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Digital Activism Masked—The Fridays for Future Movement and the "Global Day of Climate Action": Testing Social Function and Framing Typologies of Claims on Twitter

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Abstract: This article analyzed the Fridays for Future (FFF) movement and its online mobilization around the Global Day of Climate Action on 25 September 2020. Due to the COVID-19 pandemic, this event is a unique opportunity to study digital activism as marchers were considered not appropriate. Using Twitter's API with keywords "#climateStrike", and "#FridaysForFuture", we collected 111,844 unique tweets and retweets from 47,892 unique users. We used two typologies based on social media activism and framing literature to understand the main function of tweets (information opinion, mobilization, and blame) and their framing (diagnosis, prognosis, and motivational). We also analyzed its relationship and tested its automated classification potential. To do so we manually coded a randomly selected sample of 950 tweets that were used as input for the automated classification process (SVM algorithm with balancing classification techniques). We found that the automated classification of the COVID-19 pandemic appeared to not increase the mobilization function of tweets, as the frequencies of mobilization tweets were low. We also found a balanced diversity of framing tasks, with an important number of tweets that envisaged solutions to legislation and policy changes. COVID-related tweets were less frequently prognostically framed. We found that both typologies were not independent. Tweets with a blaming function tended to be framed in a prognostic way and therefore were related to possible solutions. The automated data classification model performed well, especially across social function typology and the "other" category. This indicated that these tools could help researchers working with social media data to process the information across categories that are currently mainly processed manually.

Keywords: climate change; Fridays for Future; social media; climate protests; social movements; framing

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1. Introduction

Social media, especially Twitter, are important sources of data for analyzing the public discourses on climate change (e.g., Veltri and Atanasova 2017), the information sharing behavior on protest events (e.g., Theocharis et al. 2015), and the dynamics of online polarization on climate change (Tyagi et al. 2020). The hybrid nature of social media between mass and personal media, or "Mass Self-Communication" (Castells 2009), has transformed the way individuals participate in social movements and changed the organization of collective action (Bennett and Segerberg 2012). New media are especially important when analyzing the involvement of young people in collective action and more recent and transnational social movements, such as the Fridays for Future (FFF).

The Fridays for Future is a climate movement that is unique for its appeal to young students, its mobilization power, and global success (Wahlström et al. 2019; De Moor et al. 2020). Despite the increased concern and knowledge about climate change, the evidence on the specificities of young people and climate change action is limited (Corner et al. 2015). Due to the use of social media by young people and their limited access to mainstream media, it is interesting to use social media data sources to learn more about the mobilization of young people across the globe for the climate and their demands for social action.

Different studies have relied on specific events related to climate change to gather social media information and to grasp the public and media discourses on climate change. For example, Hansen et al. (2011) focused on Climate Change Conferences (e.g., Copenhagen Climate Change Conference (COP15)). The publication of the United Nations Intergovernmental Panel on Climate Change (IPCC) working group reports have also received attention (e.g., Pearce et al. 2014; Newman 2017), as well as protest marches (e.g., Segerberg and Bennett 2011). We used this event approach to collect information on the Global Day of Climate Action that took place on 25 September 2020. Due to the COVID-19 pandemic, this event was a unique opportunity to study digital activism as marchers were considered not suitable.

To do so, we collected real-time tweets using Twitter's API with the keywords "#climateStrike" and "#FridaysForFuture" before and after the Global Day of Climate Action. We collected 111,844 unique tweets and retweets from 47,892 unique users during the event. Based on a literature review, we built two typologies of social media activism (information, opinion, mobilization, and blame) and framing tasks (diagnosis, prognosis, and motivational). We tested its automated classification potential and described the categorization results. We focused our analyses on tweets that were in English (9529 tweets) to reduce biases in the automated classification process. We manually coded a randomly selected sample of 950 tweets that were used as input for the automated classification process (Support Vector Machines (SVMs) algorithm with balancing classification techniques) and tested its classification potential through confusion matrix tables. We also performed an analysis of the most discriminant tweets. The use of social media information to analyze the Global Day of Climate Action on 25 September 2020 allowed us to integrate insights from social movement and framing studies. Simultaneously studying the functions and frames of tweets will help us to understand better the FFF movement in its social media tactics and representations.

This paper includes six sections. The next section reviews the literature. Section 3 includes information on the FFF social media use and Global Days of Climate. Section 4 presents the data and methods used. Section 5 presents the results of the analysis. The conclusion summarizes the main results of the paper.

2. Literature Review

Despite being a recent movement, the FFF has received some attention from the academic literature. Among these, there are two main streams of literature that are useful for analyzing social media information about this movement: (1) social media activism and (2) framing-oriented literature. However, we also pay attention to other approaches to the FFF movement (3).

2.1. Social Media Activism and the FFF: The Social Function of Tweets

Social movement studies have paid special attention to social media data to identify communities and to analyze the discourses of protest movements (e.g., Jost et al. 2018; Theocharis et al. 2015). Under the more general question about how and to what extent social media is shaping political participation and, particularly, non-conventional political participation, different studies reviewed the empirical evidence on diverse protest events across the globe. For example, Theocharis et al. (2015) applied a comparative content analysis on the use of Twitter in protest events in Spain, Greece, and the US, finding that Twitter was widely used for sharing information. However, contrary to the supposed mobilization power of social media, Theocharis et al. (2015) found that online calls for participation were infrequent, with a low number of tweets referring to organization and coordination issues. Similarly, Jost et al. (2018) reviewed the empirical evidence on protest movements that occurred in Turkey, Ukraine, the US, and Spain, finding that social media platforms facilitated the exchange of informational, emotional, and motivational content and that the structure of online social networks influenced the organizational efforts. Due to the transnational character of the climate movement and the young profile of the FFF protestors, it is interesting to study the specificities of the use of social media in the FFF movement.

Boulianne et al. (2020) followed this approach to study the FFF movement. They used Twitter to collect, through the #SchoolStrike4Climate hashtag, a total of 13,542 tweets. They manually coded a sample of 993 tweets to distinguish the spatial location (local, national, and global) and the social function of the tweets (information, opinion, mobilization, and attack). The last typology followed the GGI[1] codebook developed by Raynauld et al. (2016) to study the 2012 Student Strike against university tuition fee hikes in Quebec. Boulianne et al. (2020) found that the FFF tweets were more frequently used to share information and opinions, and that, like other movements (Theocharis et al. 2015), tweets considering mobilization requests were scarce. This study indicated that the global character of the climate change movement and the young composition of the FFF movement did not increase the mobilization function of tweets. However, it is interesting to know if the function of tweets of the FFF movement has changed due to the COVID-19 pandemic, for example, increasing its online mobilization function.

Literature on social media activism has frequently relied on Twitter as a source of information due, for example, to the composition of users and availability of data. However, other studies have focused on other social media, such as Instagram, to study the online mobilization patterns of the FFF movement. For example, Brünker et al. (2019) manually collected 1137 Instagram comments from two posts of Greta Thunberg and classified 439 according to three categories linked to the group identity theory (group cohesion, emotional attachment, and solidarity) finding that comments mainly expressed group cohesion ("us") and emotional attachment. These results are in line with evidence coming from the framing approach to social movement studies that we address in the following section. The framing approach shows the crucial role of emotions and motivational framing in explaining the success of mobilization in balancing the different framing tasks. In addition to the understanding of the different functions of social media content, it is important to understand how social media content is framed.

2.2. Framing the FFF Movement

Framing is a theoretical and methodological approach that has been applied in both communication research and social movement studies. It is considered a "fractured paradigm" (Entman 1993) within communication studies (Matthes 2009). Nonetheless, it has been dominant in the field over the last two decades when compared to other main approaches of media studies, namely, agenda-setting and priming (Weaver 2007). When defining a frame, media framing studies tend to use the work of Robert M. Entman (e.g., Entman 1993), William Gamson (e.g., Gamson 1992), and Todd Gitlin (e.g., Gitlin 1980) (Matthes 2009, p. 355). Frames refer to the "central organizing idea" "that provides meaning" (Gamson and Modigliani 1987) or "principles of selection, emphases and representation" (Gitlin 1980). Social movement studies have also used the framing approach,[2] and when doing so apply extensively the Snow and Benford (1988) work (Aslanidis 2012, p. 14). Snow and Benford (1988) pointed towards "three core framing tasks: (1) a diagnosis of some event or aspect of social life as problematic and in need of alteration, (2) a proposed solution to the diagnosed problem that specifies what needs to be done, and (3) a call to arms or rationale for engaging in ameliorative or corrective action" (Snow and Benford 1988, p. 199). They illustrated these with the peace movement.

The articles that study the FFF movement with a framing approach tend to refer to the work of Snow and Benford (1988). For example, Maier (2020) applied these categories in their qualitative frame analysis of 432 protest signs published on Facebook in 11 German cities in 2019. He found three main FFF frames: a policy "issue field" frame, an "intergenerational Justice" frame, and a "transnational" frame. It had the "issue field" frame as the main role in diagnostic and prognostic framing tasks, the "intergenerational justice" frame had an important role in the motivational task, and the "transnational" frame had a transversal role across tasking frames (Maier 2020, pp. 44–45). Other articles referring to Snow and Benford's work are Han and Ahn (2020) and Sorce and Dumitrica (2021). With a narrative analysis method applied mostly to speeches of Greta Thunberg, Han and Ahn (2020) explored the understanding of climate change of young activists and how to respond to it, pointing out that they had "succeeded in problematizing global climate inaction and inertia in framing climate change from a justice perspective" (p. 1). However, they pointed out that the FFF "faced limitations in converting their moral legitimacy into the power required for sweeping changes." Therefore, framing studies on the FFF indicate that certain more recent rationales for the climate change movement, such as the intergenerational justice issue, predominate in specific framing tasks (motivational). In addition, there is some indication that the three core framing tasks are not properly attended to or interconnected by the FFF movement.

