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Identifying Different Semantic Features of Public Engagement with Climate Change NGOs Using Semantic Network Analysis

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Abstract: Social media platforms have revolutionized the engagement between climate non-governmental organizations (hereafter, NGOs) and their publics on climate issues. This research diverges from the traditional use of metrics like retweets and likes as simple indicators of identical success in 'one-way' climate communication. Instead, it underscores 'two-way' interactions and their connections that may vary by specific public engagement features, such as popularity, commitment, and virality. Using semantic network analysis, we analyzed tweets and replies between high-engagement NGOs and their publics, identifying communication patterns tied to particular types of public engagement. Additionally, we investigated shared meanings in these interactions with semantic similarity metrics and assessed sentiment alignment between NGOs and their publics as potential indicators of public engagement. Our findings suggest that climate NGOs should select resonating topics, ensuring their sentiments align with those of their publics. It's also essential to tailor topics and focus points in climate communication strategies to reflect desired types of public engagement. This study offers insights into optimizing communication and engagement strategies for climate NGOs on social media.

Keywords: public engagement on social media; strategic social media communication; climate change; climate NGOs; semantic network analysis; semantic similarity

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1. Introduction

The landscape of information dissemination and accessibility has undergone a profound transformation with the advent of social media, exerting a significant influence on public discourse and engagement across socio-cultural, political, and policy domains [1,2]. Ranging from simple likes, shares, and brief comments easily accessible to a range of public audiences [3] to profound discussions taking place within topic-oriented communities on social media platforms [4–6], these cost-effective communication tools empower activists and ordinary individuals to readily participate in discussions concerning various issues, thereby amplifying their voices effectively. With this influence, social media serves as a conduit for both online and offline activism, mobilizing 'non-expert publics' (hereafter, 'publics') (In current research, the term 'non-expert publics' refers to non-expert individuals who recognize a problem or opportunity, and take action to address it (in this case, climate change), as well as those who have built or can build relationships with relevant organizations (in this case, organizations active on climate change) [7–10]) and advocating for climate policies [11–14].

Among the paramount concerns that have garnered substantial traction on social media is the predicament of climate change—an issue of utmost significance confronting our global landscape. According to the 2018 United Nations' Intergovernmental Panel on Climate Change (IPCC) report, countries worldwide are not doing enough to limit CO_2 emissions. The report highlights the urgent need to reduce global emissions by 45 percent by 2030 compared to 2010 levels [15]. Additionally, the IPCC, established in 1988, has consistently emphasized the severity of our current inaction and the future consequences of climate change [16,17]. In this context, social media serves as a means to express concerns about prominent climate change issues (e.g., extreme weather), share pertinent information, engage in discussions about climate science, and participate in climate politics [18].

Numerous non-governmental organizations (hereafter NGOs) are actively involved in advocating for climate change-related concerns, connecting global audiences and translating complex climate science for a range of public audiences [19]. Some climate change NGOs have been operating since the 1970s, with notable examples such as Greenpeace, which has been instrumental in influencing national and international discussions on environmental matters, including deforestation, since its establishment in 1971. For these NGOs, social media platforms have been valuable tools to address their diverse communication goals despite limited resources [20]. Specifically, social media has been identified as a crucial tool for climate-focused NGOs, enabling them to establish a direct information flow to a range of public audiences about climate issues, attract widespread media coverage, appeal to both internal and external audiences to take action on these issues, and establish direct communication channels with policymakers [19,21].

While the significance of social media for climate NGOs—key communicators on climate issues—has been acknowledged, we contend that there is a need for further exploration into the dynamics of engagement between these NGOs and their target audiences. While online platforms have been recognized as a means for deliberate scientific discourse with a range of public audiences [5], and dialogic two-way communication between NGOs and their audiences has been advocated for better engagement [22], existing research has primarily concentrated on the content and manner in which NGOs address climate change matters on social media, within one-way communication framework. This framework assumes that NGOs exert a unidirectional influence on publics, often relying on the metrics of public engagement on social media (e.g., number of likes) as the solo indicator of communicational success. In essence, there has been limited investigation into how various stakeholders, particularly publics, engage in discussions with climate NGOs, and consequently, there is a dearth of understanding regarding the organizations' communication strategies and how these strategies relate to these interactions.

In light of the existing research gap, this study challenges conventional public engagement metrics on social media in two ways. First, it questions the notion that *popularity*, *commitment*, and *virality*, which are gauged through metrics such as likes, replies, and shares [23], should be considered indicators reflecting the identical success of communication strategies, as each type of public engagement may be linked to distinct aspects of interactions between the organization and its corresponding audiences [24]. Second, to gain a comprehensive understanding of 'public engagement', it advocates for an exploration not only of communications from the organization, but also of dialogues between the organizations and their publics, thus shedding light on the discourses facilitated by publics.

Therefore, guided by the two-way communication approach, our objective was to investigate the distinct characteristics of discussions related to climate change, with a particular focus on the themes and focal points in conversations initiated by both climate NGOs and publics across various types of public engagement on social media. Using semantic network analysis (SNA), we uncovered distinctive patterns and conversation themes between organizations and their audiences, which reflect the specific types of public engagement on social media platforms. Additionally, our study explored the extent to which these organizations and their specific target audiences maintain alignment in the subjects and central themes of their conversations across these different modes of engagement. This was accomplished through an analysis of the semantic similarity between the discourses of the organizations and their respective publics. We also examined the emotional alignments between organizations and their publics, as it could offer valuable insights into effective social media strategies. Through these explorations, this study enhances our understanding of the dynamics at play in the 'two-way' interactions between climate NGOs and their respective audiences and improves social media communication strategies tailored to the distinct engagement objectives of each organization.

2. Literature Review

2.1. Climate Change Communication on Social Media

Climate change has been a hot topic on social media, as media attention and civil society mobilization concerning the issue has been manifested in these channels [25]. This is especially true among younger generations, such as Gen Z, as they are actively being exposed to social media posts on climate actions and engaging with social media content on climate actions [13]. The prevalence of climate change discourse on social media has prompted researchers to investigate the themes and focuses of public discussions on this subject. Previous studies have explored the various topics and issues that publics addresses when discussing climate change on social media platforms [18,26]. These investigations have provided insights into the prevalent concerns, interests, and perspectives of social media users regarding climate change. By examining the themes and focuses of public discourse, we aimed to understand public engagement with climate change and the information that circulates through social media channels.

2.2. Engagement with Publics

Engaging publics with an issue through relevant organizations is considered crucial in the fields of science communication and public relations. In those fields of communications, such engagement motivates publics to build a favorable relationship with the organizations and actively seek out the necessary information, such as climate science, to make informed decisions [27–29]. From the perspective of science communication, it is a scientific responsibility [5]. More specifically, the concept of public engagement with science (PES) argues that interactive engagement among scientists, stakeholders, and publics, driven by meaningful dialogue regarding scientific issues, allows publics to play an active role in scientific decision-making and producing social impacts [30]. From the perspective of public relations, engagement with publics and stakeholders has been understood as "part of dialogue and through engagement, organizations and publics can make decisions that create social capital" [22] (p. 384), which was considered as an orientation to ethical communication [27].

In both communication fields, communication between experts, relevant organizations, and publics are essential for engagement. Consequently, social media has emerged as a pivotal tool, facilitating direct 'two-way' communication between scientists or pertinent organizations and an array of public audiences [27,31]. However, prior studies focusing on climate NGOs' social media presence have predominantly emphasized a 'one-way' communication from these organizations. For instance, a study analyzed the framing of social media posts by 298 global climate NGOs, suggesting that these strategic messages could influence public perceptions and behaviors concerning climate change and engagement [19]. Similarly, another study spotlighted the 'one-way' communication strategies of environmental NGOs, investigating their campaigns that challenge the sustainability of corporate actions [32].

