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# Disorientation towards routine immunization, COVID-19 anxiety, and propensity to vaccinate. An analysis based on Twitter data in Italy.

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*Candidate*
**Ajovalasit Samantha**

*Supervisors*
**Prof. Angelo Mazza**
*University of Catania*
**Prof. Piero Manfredi**
*University of Pisa*

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# Contents

# Abstract

## Background

Online social media (OSM) play an importart role in our life, for many even indispensable. To speak with and to get in touch with other, people post huge amounts of contents, often personal, and often dealing with sensible topics, as health. OSM and the web are used to share and to acquire information based upon which they often take decision potentially impacting on health and quality of life. There are many positive aspects in the use of social media: reduce physical distance, share information, and retrieve knowledge from new kind of data. However, social media might become harmful e.g., when they become a vehicle for the spread misinformation capable to destabilize the public opinon - especially for controversial topics like vaccination - and generate disorientation amongst people, who can loose awareness of what they read or watch, becoming misinformed and spreaders of misinformation in their turn.

## Objectives and Methods

Using Twitter and Sentiment analysis techniques on tweets written in Italian we attempted at i) characterizing the temporal flow of communication on Twitter about vaccines related topic in the year 2018 and during the COVID-19 Pandemic, ii) identifying the main triggering events, iii) evaluate the opinion and polarity in the case of immunization policy in 2018 and study the effect of COVID-19 on Twitter, iv) investigate if contrasting announcement and decision on immunization

policy generated disorientation in public opinion in Italy on 2018 and see if Twitter flow in Italy respond to the pandemic spread at national, regional, and province level.

## Result

Political events originated, in both analyses, major reactions. On sentiment about vaccine and immunization policy we found that 75% are favorable, 11% unfavorable, and 14% undecided, with the first and latter proportions that changed in trend, synchronized with the change of government in Italy, suggesting evidence of long term disorientation in public opinion. We tested for presence of disorientation, in form of instability in polarity proportion, also for short term. Proportion of people involved in vaccination was negligible. For COVID-19 we found a clear a positive correlation between Twitter flow and Covid cases reported, especially in the most hit regions by pandemic.

## Conclusion

Use of social media analysis is useful to estimate and have a better overview of the public opinion for critical health-related topics. Disorientation appears on social media in controversial topic, such as vaccination decision, showing that health topic and healthcare should never be used to raise political consensus. Disorientation may raise also due to lack of presence of public health institutions on social media calling for efforts to contrast misinformation, which needs further analyzed to understand how this will translate in disorientation and future vaccination decision. During the most important health threath of last years, people use social media to espress concern, anxiety, and presence of denialism, it remains to be seen how these sentiments arise and spread during a pandemic and what is the role of social media exposure and misinformation.

# Chapter 1

# Web 2.0, eHealth, and behavioral choices on healthcare

## 1.1 From Web 2.0 to Big Data

Internet and Web 2.0 are nowadays sources where people retrieve and exchange unprecedented masses of information, also including health-related facts. These new forms of information are reaching unprecedented number of people across the world, and are allowing to effectively raise and maintain complicated networks of relationship (amongst relatives, friends, acquaintance, etc.) overtaking the use of old-fashioned communication means [1].

These platforms are used, among other, for an endless list of tasks, including sharing various types of contents like video, posts, newspaper articles, scientific paper, photos, and many other types of topics. However, the ultimate implications of these technologies have been often underrated by users and, sometimes also by providers. But surely a main issue is related to the fact that users systematically load - unintentionally - personal information on these platforms, becoming potentially vulnerable to fraudulent, or non-ethical, use of their data [2].

Unsurprisingly, these new types of media, are having a large impact individuals' life, also changing the relationship between the individuals and the society. This impact ranges from the active participation to debates, the creation of new contents, the faster than ever connection between. The latter issue is particularly important for e.g., political participation, with the elimination of those physical barriers in an unprecedent way. The Web 2.0 and the Internet of Things (IoT) have allowed the gradual creation of new generations of data, now labelled as Big Data. The examples are endless. For instance, more than 100 million of tweets - short texts posted on Twitter - are posted daily by more than 300 million of users in Q1-2019 [3]. Another example of big data is mass of information that users leave anytime they visit Web 2.0 or use IoT. We can extract data from devices such as smartphones, wearable, black box on cars, which can give us the position of her/him at any moment. This opens the possibility for scientist, researchers, and companies to track the data, and to use them for a wide spectrum of purposes. In this environment, it most often happens that users become passive data providers fully unaware of the potential their own data [4].

Big data refers to large, in term of massive datasets, structured or unstructured data that require advanced form of real-time analysis. The main characteristics of Big Data are summarized by the famous "3V" [5]:

1. Volume: it refers on the large size of the datasets used to store the data.

2. Velocity: is the speed at which the data are produced and collected.

3. the different type of data generated, ranging from narratives, contents, photo, geotag, but also different type of databases and storage to keep the data.

The "3V" definition can be extended to include other V such as: Value [6] and Veracity. The latter is an important feature referring to the concept of data understandability, in turn related to the critical notion of “digital breadcrumbs”.

By “digital breadcrumbs” we mean the final data that, after various processes of data filtering, cleaning, polishing etc. (such as discretization, aligning, sampling), aimed to give a context to these data, appear to the final user. For example in context of tweets, data processing and filtering help us to retrieve features that are not immediately available like, location of user when he/she tweeted, or analyse the emoji to enrich the contexts of the data available [7][8].

An example of difficulties in understandability and recalibration of big data analysis (and their use), which prove the non-automatic reliability of these data, is represented by Google Flu Trends (GFT).

GFT is a service launched in 2008 to help to predict the trends of seasonal influenza [9], based on the correlation between the occurrence of flu-related keywords on Google searches with the real trend of seasonal influenza. As widely pinpointed (e.g., [10]), GFT was a well-suited example of misestimation and recalibration problems. GFT algorithm was improved several times to overcome issues related to the search terms and other improvements that are obscure to us since Google never released data to replicate the study. Indeed, GFT reasonably reproduced the seasonal flu trend in 2009 but largely overestimated the flu incidence rate in the 2012-13 season, and completely missed the estimation of the 2009 A/H1N1 flu pandemic.

Additionally, the use of Big Data poses several important ethical issues. Though it is true that these data are available to anyone, it is also true that regulations and legislations show substantial variations between different countries. Especially for healthdata, there are strong national recommendations on anonymity and anonymization processes, such e.g., as the k-anonymity [11], a method proposed to protect privacy of individuals recorded in the data by eliminating the opportunity to retrieve private information from cross linkage. For example, using Twitter, it is possible to use Social Media data for research purposes but in their scientific publications researchers can release only the data IDs. Moreover, the terms of service supply clear rules on what can be released and what cannot be.

A further issue regards the status of sensible data i.e., when specific Big Data (which are public by definition) might be sensible. In general, every datum dealing with individual's personal sphere should be protected by privacy rules, for example the geocode and trajectory pattern that, if not properly anonymized i.e. removing obviously identifying information, can make possible the re-identification of the subject [7]. Currently, efforts are made to to prevent the hacking of any sensible information, starting from the simple encoding or elimination of identifying information. Stripping name, removing social security number may be not sufficient, even if it fulfill all legal requirements.

To sum up, a problem researchers are confronting with is that, even if the data are freely accessible from the web, the provider of data could not ensure enough anonimity. Researchers should keep it in mind this when performing a study: and "privacy and anonymity do not disappear simply because subjects participate in online social networks" [12].
The case of Tastes, Ties and Time [13] is a well known example in the literature of missing the requirement of anoninimity of data for scientific work. On a Facebook study, despite the good intentions in preserving anonimity, identity of users (students on Harvard College), analyzed was partially re-identified, and this represents a failure in data preservation [12]. Nowadays participation to principles like: i) respect for persons, ii) beneficence, iii) justice, and iv) respect for law public interest and ethics requirement are a standard for social data science research [4][12]. Important aspect is the awareness of the users of their own data, they share them unintentionally and become prey

for the data miners, personal digital data are effectively a new form of asset [7].

## 1.2 Role of Online Social Media

The social media and Online Social Media (OSM) are nowadays part of ordinary life and give new ways of communication and engagement. OSM should not be confused with Online social network, or social networks. OSM are platforms, set by providers, that help the users to build new online form of engagement and connections that we call Online Social Network [14].

OSM routinely produce Big Data. Unfortunately, not all such data are readily available for analyses, and efforts are required to better understand them. Researchers and social scientist started to collect and retrieve data from OSM and IoT, making them human readable with the support of methodologies proposed by different disciplines (e.g., epidemiology to economics, statistics, demography, and sociology). All of these field are nowadays embedded in the new field termed “Computational Social Science” that emerged for its capacity to collect and analyse data at unprecedent level [15].

Demography is a discipline strongly interested in OSM data, despite their obvious lack of representativeness, because of the unique the opportunity such data offer to find new answers to old questions and to set up entirely new research questions. For example, Big Data are making possible to nowcast the patterns of international migration [16][17], adding valuable information to commonly available data such as e.g., survey data. On the other side, there are limitations that come from biases in the data selection processes, which require careful calibration procedures to mitigate the noise present in the data [18]. Opportunities to retrieve knowledge from digital data are growing too, with new challenges for researchers.

### 1.2.1 Main types of contents on OSM

The contents generated within OSM are not unique and uniformed across the web: for example, a Facebook post is different from a Tweet, or from a wiki content or even from a blog. This makes it important to clearly distinguish between them for methodological and research purposes.

A wiki project is an example of collaborative project where user can add, change, remove contents but also control what other users do. Wikipedia is the most famous type of wiki project and it is widely used as main source of information on health topics [19]. Moreover but it was also important as a source of data for estimating the spread of infectious disease [20] much in the same way as the GFT.

Another important type of content is represented by the blogs. These are webpages where authors, called bloggers, write about particular and personal themes sharing thoughts and ideas, also including possibility to interface with readers by means of comments [21], wrapped in the field of self-publishing content. These are easy to create and to manage, can be personal or managed by a small group of persons. Generally the topic that can be read or posted are diaries, news, opinions; they have been used and updated by academic professors, or school teacher to enhance their own visibility and/or publish educational content [22].

