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The early weeks of the Italian Covid-19 outbreak: sentiment insights from a Twitter analysis

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Introduction

On the 11th of March 2020 the World Health Organization announced the COVID-19 outbreak as a pandemic [1]. Since the first cases declared by China on 31st December 2019 the number of affected countries has steadily increased. A large number of countries have chosen social distancing and partial or whole lockdown measures. This resolution was influenced also by the Imperial College's report, predicting the effects of non-pharmaceutical intervention to reduce COVID-19 mortality and healthcare demand [2]. In its first stages the COVID-19 spread was entirely dependant on the number of contacts among people, hence on the capacity to interrupt human to human virus' transmission through the social distancing. Thus it can be stated that people's behaviours and lifestyle influence both the spread and the severity of this type of infectious diseases (airborne, droplets etc…), especially when no strict countermeasures have been put in place by central governments [2]. Indeed, if it is generally true that users' participation in healthcare plays a pivotal role [3,4], it is pivotal when considering public health interventions aiming at changing behaviours both at individual and societal level [5,6].

As highlighted by Boin and McConnell [7], an effective response to the crisis also depends on the adaptive behaviours of citizens and front-line workers. A crucial aspect of the communication during crisis is to guide the people's perception on both the risks linked to the crisis and the behaviours to adopt in supporting its resolution [8]. Indeed, massive investment in communication by traditional and social media has been done by governments launching slogans such as the UK promotional "stay at home, protect the NHS, save lives", in order to make people more compliant with the social distancing rules leading hundreds of millions of people to remain at home.

In the last years Twitter analysis became a very popular way to measure people's perception, along with their social network relationships. Given the rapid growth of the number of Twitter users in the last five years it can be said that it represents a powerful tool for short run communication to mass audience as well as for testing people's sentiment on a specific topic [9]. Moreover the increasing use of social media data, enable to monitor in real time and free of cost how people react to institutional or media communication [10,11]. In this sense, social media such as Twitter are of particular interest, since they present both horizontal and vertical dynamics of communication and are characterized by both a personal dimension and aggregation practices, for instance through the use of hashtags that give a collective visibility to individual-generated contents [12].

A recent review on the use of Twitter [9] revealed that most of the studies using it refer to both infectious diseases and to other outbreaks. The advantage of using Twitter data in our case consists in the possibility to: (1) analyse users' discussions about the COVID-19 outbreak, (2) grab the personal view of the users either of consensus or disagreement, (3) trace the public debate of a large

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audience and (4) have available a high number of observations in real time [13].

Usually, Twitter analyses are based on algorithms reporting a unique value as sentiment [14] or classifying the messages [15,16] into either positive, negative or neutral sentiment. Recently, Ji et al [13] proposed an index expressing the measure of public health concern considering the negative sentiment towards the outbreak. People's reactions towards an outbreak are particularly interesting because they can lead to minimize, acknowledge or maximize the impact of the strategies put in place in order to cope with the epidemic as well as the other outbreak's related event [17]. Minimizing the real events, in the case of outbreak, may lead to non-compliance with the measures of social distancing, while acknowledging the outbreak could be in line with compliant behaviours towards containment and lockdown measures.

An analysis of the social media provides a useful tool for public health specialists and government decision makers. It allows to capture the emotional changes of the population and to provide updated and dynamic information on the public awareness and reaction to the crisis situation, improving the operational response to the crisis [18,19].

Given these premises, our study proposes a novel and original use of three indices: i) the interest in COVID-19 among Twitter's users; ii) the positive outbreak (PO) index and iii) the negative outbreak (NO) index. In particular, starting from the study of Ji et al [13], we considered not only the negative polarity but also the positive one. Indeed, both of them are important to capture the public perceptions and concern about the disease and to analyse the direct emotional impact of the coronavirus on people. Specifically, the positive sentiment, if associated to relevant contents, may reflect optimistic feelings which can be informative on the degree of compliance towards certain public health containment measures. In this perspective, we analysed the population reaction to COVID-19 using Twitter daily data during the first four weeks of the outbreak period in Italy. The analyses were executed both at national and regional level to detect any differences from geographical territories, that were hit by COVID-19 with different intensity and in different stages of the COVID-19 diffusion.

