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Refusing to be safe.
The Social Network Communication of deniers

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Abstract
This essay aims at showing the results of analysis concerning communication on social networks by focusing on the collection of comments related to the pandemic. The analysis describes the structure of the communication, showing the presence of parallel communities and the different configurations of relational dynamics, selected contents, flows of communication, category of users, and language. Complex network structures are identified branching from keywords like no-mask, covid-19, and greenpass. Further attention is paid to the connection between online communication and the triggering of protests.

Keywords: *Social Media, Pandemic, Network Analysis, hubs.*

1. Introduction

This paper shows the results of an analysis conducted through the continuous monitoring of pandemic related posts on Twitter for the period 2020-2022. The specific objective is to analyse the structure of comments among those subjects criticizing governments’ choices about how to face the risk of contagion. For this purpose, we extracted tweets containing 3 reference keywords. The extracted keywords have changed twice, in line with the changes in the public debate. Given the high number of views in the reference period, the first lemma was “No-mask” (from November 2020 to February 2021). Subsequently, the reduction of the communication led to a new selection: “covid-19”, monitored until August 2021. The last phase of monitoring concerned the “Greenpass” lemma and lasted until December 2021. A new wave of protest emerged in this phase, whose media visibility is also evident, which echoes in the increase in communication with the “Greenpass” hashtag. This work is the first phase of the whole project, which also includes a semantic in-depth study of the emerging comments and thematic clusters. In this paper, however, we only present results concerning the underlying network structure of online communication.

2. Data and methods

The work refers to networks of communication among users. In particular, samples of tweets were extracted every two weeks from November 2020 until December 2021. The extraction was carried out via NodeXL Pro Twitter data importers (Smith et *al*., 2009), monitoring the communication every two weeks (Tab. 1).

Table 1. Number of tweets for each extraction.

Hashtag	**Data of Extraction**						
no mask	***30 Nov 2020***	***14 Dec 2020***	***30 Dec 2020***	***15 Jan 2021***	***05 Feb 2021***		
	1352	1749	2923	901	606		
covid 19	***23 Apr 2021***	***13 May 2021***	***03 Jun 2021***	***24 Jun 2021***	***15 Jul 2021***	***05 Aug 2021***	
	16802	17979	9767	12045	8825	18000	
greenpass	***05 Aug 2021***	***26 Aug 2021***	***16 Sep 2021***	***07 Oct 2021***	***28 Oct 2021***	***18 Nov 2021***	***09 Dec 2021***
	9141	9269	9407	7666	9004	8868	9450

The communication was analysed by building graphs and applying Social Network Analysis tools (Borgatti and Halgin, 2011), where users are defined as nodes and the comments constitute the links among them (Hansen *et al*., 2010; 2012). The proposed method permits the rapid extraction of information on network structure, shared meanings, and main user categories given a large amount of data and comments on social networks. This can be useful for various reasons such as, for example, the evaluation of political choices, the spread of fake news, or marketing analysis.

As a first step, we selected the top-10-tweets for each extraction, so that it was possible to carry out an in-depth investigation of them. In this way, the hubs of the network are identified (i.e. those nodes on which the entire network structure depends) and the main information of the networks is reconstructed. As a second step, we applied the group analysis function and measured centrality, betweenness, and closeness (Junlong and Yu, 2017) to obtain further information.

The preliminary and in-depth analysis of the main comments refers to the hubs of the communication networks, selected through an automatic but controlled procedure. The analysis of these comments allows us to understand who are the main users, messages, groups, languages, etc. Then a quantitative study, referred to all comments, was carried out (Borgatti and Halgin, 2011). At this point, we selected - for each extraction - the entire communications structure and the main groups (as sub-networks or components) obtained by extracting clusters connected, with greater internal homogeneity and external heterogeneity of links.

3. The network hubs

The first phase of our analysis requires the identification of the main information beneath the whole network of communication so that we can understand the main content implied in a great number of comments just reading a limited number of these. We notice that the major part of the comments about “No-mask” is in English, Italian and French while those about “Covid-19” are in Asian and English languages (tweets from India, Japan, Pakistan, Thailand, United States, and Canada) and the most of “Greenpass” comments are in Italian.

