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Graphical Abstract

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Highlights

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- Research highlight 1

- Research highlight 2

The rise of #climateaction in the time of the FridaysForFuture movement: a semantic network analysis

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Abstract

We investigate the features of the online discourse over climate change, and its modifications throughout the years 2017-2019 as a result of collective actions promoted worldwide. We seek to understand the emerging connection between digital activism and the psychological processes related to its social drives. To this end, a semantic network is derived from the social platform Twitter, and its evolution is traced over time, tracking textual proxies of social identity and empowerment. Network analytic evaluations on semantic communities of related concepts further detail the shift in the rhetoric of collective actions. Finally, we explore projection of the ingroup to the future in the online discourse about climate change, which can point to developments of pro-environmental campaigns.

Keywords: Climate change, Semantic networks, Collective action, Network analysis, Community detection, Social identity, Empowerment, Future orientation, Hashtag activism
PACS: Social systems, 89.65.-s, Complex systems, 89.75.-k

1. Introduction

Social discourses about climate change have been generating significant engagement over the last few years, especially over online platforms. In 2019, a spike of global interest was reached through the actions that many credited to 16-year old Swedish activist Greta Thunberg. As a result of the "School strikes for climate" / "Fridays for future" initiatives, many voiced dissent against the world governments and their passive behavior towards the problem of anthropogenic climate change. In turn, this issued a surge of collective actions like street protestations, as well as a spread of related trends over online social media. Similar to what done for many other phenomena in the information age, the role of the Internet and online communities as nurturing and fueling the protest, and in turn being also influenced back, might be worth investigating (Vasi and Suh, 2013).

Despite the enormous and pervasive consequences of anthropogenic climate change, only few small groups are practically engaged in turning this matter into a political priority. To change the civic agenda about the environmental policies, climate change needs to increase its dominance in the public discourse. What mobilizes people to engage in public discourses about climate change in general, and specifically in online climate action? The general goal of the present study is to understand the dynamic of people's engagement (Tajfel, 1974) and empowerment (Stürmer et al., 2003) in social protest (Van Zomeren and Iyer, 2009), concerning environmental issues and particularly climate change.

Moving from this background, we are especially interested in analyzing how the semantics of the social conversation over online platforms was affected, and whether this trend may have set in motion further influences on collective actions (Stürmer and Simon, 2004). We can use this not only to detect protests against global climate change, but as a means to address broader social implications of the possible shifts of the online discourse. In this spirit, we are not only focusing on capturing trends that originate from specific initiatives, which could be achieved by just measuring the frequencies of popular keywords that appeared in 2019. We are instead concerned with dynamics involved over networks, both meant as semantic constructs and individual interconnections (Newman, 2001; Fan et al., 2007), particularly in relationship to collective actions as a response to climate change.

We look at conversations over online social networks, and most specifically Twitter contents, which seem to be especially suitable in light of their immediateness and brevity. We do not focus on the last year only, but we provide a full-rounded anal-

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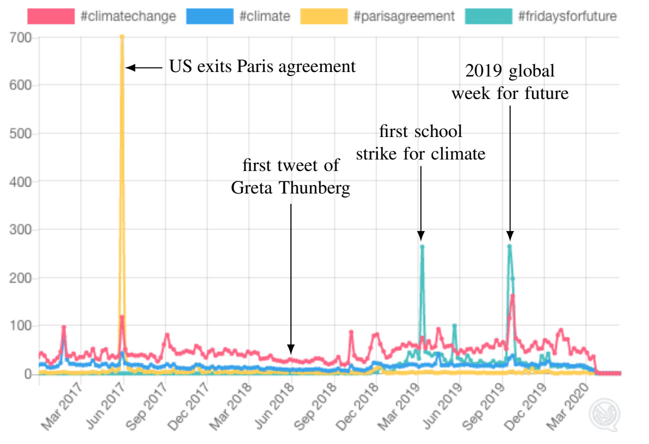


Figure 1: Historical twitter trends for some hashtags related to climate action where values represent 1/10,000th of 1% of tweets [taken from www.trendsmap.com/historical]

Table 1: Percentage of co-occurrence with hashtag `#climatechange` in different time windows.

score 2018		score 2019	
#parisagreement	12.7	#climatestrike	25.6
#climateaction	10.6	#climatecrisis	12.9
#actonclimate	10.2	#fridaysforfuture	12.5
#environment	7.0	#climate	9.5
#energy	4.9	#actonclimate	9.2
#climate	4.4	#climateaction	9.1
#globalwarming	4.0	#schoolstrike	8.0
#sustainability	2.6	#globalwarming	4.7
#stopadani	2.2	#environment	4.0
#renewables	2.1	#energy	3.9

ysis over different time epochs. Regardless of the popularity of a trend, data from Twitter has been shown to be able to assess the engagement of users to a community (Ibrahim et al., 2017). In the context of this contribution, we seek whether it also embeds a push towards collective actions, and possible evolution over time of this phenomenon. Twitter is here considered as a window, or arena, of the online protest around climate change, providing an accessible ground, for both actors and researchers, to structure relations among different individuals, issues, and events over time. Since the content is arranged through argumentation tags (i.e., hashtags), one may build rhetorical networks around which the online protest gravitates (Bastos and Zago, 2013). By focusing on the content and language of what is linked, we explore the natural structure and content of the verbal semantics, investigating the social drives associated to this specific collective action. The comparison of different time frames reveals the topics that characterize the communities of such rhetorical networks and enables the understanding of the engagement evolution in terms of psycho-social motives and processes (Borge-Holthoefer and Arenas, 2010).

To clarify our methodology, and why we believe that it captures the underlying network semantics in more depth, consider the following relevant instance of our data that will be discussed in more detail in the following. We take a set of tweets extracted over different 50-day window periods in March-April 2018 and 2019 containing the hashtag `#climatechange`. As visible from Fig. 1, this hashtag keeps a rather stable trending behavior on Twitter, as opposed to others hashtags which were basically originating in 2019 as the consequence of the aforementioned movements, or died out as being related to specific past events. Some relevant hashtags of 2018 and 2019 with simultaneous index of occurrences normalized to `#climatechange` taken 100, are reported in Table 1. From a direct comparison of the hashtags, it is visible that some specific new terms have appeared in 2019, such as `#climatestrike` or `#fridaysforfuture`, while others such as `#parisagreement` basically disappeared.

At the same time, there is an underlying mantle of related "neutral" hashtags that are apparently still present in the Twittersphere, such as `#climate` and `#environment`, albeit with different prominence (Sanlı and Lambiotte, 2015).

We would like to capture these trends in a more systematic way, as we deem to be insufficient to limit our analysis to the popularity of some specific hashtags. After all, the individual role of a keyword can be simply taken by another more trending hashtag, without any significant change in the online discourse. We also aim at characterizing the entire semantic network of related hashtags and more general online content (Breslin and Decker, 2007). For the sake of avoiding biases, we start from neutral hashtags, avoiding those that appeared in a specific time instance but rather considering the ones that were popular throughout the entire observation span, and we infer the semantic similarity in the network of tweets through topic-sensitive ranking (Haveliwala, 2003). We further analyze the resulting semantic network addressing two main social motives that foster collective action in general, and seem to be particularly relevant in this case.

First of all, we explore *social identity*, i.e., the sense of group membership as a key component of one's individuality. It can be argued that the initiatives launched in 2019 were enabled by spontaneous aggregation of individuals, especially young generations. Collective actions are fostered by such a foundation, especially when a group perceives its lower status as illegitimate and unstable (Kawakami and Dion, 1995). Thus, we would like to explore whether the social discourse in 2019 was possibly enriched through the provision of a social group to identify with, which would promote a stronger engagement in the related collective actions.

At the same time, we want to investigate *empowerment*, meant as the perceived level of efficacy towards globally desirable objectives in the online community. The feeling of empowerment and related constructs, such as group efficacy, are strongly linked to collective behavior, and in particular to crowd actions (Drury and Reicher, 2009).

Moreover, we characterize the additional dimension of semantic *communities*, a contribution that we achieve through a network-based methodology. We consider clustering of hashtags related to the online discourse on climate change and identify a rather consistent group dynamics over the year. Communities of hashtags related to similar topics are present, such as general concern towards the nature and/or corporate branding that claims to be environmental friendly. We can quantify some textual proxies of the aforementioned concepts of group identity and empowerment also specific to a semantic community and we are able to spot certain trends that are stronger for the precise context of climate change.