Another analysis of the FFF movement that used the framing approach referred to Entman (1993) (instead of Snow and Benford) who, as mentioned, is one of the main cited framing authors in media studies (Matthes 2009). This is the case of Von Zabern and Tulloch (2021) who applied a content analysis on 85 news articles from three German newspapers to identify eight frames. They also found that German media tended to depoliticize the political agenda of the protest. Nonetheless, they also found that German media framed climate change towards intergenerational justice (Von Zabern and Tulloch 2021). Similarly, Huttunen and Albrecht (2021) studied how the FFF movement was represented in Finish newspapers and social media. While social movement studies tend to focus their framing exercises on the ability of the FFF movement to conduct the three core framing tasks, the media studies approach tends to use framing focusing on how the media portrays the FFF movement. The framing approach shows that the FFF movement, in particular, and the climate change movement, despite its diversity and global dimension, needs to be able to problematize climate change, provide solutions, and motivate change, while simultaneously, paying attention to how these different framing tasks are portrayed in media.

2.3. Other Approaches to the FFF Movement

As we have seen, social media data is useful for analyzing large and transnational protest movements, such as the FFF, as it allows the analysis of the function of social media posts and their framing tasks. Nonetheless, questionnaires to protestors have been also applied and provided additional information on the FFF movement (Wahlström et al. 2019; De Moor et al. 2020). The main advantage of questionnaires to protestors over social media data is that socio-demographic information can be accurately collected at the individual level. Due to this method, we know the important demographic characteristics of the protestors.

Wahlström et al. (2019) and De Moor et al. (2020) reported the results of a project that surveyed protestors attending the March 2019 and September 2019 FFF climate protests, respectively. The first report gathered a sample of 1905 survey responses from 13 European cities (Wahlström et al. 2019), while the second reached a sample of 3154 people covering 19 cities in 15 different countries around the world (De Moor et al. 2020). Both reports followed the "Caught in Act of Protest" survey methodology (Van Aelst and Walgrave 2001). This method provided important information on the sociodemographic characteristics of the FFF protestors and the degree of involvement in formal organizations. For example, we know that young protestors were over-represented (almost one-third were 19 or under in the September event), female presence was high (nearly 60%), and the level of education was high among adults and parents of protestors. Questionnaires to FFF protestors showed that both young and adults relied primarily on social media as a source for protest information (45% of young and 39% of adults) (De Moor et al. 2020, p. 18). Other studies have relied on these databases to provide a deeper understanding of the relationship between social background and strategic orientations (Della Porta and Portos 2023), or the continuities and changes of the FFF with previous climate activism (De Moor et al. 2021).

There are other articles that analyzed the FFF movement from other perspectives. For example, Zulianello and Ceccobelli (2020) used Greta Thunberg's speeches and performed a content analysis to understand to what extent her messages shared attributes of populism. Similarly, Albanese (2021), following the geographies of collective action of Meek (2012) and a narrative approach, combined web searches and symbols carried out on the strikes to understand the interrelation of territories and narratives in the identity formation of youngsters (Tapscott 2009) in the global climate strike in Italy. Articles analyzing the FFF movement were quite diverse in data sources used for their analysis, including questionnaires-survey to protestors (e.g., De Moor et al. 2020; Wahlström et al. 2019), discourses (e.g., Zulianello and Ceccobelli 2020; Maier 2020), mass media (e.g., Von Zabern and Tulloch 2021), and new media. Interestingly, new data sources, such as social media data (i.e., Twitter, Instagram, Facebook) were frequently used.

Most of the studies considered that rely on social media data used databases that had been manually coded. Manual codification of social media data increases insights as it allows to process data to obtain more sophisticated and meaningful categories, but considerably reduces the sample sizes. That is why we are also interested in testing how automated data classification processes could help to process social media data across categories and typologies based on the previous streams of literature. Increased availability of social media content codified across functions and framing tasks could help researchers, social movements, and policy-makers. For example, this could help researchers to improve their categorization techniques. It could help social movements identify issues that need to be addressed and taken care of, leading to an increase in mobilization. Finally, it could help policy-makers to collect information on possible solutions to climate change. Due to the young age of the FFF protestors, for whom other channels of political participation are not open (many of them do not have the minimum voting age), social media information could help to channel their demands and their integration into the public discourse. The young character of protestors reduces also the opportunities to access conventional mass media. The international character of the FFF movement also makes social media more relevant for addressing climate change in an international public arena.

Building on the review of the literature, our research questions are:

RQ1. *What are the functions of tweets (information, opinion, mobilization, and blame) within a COVID-19 context?*

Previous studies on the use of social media by social movements have shown that these movements widely rely on social media. However, these studies indicate that tweets are not mainly used for mobilization purposes, with other functions of tweets prevailing, such as providing information (e.g., Theocharis et al. 2015). Despite the young age of the FFF movement supporters, their use of social media follows the same pattern, with tweets having a low mobilization frequency (Boulianne et al. 2020). These findings appear to contradict the theories on the mobilization power of social media (e.g., Bennett and Segerberg 2012) that consider that social media decreases participation costs which should lead to increased collective action (Olson 1965). Having information on the use of tweets by the FFF movement (information, opinion, mobilization, and blame) (Boulianne et al. 2020), we wanted to know if the COVID-19 context alters the functions of the tweets. This context increased the cost of participation making social media more suitable.

RQ2. *What are the main frames of tweets (diagnosis, prognosis, and motivational)?*

Snow and Benford (1988) showed the importance of social movements in balancing the three framing tasks (diagnosis, prognosis, and motivational). That is why we wanted to know how the content of social media was framed by FFF protestors and how the COVID-19-related tweets were mainly framed according to these three framing tasks. Due to the diversity and the global dimension of the FFF and the climate change movement, it is relevant to know how the possible solutions are framed in terms of the main locus of change: systems, institutions, or individuals.

RQ3. *What is the relationship between the social function of tweets and their framing content?*

Social media has a hybrid nature; it is both mass and personal media (Castells 2009). Therefore, social movements, such as the FFF, use social media in a hybrid manner with different purposes ranging from organizing and mobilizing supporters to translating their messages to society. We treated tweets both as interpersonal means of communication and as mediated content. This treatment allowed us to bring together two branches of literature (social function of tweets and framing) and we wanted to see if they were related. The results on the uses of tweets (such as the low frequencies of mobilization tweets) could be related to the functions in which they are framed (diagnosis, prognosis, and motivational).

RQ4 (methods). *To what extent do automated data classification processes work across and between typologies (social function and framing typology)? What is the content of the most discriminant tweets (high predicted probability of belonging to a category)?*

We have seen that many FFF studies rely on social media data. However, most of them used manual coding which led to small sample sizes. That is why we wanted to know if the automated data classification process works across the categories built. As this process offers an approximation of belonging to a category, we wanted to know what the content of a more selective procedure (higher predicted probability) was.

3. Materials and Methods

3.1. Data Collection and Sample

We collected real-time tweets using Twitter's streaming API with keywords "#climateStrike" and "#FridaysForFuture" before and after the Global Day of Climate Action that took place on 25 September 2020. This event was organized by the school strike FFF movement, calling for a global climate action day. Due to the COVID-19 pandemic, this event was a unique opportunity to study digital activism as marches were considered not appropriate.[3] The two selected keywords were strategically chosen as "FridaysForFuture" identified the movement and "#ClimateStrike" was the hashtag suggested by the FFF movement for social media use. Possible alternative hashtags, such as, "#ClimateJustice" or #SchoolStrike4Climate" were not included, but picked up due to the use of multiple hashtags. The dataset was collected between 24 and 28 September 2020. Most of the interaction occurred on 25 September. We collected 111,844 unique tweets and retweets from 47,892 unique users. The Twitter API already ensures that appropriate consents are verified and does not allow access to users' private data. Additionally, the tweets were kept in a private repository, and in this paper, we worked with aggregated data (metrics, confusion matrix, percentages, etc.). Some examples of tweets in public accounts are shown in Appendix A, Table A2 while maintaining the anonymity of the users.

Tweets were reported in 45 different language codes (see Table A1 in Appendix A). English (9529) and German (6817) were the most frequent languages, representing 42.84% and 30.65% of the total tweets respectively (22,241, excluding retweets). Tweets with an undefined language represented 12.69% of the total, such as tweets that included only hashtags or URLs. Spanish (968 tweets—4.35%), Japanese (483—2.17%), Italian (268—1.2%), and French (241—1.08%) followed with less than 5% of total tweets. The remaining languages showed percentages lower than 1 percent.

