Scientists, but deny science? Climate change sceptics networks on YouTube led by scientists

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Abstract

Introduction. Climate change debates have divided our society more than ever. Despite most scientists believing in anthropogenic climate change, a small group of people with scientific knowledge and reasoning are denying it.

Method. In this paper, we collect YouTube video comments' data to study the content posted by climate change sceptical scientists and their impact on comment social networks.

Analysis. We apply natural language processing and social networks analyses to study those comments and networks.

Results. We find that denying scientists question the validity of anthropogenic climate change using objective terms such as '*Co2*', '*history*', '*data*', etc., while non-scientists rarely mention these terms, instead frequently using words like '*money*', '*truth*'. Scientists-led social networks are also more structured with significant core users, while non-scientists-led networks have smaller and fragmented groups, indicating scientists-led discussions on climate change are more stable and consistent.

Conclusions. Scientists who deny human-caused climate change cast greater influence on the climate change denying social networks. Their opinions using more scientific terms cause the networks to be more centralized and form more consistent patterns.

Introduction

Despite the existence of scientifically well-established results, such as that emission of greenhouse gases produces global warming, there are sizable proportions of the population in the US who reject climate science (Lewandowsky & Oberauer, 2016). Disbelief in climate change can mean either the absolute rejection of the existence of anthropogenic climate change (ACC) or a lack of sureness about the anthropogenic cause of climate change i.e. climate change scepticism (Lübke, 2022). There have been efforts to increase the influence of environment interest (Jacques et al., 2008) and advertising campaigns to shape the public discourse about climate change (Kovaka, 2021), yet still, organized climate change deniers persist on social media platforms (Falkenberg et al., 2022; K. M. d'I. Treen et al., 2020; Williams et al., 2015) and are polarized from climate change believers (Björnberg et al., 2017; Dunlap, 2013; Hornsey et al., 2016).

Making decisions about complex scientific topics like climate change requires more than just better knowledge of the facts. It takes the ability to critically evaluate evidence and explanations, take into account the source of that information, and appreciate how the methods of science lead to specific conclusions (Sinatra & Hofer, 2021). Studies show that the disbelief in climate change is because of: (a) lack of *knowledge*, meaning people cannot comprehend scientific consensus or crucial scientific facts; (b) lack of *cognition*, meaning people have poor reasoning; and (c) *social or political identity*, as in admitting climate change may be a betrayal to people's identities (Kovaka, 2021). Accumulating knowledge can also improve one's higher cognitive process (Halford et al., 2010). Therefore, reason (a) and (b) are often interchangeable and simultaneous. For the public, many do not know or misunderstand the scientific process that produces these findings, challenging their ability to evaluate the information posted on social media (Sinatra & Hofer, 2021).

Following this line of thinking, we may assume scientists who have higher education training possess both the knowledge and cognition level to understand and agree to anthropogenic climate change. However, this is not always the case. Studies find that the general level of education, scientific knowledge, and science literacy can only modestly predict one's attitude toward and trust in science (Lewandowsky & Oberauer, 2016). General education and scientific literacy not only mitigate the rejection of science facts such as climate change, but also increase the polarization of opinions (Lewandowsky & Oberauer, 2016). A study on comments by climate change sceptics shows a particularly striking aspects of threads come from people with high level of educational backgrounds (Matthews, 2015).

In this study, we use motivated reasoning theory to study climate change sceptics scientists in the social media networks (Kunda, 1990). We conduct sentiment and content analysis using YouTube data to understand what reasons scientists give to reject human-caused climate change, and their impact on the climate change sceptics' network. We use social network analysis to test whether scientist-led networks differ from non-scientist-led sceptics' network. This paper will first briefly review studies on science denialism and climate change polarization on social media. Next, we propose hypotheses to address our research questions and justify methodologies used in this study. In discussion and conclusion, we interpret the results of analyses and discuss our contributions to the social media climate change research.