Finally, we discuss the projection of temporal evolution outside the considered time window, showing further evidence of an ongoing evolution of the climate change online semantics. This can foster further development in the years to come, and a paradigm shift in the public engagement on the matter.

2. State of the art

2.1. Collective action: Why and when people protest?

The literature on collective action explores the psychological determinants that move people toward uprising. Here, we focus on two central psychological processes that are consistently shown as predictors of protest engaging, namely *affiliation* and *empowerment*.

Since its appellation and definition, collective action embeds the concepts of groupness and agency. Any collective action mobilizes people to reach a shared goal, be it a strike, a march, an online petition, or a vote, with the aim of improving the condition of a group (Van Zomeren and Iyer, 2009). The emphasis on group enhancement is therefore the core of the action, moving people for the common good rather than of the self. Of course, personal and group interests are often congruent, but engaging in a collective action requires strong social motives and a high sense of affiliation to overcome the effort involved in the action and prioritize the utility of the group over the individual costs. Indeed, one may simply let the others fighting, and eventually enjoying the positive outcomes, without personally engaging in the actions.

The social identity theory (SIP: Tajfel, 1974) is a seminal framework to explain the reasons behind group dynamics. According to this theoretical perspective, the inclination to behave in terms of group affiliation relates to the extent by which the social identity is relevant and important to the person. This is a key constituent of the self-concepts (Tajfel et al., 1979), deriving from the self-awareness of belonging to a social group. The first step of social identity is therefore the categorization into a "we" (the ingroup, namely the group people belong to) distinct from a "they" (i.e., the outgroup, considered to be somewhat external). The value and emotional significance of this belonging influences what people do and think in the context of social relations, and explains the profound reasons that prompt people acting for the interest of the group (van Zomeren et al., 2018). A solid corpus of evidence highlights that group identification is associated to both intentions and behaviors related to collective action. For example, social identification was linked to intention to participate in collective actions for the elderly (as in Study 1 by Simon et al., 1998), LGBT minorities (Study 2 by Simon et al., 1998; Stürmer and Simon, 2004), and women rights (Kelly and Breinlinger, 1995). Ellemers et al. (1999) suggested that high identifiers are more concerned about and committed to group goals and interests than lower identifiers, who are more committed to their individual goals and interests. Importantly, social identification is also associated to actual behaviors (Foster, 1999). Kawakami and Dion (1993) showed that people were more likely to engage in positive collective actions, such as asking for help to improve the group, than negative individual actions, e.g., leaving the group, when their group membership was salient.

As mentioned, the costs associated to the protest are very high, both practically and psychologically. At the practical level, collective actions consume time and resources. At the psychological level, costs relate to a general aversion to change (see the status quo bias, Samuelson and Zeckhauser, 1988). People tend to maintain the status quo, and they rather frame the current condition as just (see the just world belief, Lerner, 1980) rather than engaging in rebellion, even when the status quo is clearly disadvantaging them and their group (see system justification theory, Jost et al., 2004). Social change is therefore repressed by socio-cognitive mechanisms that preserve the situation as is, preventing people from taking action and psychologically inhibiting remonstration against the mainstream. Therefore, people need to be highly empowered to overcome these costs associated to rebellion. Consistent with this notion, the past literature on collective action showed that empowerment is a central drive for engaging in collective action (Drury and Reicher, 1999). Empowerment refers to the sense that the goal can be achieved, and is often labeled as effectiveness (Hornsey et al., 2006), efficacy (Van Zomeren et al., 2008), or agency (Jasper, 2004). Some scholars conceptualized empowerment at the personal, some at the group, and some at the goal level. At the personal level, empowerment corresponds to the individual perception of being able to contribute to the cause (e.g., Tagkaloglou and Kasser, 2018). At the group level, empowerment refers to the idea that enough people can be mobilized to achieve the goals (Berman and Wittig, 2004; Stürmer and Simon, 2004) or the group can collectively reach a social change (Bandura, 2000). Focusing on the goal, empowerment refers to the belief that the collective goal can be achieved (Tyler and McGraw, 1983). What all these definitions share is that a lack of perceived effectiveness prevents people from engaging in collective action, with the idea that there is no point in protesting if there is no hope for future change (Abramson and Aldrich, 1982; Verba and Nie, 1972). Only when people feel that goals are achievable, they can consider joining a collective action such as a union meeting (Flood, 1993), or support a petition for bilateral disarmament (Lee Fox and Schofield, 1989). Identification and empowerment predict both online and offline actions, such as signing an online or pen-and-paper petition (Brunsting and Postmes, 2002).

2.2. Social networks: Beyond the sum of the people

Socially driven actions assume a central role in collective change and the achievement of common goals. This perspective overcomes both the individual and the group as a collection of individuals and rather approaches social processes as a network whose entirety is grasped only if regarded as an entity that is more than the sum of its parts (Robins and Pattison, 2005). From this standpoint, collective action is embedded as a complex substrate of social processes that stem from the sense of belonging expressed by "dynamic wholes" (Lewin, 2016). Nevertheless, most of the studies on collective action grounded on the theory of social identity generally measure relevant indices at the individual level, and only observe the participation of single units. Therefore, the main assessment concerns the personal contribution of group members to the collective action, whereas the group dynamic of meaning, creation, and evolution over time is somehow neglected.

The adoption of recently popular analytical instruments of network science (Newman, 2001) can represent a progress toward capturing the "dynamic wholes." Network science is a cross-disciplinary field of study investigating complex systems exhibiting a fundamental characteristic of networked interconnection, despite the different range of applications. As such, its usage has been envisaged also in computational linguistics, psychology, and sociology (Arney et al., 2013). Network science gives a *holistic* and *across* essence to network constructs, implying that a further entity arises beyond the individuals. Moreover, possible overlapping interconnections weave a deeper plot than just the contrast of multiple parts versus a "whole."

In particular, the application of network science to the process of shared reality construction tackles the co-creational perspective of activism within social media (Lewis et al., 2010). First, the rhetoric of an online discourse cannot be expressed through single semantic items but is a global drive achieved by interacting words, while in turn, the evolution of language, especially in the information era, is promoted by countless micro-interactions at the individual level, which are better represented with a holistic characterization (Kirby et al., 2014). Second, the push towards collective action also happens through multiple gradual nudges that are hard to identify through individual actions (Stürmer and Simon, 2004). Finally, there is a mutual interrelationship of semantic groups and communities of individuals who tend to use a textual lexicon with analogous inclinations (Rouwette, 2003).

Semantic networks analysis have been used to explore the belief system about vaccination (Kang et al., 2017; Getman et al., 2018), to study social influence and discourse similarity within work groups (Saint-Charles and Mongeau, 2018), to explore the epistemic structure of social and semantic networks of knowledge communities (Roth and Cointet, 2010). In the field of psychology, network science and semantics have mainly been applied to the study of emotion networks, for example in relation to diagnosis (Neuman et al., 2012) and prognosis (Sugandhi and Mahajan, 2017) of psychological disorders.

2.3. Social media as reality mirrors

Social media are dramatically popular. Since the second decade of XXI century, they have been enjoyed wider audience than traditional mass media like television and newspapers, and their use is increasing over time (Newman et al., 2017). Social online platforms allow a many-to-many communication exchange, whereas traditional media are only one-to-many. Thus, millions of people with different backgrounds can express themselves by sharing their opinions, forming online groups, and organizing both offline and online collective actions.

Among social media particularly suited to analyze online rhetoric systems, we identify Twitter, one of the biggest platforms for micro-blogging that, to some extent, also combines instant messaging, social networking, and status communication (Ross et al., 2011). Daily interactions on Twitter can be viewed as the signal of a distributed network of human sensors where the value is a product of its interconnected structure (Boyd and Crawford, 2012). Also, the messages shared on Twitter have a condensed structure which fits well with text analysis methods because tweets have to express brief but complete and meaningful concepts, which is often highlighted by the use of keywords (Bastos and Zago, 2013; Kirilenko and Stepchenkova, 2014). Due to its popularity among a big variety of social actors, from individuals to organizations, Twitter captures a discourse co-created by ordinary citizens, politicians, journalist, activists, and experts. Previous studies already showed that the texts mined from Twitter can predict offline-world features such as personality (Agarwal et al., 2020), the stock market (Bollen et al., 2011), health conditions (Paul and Dredze, 2011), crime (Wang et al., 2012), and elections (Tumasjan et al., 2011).