OSM like Facebook, Twitter, Instagram etc. have established the opportunity to generate own visible profile with the subsequent possibility to create network between real people in the world, the virtual network could (or not) match the real one that a user has. The accesses to these OSM dramatically increased with millions of contents generated every day.

In Facebook, as well as Instagram, the engagement rate (or interaction rate) increased by the fact that the algorithm gives the possibility to reach people with common interests or based on other info that previously (and maybe unconsciously) shared with the site. Facebook also gives the possibility to create pages (like blogs) and groups, both secret and public. Users can interact each other with post and comments. Given the structure of Facebook is more to likely that phenomenon of echo-chamber i.e. homogeneous and polarized communities arises [23], due to the fact that people tends to be aggregated, (by algorithm or not) according to their preferences, in clusters where the access to opposite opinion is discouraged if not forbidden by the admin of certain pages or group [24].

### 1.2.2 Data Retrieval from OSM

Data from social media are typically retrieved by means of Application Programming Interface (APIs) and scraping, can be achieved in real time detecting trends and hot topics, but also offers the chance to look in the past (and far away) to understand what happened. Twitter and Facebook supply tools, publicly available that can be used by programmer to embody the services offered by the OSM.

The contents studied are generally texts, thread of texts, network, photos, videos, geotag and so on. It also possible use tools used to estimate possible target for advertisement, such as Facebook Adverts Manager platform, for demographic purposes, as in [17] to estimate stock of migrants in a particular region. From texts we can analyse opinion and sentiments, networks allow to understand better diffusion process and community structures.

APIs offer a set of opportunities for researchers to study demographics, behavioural, mobility etc. these data demand new approach, combined with classical to offer new answers to new questions, passing from theory-driven to data-driven paradigm. The challenge to face is that the data requires calibration technique to achieve knowledge from the “digital breadcrumbs”, especially to understand demographic interests [25].

Remarkable is the experiment of "Emotional Contagion" [26] in which a sample of people was intentionally exposed to different types of expressions in News Feed, positive or negative, to test whether they changed their own behavior and interest, demostrating that emotional contagion is possible and when negative post increased the positive word decresead and viceversa. This study is controversial and poses a series of questions, the main is that participants were unaware of this experiment.

Perhaps one of the most important reason of using social media is that today represents one of the main popular sources of information [27] and propaganda. Politicians share their programs and directly interact with the electorate, with help of team of new figures called Social Media Manager to coordinate the communication. Last, social media are uses to seek health information, and share news, official communicate etc. This instrument creates a parallelism with respect to surveys to help researchers to understand the behaviour of population.

## 1.3 Web 2.0, eHealth, and Online Social Media

The concept of "eHealth" refers on use of information and communication technology in healthcare [28], a field that has grown fast in the last 15 years, particularly in terms of web search on advice with doctors, diseases, treatments, etc. Unfortunately these researches are difficult in terms of results, because often websites and OSM not always offers correct or easy read information about healthcare [29]. In this context of poor information is easy that misinformation spreads, even with bad intention or to make profits with unproven theories or alternative healthcare.

Web is widely used for search about health and in [30] with a telephone survey in 2001, about 40% of respondents assessed that they used internet to search information on healthcare and one third reported an affected decision on healthcare, in 2004, 79% of survey's respondents said that searched health information on the web [31].

People are willing to change their decision on treating illness after consulting web search; moreover, the e-health literacy decreasing when age increase and it is also influenced by education, number of digital devices used to search on the web, definitely being younger with a more education is related with high level of eHealth literacy [32].

Moreover, search on web on health topics seems to be related with diagnosis and search for further information, lower family income, problem with physician access and use web as sort of auto-diagnosis, engage in online interactions, helpful effect of inter- net in "take care of your health"[33].
Web was found responsible in increasing the alternative approach of healthcare and this creates a problem about the quality of content published. Certainly, quality is not the only factor to trust a web content but also trust the sites that reflect a social identity, or for gender-trust (the study included only woman in survey), the study shows that content written by women are conceived more credible, or people tend to believe in site with "sufficient social identification". Notable is that there is not a long "trusting relationship with one particular site". Another "problem" in this the relationship patient-physician is also the fact that first are overinformed [34].

In [35], on a Twitter search about cancer and treatment (or alternative cure), a set of users was selected according to a criteria of dissemination of alternative treatment, and was found that despite the sophisticated language used and "circulate in health domain rather than posting a rumour", they were not really involved in illness. With OSM analysis it is possible estimate outbreaks; since they are a faster vehicle of information than any other institutional presence on the web, on the other side they could enhance false myths and anxiety in the population. In this context the presence of Health institution is encouraged to develop new forms of communications with citizenship.

The WHO has public pages on Twitter, Facebook, Instagram and so on, supplying information and bulletins. Public Health concept is certain not a novelty, it has been conceptualized in 1920 "representing art of preventing disease, prolonging life and promoting health through organized efforts and informed choice of society, organization, public and private, communities and individuals" [36]. Today public health institution faced new challenges such as the H1N1 outbreak, after on Zika, Ebola and, actually, the COVID-19. These challenges involved study of new data and new instrument, not only to increase the power of estimation of the outbreak but also to improve communication with the population. Internet surveillance was particularly efficient in detecting the SARS in China in 2002 [37][38], demonstrating the power of the surveillance system[39].

Us Centres for Disease Control and Prevention (CDC) is a primary example of public institution that enter onto social media to promote good practices, especially for vaccination; this have created a new communication channel with population to answer questions related to public health [40]. Platform such as Flu Near You (FNY) [41] use crowdsourcing (voluntary reports) from US and Canada population, these reports are aggregate geographically based on the zip code. It also supplies information about vaccination and where get it. Statistics provided from FNY show an overestimation comparing with official (delayed) statistics, this is due to crowd-reported cases in FNY did not required medical care, this is another example of necessity of calibration model to reducing noise and have better estimation and prediction.

## 1.4 Twitter

Twitter is a microblogging service where anyone can create a public profile, which is by default (main difference) publicly visible. Anyone can interact with anyone until user starts to block other users, avoiding them to read and discuss about the content, or use other form of limitation in contact. Twitter is a tool widely used by political leaders to reach the public and engage with the public opinion [42][43].

The analyses processed in this thesis are based on Twitter data. Twitter is a microblogging service, which is considered, as well as Facebook, Instagram, Gab etc. a public square where anyone can express and share an opinion or take part in discussions [44]. Unlike Facebook, where interactions occur troughs pages and groups (both public and private), Twitter allows a different type of interaction i.e., user A can read what user B posts without being involved in a direct relationship (follow), making it both "a social and a newsy" or an information network. This makes Twitter different from Facebook due to its structure. For example, Facebook allows easier identification of phenomena as the echo chambers or homophily i.e., "polarized groups of like-minded people who keep framing and reinforcing a shared narrative".
Twitter was used to predict the results of political elections and polls, with contrasting evidence in the literature on the reliability of the tool [45][42].

Another use of Twitter data was in analysis of sentiment about health-related topics such as seasonal flu and other outbreaks, like the A/H1N1 pandemic outbreak which appeared in spring 2009, detected first in US. The number of cases estimated arrived at 60.8 million with 12,496 death in the entire US, with estimated died 151,700 and 575,400 [46]. A vaccine for A/H1N1 was available only in November 2009.

The outbreak was also on Twitter, where number of tweets containing "H1N1" during this pandemic increased up to 40.5% especially after the adoption as official term by the WHO from the previous term "swine-flu". A relationship was found between tweet volume and news events related to the outbreak, while the pandemics increased the number of tweet hilarious decreased in favour of the serious and worried [47].

Twitter's flow has been proved to be faster in outbreak estimation than the observed values in infected people. This demonstrate that "Twitter based surveillance" could be useful as proxy of possible outbreaks and that is possible to improve the communication of public health institutions [48].

Another example comes from the Ebola outbreak 2014 emerged in West-Africa, it started in Guinea and after the identification as Ebola virus. In March, the WHO declared the outbreak, in august was subsequently declared as the public health emergency of international concern. The virus had a serious deadliness with 11,310 deaths reported from 28,616 cases found. For the outbreak there is actually no vaccine, but thanks to continuous monitoring of the territories is actually under control by international organizations [49]. This also affected Twitter flow. When the first case of Ebola happened in the US, study on Twitter data related with digital epidemiology shows that people that have watched video related with Ebola, are more likely to see news and search information on the web. Moreover, who is likely to write a tweet or do a web search, become uninterested about the topic after a period of 3 days [50][51].

## 1.5 Misinformation on WEB 2.0 and in OSM

"Massive digital misinformation" has been listed as one of the main risks for the modern society [52]. Misinformation (or disinformation) is the production and promotion of false and unverified content that spread, intentionally or unintentionally [53]. The terms were accompanied with the Oxford Dictionaries 2016 Word of The Year "Post-Truth", an adjective "relating to or denoting circumstances in which objective facts are less influential in shaping public opinion than appeals to emotion and personal belief". Today, a large part of misinformation starts and spreads across the web and on OSM, thanks to political pages and alternative (formally independent) information website that appeared and growth fast. OSM are considered largely responsible in spread of misinformation [54], mining also their credibility.

A study [55] demonstrated that 67% of users shared misinformation content, and 94% read or had seen misinformation content posted by other users. OSM are used to study and control the spread of false content. For example, on Facebook there are pages who posts everyday misinformation content in form of videos, narratives, post etc.
Misinformation on OSM is spread by means of very particular agents such as trolls or bots (automated accounts) [56]. In view of the 2020 US Presidential Election, Twitter and Facebook announced removal of disputed or misleading information [57][58] on the topic, also from "very exposed" political figures. Spread of misinformation reached not only vaccination conspiracy theories but also the current COVID-19 pandemic, starting from the unproven theory that COVID is linked to the presence of 5G towers [59].

In misinformation's context, WHO coined the concept of Infodemic [60][61], and claimed for effort to fight the fake news and false contents by means of direct interaction with population. The contrast of misinformation is required by different actors, physician and international health organizations for health topics, politicians to prevent spread of fake news, journalists to protect themselves and their job etc.