Climate change denialism by scientists

Climate change sceptical scientists are generally people who (i) do not accept human-caused climate change, (ii) personally consider themselves to be pro-science, and (iii) are aware that most scientists agree on the reality of human-caused climate change (Kovaka, 2021). Their existence is a puzzle because they are trained with scientific knowledge and have reasoning capabilities enough to understand and appreciate scientific evidence while rejecting ACC. They are well-aware of how science works and what makes it a successful tool for producing knowledge (Kovaka, 2021). Thus, we wonder: what is leading them to disagree with ACC? One reason is that scientists also have

their own political and socio-cultural identities, such as their professional socialization and their hostility against the increasing allocation of government funding to applied research rather than to basic science (Lahsen, 2008). Many of the denying scientists are not affiliated with any academic institution but are paid through working at a think tank (Björnberg et al., 2017). The link between political/socio identity and opinions on climate change has been studied by many researchers. However, the generalizability of this link does not exactly explain how sceptics scientists deny climate change in particular. Reasons (a) and (b) are also not applicable to scientists, since studies show that general science literacy and quantitative skills do not vary between people who accept or reject human-caused climate change (Kahan et al., 2012).

Therefore, we turn to a fourth possible reason for denying human-caused climate change: (d) scepticism of the quality and validity of climate science. Some climate change sceptics are sceptical of climate science as reliable with objective scientific evidence, according to standards of good science (Kovaka, 2021; Matthews, 2015). Driven by motivated reasoning, the misconception of climate science as poor science makes it easy to deny the reality of human-caused climate change, which may cause scientists to use their knowledge and educated privilege to deny ACC. In this study, we are interested in finding out whether that is true. Our aim is to know what exactly sceptics scientists post on social media to deny ACC and what arguments they tend to propose to support this opinion. We expect sceptics scientists to have higher probability using words which indicate scientific research standards, evidence, statistical figures, etc. Therefore:

> H1: *Climate change sceptics scientists deny anthropogenic climate change by questioning the trustworthiness and validity of climate science results.*

Climate change social media network

Social media platforms are gradually replacing the role of traditional media as outlets for communication on crisis such as climate change (Duan et al., 2023). The explosion of social media platforms over the past decade has provided us with rich data, allowing us to study the communication and interactions among people with richer data than ever before (Pearce et al., 2019). Applying traditional social network analysis approach to the study of social media networks, researchers are able to break the conventional boundaries of social networks (Kane et al., 2014) as well as access much larger data. However, because social media platforms are also using algorithms to separate users based on their preference, more commonly we see homogeneous networks with people of common attitudes occupying similar network positions (Erickson, 1988). Climate change polarization on platforms such as Twitter/X, Facebook, and Reddit (Bloomfield & Tillery, 2019; Falkenberg et al., 2022; K. Treen et al., 2022) shows that users on social media are more likely to communicate with others who have shared opinions with them over complex science decisions like climate change.

In climate change sceptics' networks, we intend to study the role of scientists who deny or are sceptical of climate change and their impact on the structure of the network around their content. Scientists who are climate change sceptics receive a large amount of media attention and wield significant influence in the societal debate about climate change impacts and policy (Anderegg et al., 2010). However, little is known about this impact to social networks on social media platforms. Longitudinal studies on the climate change denier networks exhibits high stability in terms of its core leaders. The overall size of the network remains relatively stable over time, while having small groups within the climate change deniers' network fluctuate over time. A high number of small groups in a network can lead to fragmentation and reduced interactions across the whole network (Yang, 2024). Therefore, we are interested in how the involvement of scientists may or may not influence the structure of the climate change sceptics' networks on social media compared to non-scientists-led networks. We propose:

H2: Climate change sceptics networks led by scientists present different patterns compared to networks led by non-scientists.

Methods

We use YouTube as our data source to test our hypotheses. Studies show that YouTube's recommender algorithm heightens individual political opinions' polarization (Cho et al., 2020) and users on YouTube especially prioritize conspiracy theories over scientific mainstream views (Allgaier, 2019; Bessi et al., 2016). The combination of video and text contents together can also lead to higher levels of engagement than text alone (Yadav et al., 2011). Video posts create higher structural virality than images and news stories (Juul & Ugander, 2021). Therefore, we use YouTube data to test our hypotheses.

