to exert social influence.

So far, I have discussed disinformation networks and networked social influence that could play a critical role in the coordination and long-term impact of such networks. Next, I will shift our focus to the context of climate change disinformation and review previous research on key actors within the realm of climate change denial.

3. Major Types of Climate Change Denailers

There are four major types of climate change denailers that I examine in this study.

3.1. Conservative Philanthropists and Foundations

This group of deniers represents the powerful influence of wealthy conservative philanthropists and their family foundations. Since the early 1970s, conservative philanthropists such as Joseph Coors have funded conservative think tanks like the Heritage Foundation to wage a "war of ideas" against progressive ideas (Dunlap & Jacques, 2013). Such efforts have grown in power when major funders such as Richard Mellon Scaife and David and Charles Koch joined forces with other major funders to create networks of conservative foundations (Skocpol & Hertel-Fernandez, 2016). A well-known example is the Koch network, which includes sub-organizations such as the Cato Institute, Citizens for a Sound Economy (Americans for Prosperity Action), and Committee for a Constructive Tomorrow (CFACT). Recent research shows that the Scaife and Koch families have surpassed ExxonMobil and become the top funding source for climate change denialism. Even within the overall conservative political landscape, the Koch network is a formidable kingmaker, with many of its endorsed/funded candidates serving at state and federal levels (e.g., Rex Tillerson, Secretary of State; Eric Schmitt, a Missouri senator; Andrew Ogles, a Tennessee congressman).

3. 2. Conservative Think Tanks

These are non-profit, public policy research, and advocacy organizations aiming to promote conservative ideologies such as free enterprise, private property rights, and limited government. An important distinction between traditional think tanks and conservative think tanks is that the latter do not uphold objective research standards and often bend the truth to serve their "advocacy" goals (Dunlap & Jacques, 2013). A key tactic of conservative think tanks' disinformation campaign is to provide an endless supply of information/media materials that range from books, editorials, to social media posts and videos that question climate change. In addition, contrarian scientists and representatives from these think tanks often appear on TV and radio to provide "balanced viewpoints" and establish themselves as an alternative source of scientific research or "counter-intelligentsia." Through these tactics, conservative think tanks amass legitimacy to counter mainstream academia. They also routinely attack mainstream climate scientists as "leftists" or corrupted intellectuals and cast doubts on the reliability of climate science or politicize climate change facts (Dunlap & McCright, 2011).

3. 3. Conservative Media Outlets

In the U.S., conservative media has played a huge role in moving the country rightward (Dunlap & McCright, 2011). Recent research has shown that they are far more likely to spread misinformation or disinformation than left or center media outlets (Shaw & Benkler, 2012). Climate change denialism is rampant on conservative media outlets. For decades, conservative media personalities such as Fox News hosts and Rush Limbaugh have regularly labeled climate change as a hoax and spread disinformation about the IPCC and climate scientists. In recent years, many of these conservative media outlets have moved to the digital space, reaching millions of the public through social media and blogs, and emerging as a central force in the denial machine (Krange et al., 2019).

3. 4. Trade Groups/Industry Front Groups.

The coal and oil corporations, such as ExxonMobil, were among the earliest to conduct scientific research and recognize the severe consequences of climate change. Many industry leaders and executives are fully aware of the connection between burning fossil fuels and greenhouse gas emissions (Dembicki, 2022). Nevertheless, for decades, they spent millions funding the climate denial machine and often established industry associations such as the American Petroleum Institute and American Enterprise Institute to propagate climate-related disinformation (MacKay & Munro, 2012). In recent decades, pressured by public outcry, these organizations have hidden behind their front groups and run astroturfing campaigns, posing as grassroots civil society groups (Carroll et al., 2018).

4. Research Questions

So far, I have reviewed the major types of climate change deniers. Although previous research has documented their tendency to form offline disinformation coalitions (Brulle, 2021; Dunlap & Jacques, 2013; Dunlap & McCright, 2011), little research to date has examined the degree to which they build and sustain coalition networks online. Moreover, this study aims to identify the prominent influencers among climate change deniers and unpack the mechanisms that drive their influence level. To guide the analysis, I propose the following two research questions:

RQ1: Who are the top influencers among climate change deniers on Facebook?

