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Identifying the Impacts of Social Movement Mobilization on YouTube: Social Network Analysis

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Abstract: This study explores the potential of social media in improving education, engagement, and mobilization for climate change initiatives. Using the theoretical framework of resource mobilization and methods such as social network analysis (SNA) and bipartite networks, it examines how effective deployment of resources such as information, social capital, and organizational capabilities can help in the progression of collective movements. Social media platforms, particularly YouTube, significantly influences network structures by facilitating resource mobilization and driving essential engagement. This study extracted data from NodeXL and found that YouTube is an effective medium in disseminating climate change information and delivering educational content to a multilingual audience. Additionally, video affordances such as storytelling, audio–visual effects, and concise narratives enhance viewer interest and engagement, increasing resource mobilization effectiveness. This research offers insights into optimizing social media use for effective resource mobilization and engagement in climate change initiatives.

Keywords: YouTube; resource mobilization theory; social network analysis; bipartite network; climate change; social movements

Academic Editor: Arkaitz Zubiaga

Received: 18 November 2024
Revised: 19 December 2024
Accepted: 2 January 2025
Published: 15 January 2025

Citation: Osman, N.S.; Kim, J.-H.; Park, J.-H.; Park, H.-W. Identifying the Impacts of Social Movement Mobilization on YouTube: Social Network Analysis. *Information* **2025**, *16*, 55. https://doi.org/10.3390/info16010055

1. Introduction

In the modern digital age, transformations of social movements have been in the works, as catalyzed by the ubiquitous influence of social media platforms. The occurrence and revolution of digital communication technologies has transformed the outlook of social movement mobilization, enabling extensive collective action, advocacy, and grassroots organizing. The role of social media in social transformation movements is a complex and multifaceted one, with various affordances and platforms playing a critical role [1]. While digital technologies have transformed collective action, they also present challenges and unintended consequences [2]. Digital technologies have transformed collective action and social movements, enabling new forms of organizing and communication [2,3]. However, these advancements also present challenges and unintended consequences. While digital tools facilitate more decentralized and individualized forms of political action, they may not have revolutionized environmental activism as expected [4].

The Internet and various social media platforms have become an integral part of our lives, especially in the development, management, and mobilization of protests, with the Internet serving as a regulatory and action-structuring infrastructure [5]. The impact of social media on social movements is influenced by both opportunity and mobilizing structures, with social media allowing normal people to connect and organize themselves [6]. However, the interplay between digital activism and offline mobilization remains an underexplored area. While digital platforms enable widespread awareness and virtual engagement, questions remain about the extent to which these activities translate into tangible outcomes, such as policy changes or sustained grassroots movements. Understanding this dynamic is critical to evaluating the effectiveness of digital activism in achieving long-term societal transformations.

Moreover, the impact of platform-specific dynamics on movement sustainability requires further investigation. While studies have analyzed platforms like YouTube in activism contexts, insufficient research has been conducted on how other platforms, such as Twitter, TikTok, or Instagram, shape the trajectories of social movements differently. Each platform's unique affordances—ranging from algorithmic visibility to user engagement models—can influence the formation, growth, and eventual sustainability of social movements. Addressing these gaps is imperative for comprehending how digital tools can both empower and constrain collective action in a rapidly evolving technological landscape. Following this line of research gaps, the current study investigated the media affordances of YouTube to understand its impacts on initiating offline social mobilization. As social media platforms become increasingly integrated into daily lives, understanding their impacts on social movement mobilization has become a pressing imperative for scholars, activists, and policymakers alike.

The dependency between social networks, social movements, and climate change underscores the role of technology in shaping societal behaviors and mobilizing actions for environmental causes. Several studies have explored how networks and social power can influence global environmental policies and grassroots movements. Christakis and Fowler [7] investigated social networks involving cognitive and cultural factors, where they discovered that within a network of people, there are sure direct and indirect influences from the affective states of their surroundings. This in turn causes influence to spread within a network, rippling from person to person, whether what spreads is desirable or not. Such spread has exponentially multiplied due to the role of technology and the existence of hyper-connectivity and the World Wide Web. Ham characterized social power as contextual and situationally specific, particularly occurring in environments of global governance and formal authority, sustained by shared goals. This characteristic determines the concept of power in specific social situations, depending on interaction, communication, relationships, and institutions [8]. Biddix and Park investigated how U.S. college students mobilized for a campus living wage movement by employing network analysis and in-depth interviews. Their findings revealed that online communities played a key role in sustaining the movement, largely through the formation of unintentional networked groups. During the protests, online platforms were primarily used to share demonstration strategies, experiences, and to facilitate personal interactions. Interestingly, after the protests concluded, participants continued to maintain their connections through face-to-face interactions. This underscores the function of social media as community-centered platforms that help preserve relationships among individuals who share similar social interests [9]. These studies emphasize the dependency of social networks with technology, especially with the way social environments operate.

Dietz, Shwom, and Whitley [10] emphasize the importance of sociology in addressing climate change, particularly through advancing climate justice across diverse stratifications. Goodman [11] discusses how climate politics spur social movements to engage directly

with environmental issues, while McAdam [12] points to the lack of grassroots activism due to insufficient political opportunities and strategic framing. The combination of these perspectives highlights the critical role of integrating social networks and digital media to effectively mobilize climate change activism and influence environmental policies.

To understand social mobilization applied in social networks, the current study applied Resource Mobilization Theory (RMT). RMT posits that rational actors mobilize resources effectively to pursue social change goals, focusing on the process of acquiring and utilizing resources in a timely and cost-effective manner [13]. The theory encompasses three main research dimensions: resource mobilization, member mobilization, and framework mobilization. It emphasizes the importance of having the right resources at the right time and price, ensuring optimal utilization [14]. RMT provides a useful perspective for researching mass protests and understanding how marginalized groups can effectively mobilize to address their grievances [13].

Following this line of research, RMT provides a valuable lens through which to understand the mechanisms underlying social movement mobilization, particularly in the context of climate change activism. RMT emphasizes the importance of resources—both tangible (e.g., funding and infrastructure) and intangible (e.g., social capital and media platforms)—in shaping the success and sustainability of social movements. Recent research highlights the growing importance of digital platforms in environmental and climate activism. Social media platforms serve as key resources within this framework, providing not only a means to disseminate information and recruit participants but also tools for organizing, coordinating, and sustaining collective action [15]. However, the interplay between digital activism and offline mobilization remains underexplored, particularly in the context of climate activism. In particular, the effectiveness of translating online engagement into offline action remains a challenge [12]. Studies show a rapid increase in research on digital environmental activism, with a shift towards climate change as the primary focus [16]. Despite this, there is a notable lack of grassroots climate activism in the United States, attributed to unfavorable political timing, organizational structures ill suited for mobilization, and difficulties in framing the issue [12]. Additionally, research indicates that social movement organizations are struggling to effectively engage and recruit youth participants both online and offline, potentially impacting the future of these movements and youth political socialization [17]. While online platforms facilitate rapid awareness-building and virtual engagement, questions persist about their capacity to translate this momentum into sustained offline efforts capable of driving policy change or fostering long-term grassroots organization.

Furthermore, the impact of platform-specific dynamics on the sustainability of climate change movements warrants further investigation. Recent studies highlight the diverse roles of social media platforms in climate change activism. Platforms such as Twitter, TikTok, and Instagram offer distinct affordances—such as real-time updates, viral content dissemination, and creative storytelling—which influence how movements mobilize resources and sustain engagement. Twitter and Instagram exhibit distinct visual content preferences, with Instagram favoring nature imagery and Twitter emphasizing infographics and data visualization [18]. For instance, TikTok's algorithmic structure may amplify short-term awareness but struggle to support long-term organizing, while Twitter's real-time nature can enhance mobilization for immediate protests but may hinder nuanced, deliberative engagement. TikTok's unique affordances enable users to create multi-layered, affect-laden climate messages, often blending earnestness with humor [19]. The sustainability of social movements on platforms like Twitter depends on connective action tactics employed before, during, and after specific events, as demonstrated by the Women's March movement [20]. Twitter's role in climate change protests extends beyond information sharing, serving as

a cross-cutting networking mechanism and reflecting changing dynamics within protest ecologies [21]. By applying RMT, the current study can assess how these varying dynamics contribute to or detract from the success of climate change movements.

2. Research Question

The current study explores the multifaceted impacts of social movement mobilization facilitated by social media platforms, particularly YouTube. Through multiple layers of analysis using social network analysis, word pair analysis, small-world property, and bipartite networks, this study aims to discover the implications of social media-enabled mobilization for social movements across different contexts, as well as highlight the social media strategies applicable by different societal groups. This study also seeks to frame the understanding of social movement mobilization and its relationship with social media. By using insights from Resource Mobilization Theory (RMT), this study considers how digital technologies serve as tools for the strategic mobilization of resources, including information, networks, and attention, within social movements. Additionally, concepts from communication theory, such as networked communication and digital activism, provide a lens through which to analyze the transformative potential of social media in facilitating collective action. This study centers its research to answer three main questions as follows:

1. How do social movements utilize social media platforms for mobilization purposes, and what are the specific strategies and tactics employed in this digital context?
2. What are the impacts of social media-enabled mobilization on the scale, scope, and dynamics of social movements, including their ability to reach diverse audiences and invoke momentum over time?
3. How do social media platforms shape the formation and evolution of network structures within social movements, and what implications do these network dynamics have for mobilization outcomes?

For easier comprehension during the analysis process, some terms from the research questions are defined in Table 1.

Table 1. Operational definitions of research questions.

Term	Definition
Social media-enabled mobilization	Uploading of YouTube videos
Scale and scope of social media-enabled mobilization	Number of uploaded videos by the organizations and individuals
Dynamics of social media-enabled mobilization	Temporal interval from the start date and end date during the analytical period
Reachability of social media-enabled mobilization	Views of the uploaded videos
Diversity audiences	Variations of different languages on the comments of the videos
Invoke momentum over time	Comment-based engagement of the uploaded videos

3. Materials and Methods

3.1. Data Collection

Data were collected using NodeXL's YouTube Video Network (1.0.1.540 version). NodeXL is a tool for collecting, analyzing, and visualizing a network [22], which requires YouTube API keys to collect YouTube videos and comments. The function parameters were set to "Pair of videos commented on by the same user (slower)", and the number of search videos, comments, and replies was limited to 100 each. The search query for videos was set to "climate". A total of 557 videos from 340 channels were collected. For each video,

the following attributes were recorded: title, description, views, likes, comments, and date. Commenters were defined as users who left comments on both videos. Data were collected from 187,197 comments by 1880 commenters who left comments on two climate videos.

The network data were extracted on 21 March 2024, with no specific date range defined during the data collection process. The dataset represents a snapshot of the most recent data available at the time of extraction, which includes interactions and activities up to the point of collection, as retrieved through NodeXL's default query parameters.

