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 analyses the Fridays for Future (FFF) movement and their online mobilization around the Global Day of Climate Action on September 25th, 2020. Due to the Covid-19 pandemic this event is a unique opportunity to study digital activism as marchers were considered not appropriate. Using the Twitter's API with keywords "#climateStrike", "#FridaysForFuture", we collected 111,844 unique tweets and retweets from 47,892 unique users. We use two typologies based on social media activism and framing literature to understand the main function of tweets —information, opinion, mobilization and blame— and frames —diagnosis, prognosis, motivational. We also analyze its relationship and test its automated-classification potential. To do so we manually coded a randomly selected sample of 950 tweets that are used as input for the automated-classification process (SVMs algorithm with balancing classification techniques). We find that the Covid-19 pandemic appears not to have increased the mobilization function of tweets, as the frequencies of mobilization tweets were low. We also find a balanced diversity of framing tasks, with an important number of tweets that envisaged solution on legislation and policy changes. We find that both typologies are not independent. The automated data classification model performed well, especially across social function typology and the "other" category. This indicates that these tools could help researchers working with social media data to process the information across categories that are currently mainly processed manually, enlarging their final sample sizes.

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

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1 INTRODUCTION

Social media, and specially Twitter, are important sources of data for analyzing the public discourses on climate change (e.g. Veltri and Astanasova, 2017), the information sharing behavior on protest events (e.g. Theocharis et al., 2015) or 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 has 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 (Walström et al., 2019; de Moor et al., 2020). Despite the increase 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 of young people, it interesting to use these data sources to know 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) focuses on Climate Change Conferences (e.g. Copenhagen Climate Change Conference (COP15). The publication of the United Nations Intergovernmental Panel on Climate Change (IPCC) working groups 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 use this event approach and collect information on the Global Day of Climate Action that took place on September 25th, 2020. Due to the Covid-19 pandemic this event is a unique opportunity to study digital activism as marchers were considered not suitable.

To do so we collected real-time tweets using the Twitter's API with keywords "#climateStrike", "#FridaysForFuture" before and after the Global Day of Climate Action. We collected 111,844 unique tweets and retweets from 47,892 unique users. Based on a literature review, we build two typologies on social media activism —information, opinion, mobilization and blame— and framing tasks —diagnosis, prognosis, motivational; tested its automated-classification potential and describe the categorization results. We focused our analyses on tweets English language (9,529 tweets) to reduce biases on the automated classification process. We manually coded a randomly selected sample of 950 tweets that is used as input for the automated-classification process (SVMs algorithm with balancing classification techniques) and test its potential through confusion matrix tables. We also perform an analysis of the most discriminant tweets.

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

2 LITERATURE REVIEW: WHAT DO WE KNOW ABOUT THE FFF MOVEMENT AND WHAT CAN SOCIAL MEDIA TELL US ABOUT IT?

Despite of being a recent movement, FFF have received some attention from the academic literature (see Table 1). Articles analyzing the FFF movement are obviously diverse in their theoretical approaches and research questions. They also differ in methods and data sources used for their analyses. However, 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.

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 an, particularly, non-conventional political participation, different studies review the empirical evidence on diverse protest events across the glove. For example, Theocharis et al. (2015) applies a comparative content analysis on the use of Twitter in protest events in Spain, Greece and the US, finding that Twitter is importantly used for sharing information. However, contrary to the supposedly mobilization power of social media, Theocharis et al. (2015) finds out that online calls for participation are infrequent, with a low number of tweets referring to organization and coordination issues. Similarly, Jost et al. (2018) reviews the empirical evidence on protest movements occurred in Turkey, Ukraine, the US, and Spain, finding that social media platforms facilitate the exchange of information, emotional and motivational content and that the structure of online social networks influence the organizational efforts. Due transnational character of 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) follows this approach to study the FFF movement. They use Twitter to collect, through the #SchoolStrike4Climate hashtag, a total of 13,542 tweets. They manually code a sample of 993 to distinguish the spatial location —local, national and global— and the social function of the tweets —information, opinion, mobilization and attack. The last typology follows the GGI codebook developed by Raynauld et al. (2016) to study the 2012 Student Strike against university tuition fee hikes in Quebec. Boulianne et al. (2020) finds 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 indicates that the global character of the climate change movement and the young composition of the FFF movement do 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 patters of the FFF movement. For example, Brünker et al. (2019) manually collects 1,137 Instagram comments of two post of Greta Thunberg and classify 439 according to three categories linked to the group identity theory —group cohesion, emotional attachment, and solidarity— finding that comments mainly express 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. Framing approach shows the crucial role of emotions and motivational framing in explaining the success of a mobilization. In addition to the understanding of the different functions of social media content it is important to try to understand how the 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: 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 framing approach,[1] when do so applying extensively the Snow and Benford (1988) work (Aslanidis, 2012: 14). Snow and Benford (1988) points 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: 199); and illustrate 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, 1992). For example, Maier (2020) applies these categories in their qualitative frame analysis of 432 protest signs published in Facebook in 11 German cities in 2019. He finds three main FFF frames —a policy "issue field" frame, an "intergenerational Justice" frame, and a "transnational" frame—, having the "issue field" frame a main role in diagnostic and prognostic framing tasks; the "intergenerational justice" frame has an important role in the motivational task; and the "transnational" frame has a transversal role across tasking frames (Maier, 2020: 44-45). Other articles referring to Snow and Benford work are Han and Ahn (2020) and Source and Dumitrica (2021). With a narrative analysis method applied mostly to speeches of Greta Thunberg, Han and Ahn (2020) explores the understanding of climate change of young activist and how to respond to it, pointing that they have "succeeded in problematizing global climate inaction and inertia in framing climate change from a justice perspective" (p.1). However, they point that the FFF "faced limitations in converting their moral legitimacy into the power required for sweeping changes." Therefore, there is some indication that the three core framing tasks are not properly attended to or interconnected by the FFF movement.

Other analysis of the FFF movement that use the framing approach refer to Entman (1993) (instead of Snow and Benford) that, as mentioned, is one of the main cited framing authors in media studies (Matthes, 2009). This is the case of Von Zabern and Tulloch (2020) that applies a content analysis on 85 news articles of three German newspapers to identify eight frames. They also find that German media tend to depoliticize the political agenda of the protest. Nonetheless, they also find that German media frame climate change towards intergenerational justice (Von Zabern and Tulloch, 2020). Similarly, Huttunen and Albercht (2021) study how the FFF movement is 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, media studies approach tend to use framing focusing on how media portrays the FFF movement.

As we have seen, social media data is useful for analyzing large and transnational protests movements such as the FFF as it allows to analyze 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 (Walström et al., 2019; de Moor et al., 2020). The main advantage of questionnaires to protestors over social media data is that

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

socio demographic information can be accurately collected at individual level.[2] Due this method, we know important demographic characteristics of the protestors.