Further information we obtained through this procedure concerns categories of users and topics. Overall, the detected communication is mainly private, but the “No-mask” one is almost exclusively private, while the most important tweets about “Covid-19” have a higher proportion of comments related to parties or institutions. This implies the presence of more reliable information compared to the one contained in no-mask and no-greenpass networks. The comments extracted using the lemma “Covid-19”, on the other hand, are more generic and referred to different topics. Furthermore, the major part of communication about “Covid-19” is produced both by individuals and institutions. The “covid-19” tweets, addressed both to other users and the institutions, came mainly from worried people protesting against the increase of contagions, the opening of shops, the lack of social distancing, and the lack of personal protection measures (use of masks, vaccinations, etc.).

Further comments are about the official information regarding the number of infections, availability of oxygen, and beds in the hospitals.

The communication that focuses on “Greenpass”, mainly from private citizens, is among users with a high sense of political effectiveness and self-direction, largely oriented towards reaching and “influencing” political institutions and decision-makers. In particular, a strong Italian protest against the restriction policies (“greenpass”) emerges during August-December 2021, while in November2020-February2021 Italians were mostly against the No-mask movement (Miller, 2020)

This first phase of our analysis, mainly descriptive, is useful when you want to identify information about languages, kinds of comments, “sentiments” and evaluations. We can identify the typical characteristics of three phases/keywords (Fig. 1). Otherwise, looking at the content of the communication, we have noticed that No-Mask nets form many groups and popular rumors (except during the Christmas period when a single large movement against restrictions and limitations appears). These comments are divided into two clear categories: derisive or ironic purposes (mostly in Italian), and the opposite: against any form of limitation of freedom (Fig. 2). The dynamics guiding the communication change when the “Covid-19” tweets are extracted. These comments are distributed among the different voices identified, despite the prevalence of neutral positions (which are usually marginal).

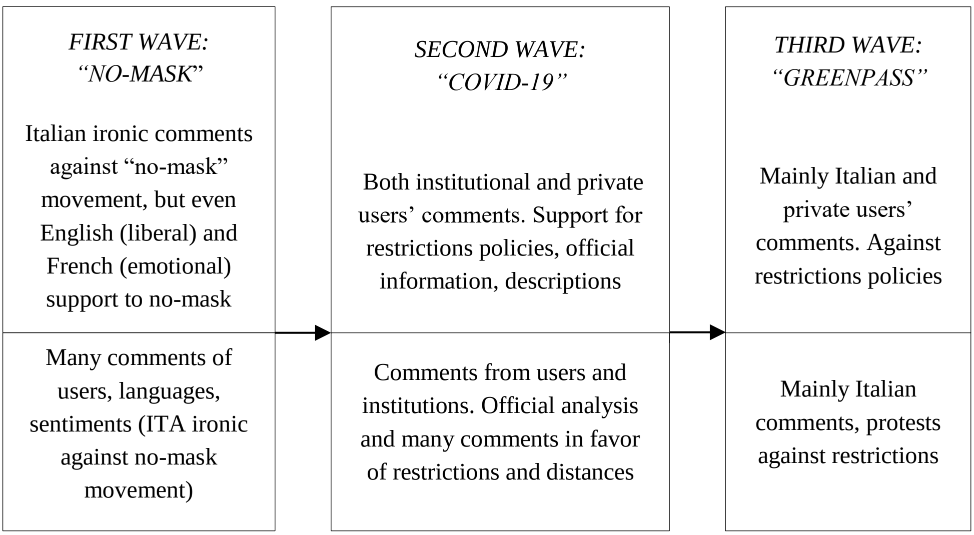

Figure 1. The three phases of communication on Twitter

As "No-mask" comments, also "Greenpass" comments come mainly from single users and are characterized by the positions against restrictions/institutions, showing the presence of a (local, mainly Italian) politically oriented movement. This model of communication, mainly private and self-referential, implies the diffusion of disinformation among users (Bessi and Quattrociocchi, 2015; Del Vicario et al., 2016).