Python (3.13 version) was also used to comprehend the languages of the video titles, descriptions, and comments [23], particularly using the automated Python package FastText. NA was excluded from the analysis when the text, except for emojis, had fewer than 3 characters. Therefore, a video without a description is expressed as NA.

To address potential biases in the extracted data, basic filtering techniques were applied, such as removing duplicate comments, non-informative entries, and off-topic content, according to their count, relevance, and significance to the topic. This ensured that the analysis was focused on meaningful user interactions. The authenticity of the YouTube profiles and bots was deduced by examining engagement patterns. For better data visualization, the distribution of centrality measures, such as degree centrality, were adjusted to remove outliers that showed abnormal high or low activity levels compared to the mean value. Additionally, YouTube channels were cross-checked by checking their profiles, comments, and activities beyond their YouTube scope.

3.2. Data Analysis

3.2.1. Social Network Analysis (SNA)

This study used social network analysis as an analytical method, which is derived from graph theory and examines a graph comprising nodes and edges that connect the nodes [24]. Social network analysis is a method that mixes quantitative and qualitative analysis and is a research method in which researchers' interpretation is involved in the process of selecting and interpreting indicators as well as statistical techniques [25]. A number of indicators are employed to identify the network, with these indicators calculated at both the network and node levels. To view the network, one may consider the density, average density, and more. To identify individual nodes, the index of centrality is employed.

Among the various indexes of SNA, this study utilized centrality measures including degree, betweenness, closeness, and eigenvector centrality [26]. Centrality is an index that indicates the degree to which a node is important within a network. Centrality generally represents good popularity and influences [27]. Degree centrality is the count of how many connections a node has in the network. Betweenness centrality computes the prevalence that a node is located at the shortest distance between other nodes. It also shows the degree of control over the flow in a network and can be an indication of the leadership status of certain actors [28]. Closeness centrality is a measure of the distance from the starting node to other nodes. It is defined as having high centrality when the distance is short. This implies that it occupies a favorable position in terms of the dissemination and propagation of information [29]. Eigenvector centrality is the measure of how influential a specific node is within the network, thus resulting in high eigenvector centrality in the presence of a highly influential node, despite the limited number of adjacent nodes [30].

For the context of this study, the network used is undirected, where videos are considered as the nodes, and the connecting lines (edges) are considered as the comments left on the videos. If two actors are connected directly by a line, they are understood (commented) to be adjacent and build the cluster. The size of the point's cluster is measured by its degree (of connections).

3.2.2. Word Pair Analysis

Word pair analysis, also known as co-occurrence analysis, is a crucial method in network research, particularly for examining social media interactions, user-generated content, and public discourse [31–34]. This method allows for the identification of thematic connections within textual data, providing insights into the relationships between key concepts [31]. It can be used to distinguish predominant themes and linguistic tendencies in global news and social media [32], as well as to reveal thematic areas of discourse on Twitter [33]. Additionally, it can be applied to identify influential nodes in textual networks, which is particularly useful for social media analytics and communication studies [34].

Word pair analysis involves several key steps to extract meaningful insights from textual data. First, the data are collected from relevant sources, such as social media posts, comments, or news articles. It is then preprocessed to ensure accuracy by cleaning the text—removing stop words, punctuation, emojis, and irrelevant symbols—and normalizing terms through processes like stemming or lowercasing. Co-occurrence patterns are then identified by analyzing the frequency with which word pairs appear together within a specific unit of text, such as a sentence or comment. These word pairings are used to construct a network, where words serve as nodes and their co-occurrences form weighted edges connecting them [35]. Network analysis techniques are applied to detect clusters of interconnected words, which often reveal distinct thematic areas or narratives. Finally, the results are visualized in network diagrams or heat maps, with color-coded clusters representing key themes. Sentiment analysis can be incorporated to highlight the emotional tones within these themes, enabling a comprehensive interpretation of the data [32].

For example, Park and Son [36] applied word pair analysis to the YouTube comment sections of the K-pop group Treasure's music video. By analyzing word co-occurrences, they identified dominant themes in the fandom discourse, such as "love", "support", and "Treasure", frequently paired with words like "best", "performance", and "amazing." This analysis highlighted how fans expressed overwhelming positivity and collective support for the group, while also identifying key nodes where emotional and thematic clusters converged. The study demonstrated how word pair analysis can reveal the structure of fan engagement, the emotional tones of comments, and the cohesive narratives that strengthen online fandom communities.

In this study, comments on videos were analyzed using content analysis and word pair analysis to identify recurring themes and messages. After preprocessing the text and identifying co-occurrence patterns, significant word pairings were grouped into thematic clusters. These clusters were color-coded to visually represent key areas of discussion, enabling a clearer understanding of the emotional and thematic landscape. This approach revealed areas of the network with predominantly positive or negative sentiments, providing deeper insights into the overall tone and focus of the discussion.

3.2.3. Small-World Property

A small-world network is described as a comparatively large, sparse network that portrays global cohesion, despite showing locally dense clusters. Simply said, irrespective of size and local density, nodes are comparably close to each other, hence concluding that the world is small. Given the fact that most nodes are embedded in overlapping triads of nodes, an observer can reasonably conclude that the network is large in the sense of there being a long path from a given node to any other given node. It can be concluded that despite high clustering, there is cohesion, where cohesion is defined as most nodes being reachable. Moreover, the cohesion is fairly high, as measured by the average shortest path between any sets of nodes, also known as the geodesic distance. In other words, a

small-world network is formed if a network has a high average clustering coefficient and a small average distance [37].

Two network measures, the geodesic distance and the clustering coefficient, can be utilized to measure a small world. The geodesic distance is the average degree value of disconnection between two nodes along their linear path. The closer individuals, resources, or ideas are in the network is theoretically linked to an average path length. Meanwhile, the clustering coefficient calculates the proportion of a node's connections that are interlinked. In other words, nodes with multiple interconnected links will form a highly clustered network. The calculation of network clustering involves finding the average clustering coefficient of all nodes in the network. Graph density is the term used for this measure [38]. To calculate the graph density of an undirected graph where every vertex is connected to every other vertex through at least one edge, divide the total number of edges by the maximum possible number of edges.

In the analysis of social networks, the clustering coefficient was idealized to calculate the degree of nodes in a graph that cluster together. The value of the average clustering coefficient implies the clustering within a network by measuring the clustering coefficients of all its nodes [37].

3.2.4. Bipartite Network

Bipartite networks are a powerful tool in network analysis, allowing for a nuanced examination of the relationships between two distinct sets of entities [39]. The degree distributions of bipartite networks and their projections play a significant role in the topology and dynamics of the projected network [40]. Unlike traditional one-mode networks, where connections exist between entities of the same type, bipartite networks feature connections exclusively between entities of different types. This unique structure allows for a nuanced analysis of interactions and relationships that are not easily captured by standard network models.

In a bipartite network, there are two disjoint sets of nodes, with edges only running between nodes of different sets. For the purpose of this study, where YouTube interactions are examined, one set consists of videos (Set A), while the other set consists of commenters (Set B). In this context, an edge represents a comment made by a user on a video, which is beneficial when studying social media platforms, educational environments, collaborative projects, and various other domains where interactions between two distinct groups are of interest.

In this study's context of social movements, bipartite networks can reveal critical insights into information spread and influential entities. In this study's network of YouTube videos and commenters, analyzing the degree centrality can identify which videos are generating the most discussion and which users are the most active, potentially highlighting key influencers and popular content. Under the bipartite network, the degree values of video nodes represent the number of different commenters who have left comments on those videos. On the other hand, the degree values of commenter nodes represent the number of videos that the commenter left comments on. Hence, videos with high degree values represent the most commented-on videos, indicating that the videos are popular and engaging, whereas commenters with a high degree value indicate the most active commenters, leaving comments on many different videos.

4. Findings and Discussion

4.1. Descriptive Statistics of Videos

The total number of videos we collected is 557 and Figure 1 shows the categories of video content based off their titles and descriptions. The videos collected were found to be a

mixture of long videos and short-form content. The highest ranked category is Educational and Explanatory Videos, followed by General Overview of Climate Change, Specialized Topics, Scientific and Expert Talks, Impact and Awareness Campaigns, Humorous and Creative Approaches, Documentaries and In-Depth Analysis and, lastly, Keynote Speeches and High-Profile Messages.

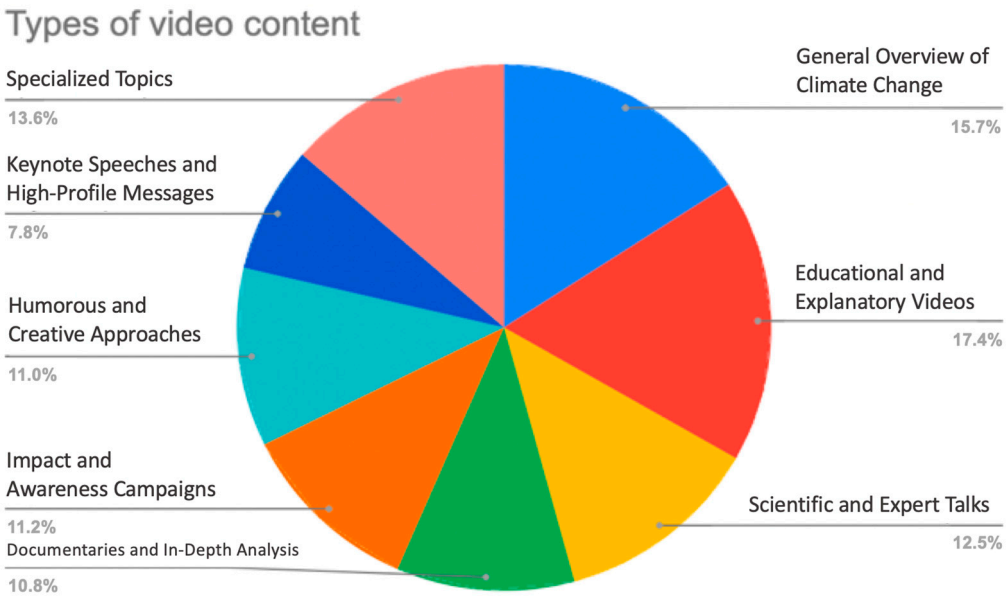

Figure 1. Categories of video content based off titles and descriptions.

4.2. Descriptive Statistics of Channels

Table 2 describes the overall statistics of the 340 unique channels concerned with climate. The mean value of videos per channel is 1.636, with a standard deviation of 1.7376. The median value of videos per channel is 1.0. The maximum number of videos uploaded per channel is 18 and the minimum is 1. The video with the highest number of views has 132,142,792 views and that with the least number of views has 19.0 views. The video with the highest number of comments has 222,089.000 comments and that with the least number of comments has 0 comments. The video with the highest number of likes has 2,463,956.0 likes and that with the least number of likes has 0 likes. The video that was published the earliest was posted on 12 April 2006 and the video that was published the latest was posted on 21 March 2024.