"Debunking , fact checking, and other similar solutions turns out to be strongly limited"[62], especially when highly polarized agents are

resilient to correction, i.e. they do not interacts in debunking posts, and users “tend to select content related to specific topic and ignore the rest” [23], there are various limitation in control the spread of misinformation [63].
A difficulty is represented by the fact that debunkers follow misinformation, using fact checking rather than a preventive approach. Detect effectively misinformation is “deeper than identifying what is fake news” [64]. Project like Newsguard offers services of misinformation detections with reports on super-spreader misinformators on hot topic [65].

Put control on social media platforms creates alternative for “free speech” like Gab which represents a sort of free island for those users banned from other OSM and attracts interests of users who spread conspiracy theories and misinformation. In Gab here is the predominant dissemination of misinformation and react proactively in events related to white nationalism and conspiracy theories. Success for “free speech” is the lack of any sort of moderation, which turned free speech into hate speech [66].

Diffusion and epidemic models have been used to study the how information (and misinformation) spreads in a complex system, which is a network system with nodes and arcs. The studies show that influence of a node (the user) is much more dependent on its location rather than the number of arcs (connections between users) that the node has [67][68].
Misinformation can boost the phenomenon of “echo chamber” , i.e., group of polarized people who tend to reinforce their theories and promote personal narratives applying a barrier for non-aligned belief. Users are somewhat attracted by misinformation and consume conspiracy news, boosting the echo-chamber, while the other way around is not true for non-conspiracy news’s consumers [24][69].

Misinformation is also presents in health-related topics, and it may be responsible in negative emotions, anxiety, or it can be used to promote misleading content that are harmful to the users [54] or in order to stigmatize certain disease [70]. Amount of health-related misinformation is not easy to detect, in [71] there is misinformation in 11.42% in health communities retrieved, but this remains somewhat difficult to find without searching for particular health related events. Zika outbreak and it's vaccine [72][73] is an example of misinformation that affect public health when consumers do not apply fact checking on contents. A misinformation fact in this context is the theory that genetically modified mosquitos were responsible for the spread if the outbreak [74].

## 1.6 Vaccination History and Hesitancy consideration

The immunization programs made across countries and decades with rational choices and development of vaccines started since the second half on twenty century and vaccination is conceived as the second most important invention after the achievement of drinking water. [75]. Long time has passed since the pioneering way to produce a vaccine from the use of the bovine to the vitro development, which was the revolution for the development of efficient vaccines on large scale. Vaccines are not equal, the history shows differences [76] between live vaccines, such as the polio, the killed whole organism like the Cholera, the purified proteins (Diphtheria) and the genetically engineered (Human papillomavirus). In context of COVID-19 pandemic, has become crucial the race for a vaccine and this created a "good" competition between countries and pharma industries [77].

After the development and the massive introduction of the vaccines, the governments of the most industrialized countries and the supranational organizations worked to made effective the use of this biological preparation to immunize population and creates a memory of the different pathogens which, *de facto*, helped to reduce the spread of infectious disease and in some cases to eradicate them from population. Actually, do not exist 100% effective vaccines [78], whose effectiveness and risk evaluation is calculated by comparing vaccinated and unvaccinated group [79]. The main success of the massive vaccination programs was the fall of outbreaks and spread of infectious and potentially very harmful disease.

### 1.6.1 Vaccine Hesitancy

The declared objective is to maintain high the coverage of immunization programs, although, this phenomenon has generated a decrease in perceived risk of Vaccine Preventable Disease (VPD), and in combination with unproven theory and misinformation dissemination, has developed the so called "Vaccine Hesitancy" (VH) [80], defined as one of the most top threat of the global health in 2019 (WHO, 2019). [18][19][20].

The VH refers *"to delay in acceptance or refusal of vaccination despite availability of vaccination services. Vaccine hesitancy is complex and context specific, varying across time, place, and vaccines. It is influenced by factors such as complacency, convenience and confidence"*[80], the concept is bounded across the three "C" model defined as:

- Confidence: refers to trust in effectiveness and safety of vaccines and on the reliability and competence of the health system.
- Complacency: which exists when the perceived risks of VPD are low and use of vaccines is not perceived as a necessary preventive action. This can be assumed as an active situation because the population do not perceive the risk of being unvaccinated, or there is the spread of misinformation, with unproven stories or conspiracy theories.
- Convenience: when there are psychological and physical factors around the supplies of vaccines, or they availability or the geographical accessibility. This might be a passive situation for the

population, due to the system failure, or other difficulties related to external events such as wars, embargos etc.

The refusal or delay of vaccination, might not be directly related on the three concepts above, example is refusal for religious matters, as happened in the state of Alberta (Canada), where many catholic schools banned Human Papillomavirus Vaccine, considered, according to the religious community, correlated with an increase of sexual activities in the teenagers [81].

Concept and definition of VH were not unanimously accepted in the scientific community, the term VH is quite unclear in some contexts, especially for the concept of Convenience where it is demanded a clear separation between the physical and nonphysical factors. Also the term Hesitancy might be misunderstood with the refusal rather than the delay or indecision in the vaccination decision by the parents [82][83]. The WHO Sage group assess that VH definition is something in a grey area, and that "vaccine hesitancy is complex and context specific, varying across time, place and vaccines. It is influenced by factors such as complacency, convenience and confidence" [83].
Moreover, the term Hesitancy is not full of meaning per se, for example considering the (in)Convenience where there are physical barriers to vaccination, this is a central point in (non) definition, where effectively the term must be "tailored" case by case, especially considering the shortcoming of immunization of the population.

### 1.6.2 Vaccine Hesitancy and antivaccination movements

Anti-vaccination movements are not born recently, first forms were born in 19 th century, in Netherlands initially and then in other country: United States, England and Wales. These movements were against the compulsory vaccination of smallpox (e.g., in 1809 in Massachusetts), then spread across the two following centuries. Not rare was the correlation between antivaccination movements and anti-scientific theories or even irregulars physicians promoting alternative medicine [84].

The advantages of smallpox vaccination were clear and once the coverage decreased; a major reappearance happened in 1870. With the discovery of new vaccinations, such as the measles vaccine, larger number of US states imposed mandatory immunization, also starting to raise penalties for unvaccinated children, that were excluded in attending school, and in "1980s all US States had school immunization requirements" [85]. Today "Anti-vaccine groups have taken advantage not only of the internet to increase their presence in the debate, but also to exaggerate, publicize and dramatize[sic] cases of vaccine reactions to the media and the public" [86].

Recently, the Web 2.0 and OSM boosted the phenomenon, starting from the retracted paper of A. Wakefield (former M.D.) on the correlation between autism and MMR vaccine. Later, was found that Wakefield wanted to put in market an alternative of MMR vaccine used [87]. These theories were responsible in the refuse or delay of vaccination, which are not always medical reasons but related to religious concepts. In this framework, the web is a place where the users may spread, also unintentionally, misinformation, and this might be also responsible for the change of user's behaviour.

Internet service providers (like OSM) may handle the widening of VH phenomenon. In the past they did not put any effort in limiting and/or preventing the diffusion of the antivax or unproven stories about vaccination including intentional misinformation, nowadays they acquired awareness in VH concepts, controlling and removing contents or, as in case of YouTube, avoiding the monetization of unappropriated contents [88][89]. The fact that perceived risk of VPD decreased with the increase of vaccination was well defined by [90] as "vaccines can be considered victims of their own success". Internet is a boost since it estimated that up to 80% of users search health information online, and 16% search for information on vaccinations (Pew Research Center, 2009).

Misinformation online is a key for vaccine refusal or delay, especially when the denialism of milestone findings is enriched by beliefs and narratives. People are willing to search on web about vaccination, and "postmodernism allows for that information to be interpreted in various ways - rather than interpretation being wrong, it can be framed as another way of knowing" [91].
Concept of denialism, enhanced by misinformation, is a problem not only for vaccinations, but also for other aspects and other diseases, the most important case in health and recent is the denialism of the HIV. Denialism found fertile ground on Web 2.0, where people sharing their ideologies "feeding each other's feelings of persecution by a corrupt elite"[92]. Tracking and analyse denialism is fundamental, first it should be recognized and not minimized. It is important the speed at which we respond to denialism, faster is better.

There are 5 main characteristics to explain denialism and the denialists [93]:

1. Identification of conspiracies: when someone believes in non-scientific opinion.

2. Use of fake experts: believe in non-expert scientists who support particular positions, e.g. case of scientist chosen for research in tobacco harmful effects.

3. Selectivity: choose those academic papers that challenge the consensus. The most famous case is the Wakefield (retracted) paper on relationship between autism and MMR vaccination.

4. Creation of impossible expectation of what research can deliver: an example is the denialism of climate changes due to inaccurate or missing information of past temperature records.

5. Use of misrepresentation and logical fallacies: use of false analogies in communication to deny a common believed fact for example on passive smoking.

Another characteristic is the manufacture of doubt [87]: where denialists highlights scientific disagreement (real or not) to create disorientation amongst content consumers.

Around the world the VH is present, with few numbers of countries without hesitancy between 6 and 7% for 2014-2016, with a prevalence in South East Asia Region and Eastern Mediterranean Region. However, hesitancy is not uniform. Considering factors like income level, or region, and other reasons underlying the hesitancy, they are not the same. In a study [94] which looked on three years VH (2014-2016), religion/culture/socioeconomic reasons to be hesitant, overtaken the knowledge/awareness in low income countries.

A study in UK [95], showed that three-quarter of parents of unvaccinated children conscious assumed this decision. A research with National Immunization Surveys in U.S. made in 2009 [96], showed that 60.2% of parents provided vaccination without any denialism, the 25.8% delayed only one or more recommended vaccine, 8.2% refused one or more vaccination, and 5.8% delayed and refuses vaccine doses for vaccination at 24 months.

Refusal or delay reasons are correlated with less agree in concern of vaccines as, a) necessary to protect health of children, b) risk to have a VPD, c) vaccines are effective in prevention of VPD, d) vaccines are safe, e) parents have good relationships with their child's healthcare provider, f) medical professional in charge of vaccinations have interests in childs' health.