Studies concentrating on the communicative interactions between organizations and publics often hone in on publics' social media engagement metrics, such as views, likes, and shares [23,24,27]. This scope, however, scarcely encapsulates the richness of dialogic interactions and the evolution of public discussions on climate change issues on social media (e.g., "What issues do publics want to discuss with climate organizations?"). Thus, the specific themes and focal points of communication between organizations and publics have not been extensively researched. Addressing this gap, Comfort and Hester posited that merely reaching a broad audience might not be an adequate measure of a climate NGO's social media messaging success [33]. They proposed three alternative metrics, including topic and valence (i.e., whether publics aligns with and supports the topics NGOs champion). Building on Comfort and Hester's insights, we venture beyond mere publics' social media engagement metrics to explore the nature of conversations initiated by both climate NGOs and their audiences.

2.3. Why Climate NGOs?

NGOs have adeptly employed public relations strategies to communicate their agendas and issues effectively with publics [34,35]. In this digital age, social media stands as an indispensable platform for NGOs, not only to elevate public consciousness about their causes but also to engage meaningfully with stakeholders. Specifically for climate NGOs, these platforms bridge the gap between scientists and the wider public, demystifying scientific research into actionable steps and galvanizing both governmental and individual action [19].

Climate change, although globally pressing [36], represents a multifaceted challenge intricately intertwined with climate science, politics, and socio-cultural dynamics. Moreover, key stakeholders in climate change—from scientists and activists to everyday citizens—may possess varying levels of perceptions, knowledge, and action plans regarding the subject [37,38]. In this context, to harness the full potential of social media, climate NGOs need to craft strategies that both simplify scientific research and resonate with public concerns, tailored to their target audiences and the core missions of their organizations [34]. In essence, it is paramount for climate NGOs to identify mutual concerns with public audiences, align with their understandings of key topics, and strategically relate prominent issues to their established frames [19,33].

Effective communication with the broader public is paramount for climate NGOs, enabling the transformation of scientific knowledge into actionable public engagement. Eschewing the narrow scope of public engagement metrics as the sole evaluative tool, we aim to scrutinize how high-engagement, in terms of popularity, commitment, and virality, climate NGOs and their publics interact on social media platforms, identifying central themes, focuses, and the features of communication.

As part of our exploratory investigation, we also examined whether the "shared meaning" between the discourses of these two parties is associated with public engagement, as argued by Taylor and Kent [39]. To measure this shared meaning between climate NGOs and their publics, we utilized semantic similarity observed in their discourses (i.e., posts from the NGOs compared to corresponding replies), following the approach outlined by Cann et al [40]. They proposed that the alignment between organizational communication and target audiences' communication, identified through semantic similarity, serves as an outcome of effective strategic communication.

Additionally, we investigated which climate NGOs achieved sentiment alignment between their organizational messages and the associated responses from their publics, using this as a potential indicator of public engagement on social media. In a previous study [41], researchers found that in the context of vaccination, information flow on social media was more frequently observed between individuals who shared the same sentiments, while the flow between individuals with differing sentiments were less frequent. Similarly, exploring sentiment [mis]alignment between the climate NGO and its public may provide valuable insights into how these groups incorporate shared or divergent issues and opinions in their communication and disseminate information, a crucial aspect of public engagement [42]. Consequently, this approach may serve as a potential metric for assessing shared interests and perspectives on contemporary climate issues.

The following research questions guide this study:

- RQ1: How did publics engage with climate NGOs' social media accounts, in terms of public engagement metrics (i.e., *popularity*, *commitment*, *virality*)?
- RQ2: What are the relationships between (a) public engagement on social media and (b) the shared meaning between tweets from the climate NGOs and the corresponding public replies, as measured by semantic similarity (e.g., Euclidean Distance, Levenshtein Distance)?

- RQ3: Which climate NGOs achieved sentiment alignment between their organizational posts and the corresponding replies they received?

As part of our exploratory investigation, we further analyzed three climate NGOs—(a) Greenpeace USA (hereafter GPU), (b) Climate Central, (c) Environmental Defense Fund (hereafter EDF)—that exhibited the highest public engagement scores, in terms of *popularity*, *commitment*, and *virality*, among our sampled 10 climate NGOs. These organizations also demonstrated alignment in sentiments with their respective publics. This analysis aimed to identify the particular characteristics of each type of public engagement with the following research question:

- RQ4-1: What are the primary themes and focal points observed in the social media communication conducted by (a) GPU and (b) its corresponding publics, which reflect the characteristics of *popularity*?
- RQ4-2: What are the primary themes and focal points observed in the social media communication conducted by (a) Climate Central and (b) its corresponding publics, which reflect the characteristics of *commitment*?
- RQ4-3: What are the primary themes and focal points observed in the social media communication conducted by (a) EDF and (b) its corresponding publics, which reflect the characteristics of *virality*?

3. Materials and Methods

To measure public engagement with the climate NGOs on social media, we adopted and revised three public engagement measures with organizational social media accounts from Bonsón and Ratkai [43] and Haro-de-Rosario et al. [23] (i.e., citizen engagement): *popularity* (i.e., popularity of messages [from the climate NGOs] in public engagement); *commitment* (i.e., commitment of public in the communication with the climate NGOs); and *virality* (i.e., virality of messages among publics' communication). More specifically, popularity measures the frequency of affective reactions from the public to social media messages, while commitment indicates a higher and more sustained level of engagement [44]. Virality represents the breadth of a message's reach [44]. The three dimensions of public engagement have been operationalized as shown in Table 1.

Table 1. Public Engagement Measures (Adopted from Bonsón and Ratkai [43]).

Name	Formula	Measures
Popularity	Number of posts with likes/ total posts	Percentage of the total posts that have been liked
Commitment	Number of posts with comments/ total posts	Percentage of the total posts that have been commented on
Virality	Number of posts with shares/ total posts	Percentage of the total posts that have been shared

This study aimed to explore the relationships between (a) public engagement and (b) shared meaning between social media communications of climate NGOs and their corresponding public. To operationalize shared meaning within this research's context, we utilized semantic similarity metrics [40]. These metrics enable the identification of similarities between terms or texts that convey the same meaning, even if they do not exhibit lexical similarity [45]. More specifically, we used two semantic similarity metrics: (a) Euclidean distance and (b) Levenshtein distance. Euclidean distance is a measure calculating the straight-line distance between the corresponding coordinates of two points in a multidimensional space [46]. Within the context of assessing semantic similarity between two texts, it quantifies the distance between their vectorized representations in a multidimensional space, ranging from 0 to positive infinity [47]. Levenshtein distance is a measurement for quantifying the dissimilarity between two strings, which calculates the number of single-character edits (e.g., insertions, deletions, or substitutions) needed to transform one string into another [48]. A lower score for the two measurements indicates a higher level of similarity between the two examined documents, possibly suggesting the presence of shared meaning as the organization and its public have common or at least similar themes or focal points in their discourses.

This study investigates the sentiment alignment between a climate NGO's tweets and the replies the organization received. To identify sentiment alignment, we conducted a correlation analysis between the trends of the organization's weekly sentiment score and the ones of the corresponding replies that we computed.

To identify the prevailing themes and focal points of climate NGOs' Twitter posts and following public discourses (represented in public audience replies to the climate NGOs), we used SNA. The method allowed us to identify key concepts—used by the NGOs and publics—and their interpretive contexts, by analyzing the significance of specific words based on their frequency and centrality measure values, as well as their co-occurrences and clustering patterns within the text [49,50]. In practice, previous studies have identified salient themes and frames within texts in various contexts, such as the ESG policies in sustainability reports of corporations, and publics' discussions on childhood vaccination and COVID-19 vaccines [49,51,52].