Table 2. Descriptive statistics of 340 channels.

Item	Minimum	Maximum	Median	Mean	Standard Deviation
Channel	1.0	18	1.0	1.638	1.7376
Comments	0	222,089.000	264.0	4892.141	16,288.835
Views	19.0	132,142,792	247,143.0	3,190,151.765	13,103,671.813
Likes	0	2,463,956.0	4693.5	62192.900	244,887.048

4.3. Findings of Research Question 1

To address RQ1, this study extracted data and applied network structure analysis, content analysis, sentiment analysis, and centrality analysis.

4.3.1. Overall Analysis of YouTube Network Structure

Table 3 describes the values of graph metrics to identify how social media platforms shape network structures within social movements. The value of average geodesic distance determines the closeness of the network. The value of average geodesic distance is 3.627543,

which indicates that the nodes are theoretically closely linked to each other, facilitating rapid information dissemination, which is essential for mobilizing resources effectively.

Table 3. Values of graph metrics extracted from NodeXL.

Graph Metric	Value
Maximum Geodesic Distance (Diameter)	15
Average Geodesic Distance	3.627543
Graph Density	0.0171719
Minimum Clustering Coefficient	0.000
Maximum Clustering Coefficient	1.000
Average Clustering Coefficient	0.259
Median Clustering Coefficient	0.292

For graph density, a number between 0 and 1 determines how interconnected the vertices are in the network. The value of graph density of 0.0171719 indicates that the vertices are distinctively diverse and unrelated to each other. In the case of clustering coefficient, a number between 0 and 1 determines the interconnectedness of nodes in the network. From Table 3, the value of the average clustering coefficient of 0.259 is similar to the value of the median clustering coefficient of 0.292. This suggests that the distribution of local clustering tendencies across the network are relatively uniform. This also implies that the small network exhibits a cohesive structure with consistent clustering behavior across its nodes. Despite a low graph density of 0.0171719, suggesting diverse and distinct vertices, the network's uniform clustering coefficient values highlight consistent interconnectedness, supporting sustained interaction and resource sharing among participants. The network structure analysis of a community's communication patterns can reveal barriers to resource management [41]. The impact of geographic distance on social ties in online networks is significant, with local ties and clusters being common [42]. In the context of humanitarian operations, the role of cluster leads as information hubs is crucial for effective information flow [43]. These findings underscore the importance of network structure in facilitating information dissemination and resource mobilization.

4.3.2. Comparing Communication Network Structures

Network analysis is used in this study to determine the network's structure of individuals or institutions within a social movement. The type of network analyzed was undirected. Figure 2 shows clusters of the network graph utilizing the Harel–Koren Fast Multiscale layout algorithm, a force-directed method that arranges vertices to equal lengths and reduces line intersections, leading to a more visually appealing graph.

Using the Harel–Koren Fast Multiscale layout algorithm, this study recognized that the network shape fits into the Tight and Polarized structure. The Tight structure is characterized by highly interconnected vertices with few isolated shared comments. The clusters here form a very interconnected network of learning communities and show how sharing and mutual support can be facilitated by social media. Meanwhile, the Polarized structure is characterized by two groups that have little connection between them. This is due to few related conversations between the groups, despite focusing on the same topic. This shows that YouTube users and commenters rely on different videos on the same topic.

The results of the duality in network structures from this study produced a densely interconnected network on YouTube, indicating that the videos and commenters are interlinked by sharing ideas and meanings. Paolillo found that content producers on the platform are closely linked, with a core group of mixed content producers and smaller cohesive groups around specific content types [44]. Cheng et al. identified distinct characteristics of YouTube videos, such as their length, access patterns, and active lifespan, and highlighted the small-world network formed by related video links [45]. Shapiro and

Park explored the potential for elite-driven discussions in the comments section of climate change-related videos, revealing the presence of climate change activists and skeptics as the most prolific commenters [46]. These findings collectively suggest that YouTube's videos and commenters are closely interlinked, sharing ideas and meanings. Cohesive with previous studies conducted by Park et al., the finding suggests that YouTube is most likely the most suitable platform for disseminating ideas and strengthening solidarity among the audience, as it is an anonymous and deindividuated broadcasting social platform that delivers politically sensitive content [47].

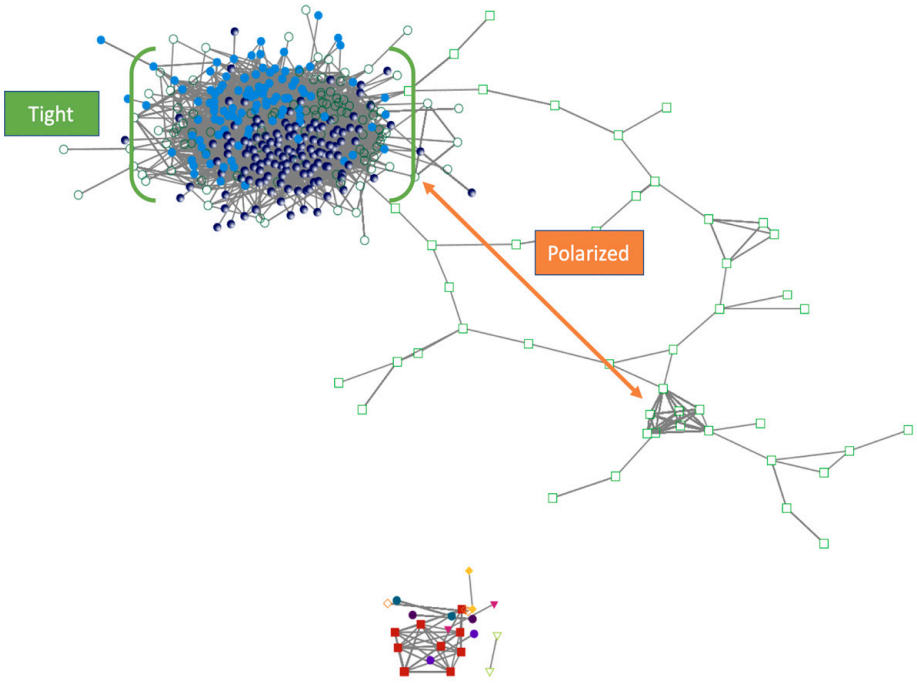

Figure 2. Clusters of the network graph using the Harel–Koren Fast Multiscale layout algorithm.

According to the Harel–Koren Fast Multiscale layout algorithm network graph, the network structure aligns with the "community clusters" structure as shown in Figure 3. Community clusters are commonly utilized to provide varied perspectives on a topic depending on its significance to various groups. This study categorized the network vertices by using the Clauset–Newman–Moore algorithm, which eases the identification of main clusters and sub-community structures [26]. To better visualize the clusters, the values of degree distribution, betweenness, and eigenvector centrality were adjusted according to the mean of their respective values.

Table 4 shows the cluster classifications according to the main themes of the vertices. From the network structure, a total of 12 clusters were identified. The biggest cluster is G1, consisting of 131 video clips, followed by G2 with 101, G3 with 98, G4 with 46, and G5 with 10. G1, G2, and G3 have a common theme of climate science in terms of socio-political dimensions, whereas G4, G6, and G9 have a common theme of educational content in terms of geography and exam preparation for students. Other smaller clusters are composed of only two to three nodes, with very niche themes such as innovation and advocacy. There might be the presence of irrelevant themes, especially about romance drama in G10 because the name of a Myanmar drama when translated to the English language is called The Love Climate. The drama revolves around the lives of four young people who have different beliefs. Overall, the diversity of topics speaks to the mobilization of social media, as these clusters provide a mix of educational content, critical viewpoints, and discussions on the socio-political aspects of climate change, appealing to a diverse audience with varying

opinions on the topic. This is in correspondence with the findings of a study carried out by Park on social media impacts regarding environmental crises [48]. The study concluded that the networks formed were shaped according to the types of video content, where professional news generated more centralized, authoritative discussions while amateur videos encouraged broad but less cohesive interactions.

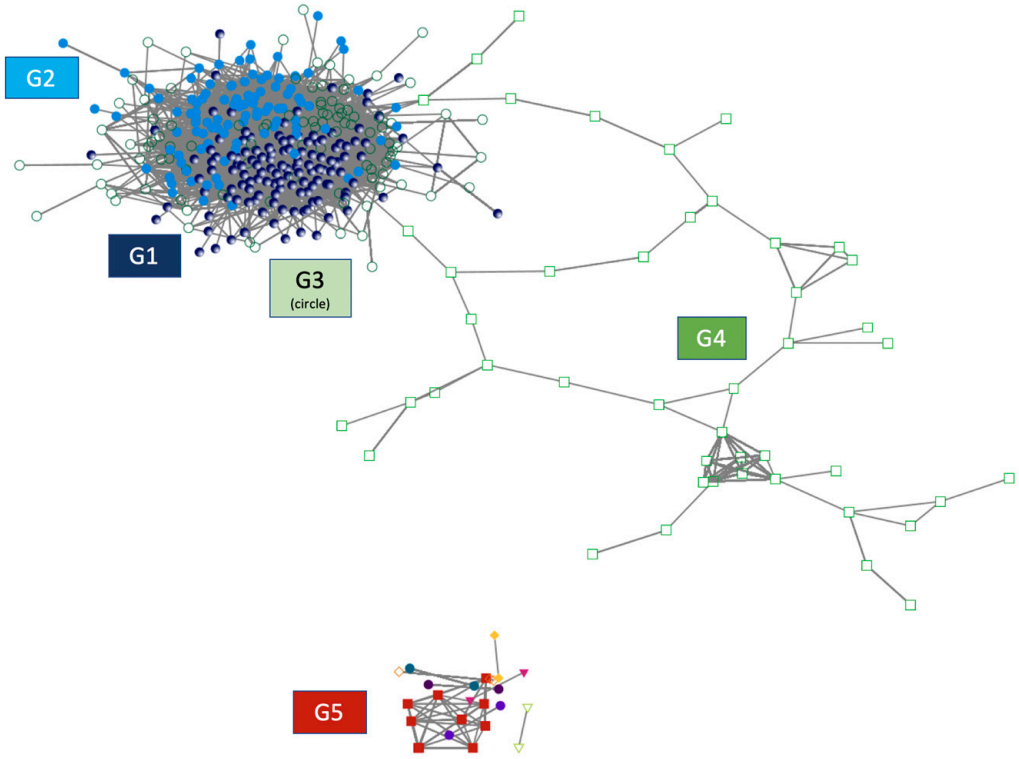

Figure 3. Classification of vertex clusters into different groups.

Table 4. Cluster classification and content of vertices ranked by number of cluster vertices.