Walström et al. (2019) and de Moor et al. (2020) report the results of a project that surveyed protestors attending to the March 2019 and September 2019 FFF climate protests respectively. The first report gathered a sample of 1,905 survey responses from 13 European cities (Walström et al., 2019), while the second reached a sample of 3,154 people covering 19 cities of 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 provides important information on the sociodemographic characteristics of FFF protestors and on the degree of involvement in formal organizations. For example, we know that young protestors are over-represented (almost one third were 19 or under in the September event), that female presence is high (nearly 60%) and that the level of education is high among adults and parents of protestors. Questionnaires to FFF protestor show that both young and adults rely primarily on social media as a source for protest information (45% of young and 39% of adults) (de Moor et al, 2020: 18). Other studies have relied on these databases to provide deeper understanding of the relationship between social background and strategic orientations (della Porta and Portos, 2021) or the continuities and changes of FFF with previous climate activism (Moor et al., 2021).

There are other articles that analyze the FFF movement from other perspectives. For example, Zulianello and Ceccobelli (2020) use Greta Thunberg's speeches and perform a content analysis to understand to what extent her message share attributes of populism. Table 1 summarizes the literature review of research publication on FFF movement that was carried out in 2021.[3] It includes their theoretical approach, research questions, methods, data sources (including sources, sample, data and language) and typologies used. These papers are quite diverse in data sources used for their analysis, including questionnaires-survey to protestors (e.g. de Moor et al., 2020; Walstrom 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) are frequently used. Most of the studies considered that use social media data use databases that have 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.

Our research questions are:

RQ1. What is function of tweets (information, opinion, mobilization and blame) within a Covid-19 context?

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

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

[2] See Barberá and Threlkeld (2020) for advantages and disadvantages of using social media data on science policy issues.

[3] As it is indicated in the table, we have excluded non-English articles and non-research publications, such as, policy briefs and scholarly comments. To find FFF related articles we conducted an open search on Google Scholar in early 2021 in order to build the typologies for our automated-classification model. We have complemented this open search in February 2022 with a systematic search on the ISI Web of Knowledge ("FFF" "movement"). We carried out an open search on google scholar as the systematic searches in 2021 resulted in low numbers of FFF-related publications. New evidence is included in the discussion section and partially integrated in the table.

RQ4 (methods). To what extent automated data classification processes work across and between typologies (social function and framing typology)? What is the content of most discriminant tweets?

Table 1. Summary of the literature review of research publications on FFF movement

Authors	Reference	Theoretical approach	Research questions	Methods	Data	Analysis-Typology
Boulianne, et al. (2020)	BOULIANNE, Shelley; LALANCETTE; Mireille and ILKIW, David. (2020). "School strike 4 climate": social media and the international youth protest on climate change. *Media and Communication*, *8*(2), 208-218.	Social movement literature Extensive literature review on youth activism; climate change; and hashtag activism	"RQ1: What are the spatial markings of tweets (local, national, global) related to #SchoolStrike4Climate? RQ2: What were the primary functions of tweets (information, opinion, mobilization, or blame) using #SchoolStrike4Climate?"	New sources-quantitative content analysis (Low- medium)	**Source:** TWITTER #SchoolStrike4Climate Multiple Netlytics queries (limited to 1000 most recent tweets no retweets and like metrics) - compensated **Sample:** (n = 13,542) sorted by frequency 1,842 →993 **Date:** March 15, 2019 16:00 to March 18 at 20h **Language:** all google translator	**Tools**: Manually coded -mutually exclusive categories Spatial markings • Local • National • Global "7 categories for spatial location: 1) local; 2) national; 3) global; 4) local and national; 5) local and global; 6) national and global; and a combination of 7) local, national, and global" Functions • Information • Opinion • Mobilization • Attack See extended categorization coding scheme from the GGI codebook
Brünker et al. (2019)	BRÜNKER, Felix; DEITELHOFF, Fabian; MIRBABAIE, Milad (2019). Collective Identity Formation on Instagram--Investigating the Social Movement Fridays for Future. *arXiv preprint arXiv:1912.05123*, 2019.	"Identity Theory" (McCall and Simmons 1966) and sub-theory Collective theory ~~(Davis et al. 2019)~~	"RQ1: How is the collective group/social identity formed on Instagram within an opinion-based community?"	New sources-quantitative content analysis (Low): manually collection and typology (words, hashtags and emoji by group cohesion, emotional attachment and solidarity) and "automated text classification" (SQL)	**Source:** INSTAGRAM (manually collected) **Sample:** 1,137 comments of two posts →584 ENGLISH Final sample 439 Instagram manually collected 1,137 comments (584 ENGLISH →439 classified) **Date:** February 2019 - July 2019	Quantitative: Content analysis (200 randomly selected comments on 2 Greta's post manually coded) → SQL classification of the rest (145 non-classified) – Non-Mutually Exclusive • Group Cohesion • Emotional Attachment • Solidarity
De Moor et al. (2020) (see also: de Moor et al. 2021 Della Porta and Portos (2021)	DE MOOR, Joost, et al. (2020). Protest for a future II: Composition, mobilization and motives of the participants in Fridays For Future climate protests on 20-27 September, 2019, in 19 cities around the world.	Social movements	Non applicable (It is a report)	Quantitative: Survey Caught in the Act of Protest	**Source**: Survey to protesters (International survey in 19 cities of 15 countries around the world) "Caught in the Act of Protest" survey methodology Van Aelst and Walgrave (2001) **Sample:** 3154 probabilistic sample (13,000) **Date:** September 2019 **Language**: Several	Variables Profile -Age, gender, and education - Mobilization networks - Emotions - The 'Greta effect' – Perceived solution (Government, science, companies, voluntary individual changes)
de Moor et al. 2021	DE MOOR, Joost, et al. (2021). New kids on the block: Taking stock of the recent cycle of climate activism. *Social Movement Studies*, 20(5), 619-625.	Social movements Framing	RQ (not explicit): What are the continuities and changes in new climate activism (FFF XR), demographics, tactics and collection action framing.	Review previous studies and insights	Review previous studies and insights (Wahlstrom et al., 2019; de Moor et al., 2020)	Not applicables
Della Porta and Portos (2021)	DELLA PORTA, Donatella; PORTOS, Martín (2021). Rich kids of Europe? Social basis and strategic choices in the climate activism of Fridays for Future. *Italian Political Science Review/Rivista Italiana di Scienza Politica*, 1-26.	Social movements	RQ1: whether and to what extent there is a cross-class constituency behind the FFF upsurge RQ2: how are different strategic orientations within the movement for climate action meaningfully connected	Review previous studies and insights Quantitative: Survey Caught in the Act of Protest	**Source**: Survey to protesters March 2019 13 European cities 1905 (Wahlstrom et al., 2019) September 2019 3154 (de Moor et al., 2020) **Sample:** 1905 + 3154 **Date:** March 2019 + September 2019	Vbles: Subjective class, age, gender, ideology, working status, etc Strategies to solve environmental problems: - Science - Government - Companies - Lifestyle