3.1. Data Collection

We collected Twitter posts (i.e., tweets) posted by ten climate-change NGOs and corresponding public replies that were sent to those organizations from 1 July 2020 to 30 June 2021. Twitter was selected as the representative social media platform for this research because it is suitable for organizations including climate NGOs to share information publicly and engage with publics [53–55]. This time range was selected to encompass various factors such as seasonal climate change issues (e.g., extreme weather conditions, flooding), U.S. national political or policy-making issues (e.g., presidential election, Keystone XL pipelines), and global climate change concerns [56]. The acquisition of Twitter data (i.e., tweets and replies) was accomplished by employing the data collection service offered by exportcomments.com (1 September 2023) [57], which enabled us to extract relevant data including the textual content of tweets and replies, the date and time of posting, the number of likes received by the post, and the number of retweets generated by the post.

The organizations were selected from a list of top NGOs working to stop climate change [58] and then screened based on (a) relevance of their posts to climate change issues and (b) comparable volumes of posts from their Twitter accounts. The finalized list of climate NGOs in this research and brief information about the accounts are available in Table 2.

Table 2. Brief Information about the 10 Climate Change NGO Twitter Accounts in this Research.

	Avg. # of Likes (Favorates)	Avg. # of RTs	# of Followers *	# of Total Post **	# of Total Replies ***
1. CCL	30.30	22.18	41,080	1507	1338
2. Earthjustice	60.54	249.12	196,989	2556	3408
3. Greenpeace USA	61.62	188.23	213,165	2733	5058
4. EDF	15.68	325.57	207,210	2776	1757
5. Nature Conservancy	58.61	24.48	990,550	2163	3285
6. RAN	10.87	24.38	94,714	1816	633
7. Wilderness	24.08	102.61	102,317	1973	878
8. Saving Oceans	15.23	22.70	108,613	936	250
9. Skoll Foundation	5.79	33.80	445,747	1802	336
10. Climate Central	10.06	10.47	132,427	729	1519
Total			2,532,812	18,991	18,462

1 = Citizens' Climate Lobby (CCL) (@citizensclimate); 2 = @Earthjustice; 3 = @greenpeaceusa; 4 = Environmental Defense Fund (EDF) (@EnvDefenseFund); 5 = The Nature Conservancy (@nature_org); 6 = Rainforest Action Network (RAN) (@RAN); 7 = The Wilderness Society (@Wilderness); 8 = savingoceans (@savingoceans); 9 = @SkollFoundation; 10 = @ClimateCentral. * The number of followers as of 15 October 2021. ** The number of posts sampled in the research period. *** The number of replies to the organization in the research period.

3.2. Analytic Approach

For RQ1, we calculated the three public engagement metrics for each organization following the formulas suggested by Haro-de-Rosario et al. [23].

For RQ2 and subsequent research questions that involve sentiment analysis and SNA, we performed pre-processing on the textual content of organizational tweets and replies that we collected. More specifically, we removed URLs, stopwords, and non-contextual elements, which included punctuation and special characters, except for the '@' symbol used to indicate mentioned accounts. Additionally, we excluded Twitter function words such as 'replying to' to focus on the relevant content for our analysis. We then lemmatized and tokenized for each corpus (e.g., a group of tweets from an organization, a group of replies sent to an organization) using packages such as spaCy [59] and TextBlob [60] on Python.

For RQ2, we computed two semantic similarity metrics, namely Euclidean distance and Levenshtein distance, between each organization's corpus and its corresponding reply corpus. We utilized Scikit-learn [61] and scipy.spatial [62] libraries to calculate the semantic similarities for each organization. To assess the relationships between three types of public engagement and the two types of semantic similarity, we performed a correlation analysis.

To conduct sentiment analysis for RQ3, we employed the Azure sentiment analysis model, developed through Microsoft Azure machine learning (version: 5.2.0), to calculate weekly average sentiment scores [63]. The sentiment analysis model provides a "sentiment label" (positive, negative, neutral) along with a confidence score for each post, ranging from 0 (lower confidence) to 1 (higher confidence). Using the model, we identified sentiment label for each preprocessed tweet/reply. To quantify sentiments and compare changes within the two groups (i.e., tweets from an organization vs. replies to the organization), we devised a "weighted sentiment score" by assigning numeric values to sentiment labels (positive = 1, negative = -1, neutral = 0) and multiplying these values by the corresponding confidence score. Higher scores close to 1 indicated more significantly positive posts, while scores close to -1 indicated more significantly negative posts. Weekly sentiment scores were determined by calculating the average sentiment scores of tweets and replies published during each week. Next, we conducted an analysis to explore the correlations between the weekly sentiment score trends of an organization's posts and the corresponding replies. Our aim was to identify organizations that exhibited a significant and positive correlation, indicating their success in maintaining alignment with the sentiments expressed by the reply public.

To address RQ4, we employed SNA, which involves examining the structure of a semantic network constructed from a large volume of unstructured text datasets [64]. In this method, each word (e.g., 'climate', 'change') is treated as a node within a network, and the analysis focuses on the co-occurrences of these words [65]. These co-occurrences, such as the words 'climate' and 'change' appearing together in a single post, are counted as instances of co-occurrence. Representing the links between nodes, these co-occurrences are crucial for calculating closeness among words (i.e., nodes). SNA allows for a spatial representation of language structure, enabling the visual grasp of relationships between main concepts (e.g., 'climate change' in the current context) originating from specific terms and their connections to other concepts derived from different terms (e.g., 'conservation' or 'wildfire' in the current context) [65]. The visualization capability of SNA empowers researchers and professionals to uncover insights that might not be immediately apparent through traditional quantitative or qualitative analysis, thereby enhancing our understanding of complex and contextual information underlying the text.

Using the preprocessed text from the previous stage, which included tokenization, lemmatization, and the removal of stop words, we first extracted the most frequent words from the corpus and converted these into a list, annotating each with the frequency of its co-occurrence with other words (i.e., weight). For example, we created a link-list showing how often words like "change", "crisis", or "disaster" co-occurred with "climate" in the same post within the corpus of the NGO's posts or replies to the NGO. Subsequently, employing NeTxt [66], we transformed the processed text and this annotated link-list into a network. In this network, the words serve as nodes, and their co-occurrences become the ties. As a result, we generated a semantic network for each corpus, resulting in six networks, each featuring the top 150 frequent words. For a more detailed step-by-step explanation, you may refer to Segev [66,67].

The generated semantic networks were then exported as weighted edge lists and converted to a format suitable for analysis in Gephi [68], using Python. Subsequently, we imported the data into Gephi to visualize and explore the networks further. Within Gephi, we conducted modularity analysis to identify distinct clusters or themes within each network and calculated various network statistical indicators, such as degree and eigenvector centrality, as outlined by Segev [66] and Luo et al. [69]. These measures helped us determine the importance and prominence of specific keywords within the networks.

4. Results

4.1. RQ1: Public Engagement Metrics

First, the results of our study provide insights into the public engagement on social media for each of the 10 climate NGOs included in our sample. In terms of follower count, Nature Conservancy leads the pack with an impressive 990,550 followers, followed by Skoll Foundation with 445,747 followers. However, GPU exhibits a high level of public response, generating the highest number of replies (5058). The organization also showcases the highest levels of popularity (GPU: 61.62), measured by the average number of likes per post. Notably, Climate Central and GPU stand out in terms of commitment, with commitment scores of 2.08 and 1.85, respectively. Finally, for virality, EDF achieves the highest average number of retweets (325.57), followed by Earth Justice (249.12). See Table 3 for overview.