The paper is organized as follows: section 2 reports the methodology; section 3 illustrates the results; section 4 contains the discussions, and the section 5 concludes providing suggestions for future research.

Methodology

Dataset

A unique and original dataset with a large fraction of Twitter messages related to the current outbreak was created. It was collected using the following keywords: "COVID-19", "coronavirus", "coronavirusitalia". Since the focus of our analysis is Italy, we asked Twitter, via application programming interfaces (API), to give us back the tweets in the Italian language only. We recovered the large majority of tweets originated in Italy, in the period between 17th February 2020 and 22nd March 2020. Our dataset allowed us to study the effects of an increase of uncertainty and or/panic among Twitter's users, hence measuring the perceived impact of COVID-19 pandemic in Italy.

Each tweet allowed us to uncover: the content, the username of the user who tweeted, the timestamp and the impact of the tweet. Using the username, we complemented the data with a call on the Twitter API (http://dev.twitter.com) to extract the description of the user and his/her declared location, as well as number of statuses (i.e., how many tweets he/she produced) and the date when the account was created. The filtering procedure eliminated the tweets originating from a user whose location could not be clearly established from the field "location" in the Twitter's query results. In this way, we were able to downscale the database to the regional level.

The data was collected in JSON format from the Twitter streaming API (the extract step), for a total amount of 4,163,138 tweets in Italian discussing "coronavirus" or "COVID" related topics and 523,609 unique users. Removing duplicated tweets made the database shrink to 774,407 unique tweets. The users reporting a geographical location in their profile were 110,985 from 4,656 unique locations. During the analysis, we discarded duplicated content, both from retweets and media sharing, in order to limit the influence of viral messages that can make the global sentiment analysis unbalanced towards popular tweets. We choose to not discard the tweets from media agencies as they represent a fraction of about the 5% of the total unique messages. They also tend to carry a more neutral sentiment.

Statistical analyses

We firstly calculated the cumulative number of Twitter users discussing about COVID-19 across time. The number of Tweets mentioning the keywords related to the outbreak can be considered a measure of the interest on this topic.

Then, we used a two-steps procedure to interpret the content of tweets and to perform a day-to-day sentiment analysis.

The goal of this sentiment analysis is to associate to each text a numerical value that represents the positive/negative mood expressed by its content. In this way, we captured the real users' feelings about a discussion on COVID-19 and avoid sample bias selection using only some keywords for the content analysis.

In fact, the most basic technique of sentiment analysis is based on counting in each sentence the number of keywords from a predefined dictionary of negative/positive words. This dictionary-based approach to sentiment analysis has the advantage of simplicity but is often biased towards the initial choice of the dictionary. Moreover, it suffers of a lack of accuracy in the case of sarcasm or in the case of positive words used with a negation in front. To solve these problems, the modern sentiment analysis that we employed in this paper makes use of manual classification of large databases of texts. A small team of human annotators attributes individually a level of sentiment (expressed by two scores: one positive and one negative) to each sentence. By averaging, sentence by sentence, the scores attributed by different annotators, it is possible to create a database of texts with associated a sentiment label. Then, a machine learning model - that often is a deep learning model such as the bidirectional long short term memory (LSTM) one – is used to learn the scores and to predict the sentiment of unseen text regardless its content.

In this paper, we used the "Italian Sentita" sentiment analysis tools described in Pelosi [20]. For each tweet, the library provides two values: a negative and a positive score. The global level of sentiment for each tweet, called polarity, can be computed as the difference between positive and negative (polarity = positive-negative). With this measure of polarity, we studied the average emotional content of the most popular hashtags in a robust way and we followed the timeline of the response. The study of the average daily mood of tweets during the initial phase of the epidemics was the key driver to understand, with some limitations due to the Twitter platform and its demographics, the general orientation of the Italian population towards the policies and the actions of the Italian authorities.