			to activists' social backgrounds?		**Language:** Several	
Haßler et al. (2021)	HAßLER, Jörg; WURST, Anna-Katharina; JUNGBLUT, Marc; SCHLOSSER, Katharina (2021). Influence of the pandemic lockdown on Fridays for Future's hashtag activism. *New media & society*, 1-23.	Social movement and framing	RQ1. How has the number of tweets published with the hashtag #fridaysforfuture been affected by the lockdowns? RQ2. How is the number of tweets with the hashtag #fridaysforfuture affected by the occurrence or absence of major protest events? RQ3. How is the use of different hashtags co-occurring with the hashtag #fridaysforfuture affected by the lockdowns? RQ4. How have the proposed topics in tweets with the hashtag #fridaysforfuture been affected by the lockdowns?	New sources – Use of hashtages and predominant topis	**Source**: Twitter (FFF) #Fridaysforfuture **Sample:** (N=46,881 tweets, N=225,562 retweets) Facepager **Date:** Every Friday From 7 June 2019 to 29 May 2020 **Language**: German	Topic model calculation gensim's latent Dirichlet allocation (LDA) 1. Protest events and mobilization calls: 2. Thematic discourse: 3. Meta-discourse on legitimacy:
Han and Ahn (2020)	HAN, Heejin; AHN, Sang Wuk (2020). Youth mobilization to stop global climate change: Narratives and impact. *Sustainability*, 2020, 12(10), 4127.	Literature review	RQ (not explicit) Analysis of "the narratives of youth climate activists to obtain an understanding of how they made sense of the current state of climate change and its causes, how they saw themselves in relation to other actors and how they reacted to resolve the existing problems"	Narrative analysis of policy framework "narratives consist of settings, characters, a plot, and a moral"	Narrative analysis Date; 2018-2019 global youth climate movements Sample: Non applicable Language: English-only? (References to discourses and other sources appeared to be limited to English language	Climate justice -systemic transformation • Settings • Characters • plot • moral
Huttunen and Albrecht (2021)	HUTTUNEN, Janette; ALBRECHT, Eerika (2021). The framing of environmental citizenship and youth participation in the Fridays for Future Movement in Finland. *Fennia*, 199(1), 46-60.	Framing	RQ: (not explicit) What are the representations of young people's environmental citizenship within the framings of the FFF movement?	Qualitative frame analysis	**Source**: Finnish newspapers (Helsingin Sanomat (HS) and YLE) and Twitter **Sample:** (N=71 articles (27 in HS and 44 in Yle) Twitter 3858 (2,023 from March 15 and 1,835 from September 27) **Date:** March and September 2019 **Language**: Finnish	Three frames: • Sustainable lifestyle frame • Active youth frame • School attendance frame
Maier (2020)	MAIER, Benedikt Martin (2020). "No Planet B": An analysis of the collective action framing of the social movement Fridays for Future. Master Thesis. Jönköping University.	Framing theory Collective action theory	RQ: "How do the youth protestors of the social movement Fridays for Future in Germany frame their engagement in the street protests? • Which sense-making frames do the youth protestors employ within their street protest? • What tasks do these frames fulfill within the social movement organization and processes?"	Qualitative frame analysis	**Source:** Protest signs Facebook **Sample:** 432 protest signs published in Facebook FFF groups in 11 German cities Ulm, Stuttgart, Karlsruhe, München, Augsburg, Hamburg, Bremen, Köln, Leipzig and Dresden **Date:** January 2019 July 2019 **Language:** German and English	Typology: In-Group Subjectivity: Diagnosis; Prognosis; and Motivation Policy-fields (extensive issue categorization)
Source and Dumitrica (2021)	SORCE, Giuliana; DUMITRICA, Delia (2021). # fighteverycrisis: Pandemic Shifts in Fridays for Future's Protest Communication	Social movement framing theory	RQ (not explicit) how FFF movement become affected by covid-19 crises that threaten to divert attention?	qualitative social media framing analysis	**Source:** Protest signs Facebook **Sample:** 457 posts across 29 public pages from FFF	Three framing processes: • adaptation (compliance, solidarity) • reframing (reclaiming the crisis, nexus between climate and health), • and mobilization (sustained involvement, digital protest alternatives).

	Frames. *Environmental Communication*, 1-13.			two-staged qualitative social media framing analysis	collectives in the European Union **Date:** March 12-April 24, 2020 **Language:**	
Von Zabern and Tulloch (2021)	VON ZABERN, Lena; TULLOCH, Christopher D. (2021). Rebel with a cause: the framing of climate change and intergenerational justice in the German press treatment of the Fridays for Future protests. *Media, Culture & Society*, *43*(1), 23-47.	Framing theory Intergenerational justice	RQ: Yes "RQ1. How are the protesters represented? RQ2. How are the demands and accusations of the protesters represented and evaluated? RQ3. How is the Fridays for Future movement represented in the wider media discourse on climate change? RQ4. Does the overall media framing of the Friday for Future movement differ from newspaper to newspaper? If so, how? RQ5. Does the overall framing of the Friday for Future movement change over time?	Methods "qualitative and quantitative content analysis"	**Source:** Mass media Newspapers (German online newspapers) **Sample:** 3 newspapers (Bild.de, Zeit Online and FAZ.net) 85 news articles **Date:** August 2018 to March 2019 (after the first Global Strike for Future) Languages: 1 German	Fostering International Justice/ Diminishing/ Others Eight frames: -David vs Goliath -Intergenerational Justice - Truancy -Threat - Activist without Activism Frame -Activism without Activists Frame - Activism without Activists Frame Tools structured qualitative content analysis (Kuckartz (2016) and Altheide (2000) cuali? a keyword search on their respective online pages, all publicly available news articles2 posted under the keywords: 'Fridays for Future', 'Schulstreik', 'Klimastreik', or 'Greta Thunberg' news and editorial No opinions
Wahlström, et al. (2019)	WAHLSTRÖM, Mattias, et al. (2019). Protest for a future: Composition, mobilization and motives of the participants in Fridays For Future climate protests on 15 March, 2019 in 13 European cities.	Non applicable (report)	Non applicable (report)	Quantitative	**Source:** Survey to participants FFF protests n 13 cities in nine European countries **Sample:** 1905 **Date:** strike on March 15, 2019 **Language:** multiple	Motivations: -express views - pressure politicians - rise awareness Instrumental motivation vs expressive motivations
Zulianello and Ceccobelli (2020)	ZULIANELLO, Mattia; CECCOBELLI, Diego (2020). Don't call it climate populism: on Greta Thunberg's technocratic ecocentrism. *The political quarterly*, *91*(3), 623-631.	No specific theoretical approach Literature review integrated along the text	Not explicit: "goal of this article is to determine whether, and to what extent, Greta Thunberg's message presents the core attributes of populism as identified by the ideational approach."	Qualitative content analysis	**Source:** Speeches (Greta Thunberg) **Sample:** Not clear **Date:** Not clear **Language:** English (not clear)	• eco-centrism • technocracy • exaltation of the vox scientifica
Other (excluded):	• Non-English articles: e.g. Carrasco (2020). • Non-research publications: o Policy Briefs (e.g. Dirth, 2019) o Scholarly comments (e.g. Evensen, 2019; Kühne, 2019) Note: Thesis (e.g. Maier, 2020) and academic project reports (e.g. Wahlström, et al., 2019) included.					