Narratives on OSM and Web 2.0 about vaccination are various, very different and available. They can be short videos, stories, post, or photos. For example un a study on YouTube videos, [97] 50% on vaccination were vaccine-critical. The challenges that Web 2.0 poses may influence the risk of VPD, making difficult to understand the risk for nonvaccinate children, while positive effect on vaccination decision can be retrieved in related knowledge of VPD.

### 1.6.3 Role of Public Health

Public health websites are not easy to find especially for less informed individuals [98]. Narratives are more powerful than statistics in the influence of vaccine adverse events and even more powerful when narratives are combined to statistics, this increase the perceived vaccination risk that evidence a narrative bias [99][100]. Public Health communication is delegated to physicians who spend time on OSM and Web 2.0 to communicate and analyse facts on healthcare. Efficient healthcare communication is a major concern for WHO [101], the organization asked for efforts in this sense, also using new type of media, especially during outbreaks when the overflow of information (and disinformation) creates new challenges [37] for actors in public health.

Misrepresentation of the narratives brought to the distrust not only versus vaccination, but also versus immunization policy and health policy in general, generating unproven theories on corruption of politicians from Big Pharma industries to increase the profits with vaccinations.

## 1.7 The Covid-19 outbreaks

The COVID-19 pandemics is the largest outbreak since the Spanish Flu in the early XX century. On October 31, 2020, the are 49,529,936 cases, with 1,188,906 deaths [102], the most infected country is the US with 9 million cases and 235,000 deaths, followed by India and Brazil. The outbreak began in the Wuhan City, Province of the Hubei, China in December 2019 with about 84,596 cases in the whole country. Then it spreads in the world. The Chinese government imposed a strict lockdown measure to hold the outbreak. Between January and February

2020, the outbreak spread across the Europe where the northern regions of Italy were the most affected.

In Italy the first case was reported on February 20, 2020, [103] in the Province of Lodi - Lombardy, then the pandemics increased in all the northern of Italy with hospitals collapsed and afterwards reported the highest level of deaths in Europe as for April 2020, and the government imposed restriction on mobility of the citizens and on march 11 the lockdown.

The world faced other pandemic, SARS, and MERS, but COVID-19 spread more rapidly and created fears in the physicians. Actually there is not treatment for the SarsCov2, which is responsible for flu like illness [104] with pneumonia. The WHO promotes non-pharmaceutical intervention (NPIs) such as Hand hygiene, social distancing, wearing a mask, and lockdown measures. “Unfortunately, some lessons were not heeded” [105]. Together with the spread of the virus, denialism spreads too, with protests in many countries. Measures that have been disputed were lockdown and social distancing, and wear mask [106], seen as a limitation of freedom and form of health-dictatorship.

Countries adopted regulations and laws to make mandatory the use of face masks, especially in indoors places to reduce transmission rate. Face masks are most of time accepted as a sort of social contract and necessary to effectively prevent higher spread of the virus [107]. Effectively, social contacts decreased more for elderly than younger [108], and in the second, incumbent, wave of the outbreak there is a debate if it would be better isolate elderly as a measure to avoid a second lockdown.

Misinformation hit also the COVID-19 pandemic, on OSM, websites, [109], with differently type of denialism: starting from unconfirmed theory that is not a natural virus, but laboratory-made [110], or that is correlated with the presence of 5G antennas in [111], or that is a virus created to implement new type of mandatory vaccination [112].

# Chapter 2

# Evidence of disorientation towards immunization on online social media after contrasting political communication on vaccines. Results from an analysis of Twitter data in Italy

## 2.1 Rationale

In Italy, the MMR (measles, mumps, and rubella) vaccination coverage at 24 months, which was in the region of 91% in 2010, fell at 85.3% in 2015 and remained low thereafter. Parallel to this, large measles outbreaks, with 844 cases in 2016, 4,991 in 2017 (with 4 deaths), and 2,029 cases in the first six months of 2018 [113][114][115] were observed.

As a response, the Italian government acted to increase the number of mandatory immunizations [116], by introducing penalties for non-vaccinators in the form of fines and restrictions to admittance to kindergarten and school (Decree-Law No. 73 of June 7, 2017 "Disposizioni urgenti in materia di prevenzione vaccinali", Italian National immunization plan 2017-2019). The ethical implications of the decree, principally the introduction of penalties, were fiercely disputed, especially on online social media (OSM). With the upcoming 2018 general elections, immunization policy pervaded the political debate, with the government accusing oppositions of fuelling vaccine scepticism.

The new government established in June 2018 and composed by a coalition between an anti-establishment movement and a far-right party, allowed, after several contrasting announcements, unvaccinated children to be admitted to school, despite the potential disorientation that this might create among parents, the school system, and the general community as a whole. We focused our analysis on Twitter and used sentiment analysis to:

- describe the trend of communication on vaccines on Twitter in Italy during the entire 2018 year,
- evaluate polarity in the opinions about immunization and the potential usefulness of current Twitter data to estimate key epidemiological parameters such as e.g., the hesitant proportion in the population
- bringing evidence that the recent prolonged phase of contrasting announcements at the highest political level on a sensitive topic such as mass immunization might have originated a condition of disorientation (a concept specifically defined in the Material and Methods section) among the Italian public.

## 2.2 Data extraction, transformation, and cleaning

In a first stage, we collected tweets in Italian containing at least one of a set of keywords related to vaccination behaviour and vaccine-preventable infectious diseases posted on Twitter in the 2018. Keywords were chosen based on a review of previous literature (table 2.1) [117][118] and suitably extended for our objectives. In a second stage, we applied supervised classification techniques to filter-out irrelevant tweets and identify their polarity. We deliberately selected a broader set of keywords to retrieve the largest possible set of tweets and subsequently apply more refined tools to identify and leave out noise.

Data cleaning was performed using the Python programming language. We applied a probabilistic approach based on the Naïve Bayes algorithm which, according to specific peculiarity of each language, assign a probability for a given text to be written in a specific language, in our case Italian. We removed also possible duplicates, downloaded because of two keywords present in the tweet, were removed by means of the tweets IDs field then, for each message, we kept track of subsequent interactions by counting the number of retweets and likes received by each tweet.

## 2.3 Tweets Classification, sentiment analysis, and training set

Sentiment analysis deals with the computational treatment of opinion, sentiment, and subjectivity within texts [119][23]. Here, we used the instrument for classifying tweets. For the sake of our analysis, we defined the following four classes:

- favorable (F), if the tweet unambiguously showed a convinced pro-vaccine position,
- contrary (C), if the tweet unambiguously showed a position contrary to vaccination,
- undecided (U), if the tweet was neither favorable nor unfavorable,

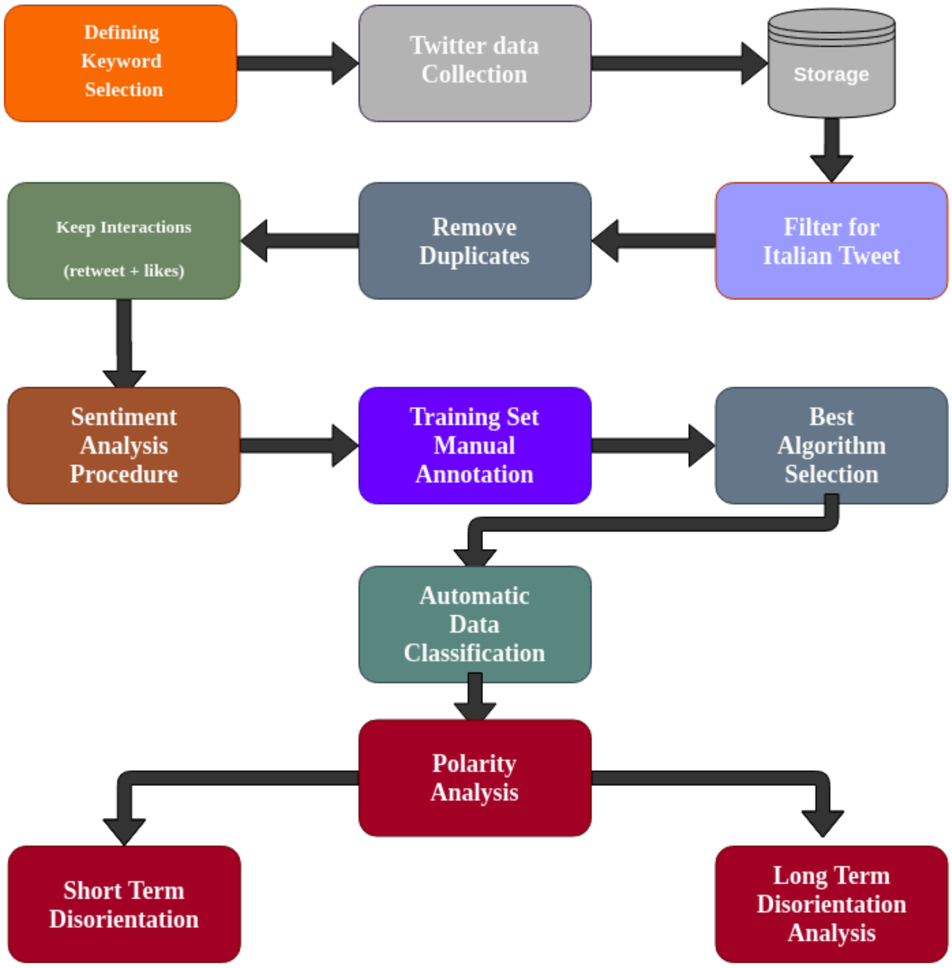


*Diagram 1. Flow of Analysis Process*

- out-of-context, if the tweet was unrelated to immunization or if it did not fit any of the preceding categories (e.g., if it was merely spreading news or linking to another source, without expressing an opinion or a clear position). Out of context tweets were discarded from subsequent analysis.

Supervised classification procedure [120][121] was used to automatically classify tweets into the four categories previously defined.