Cluster	Content of Cluster	No. of Cluster Vertices
G1	Causes, impacts, solutions, and related socio-political topics	131
G2	Skepticism, debate, and the politicization of climate science	101
G3	Scientific explanations, public education, activism, and the socio-political dimensions of climate change	98
G4	Geography education and exam preparation in relation to climate change	46
G5	Climate fasting and activism in Ladakh, by Sonam Wangchuk	10
G6	Climate of India for Class 10 ICSE Geography	3
G7	Climate zones and related topics	2
G8	Innovative and critical approaches to addressing climate change and weather	2
G9	Climatology and geography education for Union Public Service Commission (UPSC) preparation.	2
G10	Educational content and resources for students on climate change and environmental issues	2
G11	Sonam Wangchuk's climate fast campaign and his advocacy efforts for Ladakh's inclusion in the 6th Schedule	2
G12	Myanmar-language romantic drama series (*Oak Kyar Myet Pauk* or *The Love Climate*)	2

4.3.3. Identifying Influential YouTube Channels and Recurring Themes in YouTube Video Titles

Measuring influential YouTube channels within networks has become a major interest for academic research, specifically for this study; identifying them is important to identify how they spread their movement's message. This study used the values of betweenness centrality and degree centrality to identify the key influential YouTube channels within the network. Table 5 shows the networks' analysis and rankings of the top 20 video authors. The most influential YouTube channels generally rank the highest in all the centrality measures, as they are located in the middle of the network [26]. In particular, the YouTube channel *National Geographic* scores the highest in degree, closeness, and eigenvector centrality, and second highest for betweenness centrality, which indicates that it is the most influential channel.

Table 5. Top 20 video clips ranked by degree centrality.

Rank	Video Title	Name of Channel	Degree Centrality	Betweenness Centrality	Closeness Centrality	Eigenvector Centrality
1	Climate Change 101 with Bill Nye | National Geographic	National Geographic	114	2023.364	0.386	0.152
2	Why humans are so bad at thinking about climate change	Vox	105	1076.449	0.369	0.145
3	Climate Science: What You Need To Know	Be Smart	105	2253.529	0.383	0.144
4	Climate Change: How does it really work? | ClimateScience #1	ClimateScience—Solve Climate Change	104	1394.270	0.369	0.144
5	Bill Nye Takes On Climate Change Deniers | Mach | NBC News	NBC News	93	1129.339	0.364	0.128
6	Are climate doomers right?	DW Planet A	93	736.087	0.360	0.119
7	John Christy on The Economics and Politics of Climate Change	Uncomfortable Learning	92	1278.505	0.362	0.117
8	How scientists calculate climate change	The Economist	91	1438.328	0.376	0.124
9	The scariest climate science paper I've ever read?	Simon Clark	88	598.136	0.360	0.128
10	Why it's hard to care about climate change	DW Planet A	87	583.005	0.358	0.124
11	The Tipping Point | Climate Change: The Facts | BBC Earth	BBC Earth	87	936.471	0.361	0.117
12	Have We Made ANY Progress on Climate Change? Here's The Data, You Decide	PBS Terra	86	813.643	0.361	0.131
13	Is Climate Change Slowing Down the Ocean? | Susan Lozier | TED	TED	86	710.670	0.362	0.113
14	Climate Spiral	NASA Climate Change	84	497.009	0.362	0.129
15	When The World Gets 1 °C Hotter | Climate Change: The Facts | BBC Earth	BBC Earth	83	563.496	0.358	0.119
16	The climate crisis: Can smart ideas save the planet? | DW Documentary	DW Documentary	82	594.364	0.359	0.120
17	New climate data shows global temperatures continuing to rise sharply | DW News	DW News	82	696.259	0.364	0.103
18	What the Hockey Stick missed about climate change	Simon Clark	77	785.065	0.356	0.093
19	Why People Don't Believe In Climate Science	Be Smart	77	809.923	0.367	0.116
20	We WILL Fix Climate Change!	Kurzgesagt—In a Nutshell	77	605.849	0.352	0.102

High degree centrality in the network denotes that the videos received a lot of shared commenters, whereas high closeness centrality signifies that the videos are well connected to other vertices in the network. Meanwhile, high betweenness centrality indicates that the videos performed the crucial role of being intermediaries that influence and control the information flow between different parts of the network, making them important for the

movement's mobilization efforts. The YouTube channels *Be Smart* and *National Geographic* have the highest values of betweenness centrality, with 2253.529 and 2023.364, respectively. The *National Geographic* YouTube channel, with 23.1 million subscribers (as of May 2024), is a global non-profit organization that invests in science, exploration, education, and storytelling. *Be Smart*, with 5.15 million subscribers (as of May 2024), is an educational YouTube channel created and hosted by Joe Hanson, who is a PhD holder, science writer, biologist, and educator.

However, the influence or the positions of the YouTube videos and channels in the network differ by each centrality. Upon close inspection, it can be noted that some YouTube channels rank multiple times within the top 50 rank, which indicates that they post multiple videos with significant influence in the network. For example, *The Economist* and *BBC News* ranked five times; *Simon Clark*, *BBC Earth*, and *Be Smart* ranked four times; and *National Geographic* ranked three times. It can be noted that among this list, apart from *Be Smart*, *Simon Clark* is the only other influential individual YouTube channel with 528 thousand subscribers (as of May 2024). He is an award-winning full-time science communicator with a PhD background in physics, and his YouTube consists of academic-related content about science and graduate life, where he also collaborates with other pioneering science enthusiasts.

The key recurring themes that can be found from the video titles represent the complexity of scientific understanding, public perception, political debate, economic implications, and potential solutions revolving around the issues of climate change. Also included are a diverse range of themes from controversies and debates (*Are climate doomers right?*) to solutions and mitigations (*We WILL Fix Climate Change!*), as well as impacts and consequences (*When The World Gets 1 °C Hotter | Climate Change: The Facts | BBC Earth*). They highlight the diverse angles from which the topic is discussed in public discourse. The resonance with key themes shows that these channels are productive, as they often align their content with current themes and concerns, like the urgencies of climate change, political and economic implications, and personal responsibility. This ensures that their content remains relevant and compelling. A study conducted by Choi and Park suggested that highly influential videos, defined as those with high centrality within the social network, are successful at capturing public attention and amplifying their intended messages [49].

The complexity of climate change is reflected in the diverse themes of YouTube videos, which encompass scientific understanding, public perception, political debate, economic implications, and potential solutions [50,51]. These videos are effective in raising awareness and driving action, particularly when they are structured to engage viewers and address misconceptions [52]. The platform itself is a key battleground for authority and control in the new media environment, with implications for culture, society, and the economy [53].

4.4. Findings of Research Question 2

4.4.1. Identifying Productive Channels and Their Characteristics

In this study, a productive YouTube channel serves as a powerful medium for education, engagement, and mobilization. It helps spread awareness, builds a supportive community, and fosters action among its viewers, all of which are essential for the success of social movements focused on climate change.

High levels of social media affordances, including number of posted videos, views, comments, and shares, indicate strong audience engagement. This engagement is vital for significantly mobilizing or influencing public opinions. Engaged viewers may also have higher tendencies to be proactive in climate change advocacy, such as spreading awareness through their networks and participating in related online and offline discussions and programs. Table 6 shows the top 10 most productive channels in terms of number of videos,

likes, views, and comments. The most productive channel is *DW Documentary*, followed by *National Geographic*, *Kurzgesagt—In a Nutshell*, *LEGO*, *BLACKPINK*, *The Telegraph*, *ANGRY EARTH*, *MR TRENDING*, *Official Pink Panther*, and *Out of Mind Experiments*. This is in line with a study carried out by Choi and Park, where they concluded that there is a positive relationship between the influence of videos in a social network and their engagement metrics such as views, comments, likes, and dislikes. They also found that channels with higher engagement metrics influenced opinions and sustained the momentum of their study's social movements [49].

Table 6. Top 10 most productive channels ranked by number of videos.

Rank	Name of Channel	Channel Classification (General/Climate/ Environment-Related)	Videos	Views	Comments	Likes
1	DW Documentary	General press	18	23,436,899	22,055	141,763
2	National Geographic	Climate-related press	8	19,402,795	31,909	173,132
3	Kurzgesagt—In a Nutshell	Science-related individual content creator	5	50,345,956	222,089	2,415,627
4	LEGO	Toy company	4	39,645,016	0	138,690
5	BLACKPINK	K-pop girl group	3	21,092,040	103,051	2,463,956
6	The Telegraph	General press	2	132,142,792	63,630	1,717,325
7	ANGRY EARTH	Climate-related institutional content creator	1	36,310,398	4554	661,431
8	MR TRENDING	Individual content creator	1	121,702,858	721	1,536,745
9	Official Pink Panther	Cartoon content creator	1	124,380,331	0	640,193
10	Out Of Mind Experiments	Science-related individual content creator	1	59,128,976	5960	1,095,828

Interestingly, despite *DW Documentary* ranking first as the most productive channel with 18 videos posted about climate change, *MR TRENDING* and *Official Pink Panther*, which only posted one video, have a higher viewership of 121,702,858 and 124,380,331, respectively. This shows that despite ensuring consistent production and output of video content, the visual elements of an impactful video, such as storytelling, are enough to garner engagement. Similarly, despite *Kurzgesagt—In a Nutshell* only posting five videos, it accumulated the highest comment count of 222,089 compared to *DW Documentary* at 22,055. Additionally, the K-pop girl group *BLACKPINK*, with a YouTube subscriber count of 93 million (as of May 2024), accumulated the most likes. They are the most subscribed-to YouTube artist channel and were appointed as Advocates for the United Nations Conference on Climate Change (COP26) in 2020.

In cohesion with the results of this study, previous research on the effectiveness of videos about climate change on YouTube [51] and the portrayal of the IPCC report on global warming on the platform [54] highlights the importance of visual communication in driving awareness and action. In a study conducted by Shahbazi and Nowaczyk, it was found that videos with concise information had tendencies to produce more affirmative feedback from the audience, and features such as audio–visual storytelling, content continuity, and relevance attracted the audiences' interests [51]. The use of affective affordances on TikTok for climate activism [19] further underscores the potential of social media platforms in engaging and mobilizing audiences. These studies highlight the need for strategic and impactful visual content to effectively convey the urgency and severity of climate change, and to counteract misinformation and denialism.

Table 7 shows the top 10 most productive channels in terms of their characteristics. *DW Documentary*, part of Germany's international broadcaster Deutsche Welle, leads in producing a vast array of videos that address global issues and holds the record for the most video uploads. *National Geographic*, established in 1888, delves deeply into climate-related topics alongside geography and natural sciences, significantly boosting

environmental consciousness. *Kurzgesagt—In a Nutshell* excels with its concise, engaging animated videos that simplify complex scientific and philosophical ideas, attracting a high volume of comments. *LEGO*, a renowned Danish toy company founded in 1932, is celebrated for its educational interlocking bricks. *BLACKPINK*, a popular K-pop girl group, uses its platform to enhance awareness of climate change and consistently receives the most likes for its content. *The Telegraph*, a storied British newspaper first published in 1855, offers extensive coverage on a diverse array of topics. Lastly, *ANGRY EARTH* engages viewers with animations that clarify various environmental issues, while *MR TRENDING* is known for a viral video that creatively underscores the urgency of climate change, making it the most viewed content in its category.