Table 3. Public Engagement Scores for Each NGO's Twitter Accounts and their Semantic Similarity Scores with Publics' Replies.

	Popularity	Commitment	Virality	Euclidean	Levenshtein
1. CCL	30.3	0.89	22.18	983.11	174,258
2. Earthjustice	60.54	1.33	249.12	1583.78	357,155
3. Greenpeace USA	61.62	1.85	188.23	1326.76	252,773
4. EDF	15.68	0.63	325.57	1583.77	256,464
5. Nature Conservancy	58.61	1.52	24.48	1436.28	331,862
6. RAN	10.87	0.35	24.38	957.85	159,422
7. Wilderness	24.08	0.45	102.61	959.66	182,587
8. Saving Oceans	15.23	0.27	22.7	554.34	86,867
9. Skoll Foundation	5.79	0.19	33.8	1054.25	188,157
10. Climate Central	10.06	2.08	10.47	506.59	75,228

1 = Citizens' Climate Lobby (CCL) (@citizensclimate); 2 = @Earthjustice; 3 = @greenpeaceusa; 4 = Environmental Defense Fund (EDF) (@EnvDefenseFund); 5 = The Nature Conservancy (@nature_org); 6 = Rainforest Action Network (RAN) (@RAN); 7 = The Wilderness Society (@Wilderness); 8 = savingoceans (@savingoceans); 9 = @SkollFoundation; 10 = @ClimateCentral.

4.2. RQ2: Public Engagement on Social Media and Shared Meaning

Second, to investigate the potential relationships between public engagement and the level of shared meaning between a climate NGO and its audiences, we conducted a study analyzing the correlations between public engagement metrics and semantic similarities. In order to assess the extent of shared meaning, we used two semantic similarities measures: Euclidean distance and Levenshtein distance. As shown in Table 4, only two pairs of measures displayed significant positive correlations. Specifically, the correlation between popularity and Levenshtein distance was (0.760 *), and the correlation between virality and Euclidean distance was (0.729 *). These findings suggest that higher levels of public engagement, as measured by popularity and virality, may be associated with a decrease in shared meaning between the climate NGO and its audiences.

Table 4. Correlations between Engagement Measures and Semantic Similarity Measures.

		Popularity	Commitment	Virality	Euclidean Distance	Levenshtein Distance
Popularity	Pearson Correlation	1	0.580	0.342	0.583	0.760 *
	Sig. (2-tailed)		0.079	0.333	0.077	0.011
Commitment	Pearson Correlation		1	0.103	0.462	0.530
	Sig. (2-tailed)			0.778	0.179	0.115
Virality	Pearson Correlation			1	0.729 *	0.552
	Sig. (2-tailed)				0.017	0.098
Euclidean Distance	Pearson Correlation				1	0.931 **
	Sig. (2-tailed)					<0.001
Levenshtein Distance	Pearson Correlation					1
	Sig. (2-tailed)					

Note: * Correlation is significant at the 0.05 level (2-tailed). ** Correlation is significant at the 0.01 level (2-tailed).

Third, we conducted an analysis to examine the sentiment alignment between organizational posts and the corresponding replies they received. Based on the assertion that aligned sentiments on social media are indicative of shared interests or attention towards specific issues, as well as the strategic incorporation of publics' agendas and concerns [42], our objective was to investigate the potential connections between sentiment alignment and public engagement driven by shared perspectives on these issues. Among the organizations included in the analysis, three organizations showed a significant positive correlations with weekly sentiment scores of their respective organizations' posts and the corresponding replies: GPU (r = 0.322, p = 0.019), EDF (r = 0.320, p = 0.019), and Climate Central (r = 0.389, p = 0.004). Notably, these organizations also received top scores in terms of public engagement metrics as discussed above. These findings suggest that these organizations not only effectively maintained alignment with their audience in terms of sentiment but also achieved successful public engagement (see Table 5 for overview).

Table 5. Pearson's Correlations of Weekly Sentiment Scores between Posts from Organizations and Replies Sent to the Organizations.

	Pearson	Sig. (2-Tailed)
1: Citizens' Climate Lobby	−0.212	0.132
2: Earthjustice	−0.029	0.836
3: GPU	0.322	0.019
4: EDF	0.320	0.019
5: The Nature Conservancy	−0.114	0.417
6: RAN	0.003	0.984
7: The Wilderness Society	0.243	0.080
8: Saving Oceans	0.137	0.342
9: Skoll Foundation	−0.035	0.808
10: Climate Central	0.389	0.004

Note: Pairwise dropped.

4.3. RQ4: Central Themes and Focuses

To address RQ4, we selected a total of three organizational accounts (GPU, Climate Central, and EDF) to explore the central themes and focuses of the discourses facilitated by these organizations and their publics with SNA. In addition to the commonly used public engagement measures (e.g., the number of retweets), which often fail to capture the emergence, convergence, or divergence of themes and focal points within discussions between organizations and their publics, this approach may offer a more insightful and holistic view of public engagement in this exploratory study. With the focus, we sampled three climate NGOs: high popularity: GPU; (b) high commitment: Climate Central; (c) high virality: EDF. Then, we identified and compared the key concepts (i.e., words), themes, and focal points between organizational tweets and the corresponding replies, based on (a) the centrality of words, (b) the associations between two words, and (c) the clusters of words within the network [70].

4.3.1. Greenpeace USA (GPU): High Popularity

The keywords with the highest degrees in GPU tweets are "nature" (degree = 1897), "new" (degree = 1202), and "climate" (degree = 995). In the replies, the top keywords include "climate" (degree = 658), "fossil" (degree = 585), and "fuel" (degree = 475) (Table 6).

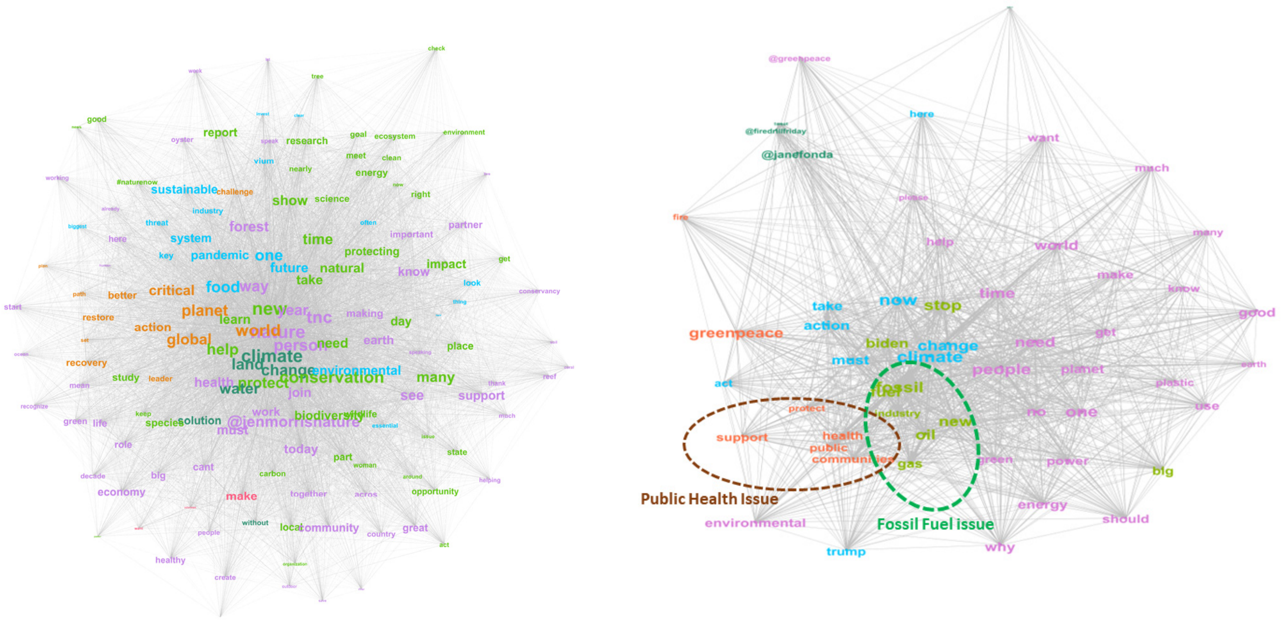
Table 6. Top Key Words by Degree of Tweets from GPU and Replies Sent to GPU.