First, a training set was created by manually labelling a random sample of 15,000 tweets, out of the 323,574 kept for the analysis. Manual labelling was performed by 15 trained university students. Note that 15% of the tweets in the training set were intentionally dupli-

| **Context** | **Italian keyword** (English translation) |
|---|---|
| Vaccination Topic | "copertura vaccinale" (vaccination coverage); "vaccini","vaccino" (vaccine(s)); "vaccinazione" (Vaccination); "iovaccino" (I vaccine), "comilva"; "corvelva"; "thimerosal", "esami prevaccinali" (prevaccination exams); "vaxxed"; "trivalente" (trivalent); "esavalente" (hexavalent); "obbligo vaccinale" (mandatory vaccines); "varicella party" (chickenpox party); "autismo" (autism); "lobby vaccini" (vaccine's lobby), |
| Vaccine preventable disease | "meningite" (meningitis), "morbillo" (measles); "rosolia" (rubella); "parotite" (mumps); "pertosse" (whooping cough); "poliomelite" (polio); "varicella" (chickenpox); "MPR" (acronym for measles, mumps,rubella); "HPV", |
| Hashtags | #novaccino (no vaccine); #iovaccino (I vaccinate); #libertadiscelta (Freedom of Choice); #vaxxed, |

Table 2.1: *Keyword adopted to retrieve tweets*

cated, to measure the mutual (dis)agreement among annotators. The resulting accuracy was 0.6298, (CI 0.6034 - 0.6557), with a Cohen's kappa [122] of 0.412, resulting in a Fair agreement and a Fleiss' Kappa [123] of 0.410, resulting again in a Fair agreement [124], Fleiss' Kappa is the appropriate measure because we have more than two annotators.

Next, we added set of tweets analysed in exploratory analysis and reviewed the "intentionally" duplicated tweets used for the cross annotation. Other duplicated tweets were removed from the training set, as well as tweets that did not have valid content, leaving a set of 14,411 unique tweets. The training set was used to compare five, widely used in similar work in literature, classification models based on the following algorithms: Classification Tree, Random Forest, Naïve Bayes, Support Vector Machine (SVM), and K-Nearest Neighbours.

All of them were runned with different features, and hyper-parametrized to find the best one for our purpose, using SkLearn library in Python

[125]. Model was chosen according to optimization process using either uni-grams, bi-grams, and tri-grams, TF-IDF, stemming and lemming procedure. All the models were tested with a 10-fold cross validation function working as follow. The original training set is divided in 80-20% training-validation set. Then for each of k(10) iteration, the model is trained dividing the cross-validation training set (the 80%) in k(10) portions, using k-1 portions as training and in the last portion the model is performed. At the end of $k^th$ iteration, the average scores of the classifier are computed. Each algorithm tested on cross-validation is then tested on the validation set (20%), and the best one in terms of performance was chosen.

### 2.3.1 "True" hesitant parents

Given the general interest of the current literature towards vaccination hesitancy, we explored the possibility to estimate the "true hesitant" parents proportion, which we defined as the "social media hesitant" proportion among the subset of tweeters composed by parents whose children were eligible for immunization (say, currently or in the near future), and therefore potentially relevant for the true future vaccination coverage.

To this aim, we used, as a proxy for the "true" hesitant proportion, the "social media hesitant" proportion computed on a random sample of 1,000 tweets extracted from the subset of the tweets (7,870) containing one of a set of specific to parenthood-during-vaccination related keywords, such as "pregnant", "new-born", "mother", "father", "paediatrician", etc.

### 2.3.2 Defining disorientation

To the best of our knowledge, the concept of "disorientation" referred to highly controversial topics, does not seem to have been well defined in the literature of online social media. Properly defining the concept of "disorientation" can be complicated e.g., it can be simply a consequence of the lack of adequate information, but also of the over-exposition to information, including misinformation. All these factors can make it difficult for people to properly filter the masses of available information.

We assumed that disorientation (towards vaccines) can be coarsely identified as the lack of well-established and resilient opinions among individuals, therefore causing individuals to change their opinions because of sufficient external perturbations. The question then shifts on which the perturbations might be "sufficient". Some perturbations - typically those arising as direct responses of the public to media news can be very short-lasting.

In relation to this, we might define a concept of "disorientation" as a state in which people keep changing suddenly (but often) their opinion on the debated subject because of the overwhelming impact of multiple contrasting information. However, other perturbations, for example those following from non-scientific arguments promoted or supported at the highest political level e.g., a political party, or even a government, might show longer-term effects.

### 2.3.3 Seeking evidence of disorientation in Twitter data

According to the previous twofold definition of disorientation, to seek symptoms of disorientation in the data, we proceeded as follows: first, as for the identification of short-term disorientation, we applied a number of tests relying on the size of the deviations (measured through the variance) from appropriately defined average opinions.

The tests were made despite we considered all retained tweets, on the assumption that these represented a random sample from a proper underlying superpopulation. In particular, we proposed three different tests. All the following test have been made in R environments, with the following libraries: "EMT","DBKGrad" [98],"Ineq".

### 2.3.4 Basic multinomial test of daily tweeting trends

As a first way to identify those changes in the polarity frequencies that likely originated from randomness and separating them from those that were not, and therefore might be associated to perturbating or "triggering" events, we applied a simple multinomial test to the daily flow of tweets, taking as null hypothesis that the polarity proportions were those observed throughout the entire year.
We tested the hypothesis that the daily distribution of the polarity proportion of the opinion is a (random) sample drawn from a multinomial population whose parameter vector is computed as the overall yearly mean of the polarity proportions. We computed hence for every day the probability value (p-value), then checked if the value was larger than 90, 95, and 99% (i.e., tested significativity at 10, 5 and 1%).

#### A "running" multinomial test for fast-changing opinions

Additionally, we computed for every day, the p-value of the observed vector of opinion proportions where we tested whether this represented a random (sample) drawn from a "running" multinomial population whose parameter vector is computed as the mean of the daily proportions observed in the preceding 15 days. The figure of 15 days, representing our null hypothesis, was selected somewhat arbitrarily as a minimal duration representing a "stable" opinion (or "average preferences persistence") in the short term.

#### A running-variance test

Furthermore, all along the observed period, we computed a running 15-days variance of the proportion favourable to vaccination. We tested (by the standard Chi-square) the null hypothesis that the 15-days variance is equal to the overall variance throughout the entire year.

### Longer-term disorientation

As for long-term perturbations, we resorted to a polynomial fit of the trend of the smoothed polarity proportions over time as possible evidence of the long-term evolving rates of disorientation amongst the public, motivated by the switch between two governments promoting different messages on immunization. The smoothing was carried out by a discrete beta kernel-based procedure proposed by [38], overcoming the problem of boundary bias, commonly arising from the use of symmetric kernels. The support of the beta kernel function, in fact, can match our time interval so that, when smoothing is made near boundaries, it allows avoiding the allocation of weight outside the support. The smoothing bandwidth parameter has been chosen using cross-validation.

## 2.4 Results

### Automatic data classification and polarity proportions

Among the five classification algorithms tested (see section 2.3), Support Vector Machine (SVM) [127] performed best in terms of accuracy and f1-score which is a weighted harmonic mean of precision and recall, and it was consequently adopted (table 2.2). SVM separates classes by creating a line or hyperplane in n-dimensional space calculating a maximum-margin separator, this may be based on linear, polynomial or kernel function, in this case polynomial. As mentioned in the earlier section, by selecting a broad set of keywords, we chose to retrieve a larger set of tweets and left to supervised classification algorithms the task of identifying noise. Consistently, 93% of the total tweets (299,643 out of 323,574) were classified as out-of-context and discarded. Of the remaining tweets (23,931), the overall proportions of classified as favourable, contrary, and undecided were: F=75,2% (CI: 74,6-75,7), C=10,4% (CI: 9,9-11,0), U=14,4% (CI: 13,9-15,0).

| | Recall | Precision | F1-Score | Support |
|---|---|---|---|---|
| Favorable | 0.59 | 0.48 | 0.53 | 942 |
| Contrary | 0.09 | 0.35 | 0.15 | 83 |
| Undecided | 0.03 | 0.32 | 0.06 | 31 |
| Out of Context | 0.79 | 0.65 | 0.71 | 1807 |
| Accuracy | | | 0.54 | 2883 |
| Macro Avg | 0.38 | 0.45 | 0.36 | 2883 |
| Weighted Avg | 0.69 | 0.58 | 0.63 | 2883 |

Table 2.2: *Report of the result for classification with SVM*

#### Hesitancy

The proportion of people actually involved in a incoming vaccination decision, representing the appropriate proxy for the computation of the "true" hesitant proportion, resulted quite small (less than 0.2% of sample analysed). Among these, the social media hesitant proportion (given by the sum of tweets classified as contrary or undecided) was about 20%.

#### Institutional presence on Twitter

The Italian Ministry of Health use of Twitter is relegated to press communications or to the publication of statistics. We analysed the official Twitter account and between 2013 and September 18 th , 2019, the Italian Ministry of Health tweeted 2,454 times (of which 172, the 7%, included the lemma for vaccination), which is the 25% the figure observed, in the same period, in France from the Ministére des Solidarité et de la Santé.

#### Temporal trends

The daily intensity of tweets interactions (including original tweets as well as subsequent likes and/or retweets) during the period considered (Figure 2.1) is strongly concentrated around three dramatic peaks, each one accounting for hundreds of thousands of interactions.

These three peaks represent the users' responses to well-identified triggering events. In particular

- the highest peak (on August 3, 2018) corresponded to a major decree by the Italian government, where the penalties (as non-admission to school) imposed by the previous government, for unvaccinated children, was temporarily suspended. The proportion of favourable, contrary, and undecided in the surrounding days were F=80.5%, C=7.6%, and U=11.9%, respectively.
- The second highest peak (June 22, 2018) appeared after a public speech of the Italian Minister of Interior, who severely criticized the number of mandatory immunizations in the National Immunization Plan, that - he explicitly said - was "intolerably excessive" (F=70.8%, C=14.2%, U=15%).
- The third highest peak (September 4, 2018) appeared after the change in the position by the government about the penalties relax in the previous decree (F=80,2%, C=9,3%, U=10,5%). The graph shows a number of further lower peaks, still attributable to interventions in the political debate, over a long-term background of low-level activity.