In the second step, we measured the negative outbreak (NO) index following Ji et al. [13]. The NO index was calculated as the square number of personal negative tweets on the total number of tweets in the same days. We applied the same algorithm to the positive tweets calculating the measure of positive outbreak (PO) index.

The NO index formula is reported in the following equation:

$$N_o = \frac{\left(\sum_{i=1}^{n} T_i\right)^2}{n} \quad (1)$$

Where i is an index representing each tweet, T(i) = 1 if there is a negative tweet, T(i) = 0 otherwise and n is the total number of tweets in the same days.

Similarly, the PO index formula is reported in the equation:

$$P_o = \frac{\left(\sum_{i=1}^{n} T_i\right)^2}{n} \quad (2)$$

where T(i) = 1 if there is a positive tweet and 0 otherwise and n is the total number of tweets in the same day.

The equation 1) and 2) are considering only positive and negative tweets.

All the three indicators have been computed at both national and regional level to capture whether there were significant differences across the Italian Regions concerning the different diffusion of COVID-19.

Finally, we normalized the regional indicators following a two-step procedure. First, the cumulative distribution of the unique users (per 100,000 inhabitants) was computed for each region; second, we normalized the functions dividing by the average distribution obtained from all regions. We used this procedure to remove the national (i.e., average) behaviour effect from each regional curve and to make clearer the temporal pattern of interest on Twitter, at regional level.

To provide a clearer picture, a list of the main hashtags/topics on Twitter was used to comment the analyses. We studied the sentiment associated to the most popular hashtags having at least 500 mentions in unique tweets. The idea was to capture the main concepts discussed during the epidemics, their popularity, to assess the usefulness of the sentiment analysis while investigating the propensity of the users to respect the rules of the social distancing (see the appendix to deepen the analysis conducted).

Results

Findings were grouped into two sub-sections as follows: (i) the Twitter users' interest in the COVID-19 related crisis, and (ii) the perception of the crisis measured using the rescaled negative and positive outbreak indices (NO/PO)

National and regional interest and COVID-19 outbreak

Fig. 1 shows that the total number of unique Twitter users who tweeted on the COVID-19 rose steadily starting from the day before the formal Government's announcement when were discovered the first cases in Lombardia and Veneto (21 February). The growth flattened until the first two weeks of lockdown and then it after the first four weeks of COVID-19 spread, the curve seemed to be achieved the growth saturation of twitter users.

Similarly, Fig. 2 reflects the number of unique Twitter users normalized by population per Region. In particular, Fig. 2 shows the growth rate of the new Twitter user across Regions over time. Apart from the case of Lazio, where the Capital, Rome, is settled and where there are many press agencies, Fig. 2 highlights two groups of Regions with a similar trend: those above the National average (dashed line) and those below the National average.

We note that in the case of Regions that are above the average (Lombardia, Emilia-Romagna, Piemonte, Veneto, Liguria and Toscana) the interest among Twitter's users was significantly high in the beginning and then the growth rate of new users stabilizes. These Regions were those more hit by the outbreak in the first

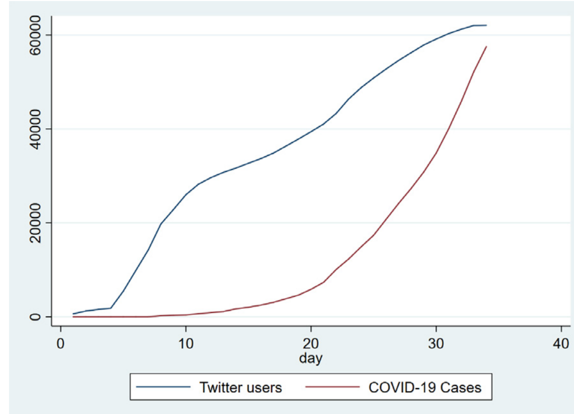

Fig. 1. The cumulative number of unique Twitter users mentioning COVID-19 per day and the cumulative national COVID-19 cases.

two weeks. In the second group of Regions, those below the average (Trentino-Alto Adige, Marche, Sicilia, Calabria, Puglia and the mostly part of Southern Italian regions), the interest grows over time until few days after the complete lockdown.