Moreover, messages on Twitter are publicly available; therefore, Twitter allows the web-scraping of the messages through its API without putting particular issues for the users' privacy. Finally, Twitter uses hashtags for semantic and channel tagging, and meta-communication. Hashtags can be used to organize online content and offer a pointer toward a topic; tweets often use hashtags in both ways by putting multiple hashtags in a single message. Previous literature showed that hashtags on Twitter are also used to brand advocacy movements and archive messages for the movements (Saxton et al., 2015; Bruns and Burgess, 2011). These aspects allow creating a semantic network in which two hashtags are connected when they are part of the same tweet (Hellsten and Leydesdorff, 2020). The structure that is created with the hashtag network depicts the dependency among messages, and with community detection techniques we may describe the discussion revolving around specific topics. Moreover, as hashtags are part of a tweet, it is possible to establish a relationship between hashtags and messages where the latter are connected by common topics, making it possible to formalize and test a variety of societal and psycho-linguistic phenomena.

Online social networks create the opportunity for large scale collective action in which the created content triggers cascade effects of social influence. The persuasion processes exerted within social media crosses the borders of the virtual reality affecting actual behaviors. For example, an experimental study involving 61 million Facebook users showed that people are affected by the visualization of their Facebook friends' voting behavior (Bond et al., 2012). Specifically, Facebook users are more likely to vote when they see that their Facebook friends already voted and they are in turn more inclined to share their own behaviors, turning into collective actors themselves and influencing other users.

On the one hand, digital activism faces specific hurdles, related to anonymity, lack of accountability, heterogeneity, uncertainty, and emotional detachment (Jagers et al., 2019). On the other hand, the ease, velocity, and width of information sharing facilitates the creation and mobilization of huge social communities, fostering the discussion and conceptualization of the social issue (Keller, 2012; Pudrovska and Ferree, 2004). The so-called *hashtag activism* is the ground for awareness rising and public debating on several causes and targets, including protest to defend the rights of racial minorities (`#blacklivesmatter`; `#ferguson`, `#georgefloyd`), to promote gender equality (`#dresslikeawoman`; `#heforshe`), or to fight hate speech (`#stopfundinghate`). González-Bailón and Wang (2016) investigated the interpersonal network of hashtag activists of the 2012 campaign "United for Global Change" sponsored by the protest groups Indignados and Occupy and, contrary to naïve expectations, showed that the online networks of protesters are fragmented, therefore dampening the information flow.

The application of network analysis to understand online collective action is another growing and promising field of investigation. For example, Xiong et al. (2019) analyzed a semantic network of tweets related to the feminist initiatives to examine the co-creation process of meanings in the `#metoo` movement, identifying the core themes of this collective action, among which there are rhetoric on obstacles to gender equality, encouragement to act, and promotion of specific events. By comparing `#blacklivesmatter` and `#alllivesmatter` networks, Gallagher et al. (2018) uncovered content injection. Despite all of these contributions, the psychological processes have not yet received enough attention, and the topic of climate change, despite its considerable online presence, was not thoroughly investigated through these approaches, as we will show in the next subsection.

2.4. The scenario of climate change

The discussions toward climate change are frequent in a variety of media. In particular, social media have several important features that make them one of the best contexts for studying the attitudes of people and the rhetoric of messages around climate change. According to Boykoff (2011), topics involving anthropogenic global warming are actually discussed more on social media rather than traditional media. In particular, Twitter seems to be especially relevant. For example, the Twitter account of Greta Thunberg, the famous environment activist, has a following by more than 4 million users, and overall Twitter represents an important tool for her movement, FridayForFuture. Tweeting is therefore the main communication strategy and the primary channel to spread awareness about climate change and call to action. At the same time, a time-consistent interest is shown on Twitter, with some choices of hashtags being occasionally more trending, yet with an overall steady behavior, as visible from Fig. 1.

Additionally, all of the psycho-sociological threads previously mentioned as motives for collective action engagement, i.e., social identity, empowerment, the role of network, find a particularly suitable declination in the case of climate change.

For example, the SIT approach is relevant to pro-environmental action, as shown by Fritsche et al. (2018), and several studies confirmed the relation between social identification and environmentalism (Dono et al., 2010; Fielding et al., 2008; Brügger et al., 2011). Moreover, Rees and Bamberg (2014) found that the intention to participate in a local pro-environment action was stronger among those who reported a high sense community related to their neighbourhood. Schmitt et al. (2019) argued that the engagement in environmental activism was predicted by the extent respondents self-identify as politicized environmentalist.

Empowerment is also evident for climate change activism (Fritsche et al., 2018). The salience of the threat associated to climate change enhances collective efficacy (Hornsey et al., 2015), which in turn promotes collective action (van Zomeren et al., 2010) such as taking part in a neighborhood-based climate protection initiative (Rees and Bamberg, 2014).

Also in relation to the underlying interconnection between real-world events and the online semantics, the context of climate change can be viewed as particularly relevant. For example, Kirilenko et al. (2015) showed that weather anomalies predicted the volume of tweets about climate change. Thus, even though many other topics discussed over social platforms are not confined to expressions of opinions but rather mirror what is happening in the real world, climate change can surely be regarded as a prime example of this trend.

Orientation to the future may be indeed critical for the collective action related to the environment, since the consequences of climate change need a long-term appraisal to concern people (Sarigöllü, 2009). The literature on the timeframe issue in this context provides support for an association between pro-environment attitudes and behaviors, and future orientation; for a meta-analysis, see Milfont et al. (2012). For example, Corral-Verdugo et al. (2006) investigated the relationship between time perspective and pro-environmental behavior. Specifically, they assessed time perspective with the Zimbardo's time perspective inventory (Boyd and Zimbardo, 2005) and showed that future orientation, namely the tendency to foreseeing future events, was positively associated to the extend participants reported water preserving behaviors such as conserving water while washing dishes. Along the same line, considering future consequences was associated to higher pro-environment attitudes, such as support to public transports (Joireman et al., 2001, 2004) and sustainable consuming (Lindsay and Strathman, 1997).

3. Methods

3.1. Data collection

To analyze the online semantic network about climate change, we considered posts, also referred to as "tweets," on the social media site Twitter. They can be downloaded through the free web APIs,[5] that enable textual searching by specifying various parameters, such as language, time range of posting, or the presence of specific hashtags.

We limited our scope to tweets in English language and we identified three analogous time intervals for the years from 2017 to 2019. Namely, the chosen intervals were:

- March 1st, 2017 to April 19th, 2017
- March 1st, 2018 to April 19th, 2018
- March 1st, 2019 to April 19th, 2019

We chose the same period within a year so as to limit seasonal events influence. Each of these time intervals lasts 50 days, which is the longest span that can be retrieved by sampling a batch of 100 tweets per day, summing up to 5000 tweets per year. Daily batches were uniformly sampled over each of the 24 hours (in UTC time), to limit the biases of time vs. location. The specific choice of intervals permits capturing the semantic of climate change discourses around two main events, namely the U.S. withdrawal from Paris Agreement in June 2017, and the first Strike for Climate on the 15th of March 2018 (see Fig. 1).

The selection of hashtags to be used in the query followed a two-step process aimed at identifying *neutral* (but relevant) hashtags related to the climate change issue, in such a way to prevent from a bias towards keywords more closely related to a specific event or year (e.g., `#fridaysforfuture` or `#parisagreement`). Building the network upon hashtags that were not related to specific collective actions, events, celebrities, or organizations was fundamental to have a balanced comparison among the years and an unbiased measure of the importance of semantic communities around the climate change discourse. For example, if the network were created from hashtags related to events of a precise year, the centrality of the hashtags related to that year would have been overestimated. Similarly, a network generated from hashtags related to a specific movement (i.e., `#fridayforfuture`), would have overestimated the centrality of hashtags more related to that movement.