Table 7. Top 10 most productive channels in terms of their characteristics.

Rank	Name of Channel	Channel Characteristics
1	DW Documentary	A series produced by Deutsche Welle, Germany's international broadcaster. It is also the channel with the greatest number of videos posted about climate change.
2	National Geographic	A channel that focuses on geography, archeology, natural science, conservation, and education.
3	Kurzgesagt—In a Nutshell	A popular YouTube channel known for its engaging animated videos that explain complex scientific and philosophical concepts in a concise and accessible manner. It is also the channel with the greatest number of comments under its videos.
4	LEGO	A toy company known for its interlocking plastic bricks, founded in Denmark in 1932.
5	BLACKPINK	A K-pop girl group channel that develops content to raise awareness of problems with climate change. It has the most liked video about climate change and is the most subscribed-to artist channel on YouTube.
6	The Telegraph	A British newspaper with a long history, first published in 1855.
7	ANGRY EARTH	A channel that expresses various issues about the Earth through animation.
8	MR TRENDING	A short 3 min video that expresses the seriousness of climate change in a fun way. It has the highest view count regarding climate change.
9	Official Pink Panther	A channel that expresses various issues regarding the Earth through animation, with the famous character Pink Panther as the main character.
10	Out Of Mind Experiments	A channel that focuses on exploring various intriguing and thought-provoking topics related to the mind, consciousness, and human behavior.

4.4.2. Analysis of Temporal Intervals

The dynamics of social media-enabled mobilization are defined by the temporal interval from the start date to the end date during the analytical period. The higher the values of the temporal interval are, the more dynamic a channel is. Table 8 describes the top 10 dynamic channels in terms of the start- and end-of-publication dates, duration in days, and temporal interval. Ranked first is the *United Nations* with a temporal interval value of 1732.5, and next is *NASA Goddard* with 1688.5, followed by *Real Time with Bill Maher* with 1500.5, *MSNBC News* with 1241.5, *Intergovernmental Panel on Climate Change (IPCC)* with 996.67, *Peekaboo Kidz* with 831.5, *Sky News* with 757, *CrashCourse* with 724, *NASA Climate Change* with 632.5, and *SciShow* with 620.

Although the most dynamic channels, such as *United Nations*, *NASA Goddard*, and *Real Time with Bill Maher*, post only 2 videos related to climate, they likely post content more frequently and have sustained engagement over the analyzed period, hence have high temporal interval values. Furthermore, other channels such as *Sky News*, and *CrashCourse* post more videos than the most dynamic channels but are considered moderately dynamic, indicating that they post regular but less frequent updates compared to the top channels.

Shapiro and Park [46] and Yang and Leskovec [55] highlight the dynamic nature of online content, with Shapiro specifically discussing the potential for elite-driven discussions on YouTube. This is particularly relevant to the analysis of climate-related videos, as it suggests that certain individuals or groups may have a significant influence on the content and engagement levels. In the study carried out by Shapiro and Park [46], it was found that the core group of elite commenters were climate change activists or skeptics. A study carried out by Ritter found that authorized news institutions, such as BBC News and

Sky News, were influential during the COP26 Summit, suggesting a significant role for traditional media in shaping public opinion [56].

Table 8. Top 10 dynamic channels ranked by temporal interval values.

Rank	Name of Channel	Channel description (General/Climate/ Environment Related)	No. of Videos	Start-of -Publication Date	End-of -Publication Date	Temporal Interval
1	United Nations	Intergovernmental institution	2	23 September 2014	19 March 2024	1732.5
2	NASA Goddard	Space-related institution	2	3 August 2012	1 November 2021	1688.5
3	Real Time with Bill Maher	TV talk show	2	11 November 2014	29 January 2023	1500.5
4	MSNBC News	General press	2	3 June 2017	21 March 2024	1241.5
5	Intergovernmental Panel on Climate Change (IPCC)	Climate-related institution	3	31 March 2014	7 June 2022	966.67
6	Peekaboo Kidz	Education-related institutional content creator	2	10 November 2017	31 May 2022	831.5
7	Sky News	General press	4	4 December 2015	19 March 2024	757
8	CrashCourse	Education-related institutional content creator	5	8 January 2013	7 December 2022	724
9	NASA Climate Change	Climate-related institution	2	27 September 2018	15 March 2022	632.5
10	SciShow	Science-related institutional content creator	2	29 March 2018	20 August 2021	620

It can be noted from Table 8 that most of the dynamic channels are related to education, climate, and science, indicating a preference for credible sources regarding the topic. Shapiro and Park [57] noted the preference for professional content on YouTube, finding that science-based comments dominated public responses to climate change videos. They suggest that YouTube plays a substantial role in constructing public opinion on climate change, with traditional media and influential users playing a key role in this process.

4.4.3. Analysis of Linguistic Data of Video Titles and Comments

This study examined the linguistic differences between those who promote climate change campaigns and those who accept them. By analyzing these differences, we can obtain their linguistic identity. This identity is not necessarily tied to traditional language ability or native language [58]. Table 9 shows the language identity of YouTube channels that promote climate change. It was found that English was overwhelmingly used in both the titles and video descriptions. Apart from English, most of the languages used were from emerging countries, with Hindi, Burmese, and Malaysian being the most common. The language ratio of titles and descriptions indicates that English is more prevalent in titles. This is likely a strategy for search engine optimization and attracting a diverse audience.

Table 9. Percentage of languages between video title and description.

Language	Video Title	Video Description
English	96.751%	92.998%
Hindi	1.444%	0.718%
Burmese	0.361%	0.359%
Malayalam	0.361%	0.359%
German	0.361%	0.180%
Netherland	0.181%	0.180%
Korean	0.181%	0.180%
Urdu	0.181%	0.180%
Tamil	0.181%	0.180%
NA	0.000%	4.668%

In contrast to those promoting action for climate change, the language identity of the audience was somewhat different as shown on Table 10. Although English was the

predominant language, it was found that languages from developed countries, not just emerging ones, were represented. Aside from English, Italian, Burmese, and Japanese were the most common languages. This confirms that videos related to climate change have reached global audiences with diverse linguistic identities.

Table 10. Percentage of language distribution across audiences' comments.

Language	Comments
English	98.882%
Italian	0.242%
Burmese	0.126%
Japanese	0.077%
German	0.067%
Turkish	0.063%
French	0.060%
Spanish	0.050%
Hindi	0.017%
Russian	0.017%
Portuguese	0.009%
Dutch	0.003%
etc	0.026%
NA	0.362%

4.5. Findings of Research Question 3

4.5.1. Identifying Co-Occurring Topics in Comments

Figure 4 shows the classification of word pair analysis into clusters. From the content analysis, a total of 47 clusters were identified. Table 11 shows the top 10 clusters and their content. The biggest cluster is G1, consisting of 41 nodes (words), followed by G2 with 33, G3 with 30, G4 with 25, and G5 with 19. G1 and G5 have a common theme of positive engagement from users, whereas G4, G8, and G10 have a common theme of educational involvement in terms of online platforms and academic journals. Other smaller clusters are composed of only two to eleven nodes, with niche themes such as climate change processes and public figures leading climate change awareness. Overall, the diversity of the recurring themes identified speaks to the varying engagement levels of social media users regarding climate change, as these clusters provide a combination of academic content, positive engagement, and active participation, appealing to an audience with varying opinions on the topic.

The classification of word pair analysis into clusters, as shown in Figure 4, reveals consistency with previous research that has emphasized the importance of understanding user engagement patterns and behaviors on social media platforms [59]. Kim and Hara emphasize the importance of resonating topics and sentiment alignment in communication strategies [60]. Furthermore, the use of machine learning techniques in aligning climate-related discourses on social media has provided valuable insights into the communication gap between the public and administration on the topic of climate change [61].

The top words and top word pairs presented messages that correspond to climate change and the severity of the issue. Table 12 provides the top 25 words commented under Video 1 and 2 ranked by count in which the top 3 words are climate (85,118), video (49,196), and year (36,334). The key themes of the top 25 words encapsulate the understanding of climate change and its global effects, emphasized by various factors such as fossil fuel.

Table 13 shows the top 20 word pairs for Video 1 and 2 comments, where ranked first is climate–change, followed by fossil–fuel and global–warming. Particularly noteworthy is that richard–lendzen appears significantly as a word pair. Upon further search, it is found that Lendzen is a senior fellow of CATO Institute—a well-established public policy research organization that encourages academic research and public debates—as well as an emeritus professor of meteorology at Massachusetts Institute of Technology (MIT). This

further explains the appearance of mit–colleagues and scientific–literature as prominent word pairs. Lendzen conducted a study where he challenged the scientific consensus on global warming; however, with the emergence of social media and the utilization of resource mobilization amongst society, the public discourse about climate change and global warming has shifted towards the urgency of it [62]. This is proven as the prominence of the scientific–literature word pair particularly signifies the increase in publication regarding climate change.