Tweets from GPU				Replies Sent to GPU		
Word	**Degree**	**Eigenvector**	**Rank**	**Word**	**Degree**	**Eigenvector**
nature	1897	0.376	1	climate	658	0.337
new	1202	0.248	2	fossil	585	0.412
climate	995	0.225	3	fuel	475	0.378
world	840	0.184	4	people	453	0.191
food	781	0.164	5	oil	410	0.213
person	767	0.178	6	now	343	0.171
tnc	681	0.144	7	change	322	0.222
protect	669	0.149	8	need	322	0.146
change	656	0.161	9	new	289	0.171
planet	605	0.126	10	must	282	0.165
conservation	604	0.119	11	stop	267	0.151
future	598	0.131	12	health	248	0.153
global	581	0.129	13	action	240	0.149
way	562	0.125	14	public	235	0.145
land	557	0.128	15	take	226	0.135
one	550	0.113	16	no	220	0.109
year	543	0.130	17	gas	217	0.135
water	523	0.117	18	one	217	0.094
help	517	0.116	19	industry	210	0.171
time	502	0.102	20	biden	209	0.133

Note: Degree: The number of connections that a word (i.e., node) has to other words within the network. The degree of a word reflects the strength of its relationships with other words. Eigenvector (centrality): Eigenvector centrality indicates importance or centrality within a network reflecting both the number of connections a word (i.e., node) has and the importance of those connections.

Table 7 illustrates the weighted associations between words in GPU tweets and replies. Noteworthy associations in GPU's tweets include "climate" and "change" (weight = 68), "nature" and "person" (weight = 56), and "nature" and "new" (weight = 52). In replies, significant associations include "climate" and "change" (weight = 113), "oil" and "gas" (weight = 56), and "public" and "health" (weight = 47).

The most prominent findings from the case of GPU were that GPU's posts and its public's replies had very specific and different key topics and frames in the discourses. For example, the tweets from GPU were commonly used to discuss a range of general and worldwide topics, including "nature", "world", and "planet" and broader climate change-related subjects such as "forest" and "water". In contrast, the replies sent to GPU focused more on "fossil fuel" and "oil", which is more tangible and associated with specific policies and expanded it as public health issue (e.g., Rank 29: "fossil" and "health" in Table 7). See Figure 1 for an overview.



(**a**) (**b**)

Figure 1. (**a**) Visualization of the Semantic Network Map of Top Words in 'Tweets from GPU'; (**b**) Visualization of the Semantic Network Map of Top Words in 'Replies Sent to GPU'. (The different colors correspond to the various modularity classes within the semantic network. The size of each term (i.e., node) indicates its comparative frequency within the corpus. The lines connecting the terms represent their co-occurrence (i.e., ties) in specific posts. The thickness (i.e., width) of each line denotes the tie strength (or weight), reflecting the frequency of co-occurrence between the connected terms. The concept of 'closeness' between two terms is reflected by their distance, suggesting that a shorter distance between terms indicates they are more frequently used together within the corpus and share similar themes, often belonging to the same cluster [67]. While 'Tweets from GPU' represent broad and general keywords such as 'nature', 'world', 'planet', and 'conservation', 'Replies to GPU' correspond to groups of cohesive keywords relevant to public health issues (e.g., 'public', 'health', 'communities', 'help') and fossil fuel issues (e.g., 'fossil', 'oil', 'gas', and 'industry').).

Table 7. Top Associations of Word by Weight of Tweets from GPU and Replies Sent to GPU.

Tweet from GPU				Tweets Sent from GPU		
Source	**Target**	**Weight**	**Rank**	**Source**	**Target**	**Weight**
climate	change	68	1	fossil	fuel	154
nature	person	56	2	climate	change	113
nature	new	52	3	oil	gas	56
nature	climate	44	4	public	health	47
nature	year	41	5	take	action	40
nature	world	40	6	fossil	industry	36
food	system	36	7	fuel	industry	35
new	report	34	8	tweet	@firedrillfriday	34
nature	tnc	32	9	oil	new	31
nature	way	31	10	climate	action	30
nature	protect	31	11	new	green	29
nature	future	30	12	oil	big	24
new	show	28	13	need	get	24
nature	learn	27	14	help	please	24

Table 7. *Cont.*

Tweet from GPU				Tweets Sent from GPU		
Source	**Target**	**Weight**	**Rank**	**Source**	**Target**	**Weight**
nature	health	27	15	climate	must	24
nature	change	27	16	climate	new	24
nature	take	26	17	no	one	23
nature	speak	26	18	need	now	23
nature	conservancy	25	19	communities	health	23
new	climate	25	20	climate	fossil	23
nature	need	25	21	oil	industry	22
energy	clean	25	22	people	power	21
nature	global	23	23	now	must	21
nature	forest	23	24	fossil	stop	20
climate	water	23	25	fossil	must	20
new	world	23	26	climate	people	19
tnc	join	23	27	planet	earth	19
nature	know	23	28	@janefonda	@firedrillfriday	19
nature	help	22	29	fossil	health	19
nature	@jenmorrisnature	22	30	people	act	19

Note: Each 'weight' value represents the frequency of the word pairs presented in individual tweets.

4.3.2. Climate Central: Low Popularity, High Commitment, Low Virality

Climate Central was a unique case, in that its public engagement score was high on commitment, while low on popularity and virality. In tweets from Climate Central, the most frequently used keyword is "climate" (degree = 1112), followed by "temperature" (degree = 654) and "change" (degree = 646). Similarly, in replies sent to Climate Central, the most prominent keyword is "quote" (degree = 1192), followed by "climate" (degree = 1165) and "change" (degree = 719) (Table 8).

Table 8. Top Key Words by Degree of Tweets from Climate Central and Replies Sent to Climate Central.