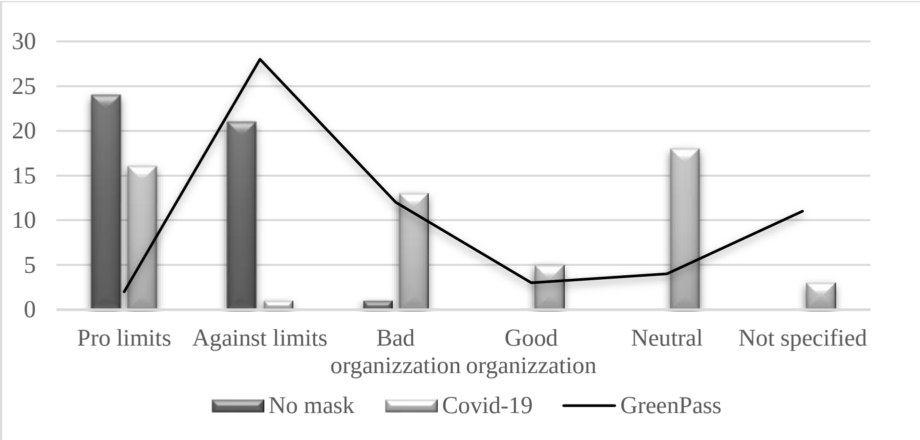

Figure 2. Number of Hashtag for evaluation about politics against the spread of infections

The keywords also affect the structure of communication (Fig. 3). The "No-mask" communication shows the presence of parallel communities with only one or two big main components, while the "Covid-19" communication is subsetted into a huge number of small groups.

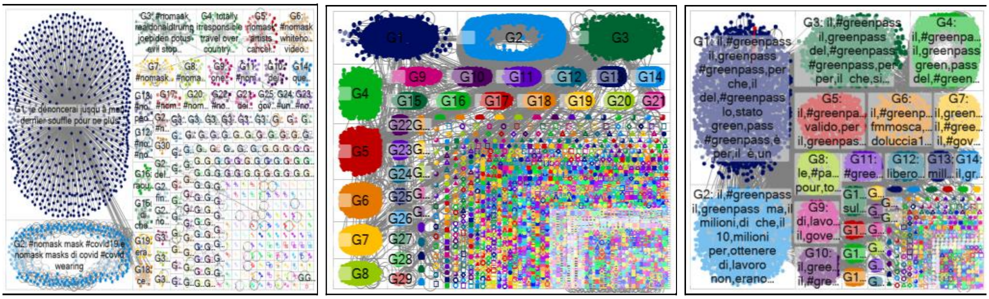

Figure 3. The representative graphs about "No-Mask", "Covid-19" and "Greenpass"

Only in June and in the first part of July there is a larger component that identifies a greater tendency of users to focus on common themes while in August the communication is divided into many groups with few users. Finally, the "Greenpass" communication has a structure that is intermediate between the others, with a fairly high number (7-12) of numerous groups.

4. Longitudinal Trend Description

In an attempt to understand the diachronic dynamics underlying the structure of the groups and their communication, the major network measurements were applied to the *tweet* analysis (Priyanta et al., *2019*). The first of these measurements is *closeness* centrality – calculated as the sum of reciprocals of the smallest distance between each node, in formula:

$$C_c(n_i) = \left[\sum_{j=1}^{g} d(n_i, n_j)\right]^{-1} \quad (1)$$

where $d(n_i, n_j)$ is the distance between the *i*-th node and all the other *g-th* nodes. In other words, the closeness average value returns information about the presence of peculiarly themed networks. The higher the closeness, the higher the presence of compact communities sharing a specific subject. From the analysis run (Fig.4), *closeness* values appear to be constant over the considered period. On the other hand, low levels of closeness suggest communication with no specific focus and composed of small groups, which implies that the various nodes characterizing the network are rarely intertwined.

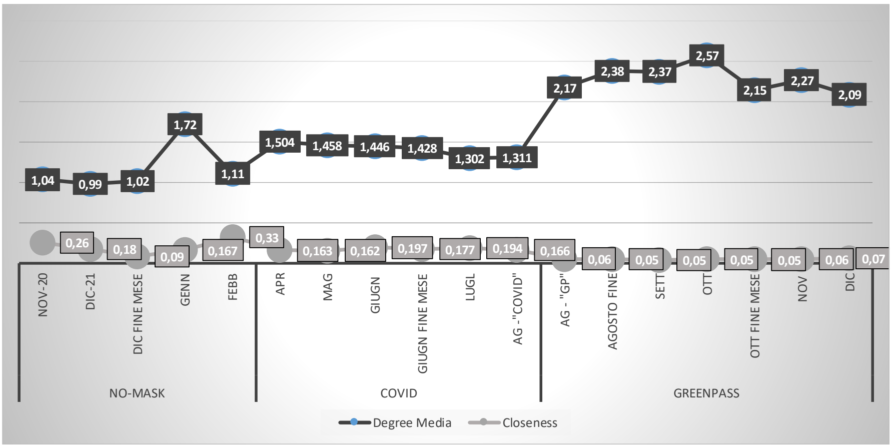

Fig. 4 – Network measurements: Degree e Closeness centrality

While closeness stays constant, it seems important to stress how centrality degree (C'_d) levels significatively increase throughout the study. (Standardized) Centrality degree is obtained considering the number of linkages each node has - $d(n_i)$ on the total amount of possible linkages underneath the network (g-1), in formula:

$$C'_d = \frac{d(n_i)}{g-1} \quad (2)$$

In the specific case, centrality degree refers to the number of relations among nodes, detected by looking at the reactions linked to the tweet, i.e. visualization, retweet, likes, etc.