We limited the coding process to English. The proper application of machine learning algorithms necessitates training a model for each of the presented languages because this allows the algorithms to obtain a more precise identification of the words/sets of words that correspond to each category. Training an algorithm with multiple languages yields poor results. Therefore, English was chosen due to being the language that had the highest frequency and impact on the debate. Therefore, our final sample consisted of 9529 tweets.

3.2. Data Codification

The coding process followed the next procedure: After building the codebooks on the literature, we tested them using two sets of twenty randomly selected tweets. After resolving doubts and inconsistencies across coders, an improved codebook was manually applied over a randomly selected sample of 950 tweets. Finally, an automated classification process was applied. Tweets can have different functions or frames. As this was the case, we classified the tweets according to the dominant function and frame, following previous exercises (see below). We applied two coding schemes to each tweet according to the social function of the tweet and its dominant frame. "Social" and "framing" coding schemes were based on previous studies. The social codebook was developed for analyzing the 2012 student strike in Quebec (GGI codebook) by Raynauld et al. (2016) and further applied by Boulianne et al. (2020) to analyze the FFF student strike on 15 March 2019. Following their procedure, categories were considered mutually exclusive. The main five categories of the social typology were information tweets; opinion tweets; mobilization tweets; blame tweets; and other types of tweets that comprised tweets that do not belong to previous categories. These categories included the following subcategories that were also adapted from Boulianne et al. (2020) for this study (Table A2 in Appendix A includes examples of tweets across categories of social function typology).

The information category (1) included tweets that pertained to the subcategories of (1.1) tweets documenting the protest or about an issue of the event directly related to the strike[4], (1.2) news reports related to the strike, and (1.3) tweets sharing climate or environmental information. The category of (2) opinion tweets was comprised of (2.1) tweets expressing an opinion about the protest, (2.2) tweets expressing an opinion about climate change, and (2.3) tweets expressing an opinion about the youth or young protesters[5]. Following Boulianne et al. (2020), and based on Merry (2013) and Hodges and Stocking (2016), mobilization tweets included (3.1) online request tweets and (3.2) offline request tweets. Similarly, the blaming subcategorization followed Boulianne et al. (2020) based on Merry (2013) However, differently to Boulianne et al. (2020), we added a new blaming subcategory including companies. Therefore, the blame tweets category (3) included (3.1) tweets blaming the government, (3.2) tweets blaming the media, or (3.3) tweets blaming companies. Finally, we identified an important number of tweets that used the mobilization hashtags for marketing purposes. Therefore, the category of other tweets (5) included (5.1) tweets that were not about the strike or climate change and (5.2) marketing purposes tweets.

These subcategories were merged in the automated classification process as the number of manually detected tweets in several subcategories was very low for using them as input in the automated process.

The framing codebook was adapted from several studies that focused on FFF and built categories on collective action framing theories (Snow and Benford 1988), such as Wahlström et al. (2013) and Maier (2020). Different from them, we used tweet content instead of survey questions on solutions (Wahlström et al. 2013) or protest signs published on Facebook (Maier 2020). Our main framing categories were (1) tweets that focused on the diagnosis (tweets that define what the problem is), (2) prognosis (tweets that include possible solutions to the problem), (3) motivational (tweets that provide a rationale for engaging), and (4) other (Table A3 in Appendix A includes examples of tweets across categories of framing typology). These main categories followed the classic Snow and Benford (1988) approach to study mobilization and framing tasks. We also distinguished different framing solutions following Wahlström et al. (2013) and broke down the prognosis category of tweets into (2.1) tweets that framed the solutions on individual actions or aware-raising initiatives, (2.2) tweets that framed the solution on system-oriented changes, and finally (2.3) tweets that framed solutions on legislation and policy changes. These prognosis subcategories were also merged for the automated classification process for the same reason.

We also identified COVID-related tweets by identifying in which tweets "COVID" was mentioned.

Automated Classification Process

For preprocessing the tweets, we employed the Python libraries Gensim and NLTK. The tweets were tokenized and stop-words were removed. The text-cleaning process ensured optimal analysis. The initial step involved standardizing the text by removing uppercase letters, special characters, punctuation, numbers (if irrelevant), URLs, or double spaces. Subsequently, tokenization was applied, which entailed segmenting the text into its linguistic units, using unigrams in this case. This means that the text was divided into all the different words it contained. Due to the high frequency of occurrence of tokens (linguistic units) that lack relevance, such as determiners, prepositions, auxiliary verbs, etc., known as stopwords, they were eliminated. This process ensured the ability to work with words as the unit of analysis, where their potential contribution to the text was deemed relevant. Also, tokens with a frequency of less than five occurrences or above 75 percent of the tweets were removed. A total of 553 words were found relevant to these criteria. Finally, each tweet was converted into a numerical vector of 553 values, that contained for each relevant word the number of occurrences of the word in the tweet.

With this dataset of about 1000 rows and 553 columns, we tried different supervised machine-learning methods with different values for the hyper-parameters included in the Python library scikit-learn. SVMs were the machine learning algorithms that showed the best results, surpassing neural networks, multiclass logistic regression, decision trees, random forests, or naive Bayes algorithms in this task. Considering the critical importance of accurate classification, we opted for SVM due to their superior performance both on the Cohen's Kappa and on the F1 score, measurements that balance sensitivity and specificity compared to the other methods. The results are the average of 1000 experiments. For each experiment, we calculated Cohen's Kappa and F1 measures to record the performance of the model. In particular, we obtained the best results with the regularization parameter C equal to 0.7.

3.3. Methods

Our section on results includes descriptive statistics across typologies and tests on their bivariate relationship (Chi-square test and V-Cramer). In addition, it includes the results of Confusion matrix tables that describe the performance of the supervised classification model across typologies, including the Kappa and F evaluation metrics. We tested the difference in the performance between typologies using a *t*-test on the mean of the result of a 1000 times experiment. Finally, we detected and analyzed the most discriminant tweets. To convey the most representative content of each category, we selected messages with a predicted probability belonging to the last decile per category (90% or higher).

4. FFF Social Media and Global Days of Climate

In August 2018, a 15-year-old Swedish girl named Greta Thunbergs and other student activists started a school strike for the climate outside the Parliament of Sweden (FFF 2021). This was the starting point of what is currently known as the FFF movement. In 2021, the movement reported actions in 7500 cities across all continents that gathered more than 14 million people (FFF 2021, April 27). Social media actions have been present in the FFF movement since its inception. FFF web pages recognize the importance of social media activity since the initial actions: "She posted what she was doing on Instagram and Twitter and it soon went viral" (FFF 2021, April 27). Greta's Twitter and Instagram pages were launched in June 2018 and reached, in 2021, a total of 11 million followers on Instagram and 5 million on Twitter (Instagram and Twitter 27 April 2021). Facebook's public figure page was launched on 7 December 2018 and reached 3 million followers in 2021.

The following graph indicates the number of FFF events worldwide, including countries, cities, and people (see Figure 1). The data clearly shows a decrease in mobilization activity of the FFF in 2020, indicating that COVID-19 had, importantly, impacted the figures of the FFF movement. This data shows that the Global Day of Climate Action of 25 September 2020 was the most successful mobilization day after the COVID-19 crisis in 2020 in terms of countries, cities, and events and with roughly the same number of people as on 24 April 2020 (see Figure 1).[6] The number of countries involved over the period confirms that the FFF is a transnational movement that has helped to provide a new impetus to the Climate Justice movement. FFF figures show a total of 156 countries were involved in the 20 September 2019 actions within the "Global Week for Future" (20–27 September) that was organized around the United Nations Climate Summit (see Figure 1). This figure represents the peak in the number of countries involved in Global Days of Climate Justice Actions (since 2005), surpassing the previous peak of 2014 reported by Chase-Dunn and Almeida (2020, p. 81) with the occasion of the UN Climate Summit.

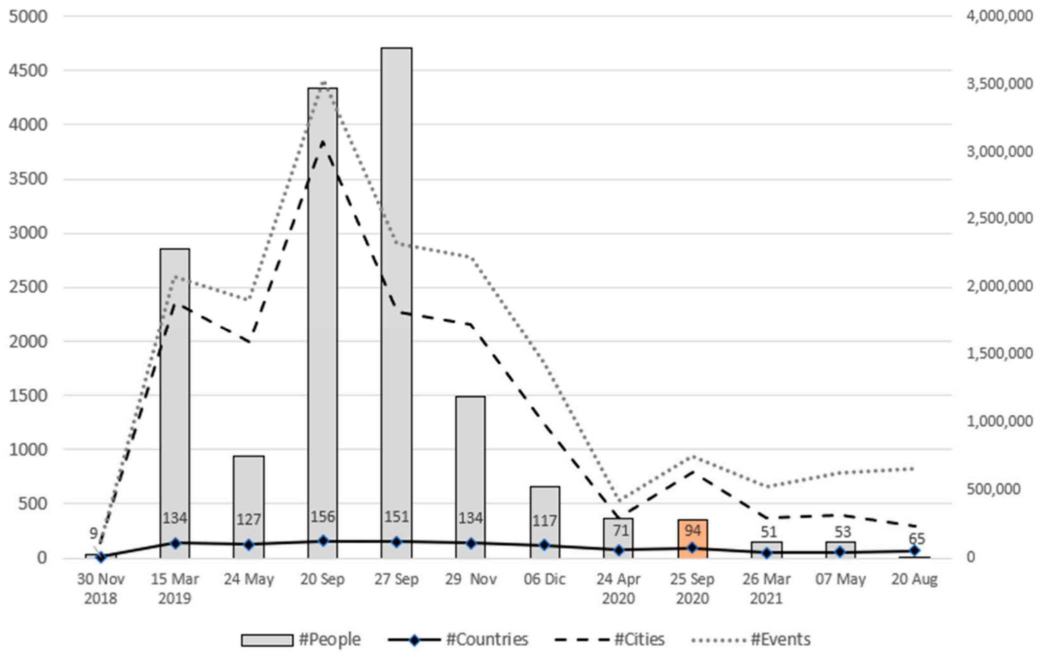

Figure 1. Number of people (right axis), countries, cities, and events (left axis) of FFF mobilization actions (2018–2021). In orange, the mobilization day studied. Own elaboration with FFF data, extracted on 20 August 2021.