Thus, we adopted the following procedure. First, a search over the three time intervals was carried out with the sole hashtag `#climatechange` to identify the most relevant hashtags connected to the climate issue in 2017, 2018, and 2019, separately. A shortlist was built by joining together the 20 most frequent hashtags of each year, and discarding the non-neutral ones (e.g., related to a specific event). Neutrality and importance of hashtags in the shortlist were verified by an Historical Twitter Trends search,[6] with the aim of selecting only hashtags active through all the chosen intervals (neutrality), as well as highly ranked (importance). The resulting selection identified the top ranked neutral hashtags `#climatechange`, `#climate`, `#sdgs`, `#sustainability`, `#environment`, `#globalwarming` as appropriate for the search. Their historical twitter trend is avalable from Fig. 1

[5]http://developer.twitter.com/en/docs
[6]http://www.trendsmap.com/historical

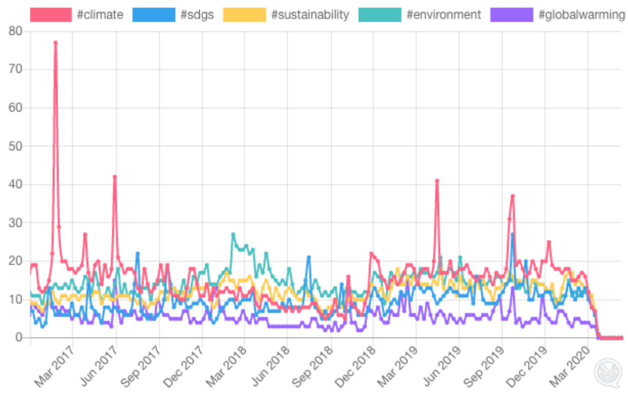


Figure 2: Historical twitter trends for the selected hashtags, where values represent 1/10,000th of 1% of tweets [taken from www.trendsmap.com/historical].

and Fig. 2, from which it is evident that the most relevant hashtag is by far `#climatechange`. In conclusion, these hashtags were considered a good starting point for building the network because of their stability during 2017, 2018, and 2019, the absence of excessive peaks during the chosen intervals, and their overall relevance toward the topic of climate change.

3.2. Social identity and empowerment metrics

Using the Linguistic Inquire and Word Count 2015 (LIWC, Pennebaker et al., 2015), a well-established tool for quantitative analysis of psychological processes through text samples (Hawkins et al., 2017), we content-analyzed all the tweets collected. LIWC enables a dictionary-based quantitative content analysis in which every message receives a score on several word categories based on the number of words belonging to the specific category adjusted for the total number of words within the message. Coherently with our research questions and hypotheses, the focus of our analyzes was on the following main concepts:

a) Affiliation. The LIWC score for the category *affiliation* (e.g., ally, friend, social) was used for measuring the in-group community orientation within the text. This proved to be a reliable index of implicit motives for affiliation (Schultheiss, 2013).

b) Group-identity salience. The frequency of personal pronouns can be used to assess the salience of group membership. In particular, the first person plural pronouns (i.e., *we*) mark the sense of belonging (Zhang, 2010). Michinov et al. (2004) experimentally manipulated group-identity salience and showed a resulting increased use of first-person plural pronouns. Indeed, this type of word has been already analyzed as a marker of social identity of the online action `#occupywallstreet` (Smith et al., 2015).

c) Empowerment. We computed the Empowerment scores aggregating with a mean the LIWC scores for the categories *power*, *achieve*, *reward*, *insight* and *cause*. Previous studies (e.g., Decter-Frain and Frimer, 2016; Pietraszkiewicz et al., 2019) reported that these categories are good proxies of agency, which "refers to a person's striving to be independent, to control one's environment, and to assert, protect and expand one's self" (Abele et al., 2008). This is related to intelligence, skill, creativity, achievement, power, mastery, and assertiveness, whereas the lack of agency refers to being weak, submissive, incompetent, and likely to fail (Fiske et al., 2007). Thus, agency can be assimilated with empowerment.

d) Temporal perspective. The orientation of tweets to the past, present, and future was measured using the specific LIWC categories of *past* (e.g., ago, did) and *future focus* (e.g., will, soon).

3.3. Climate change network construction

We infer the essence of the climate change social network by exploiting the semantic relatedness among hashtags (Hellsten and Leydesdorff, 2020). The overall rationale is that tweets carry the semantics content, while hashtags (the topics) may reveal those inter-dependencies that constitute the implicit holistic information. Hashtags extraction was obtained by using Python's part of speech (POS) non deterministic tagger (Gimpel et al., 2011; Owoputi et al., 2013). To avoid the presence of super-hubs that hide the social structure and complicate the analysis, the hashtags used in the tweet search are discarded. This practically limits the number of effectively used tweets to $N_{2017} = 3459$, $N_{2018} = 4031$, and $N_{2019} = 3931$.

The semantically structured representation of tweets and their occurring hashtags is captured by a bipartite graph linking each tweet to those hashtags that appear in the tweet. A weighting is applied to the links of the bipartite graph representation, see Fig. 3(a), so as to better retain the original information as well as to guarantee a correct network projection (Zhou et al., 2007). Specifically, the links departing from each tweet towards the hashtags are equally weighted and the sum of their weights is normalized to one, to identify the tweet as the central entity in our study. We incidentally observe that the specific weight choice will strongly influence the analytics that will be extracted from the network (Fan et al., 2007).

With this idea in mind, four different bipartite networks are built, namely:

a) three bipartite networks $\mathcal{B}_{2017}$, $\mathcal{B}_{2018}$, and $\mathcal{B}_{2019}$, corresponding to the years 2017, 2018, and 2019, respectively, where the connections are active only among the tweets that belong to one specific year and the hashtags that appear in those tweets; these networks are used for evaluations on a year-by-year basis, e.g., for the study of a temporal evolution;

b) a bigger bipartite network $\mathcal{B}_{\text{all}}$ collecting the tweets and hashtags from all the years (2017, 2018, and 2019); an additional weight inversely proportional to the number of effectively used tweets per year was also employed to equalize temporal effects; this network serves as a benchmark for extracting average values, e.g., for the identification of communities that can then be temporally studied through the networks in a).

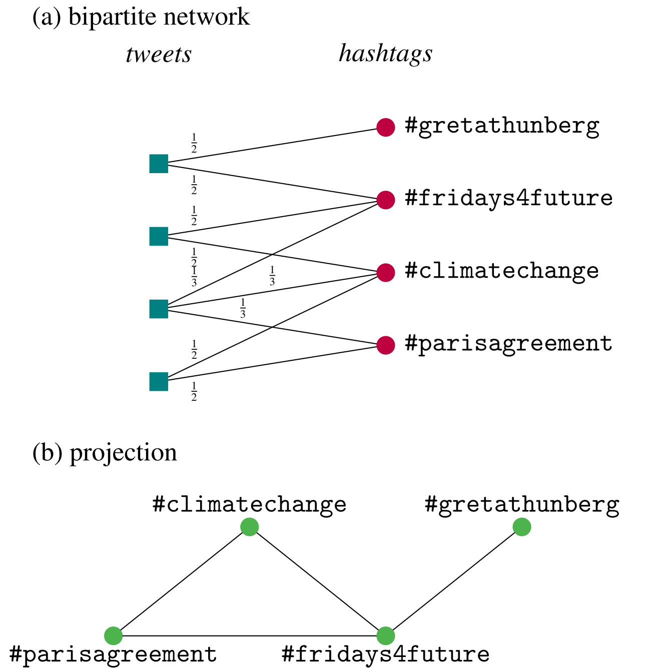


Figure 3: Illustration of (a) the bipartite network of tweets and hashtags, and of (b) the projection onto a network of hashtags; note that the links in the bipartite network (a) are weighted in such a way that each tweet node sees links with equal weights summing up to one (i.e., normalized); also, the projection network (b) activates a link only in case the hashtag nodes have at least one tweet node in common.

3.4. Obtaining the social structure via community detection

The social structure is derived by investigating the organization of the network into communities, i.e., into groups of nodes that are more strongly connected among themselves than with the rest of the network (Fortunato, 2010). The identification of communities is applied to the larger network $\mathcal{B}_{\text{all}}$, to reveal patterns that have a consistent thread over the years, and/or indirectly monitor modifications through time.

Technically, the identification of communities is as follows:

1. a standard projection of the bipartite network $\mathcal{B}_{\text{all}}$ (collecting tweets and hashtags) into an all-hashtags network $\mathcal{P}_{\text{all}}$ is performed by following the classical approach of Newman (2001), see also Zhou et al. (2007); note that the projection $\mathcal{P}_{\text{all}}$ activates a link only between those hashtags that appear together in a tweet at least once, see Fig. 3(b);
2. Louvain modularity (Blondel et al., 2008; Lancichinetti and Fortunato, 2009; Fortunato, 2010) is used to extract hashtags communities $C_{\#}$ from the projected network $\mathcal{P}_{\text{all}}$; compared to more sophisticated but less usable solutions, the Louvain approach was chosen for its generality, reliability, and robustness;
3. finally, tweets are assigned to communities by performing a projection through the bipartite network $\mathcal{B}_{\text{all}}$, with an original approach that we detail in what follows.