RQ2: What factors drive the networked influence level among climate change deniers on Facebook?

5. Method

5.1. Sample

In order to construct a sample of prominent climate change deniers, I initially compiled notable deniers previously studied in relevant research (Brulle, 2021; Dunlap & Jacques, 2013; Dunlap & McCright, 2011). These previous studies each identified a list of denier organizations and I compiled a comprehensive, non-redundant list based on previous lists. Secondly, I conducted a search on Crowdtangle (https://www.crowdtangle.com), a data archive hosted by a Meta-affiliated organization that contains extensive Facebook historical data. Some of the denial organizations do not have Facebook pages and are therefore removed from the sample. Thirdly, I collected data from the Facebook accounts of these climate change deniers using specific keywords derived from credible sources such as NASA (2022) and the United Nations (2022) to describe climate change. The selected keywords included climate, climate change, greenhouse, greenhouse emission, global warming, sea level rise, global temperature, and arctic ice. The search was conducted in December 2022, encompassing the entire account history (with the earliest account dating back to 2009). Figure 1 depicts the distribution of climate change-related Facebook posts made by these deniers over time. The figure illustrates that the initial surge occurred around 2013 and persisted throughout the subsequent years until 2022, covering a span of ten years. We retained this ten-year dataset for further analysis.

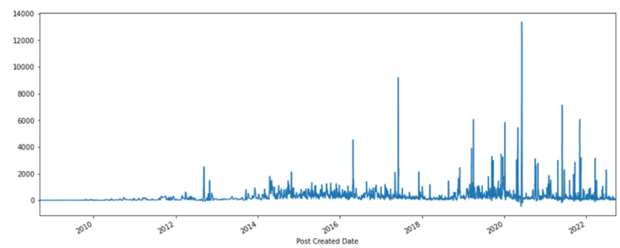

Figure1. Daily posts distribution over time.

5. 2. Analytic Procedures

5. 2. 1. Networked Social Influence. I utilized the open-source software developed by Williams et al. (2022) to calculate the level of influence each account has on the engagement of other accounts. To compute each actor's networked influence, I followed five steps.

First, I built models to predict the total engagement of all actors. The model estimation and codes are adopted from Williams et al. (2021) with modifications based on the current study. For original codes, example data, and data structure requirement, please visit https://github.com/eunakhan/social-value.

Specifically, I took several steps to build models to estimate the amount of total engagement or re-shares for all actors. First, I build models that used data up to time t to predict actors' total engagement or re-shares in interval τ = (t, t+ τ). This step essential records actors' performance at each time points, make an estimation about how they would perform at the next time points, and then compare observation from t+ τ against the observation to record errors.

Second, based on the co-sharing network at time t, I found all actors (U) whose neighbors were absent in this interval τ and considered the pairwise networked social influence each of these users had on their neighbors. This step uses the network information to consider who could have the chance to exert networked influence on a given actor.

Next, I predicted actors' total engagement or re-shares at τ for each actor u ∈ U, using the models from step 1, denoting this estimate as engagement/ $\mathrm{re-shares}_u^{\tau}$ (t). This step essentially brings the network information into the model estimation at step 1 to further record errors and make model estimation. At this point, fitted models should be ready to produce estimations of networked social influence, as further explained below.

At the last step, for each actor u ∈ U, I subtracted the sum of pairwise networked social influence value of all absent neighbors on actor u, forming the total engagement or re-shares estimate of the previous step, to get the networked influence adjusted value amount: $AdjTotalEngagement/Virality_u^{\tau}$ (t)= $\mathrm{TotalEngagement/Re-shares}_u^{\tau}$ (t)$-\sum_{y \in N(u) \& y\ churned\ in\ \tau} SV_{yu}^{\tau}$(t). In addition, I compared $AdjTotalEngagement/Virality_u^{\tau}$ (t) and $\mathrm{TotalEngagement/Re-shares}_u^{\tau}(t)$ with the actual observed data. It was expected that $AdjTotalEngagement/Virality_u^{\tau}$ (t) would be more accurate than$\mathrm{TotalEngagement/Re-shares}_u^{\tau}(t)$.