### Characterizing disorientation

With the caveats reported above, the proportion of people "not completely favourable" to immunization - around 25% - was a worrying symptom of the complicated state of opinions about vaccination in Italy. The results of the various procedures proposed to investigate disorientation are reported below.

### Testing short-term disorientation

By the basic multinomial test, taking as null hypothesis that the polarity proportions observed throughout the entire year (the aforementioned figures F=75,2%, C=10,4%, U=14,4%) represented the true population proportions, we counted the days laying in the rejection

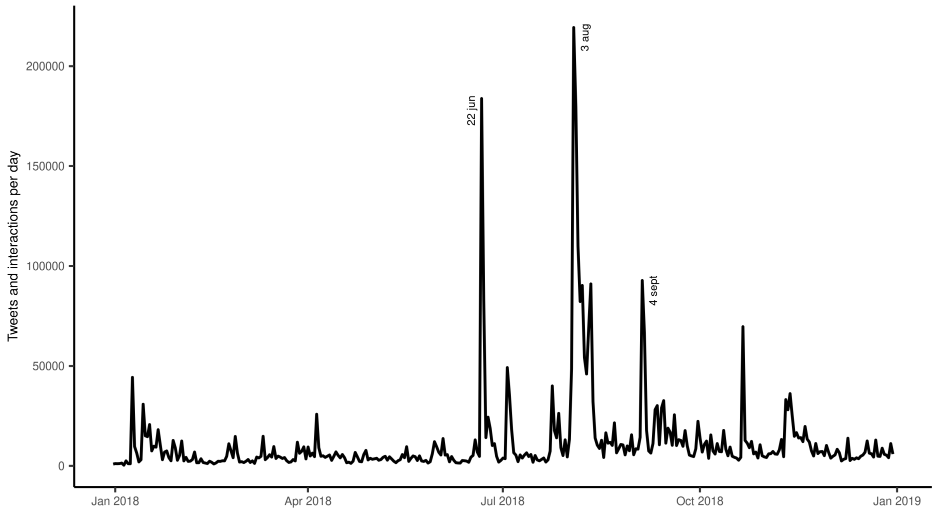


Figure 2.1: *Tweeting about vaccines in Italy during 2018: time series of total daily interaction counts (tweets, like and retweets) and exact dates at main triggering political events or speeches.*

region. We found that, at $\alpha$=5% significance, the rejection of the null hypothesis occurred in 62 days (Figure 2.2).

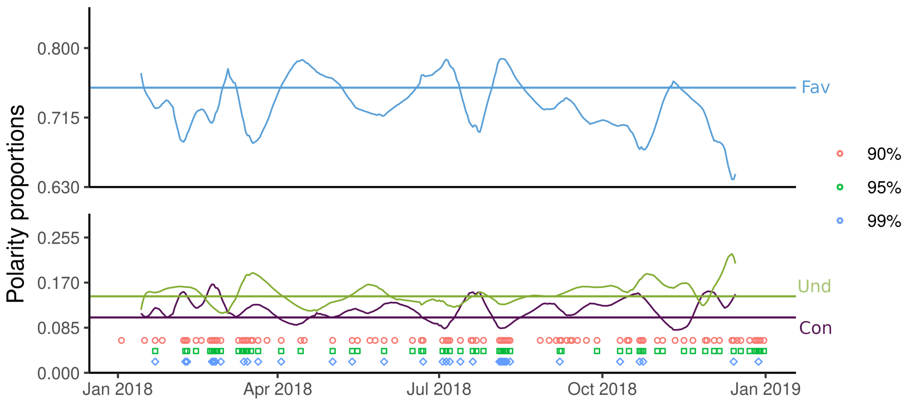


Figure 2.2: *Results of the basic multinomial test. Blue circles, green squares, and purple diamonds denote the days when the null hypothesis was rejected at the significance levels of 10%, 5%, and 1%, respectively. For readability we also showed the smoothed polarity proportions. In the appendix, we have reported the raw proportions used in the multinomial tests*

As for the running multinomial test, at $\alpha$ 5% significance level we detected 91 days lying in the rejection region (Figure 2.3), as a further sharp evidence of instability in the polarity proportions, especially we have found significative days around certain periods, i.e., the election day (March 4, 2018) and the August 2018 when some penalties imposed by former government were relaxed.
Last, the running-variance test (Figure 2.4) showed that values significantly higher than the overall yearly variance appeared in February and March, during the electoral campaign and in November, concurrently with the beginning of the winter flu vaccination campaign. Significantly lower running variances were recorded from July to October, suggesting a possible stabilization of opinions after the switch between governments.

Overall, the three performed tests agree in bringing statistical evidence towards a rapid shift in vaccination opinions, denoting disorientation according to the first definition provided.

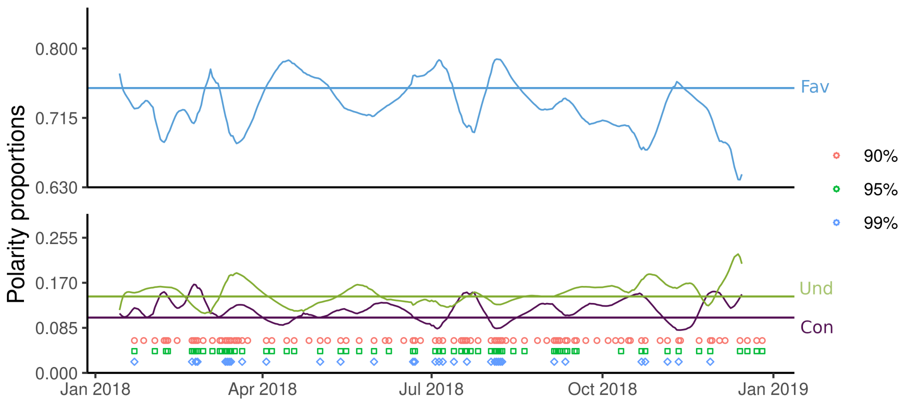


Figure 2.3: *Results of the running multinomial test at 15 days. Blue circles, green squares, and purple diamonds denote the days when the null hypothesis was rejected at the significance levels of 10%, 5%, and 1%, respectively. For readability we also showed the smoothed polarity proportions. In the appendix, we have reported the raw proportions used in the multinomial tests.*

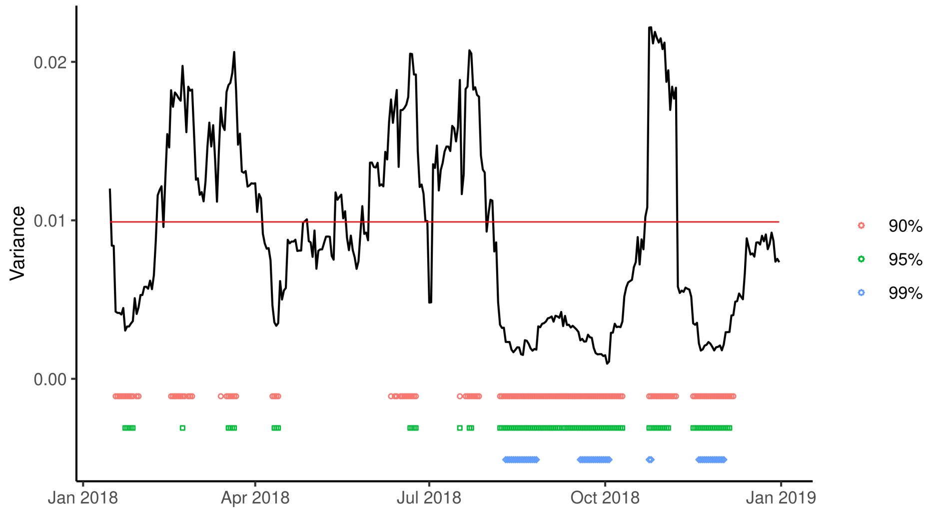


Figure 2.4: *15-days running variance of the proportion favorable to vaccination (black line). Blue circles, green squares, and purple diamonds denote the days when the null hypothesis was rejected at the significance levels of 10%, 5%, and 1%, respectively.*

### Smoothing and longer-term disorientation

The results of the smoothing procedure showed that the many sudden changes in the daily polarity shares of tweets can be reduced to a rather small number of more stable and longer-lasting fluctuations (Figure 2.5). Regarding the proportion favourable to immunization, the amplitude of these more stable oscillations is substantial (from 66% to 79%), proving evidence of the size of the "non-resilient" component of the population favourable to vaccination.

As for the overall trend during the entire 2018 year, a stepwise polynomial fit to the smoothed trend in the polarity proportions showed (see still Figure 2.5) that the parabolic fit was the best one, allowing a dramatic increase in the determination coefficient $R^2$ ($R^2 = 0.287$) compared to the linear case ($R^2$=0.007), while further power terms increased $R^2$ only negligibly. The parabolic trend showed a marked increase in the pro- portion favourable to vaccination (and a parallel decline in the proportions undecided and contrary) between January and May, possibly reflecting the tail of the positive effects of the "vaccine decree" by the previous government, and a marked decline thereafter,

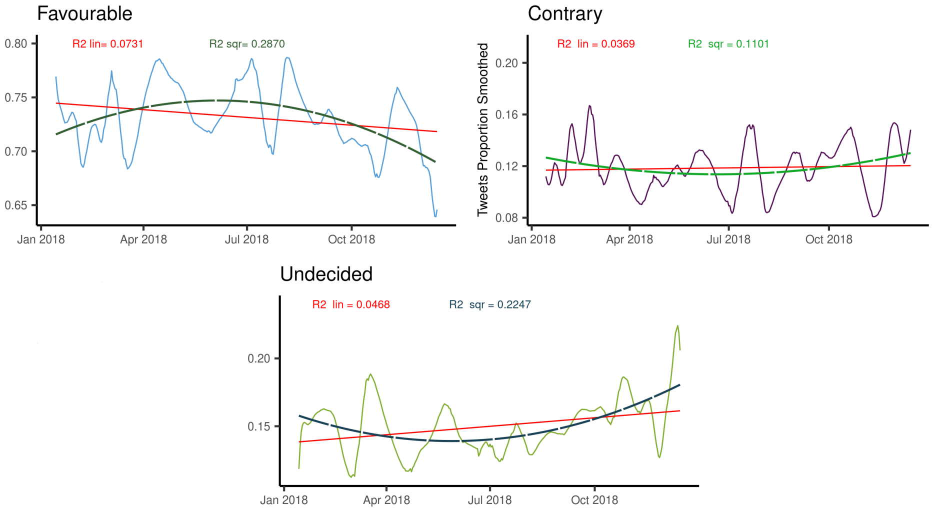


Figure 2.5: *Kernel smoothing of daily polarity proportion jointly with the corresponding linear and quadratic interpolations. Panels (a),(b),(c) report the favourable, contrary and undecided proportions, respectively*

when the new government was fully established, losing more than 5 percentage points by the end of the year. Though we are not in the position to provide a direct causality link between the governments' switch and this persistent change in opinions towards immunization, the association is nonetheless worrying given its political back ground.