The approach for assigning tweets to a specific community of hashtags exploits the PageRank algorithm (Page et al., 1999;

Table 2: Description of the communities

#	Community name	Descriptive hashtags	Brief description
1	climate action	#climateaction, #actonclimate, #energy, #science, #cdnpoli, #renewableenergy, #renewables, #greennewdeal, #climatestrike	calls to action related to climate change
2	nature	#nature, #earthday, #conservation, #biodiversity, #oceans, #ecology, #trees, #forests, #wildlife	photos ad videos about naturalistic environments and animals
3	recycling	#innovation, #circulareconomy, #plastic, #sustainabledevelopment, #recycling, #ecofriendly, #recycle	business solutions for the circular economy, and recycling techniques
4	work life	#leadership, #employment, #creativity, #partnerships, #decentwork, #career	professional-life and working environment aspects
5	developments goals	#globalgoals, #education, #parisagreement, #un, #2030agenda, #community, #migration, #teachsdgs	2030 Global Goals for Sustainable Development
6	green economy	#green, #eco, #sugarcane, #ecofashion, #sustainablefashion, #vegetarian	promoting green and eco-friendly products
7	international politics	#trump, #epa, #resist, #coal, #p2, #environmentaljustice, #tcot, #usa, #2a, #oil, #theresistance, #eu	political topics
8	digitalization	#ai, #iot, #dataviz, #data, #bigdata, #digital, #smartcity, #digitaltransformation, #smarthome	methods and procedures for the digital transformation and innovations
9	pollution and health	#health, #pollution, #airpollution, #cities, #healthforall, #publichealth, #wellbeing, #airquality, #worldhealthday	topics of air pollution and public health
10	lifestyle	#weather, #travel, #coffee, #worldmetday, #europe, #spring, #thursdaythoughts, #london, #sxsw, #snow, #summer, #noaa, #greenland	big variety of free-time-related topics
11	food	#agriculture, #food, #zerohunger, #foodsecurity, #regenerativeagriculture, #insect, #urbanfarming, #learn, #foodtech	food issues and food technologies
12	Australia	#auspol, #extinctionrebellion, #climatecrisis, #greatbarrierreef, #stopadani, #australia, #extinction, #factsmatter, #ausvotes, #actnowforfuture, #brisbane	climate collective actions in Australia
13	women	#genderequality, #women, #womensday, #gender, #internationalwomensday, #iwd2018, #sdg5, #unea4, #localgov, #solvedifferent, #women4climate	gender-related topics
14	green technology	#earth, #carbon, #jobs, #blockchain, #emissions, #cleantech, #engineering, #startups, #ghg, #electric, #natural, #paris, #life, #mining, #crypto	technological and sustainable innovations
15	architecture	#architecture, #fashion, #design, #construction, #greenbuilding, #building, #webinar, #steamdrills, #5star, #innovative, #free, #interiordesign	architecture topics
16	other	#agenda2030, #brexit, #news, #healthcare, #fracking, #ocean, #photography, #art, #wednesdaywisdom, #infrastructure, #climatejustice, #tourism, #mentalhealth	mixed topics

Gleich, 2015) in a suitable form to measure centrality with respect to a specific topic, as originally proposed by Haveliwala (2002, 2003). The idea is to activate the teleportation vector only in a selected subset of nodes related to a specific topic, in our case a community, so as to assess the similarity of nodes (tweets) with respect to that topic (community). A tweet will then be assigned to the community it is most similar to. Interestingly, this method is effective, and finds justification in a number of literature findings. It follows the rationale of Zhou et al. (2007) and Stram et al. (2017) to implement the idea of Larremore et al. (2014) that one-mode projections should be avoided, and more elaborate information is needed to properly measure dependencies between nodes. With our topic specific PageRank approach we are able to readily apply this rationale on a networked level, as opposed to the local solutions available. The idea of exploiting the similarity measure of a topic specific PageRank for clustering purposes was also proven to be effective (Avrachenkov et al., 2008; Cho and MuLee, 2010; Tabrizi et al., 2013).

We finally observe that throughout the results section, the relevance of communities is quantified through a PageRank approach (Latora et al., 2017), i.e., we are identifying the importance of a community as the sum of the PageRank centrality scores of the hashtags belonging to that specific community. The projection matrix used for this purpose is a yearly projection $\mathcal{P}_{201x}$ of the corresponding bipartite graph $\mathcal{B}_{201x}$, whose columns carry the topic specific PageRank similarity to each single node in the network, in such a way to guarantee that knowledge on nodes interdependence is fully kept, and that valuable information is not lost in the projection.

4. Results

4.1. Community detection on hashtags

Semantic networks are generally globally sparse yet locally dense, meaning that communities of locally interacting nodes can be identified and this might reveal important features that are not evident from the analysis of a single node. This is another aspect that justifies our holistic approach. At the same time, since the online rhetoric about climate change spans across several topics, not necessarily related to anthropogenic global warming, detecting communities can give a general first idea of what similar or even sometimes contrasting topics are present. Moreover, monitoring these aggregating trends can give further insight on the functional properties of the network, especially for our psycho-social context where collective actions are promoted.

We performed the community detection procedure described in Section 3.4 and we report in Table 2 the 16 communities with size bigger than 200. Naming and descriptions are provided as the authors' interpretation of the semantic meaning of each community, based on the most descriptive hashtags that belong to it. In particular, Table 2 provides the list of all communities, also including the 16th that is kind of marginal to the entire analysis as it contains a plethora of unrelated topics, some of which even connected to climate change, albeit in a very marginal fashion and with hashtags of little importance overall. We also computed the relevance of these communities on a per-year basis as reported in Fig. 4. Especially, for the sake of brevity, we concentrate here on the description of the most relevant (while still pertinent) communities, meant as the ones

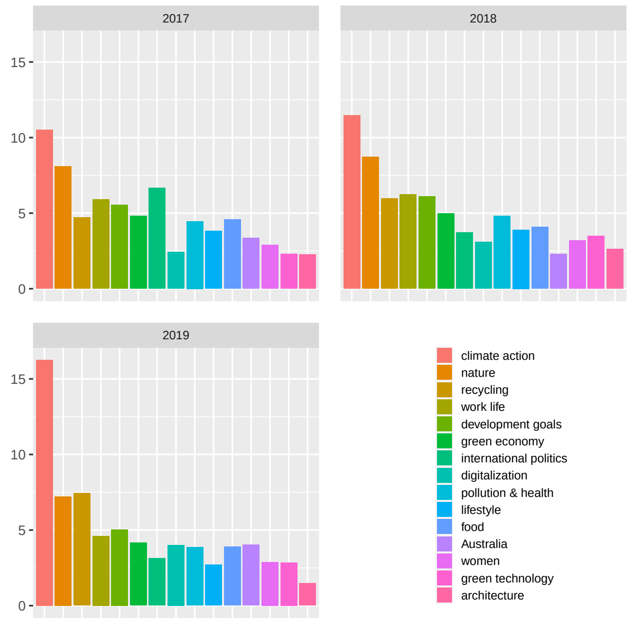


Figure 4: Relevance of communities over the years 2017-2019 measured by PageRank centrality (0-100% scale); see a description of communities in Table 2.

that obtained the highest score in Fig. 4 when considering the entire span of 3 years. We also remark that a pictorial representation of the community structures in 2017, 2018, 2019 is available in Fig. 5. Here, the size of a hashtag correlates with its individual relevance. In this spirit, we remark the importance of our network analysis since we are able to highlight that, even though the individual hashtag `#climateaction` alone heavily increased in relevance in 2019, its entire community also grew as a result, thereby suggesting a mutual interaction that is not limited to a self-standing trend of a single concept.