Global Days of Climate follows the transnational organizing model "Global Days of Action" of the Justice movement (Wood 2004; Chase-Dunn and Almeida 2020). This innovative organizing model involved "mobilizing a massive series of actions at the focal conference/summit/financial meeting while simultaneously holding dozens of solidarity actions across the globe" Chase-Dunn and Almeida (2020, p. 76). Increasing the availability of internet access makes social networks more important for mobilization purposes. In 2000, the climate movement became more contentious in arranging marches and rallies across the world with the occasion of United Nations Climate Summits and COP meetings (Garrelts and Dietz 2014). Climate movement is the "most extensive social movement on the planet in terms of the capacity to hold multiple and simultaneous global actions" (Chase-Dunn and Almeida 2020, p. 74). This movement was, importantly, expanded by the FFF strikes (Chase-Dunn and Almeida 2020; De Moor et al. 2020).

5. Results and Discussion

5.1. Descriptive Statistics and Bivariate Relationship

The distribution of tweets of the Global Day of Climate Action of 25 September 2020, across main functions showed that the most frequent function of tweets was expressing an opinion (45.9% see Table 1), followed by sharing information (24.1%), attributing blame (10.6%) and mobilizing support (7.9%). An important share of tweets (11.5%) had other functions, with marketing purposes a dominant share of these "other" tweets. Across the subcategories, "documenting and sharing information about an issue or event related directly to the strike" was the most frequent subcategory for the "information" function, sharing an opinion about the protest or climate change showed similar frequencies within the "opinion" function, blaming the government dominated within the "blaming" category, and offline mobilization requests tweets were rare within the "mobilization" category. A total of 5% of the tweets referred to COVID-19 (include the word "COVID" in the text). The distribution of tweets across the main functions was quite similar across COVID and non-COVID-related tweets, except for tweets attributing blame and other tweets. Tweets attributing blame were less frequent when COVID-19 was taken into consideration. However, the difference was not statistically significant. The low frequencies of COVID-related Tweets attributing blame might have affected the lack of significance of this category. The lack of significance of the differences between COVID and non-COVID-related tweets indicated that COVID-19 content did not alter the main functions of the tweets (Opinion and Information) and did not appear to increase its mobilization function.

Table 1. Frequency and percentage of tweets and COVID-related tweets across social function typology.

	COVID		No COVID		Total	
	N	%	N	%	N	%
1. Information	**12**	**23.1%**	**217**	**24.2%**	**229**	**24.1%**
1.1 Documentation tweet or tweet about an issue or event related directly to the strike	7	13.5%	165	18.4%	172	18.1%
1.2 News reports related to the strike	0	0.0%	21	2.3%	21	2.2%
1.3 Climate/environmental information tweet	5	9.6%	31	3.5%	36	3.8%
2. Opinion	**23**	**44.2%**	**413**	**46.0%**	**436**	**45.9%**
2.1 Opinion about the protest	11	21.2%	186	20.7%	197	20.7%
2.2 Opinion about climate change	7	13.5%	182	20.3%	189	19.9%
2.3 Opinion about youth or young protesters	5	9.6%	45	5.0%	50	5.3%
3. Mobilization	**4**	**7.7%**	**71**	**7.9%**	**75**	**7.9%**
3.1 Online mobilization request	3	5.8%	63	7.0%	66	6.9%
3.2 Offline mobilization request	1	1.9%	8	0.9%	9	0.9%
4. Attack/Blame	**3**	**5.8%**	**98**	**10.9%**	**101**	**10.6%**
4.1 Attack/blame government	3	5.8%	83	9.2%	86	9.1%
4.2 Attack/blame media	0	0.0%	4	0.4%	4	0.4%
4.3 Attack/blame companies	0	0.0%	11	1.2%	11	1.2%
5. Other	**10**	**19.2%**	**99**	**11.0%**	**109**	**11.5%**
5.1 Not about strike or climate change	1	1.9%	37	4.1%	38	4.0%
5.2 Marketing	9	17.3%	62	6.9%	71	7.5%
TOTAL	**52**			**989**	**950**	

Totals of the main categories in bold.

These results showed similarities with other protest events (Boulianne et al. 2020; Theocharis et al. 2015; Raynauld et al. 2016). As expected, and despite the COVID-19 context, mobilizing tweets were scarce. The share of tweets that had a blaming function was also similar to other studies (e.g., Boulianne et al. 2020; Raynauld et al. 2016). However, differently to Boulianne et al. (2020) and Raynauld et al. (2016), we found that the primary function of tweets was to express an opinion instead of sharing information. This difference could be explained by context-related reasons or methodological reasons. The specificities of the context, with street marches being considered inappropriate due to the COVID-

19 crisis, could have increased the need to express the opinion of supporters about the protest or climate change. There could be also a methodological reason behind these different results. Boulianne et al. (2020) used a tool that limited the scraps per query to the 1000 most recent tweets, repeated the search several times (Netlytics), focused on a different hashtag (#ShoolStrike4Climate), and codified the most frequent tweets, while we scrapped continuously, used two hashtags (#climateStrike and #FridaysForFuture), and manually codified a random sample. To test if the selection of the most frequent tweets changed our result, we checked the distribution of tweets across the main categories for highly retweeted tweets and found similar results with opinion tweets being dominant. Haßler et al. (2021) showed that COVID-19 had changed the relative frequencies of some hashtags, but this difference did not alter the top frequency of our selection of hashtags. Our distribution of tweets that referred to COVID-19 indicated that the distribution of functions was similar to those that did not mention it. The low frequencies of the mobilization tweets (COVID-19-related or not) might raise certain reservations about an over-optimistic view of the influence of social media on collective action. However, this does not imply that we should interpret the results in terms of "Slacktivism" (e.g., Morozov 2009). Information-sharing behavior requires effort and social exposure that cannot be diminished (e.g., Halupka 2018). Similarly, opinion-sharing behavior requires similar efforts that, as we show below, also frequently offer possible solutions.

Considering the framing typology of tweets (see Table 2), the highest percentage of tweets belonged to the motivational framing category (39.2%), followed by the prognosis and the diagnosis categories with 26.8% and 21.8% of tweets, respectively. Regarding the subcategories of the different solutions to the problems (prognosis), nearly half of the prognosis tweets focused on legislation and policy change solutions, followed by system-oriented solutions and solutions focused on individual action and awareness raising. These results could be compared to other climate change studies, such as Wahlström et al. (2013), that also found an important percentage of individual opinions framing how to solve the climate crisis on legislation and policy changes. Considering the COVID-related tweets and their distribution across frames, COVID-related tweets were less frequently prognostically framed, with the difference statistically significant, χ^2 (1, N = 834) = 2.769, $p = 0.096$. This could indicate that the FFF movement had problems integrating climate change frames with COVID-19 issues when envisaging possible solutions. The solutions offered by the FFF movement included a different locus of change (institutional, systems, or individual) showing the diversity of the movement. However, the high percentage of possible solutions based on legislation and policy change appeared to indicate a reliance on current institutions to provide solutions to climate change over systemic changes.

Table 2. Frequency and percentage of tweets and COVID-related tweets across framing typology.

	COVID		No COVID		Total	
	N	%	N	%	N	%
1. Diagnosis	**14**	**26.9%**	**193**	**21.5%**	**207**	**21.8%**
2. Prognosis	**8**	**15.4%**	**247**	**27.5% ***	**255**	**26.8%**
2.1 Individual action-oriented/awareness-raising	3	5.8%	53	5.9%	56	5.9%
2.2 System oriented	3	5.8%	71	7.9%	74	7.8%
2.3 Legislation and policy change	2	3.8%	123	13.7%	125	13.2%
3. Motivational	**20**	**38.5%**	**352**	**39.2%**	**372**	**39.2%**
4. Other	**10**	**19.2%**	**106**	**11.8%**	**116**	**12.2%**
TOTAL	**52**		**898**		**950**	

Note: * $p < 0.1$. Main categories in bold.

Retweet metrics on individual posts across typologies indicated that motivational tweets tended to be retweeted less frequently across typologies, showing a low average of retweets. Tweets attributing blame showed the highest average of retweets, but this was due to the presence of outliers. Similarly, outliers were present in the diagnosis and prognosis category of framing typology. Differences in retweet metrics across categories for social function and framing typologies were not statistically significant due to the high dispersion of data (see Figure A1 for Box plots and error bars of the number of average retweets across typologies in Appendix A). COVID-related tweets were less frequently cited, replicated, retweeted, and marked as favorites than non-COVID-related tweets.