Data

We selected the ten most-viewed YouTube videos using the search term 'climate hoax scientist' for scientist-led videos and fifteen videos using the search term 'climate hoax' for non-scientist-led videos. Comments are collected using the YouTube API and *vosonSML* package in R (Gertzel et al., 2022). The *'climate hoax scientist'* videos are created by scientists or scientists' interviews or speeches with a doctoral degree according to their academic personal webpages. The *'climate hoax'* search term represents the general climate change sceptics videos, usually created by influencers. The total number of comments from scientists' videos is 64,604 and the total number of comments from non-scientists' videos is 230,103. We excluded irrelevant videos that are about specific organizations/conferences/activists, education materials, children's lyrics, etc. We use the two types of comments data separately to test our hypotheses on scientists' claims and social networks.

We also collected the transcripts of all 25 videos to conduct content analysis. We are aware that this data only represents a partial scope of the climate change denial discussion space. Our goal is to explore the phenomena of climate change scepticism by scientists and discuss their impact on climate change sceptics' network.

Natural language processing (NLP) and sentiment analysis

We identified significant keywords from the video transcripts and calculated sentiments of the comments data using natural language processing (NLP) techniques. First, we cleaned the comments data by removing URLs and user mentions. In identifying significant keywords in the comments, we extracted nouns from the transcript data using the NLTK package (Bird et al., 2009) and drew it as a word cloud.

For sentiment analysis, we fine-tuned DistilBERT (Sanh et al., 2019), a distilled version of the BERT model, using Twitter data related to climate change sentiments (Twitter). This ensures the model would incorporate relevant knowledge for sentiment analysis. The training data consisted of tweets annotated with four labels: news, positive, neutral and negative. For our analysis, we excluded the news label focusing on the remaining three sentiment labels. The dataset was split in a ratio of 80:20 for training and testing.

We trained DistilBERT with a batch size of 16 over two epochs, using a learning rate of 2e-5. The model achieved an F1-score of approximately 0.78, indicating decent performance. Using the fine-tuned model, we inferenced our YouTube comments dataset to calculate the probability score for each sentiment.

Social network analysis (SNA)

To explore the network structures of climate change sceptics videos, we conducted SNA on the user comment data for the two types of videos we collected (referred as scientists network and non-scientists network). We created edgelists to represent the relations between users. One key

issue in this process is expanding the levels of nested comments. YouTube limits the number of nested comments from exceeding two layers, shown in figure 1. Expanding the second layer of nested comments gives us higher degrees of the networks. Thus, our first step is to extract usernames from the nested comments and assign them to the lower level, which would indicate one user referring to a previous user's comment (see figure 1). Next, we use the *igraph* package in R to generate the network plots (Csardi & Nepusz, 2006). For the plots, we used the stress-minimization algorithm known as the Kamada-Kawai (KK) layout (Kamada & Kawai, 1989). In this layout, the spatial distance between nodes is longer (shorter) when the shortest path those two nodes is longer (shorter). Note that we have excluded the nodes for videoIDs and their edges as well as any self-commenting edges for improved visualization.

Figure 1. Example of how we expanded the nested comments to retrieve the original degrees of the commenting networks

Figure 2. Word cloud of the most mentioned nouns from YouTube video transcript. Word cloud (a) is from skeptic scientists videos and word cloud (b) is from non-scientists videos.
Word size reflects frequency of mention.

Results

The word cloud of '*climate hoax scientist*' videos (figure 2a) emphasize the words '*science*' and other terms that convey objectivity, such as '*graph*', '*percent*', and '*degree*', more frequently than '*climate hoax*' videos (figure 2b). This suggests that these videos focus more on scientific facts. Words such as '*co2*', '*history*', and '*ice age*' further support the stance of scientists denying anthropogenic climate change, at the same time using data-driven language to back their opinions. The use of these terms supports H1, as scientists question the validity of climate science results.

On the other hand, '*climate hoax*' videos frequently mention intuitive weather-related terms, such as '*temperature*' and '*warming*'. Notably, while '*truth*' is mentioned often, objective terms are used less frequently compared to the '*climate hoax scientist*' videos. Another unique aspect is the use of the word '*money*', possibly highlighting economic factors associated with climate change.