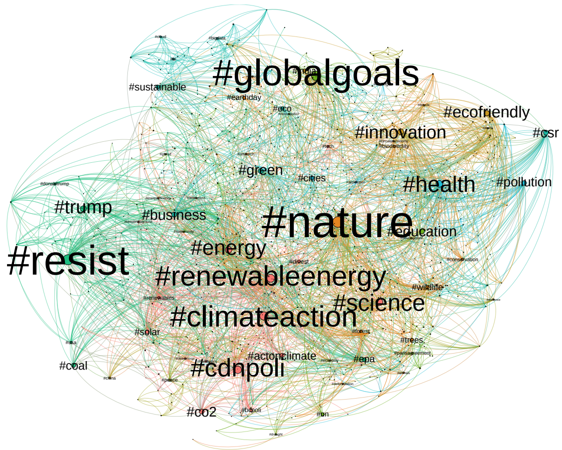
The most relevant communities are the ones listed first in Table 2, which reports them in increasing order of ranking. The first one, dubbed “climate action,” is indeed the most pertinent throughout the years, but soars in importance especially in 2019, thereby confirming the increased visibility of these topics within the online social rhetoric. Remarkably, this trend is present despite our data collection starting from only neutral hashtags that did not involve collective action per se, thereby proving the underlying thread of call to action that can be inferred when discussing climate online.

Another community is “nature,” comprising the namesake hashtag and several other items related to the beauty of the planet. Here, the focus is more contemplative rather inviting to action, even though we believe that some hashtags hint at an underlying sense of preservation for the natural environment that can be generically connected to online activism.

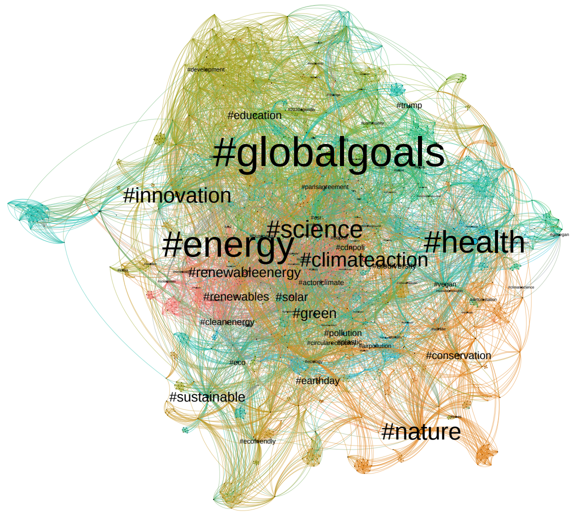
Community number three, which we labeled as “recycling,” relates instead to pragmatic actions to contrast anthropogenic climate change, albeit the focus is now distributed on individual actions and generally detached from collective protestation.

The fourth community is “work life” and its presence in our

(a) Hashtag network in 2017



(b) Hashtag network in 2018



(c) Hashtag network in 2019

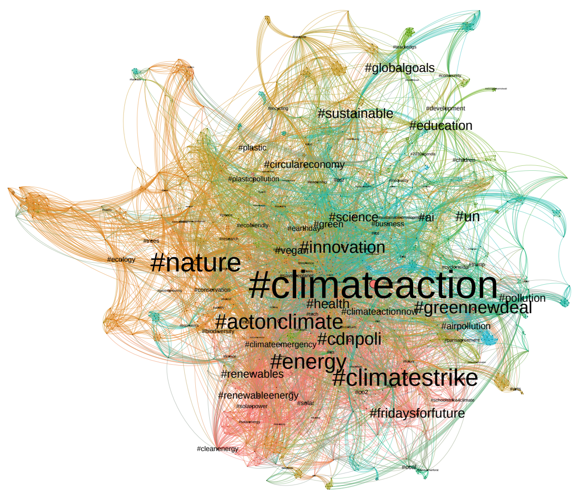


Figure 5: Gephi graphical representation of communities (same colours as in Fig. 4) where the hashtag dimension corresponds to its PageRank centrality in the corresponding year.

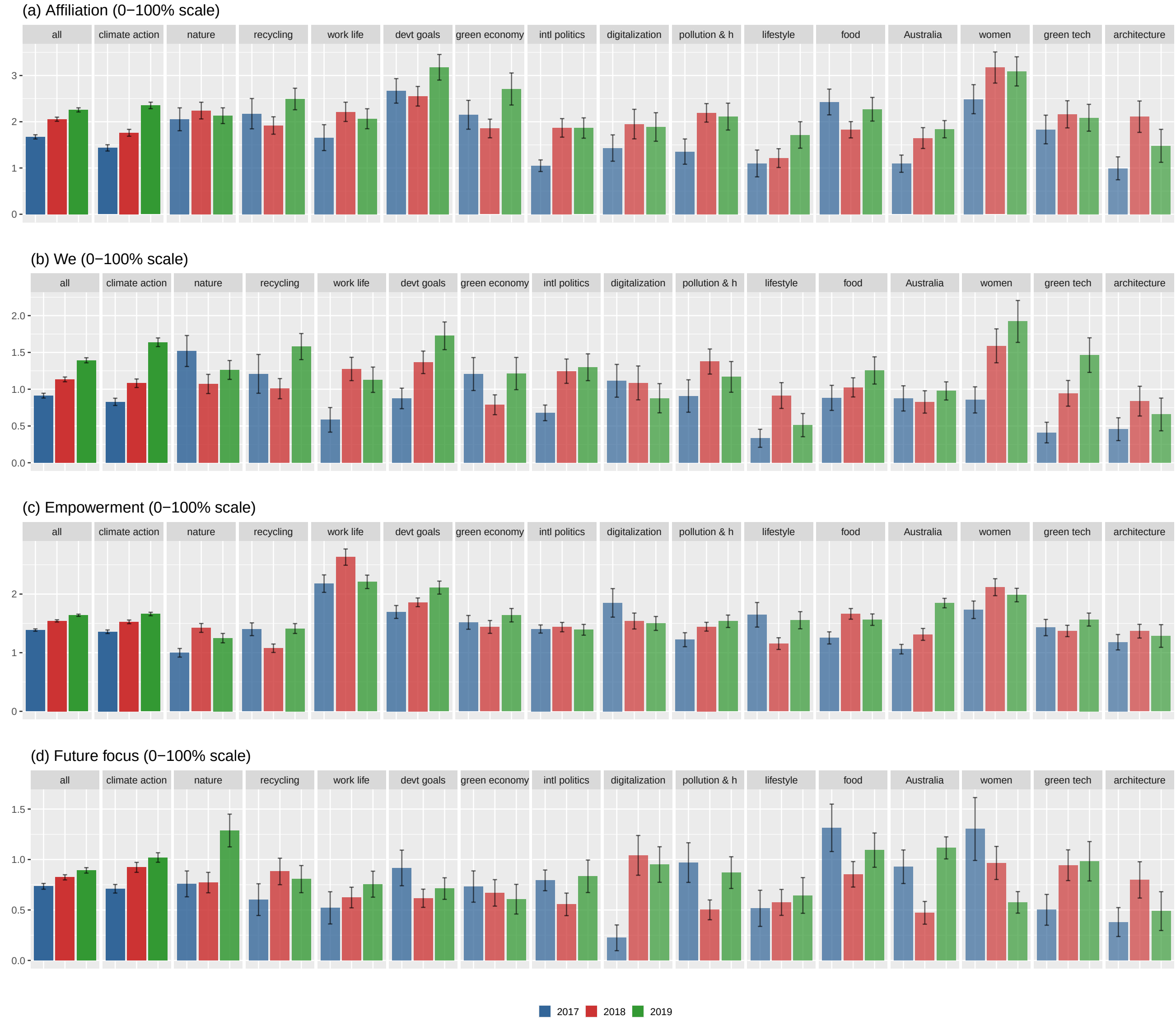


Figure 6: Average value per tweet of (a) affiliation, (b) we, (c) empowerment, and (d) future focus measures for each community and for each of the years 2017-2019, where: shading corresponds to the relevance of the community, as from Fig. 4, to highlight the most important communities; measures appear on a 0 – 100% scale, with histograms representing average values and error bars being constructed using 1 standard deviation from the mean.

analysis is probably more spurious than the previous communities. It is originated by the double meaning of *climate* as a term for the overall milieau in the workplace and involves mostly hashtags unrelated to environmental changes. We will therefore take it less into consideration in the analysis.

"Developments goals" is a community embedding terms from UN initiatives, and it refers to global goals, the agenda of sustainable development, and the international efforts on mitigation of greenhouse gas emissions (see Paris agreement).

The sixth community addresses and promotes eco-friendly products and green merchandising, and for this reason we labeled it as "green economy". It seems to be more connected to branding and marketing and the environmental concerns are not strictly related to global warming.