Table 3 shows the results of the relationship between social function and framing typologies. We observed that most of the mobilization tweets belonged to a motivation framing category (84% of mobilization tweets). Tweets with an information function also tended to be mostly framed in a motivational way (67% of information function tweets belonged to a motivational framing category). However, blaming function tweets could be mostly considered prognostic framing, and therefore related to possible solutions. Curiously, opinion tweets were framed in quite diverse ways, with similar percentages across framing categories of around 30–35 percent. As mentioned above, this shows that tweets that share opinions gained value when considered below the lens of the different framing tasks. In addition to sharing values, they also were able to define problems, envisage solutions, and mobilize people. The relationship between the different categories of the social function and framing typologies were significantly different (Chi-square test) and, therefore, were not independent. The level of association was low to moderate according to the V Cramer.

Table 3. Relationship between social function and framing typologies.

	Diagnosis		Prognosis		Motivational					Total	
	%	N	%	N	%	N	Chi^2	*p*	V Cramer	%	N
Information	20.8	46	12.2	27	67	148 ***	68.801	0.000	0.287	26.5	221
Opinion	29.4	128	34.2	149	36.5	159 ***	25.009	0.000	0.173	52.3	436
Mobilization	1.3	1	14.7	11	84	63 ***	53.813	0.000	0.254	9	75
Attack/Blame	31.7	32	66.3	67	2	2 ***	97.054	0.000	0.341	12.1	101
TOTAL		**207**		**255**		**372**					**834**

Note: *** $p < 0.01$. Totals of the main categories in bold.

To further explore the relationship between the social function typology and the framing typology we explored the engagement values of cross categories (see Table 4). The results indicated that tweets with an information function that were framed in a prognostic way were retweeted more frequently than tweets that were framed in a diagnostic way. However, tweets with an opinion function that were framed in a diagnostic way were tweeted more frequently than tweets that were framed in a motivational way. Due to the non-parametric distribution of data across groups, we tested the significance of these results with a Kruskal-Wallis test (see Figure A2 in Appendix A).

Table 4. Retweets scores across social function and framing typology.

	Diagnosis		Prognosis		Motivational		Total	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Information	4.91	23.46	32.26	98.83	99.70	589.07	71.73	483.73
Opinion	126.14	1000.63	326.75	3739.82	13.35	93.01	153.57	2252.04
Mobilization	88.00	.	0.90	0.30	12.75	52.73	11.89	49.29
Attack/Blame	4341.59	24,469.32	0.54	2.21	0.00	0.00	1375.91	13,774.31

Totals of the main categories in bold.

5.2. Performance of the Classification Model across Typologies

This section presents the results of the automated classification model across social function and framing typologies. Figure 2a,b shows the confusion matrix results that allowed us to compare the performance of the classification model across social function and framing typologies. These were generated with the support vector machine model.

In each experiment, 70% of the data was used to train and the remainder 30% was used for the test, comparing the predicted category (Pred.) with the true values that corresponded to the human labels (Real). The values of the confusion matrix and the evaluation metrics of the model (i.e., Kappa and F1) showed the averages of the result from the 1000 times experiment. We applied class rebalancing techniques as the frequency of values across classes (categories) was unbalanced (Synthetic Minority Oversampling Technique (SMOTE)). Different techniques were applied, such as oversampling, with no different impact on the results.

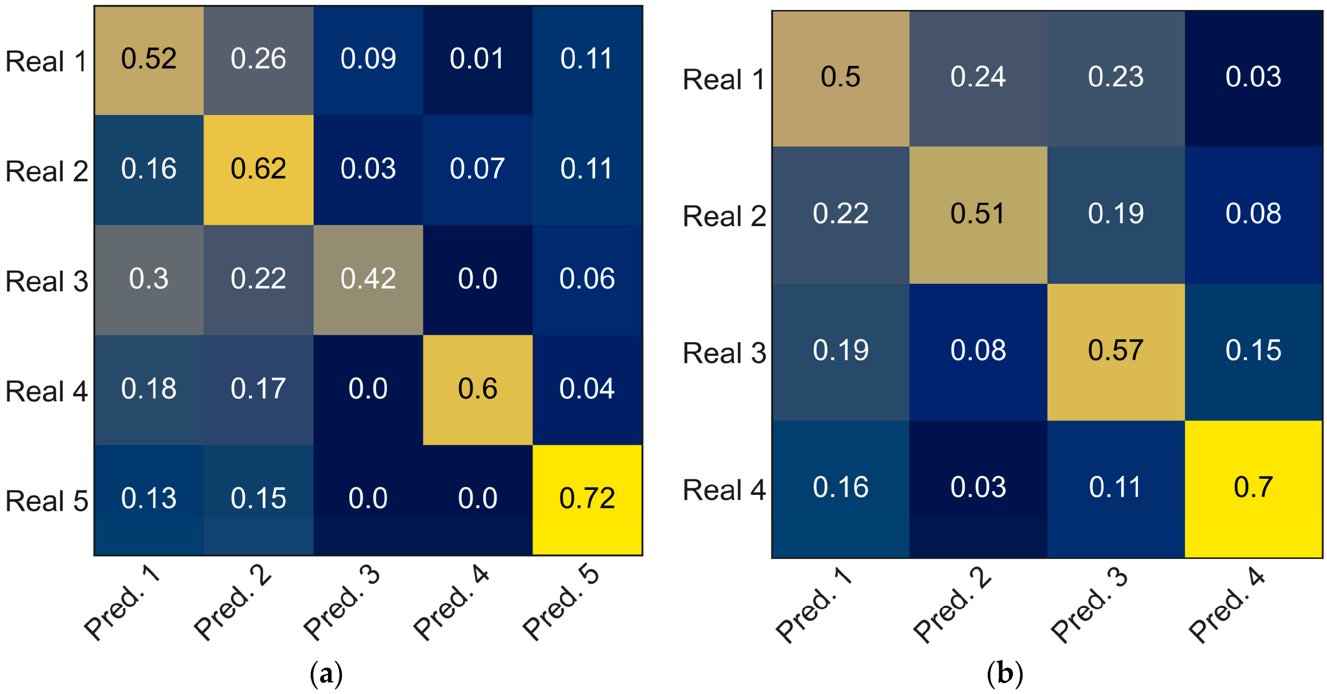

Figure 2. (**a**) Confusion matrix (social function typology). Evaluation metrics: Kappa, 0.43; F1, 0.60 SVC (C = 0.7, Kernel = 'linear'); (**b**) Confusion matrix (framing typology). Evaluation metrics: Kappa, 0.39; F1, 0.56.

The results showed that the "other" category was accurately predicted for both typologies, with an agreement of real and predicted values of 0.72 and 0.7 for social function and framing typology, respectively. This means that 72% of "Other" cases were successfully predicted by our model for the social function typology. This indicates that automated data classification techniques could help researchers to clean their data. The values of successfully predicted categories were always higher than 0.5, except for the third category of the social function typology ("mobilization") with a value of 0.42. This "mobilization" category had the lowest real frequency (n = 75). Confusion matrixes also allow us to know where the confusion arose from. In the case of the "mobilization" category of social function typology (Figure 2a), we see that our model wrongly predicted the real third category, especially with the first (0.3) and second category (0.22), namely the "information" and "opinion" categories. Figure 2a also indicates that the "opinion" category was accurately predicted 62% of the time on average. This category also captured a good part of the rest of the wrongly predicted categories. This category had the highest real frequency (n = 436). It is also worth noting that the "blame" category was accurately predicted 60% of the time on average, despite having low real frequencies (n = 101).

Regarding framing typology (Figure 2b), the three categories besides the "Other" category showed quite similar results. On average, around 50% correctly predicted the probability. The third category ("motivational" framing) was the best performing of these categories (0.57). This category had the highest real frequency (n = 372). The first category ("diagnosis") showed the highest values of wrongly predicted values, indicating that this category was usually confused with the second ("prognosis") and third ("motivational") by the model.

The evaluation metrics of the mode" for each typology were correct and showed values from fair to moderate (social function typology: Kappa 0.43, F1 0.60; framing typology: Kappa 0.39, F1 0.56). The difference between the average performance between typologies was significantly different social function typology (M = 0.43, SD = 0.000259) and framing typology (M = 0.39, SD = 0.000329), *t*-student (1000) = 56.50, p <0.001, indicating that the performance of the model in the social function typology was better than the performance for the framing typology.

5.3. Detection and Analysis of the Most Discriminant Tweets

As we have seen in the previous section, the predicted probability of the different categories varied across typologies. This section focuses on the content of the most discriminant tweets, those with a predicted probability belonging to the last decile, 90% to 100%, per category (see Tables A2–A5 in Appendix A). This allowed us to analyze the most representative content of each category. We used the Support Vector Machines (SVMs) algorithm as a supervised learning method (cost = 0.5 for social function typology and cost = 0.1 for framing typology). We considered words with a minimum frequency of five in the global corpus and that appeared, at least, in 3 tweets. Once these tweets were selected, we deleted the stopwords, reaching the number of tweets, words, and different words per category by social function (Table 5) and framing typology (Table 6).