Differences across Regions smoothened till the full lockdown when they seem to converge.

NO and PO trend analysis

Fig. 3 reports the timeline of PO and NO time series. It clearly emerges that NO index is always higher than the PO although the distance between the two curves is reduced after the national lockdown.

It is worth noticing that the NO index seems to be strongly related to official COVID-19 communications reaching a first peak after the outbreak of Codogno, Lombardia (on the 23rd of February). We can see that the number of negative tweets and the relative concern is systematically higher after the announcements of the Prime Minister Giuseppe Conte and/or after an increase of diagnosed cases of COVID-19. This is not surprising given both the high media coverage and people's interest in the Government announcements.

The timeline shows that before the announcement of the first cases in Lombardia and Veneto on the 21st February, the NO time series was flat as the PO ones. Interestingly, the two curves seem to have similar peaks in the same period, which suggests quite opposite reactions to the same events. The negative outbreak series (NO) reaches a maximum value in consequence to the first COVID-19 cases of the 24th February, the day after the first national restrictive measure that completely locked down the city of Codogno, in the Lombardy region. The NO time series starts to decline by March the 2nd. The most popular hashtags relative to this period were #Conte (the Prime Ministry who mostly communicated the measures), #quarantena (quarantine) and the events linked to the first lockdown.

Similarly, at the end of February, the PO time series rose in coincidence of the hashtag #milanononsiferma (Milan doesn't stop), with the idea to keep both the lifestyle and economy going on as usual and minimizing the negative events. In the same period, NO has grown up for the increase of uncertainty. It registered another peak around the 11 March, concurrently with the closure of restaurants, pubs, coffees, and of all the "not essential shops" and services at National level: a tighter lockdown was officially extended to the whole Country (DPCM 11 marzo 2020). The negative tweets of that period referred to the political debate of that days related to the insufficient support of the European Commission and the

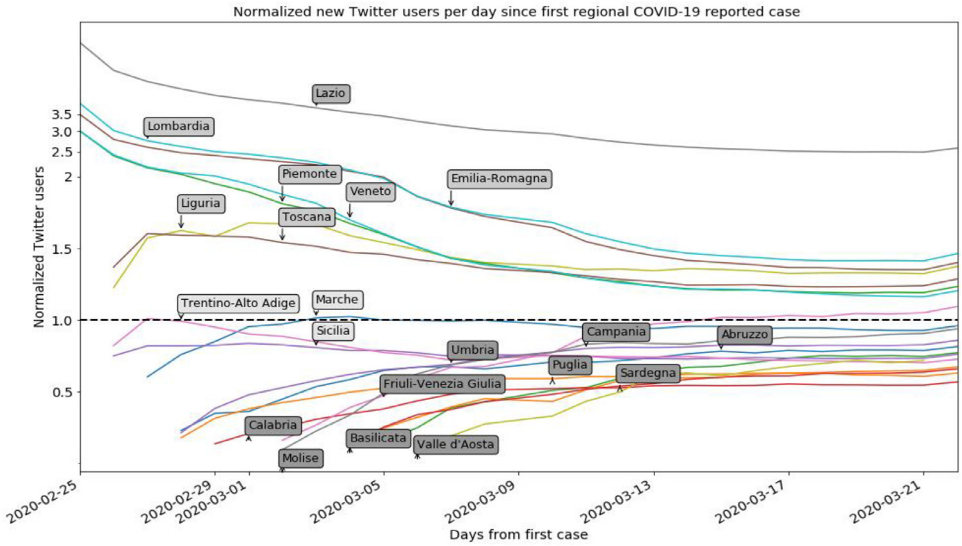

Fig. 2. Normalized new unique Twitter users per day, since the first regional COVID-19 reported case, by region