The seventh community, "international politics", focuses on issues in the international arena, including broader references to environmental justice and political actors. This community was particularly relevant in 2017, possibly also because of the US withdraw from the Paris Agreement during that year, which prompted international signals of disapproval (Payne, 2018).

The other communities scored below 5% of relevance in all the years considered, see Fig. 5(a), and will therefore not be discussed further.

4.2. Social-psychological linguistic markers

In Fig. 6 we report an overview on the linguistic markers of social psychological processes in our Twitter corpus, organized per community and over the years 2017-2019. Panels display the average value per tweet of *affiliation*, *we*-terms, *empowerment*, and *future focus* proxies (see their meaning in Section 3.2), respectively. The histograms "all" provide the average values across all the communities, and therefore identify the

Table 3: Pairwise comparisons (Cohen's-d values) per each community, and among the years, for the measures of Fig. 6: a red asterisk * identifies a statistically significative difference (FDR adjusted p-value< 0.05), and a double orange asterisk ** identifies an enhanced significance (p-value< 0.01).

	2017→2018				2018→2019				2017→2019			
	affiliation	we	empower	future	affiliation	we	empower	future	affiliation	we	empower	future
all	0.1057 **	0.1039 **	0.0752 *	0.0043	0.0448	0.0593	0.0609	0.0386	0.1505 **	0.1631 **	0.1361 **	0.0429
climate action	0.1059 *	0.1111 *	0.1306 **	0.1132 *	0.1909 **	0.2434 **	0.1026 *	0.0519	0.2967 **	0.3545 **	0.2332 **	0.1651 **
nature	0.0582	0.1973	0.3208 **	0.0325	0.0332	0.0849	0.1293	0.2483	0.0251	0.1125	0.1916	0.2807 *
recycling	0.0826	0.0879	0.248	0.1481	0.1849	0.25 *	0.2575 *	0.0403	0.1024	0.162	0.0094	0.1078
work life	0.1798	0.3021 *	0.3462 **	0.0543	0.0482	0.0639	0.3229 **	0.0702	0.1316	0.2382	0.0233	0.1245
development goals	0.0375	0.2145	0.1259	0.1594	0.202	0.1575	0.1921	0.051	0.1645	0.3719 **	0.318 **	0.1085
green economy	0.0956	0.1823	0.0597	0.0333	0.2753	0.1852	0.1531	0.0332	0.1798	0.0029	0.0934	0.0665
international politics	0.2638 *	0.2476 *	0.0252	0.1262	0.001	0.0233	0.0354	0.1477	0.2628 *	0.2709 *	0.0102	0.0214
digitalization	0.1672	0.0125	0.237	0.4337	0.0203	0.0908	0.0314	0.0482	0.1469	0.1034	0.2684	0.3854
pollution and health	0.2702	0.2047	0.1695	0.2486	0.0262	0.0912	0.0713	0.1959	0.244	0.1134	0.2408	0.0528
lifestyle	0.0372	0.2538	0.3764 *	0.0311	0.1615	0.1756	0.3052	0.0366	0.1987	0.0782	0.0712	0.0677
food	0.1938	0.0623	0.314 **	0.2444	0.143	0.1005	0.0759	0.1271	0.0508	0.1628	0.2382	0.1173
Australia	0.1786	0.0211	0.1929	0.2422	0.0619	0.0654	0.4088 **	0.3415 *	0.2405	0.0443	0.6016 **	0.0993
women	0.221	0.321	0.2952	0.1787	0.027	0.1449	0.1026	0.2071	0.1939	0.4658 **	0.1926	0.3859
green technology	0.1126	0.235	0.0443	0.1055	0.024	0.2269	0.1489	0.0207	0.0887	0.4619 *	0.1047	0.1262
architecture	0.3601	0.1666	0.1438	0.2217	0.2032	0.0791	0.0625	0.1642	0.1569	0.0875	0.0813	0.0575
misc	0.1458 *	0.0444	0.1043	0.1617 *	0.1201 *	0.0327	0.0953	0.18 **	0.0258	0.0116	0.1996 **	0.0183

overall yearly trends. Shading corresponds to the relevance of the community, as from Fig. 4. The relevant highlight of Fig. 6 is that the considered proxies are linearly increasing over the years (see the "all" histograms), and that the only community consistently capturing this trend is that of climate action. Furthermore, climate action takes off as the most prominent community. Observe that some other communities locally display high values but this apparently relates to some specific focus of that community, such as leadership or productivity, and is of peripheral importance in the context of climate action, also given the limited relevance of these communities.

Because of its primary role, the effect of time, which we graphically inferred from Fig. 6, can also be statistically tested. A confirmation on the presence of a linear trend along the years comes from the pairwise comparisons of Table 3, detailing effect sizes by Cohen's-d values, and highlighting in orange or red the presence of a statistically meaningful difference between the considered years. As visible from Table 3, climate action is the only community that exhibits a meaningful difference in all the transitions, with the only exception of the future focus proxy in 2018 $\rightarrow$ 2019, which confirms our hypothesis. The above suggests that the online discourse about climate change is characterized by a steady increase over the three years of our corpus.

To get a further confirmation, the positive linear trend of climate action was also tested with a generalized linear model by using the software JMP (Sall et al., 2017). Two full factorial generalized linear models were applied, with the variable year and the six most relevant, yet pertinent, communities (i.e., climate action, nature, recycling, development goals, green economy, and international politics) as predictors, using *affiliation* or *empowerment* as outcome variables – *we* and *focus future* variables will be discussed in the following subsection. The results are reported in Table 4, which shows that the use of both affiliation and empowerment related words changed over time (see the main effect of the *year* variable), and were used to different extents in the six considered communities (main effect of the *community* variable). The interaction between *year* and *community* further confirms that the increase across the years is uneven across the communities, which is coherent with and justifies the findings of Table 3.

Table 4: Full factorial generalized linear model outcomes: $F(d,e)$ is the Fisher value with d the degrees of freedom and e the levels of error due to the sample size; p denotes its associated statistical reliability p-value; η_p^2 is the partial eta squared effect size.

(a) Fisher values for affiliation

variables	F	d	e	p	η_p^2
year	10.53	2	8237	$< .0001$	.003
community	14.25	5	8237	$< .001$	.008
year & community	2.08	10	8237	.023	.003

(b) Fisher values for empowerment

variables	F	d	e	p	η_p^2
year	6.44	2	8237	.001	.002
community	21.93	5	8237	$< .0001$	.013
year & community	2.95	10	8237	.001	.004

4.3. *Temporal perspective on climate rhetoric*

To investigate the involvement of a temporal perspective in the climate change rhetoric, and to further explore the involvement of identity processes, we analysed the extent of use of words referring to the in-group (such as "we," "our," "ours") versus words referring to others (such as "they," "their," "theirs") in association to words marking the future or the past temporal frame. With this aim, Fig. 7 shows a linear regression (with confidence intervals) of we/they versus past/future focus markers. We observe that there is general association between the pronouns (we, they) and time (past, future) markers: the more tweets include words about time, the more also include plural pronouns. This is certified by the presence of positive slopes in all the diagrams of Fig. 7, and may suggest an association between temporal focus and intergroup discourses where "we" and "they" are put in contrast with each other.

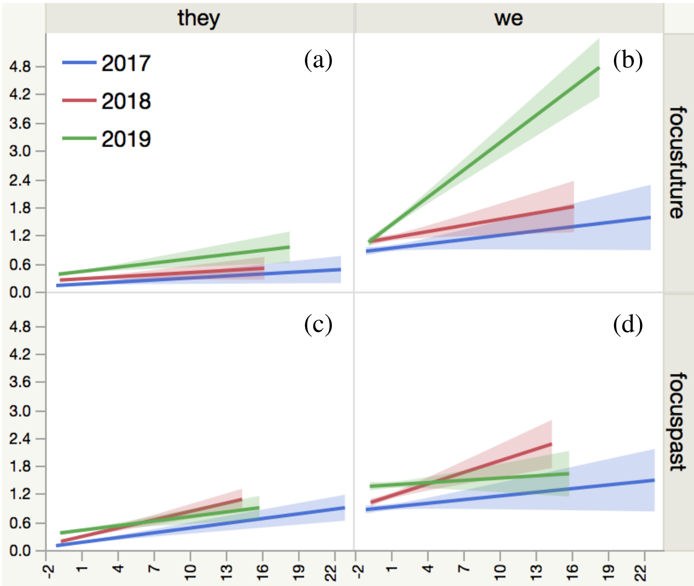


Figure 7: Linear regressions with confidence intervals over the three considered years for we/they versus past/future focus markers.