Table 5. Number of most representative tweets, words, and different words across categories of social function typology.

Grupo	N_Tweets	N_Words	N_Different_Words
Information	60	960	533
Opinion	8	140	92
Mobilization	246	3927	1883
Attack/Blame	199	2990	1510
Other	206	3085	1542

Table 6. Number of most representative tweets, words, and different words across category framing typology.

Grupo	N_Tweets	N_Words	N_Different_Words
Diagnosis	30	602	430
Prognosis.	5	104	89
Motivational	1	17	16
Other	80	1492	954

The following figures represent word clouds across categories and typologies. The top-10 list of most frequent words across categories and typology are in Appendix A (Tables A4 and A5). There were several words that were common across categories. For example, "climate", "fridaysforfuture", "climatestrike", "global", "today", "action", and "gretathunberg". These words were essential for all discriminant tweets and referred to the identity of the FFF movement ("Fridaysforfuture"), the action ("climatestrike"), its character ("global"), a call for action ("today" and "action"), and its leader ("gretathunberg"). These were also dominant in the "Information" category of the social function typology (Figure 3). The "Opinion" category included distinct concepts such as the nouns "activists", "emissions", and "industry", and the adjective "responsible". It also included references to places like Karnataka, a region of India affected by climate change. Other places, such as Berlin, Bristol, Ullapoo, and countries such as India or Australia appeared in this category, together with climate activist, Ridhima Pandey. © "mobilization" category singled out the verb "join" and more direct calls for actions (i.e., "fightclimatejustice"). Finally, the "Attack/blame" category included references to justice, youth, or Trump.

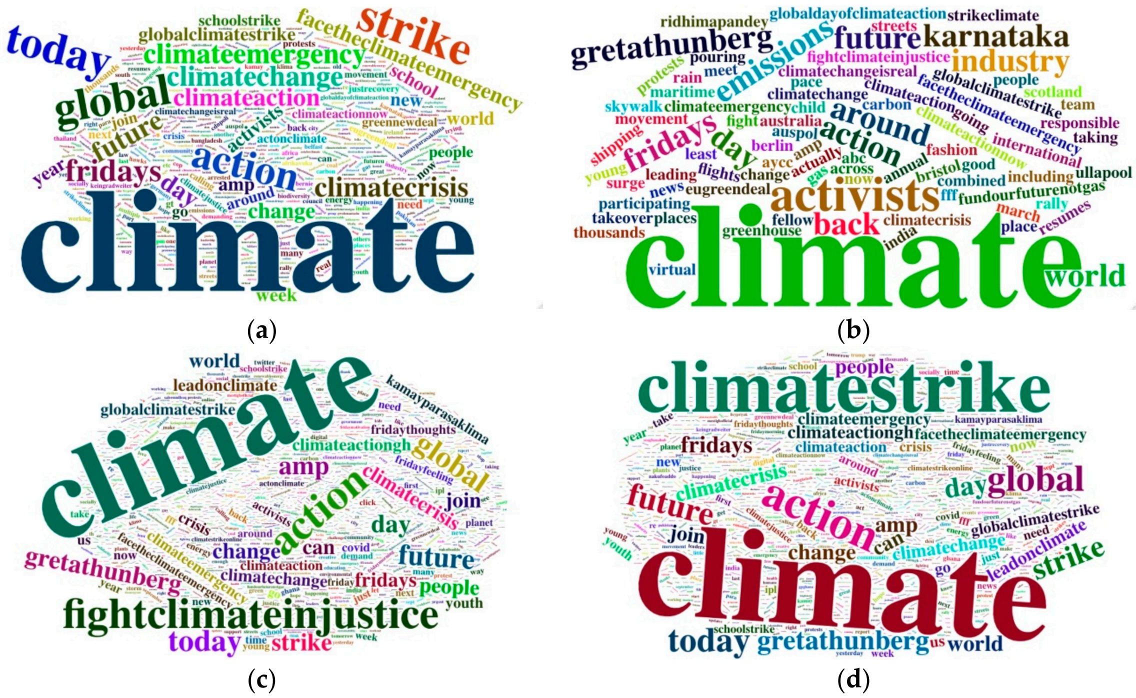

Figure 3. Word clouds across categories of social function typology: (**a**) Information; (**b**) Opinion; (**c**) Mobilization; (**d**) Attack/Blame.

Regarding the framing typology (Figure 4), the concept of "COVID" emerged more clearly in both the "diagnosis" and "prognosis" categories.

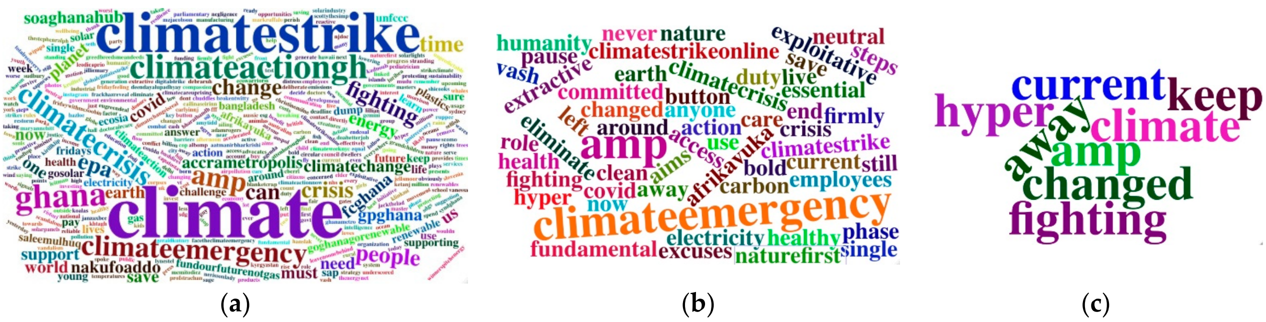

Figure 4. Word clouds across categories of framing typology: (**a**) Diagnosis; (**b**) Prognosis; (**c**) Motivational.

6. Conclusions

This article analyzed the social media use of the FFF climate movement on the Global Day of Climate Action held on 25 September 2020. The analysis of the social media activity of this movement is especially relevant due to its transnational character and the young profile of protestors (Wahlström et al. 2019; De Moor et al. 2020). It is recognized that the FFF has provided new momentum to the climate movement (Chase-Dunn and Almeida 2020; De Moor et al. 2020). Social media data allows young people around the globe to share their opinions and is the preferred method to get information (Wahlström et al. 2019; De Moor et al. 2020). Social media is especially relevant as young protestors have fewer opportunities to access conventional political participation forms, such as voting, and have also fewer opportunities to access traditional mass media. In addition, the COVID-19 pandemic made the analysis of social media activity of this movement more relevant.

The literature review on the FFF movement has allowed us to identify two main streams of literature that are especially relevant to analyzing social media data: social media activism and framing literature. From this literature review, we identified two relevant typologies: the social function typology and the framing tasks typology. Social function typology has allowed us to measure how tweets are used, compare these results with previous studies, and test if COVID-19-related context and content alter the uses of tweets, increasing the mobilization power of social media. The framing typology has allowed us to see if the FFF movement is able to balance the three framing tasks (diagnosis, prognosis, and motivational) (Snow and Benford 1988) in its social media content and how COVID-19-related tweets are framed according to these tasks. The combination and comparison of the two typologies have helped us to deal with the hybrid nature of social media and to treat tweets both as interpersonal means of communication and as mediated content that helps social movements simultaneously organize, mobilize, and translate their messages to society. The literature review on the FFF movement has also revealed a diversity of sources of data used. Social media data is frequently used as a data source for the study of the FFF movement, but we found that this data is usually manually coded, leading to a small final sample size. This evidence encouraged us to test the potential of automated classification processes across typologies.

These typologies were tested using the following data. We collected 111,844 unique tweets and retweets from 47,892 unique users Through Twitter's API with the keywords "#climateStrike" and "#FridaysForFuture" before and after the Global Day of Climate Action of 2020. We focused our codification process on English language tweets that represented a total of 9529 tweets and 42.87% of total tweets. We tested the codebooks with 20 randomly selected tweets and manually coded 950 randomly selected tweets. These tweets were used as input for the automated classification process that relied on the Support Vector Machines algorithm as a supervised learning method (Kernel lineal) with balancing classification techniques (i.e., SMOTE).