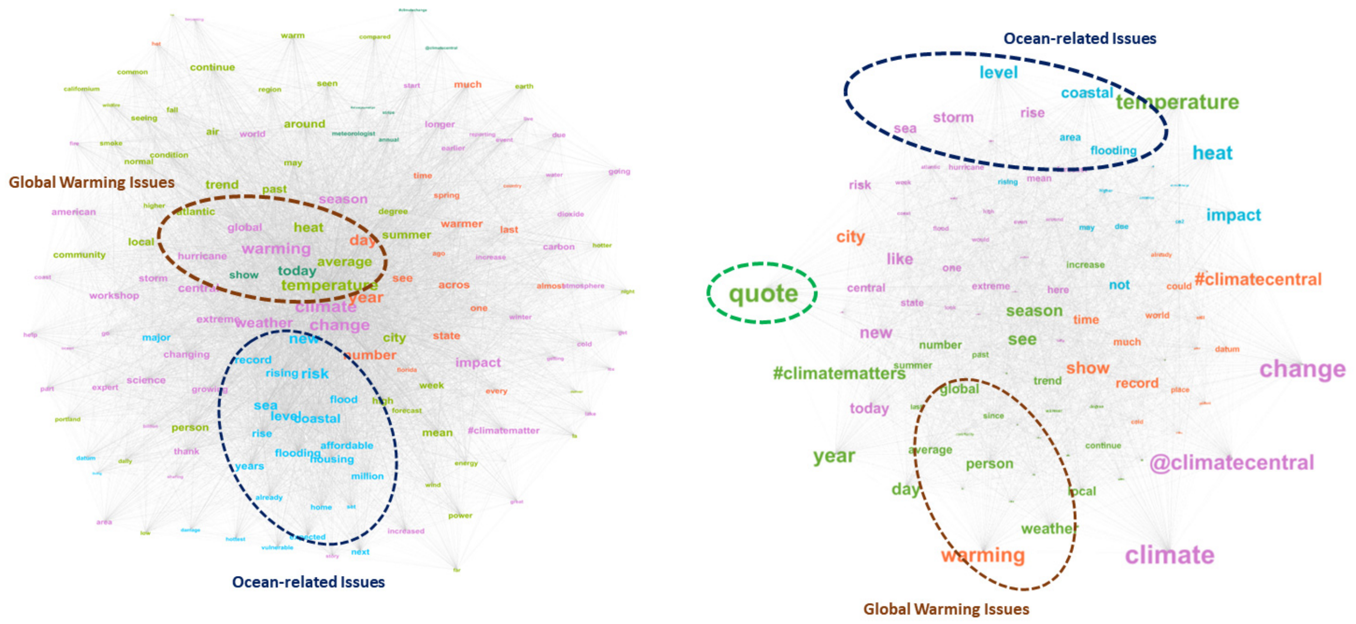
Tweets from Climate Central				Replies Sent to Climate Central		
Node	**Degree**	**Eigenvector**	**Rank**	**Node**	**Degree**	**Eigenvector**
climate	1112	0.380	1	quote	1192	0.380
temperature	654	0.234	2	climate	1165	0.434
change	646	0.265	3	change	719	0.340
year	546	0.194	4	temperature	536	0.177
warming	504	0.177	5	year	491	0.156
day	489	0.177	6	@climatecentral	445	0.153
new	404	0.157	7	warming	422	0.160
risk	403	0.145	8	level	377	0.129
sea	397	0.148	9	sea	347	0.126
today	394	0.153	10	day	343	0.108
average	388	0.145	11	average	339	0.116
level	386	0.147	12	coastal	319	0.106
weather	374	0.143	13	heat	314	0.104
season	363	0.135	14	rise	301	0.109
coastal	331	0.121	15	flooding	292	0.099
city	312	0.119	16	new	277	0.106
number	306	0.120	17	impact	276	0.120
heat	300	0.104	18	weather	275	0.118
flooding	280	0.100	19	#climatecentral	273	0.096
record	264	0.100	20	#climatematters	273	0.092

As shown in Table 9, the associations of words with the highest weights were “climate” and “change” (weight = 61) in tweets from Climate Central and “climate” and “change” (weight = 120) in replies. Other notable associations in tweets from Climate Central include “climate” and “temperature” (weight = 27), as well as “temperature” and “average” (weight = 27). In replies sent to Climate Central, the association between “climate” and “quote” has a weight of 64, and the association between “level” and “sea” has a weight of 39.

Table 9. Top Associations of Word by Weight of Tweets from Climate Central and Replies Sent to Climate Central.

Tweets from Climate Central				Replies Sent to Climate Central		
Source	**Target**	**Weight**	**Rank**	**Source**	**Target**	**Weight**
climate	change	61	1	climate	change	120
climate	temperature	27	2	climate	quote	64
temperature	average	27	3	level	sea	39
climate	warming	24	4	temperature	average	35
sea	level	24	5	quote	change	35
climate	today	22	6	level	rise	34
climate	new	22	7	sea	rise	34
climate	year	21	8	climate	central	32
climate	weather	21	9	quote	temperature	31
sea	rise	21	10	quote	year	29
climate	day	19	11	@climatecentral	climate	28
level	rise	19	12	@climatecentral	#climatecentral	28
climate	central	18	13	climate	impact	26
climate	season	18	14	quote	warming	26
year	day	18	15	climate	warming	26
housing	affordable	18	16	climate	weather	25
climate	average	15	17	coastal	flooding	24
temperature	change	15	18	quote	sea	21
climate	risk	15	19	affordable	housing	21
climate	impact	15	20	quote	season	20
temperature	day	14	21	quote	level	20
coastal	flooding	14	22	climate	today	20
warming	trend	14	23	quote	coastal	20
climate	number	14	24	climate	science	20
climate	city	13	25	climate	changing	19
climate	changing	13	26	change	impact	19
climate	level	13	27	quote	weather	19
temperature	year	12	28	@climatecentral	change	19
day	today	12	29	quote	risk	18
temperature	city	12	30	quote	average	17

While both organizational posts and replies focused on the similar topics such as ocean-related issues (e.g., “sea level”) and global warming issues (e.g., “warming”), we identified that publics’ replies widely adopted “quote” to bring information from external sources. It implies that the organization and its public tended to focus on accumulating concrete scientific information in the organizational account, which might be less favored by the lay publics who are not ‘committed’ to the community of the organization. See Figure 2 for overview.



(**a**) (**b**)

Figure 2. (**a**) Visualization of the Semantic Network Map of Top Words in 'Tweets from Climate Central'; (**b**) Visualization of the Semantic Network Map of Top Words in 'Replies Sent to Climate Central'. (The different colors correspond to the various modularity classes within the semantic network. The size of each term (i.e., node) indicates its comparative frequency within the corpus. The lines connecting the terms represent their co-occurrence (i.e., ties) in specific posts. The thickness (i.e., width) of each line denotes the tie strength (or weight), reflecting the frequency of co-occurrence between the connected terms. The concept of 'closeness' between two terms is reflected by their distance, suggesting that a shorter distance between terms indicates they are more frequently used together within the corpus and share similar themes, often belonging to the same cluster [67]. Both 'Tweets from Climate Central' and 'Replies to Climate Central' feature keywords relevant to global warming and ocean-related issues, with specific terms such as 'sea', 'level', and 'rise'. In the case of 'Replies to Climate Central', the term 'quote' was frequently used, as indicated by its comparatively large size.).

4.3.3. Environmental Defend Fund (EDF): High Virality

EDF was the organization that succeeded in making their posts be shared by their public (i.e., viral). In EDF tweets, the highest degree keywords were "climate" (degree = 4546), "rt" (degree = 2814), and "biden" (degree = 1723). The top keywords in replies include "environmental" (degree = 840), "health" (degree = 773), and "forest" (degree = 769) (Table 10).

Table 11 showcases the weighted associations between words in EDF tweets and replies that EDF received. Noteworthy associations in tweets include "climate" and "change" (weight = 277), "climate" and "rt" (weight = 168), and "climate" and "action" (weight = 154). In replies, significant associations include "climate" and "change" (weight = 83), "forest" and "burn" (weight = 44), and "environmental" and "health" (weight = 43).