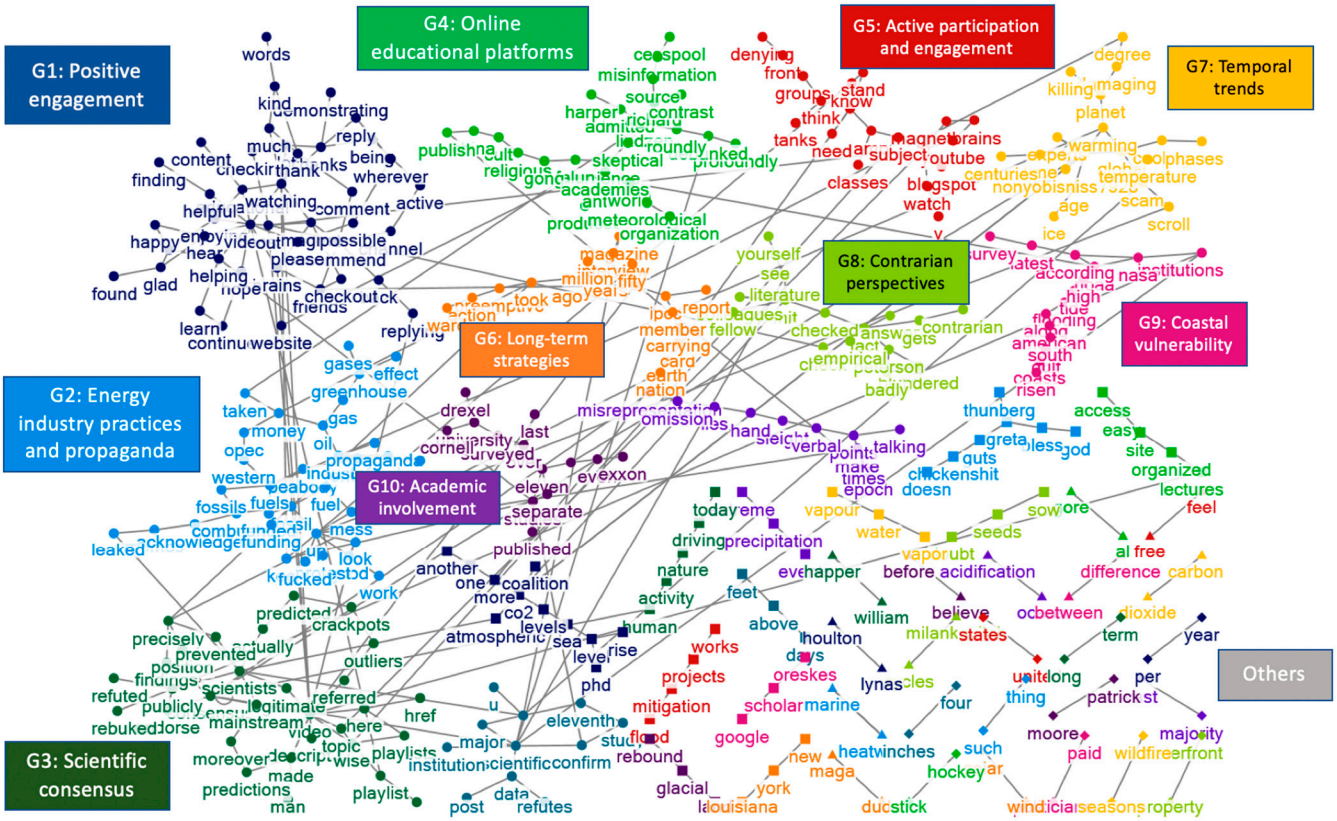

Figure 4. Classification of word pairs into clusters.

Table 11. Top 10 clusters and content of word pairs ranked by number of cluster vertices.

Cluster	Content of Cluster	No. of Cluster Vertices
G1	Positive engagement	41
G2	Energy industry practices and propaganda	33
G3	Scientific Consensus	30
G4	Online educational platforms	25
G5	Active participation and engagement	19
G6	Long-term strategies	18
G7	Temporal trends	18
G8	Contrarian perspectives	16
G9	Coastal vulnerability	15
G10	Academic involvement	13

Furthermore, Koteyko et al. [63] and Dayeen et al. [64] both explore the discourse surrounding climate change. The study carried out by Koteyko et al. focuses on the role of online reader comments in shaping public awareness of climate science, particularly in the aftermath of the "climategate" controversy [63]. The study reveals the appropriation of science and political stereotypes, changes in readers' perceptions of climate science, and the adoption and contestation of climate-skeptic arguments. In the study conducted by Dayeen et al., text mining analysis of the climate change literature in industrial ecology highlights the quick surge in climate change publications and the increasing importance of

terms such as "climate change adaptation" and "resilience" [64]. On the other hand, Chen delves into the cognitive and emotional impact of online climate change videos, identifying key themes such as emissions, temperature, and renewable energy [65]. These studies collectively underscore the complexity and diversity of public perceptions and responses to climate change.

Table 12. Top 25 words ranked by count in commented videos.

No.	Word	Count
1	climate	85,118
2	video	49,196
3	year	36,334
4	co2	35,272
5	change	33,890
6	science	32,538
7	up	30,905
8	scientist	30,395
9	scientific	29,546
10	more	29,327
11	warming	28,772
12	fuel	27,138
13	over	26,064
14	consensus	25,106
15	out	24,596
16	fossil	22,214
17	earth	21,766
18	global	21,608
19	world	20,897
20	even	20,054
21	https	19,257
22	one	18,588
23	com	17,991
24	fact	17,348
25	studies	16,814

Table 13. Top 20 word pairs for Video 1 and 2 comments ranked by count.

Rank	Word 1	Word 2	Count	Salience	Mutual Information
1	climate	change	27,723	0.005	1.742
2	fossil	fuel	22,017	0.004	2.321
3	global	warming	10,417	0.002	1.983
4	climate	scientist	8842	0.002	1.293
5	richard	lindzen	8401	0.002	2.565
6	magnet	brain	8374	0.002	2.811
7	scientific	consensus	8333	0.002	1.827
8	fuel	industry	8095	0.002	2.037
9	out	video	8038	0.002	1.608
10	pabbly	com	7706	0.002	2.502
11	www	pabbly	7706	0.002	2.566
12	year	ago	7183	0.002	2.171
13	climate	science	6790	0.002	1.153
14	video	playlist	6442	0.002	1.969
15	scientific	literature	6387	0.002	2.262
16	recommend	friends	6217	0.002	2.545
17	mit	colleagues	6111	0.002	2.773
18	human	activity	6062	0.002	2.688
19	confirm	scientific	5915	0.002	2.283
20	warming	planet	5902	0.002	1.893

4.5.2. Analysis of Bipartite Network

Figure 5 shows the bipartite network graph of videos and commenters, where videos are indicated with solid triangles and commenters are indicated with disk shapes. Tables 14 and 15 show the top 10 most commented-on videos in Set A and B, respectively. In Set A, the recurring themes encapsulate various aspects addressing climate change, particularly about the urgency of the issue (*"code red for humanity"*), the scientific basis and predictions, the public perception, and the potential solutions to solve the issue, as

well as critiques of awareness-leading figures, similar to a study carried out by Shapiro and Park [57]. Meanwhile, in Set B, the themes cover the understanding of climate change in terms of the scientific principles, psychological aspects, societal challenges, and policy discussions related to climate change. This result is similar to what was discovered by a study conducted by Shapiro and Park [46]. The persuasiveness of these videos is influenced by the presenter's type and style, with scientist presenters and solution-oriented videos eliciting more positive comments [66]. The IPCC Special Report on Global Warming of 1.5 °C also sparked discussions on disaster impacts, policy options, political struggles, and contested science [54]. These key recurring themes show that they are the most relevant topics of discussions regarding climate change, as indicated by their respective degree values. Particularly noteworthy in Set B, three of the most commented-on videos are introductory videos about climate change, which indicates that there is an increase in interest and awareness about the crisis.

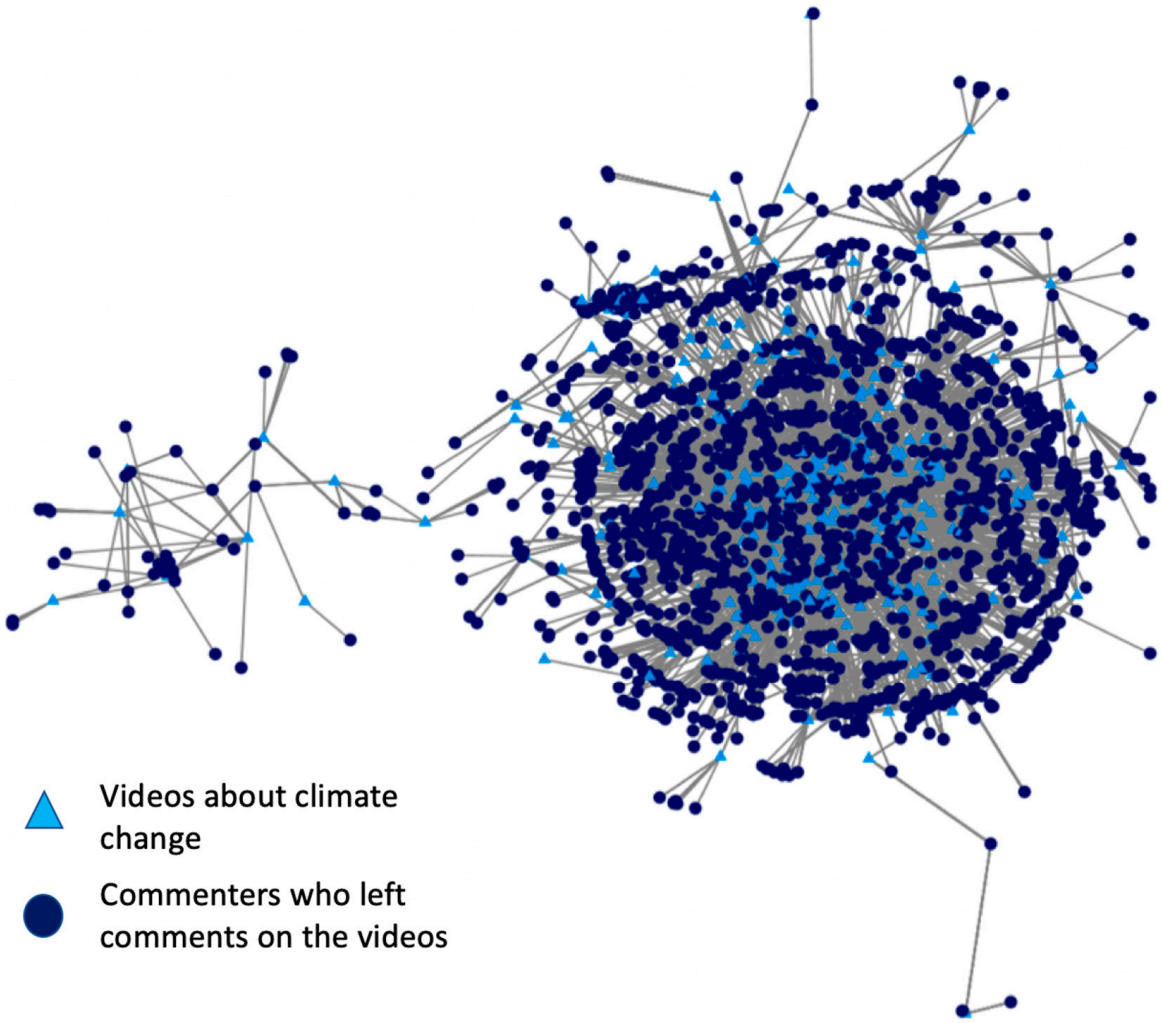

Figure 5. Bipartite network graph of videos and commenters.

Among the top 10 most active commenters as shown in Table 16, *@DWDocumentary* is the only channel with a significant number of subscribers and activity. The other commenters have fewer than 30 subscribers and can be considered anonymous. This result is in cohesion with research carried out by Pastukhov et al., where they emphasize the need to consider both user activity and influence, as the most active commenters are not always the most influential [67]. Yu et al. [68] and Alassad [69] both highlight the importance of identifying influential users and coordinating commenters, with Alassad's focus on

identifying intensive groups in YouTube commenter networks. These studies collectively underscore the significance of bipartite network analysis in understanding the dynamics of information spread and influence in social movements on YouTube.

Table 14. Top 10 most commented-on videos in Set A.