The analysis of the distribution of tweets across social function categories showed that tweets were not frequently used to mobilize support, being more frequently used to express an opinion, share information, or attribute blame. These results showed similarities with other FFF protest events (i.e., Boulianne et al. 2020) and other protest events (e.g., Raynauld et al. 2016; Theocharis et al. 2015). These results led us to conclude that the COVID-19 context has not increased the mobilizing function of tweets on the Global Day of Climate Action on 25 September 2020. The share of tweets that have a blaming function was also similar to other studies (e.g., Boulianne et al. 2020; Raynauld et al. 2016). However, differently to Boulianne et al. (2020) and Raynauld et al. (2016), we found that the primary function of tweets was to express an opinion instead of sharing information. We found a balanced diversity of framing tasks (diagnosis, prognosis, and mobilization), with an important number of tweets that envisaged solutions to legislation and policy changes. These results could be compared to other climate change studies, such as Wahlström et al. (2013), that also found an important percentage of individual opinions framing how to solve the climate crisis on legislation and policy changes. We found that there was a relationship between the social function of tweets and their framing content (the typologies were not independent). For example, mobilization tweets were mostly framed in a motivational fashion, while tweets that attributed blame tended to be associated with prognostic framing relating to possible solutions. This indicates that social media messages that could be considered negative for institutional powers, such as those attributing blame to governments, companies, or traditional media, could also help policy-makers find solutions to climate change and increase the support of young people. We found that the solutions offered by the FFF movement included a different locus of change (institutional, systems, or individual), showing the diversity of the movement. In any case, the high percentage of possible solutions based on legislation and policy change indicated that the FFF movement relied on current institutions to provide solutions to climate change over systemic changes. Interestingly, we found that mobilization and motivational tweets were retweeted less frequently and, therefore, had less connective power. The low frequencies of the mobilization tweets (COVID-19-related or not), and the low engagement of mobilization and motivational tweets, raised some concerns about an over-optimistic view of the influence of social media on collective action. However, we also distanced ourselves from interpretations in terms of "Slacktivism" (e.g., Morozov 2009) that diminished social 'media's contribution to social mobilization. Information and opinion-sharing behavior requires effort and social exposure that cannot be diminished. By combining both typologies (social function and framing) we were able to see opinion-sharing behavior with a new lens. Tweets with the function of sharing values also importantly contribute to the different framing tasks by defining problems, envisaging solutions, and motivating people. The tests on the performance of the automated data classification process across typologies indicated that the classification model for each typology worked well, with values from fair to moderate (social function typology: Kappa 0.43, F1 0.60; framing typology: Kappa 0.39, F1 0.56). We found a significantly better performance of the model across the social function typology. The confusion matrix results of the average of the results of a 1000 times experiment (the random forest machine learning algorithm and class rebalancing techniques SMOTE) showed that the model predicted, with high accuracy levels, the "other" category across typologies and indicated where the confusion arose from. This indicates that these methods could especially help for cleaning purposes and refining typologies, allowing researchers to enlarge their codified data samples. We were also able to identify general (essential) and specific words of most discriminant tweets (messages with a predicted probability of belonging to the last decile per category (90% or higher)) considering words with a minimum frequency of five and that appeared at least in three tweets. These lists of the most discriminant words could help researchers in their codification tasks and stakeholders for communication purposes.

Other recent studies that have analyzed the FFF movement under the COVID-19 pandemic (e.g., Haßler et al. 2021; Sorce and Dumitrica 2021). Haßler et al. (2021) analyze German tweets showing that the number of tweets has declined, and that the use of hashtags has suffered some changes (e.g., #climatecrisis increase, while #climatechange decreased; #klimakrise for #klimawandel), and that the tweets about protest and mobilization calls have decreased over time. Haßler et al. (2021) confirmed that online mobilization is highly dependent on offline events. We confirm that this is also the case for online mobilization events. With a framing perspective, Sorce and Dumitrica (2021) performed a qualitative social media framing analysis on 457 Facebook protest signs of FFF in Eource. Sorce and Dumitrica (2021) showed the discursive changes of the FFF movement to the pandemic crisis ranging from adaptation, reframing, and mobilization, showing that the three framing adaptation processes coexist. These studies covered the early phases of the COVID-19 pandemic, while we focused on the September 2020 FFF mobilization. The September events tended to concentrate on high mobilization power. We confirmed that online mobilization is highly dependent on both offline and online events, and that framing tasks coexist in a mobilization event.

Our research had several limitations, we did not pay enough attention to the media ecology of our database as we did not analyze the web links in tweets. These data could have provided a more detailed picture of the links between traditional media and social media discourse. We recommend exploring the long-term impact of the COVID-19 pandemic on climate activism and examining how different media ecologies influence online discourse. Categorization of framing tasks is an oversimplification of the framing approach that could be complemented with a mixed-method approach diving deeper into the nuances of framing strategies employed by climate activists. Manually coded typologies were forced to be mutually exclusive, while automated data processes could identify the percentages of typologies within a message. Further studies should consider the advantages and disadvantages of applying different coding strategies (mutually and non-mutually exclusive).

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Appendix A

Table A1. Tweets by language (lang) and lang codes (Number and percentages).

	Language (Lang)	Lang Code	Num	%	%
1	Arabic	ar	11	0.01%	0.05%
2	Bengali	bn	2	0.00%	0.01%
3	Catalan	ca	81	0.07%	0.36%
4	Czech	cs	8	0.01%	0.04%
5	Welsh	cy	5	0.00%	0.02%
6	Danish	da	15	0.01%	0.07%
7	German	de	6.817	6.10%	30.65%
8	Divehi	dv	2	0.00%	0.01%
9	Greek	el	6	0.01%	0.03%
10	English	en	9.529	8.52%	42.84%
11	Spanish	es	968	0.87%	4.35%
12	Estonian	et	28	0.03%	0.13%
13	Euskera	eu	3	0.00%	0.01%
14	Persian	fa	3	0.00%	0.01%
15	Finnish	fi	30	0.03%	0.13%
16	French	fr	241	0.22%	1.08%
17	Gujarati	gu	2	0.00%	0.01%
18	Hindi	hi	132	0.12%	0.59%
19	Haitian	ht	19	0.02%	0.09%
20	Hungarian	hu	3	0.00%	0.01%
21		in	121	0.11%	0.54%
22	Italian	it	268	0.24%	1.20%

Table A1. *Cont.*

	Language (Lang)	Lang Code	Num	%	%
23		iw	5	0.00%	0.02%
24	Japanese	ja	483	0.43%	2.17%
25	Korean	ko	13	0.01%	0.06%
26	Lithuanian	lt	14	0.01%	0.06%
27	Latvian	lv	6	0.01%	0.03%
28	Nepali	ne	2	0.00%	0.01%
29	Dutch	nl	95	0.08%	0.43%
30	Norwegian	no	25	0.02%	0.11%
31	Polish	pl	41	0.04%	0.18%
32	Portuguese	pt	116	0.10%	0.52%
33	Romanian	ro	11	0.01%	0.05%
34	Russian	ru	18	0.02%	0.08%
35	Slovenian	sl	5	0.00%	0.02%
36	Swedish	sv	89	0.08%	0.40%
37	Tamil	ta	24	0.02%	0.11%
38	Thai	th	1	0.00%	0.00%
39	Tagalog	tl	75	0.07%	0.34%
40	Turkish	tr	89	0.08%	0.40%
41	Ukrainian	uk	4	0.00%	0.02%
42	Undefined	und	2.822	2.52%	12.69%
43	Urdu	ur	3	0.00%	0.01%
44	Vietnamese	vi	2	0.00%	0.01%
45	Chinese	zh	4	0.00%	0.02%
46	Retweets	n.a.	89.600	80.11%	
	Total (excluding retweets)				22.241
	Total		111.841		

Table A2. Example of tweets across categories of social function typology.

1. Information	
1.1 Documentation tweet or tweet about an issue or event related directly to the strike	#FridaysForFuture ǀ Young people are back on the Streets for climate in at least 3500 locations around the globe. ?????? As students take to the streets in a global climate strike today, we asked young people around the world to explain why they're striking ?? ✊ #FridaysForFuture #FightClimateInjustice @BelfastFff @yca_ni
1.2 News reports related to the strike	On today's front page, we're taking a look at @GretaThunberg #fridayforfuture youth #climatestrike taking place today around the world. 1000's of young people are demanding urgent action is taken to tackle the #climatecrisis
1.3 Climate/environmental information tweet	"This summer was the hottest ever recorded in the northern hemisphere Past 3 months were 1.17C above 20thcentury avrg 2020 on track to be 1 of 3 warmest years #facetheclimateemergency #climateactionnow #endfossilfuels #renewableresources #FridaysForFuture

Table A2. *Cont.*

2. Opinion	
2.1 Opinion about the protest	Glad to see the return of #FridaysForFuture demonstrations in Vienna and elsewhere.
2.2 Opinion about climate change	"Nature does not care for anyone. It only provides opportunities to live. It's our duty to keep Earth clean and healthy. There is no time left for excuses. It is now or never. #FightClimateInjustice #FridaysForFuture #ClimateCrisis #ClimateEmergency"
2.3 Opinion about youth or young protesters	Today, Sep 25, is the 2020 #GlobalClimateStrike, COVID-version, where we cannot be in the streets like last year. My gratitude to youth worldwide for their rising voices and creative methods to make this year count. Retweet to amplify their voices!
3. Mobilization	
3.1 Online mobilization request)	BUKAS NA ANG KAMAY PARA SA KLIMA! Join our Tweetstorm tonight demanding longterm policies to address the climate crisis! Click JOIN OUR ONLINE CLIMATE ACTION: ht #KamayParaSaKlima #FridaysForFuture #FightClimateInjustice
3.2 Offline mobilization request	TODAY!! Support the youth-led climate shoe strike today, Sept 25th, in front of #StratfordON CityHall. It's a global day of climate action! Drop off your shoes 3–3:30. Details >> And follow >> #FridaysForFuture
4. Attack/Blame	
4.1 Attack/blame government	See how this works, WP says we have 7 yrs, CA Gov Newsom requires all cars be zero emission ©2035. . . that is about 8 yrs to late. Doesn't matter your politics. #FridaysForFuture #ClimateAction #ClimateStrike
4.2 Attack/blame media	Remember: 1. The oceans are being killed. 2. Forests will soon be gone. 3. Fertile soil is disappearing. 4. Megafauna risk extermination. 5. Insects are vanishing. 6. Climate chaos is inevitable. 7. Extinction is now. 8. Plastic is in our blood. None of this is front page news.
4.3 Attack/blame companies	We demand accountability from large-scale polluters! Reparations for the injustices made against the environment & the people! @Chevron @exxonmobil @bp_plc @Shell Join our Twitter storm! Click #KamayParaSaKlima #FridaysForFuture #FightClimateInjustice
5. Other	
5.1 Not about strike or climate change	What is your relationship status? Are you sure you are not in a situationship? Find out here 7 Signs That You Just Might Be In a Situationship #FridaysForFuture #FridayVibes #TGIF
5.2 Marketing	"@SenHawleyPress @realDonaldTrump Hello. Please, if you need a Book Writer (Fiction and Non-Fiction), I am very available. You can reach out to me via this link: #COVID19 #lockdown #FridaysForFuture #Biden #Europe #China #Russia #Trump #Fiverr"

Table A3. Example of tweets across categories of framing typology.