The model estimation rely on random forest models (see details and codes at https://github.com/eunakhan/social-value). The assessment of model fitness is consistent with that of any random forest model based studies. These models generated Social Value for each account, which captures the degree to which they influence others' behaviors (Williams et al., 2022). In the model estimation, I employed random forest regression models within the Social Value algorithm. I configured the model to have 100 trees in the forests. The R-squared values and accuracy percentages for the three individual models in each time period, as well as the overall model, are as follows: R-squared for time period 1 = 0.97, accuracy percentage = 90.2%; R-squared for time period 2 = 0.93, accuracy percentage = 89%; R-squared for time period 3 = 0.96, accuracy percentage = 95%; and the overall R-squared = 0.89, accuracy percentage = 87%.

5.2.2. Topic Modeling: To analyze the topics of the messages posted by climate change deniers, this study utilizes the state-of-the-art BERTopic algorithm, which leverages deep learning capabilities in Natural Language Processing (NLP) (Grootendorst, 2022). BERTopic incorporates transformers and a class-based TF-IDF to generate dense clusters, enabling the creation of easily interpretable topics. It supports various modes of topic modeling, including guided, supervised, semi-supervised, manual, long-document, hierarchical, class-based, dynamic, and online topic modeling (Grootendorst, 2022, p. 1). Notably, BERTopic has consistently outperformed traditional NLP models like Latent Dirichlet Allocation (LDA) on short texts, such as social media posts, as demonstrated by previous research (de Groot et al., 2022). In this study, the "bertopic" package in Python was employed to analyze how topics evolve over time. After the initial model predictions, we manually reviewed and corrected some potentially questionable topic classifications. These manual corrections were incorporated into the final models to ensure reliable results.

5.3. Variables

Organization Types. Drawing on previous literature on denier typology (Brulle, 2021; Dunlap & McCright, 2011), we manually categorized each organization into one of four types: conservative think tanks (59%), conservative foundations (4%), conservative media outlets (9%), and trade groups/industry front groups (28%).

Total Engagement. This variable represents the overall level of audience reactions received by a post, including likes, haha, love, care, sad, wow, anger, as well as the number of comments. Specifically, the total engagement for Period 1 is 3,062,299; for Period 2 is 3,195,807; and for Period 3 is 2,987,532. In other words, over the course of the decade, climate change deniers' posts on Facebook have generated close to ten million engagements.

Account Social Media Status. We assessed the prominence of each account on social media based on the number of followers it has.

6. Results

RQ1 explores the top influencers among climate change deniers. Table 1 provides an overview of the top influencers from each period, as well as the top influencers calculated based on the ten-year timeframe. Consistent with our network stability analysis, the top influencers are also relatively consistent over time. Organizations such as the Heritage Foundation, The Heartland Institute, Tax Foundation, Cato Institute, and Turning Point USA consistently rank among the most prominent organizations.

Period 1 Top Influencers		Period 2 Top Influencers	
Accounts	Social Value	Accounts	Social Value
Media Research Center	1.112	Turning Point USA	1.930
Fraser Institute	.728	Reason Magazine	1.559
Heritage foundation	.699	Energy Citizens	1.297
ACSHorg	.673	Spemembers	1.145
Freedom Works	.653	Energy Environment Legal	1.043
TheCO2 Coalition	.538	Friends of Coal	.991
Fightback	.437	Heritage Foundation	.978
Reason Magazine	.399	Ayn Rand Institute	.977
Mercatus Center	.372	CFACT	.975
i2idotorg	.308	Friends of Coal America	.946

Period 3 Top Influencers		Overall Top Influencers	
Accounts	Social Value	Accounts	Social Value
Freedom Works	2.244	Heritage Foundation	1.974
Turning point USA	1.737	Media Research Center	1.555
American Coal	1.446	Fightback	1.218
Cornwall Alliance	1.167	Heartland Institute	.608
National Review	1.137	Tax Foundation	.430
Spemembers	1.088	PERCgroup	.365
The CO2 Coalition	1.087	Turning point USA	.353
Competitive Enterprise Institute	1.026	Competitive Enterprise Institute	.327
Fraser Institute	.983	Cato Institute	.317
Heritage Foundation	.938	Institute for Humane Studies	.290

Table 1. Top ten influencers in each time period and overall.