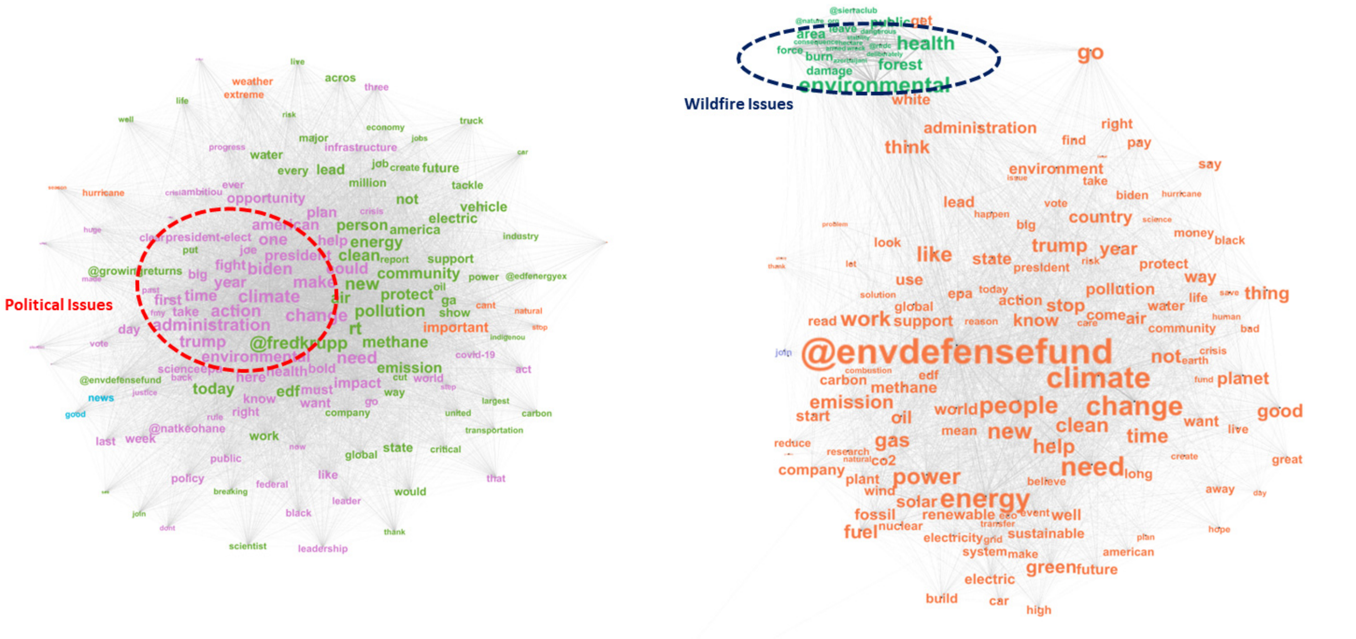
Table 10. Top Key Words by Degree of Tweets from EDF and Replies Sent to EDF.

Tweets from EDF				Replies Sent to EDF		
Node	**Degree**	**Eigenvector**	**Rank**	**Node**	**Degree**	**Eigenvector**
climate	4546	0.492	1	environmental	840	0.243
rt	2814	0.319	2	health	773	0.240
biden	1723	0.236	3	forest	769	0.244
change	1685	0.277	4	@envdefensefund	767	0.035
new	1509	0.193	5	burn	723	0.241
action	1225	0.191	6	public	718	0.238
administration	1173	0.160	7	area	718	0.237
pollution	1080	0.135	8	damage	716	0.237
@fredkrupp	1009	0.142	9	force	699	0.235
need	952	0.120	10	hectare	698	0.241
make	919	0.126	11	leave	696	0.235
clean	916	0.101	12	deliberately	687	0.239
trump	886	0.115	13	dangerous	684	0.236
air	790	0.094	14	wreck	679	0.235
president	770	0.116	15	consequence	674	0.234
methane	741	0.084	16	armed	673	0.234
energy	731	0.088	17	stability	669	0.234
environmental	727	0.088	18	azerbaijani	655	0.229
year	723	0.098	19	climate	581	0.010
emission	667	0.085	20	@nrdc	561	0.193

Table 11. Top Associations of Word by Weight of Tweets from EDF and Replies Sent to EDF.

Tweets from EDF				Replies Sent to EDF		
Source	**Target**	**Weight**	**Rank**	**Source**	**Target**	**Weight**
climate	change	277	1	climate	change	83
climate	rt	168	2	forest	burn	44
climate	action	154	3	environmental	health	43
climate	biden	149	4	forest	hectare	43
rt	@fredkrupp	125	5	health	public	43
administration	trump	111	6	forest	area	42
climate	new	99	7	forest	health	41
biden	president	83	8	forest	damage	41
rt	new	81	9	environmental	forest	41
climate	pollution	81	10	environmental	damage	41
pollution	air	79	11	environmental	public	41
climate	need	75	12	forest	deliberately	41
climate	administration	75	13	environmental	burn	41
climate	bold	73	14	damage	hectare	41
biden	joe	71	15	area	hectare	41
biden	administration	71	16	burn	hectare	41
climate	fight	71	17	burn	deliberately	41
climate	make	68	18	hectare	deliberately	41
clean	energy	65	19	forest	public	40
climate	president	64	20	health	burn	40
rt	change	63	21	health	consequence	40
climate	year	60	22	health	deliberately	40
biden	president-elect	56	23	damage	area	40
climate	@fredkrupp	54	24	damage	force	40
rt	biden	52	25	environmental	leave	40
climate	crisis	52	26	area	burn	40
climate	emission	51	27	forest	force	40
biden	action	47	28	public	burn	40
rt	action	46	29	public	hectare	40
public	hectare	29	30	public	deliberately	40

We observed that the tweets from EDF and replies sent to EDF had different themes and frames than others. For example, while EDF associated the issues of climate changes with politics (e.g., "[T]rump administration", "[P]resident [B]iden" in Table 11), its public focused more on public health issues (e.g., "environmental health") and forest losses (e.g., "burn[ed] forest" in Table 11) associated with wildfire. Interestingly, EDF widely used "rt" (i.e., retweet) in their posts, possibly to motivate their public to retweet. The use of political frames and call for retweets may likely account for its high virality. See Figure 3 for overview.



(**a**) (**b**)

Figure 3. (**a**) Visualization of the Semantic Network Map of Top Words in 'Tweets from EDF'; (**b**) Visualization of the Semantic Network Map of Top Words in 'Replies Sent to EDF'. (The different colors correspond to the various modularity classes within the semantic network. The size of each term (i.e., node) indicates its comparative frequency within the corpus. The lines connecting the terms represent their co-occurrence (i.e., ties) in specific posts. The thickness (i.e., width) of each line denotes the tie strength (or weight), reflecting the frequency of co-occurrence between the connected terms. The concept of 'closeness' between two terms is reflected by their distance, suggesting that a shorter distance between terms indicates they are more frequently used together within the corpus and share similar themes, often belonging to the same cluster [67]. Key differences between the discourses of 'Tweets from EDF' and 'Replies to EDF' lie in distinct key topics. 'Tweets from EDF' address political issues, featuring terms like 'trump', 'biden', 'administration', and 'president-elect.' In contrast, 'Replies to EDF' focus on wildfire issues, with terms such as 'forest', 'burn', 'area', and 'damage.').

5. Discussion

The aim of this exploratory study was to enhance our understanding of public engagement on social media, focusing on the features of two-way communications on social media. In addition to traditional public engagement metrics, we employed sentiment analysis and examined shared meaning with semantic similarity measures in our research. Furthermore, by utilizing SNA, we identified and compared key themes and focal points within climate NGOs' tweets and the corresponding replies they received. Through our explorations, we discovered several noteworthy findings.

First, we observed that climate NGOs developed unique themes and focuses within their discourses. This highlights the distinct characteristic of science/organizational communication on social media, where organizations can participate in or establish topic-driven communities [34]. Social media allows individuals and organizations to engage in focused discussions on particular topics. To effectively connect with and mobilize like-minded individuals who share climate-related interests, climate NGOs may strategically monitor and select topics and issues to allocate their attention and communication efforts. Our study revealed that strategically selecting topics and discussion foci may encourage specific types of public engagement. For instance, Climate Central, by aligning its topics and foci with those of publics in terms of scientific information about climate change (with aligned sentiments with publics (Table 5)), it maintained shared interests with the committed publics and generated a high level of public commitment. In other words, both organization and the engaged publics aligned their perspectives and sentiments on the issues [71], incorporating their discussed issues (This alignment is facilitated potentially by both inviting certain groups of publics who share interests and knowledge about the issues that the specific NGO advocates for, and by mutually shifting their agendas and frames to reflect each other's viewpoints). For example, when the organization focused on the 'extreme temperature' issue, the committed public shared their knowledge and opinions with the organization as below.