Source: Own elaboration.

3 DATA AND METHODS

3.1 Data collection and sample

We collected real-time tweets using the Twitter's streaming API with keywords "#climateStrike", "#FridaysForFuture" before and after the Global Day of Climate Action that took place on the September 25th, 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 is a unique opportunity to study digital activism as marches were considered not appropriate. [4] The dataset was collected between September 24th to 28th 2020. Most of the interaction occurred in September 25th. We collected 111,844 unique tweets and retweets from 47,892 unique users.

Tweets were reported in 45 different language codes (see Table A.1 in the Annex). English (9,529) and German (6,817) were the most frequent languages, representing 42.84% and 30.65% of the total tweets respectively (22,241, excluding retweets). Undefined tweets represented 12.69% of the total. 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 show percentages lower than 1 per cent. We limited the coding process to English language tweets because it was the most frequent language and the codification tools need to consider one language to provide better results. Therefore, our final sample consist of 9,529 tweets.

3.2 Coding

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 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 are based on previous studies. Social codebook was developed for analyzing the 2012 student strike in Quebec (GGI codebook) by Raynauld et al. (2016, 2019) and further applied by Boulianne et at. (2020) to analyze the FFF student strike on March 15, 2019. Following their procedure, categories are considered mutually exclusive. The main five categories of the social typology are: information tweet; opinion tweet; mobilization tweet; blame tweet; and other type of tweet.

We also adapted the subcategories of Boulianne et al. (2020) for this study. The information tweets category (1) includes the following subcategories of tweets: (1.1) tweet documenting the protest or about an issue of event directly related to the strike[5]; (1.2) news reports related to the strike; and (1.3) tweet sharing climate or environmental information. The category of (2) opinion tweets comprise: (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[6]. Following Boulianne et al (2020) and based on Merry (2013) and Hodges and Stoking (2016),

[4] See press release: https://fridaysforfuture.org/september25/#press-release [visited on 09.12.2020]

[5] We merged Boulaine et al. (2020) firsts 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.

[6] We merged two categories of Boulaine et al., 2020 as the number of tweets was very low.

mobilization tweets include: (3.1) online request tweet and (3.2) offline request tweets. Similarly, blames subcategorization follows Boulianne et al. (2020) based on Merry (2013) However, differently to Boulianne et al. (2020) we added a new blaming subcategory including companies. Therefore, blame tweets category (3) include: (3.1) Tweets blaming government; (3.2) tweets blaming media; or (3.3) tweets blaming companies. Finally, we identified an important number of tweets that use the mobilization hashtags for marketing purposes. Therefore, the category of other tweets (5) includes: (5.1) tweets that were not about the strike or climate change; and (5.2) marketing purposes tweets.

Table A.2 in the Annex includes examples of tweets across categories of social function typology.

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

The framing codebook is adapted from several studies that focused on FFF and built categories on collective action framing theories (Snow and Benford, 1988), such as, Wahlstrom et al. (2013) and Maier (2020). Differently to them we used tweet content instead of survey question on solutions (Wahlstrom et al., 2013) or protest signs published in Facebook (Maier, 2020). Our main framing categories are: (1) tweets that focused on the diagnosis; (2) prognosis; (3) motivational; and (4) other. These main categories follow the classic Snow and Benford (1988) approach to study mobilization ~~("the most prominent scholars of frame theory in the social movement literature" (Aslanidis 2012: 14)~~. We also distinguish different framing solutions following Wahlstrom et al. (2013) and break down the prognosis category of tweets into: (2.1) tweets that frame the solutions on individual actions or aware raising initiatives; (2.2) tweets that frame the solution on system-oriented changes; and finally (2.3) tweets that frame solutions on legislation and policy changes. These prognosis subcategories were also merged for the automated-classification process for the same reason.

Table A.3 in the Annex includes examples of tweets across categories of framing typology.

Automated-classification process

For preprocessing the tweets, we employed the Python libraries *Gensim* and *NLTK*. The tweets were tokenized, stop-words were removed. To keep only relevant words, disregarding very uncommon as well as very frequent words, we required that words appear in at least five tweets and in less than the 75% of the tweets. A total of 553 words were found relevant with 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, using the Cohen's Kappa as metric to predict both typology labels. We found that in both cases the best results were obtained employing Support Vector Machines (SVMs) with a regularization parameter C equal to 0.7.

3.3 Methods

The next section includes the results of the descriptive statistics across typologies and test 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 test the difference of the performance between typologies using a t-test on the mean of the result of a 1000 times experiment. Finally, we detect and analyze 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 THE BASICS OF FFF AND THE GLOBAL DAYS OF CLIMATE