RQ2 explores factors that drive deniers' networked social influence. I conducted logistic regression analysis on Social Values calculated based on the entire decade. Table 2 reports detailed coefficients and significance for significant predictors. Our findings indicate that both disinformation topics and organization types can significantly influence accounts' social influence levels. Specifically, in terms of topics, compared to topic 0 (the most frequent topic), discussions related to topics 1, 2, 3, 4, 5, 7, 20, and 24 significantly boost accounts' social influence levels. Upon closer examination, these topics are also highly engaging and mostly pertain to the social and economic harm of environmental policies, attacking oppositions, and questioning climate change science.

These types of combative and controversial posts are more likely to propel organizations to be highly influential among their peers. In terms of organization types, conservative media outlets are significantly more influential than any other types of climate change deniers, with conservative think tanks (the most common type accounting for 59% of all accounts) used as the reference group. Finally, the analysis showed that the number of followers could also contribute to high level of social influences. Although the effect size is smaller for this variable.

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	.148	.004	36.162	.000***	.141	.157
Topic 1	.057	.013	4.507	.000***	.032	.082
Topic 2	.049	.018	2.674	.008**	.013	.085
Topic 3	.090	.026	3.472	.001**	.039	.142
Topic 4	.089	.03	2.969	.003**	.03	.148
Topic 5	.166	.028	5.957	.000***	.112	.222
Topic 7	-.075	.031	-2.401	.016*	-.136	-.014
Topic 12	-.222	.032	-6.917	.000***	-.286	-.16
Topic 17	-.115	.041	-2.835	.005**	-.196	-.036
Topic 20	.128	.051	2.539	.011*	.029	.228
Topic 24	.176	.054	3.265	.001**	.07	.282
Topic 27	-.488	.047	-10.341	.000***	-.581	-.396
Topic 30	-.145	.069	-2.109	.035*	-.28	-.01
Topic 31	-.120	.057	-2.108	.035*	-.233	-.008
Topic 36	.291	.146	1.998	.046*	.005	.577
Conservative Foundations	-.055	.017	-3.184	.001**	-.089	-.021
Trade Group/Front Groups	-.220	.005	-40.485	.000***	-.231	-.21
Conservative Media Outlets	.219	.009	24.71	.000***	.202	.237
Follower Number	3.68E-07	4.31E-09	85.39	.000***	3.60E-07	3.77E-07
R-square	0.430					
Adjusted R-square	0.429					

Note: Only significant predictors are included in the table. For the topics category, topic 0 is the reference

group. For the spreader type category, conservative think tanks are the reference group. *, p<.05, **, p<.01, ***, p<. 001.
Table 2. Logistic regression model for networked social influence among climate change denailers.

7. Discussion

7.1. Theoretical and Practical Implications

The study zooms in on the prominent influencers among climate change deniers on Facebook. My analysis showed that many of the organizations that previous studies have identified as the most aggressive climate deniers are also active on Facebook (Brulle, 2021; Dunlap & Jacques, 2013; Krange et al., 2019).

While previous research tends to focus on the roles of conservative think tanks and conservative foundations, the study extends this by demonstrating that, on social media, conservative media outlets have the most influence among their peers. When they co-share a message with their peers, such actions significantly drive up engagement and benefit the disinformation network.

Upon closely examining the network structure, we can see that conservative media outlets are not necessarily the most central actors. In terms of structure, the most central actors are conservative think tanks, but these conservative media outlets are far more likely to achieve higher levels of social influence. This finding suggests that in the domain of social media, a new set of climate change deniers may be more influential than the ones extensively studied in previous research. These climate change deniers thus need to be further studied and closely monitored. Another key aspect to consider is that unlike conservative think tanks, conservative media outlets may have be easier to set up and build a presence on social media. This may be quite worrisome considering how many more such outlets that climate change deniers could produce and influence the public's view on climate change.