(Bild *et al.*, 2015). As it is possible to notice from figure 1, the degree shows a trend of growth over time. Such an increase seems to be characterized by the specific topic observed and it reaches its acme when dealing with communication on greenpass.

Unlike what has been observed monitoring the hashtag "No Mask" (scattered communication, not centered in any special node, and outcome of private users only), the analysis of the hashtag "Covid 19" has shown a growing communicative dynamicity. If it is true that being it a general topic the interaction among nodes grows, it is also true that in this case, compared with the previous one, public-derived nodes emerge: association, politicians, and healthcare-related users. On the other side, the private nature of the communication related to the "No Mask" theme generates a huger number of reactions that, due to specific characteristics (being them professional, political, or institutional), turns into a major interest even in terms or triggering the research of further information, which makes the communicative flow growing (Miller, 2020). This flow, however, reaches its acme when observing the network structures related to the third focus of our analysis: the hashtag "greenpass". In the last case, the centrality degree, which reaches its peak in October (2,57), highlights the existence of a wider communicative dynamic. In such a case, communication does not only imply reactions – which are still present – but it becomes more direct, creating an actual debate between private and public users who "communicate" with one another.

This peculiar aspect of the last analysed communication seems to be confirmed by the third measurement calculated on the network: betweenness centrality, obtained through the sum of all of the partial betweenness calculated for each couple of nodes, in formula:

$$C_b(n_i) = \sum_{j<k} g_{jk}(n_i)/g_{jk} \tag{3}$$

where $g_{jk}(n_i)$ is the number of geodesics that connect two nodes containing an i-th node.

This means that betweenness centrality highlights the presence of users that play an intermediate role between either users or groups of users.

Nodes are not only constituted by reactions in this case but, rather, they involve many occasions of sharing tweets, contributing to its diffusion. This appears more evident looking at the betweenness centrality in the first period, characterized by the hashtag "No Mask". In this case, the communicative structure seems sparser, being it a sort of pseudo-dialogue among people sharing the same thoughts (the maximum value is 1200). The presence of intermediaries emerges instead when looking at the "Covid" centered communications (the maximum value is 26987) and with "greenpass" centered discussions, configuring complex relational structures, though emerging from social networks (the maximum value is 25874). This created occasions and conditions for protest movements in Italian (and beyond) squares to rise.

5. Conclusions and further developments

What's immediately noticeable from the obtained results is how the structure of social communication has turned into a protest movement destined to become widespread. No-mask-centered communication has two peculiar traits: structurally, it's closed and formed by many small and self-referential groups. The communication, spread locally, nationally, and internationally, reaches a peak in December 2020. Then, it gradually reduces its extent and significance. The network structure thus shows the presence of a fluid online movement that gradually fades away around February 2021. Another hashtag progressively gained attention between April and June 2021: Covid-19. In this case, the communicative structure shows less weak than the previous one, with more links and nodes and fewer scattered groups. Moreover, Covid-centered communication appears to be more heterogenous and spread: it's not a movement anymore; rather it shows as the center of many discussions. The last hashtag extracted ('greenpass') is mainly an Italian topic, selected because of the huge number of comments. This last focus seems to lay the *statu nascenti* of the movement against the Greenpass in Italy. Compared with the No-Mask, the green-pass communication is more connected and compact.

The data presented are not always suitable to describe the behaviour of citizens of different nationalities at different stages of the pandemic situation. The work does not aim at this but identifies trends. Certainly, the online comments allow comparisons and identify salient themes also on a trans-national level and this will be the subject of further developments. Here the main focus is, however, the analysis of the network structure underlying the communication (albeit including a qualitative investigation of the comments of the network hubs). It will be necessary, as a further step, to link this analysis of the structure to a more comprehensive and in-depth investigation of the content.

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