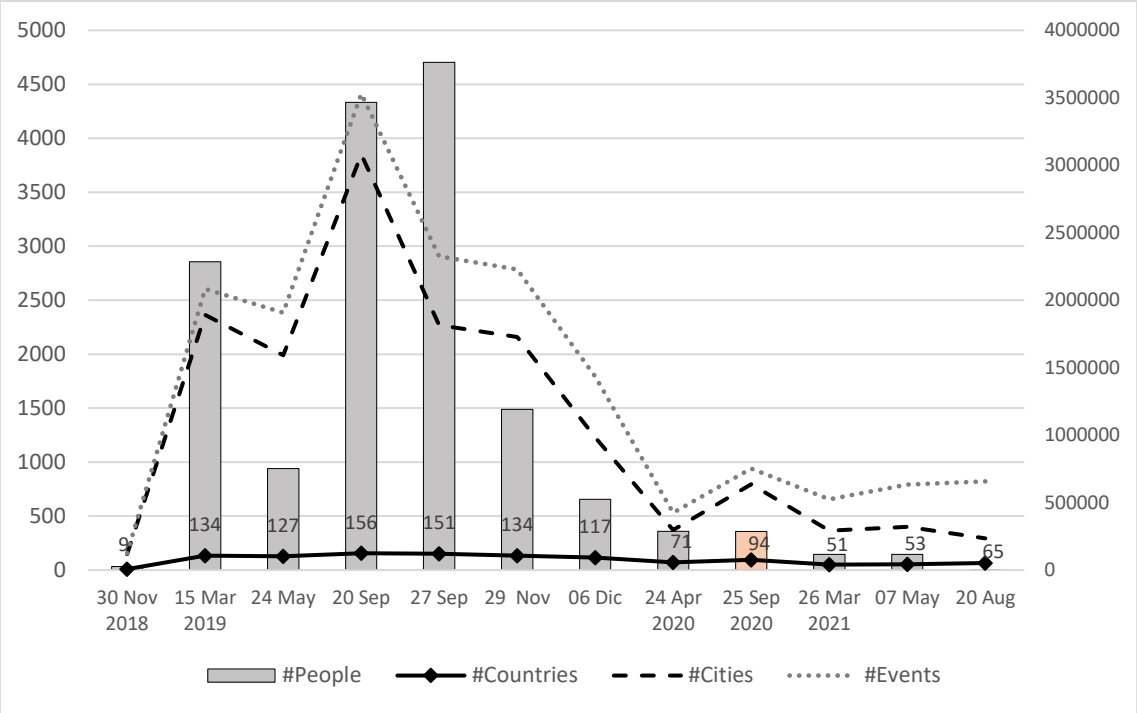
In August 2018 a 15-year-old Swedish girl, named Greta Thunberg, and other student activist started a school strike for the climate outside the Parliament of Sweden (Thunberg, 2019; FFF, 2021). This was the starting point of what it currently known as the FFF movement. In 2021, the movement reported actions in 7,500 cities across all continents that gathered more than 14 million people (FFF, 27.04. 2021). Social media actions have been present in the FFF movement since its inception. FFF web pages recognizes 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, 27.04. 2021). Greta's Twitter Instagram and Twitter pages were launched in June 2018 and reached in 2021 a total of 11 million followers in Instagram and 5 million in Twitter (Instagram and Twitter 27.04.2021). Facebook public figure page was launched on 7 December 2018 and reached 3 million followers in 2021.

School strikes for climate quickly spread globally. On 15 March 2019 the movement organized its First Global Climate Strike that gathered more than two million people from 134 different countries through more than 2,600 events organized across 2,363 cities around the world (see Figure 1). The September 2019 actions within the "Global Week for Future" (20-27 September) that was organized around the United Nations Climate Summit has been the most successful event to this date (see Figure 1). Data clearly shows a decrease in mobilization activity of FFF in 2020, indicating that the Covid-19 has importantly impacted the figures of the FFF movement. This data shows that the Global Day of Climate Action of 25 September 2020 has been the most successful mobilization day after the Covid-19 crisis in 2020 in terms of countries, cities, events and with roughly the same number of people that on 24th April 2020 (see Figure 1).[7]

The number of countries involved over the period confirms that FFF is a transnational movement that has helped to provide new impetus to the Climate Justice movement. FFF figures reached in September 2019 represent 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: 81) with the occasion of the UN Climate Summit. Global Days of Climate follow the transnational organizing model "Global Days of Action" of the Justice movement (Wood, 2004; Almeida and Lichbach, 2003; Chase-Dunn and Almeida, 2020). This innovative organizing model involves "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: 76). Increasing availability of internet access makes social networks more important for mobilization purposes. In 2000 the climate movement became more contentious arranging marches and rallies across the world with the occasion of United Nation 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: 74). This movement has been importantly expanded by the FFF strikes (Chase-Dunn and Almeida, 2020; de Moor et al., 2020).

Figure 1. Number of people (right axis), countries, cities and events (left axis) of FFF mobilization actions (2018-2021)

[7] In 24 September 2022, the figures reached pre-Covid-19 levels of November and December.



Source: Own elaboration with FFF data, extracted on 20th August 2021.

5 RESULTS

5.1 Descriptive statistics and bivariate relationship

The distribution of tweets of the Global Day of Climate Action of September 25th, 2020, across main functions shows that the most frequent function of tweets is expressing an opinion (45,9% see Table 2), followed by sharing information (24.1%), attributing blame (10.6%) and mobilizing support (7.9%). An important share of tweets (11.5%) has other functions, having marketing purposes a dominant share of these "other" tweets. Across subcategories, "documenting and sharing information about an issue or event related directly to the strike" is the most frequent subcategory for the "information" function; sharing an opinion about the protest or the climate change show similar frequencies within the "opinion" function; blaming at the government dominates within the "blaming" category; and offline mobilization requests tweets are rare within the "mobilization" category.

Table 2. Frequency and percentage of tweets across social function typology

	Frequency	Percentage
1. Information	**229**	**24.1%**
1.1 Documentation tweet or tweet about an issue or event related directly to the strike	172	18.1%
1.2 News reports related to the strike	21	2.2%
1.3 Climate/environmental information tweet	36	3.8%
2. Opinion	**436**	**45.9%**
2.1 Opinion about the protest	197	20.7%
2.2 Opinion about climate change	189	19.9%
2.3 Opinion about youth or young protesters	50	5.3%
3. Mobilization	**75**	**7.9%**
3.1 Online mobilization request	66	6.9%
3.2 Offline mobilization request	9	0.9%
4. Attack/Blame	**101**	**10.6%**
4.1 Attack/blame at government	86	9.1%
4.2 Attack/blame at media	4	0.4%

4.3 Attack/blame at companies	11	1.2%
5. Other	**109**	**11.5%**
5.1 Not about strike or climate change	38	4.0%
5.2 Marketing	71	7.5%
TOTAL	**950**	

Source: Own elaboration.

These results show 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 are scarce. The share of tweets that have a blaming function is 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 find that the primary function of tweets is to express and opinion instead of sharing information. This difference could be explained for context-related reasons or methodological reasons. The specificities of the context, with street marches being considered not appropriate due to the Covid-19 crisis, could have increased the need of expressing the opinion of supporters about the protest or the climate change. There could be also a methodological reason behind these different results. Boulianne et at. (2020) used a tool that limited the scraps per query at 1,000 most recent tweets and 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 changes our result, we checked the distribution of tweets across main categories for highly retweeted tweets, finding similar results, with opinion tweets being dominant. Haßler et al. (2021) shows that COVID-19 have changed the relative frequencies of some hashtags, but this difference does not alter top frequency of our selection of hashtags.

Considering the framing typology of tweet (see Table 3), the highest percentage of tweets belong to the motivational framing category (39.2%), followed by the prognosis and the diagnosis categories with 26.8% and 21.8% of the tweets, respectively. Regarding the subcategories of the different solutions to the problems (prognosis), nearly half of the prognosis tweets focus on legislation and policy changes solutions, followed by system-oriented solutions and solutions focused on individual action and awareness raising. These results could be compared to other climate changes studies, such as Wahlstrom et al. (2013), that also found an important percentage of individual opinions framing of how to solve the climate crisis on legislation and policy changes.