## 2.5 Discussion

Compared to traditional media, like television and newspapers, the current dramatic spread of online social media, whereby scientific healthcare institutions can have a lower impact compared to various types of social media influencers, including politicians [42][43][128][129], is a critical phenomenon, due to the inherent risks of misconceptions and misinformation spreading.

Motivated by this complicated role of online social media [24][69][91][130], as well as by the fact that, for at least the two previous years, immunization policy has been a hot topic in the Italian political debate at the highest level, with continued ambiguous announcements and promises by policymakers, we carried out a sentiment analysis on Tweets posted in Italian during 2018 on the subject of vaccination.

Our results are as follows. First, only a small proportion (7%) of total tweets expressed a well-defined sentiment (favourable, contrary, or undecided). This is in line with the idea of "digital breadcrumbs" typically embedded in such data when used to understand human behaviour [44].

The tweets retained for the analyses showed a strong concentration, with a few individuals contributing to a large proportion of tweets and tweeting about essentially everything of current public concern (especially topics debated in the current political phase) regardless of their awareness of the topic. Many of the most active users analysed were clearly polarized around sceptical positions about immunization policies. This subpopulation, besides preventing reliable estimates of parameters of socioepidemiological interest, could represent the key determinant of misinformation spread [23][69][131].

A polarity analysis showed that the proportion favourable to vaccination was about 75%, the unfavourable one about 11%, and finally the "undecided" accounted for 14%, in line with similar studies [132][133][134].

We attempted at estimating the "true hesitant" proportion relevant for the future vaccination coverage defined as the hesitant proportion among tweeters declaring, in a clearly identifiable manner, their role of parents of children currently eligible for immunization. Unfortunately, the proportion of tweeters mentioning involvement in an actual immunization decision was negligible.

This was surprising to us if one considers the large age-band involved in compulsory immunizations (from 0 to 15 years of age) and therefore the (even larger) number of parents'cohorts involved. This might be due to the fact parents tend not to use Twitter to specifically speak about their children for a number of reasons, including avoiding potential online harassment [135]. On the other hand, the fact that many people posted tweets with generic contents on immunization is suggestive of the fact that, in the period we considered, the topic of immunization had become a controversial topic of general interest amongst the public opinion, to the point that it was indeed used by politicians for purposes of political consensus rather than for general interest.From this viewpoint, in such situations, Twitter might have acted as a sort of large scale "echo chamber".

As for the temporal trends of tweets, vaccine relevant Twitter interactions showed clear peaks in correspondence with relevant political news and speeches, showing that Twitter "is used as an agora for matters of public interest" [136].

Finally, as for the key category of "disorientation" among the public, for which a twofold definition was proposed in this paper, our results documented - based on multiple tests - the presence of disorientation intended as instability of opinions about vaccination over the short term (the first definition).
Additionally, a clear yearly trend emerged, showing that the proportion favourable to vaccination increased up to when the previous government - strongly supporting immunization on the media - was up, and started declining as soon as the new government, promoting a more ambiguous position, was fully established. We felt hard to believe that this association was unrelated with the continued ambiguous announcements made by the new government (also before the elections), and rather was a possible evidence of a longer-term disorientation arising from the promotion of non-scientific arguments from the highest political level.

Compared to similar studies, we believe that the attempt to defining the concept of disorientation, and documenting it, was a major strength of the present work. Our idea was that disorientation can arise, (i) in the short-term in the form of instability, and lack of resilience, of opinions, when individuals are overwhelmed by the massive exposition to multiple and ambiguous, information, (ii) in the longer term, when information sources at the highest level, systematically spread non-scientific information by supporting it with a mediatic system, for mere purposes of political consensus.

The reported evidence of disorientation on vaccination is suggestive of the potentially harmful role played using such topics for purposes of political consensus for public health policies. This aspect is especially worth given the increasing role of online social media as a source of information (and especially, misinformation) [39]. These concurrences might yield to social pressures eventually harmful to vaccine uptake. Indeed, we feel that persistent disorientation can drift into disinformation, think e.g., to the dramatic impact of the HIV virus denialism promoted by the president of South-Africa in a critical phase of the HIV epidemic [137]. From this viewpoint, we believe that the category of disorientation will deserve future inquiry in more focused studies.

In the Italian case, the effect of disorientation might have been worsened by the almost lack, till the end of 2018, of a stable institutional presence on Twitter by Italian Public Health institutions. This fact, that appears in continuity with the traditional lack of communication between Italian public health institutions and citizens long before the digital era [129], calls for rapid public efforts in terms of an active presence on online social media, aimed to detect and contrast the spread of misinformation and the possible further spread of vaccine hesitancy [138][139]. This might be especially important in the forthcoming periods to achieve adequate vaccination coverage at the moment a vaccine against COVID-19 could be made available. Indeed, even now at the end of the first pandemic wave, an amazing large (41%) proportion of Italian adults declare themselves contrary to COVID-vaccination [140].

Though not designed for this purpose, this analysis might supply useful suggestions for vaccine decision-makers. Surely, the very large proportion of people who were either “contrary” or “undecided” (in the region of 25%) even if could be somewhat biased as a proxy to estimate the true proportion in the real population, should be carefully considered, if not for their potential impact on current coverage, at least for the social pressure they might enact within online social media given the increasing influence of social media on public opinion and policymakers, this might eventually feedback negatively on future vaccine coverage, as previously pinpointed.

Partial limitations of Twitter for the analyses of the present work lie in the maximum length text, which is both an advantage (e.g., texts will have similar structure) and disadvantages, due to the use of slang and abbreviation, as well as the use of the emoji which could e.g., be helpful to understand a sarcastic text (i.e., a tweet having a completely opposite meaning), especially for a complex language as the Italian.

A further drawback arising from the fixed-text length is that it often happens that a single thread is subdivided into multiple tweets, which - if individually considered as in this and similar studies - might convey unclear information. Improved work should, therefore, better tackle these issues, and also attempt to look deeply into the network structure and whether echo-chambers phenomena are identifiable in Twitter [141].

From a broader perspective, it must be recalled that the spread of vaccine hesitancy pairs with the widespread diffusion of the so-called “Post Trust Society” [142] and of the “Post Truth Era” [143]. The present investigation can aid public health policy makers to better orient vaccine-related communication in order to mitigate the impact of vaccine hesitancy and refusal. From this standpoint, a best practice to re-establish trust in the public health authorities in the field of immunization is that of ensuring a highly qualified vaccine communication on online social media.

This is however only a part of the story. Indeed, it is fundamental for public health systems to be able to develop real-time tools to identify fake news as well as tweets hostile to immunization - that might have the largest impact - and appropriately reply to them. This would require that public health communication agencies and institutions be also active in the real-time analysis of online media data, not just in the production of regular communication. On top of this, given the sensible role of the immunization topic, it is surely urgent to develop a moral code preventing the use of such topics for purposes of political consensus and ensuring avoidance of contradictions and ambiguities amongst government members.

A number of previous points might be worth considering in future research, by comparing the language used by tweeters (regardless of their position towards vaccination) and the language of the tweets posted by public health institutions, which represent an important aspect in the communication with agents, particularly with respect to "undecided" individuals, in order to enhance their vaccine confidence. A further point deals with the frequency of fake users.

In this work, we took users as they were, without further control over their profiles. However, this is a key issue deserving careful investigation in future work. Also, the quantitative importance of the followers, which could represent a vehicle for misinformation spreading, possibly distinguished by polarity, as well as that of highly active tweeters, as it emerged in this study, is worth considering in future work on the subject.

# Chapter 3

# COVID Anxiety and OSM Activity: analysis on global and local correlation between Twitter activity and Covid-19 Pandemics.

## 3.1 Background

The COVID-19 Pandemic is responsible for high levels of interactions over the Social Media, overwhelming any other documented past event, especially during the lockdown period when people, forced to remain at home applying social distancing, moved from social "vis a vis" contacts to "cam-to-cam" contacts [144].

In this context, the use of Web 2.0 related applications increased dramatically, with professional apps such as, Zoom, Skype, MS Teams being used to communicate by people who, until the day before, have shared the same office; also the use of OSM has increased during the lockdown period, and the reasons to explain this can be summarized by a list of fundamental human needs: to overcome the social distancing, to share feelings, to ask for help, to express opinions on measures, and so on.

The COVID-19 pandemic spread differently in each country [145]; started in in the Hubei province in China, at the end of December 2019, and then it rapidly spread in Europe and worldwide yield. The pathogen, which belongs to the family of Coronaviruses and has been termed Sars-Cov2 [104], is responsible for a flu-like illness and can lead to serious sequelae including serious interstitial pneumonia and death. The risk of is especially high in patients with immuno-compromising, serious comorbidities, and the elderly's people. Given its strong diffusion potential, as summarized by the quite high levels of the basic reproduction number ($R_0$), that have observed worldwide, implying attack rates on the order of 70-90% on the assumption of homogeneous mixing, COVID-19 has threatened public health system worldwide during its first wave (since February 2020) and during the currently ongoing second wave.