Rank	Video Title	Degree Value
1	Climate change IPCC report is 'code red for humanity', UN scientists say—BBC News	39
2	When The World Gets 1 °C Hotter | Climate Change: The Facts | BBC Earth	34
3	Why it's hard to care about climate change	29
4	Climate change is simple: David Roberts at TEDxTheEvergreenStateCollege	29
5	We're NOT about to pass the 1.5 degree climate change limit	28
6	How accurate are scientific predictions about climate?	27
7	Bill Nye Takes On Climate Change Deniers | Mach | NBC News	26
8	The climate crisis: Can smart ideas save the planet? | DW Documentary	26
9	Arnold Schwarzenegger calls leaders 'liars' over climate change—BBC News	25
10	Shocking Global Temperature Extremes Show an Out of Control Climate	25

Table 15. Top 10 most commented-on videos in Set B.

Rank	Video Title	Degree Value
1	Climate Change 101 with Bill Nye | National Geographic	114
2	Why humans are so bad at thinking about climate change	105
3	Climate Science: What You Need To Know	105
4	Climate Change: How does it really work? | ClimateScience #1	104
5	Bill Nye Takes On Climate Change Deniers | Mach | NBC News	93
6	Are climate doomers right?	93
7	John Christy on The Economics and Politics of Climate Change	92
8	How scientists calculate climate change	91
9	The scariest climate science paper I've ever read?	88
10	Why it's hard to care about climate change	87

Table 16. Top 10 most active commenters ranked by degree value.

Rank	Commenter	Degree Value
1	samlair3342	32
2	OldScientist	23
3	anthonymorris5084	18
4	mrunning10	18
5	karlwheatley1244	16
6	rps1689	14
7	TechnicalShivam-bh1hv	13
8	user-ww5oc9bh1e	13
9	allergy5634	13
10	DWDocumentary	13

5. Conclusions

In conclusion, this study highlights the potential of social media to enhance education, engagement, and mobilization for climate change initiatives. It examined the role of social media in shaping network structures within social movements, focusing on climate change through the lens of Resource Mobilization Theory. By analyzing using RMT, this study identified how effective deployment of resources such as information, social capital, and organizational capabilities contributes to the success and engagement of social movements. Social media significantly shapes network structures within social movements by facilitating effective resource mobilization. Influential channels and diverse content drive engagement and support, essential for addressing climate change. These platforms

enable strategic resource allocation, ensuring information, support, and participation are directed toward the movement's objectives.

This study underscores YouTube as a powerful platform for spreading information and determining public discourse on climate change by analyzing empirical data extracted from NodeXL. The accessibility of YouTube allows it to act as an efficient medium for disseminating educational content to multilingual audiences, signifying the importance of inclusivity of diverse outreach for broader engagement. Recognizing the importance of other video affordances such as storytelling, audio–visual effects, concise narrative, and more, can impact engagement and attract viewers' interest towards the videos, increasing the effectiveness of resource mobilization for social movements. Furthermore, there is a shifting trend where instead of delivering effective messages to educate the public, social movements should incorporate "two-way" communication and introduce more tailored communication strategies to understand and represent the public's interests [60]. This is emphasized by Cho et al., where the role of social media in decentralizing crisis responses, utilized by active individuals and communities in managing information dissemination, can enhance responsiveness and community resilience while demanding governments to reconsider their communication strategies [70].

Various stakeholders can elevate their resources mobilization according to the actionable insights offered from the findings. For NGOs and activists, the findings emphasize the importance of incorporating storytelling and concise narratives to maximize the impact of their campaigns, while multilingual content ensures inclusivity and broadens outreach. Educators can utilize the results as a blueprint for designing engaging and accessible digital educational materials. Policymakers are encouraged to foster decentralized, two-way communication strategies to enhance public resilience and promote effective climate action. Businesses, meanwhile, can align their corporate social responsibility efforts with public interests by leveraging impactful digital campaigns that resonate with diverse audiences. Collectively, these insights highlight the necessity of tailoring communication strategies to specific audiences, thereby ensuring efficient resource mobilization. Future research could build on these findings by exploring their applicability across platforms such as Twitter or TikTok and conducting sentiment analysis to further refine communication strategies for key public groups.

This study also acknowledges limitations, such as the need to explore different social media platforms and the influence and sentiments of specific words across multiple platforms within specific time periods, such as using semantic analysis to analyze Twitter data on international and local network bases as conducted by Song et al. [71], and the influence of multiple actors in society to spread effective awareness about climate change. Future research in this area can further expand on these limitations to better understand the multiple layers of public engagement and communication strategies practiced across various social media platforms.

NodeXL was used to apply SNA and this study recognized the limitations of its application, such as manual lemmatization, clustering networks, and identifying distinctive themes within textual data. Other automated programs can be utilized, such as lemmatization using Python or graph visualizations using VOSviewer, which address such limitations and hopefully can be considered in future studies. This study would also like to propose future studies to conduct comprehensive sentiment analysis of video titles and comments. This can help provide better insights into what effective communication strategies can be applied by different societal actors such as NGOs, researchers, business or industry experts, and more.

Author Contributions: Conceptualization, N.S.O. and H.-W.P.; methodology, N.S.O., H.-W.P., J.-H.K. and J.-H.P.; software, N.S.O., H.-W.P., J.-H.K. and J.-H.P.; validation, N.S.O., H.-W.P., J.-H.K. and J.-H.P.; formal analysis, N.S.O., J.-H.K. and J.-H.P.; investigation, N.S.O.; resources, N.S.O., H.-W.P., J.-H.K. and J.-H.P.; data curation, N.S.O., H.-W.P., J.-H.K. and J.-H.P.; writing—original draft preparation, N.S.O., J.-H.K. and J.-H.P.; writing—review and editing, N.S.O. and H.-W.P., visualization, N.S.O.; supervision, H.-W.P.; project administration, H.-W.P.; funding acquisition, H.-W.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All the data generated and used for analysis during this study are included in this published article and can be provided upon request.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Harindranath, G.; Bernroider, E.W.; Kamel, S.H. Social Media and Social Transformation Movements: The Role of Affordances and Platforms. *Eur. Conf. Inf. Syst.* **2015**, paper 73. [CrossRef]
2. Young, A.; Selander, L.; Vaast, E. Digital organizing for social impact: Current insights and future research avenues on collective action, social movements, and digital technologies. *Inf. Organ.* **2019**, *29*, 100257. [CrossRef]
3. Kavada, A. Social Movements and Political Agency in the Digital Age: A Communication Approach. *Media Commun.* **2016**, *4*, 8–12. [CrossRef]
4. Jacqmarcq, M. Environmental Activism in the Digital Age. *Flux Int. Relat. Rev.* **2021**, *11*, 42–47. [CrossRef]
5. Dolata, U. Social Movements and the Internet: The Sociotechnical Constitution of Collective Action, 2017. SOI Discussion Paper, No. 2017-02, Universität Stuttgart, Institut für Sozialwissenschaften, Abteilung für Organisations- und Innovationssoziologie, Stuttgart. Available online: https://www.econstor.eu/handle/10419/156395 (accessed on 17 November 2024).
6. Lopes, A.R. The Impact of Social Media on Social Movements: The New Opportunity and Mobilizing Structure. *J. Political Sci. Res.* **2014**, *4*, 1–23.
7. Christakis, N.; Fowler, J. *Connected: The Amazing Power of Social Networks and How They Shape Our Lives*; Little, Brown Spark: New York, NY, USA, 2011.
8. Van Ham, P. Social Power in International Politics. In *Routledge eBooks*; Routledge: London, UK, 2010. [CrossRef]
9. Biddix, J.P.; Park, H.W. Online networks of student protest: The case of the living wage campaign. *New Media Soc.* **2008**, *10*, 871–891. [CrossRef]
10. Dietz, T.; Shwom, R.L.; Whitley, C.T. Climate change and society. *Annu. Rev. Sociol.* **2020**, *46*, 135–158. [CrossRef]
11. Goodman, J. Social movements and climate change: "Climatizing" society from within. In *Oxford Research Encyclopedia of Climate Science*; Oxford University Press: Oxford, UK, 2022. [CrossRef]
12. McAdam, D. Social Movement Theory and The Prospects for Climate Change Activism in The United States. *Annu. Rev. Political Sci.* **2017**, *20*, 189–208. [CrossRef]
13. Edwards, B.; Gillham, P.F. *Resource Mobilization Theory. The Wiley-Blackwell Encyclopedia of Social and Political Movements*; Wiley: Hoboken, NJ, USA, 2013. [CrossRef]
14. Golhasani, A.; Hosseinirad, A. The Role of Resource Mobilization Theory in Social Movement. *Int. J. Multicult. Multireligious Underst.* **2017**, *3*, 1. [CrossRef]
15. Leong, C.; Pan, S.L.; Bahri, S.; Fauzi, A. Social media empowerment in social movements: Power activation and power accrual in digital activism. *Eur. J. Inf. Syst.* **2018**, *28*, 173–204. [CrossRef]
16. Baran, Z.; Stoltenberg, D. Tracing the Emergent Field of Digital Environmental and Climate Activism Research: A Mixed-Methods Systematic Literature Review. *Environ. Commun.* **2023**, *17*, 453–468. [CrossRef]
17. Elliott, T.; Earl, J. Organizing the Next Generation: Youth Engagement with Activism Inside and Outside of Organizations. *Soc. Media + Soc.* **2018**, *4*, 3–4. [CrossRef]
18. Qian, S.; Lu, Y.; Peng, Y.; Shen, C.; Xu, H. Convergence or divergence? A cross-platform analysis of climate change visual content categories, features, and social media engagement on Twitter and Instagram. *Public Relat. Rev.* **2024**, *50*, 102454. [CrossRef]
19. Hautea, S.; Parks, P.; Takahashi, B.; Zeng, J. Showing They Care (Or Don't): Affective Publics and Ambivalent Climate Activism on TikTok. *Soc. Media + Soc.* **2021**, *7*, 1–12. [CrossRef]