Table 3. Frequency and percentage of tweets across framing typology

	Frequency	Percentage
1. Diagnosis	**207**	**21.8%**
2. Prognosis	**255**	**26.8%**
2.1 Individual action oriented/awareness raising	56	5.9%
2.2 System oriented	74	7.8%
2.3 Legislation and policy change	125	13.2%
3. Motivational	**372**	**39.2%**
4. Other	**116**	**12.2%**
TOTAL	**950**	

Source: Own elaboration.

Retweet metrics on individual post across typologies indicate that motivational tweets tend to be retweeted less frequently across typologies, showing low average of retweets. Tweets attributing blame show the highest average of retweets, but this is due to the presence of outliers (tweets with high frequency of retweets). Similarly, outliers are present in the diagnosis and prognosis category of framing typology. Differences of retweet metrics across categories for social function and framing typologies are not

statistically significant due high dispersion of data (see Figures A.1 to A.4 Box plots and error bars of number of average of retweets across typologies in the Annex).

Table 4 shows the results of the relationship between social function and framing typologies. We can see that most of the mobilization tweets belong to a motivation framing category (84% of mobilization tweets). Tweets with an information function also tend to be mostly framed in a motivational way (67% of information function tweets belong to a motivational framing category). However, blaming function tweets could be mostly considered prognostic framing, and therefore relate to possible solutions. Curiously, opinion tweets are framed in a quite diverse way, with similar percentages across framing categories around 30-35 per cent. The relationship between the different categories of the social function and framing typologies are significantly different (Chi-square test) and, therefore, are not independent. The level of association is low to moderate according to the V Cramer.

Table 4. Relationship between social function and framing typologies

	Diagnosis		**Prognosis**		**Motivational**						**Total**	
	%	N	%	N	%	N		*Chi2*	*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<0,1; **p<0,05; ***p<0,01.
Source: Own elaboration.

5.2 Performance of the classification model across typologies

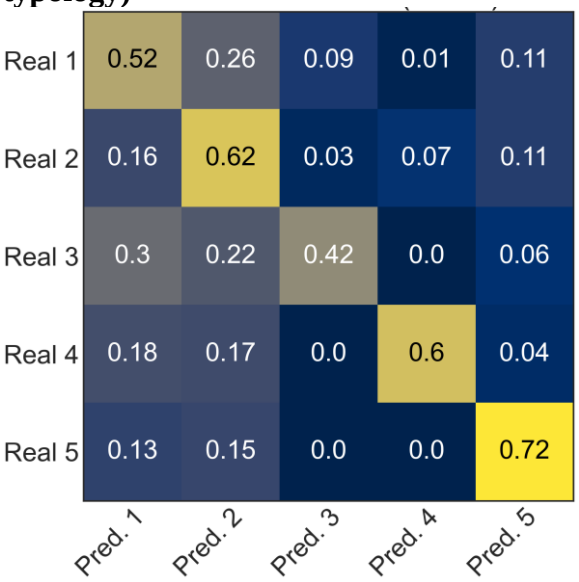
This section presents the results of the automated classification model across social function and framing typologies. Table 5 and 6 show the confusion matrix results that allow us to compare the performance of the classification model across social function and framing typologies. These are generated with the support vector machine model. The results are the average of 1000 experiments. In each experiment the 70% of the data was used to train and the remainder 30% for the test, comparing the predicted category (Pred.) with the true values which correspond to the human labels (Real). The values of the confusion matrix and the evaluation metrics of the model (i.e. Kappa and F1) show averages of the result of a 1000 times experiment. We applied class rebalancing techniques as the frequency of values across classes (categories) are unbalanced (Synthetic Minority Oversampling Technique – SMOTE). Different techniques were applied, such as oversampling, with no different impact on the results.

The results show that the "other" category is accurately predicted for both typologies, with agreement of real and predicted values of 0.72 and 0.7 for social function and framing typology, respectively. That means that 72% of "Other" cases are successfully predicted by our model for the social function typology. The values of successfully predicted categories are 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 has the lowest real frequency (n=75). Confusion matrixes allow also to know where the confusion arises from. In the case of the "mobilization" category of social function typology (Table 5), we see that our model wrongly predicted the real third category specially with the first (0.3) and second category (0.22), namely "information" and "opinion" categories. Table 5 also indicates that the "opinion" category is accurately predicted 62% average times. This category also captures good part of the rest of wrongly predicted categories. This category has the highest real frequency (n=436). It is also worth

noting that "blame" category is accurately predicted 60% of average times, despite of having low real frequencies (n=101).

Regarding framing typology (Table 6), the three categories besides the "Other" category shows quite similar results, around 50% of average correctly predicted probability. The third category ("motivational" framing) is the best performing of these categories (0.57). This category has the highest real frequency (n=372). The first category ("diagnosis") shows the highest values of wrongly predicted values, indicating that this category is usually confused with the second ("prognosis") and third ("motivational") by the model. The evaluation metrics of the model for each typology are correct and show values from fair to moderate (social function typology -Kappa, 0.43; F1, 0.60-; and framing typology -Kappa, 0.39; F1, 0.56). The difference between the average performance between typologies is significantly differently 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 is better than the performance for the framing typology.

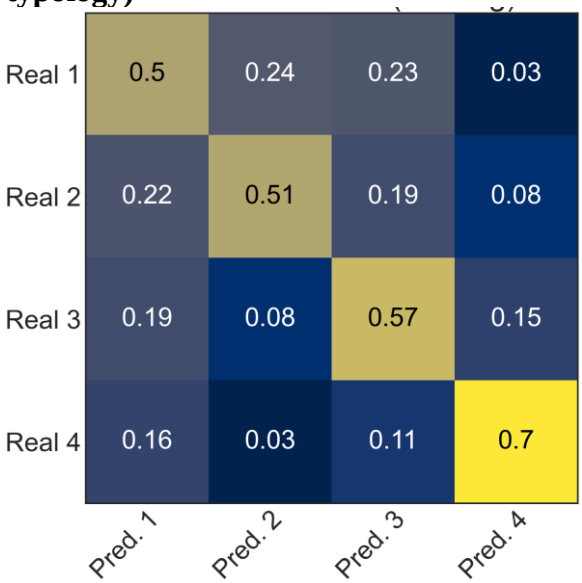
Table 5. Confusion matrix (social function typology)



Evaluation metrics: Kappa, 0.43; F1, 0.60

Source: Own elaboration. SVC (C=0.7, Kernel='linear').