Another mechanism that propels certain deniers to influencer status is their discussion of specific topics. Our analysis reveals that when deniers discuss the social and economic harm of environmental policies, attack oppositions, and question climate change science, they tend to gain influence. These topics are highly combative and controversial, often using politically charged language and labels to invoke political tribalism. Future studies should closely examine the impact of climate change deniers' discourse on the politicization of the issue of climate change and polarization among partisans. Considering that they engage in such discourse for decades, the cumulative impact on political polarization may be substantial.

7. 2. Limitations and Future Research

The study has several limitations that could be addressed through future research. First, the study primarily focused on disinformation on Facebook. Future studies could incorporate a comparison of multiple social media platforms to gain valuable insights into how climate change denialism spreads across different platforms.

Second, the study does not include a qualitative analysis of the actual rhetoric used by climate change deniers. Future studies could employ rhetorical analysis to provide additional insights.

Third, the study relies on a sample of climate change denial groups. However, prominent individuals (e.g., celebrities), activists, and politicians also wield considerable influence in this regard. Future studies should consider expanding the sample to include other types of disinformation spreaders.

As global temperatures continue to rise year after year, the grim reality of climate change poses severe threats to the future of the human race. Extensive research is urgently needed to explore the best practices that could curb the spread of climate change denialism and better build public support and consensus around public policy initiatives aimed at actively addressing climate change. This study is one step in this direction and also contributes an innovative approach to identifying, monitoring, and, hopefully, curbing the harmful impact of the most dangerous influencers.

8. References

Aral, S., Muchnik, L., & Sundararajan, A. (2009). Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. Proceedings of the National Academy of Sciences, 106(51), 21544-21549.

Aral, S., & Walker, D. (2012). Identifying influential and susceptible members of social networks. Science, 337(6092), 337-341.

Belanche, D., Casaló, L. V., Flavián, M., & Ibáñez-Sánchez, S. (2021). Understanding influencer marketing: The role of congruence between influencers, products and consumers. *Journal of Business Research, 132*, 186-195.

Brulle, R. J. (2021). Networks of opposition: A structural analysis of US climate change countermovement coalitions 1989–2015. Sociological Inquiry, 91(3), 603-624.

Burt, R. S. (2004). Structural holes and good ideas. American Journal of Sociology, 110(2), 349-399.

Butler, B. S. (2001). Membership size, communication activity, and sustainability: A resource-based model of online social structures. Information Systems Research, 12(4), 346-362.

de Groot, M., Aliannejadi, M., & Haas, M. R. (2022). Experiments on Generalizability of BERTopic on Multi-Domain Short Text. arXiv preprint arXiv:2212.08459.

Carroll, W., Graham, N., Lang, M. K., Yunker, Z., & McCartney, K. D. (2018). The corporate elite and the architecture of climate change denial: a network analysis of carbon capital's reach into civil society. Canadian Review of Sociology, 55(3), 425-450.

Dembicki, G. (2022). The petroleum papers: Inside the far-right conspiracy to cover up climate change. Greystone Books Ltd.

Dunlap, R. E., & Jacques, P. J. (2013). Climate change denial books and conservative think tanks: Exploring the connection. American Behavioral Scientist, 57(6), 699-731.

Dunlap, R. E., & McCright, A. M. (2011). Organized climate change denial (pp. 144-160). In Dryzek et al., (Eds), The Oxford handbook of climate change and society. Oxforx, UK: Oxford University Press.

Elswah, M., & Howard, P. N. (2020). “Anything that causes chaos”: The organizational behavior of Russia Today (RT). Journal of Communication, 70(5), 623-645.

Giglietto, F., Righetti, N., Rossi, L., & Marino, G. (2020). It takes a village to manipulate the media: coordinated link sharing behavior during 2018 and 2019 Italian elections. Information, Communication & Society, 23(6), 867-891.