We used the results of sentiment analysis on the social network plots – blues nodes are positive, red nodes are negative, gray nodes are neutral, and green nodes are sentiment unknown. Both scientists and non-scientists network show highly homogeneous positive sentiments (see table 1), indicating most users agree with climate change denialism. Scientists-led networks show a significant core at the centre with dense edges between the nodes in the centre. There are also nodes outside the core but form circle layers. This is due to the KK layout which optimizes the space of the plot such that the nodes are spaced farther apart if the path in the network between two nodes are longer. Two nodes are closer together if there are fewer hops between nodes connecting them, so nodes that are on the same '*circle*' are ones that share equal number of '*hops*' to reach other nodes. Whereas the non-scientists-led networks are messier, with less significant core and having more outliers isolated from the rest of the network. This may imply these non-science users are less connected to other users, which means they could be complaining about climate change rather than having meaningful discussions over the issue. The scientists-led networks are more structured, which confirms our *H2* that scientists are commenting on climate change negatively but with an understanding of science.
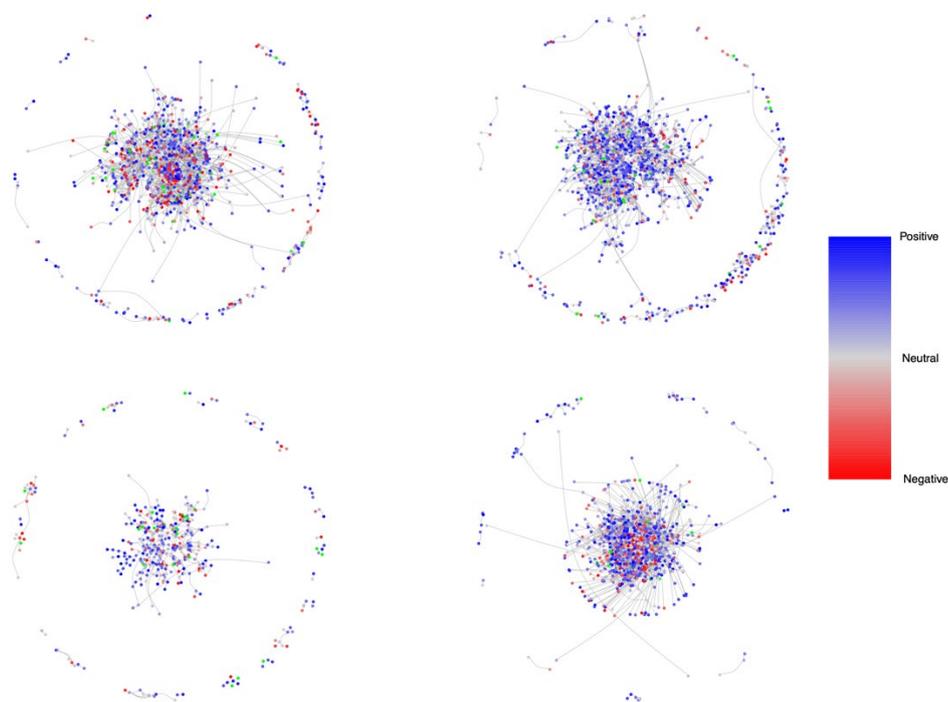