1. Diagnosis	"COVID-19 has firmly underscored the fundamental role that access to reliable electricity plays in protecting health and wellbeing, and in supporting essential public services.—@NerissonLady #GoGhanaGoRenewable #ClimateStrike #FightClimateInjustice #FridaysForFuture #AfrikaVuka"
2. Prognosis	
2.1 Individual action-oriented/awareness-raising	Recycling still the most effective waste disposal method, report finds #TiredEarth #Recycle #Wastemanagement #ClimateChange #ClimateCrisis #UK
2.2 System oriented	"System Change not Climate Change! #KeinGradWeiter CO_2/Greenhouse Gases Exclusion (& Economic Inclusion for all), now! #EveryDayForFuture #DemocratizeMoney"
2.3 Legislation and policy change	This is the harsh reality: Countries must increase their commitments to Paris agreement by 3 to 5 times—by 3 to 5 times, folks!—their current commitments! (Illustration from @UNDP) #ClimateEmergency #FridaysForFuture
3. Motivational	Go Greta and friends!
4. Other	"✨ queen things only ✨ stanning @joyangtv harder huhu ??"

Totals of the main categories in bold.

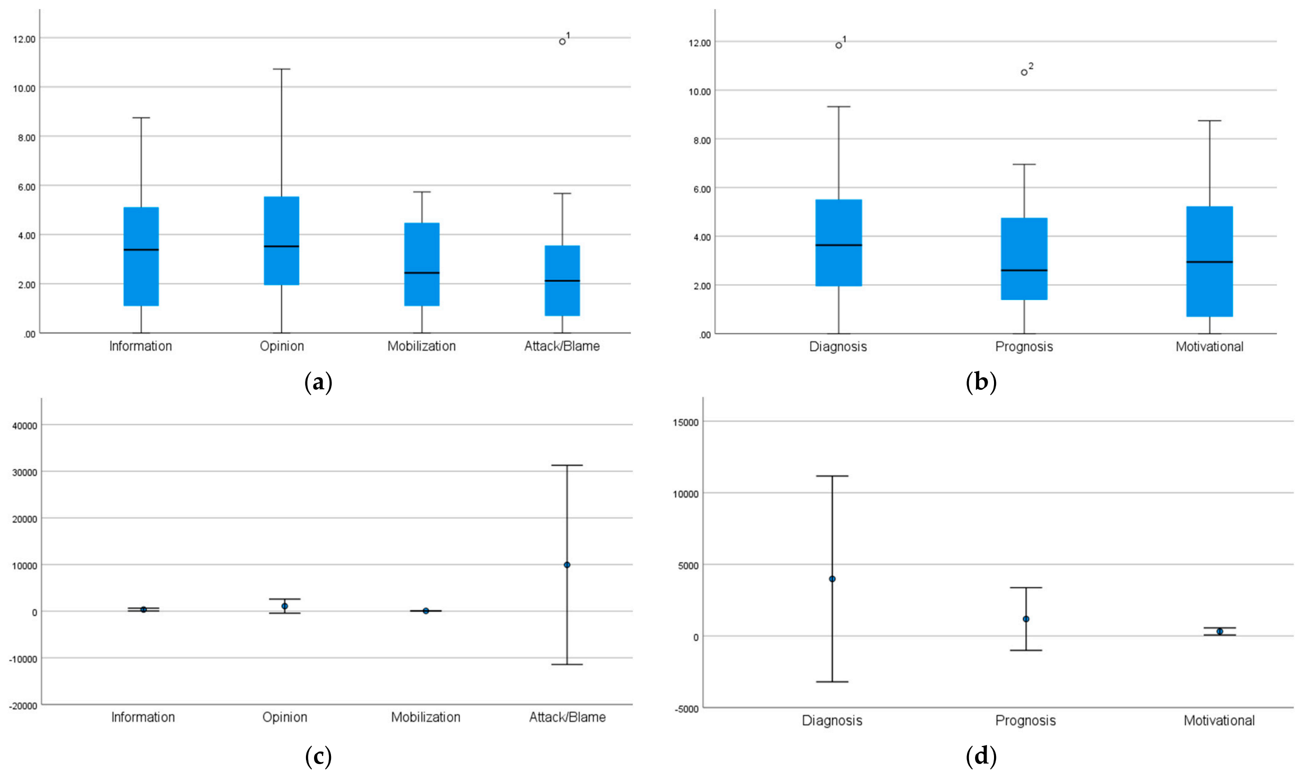

Figure A1. Box plots and error bars (95% IC) of retweets across social function and framing typology: (**a**) Box plot of retweets (Lnretweets) across social function typology; (**b**) Box plot of retweets (Lnretweets) across framing typology; (**c**) Error bars (95% IC) average retweets across social function typology; (**d**) Error bars (95% IC) average retweets framing typology. Note: (**a**,**b**) show the logarithmic transformation of a number of retweets (Lnretweets) and (**c**,**d**) exclude tweets with 0 retweets.

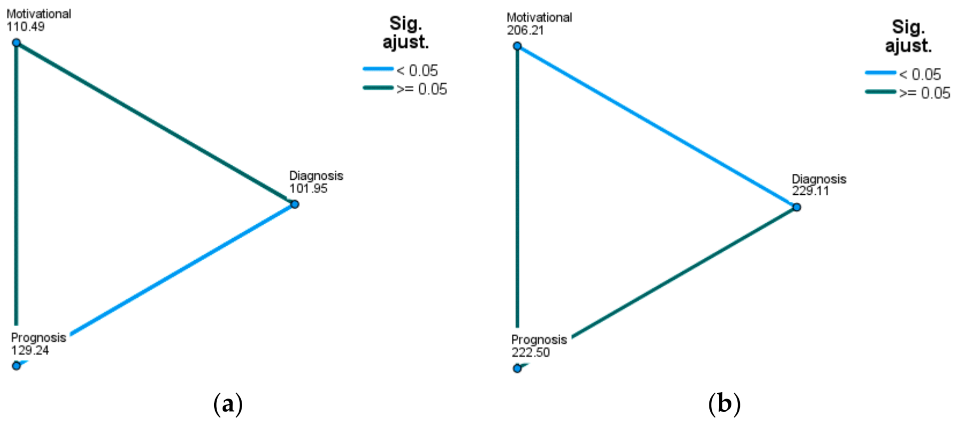

Figure A2. (**a**) Pairwise comparison of Information social function across framing categories (each node shows the sample average rank); (**b**) Pairwise comparison of Opinion social function across framing categories (each node shows the sample average rank).

Table A4. Distribution of predicted probabilities belonging to the last decile, mean, and standard deviation across categories of social function typology.

Label	0%	...	90%	100%	Mean	SD
Information	0.007	...	0.499	0.797	0.236	0.164
Opinion	0.013	...	0.725	0.897	0.455	0.200
Mobilization	0.004	...	0.180	0.929	0.084	0.144
Attack/Blame	0.005	...	0.243	0.837	0.119	0.144
Other	0.001	...	0.218	0.766	0.104	0.104

Table A5. Distribution of predicted probabilities belonging to the last decile, mean, and standard deviation across categories of framing typology.

Label	0%	...	90%	100%	Mean	SD
Diagnosis	0.015	...	0.451	0.730	0.212	0.153
Prognosis.	0.017	...	0.656	0.908	0.262	0.216
Motivational	0.013	...	0.723	0.931	0.406	0.239
Other	0.002	...	0.252	0.780	0.118	0.144

Notes

1 GGI stands for "Grève Générale Illimitée" Unlimited General Strike.

2 Aslanidis (2012) in his review of social movement studies points out that some social movement approaches maintain "an uneasy relationship with framing approaches" (p. 10).

3 See press release: https://fridaysforfuture.org/september25/#press-release (accessed on 9 December 2020).

4 We merged Boulianne et al. (2020) first two sub-categories ("documentation tweet" and "tweet about an issue or event related directly to the strike") as they were sometimes difficult to differentiate for different coders.

5 We merged two categories (Boulianne et al. 2020) as the number of tweets was very low.

6 On 24 September 2022, the figures reached pre-COVID-19 levels reached November and December 2019.

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