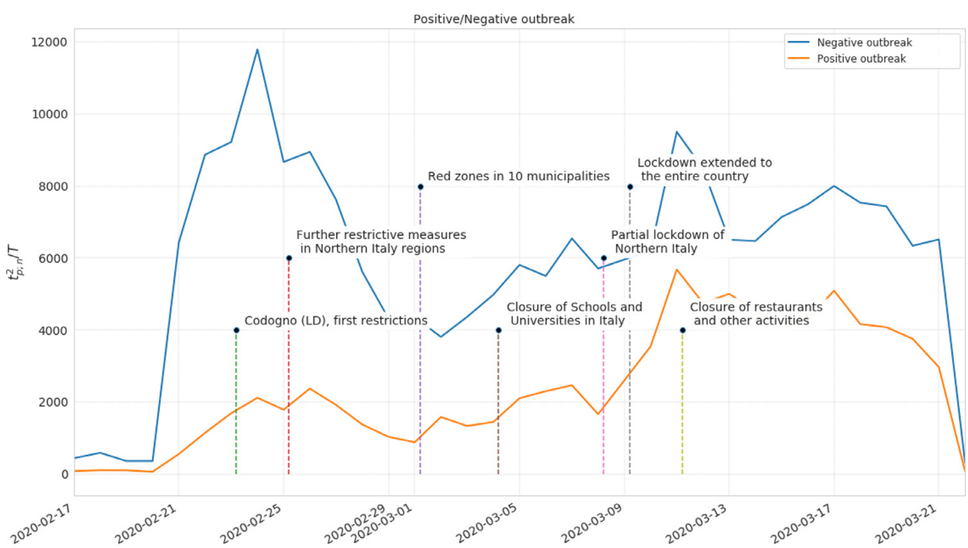

Fig. 3. plots the national rescaled daily PO and NO indexes time series during the first four weeks of the Italian coronavirus outbreak. The dashed vertical lines indicate the main government announcements or events.

European Central Bank leaders. Indeed, #lagarde and #bce were the “key hashtags” in those days.

On the 11th of March, WHO [21] announced that the COVID-19 outbreak was actually a global pandemic. On that day, #iorestoacasa (I stay at home) and #pandemia (pandemic) were at the top of the Italian hashtag ranking, reflecting both positive and negative sentiments. On one side, the idea that the epidemic is a global issue could have reassured people (positive sentiment) about the fact that all countries and international institutions, such as WHO, are fighting the same enemy on Italy' side [21]; on the other side, the perception of a cross boundary crisis could have led to a sense of deep uncertainty for the future evolution of the pandemic itself (negative sentiment), and on the capacity of the Countries to successfully and quickly face it [16].The first hashtag (#iorestoacasa, I stay at home) became an important keyword on several social media, such as Instagram and Facebook. In terms of positive tweets, it could have represented a sort of slogan of national unity, a way of making sense of common struggles, of an existing problem. Moreover, a clearer communication of the National measures could have reduced the people's sense of uncertainty and the perception of the risk. At the same time, the lockdown could have increased the negative feelings such as depression, fear, angry related to a reduction of the personal liberties and rights.

In the period between the last two subsequent positive peaks, several social media have helped to maintain a positive feeling. During the days around the 15th of March, the hashtag #andratuttobene (it's going to be okay) was the most frequent. Several Italians crafted and hanged out of their windows and balconies colourful posters with this phrase: a positive wave felt down on the social media together the #andratuttobene slogan.

Finally, the PO series exhibits the last one positive peak around the 17th of March, aligned with a higher negative peak of the NO

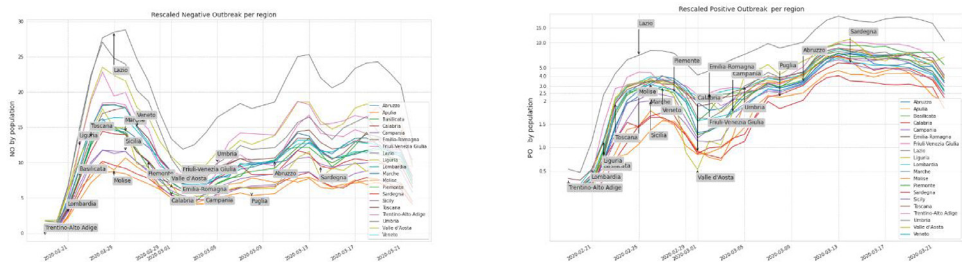

Fig. 4. plots the rescaled negative and positive outbreak (NO/PO) indexes with respect to the timeline of the evolution of COVID-19 in Italy