Harrigan, P., Daly, T. M., Coussement, K., Lee, J. A., Soutar, G. N., & Evers, U. (2021). Identifying influencers on social media. *International Journal of Information Management, 56*, 102246.

IPCC. (2022). Climate Change 2022: Impacts, Adaptation and Vulnerability. Available at https://www.ipcc.ch/report/ar6/wg2/

Kapantai, E., Christopoulou, A., Berberidis, C., & Peristeras, V. (2021). A systematic literature review on disinformation: Toward a unified taxonomical framework. New Media & Society, 23(5), 1301-1326.

Keller, F. B., Schoch, D., Stier, S., & Yang, J. (2020). Political astroturfing on Twitter: How to coordinate a disinformation campaign. Political communication, 37(2), 256-280.

Krafft, P. M., & Donovan, J. (2020). Disinformation by design: The use of evidence collages and platform filtering in a media manipulation campaign. Political Communication, 37(2), 194-214.

Krange, O., Kaltenborn, B. P., & Hultman, M. (2019). Cool dudes in Norway: climate change denial among conservative Norwegian men. Environmental Sociology, 5(1), 1-11.

Krishna, A. (2017). Motivation with misinformation: Conceptualizing lacuna individuals and publics as knowledge-deficient, issue-negative activists. Journal of Public Relations Research, 29(4), 176–193.

Kwanda, F. A., & Lin, T. T. (2020). Fake news practices in Indonesian newsrooms during and after the Palu earthquake: A hierarchy-of-influences approach. Information, Communication & Society, 23(6), 849-866.

Lewandowsky, S. (2021). Climate change disinformation and how to combat it. Annual Review of Public Health, 42, 1-21.

Linvill, D. L., & Warren, P. L. (2020). Troll factories: Manufacturing specialized disinformation on Twitter. *Political Communication, 37*(4), 447-467.

Lu, Y., & Pan, J. (2021). Capturing clicks: How the Chinese government uses clickbait to compete for visibility. *Political Communication, 38*(1-2), 23-54.

MacKay, B., & Munro, I. (2012). Information warfare and new organizational landscapes: An inquiry into the ExxonMobil–Greenpeace dispute over climate change. Organization Studies, 33(11), 1507-1536.

Marwick, A. E., & Lewis, R. (2017). Media manipulation and disinformation online. Data & Society, available at: https://www.posiel.com/wp-content/uploads/2016/08/Media-Manipulation-and-Disinformation-Online-1.pdf

NASA (2022). Global climate change. Article available at https://climate.nasa.gov/effects/

Oh, W., & Jeon, S. (2007). Membership herding and network stability in the open source community:

The Ising perspective. Management Science, 53(7), 1086-1101.
Pew Research (2021). 10 facts about Americans and Facebook. Available at https://www.pewresearch.org/fact-tank/2021/06/01/facts-about-americans-and-facebook/
Shaw, A., & Benkler, Y. (2012). A tale of two blogospheres: Discursive practices on the left and right. American Behavioral Scientist, 56(4), 459-487.
Skocpol, T., & Hertel-Fernandez, A. (2016). The Koch network and republican party extremism. Perspectives on Politics, 14(3), 681-699.
United Nations (2022). Climate action. Article available at https://www.un.org/en/climatechange
Valkenburg, P. M., Peter, J., & Walther, J. B. (2016). Media effects: Theory and research. *Annual Review of Psychology, 67*, 315-338.
Vargo, C. J., Guo, L., & Amazeen, M. A. (2018). The agenda-setting power of fake news: A big data analysis of the online media landscape from 2014 to 2016. *New Media & Society, 20*(5), 2028-2049.
Wagnsson, C. (2022). The paperboys of Russian messaging: RT/Sputnik audiences as vehicles for malign information influence. Information, Communication & Society, 1-19.
Wardle, C., & Derakhshan, H. (2017). Information disorder: Toward an interdisciplinary framework for research and policymaking (Vol. 27, pp. 1-107). Strasbourg: Council of Europe.