20. Syed, R.; Silva, L. Social Movement Sustainability on Social Media: An Analysis of the Women's March Movement on Twitter. *J. Assoc. Inf. Syst.* **2023**, *24*, 249–293. [CrossRef]
21. Segerberg, A.; Bennett, W.L. Social Media and the Organization of Collective Action: Using Twitter to Explore the Ecologies of Two Climate Change Protests. *Commun. Rev.* **2011**, *14*, 197–215. [CrossRef]
22. Smith, M.A. NodeXL: Simple network analysis for social media. In Proceedings of the 2013 International Conference on Collaboration Technologies and Systems (CTS), San Diego, CA, USA, 20–24 May 2013; pp. 89–93.
23. Joulin, A.; Grave, E.; Bojanowski, P.; Douze, M.; Jégou, H.; Mikolov, T. Fasttext.zip: Compressing text classification models, arXiv 2016. *arXiv* **2016**. [CrossRef]
24. Park, H.W.; Yoon, J.; Leydesdorff, L. The normalization of co-authorship networks in the bibliometric evaluation: The government stimulation programs of China and Korea. *Scientometrics* **2016**, *109*, 1017–1036. [CrossRef]
25. Yousefi Nooraie, R.; Sale, J.E.; Marin, A.; Ross, L.E. Social network analysis: An example of fusion between quantitative and qualitative methods. *J. Mix. Methods Res.* **2020**, *14*, 110–124. [CrossRef]
26. Lee, M.K.; Yoon, H.Y.; Smith, M.; Park, H.J.; Park, H.W. Mapping a Twitter scholarly communication network: A case of the association of internet researchers' conference. *Scientometrics* **2017**, *112*, 767–797. [CrossRef]
27. Zhang, J.; Luo, Y. Degree centrality, betweenness centrality, and closeness centrality in social network. In *2017 2nd International Conference on Modelling, Simulation and Applied Mathematics (MSAM2017)*; Atlantis Press: Amsterdam, The Netherlands, 2017; pp. 300–303.
28. Katerinkakis, T.A. Network indicators. In *Encyclopedia of Social Network*; Barnett, G.A., Ed.; Sage Publications: Thousand Oaks, CA, USA, 2011; pp. 607–609.
29. Wasserman, S.; Faust, K. *Social Network Analysis: Methods and Applications*; Cambridge University Press: Cambridge, UK, 1994. [CrossRef]
30. Maharani, W.; Gozali, A.A. Degree centrality and eigenvector centrality in twitter. In Proceedings of the 2014 8th International Conference on Telecommunication Systems Services and Applications (TSSA), Kuta, Bali, Indonesia, 23–24 October 2014; pp. 1–5.
31. Hansen, D.L.; Shneiderman, B.; Smith, M.A.; Himelboim, I. *Semantic Networks*; Elsevier eBooks; Elsevier: Amsterdam, The Netherlands, 2020; pp. 115–125. [CrossRef]
32. Segev, E. Textual network analysis: Detecting prevailing themes and biases in international news and social media. *Sociol. Compass* **2020**, *14*, 12. [CrossRef]
33. Hemsley, J.; Erickson, I.; Jarrahi, M.H.; Karami, A. Digital nomads, coworking, and other expressions of mobile work on Twitter. *First Monday* **2020**, *25*. [CrossRef]
34. Garg, M.; Kumar, M. Comprehensive Study of Keyphrase Extraction Metrics for Uncertain User-Generated Data. In *Applications of Computing, Automation and Wireless Systems in Electrical Engineering*; Lecture Notes in Electrical Engineering; Springer: Singapore, 2019; pp. 1191–1200. [CrossRef]
35. Thelwall, M. Word Association Thematic Analysis. In *Synthesis Lectures on Information Concepts, Retrieval, and Services*; Springer: Berlin/Heidelberg, Germany, 2021. [CrossRef]
36. Son, J.H.; Park, H.W. YouTube and K-POP Idol Fandom: Focusing on the 'Treasure' Video. *Korean Data Anal. Soc.* **2021**, *23*, 2713–2725. [CrossRef]
37. Li, Y.; Shang, Y.; Yang, Y. Clustering coefficients of large networks. *Inf. Sci.* **2017**, *382–383*, 350–358. [CrossRef]
38. Uzzi, B.; Amaral, L.A.; Reed-Tsochas, F. Small-world networks and management science research: A review. *Eur. Manag. Rev.* **2007**, *4*, 77–91. [CrossRef]
39. Kunegis, J. Exploiting the Structure of Bipartite Graphs for Algebraic and Spectral Graph Theory Applications. *Internet Math.* **2014**, *11*, 201–321. [CrossRef]
40. Filho, D.V.; O'Neale, D.R.J. Degree distributions of bipartite networks and their projections. *Phys. Rev. E* **2018**, *98*. [CrossRef]
41. Crona, B.; Bodin, R. What You Know is Who You Know? Communication Patterns Among Resource Users as a Prerequisite for Co-management. *Ecol. Soc.* **2006**, 11. [CrossRef]
42. Scellato, S.; Mascolo, C.; Musolesi, M.; Latora, V. Distance Matters: Geo-Social Metrics for Online Social Networks. In Proceedings of the 3rd Workshop on Online Social Networks, Boston, MA, USA, 22–25 June 2010.
43. Altay, N.; Pal, R. Information Diffusion among Agents: Implications for Humanitarian Operations. *Prod. Oper. Manag.* **2014**, *23*, 1015–1027. [CrossRef]
44. Paolillo, J.C. Structure and Network in the YouTube Core. In Proceedings of the 41st Annual Hawaii International Conference on System Sciences (HICSS 2008), Waikoloa, HI, USA, 7–10 January 2008; p. 156. [CrossRef]
45. Cheng, X.; Liu, J.; Dale, C. Understanding the Characteristics of Internet Short Video Sharing: A YouTube-Based Measurement Study. *IEEE Trans. Multimed.* **2013**, *15*, 1184–1194. [CrossRef]
46. Shapiro, M.A.; Park, H.W. Climate Change and YouTube: Deliberation Potential in Post-video Discussions. *Environ. Commun.* **2017**, *12*, 115–131. [CrossRef]

47. Park, S.J.; Lim, Y.S.; Park, H.W. Comparing Twitter and YouTube networks in information diffusion: The case of the "Occupy Wall Street" movement. *Technol. Forecast. Soc. Chang./Technol. Forecast. Soc. Chang.* **2015**, *95*, 208–217. [CrossRef]
48. Park, H.W. YouTubers' networking activities during the 2016 South Korea earthquake. *Qual. Quant.* **2017**, *52*, 1057–1068. [CrossRef]
49. Choi, J.A.; Park, S.J. Examining Public Responses to Transgressions of CEOs on YouTube: Social and Semantic Network Analysis. *J. Contemp. East. Asia* **2024**, *23*, 18–34. [CrossRef]
50. Burgess, J.; Green, J. *YouTube: Online Video and Participatory Culture*, 2nd ed.; Polity: Cambridge, UK, 2018.
51. Shahbazi, Z.; Nowaczyk, S. Effective Elements of Climate Change Videos on the YouTube Platform. *Eur. Conf. Soc. Media* **2024**, *11*, 243–250. [CrossRef]
52. Monroe, M.C.; Plate, R.R.; Oxarart, A.; Bowers, A.; Chaves, W.A. Identifying effective climate change education strategies: A systematic review of the research. *Environ. Educ. Res.* **2017**, *25*, 791–812. [CrossRef]
53. Harmer, B. YouTube: Online Video and Participatory Culture. *Online Inf. Rev.* **2010**, *34*, 350–351. [CrossRef]
54. Bounegru, L.; De Pryck, K.; Venturini, T.; Mauri, M. "We only have 12 years": YouTube and the IPCC report on global warming of 1.5 °C. *First Monday* **2020**, *25*. [CrossRef]
55. Yang, J.; Leskovec, J. Patterns of temporal variation in online media. In Proceedings of the fourth ACM international conference on Web search and data mining (WSDM '11), Hong Kong, China, 9–12 February 2011; Association for Computing Machinery: New York, NY, USA, 2011; pp. 177–186. [CrossRef]
56. Ritter, C.; Goel, R.; Sharma, R. Decolonizing Newsmaking On Youtube: The Case of Climate Journalism During The Cop26 Summit. In Proceedings of the 23rd Annual Conference of the Association of Internet Researchers, Dublin, Ireland, 2–5 November 2022. [CrossRef]
57. Shapiro, M.A.; Park, H.W. More than entertainment: YouTube and public responses to the science of global warming and climate change. *Inf. Sur Les Sci. Soc. /Soc. Sci. Inf.* **2014**, *54*, 115–145. [CrossRef]
58. Biró, E. Linguistic identities in the digital space. *Acta Univ. Sapientiae Philol.* **2019**, *11*, 37–53. [CrossRef]
59. Kanavos, A.; Karamitsos, I.; Mohasseb, A. Exploring Clustering Techniques for Analyzing User Engagement Patterns in Twitter Data. *Computers* **2023**, *12*, 124. [CrossRef]
60. Kim, E.; Hara, N. Identifying Different Semantic Features of Public Engagement with Climate Change NGOs Using Semantic Network Analysis. *Sustainability* **2024**, *16*, 1438. [CrossRef]
61. Kaushal, A.; Acharjee, A.; Mandal, A. Machine learning based attribution mapping of climate related discussions on social media. *Sci. Rep.* **2022**, *12*, 19–20. [CrossRef] [PubMed]
62. Lendzen, R. Global Warming: The Origin and Nature of the Alleged Scientific Consensus. *Probl. Sustain. Dev.* **2010**, *5*, 13–28.
63. Koteyko, N.; Jaspal, R.; Nerlich, B. Climate change and 'climategate' in online reader comments: A mixed methods study. *Geogr. J.* **2012**, *179*, 74–86. [CrossRef]
64. Dayeen, F.R.; Sharma, A.S.; Derrible, S. A text mining analysis of the climate change literature in industrial ecology. *J. Ind. Ecol.* **2020**, *24*, 276–284. [CrossRef]
65. Chen, N. Exploring the Cognitive and Emotional Impact of Online Climate Change Videos on Viewers. *Sustainability* **2020**, *12*, 9571. [CrossRef]
66. Aharonson, V.; Joselowitz, J. On Presenters and Commenters in YouTube Climate Change Videos. *Eur. Conf. Soc. Media* **2024**, *11*, 9–12. [CrossRef]
67. Pastukhov, R.K.; Drobyshevskiy, M.D.; Turdakov, D.Y. Detecting Influential Users in Social Networks Based on Bipartite Comments Graph. *Tr. Instituta Sist. Program. RAN/Tr. Instituta Sist. Program.* **2022**, *34*, 127–142.
68. Yu, T.; Bai, L.; Guo, J.; Yang, Z. Construct a Bipartite Signed Network in YouTube. *Int. J. Multimed. Data Eng. Manag.* **2015**, *6*, 56–77. [CrossRef]
69. Alassad, M.; Agarwal, N.; Hussain, M.N. Examining Intensive Groups in YouTube Commenter Networks. In *Social, Cultural, and Behavioral Modeling. SBP-BRiMS 2019*; Lecture Notes in Computer Science; Springer International Publishing: Cham, Switzerland, 2019; pp. 224–233. [CrossRef]
70. Cho, S.E.; Jung, K.; Park, H.W. Social Media Use during Japan's 2011 Earthquake: How Twitter Transforms the Locus of Crisis Communication. *Media Int. Aust.* **2013**, *149*, 28–40. [CrossRef]
71. Song, M.; Jung, K.; Kim, J.Y.; Park, H.W. Risk Communication on Social Media during the Sewol Ferry Disaster. *J. Contemp. East. Asia* **2019**, *18*, 173–200.