series in the same period. The emotional changes match with the decision of the Italian Central Government of introducing measures of financial assistance to individuals, families and firms (DPCM 17 marzo 2020). This move could have been interpreted as the beginning of a long-term country's restructuring, which could have enhanced the societal resilience [7].

Regional differences in NO and PO indices

Fig. 4 (a-b) shows the time trend of the PO and NO indexes normalized at regional levels.

Interestingly, the differences across Regions over time seem to be constant since the first cases assessed in Italy.

Fig. 4 depicts that both indices for some Regions (Lazio, Lombardia, Emilia-Romagna, Veneto, Piemonte and Toscana) are systematically above the national average line (dashed line) showing more intense reaction on Twitter than the others.

With respect to Fig. 2 on the Twitter's users, it is possible to identify a significant shift in the position of two Southern Regions, namely Campania and Sicilia: these two Regions show a higher PO and NO values than the National line, whilst in the Fig. 2 they appear to be below the National line. A possible explanation can be related to the fact that people studying or working in the North of Italy went back home during the first lockdown measures. This mass mobility may potentially have had a negative impact on the spread of the outbreak in previously unaffected areas [22]. These events generated a debate around the civic sense on one side, and the police officers and armed forces' members role in enforcing the lockdown on the other side. Hence, despite the number of Twitter's users is lower, their activity on the social is higher than the national average.

Discussion

This paper provides an analysis of the public interest and concern, expressed on Twitter, in consequence to the Italian Government communications during the spread of COVID-19. During the study period, the uncertainty on the nature of contagion and on the measures of Public Health to be adopted, caused significant changes in the timeline trend of positive and negative outbreak (respectively, PO and NO) indices. Our study is based on an original and unique dataset consisting of tweets collected from 523,609 unique Twitter's users. This paper is, to the best of our knowledge, the first study on the emotional effects of COVID-19 outbreak using PO and NO indices. The implications of the findings are twofold.

First, we compared the volumes of tweets drawn from the Italian regions' users to the National average investigating how the local movements tend to converge once the interest expressed as number of new users across time saturate. This result shows how the Country has reacted in a compact manner similar to a unique body of users while the local debate assumed a secondary role during the outbreak. This phenomenon represents an indirect measure of the ability of the Government and the media in creating a National perception of the outbreak, a common narrative and a shared set of rules and behaviours to adopt in face of the outbreaks.

Second, the timeline of the PO and NO time series through Twitter mirrored in detail the lively and daily debate on COVID-19. NO index has always registered higher scores than the PO, as a signal of the fear of the COVID-19 outbreak. It is possible to underline significant differences in NO and PO indices across Regions, which seem to be constant along the timespan analysed. Sentiment analyses could help to disentangle different people's reactions for predictive purposes [23]. However, our study highlighted that a careful analysis should be undertaken. Indeed, the combined analysis of the PO and NO indices together with the hashtag revealed that both NO and PO indices may assume different interpretations before and after the lockdown. When the lockdown is less rigid and people are free to move, a rising of PO index could be a signal of undermining the outbreak (#milandoesntstop), while NO index a signal of a higher attention on the problems and consequently a proxy of people behaviour. Instead, when people were asked to stay at home, the PO values can be interpreted as a positive feeling, such as newfound national pride [24-26]. It can also reflect the positive reactions towards the Governmental plans to sustain citizens and firms in coping with the crisis, such as suspension of home loans, baby-sitting bonus, temporary lay-off scheme for employees [27,28]. Conversely, the NO index could reflect both concern about personal limitations and economic consequences [26] as well as anxiety for the delay of the implementation of governmental measures and the yet uncovered issues. In fact, the Government-citizens and Government-firms relationships are the key drivers in building a positive perception of Government's capacity of action [29,30]. The Italian Government's economic measures combined with information (see for instance #andratuttobene) could have reassured Italian citizens [27,28], thus activating a societal resilience [7]. The combined analysis of PO/NO indices and hashtag are relevant for interpreting the meaning of PO and NO in the different phases of the first weeks of the epidemiological emergency. Despite additional in-dept analysis are needed, this study already shows a different interpretation of the two waves of positive sentiments occurred during the first four weeks of the outbreak onset. Combining the PO index with the relative hashtags, it is possible to realize that the initial PO was represented by less supportive behaviours towards the restrictive policies with a minimization of the crisis scale; while the second positive wave seems to indicate acceptance and adaptation to the measures on containment and management of the diffusion of COVID-19 policies, which may have affected their effectiveness [31]. PO and NO should be carefully interpreted using hashtags or specific in-dept indicators on the meaning of the texts, in order to use to capture the real feelings behind the people's behaviours.