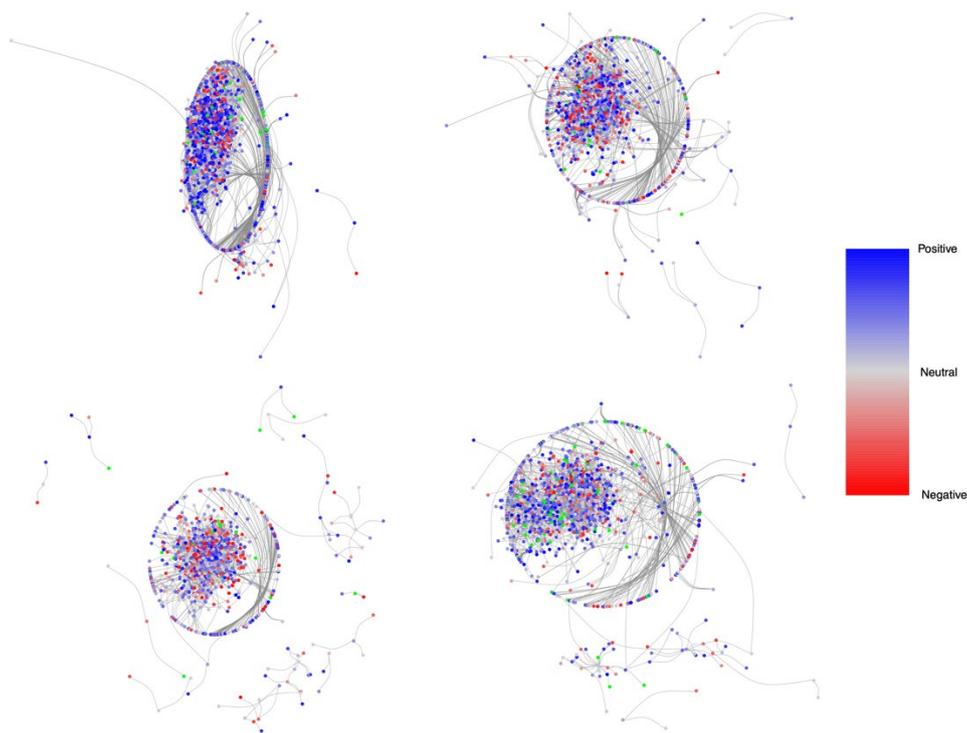**Figure 3.** Scientists-led network (green nodes are sentiment unknown)

Figure 4. Non-scientists-led network (green nodes are sentiment unknown)

Network Type	Positive Sentiment Overall Probability	Negative Sentiment Overall Probability	Neutral Sentiment Overall Probability
Scientists network	53.03%	21.18%	25.79%
Non-scientists network	51.89%	22.62%	25.49%

Table 1. Sentiment of scientists and non-scientists networks

Discussion

The results of our study confirm our hypotheses that scientists deny climate change by questioning whether climate science meets the standards of good science inquiries (*H1*), and they lead social networks perform different structures from non-scientist led networks (*H2*). Their objection to some climate change evidence as being invalid is quite popular among deniers. This could be due to the general social media user not having sufficient understanding of how science is really conducted and how it differs from what they imagined it to be (Kovaka, 2021). Influenced by motivated reasoning, they are more likely to believe in claims saying climate scientists and their results are not objective but biased and based on self-interests. The spread of misinformation and disinformation about science, magnified by social media algorithms and echo chambers is creating more scepticism and mistrust (Sinatra & Hofer, 2021).

The conflict over how to address climate change can be seen as a symbolic political and cultural struggle over the dominant cultural understanding of this issue (Brulle, 2021). The rejection of this environmental issue derived from political, cognitive, and identity concerns can be seen as an objection and rebellion against science as the privileged epistemic position in society (Kovaka, 2021). With scientists who belong to this privileged community taking the lead in the organized

scepticism of anthropogenic climate change, we see a tighter social network than networks led by non-scientists such as influencers. This means that scientists still play an important role in influencing public opinions over complex scientific issues. The scepticism on anthropogenic climate change expressed by scientists probably increases polarization around climate change. However, we do not believe having such diverse and disagreeing opinions is entirely unbeneficial to society. '*There is nothing more anti-scientific than the very idea that science is settled, static, impervious to challenge.*' (Krauthammer, 2014). This idea urges climate science research communities to provide more solid and transparent evidence of their scientific process to convince the public who are temporarily sceptical only due to the lack of trustworthy results.

Conclusion

We study the involvement of climate change sceptical scientists on social media and their impact on social networks of commenting users. We find that these scientists are inclined to use more scientific terms to deny anthropogenic climate change, casting a greater influence on the social network structure. Compared to non-scientists' networks, these networks are more centralized and form more consistent patterns. One limitation of this study is that we only focus on a segment of the large social media data available on a particular group of subjects. Further research is required to fully understand the activities and impact of scientists on anthropogenetic climate change scepticism and societal science denialism.

About the authors

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