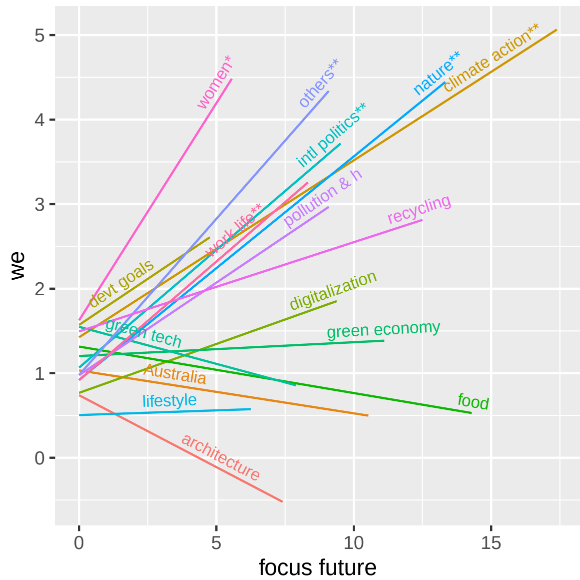


Figure 8: Linear regression of first person plural pronouns (we) as a function of future-framed wording (focus future) by community: an asterisk denotes a $p < 0.05$ significance of the slope coefficient, two asterisks a $p < 0.01$ significance.

A few interesting aspects can be appreciated in Fig. 7 by differentiating between past and future focuses, namely:

- **past focus**, Fig. 7(c)-(d): the association seems to be more pronounced in 2018 (see the increasing 2018 red regression);
- **future focus**, Fig. 7(a)-(b): the association seems to increase over time, and is more pronounced in 2019 (see the 2019 green regression); incidentally, it is very clear that the use of future words in association with the words referring to the in-group (we) was particularly marked in 2019, see Fig. 7(b), which is also the year most characterized by words related to the in-group, see Fig. 6(c).

A more detailed view on the 2019 green regression of Fig. 7(b) is given in Fig. 8, showing how the projection of the in-group into the future is common to several of the communities, namely to all the six most relevant communities considered in Section 4.2, with the only exception of green economy in which, however, future concerns are not associated to the social identity (and in fact green economy is mainly advertising products that flag the green label). Yet, this association is particularly striking in the community of climate action in which future words are the most used and clearly associated with the pronoun we.

These results were further statistically confirmed through two full factorial mixed linear models, applied on past and future focuses, respectively, with the pronouns used as dependent variables, and the type of pronoun (we, they), year, community, and past or future temporal frames included as factors, with the type of pronoun being nested within the tweet, which was added as random factor. The models revealed that:[7]

- **past focus**: the use of both types of pronouns (we, they) was positively associated with ratio of words signaling the past, $F(1, 14442) = 56.83$, $b = .04$ slope, $p < .01$; there was an increase over the years of the use of pronouns, $F(1, 14442) = 98.97$, $p < .01$, which was further characterized by the type of pronoun, $F(1, 14442) = 8.75$, $p < .01$, and by past words, $F(1, 14442) = 6.13$, $p < .01$, so that a focus on the past is positively associated with both type of pronouns; the use of words referring the past did not interacted with the type of pronoun;
- **future focus**: all the effects of type of pronoun and year already described for the past focus apply to the future focus; in addition, the role of future words had a main effect, $F(1, 14442) = 91.97$, $b = .05$, $p < .01$, and interacted with year, $F(1, 14442) = 28.82$, $p < .01$; a three-way interaction is appreciated between year, future and pronouns, $F(1, 14442) = 16.74$, $p < .01$.

5. Discusssion and Conclusions

The analysis of the increased relevance and the traits of affiliation and empowerment in the online discourse about climate action brings some general deductions. First of all, underneath the global increase in popularity simply due to trending topics, our data show a substantial increase in awareness and involvement of messages exchanged online related to climate action. We therefore claim a quantifiable impact from online and practical activism.

Also, our investigations performed at a more detailed community level seem to imply that such phenomena are mainly related to the specific semantic group of climate action keywords,

[7] The notation used in the following is defined in Table 4; in addition, b identifies the slope of the linear model fitting.

where we observe reliable increases for each pairwise comparison, and only marginally influenced by other unrelated aspects. Thus, the increased awareness about the anthropogenic climate change and the global initiatives to protest against it had a direct impact on the social discourse, without undermining other important issues and/or creating barriers with them. Rather, the topic of climate change seems to be firmly embedded in the online rhetoric and an important source of momentum. This further corroborates the interpretation that the growth of climate activism over time is fostered by social drives that are common to general collective actions. Together with affiliation, empowerment is a milestone for action engagement and its constant increase hints at even bigger actions for climate in the next years.

A further analysis of the mutual interaction between the semantic networks and the online community, assessing how the latter shapes the former, may in turn enable predictions over future evolution of the activism. In other words, our results may inform how to communicate about climate change in ways that inspire people to take action, and how these communications can be tailored to specific online communities. Along this line, Morton et al. (2011) addressed linguistic framing in communication on climate change by manipulating the certainty and positive vs negative in a future framed message, yet the time frame was not experimentally manipulated. Hence, a key contribution of the present paper is also the option to restrict or amplify the level of our analysis, for example, to specific communities of similar concepts, and identify their mutual interaction in changing the online discourse.

Even though our analysis does not detail the individual traits of online contributors on these topics, a possible future development may be to explore possible motivations and perspectives to look at the results so as to give socio-psychological interpretations. In particular, the increase of affiliation or empowerment terms may be gauged from different perspectives of age, gender, and/or political affiliation.

For example, climate change is generally considered as a more central topic within a progressive political ideology (Cruz, 2017), which is in turn characterized by focus on social issues and a more frequent use of affiliation words (Fetterman et al., 2015). Thus, one may argue that the increased use of affiliation terms correlates with the association between climate action and a left-wing political agenda. On the other hand, empowerment terminology, which is also shown to have an increasing trend, is often associated with conservative positions (Salmela and von Scheve, 2017). Thus, it may be worth investigating these connections further to see how much of climate change rethoric regarding the use of affiliation and empowerment words is influenced by the positioning on the political compass, and possibly arguing against traditional preconceived political classifications (Ife, 2018).

More recent studies also suggest that the environmental support in relationship to the political spectrum might also correlate on how individuals perceive it as juxtaposed with economic growth and individual development (Harring and Sohlberg, 2017). Thus, it may definitely be worth exploring the relationship with other factors, such as age. Other studies (de Moor et al., 2020) show that young individuals are more concerned with climate action, while being also more prone to engage in online communications. An interesting extension of the present study can be to explore the interconnection of age and political orientation, within the specific scenario of climate action.

Similar considerations could also be done in relation to gender. In fact, the specific increase on affiliation in the collective action discourse that developed in 2019 may be related to an increased online rhetoric from female social media users, not necessarily limited to the specific trend of climate action. Female media users are more likely to use affiliation linguistic expressions compared to male users (Park et al., 2016). Yet, we may speculate that the increase also of empowerment words supports the idea that collective action motivations are the likely underpinnings of these linguistic cues, rather than gender roles.

Finally, we provided evidence of the intersectional role of social identity and orientation toward the future as central for the growth of the online debate on climate change. We also showed an association between future orientation and ingroup mobilization in the rhetoric around climate change. Importantly, this association is increasing over time, suggesting a general trend in climate discourse to envisage the ingroup in the future. Further studies can experimentally investigate the consequences this future oriented frame of the ingroup for social mobilizing people about the climate change matter. In fact, our results are consistently showing across all the communities pertaining to environmental concerns that the more people are focusing in the future, the more they also use pronouns related the ingroup.

The identification of linguistic markers that specifically characterize the evolution of a collective action over time may have important implications and applications. The data may be informative at the diagnostic and prognostic levels. Indeed, the analysis of the evolution the linguistic markers may help detecting the communities which are more likely engaged in activism. This may have critical application in several fields of collective action, including those that are morally despicable, such terrorist groups. Moreover, our results inform about the progression of such communities, possibly pointing to the future. We finally remark that we compared a span of three years, which is still a limited range, therefore the predictive potential of the linear trends should be taken cautiously. Further studies can focus on longer time frames to build proper historical series so as to follow up on our findings in the years to come.

Declaration of interest

None.

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