Whilst trends of both the unique Twitter users and NO and PO indices highlighted that differences across Regions seem to remain constant over time (especially after the full lockdown), as shown in Fig. 2 and 4, significant differences persist across Regions. Some of these could be explained by the increasing of diagnosed cases occurred from the lockdown in some Regions such as in Lombardia, others instead deem further investigation. Additional analyses are needed to understand whether discrepancies can emerge between public, stakeholder and institutional Twitter's users such as the appraisal of risk events [32,33]. In particular, it would be interesting to realize the role played by the different users 'profiles in affecting the public/population feelings regarding the outbreak.

Despite the authors analysed the use of specific keywords and hashtag in the tweets, this study does not include a specific content analysis correlating beliefs or behaviours to positive and negative feelings. In this perspective, further research may investigate the association between PO and trust in public authority, and the consequent behaviours along a continuum from the compliance with the rules, to a more relaxed attitude in respecting restrictive measures.

Another aspect which was not investigated in this paper refers to misinformation. Indeed, misinformation and fake news may have persisting effect on people's behaviours as reported by some recent articles on vaccination coverage and lead to high societal costs for bias sample selection [34,35]. However, in the first stages of the outbreak when uncertainty is very high and scientific evidence is scarce, it cannot be easy to identify what is misinformation and what is not.

Finally, the study focuses only on the first four weeks of COVID-19 outbreak. This is a limit because the feelings of people may change in different context such as the kick-start.

Conclusion

This study contributes to literature in three ways. First, it provides a novel approach to measure people's reaction towards coronavirus outbreak using Twitter data. Second, it presents a wider picture of the Italian COVID-19 outbreak responses in terms of public feelings during the first four weeks of the epidemic. Since Italy was the first Western country having to cope with coronavirus [36], many authors have already analysed the Italian case mainly to: (a) study the epidemiological responses [37]; (b) learn from the Italian experience; (c) to create awareness and preparedness in other countries [38-40]; (d) to understand the impact of the institutional and governance asset of the Italian National and Regional Health Systems [22;41]. Until now, few studies have been devoted to social network analysis. Third, the analyses of positive and negative outbreak indices, highlighted that during the first four weeks the positive and negative feelings may be interpreted in different ways overtime whether combined with a qualitative analysis on the hashtags.

Specifically, this article represents the first analysis of the emotional response in Italy to the COVID-19 outbreak. We analysed how the initial negative emotional impact changed over time during the initial phase of the lockdown. It is interesting to notice that the public concern smoothened during the quarantine and became more similar among the Italian Regions and close to a positive sentiment. After several weeks the interest as expressed by the number of Twitter per user, reached a *plateau*. The result is a general mood transitioning to a more positive level. We can interpret this phenomenon as a media channel saturation, the debate and the attention cannot be larger, but this transition is also one of the first effects of the national lockdown that made the Italian response in terms of feelings more homogeneous across the Regions. The people on Twitter are paying attention to the initiatives of the government, and their discussions appear to be more interested in the national debate than in the local situation. This result appears in line with the initial general adaptation to the acceptance of the first tighter lockdown, which has contributed to realize positive outcomes in containing the contagion diffusion in Italy [40]. Caring for the communication of strategies and containment measures will be crucial in maintaining trust and collaboration of the general population, whose resilience requests great psychological efforts [31].