Climate Central: "RT @afreedma: This graph helps explain why heat extremes are becoming so much more common/severe in a warming world. [link redacted]"

A public: "On average, July in Raleigh-Durham is 4 degrees hotter now than it was in the 1970s. (See all locations here: [link redacted]) #ClimateMatters"

Understanding the themes and focuses that resonate with the public may enable climate NGOs to tailor their communication strategies and content effectively, thereby enhancing engagement and mobilization.

This finding highlights the significance of effectively managing organizational discourses while simultaneously monitoring public interests and concerns, considering the specific types of public engagement being targeted. Similar to the GPU in our sample, when attempting to engage a broader audience like publics, it would be advisable to concentrate on uncontested climate change topics such as nature, rather than delving into specific issues like "fossil fuel" that may have been raised by more active segments of publics (See Table 7).

Second, our findings highlight the importance of avoiding a one-size-fits-all strategy focusing solely on increasing public engagement scores, such as likes and retweets, in the research context. Instead, we recommend that climate NGOs tailor their communication strategies based on the specific types of public engagement they are targeting on social media [24]. We found that organizations that succeeded in generating specific types of public engagement on social media did not necessarily succeed in generating other types. For example, Climate Central achieved a high level of commitment but had low virality. This could be attributed to the nature of the topics chosen by Climate Central, which focused on climate sciences and meteorology: topics requiring a high level of science literacy from publics. If Climate Central aimed to engage more informed and active participants in the discourse, the low popularity and virality might be an insignificant concern. Conversely, organizations like GPU, which focused on climate topics generally applicable to the wider public, achieved high popularity but avoided highlighting national or regional political issues (e.g., U.S. presidential election). In contrast, EDF achieved high virality by actively mentioning political figures and associating climate change issues with the responsibility of the government (e.g., Biden action, Biden administration). Although EDF's approach might have appealed more to the U.S. public than international audiences, it generated intense virality as engaged individuals shared EDF's messages with like-minded individuals on social media. These examples suggest that organizations need to establish specific objectives regarding the types of public engagement on social media. Accordingly, they should allocate attention and interest to specific issues, as each objective necessitates different communication strategies.

Third, our analysis revealed significant and positive correlations between the weekly sentiment scores of the three organizations, namely GPU, Climate Central, and EDF, and the corresponding sentiment scores of the replies they received. Remarkably, the three organizations demonstrated commendable performance in at least one public engagement metric, such as popularity, commitment, and virality. While the correlations based on weekly sentiment scores may not provide a complete depiction of how organizations align with publics' interests, they do highlight the importance of organizations focusing on current issues that evoke a range of sentiments [72]. By aligning their interests and attitudes with publics on these issues, climate NGOs may enhance public engagement by leveraging the incorporated attentions and shared sentiment surrounding these topics [42].

Furthermore, the study uncovered counter-intuitive findings. Specifically, the semantic similarity between organizational posts and public replies did not have a positive relationship with public engagement on social media. In other words, when organizations generated higher engagement from publics in terms of popularity, commitment, and virality, the use of similar themes and focuses was either insignificant or low. This might be due to the fact that organizations with more engagement are likely to have more diverse audiences, as their posts are shared not only with like-minded individuals but also individuals with different perspectives and opinions on climate issues. Investigating the network attributes of organizations' social media communities could confirm these counter-intuitive findings in future studies.

There are several limitations and opportunities for further development in this study. First, to fully understand the implications of specific themes and focuses in generating public engagement, one must delve further into the influence of specific words and frames used in posts or posts within shorter time periods, such as a few days or weeks. Since Twitter imposes a 280-character limit, we had to explore the semantic features of all posts and replies within a one-year period, which may not fully capture the 'real-time' dynamics of dialogues between organizations and publics. Second, as a case study, we only investigated a few organizations with successful public engagement generation. To gain a more comprehensive understanding, it is important to explore whether our findings are generally applicable to a wider range of organizations and other contexts. Additionally, to comprehend the implications of specific types of public engagement on social media, it would be beneficial to investigate the network characteristics of an organization's communities. For example, understanding how posts become viral can be better understood by examining how these posts are shared with individuals outside an organization's immediate network. By conducting larger-scale investigations and employing additional analytic approaches, we can gain deeper insights into public engagement within this context.

6. Conclusions

In conclusion, our study sheds light on the themes, focuses, and sentiments identified in social media discourses of climate NGOs and their publics, within the framework of public engagement. Recognizing the imperative for climate NGOs to maximize the 'two-way' communication capabilities of social media to educate, persuade, captivate, and understand their target audiences concerning climate change issues, we delved into the interactive dynamics of these discourses. Based on our exploration, we advocate for communication strategies that are more oriented toward the public audience's understanding of and interest in climate issues. This involves:

1. Assessing public perceptions and understanding of climate topics, as exemplified by the challenges faced by Climate Central in making scientific discourses appealing to lay public audiences.
2. Exploring the depth and variety of climate-related issues that captivate publics' interest, demonstrated by the case of GPU, which focused on broader climate issues.
3. Understanding how different publics associate different issues with climate change, such as the disparate linking of climate change with political and wildfire issues in the communications of EDF and its public audiences.

When these tailored strategies align with each organization's specific communication objectives and target audiences (e.g., individuals with interests and knowledge in climate science, in the case of Climate Central), they are likely to contribute to more desirable public engagement in climate change discourses. These shifts in strategies from 'delivering effective messages to the public audiences in order to educate them' (e.g., the IPCC report) to 'understanding and representing the interests and issues of the public audiences' also resonate the call for the shift in first-order thinking to second- and third-order thinking in science communication [73].

Specifically, with the 'two-way' approach indicative of second-order thinking, climate NGOs can not only build consensus on climate change issues but also directly address the uncertainties and concerns of publics [73]. This approach aligns with the principles of second-order thinking by prioritizing dialogue, engagement, and building trust through a transparent and accountable communication style.

Furthermore, by embracing the diverse perspectives and agendas of different public audiences, which is a hallmark of third-order thinking, these organizations can situate climate change within a wider cultural, societal, and political context of the publics as in the case of EDF. This approach goes beyond organization-led initiatives, recognizing the importance of heterogeneity and constructive disagreement as valuable societal resources to address climate change issues [73]. This multidimensional perspective will enhance reflexivity and critical analysis in climate communication, which is crucial for addressing 'wicked problem' [74] like climate change.

We also acknowledge the additional limitations of our study in terms of application, including the need to explore the influence of specific words and frames within shorter time periods, expand the scope of organizations and contexts studied, and investigate network characteristics for a more comprehensive understanding. Continued research in this area can contribute to a better understanding of public engagement and communication strategies of climate NGOs' social media presence.

The current study used SNA, following previous studies [75,76], and recognized the limitations of methods like topic modeling in comparing multiple corpora and identifying nuanced themes within a topic [77]. Newly designed methods, such as contrastive topic modeling [77] and qualitative approaches (e.g., Haupt et al. [78]), which address these limitations, may be considered in our future studies.

We conducted sentiment analysis using the Microsoft Azure API (version: 5.2.0), which offers a parsimonious and accessible analytic approach for communication professionals to capture current public sentiments and potential sentiment gaps between the organization's communication and publics' responses. We propose that the practitioners may monitor what leads to specific sentiments among public audiences during specific periods, with a more careful review of the original posts and replies from these publics. However, to develop more sophisticated sentiment analysis, practitioners need to consider dictionary-based approaches or develop their own trained models for such analysis to reflect their organization's specific context.

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