Table 6. Confusion matrix (framing typology)



Evaluation metrics: Kappa, 0.39; F1, 0.56

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 vary across typologies. This section focuses on the content of the most discriminant tweet, those with a predicted probability belonging to the last decile, 90% to 100%, per category (see Table A.4. and Table A.5 in the Annex). This allows us to analyze the most representative content of each category. We used 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 7) and framing typology (Table 8).

Table 7. Number of most representative tweets, words and different words across category of social function typology

Grupo	N_tweets	N_words	N_different_words
1	60	960	533
2	8	140	92
3	246	3927	1883
4	199	2990	1510
5	206	3085	1542

Source: Own elaboration.

Table 8. Number of most representative tweets, words and different words across category framing typology

Grupo	N_tweets	N_words	N_different_words
1	30	602	430
2	5	104	89
3	1	17	16
4	80	1492	954

Source: Own elaboration.

The following figures represent word clouds across category and typology. The top-10 list of most frequent words across categories and typology are in the Annex (Table A.6 and A.7). There are several words that are common across categories. For example, “climate”; “fridaysforfuture”; “climatestrike”; “global”; “today”; “action”; “gretathunberg”. These words are essential for all discriminant tweets and refer 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 are also dominant in the “Information” category of the social function typology (Fig. 1). The “Opinion” category includes as distinct concepts, such as, the nouns “activists”; “emissions”; “industry” and the adjective “responsible”. It also includes references to places, like, Karnataka a region from India importantly affected by climate change. Other places, such as, Berlin, Bristol, Ullapool and countries India or Australia appear in this category, together with climate activists, Ridhima Pandey. Within the “mobilization” category singles out the verb “join” and more direct calls for actions (i.e. “fightclimatejustice”). Finally, the “Attack/blame” category includes references to justice and youth or Trump.

Figures 1 to 4-Word clouds across categories of social function typology

Fig 1. Information

Fig 2. Opinion

Fig 3. Mobilization

Fig 4. Attack/Blame

Source: Own elaboration.

Regarding the framing typology (Fig. 5-7), the concept of "covid" emerge more clearly in both the "diagnosis" and "prognosis" categories.

Figures 5 to 8. Word clouds across categories of framing typology

Fig 5. Diagnosis

Fig 6. Prognosis

Fig 7. Motivational

Source: Own elaboration.

6 CONCLUSION

This article has analyzed the social media use of the FFF climate movement on the Global Day of Climate Action held on September 25th, 2020. The analysis of social media activity of this movement is especially relevant due to its transnational character and the young profile of protestors (Walström 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 allow young people around the glove to share their opinions and is the prefer method to get information (Walström et al., 2019; de Moor et al., 2020). 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 analyze social media data: social media activism and framing literature. From this literature review we identified two relevant typologies the "social function" typology and framing tasks typology. The literature review on the FFF movement 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 sizes. 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 the Twitter's API with keywords "#climateStrike", "#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 9,529 tweets and 42.87% of total tweets. We tested the codebooks with 20

randomly selected tweets and manually code 950 randomly selected tweets. These tweets were used as input to the automated-classification process that relies on Support Vector Machines algorithm as a supervised learning method (Kernel lineal) with balancing classification techniques (i.e. SMOTE).

The analysis on the distribution of tweets across social function categories showed that tweets are not frequently used to mobilize support, being more frequently used to express and opinion, to share information or to attribute blame. These results show similarities with other protest events FFF related (i.e. Boulianne et al., 2020) or not FFF related (e.g. Raynauld et al., 2016 and Theocharis et al., 2015). These results lead us to conclude that the Covid-19 context has not increased mobilizing function of tweets. In addition, we showed that mobilization tweets are retweeted less frequently and, therefore, have less connective power. The share of tweets that have the blaming function is 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 is to express and 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 on legislation and policy changes. These results could be compared to other climate changes studies, such as Wahlstrom et al. (2013), that also found an important percentage of individual opinions framing of how to solve the climate crisis on legislation and policy changes. We found that there is a relationship between the social function of tweets and their framing content (the typologies are not independent). For example, mobilization tweets are mostly framed in a motivational fashion, while tweets that attribute blame tend to be associated to prognostic framing relating to possible solutions. Interestingly, we found that mobilization and motivational tweets are retweeted less frequently and, therefore, have less connective power.

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-; and 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 (random forest machine learning algorithm and class rebalancing techniques SMOTE) showed that the model predicts with a high accurately levels the “other” category across typologies and indicates where the confusion arises from. This indicates that these methods could specially help for cleaning purposes and for 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 3 tweets. These lists of most discriminant words could help researches in their codification tasks and stakeholders for communication purposes.

Other recent studies have analyzed the FFF movement under the Covid-19 pandemic (e.g. Haßler et al., 2021; Source and Dumitrica, 2021). Haßler et al. (2021) analyze German tweets showing that the number of tweets has declined, 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) confirms 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 Source and Dumitrica (2021) performed a qualitative social media framing analysis on 457 Facebook protest signs of FFF in Europe. Source and Dumitrica (2021) shows 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 cover early phases of the Covid-19 pandemic, while we focus on September 2020 FFF mobilization. September events tends to concentrate high mobilization power. We confirm that online mobilization is highly dependent on both offline and online events and that framing tasks coexists in a mobilization event.

Our research has several limitations, we have not paid enough attention to the media ecology of our database as we didn't 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. Categorization of framing tasks is an oversimplification of framing approach, that could be complemented with a mix-method approach. Manually coded typologies were forced to be mutually exclusive while automated data process could identify percentages of typologies within a message. Further studies should consider the advantages and disadvantage of applying different coding strategies (mutually and non-mutually exclusive).

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ANNEX

Table A.1. 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%
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 A.2 Example of tweets across categories of social function typology

1. Information	
1.1 Documentation tweet ort tweet about an issue or event related directly to the strike	#FridaysForFuture| Young people are back on the Streets for climate in at least 3,500 locations around the globe. ?????? https://t.co/AlH1YO58PJ 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 https://t.co/NdQ9GJFXu0
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 https://t.co/K2GyOuiuBW
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 https://t.co/wZLA65OBXM"
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 https://t.co/ZOqfU8gwfL"
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 https://t.co/JHPQDnUHeE JOIN OUR ONLINE CLIMATE ACTION: https://t.co/xTU81AlCKP #KamayParaSaKlima #FridaysForFuture #FightClimateInjustice https://t.co/andFoYQOr7
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 >> https://t.co/Daj7UWn4WL… And follow >> https://t.co/f4dGec1fuK… #FridaysForFuture https://t.co/zVFALBr9jP
4. Attack/Blame	
4.1 Attack/blame at goverment	See how this works, WP says we have 7 yrs, CA Gov Newsom requires all cars be zero emission by 2035... that is about 8 yrs to late. Doesn't matter your politics. #FridaysForFuture #ClimateAction #ClimateStrike https://t.co/sTVtfnBlnK
4.2 Attack/blame at 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 at 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 https://t.co/XqpqpQEo9t #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 https://t.co/heSLIe2fsZ #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: https://t.co/lPvqlp9vxT #COVID19 #lockdown #FridaysForFuture #Biden #Europe #China #Russia #Trump #Fiverr"

Table A.3 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 https://t.co/Hp84lA7YAw
2.2 System oriented	"System Change not Climate Change! #KeinGradWeiter CO2/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 https://t.co/1BZX8S7U96
3. Motivational	Go Greta and friends!
4. Other	"✨ queen things only ✨ stanning @joyangtv harder huhu ??"