Conversely, we can also say that the local cases such as the ones in Lombardia became of national interest and the comments and the discussions lose their prevalent local dimension. We see this effect in particular in the hashtags that are focusing on a wider set of topics from the effects on the economy, to the lockdown rules, to the initiatives of the prime minister: after the initial phase of the outbreak, the central government introduces a set of common regional measures making the local response more uniform and then the emotional response smoothened.

Conflict of Interest statement

None.

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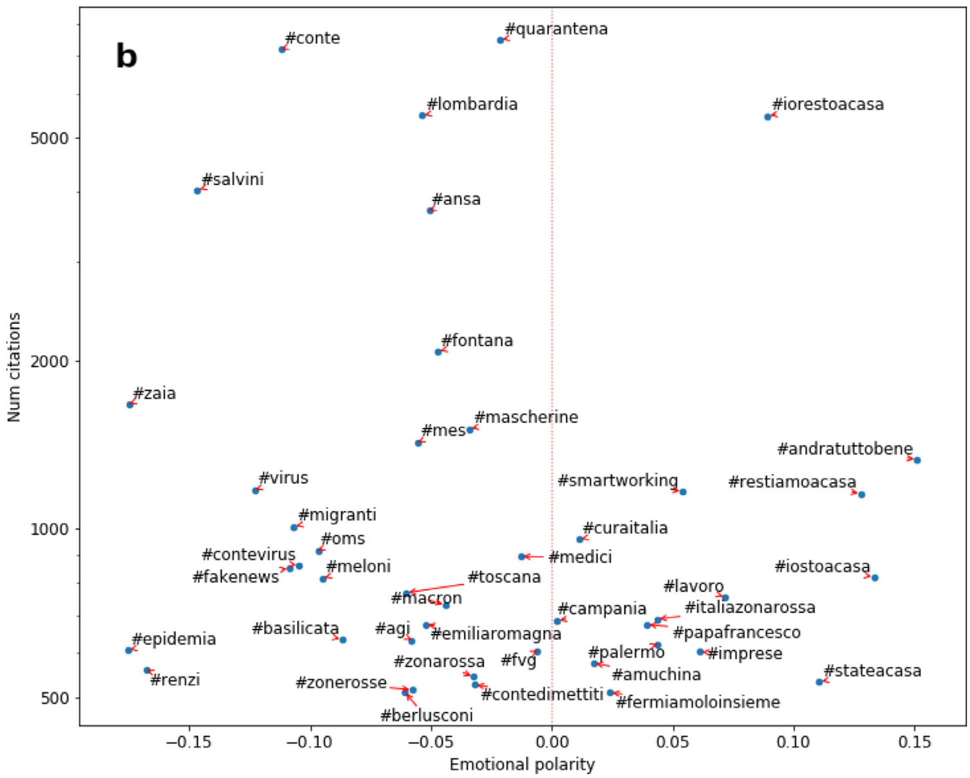
Appendix

Fig. 1 reports evidence of the usefulness of the sentiment analysis associated with several of the most popular hashtags (with more than 500 individual citations). This plot allows us to study several hashtag's trends at once. The sentiment linked to the Italian regions is proportional to the severity of the epidemics, with a negative sentiment for the Northern regions, and a positive sentiment for the Southern ones. This is not surprising given as the first wave of Covid-19 hit severely the Northern Italy while the Southern regions were spared.

We find a general positive mood about a set of hashtags associated with "io resto a casa" (I stay home). Instead, the "#quarantena" is almost neutral. The "#italiazonarossa" (the complete lockdown) was accompanied by a general positive sentiment, while the creation of individual tighter lockdowns ("#zonarossa" and "#zonerosse") was seen as negative.



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