Figures A.1 to A.4 Box plots and error bars (95% IC) of retweets across social function and framing typology

Fig. A.1 Box plot of retweets (Lnretweets) across social function typology

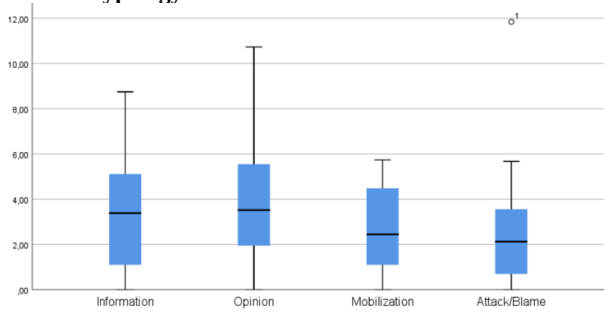


Fig. A.2 Box plot of retweets (Lnretweets) across framing typology

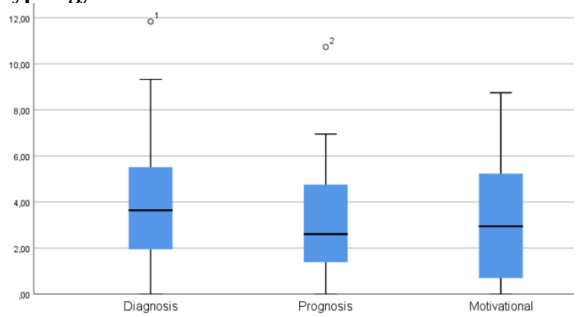


Fig. A.3 Error bars (95% IC) average retweets across social function typology

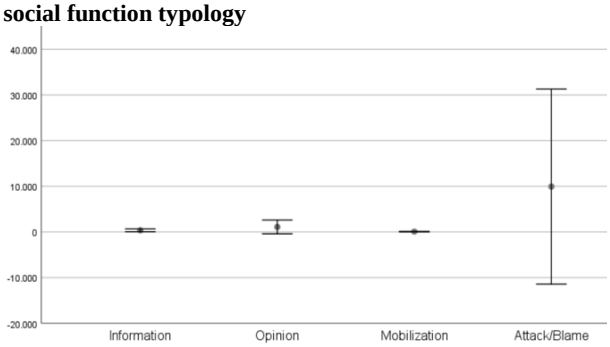
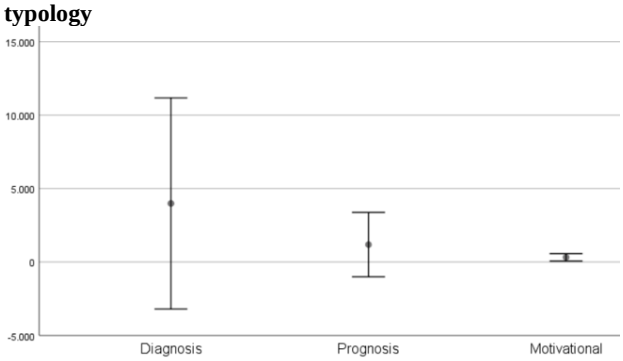


Fig. A.4 Error bars (95% IC) average retweets framing typology



Note: Figures A.1 and A.2 show logarithmic transformation of number of retweets (Lnretweets) and A.3 and A4 exclude tweets with 0 retweets.

Table A.4. 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
1	0.007	…	0.499	0.797	0.236	0.164
2	0.013	…	0.725	0.897	0.455	0.200
3	0.004	…	0.180	0.929	0.084	0.144
4	0.005	…	0.243	0.837	0.119	0.144
5	0.001	…	0.218	0.766	0.104	0.104

Table A.5. Distribution of predicted probabilities belonging to the last decile, mean and standard deviation across categories of framing typology

Label	0%	…	90%	100%	Mean	Sd
1	0.015	…	0.451	0.730	0.212	0.153
2	0.017	…	0.656	0.908	0.262	0.216
3	0.013	…	0.723	0.931	0.406	0.239
4	0.002	…	0.252	0.780	0.118	0.144

Table A.6. Top-10 most frequent words of the most representative tweets of social function typology (categories and frequencies)

Cat	Token	N
1	climate	46
1	fridaysforfuture	33
1	climatestrike	30
1	strike	15
1	fightclimateinjustice	14
1	global	14
1	today	14
1	action	13
1	gretathunberg	13
1	fridays	10
2	climate	9
2	climatestrike	6
2	fridaysforfuture	6
2	strike	6
2	global	5
2	school	4
2	activists	3
2	today	3
2	week	3
2	action	2
2	around	2
2	back	2
2	day	2
2	emissions	2
2	fridays	2
2	future	2
2	gretathunberg	2
2	industry	2
2	karnataka	2
2	schoolstrike	2
2	world	2
3	fridaysforfuture	148
3	climate	113
3	climatestrike	66
3	action	42
3	fightclimateinjustice	42
3	global	30
3	today	30
3	future	28
3	amp	26
3	day	25
3	gretathunberg	25
4	fridaysforfuture	115
4	climate	100
4	climatestrike	56
4	action	35
4	fightclimateinjustice	34
4	global	28
4	today	26
4	future	25
4	strike	23
4	day	21
4	gretathunberg	21

Table A.7 Top-10 most frequent words of the most representative tweets of framing typology (categories and frequencies)

Cat.	**Token**	**n**
1	fridaysforfuture	23
1	climate	13
1	climatestrike	10
1	climateactiongh	6
1	fightclimateinjustice	6
1	ghana	6
1	leadonclimate	6
1	amp	5
1	climatecrisis	5
1	climateemergency	5
1	gretathunberg	5
2	fridaysforfuture	5
2	climate	3
2	fightclimateinjustice	3
2	amp	2
2	climateemergency	2
2	keep	2
2	lives	2
2	need	2
2	sap	2
2	time	2
3	lives	2
3	amp	1
3	away	1
3	changed	1
3	climate	1
3	current	1
3	exploitative	1
3	extractive	1
3	fightclimateinjustice	1
3	fighting	1
3	fridaysforfuture	1
3	hyper	1
3	justice	1
3	keep	1
3	system	1
3	taken	1

Note: “Other” category excluded