This arises from the potential of COVID-19 to overwhelm key public health resources, namely hospitals and Intensive Care Units (ICUs). Italy has been for a while the second most attacked country worldwide after china, with about 35,000 deaths. The need to rapidly bring the epidemic, and its health consequences under control, has obliged many countries to resort to what is now called "generalized lockdown", namely abrupt and intensive social distancing based on long-lasting closure of all non-fundamental economic and social activities, bringing dramatic economic and social cost.

Due to its multidimensional impact on health, the economy, society etc. everyone life have been touched by COVID-19 pandemic. As such the pandemic has triggered several sentiments in individuals. These have, ranged depending on the different phases of the pandemic: from scepticism to anxiety, to the demand for rapid measures to hold the pandemic under control, and to disputes on these measures. These sentiments were triggered by the phases of the pandemic and related events. The first cases reported in the country regarded two Chinese tourists hospitalized at the hospital "Spallanzani" with COVID symptoms was on January 30, 2020. However, by February 20, 2020, the discover of the first indigenous case reported in Northern Italy with the sudden growth of hospitalization and cases, and the creation of the first hotspots suddenly put the country into a dramatic emergence situation, with entire emergency wards saturated in a few days.

The Italian government reacted with a series of measures non-pharmaceutical interventions (NPIs), aimed to halt the diffusion, and protect hospitals from the risk of collapse. These included, besides the creation of the first hotspot in Codogno and Province of Lodi, a number of National Governmental decrees implementing: i) the closure of all schools and universities (March 4), ii) the closure of all non-fundamental economic activities and of social and recreational activities (March 11) up to finally, iii) the hardest measure, namely the generalized lockdown, implemented between March22 and March 25 with the closure of most economic activities. The lockdown lasted until May 4, 2020 when a partial relaxation of restriction was decreed.

During the lockdown period, the mobility in the country decreased; only essential workers were free to move. Reduction of mobility is clear in the first stage of the outbreak (February 29 - March 6) in some province. After March 7, with the reinforcement of measures, the increase of non-traveling users was 128% (Lodi) and 108% (Piacenza) and "the traffic towards/from the most affected provinces declined by about 50%" [146].

The impact of NPIs measures had consequences on mental health too; in a survey study [147] the effect of the outbreak and of the lockdown measures was related to post-traumatic stress symptoms, depression, anxiety, and insomnia, especially for young woman, suggesting the urge of an intervention to help people with psychological support. The study was carried out on an online survey with social media recruitment, with questions regarding education level, occupation, quarantine (or not) status, working activity and engagement status.

This work focuses on Twitter interactions related to the COVID-19 pandemic in Italy in the period from January 24, 2020, the first day of daily upgrades on the pandemic situation provided by the "Dipartimento della Protezione Civile" (Civil Protection) to July 8, 2020 [148]. The "Civil protection" has since then made available data of COVID-19 Pandemic at national, and regional level (NUT2) on main stock ad flows (diagnosed cases, hospitalization, ICUs, deaths, and tests). Moreover, some informations - mainly confirmation of new cases - are also provided at the province level.

In this paper we aim at investigating the relation between the diffusion concern and anxiety towards COVID-19 on Online Social Media, as proxied by tweeting activity analysing the number of tweets posted daily on specific locations, and the observed epidemic trends (as represented by official data), at different spatial scales.

To do this, we investigated the trend and timing of COVID-related Twitter activity (i.e., number of tweets posted daily at specific geographic locations) and analysed its relationship with real epidemic data at different geographic scales. "Twitter provides direct access to an unprecedented amount of content and may amplify rumours and questionable information"[149].

Twitter in similar context has been used to analyse and track disease activity as Influenza like illness (ILI) and public interest in a study focused in the U.S. during the A/H1N1 pandemic [48]. The study focused also on reported and estimated - by means of Twitter data - ILI in specific Center for Disease Control (CDC) regions. In another "A/H1N1" related study [133], geocoded tweets were used to correlated sentiment about immunization policy and CDC estimated vaccination rate per region. Then a simulation of disease was applied according to vaccination confidence pa rameters. In a study similar to our work [150], the authors analysed the tweets related to ILI and flu with real outcome in local flu outbreak reports, analysing correlation both at national level and at local level.

## 3.2 Data and Methods

By means of Twitter Streaming API's [151], we draw 19,327,845 tweets written in Italy according to a series of COVID-19 related keywords (table 3.1) since January 19, 2020. These keywords were updated when new terms started to become popular on Twitter trends or when coined by institutions such as the WHO; for example, the acronym "COVID-19" has been coined quite late in March 2020.

| **Context** | **Italian keyword** (English translation) |
|---|---|
| Covid Topic and fact | Coronavirus, Covid-19, Lockdown, Fase 2 (phase 2), Riapertura (reopening), dpcm, OMS (WHO), tamponi covid (covid swabs), test rapido (quick test), quarantena (quarantine), zona rossa (red zone), chiusura italia (italy closure), Sars-Cov2, wuhan, bollettino Protezione civile (civil protection bulletin) |
| Variants due to misspelling | "corionavirus", "coronavirius", "covid-19", "corvid-19", etc. |
| Hashtags | #andratuttobene (everything will be fine), #lockdown, #celafaremo, #iorestoacasa (I stay at home), #medicieroi (doctors heroes), |

Table 3.1: *Keyword adopted to retrieve tweets*

From the original set of tweets, first we removed possible duplicates by their IDs, then we extracted the location where each tweet was - tweeted. Twitter supplies different types of geo-code locations; the first, that we call "dynamic location", is the location provided by the users if she/he previously enabled the GPS and allowed geotagging. This is very accurate, and we take it as is, extracting the subsequent point-coordinates, city, province, and region name.

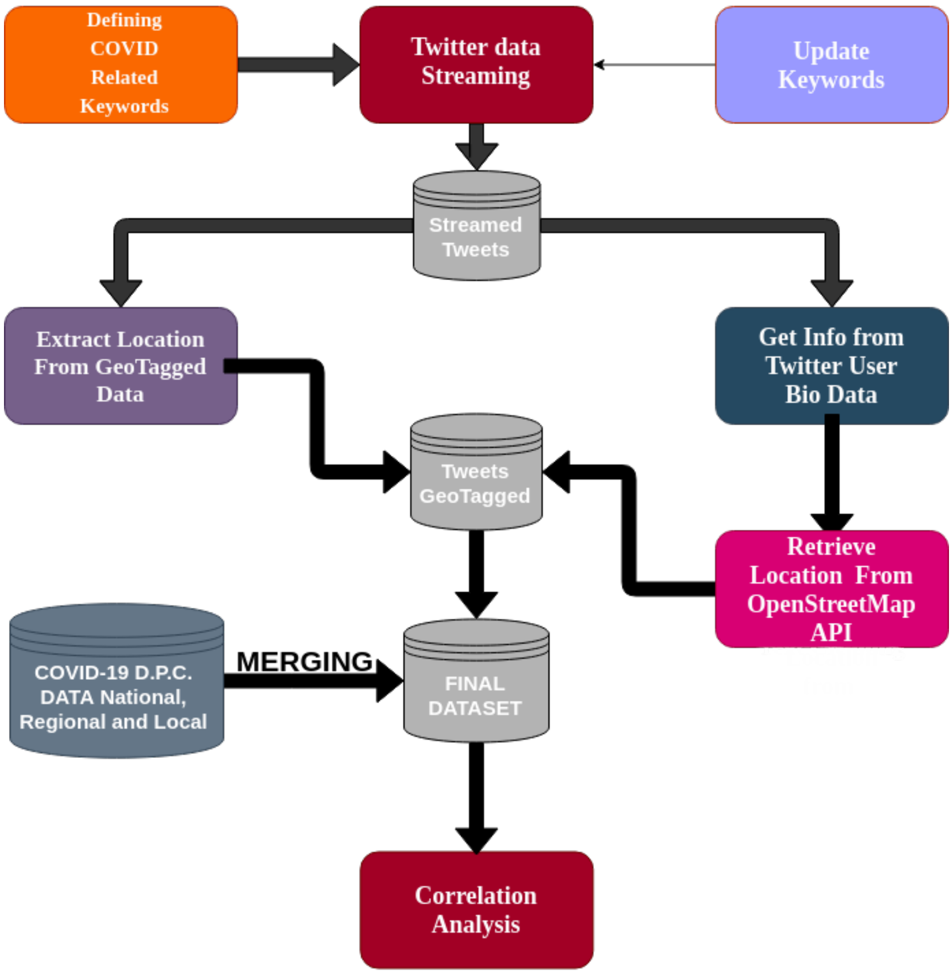


*Diagram 2. Flow Diagram of Analysis Process*

Most of the tweets do not have a geotag. To extract the possible location where the tweet has been tweeted, we looked to the "static location", which is the location that each user declared in her/his short biography on Twitter, assuming that it represents the place where user tweeted. Since users are free to write anything in this space, we processed the strings to clear all the unfeasible locations (e.g., the moon, mars, "your heart"). Using Open Street Map API, all feasible locations were passed through it and we fetched all useful data as for the "dynamic location": geographical point coordinates, city, region, and province (the lowest administrative level considered in the analysis).

The final dataset of geocoded tweets, after the cleaning, counts for 8,368,940 tweets and retweets, including IDs, dates, and locations. Then, we combined the tweets geocoded dataset with the official Italy COVID-19 dataset provided by Civil Protection [148] to perform the analysis at national, regional and local level.

## 3.3 Results

### 3.3.1 Temporal trends of Twitter and underlying events

The analysis of the temporal pattern of the number of tweets shows a clear underlying trend to which sharp peaks are super-imposed. Most peaks are associated to well-identified particular events happened (Figure 3.1).

The events reported are the following:

- January 30, 2020, two Chinese tourists affected by COVID-19 were hospitalized at Ospedale Spallanzani di Roma [12].
- February 20, 2020, first confirmed case of Italian resident in the municipality of Codogno.
- February 23, 2020, the province of Lodi declared "Red Zone".
- March 4, 2020, by decree all schools and universities were closed, the stations during the night overcrowded by people who are non-permanent resident in the main cities of northern Italy.

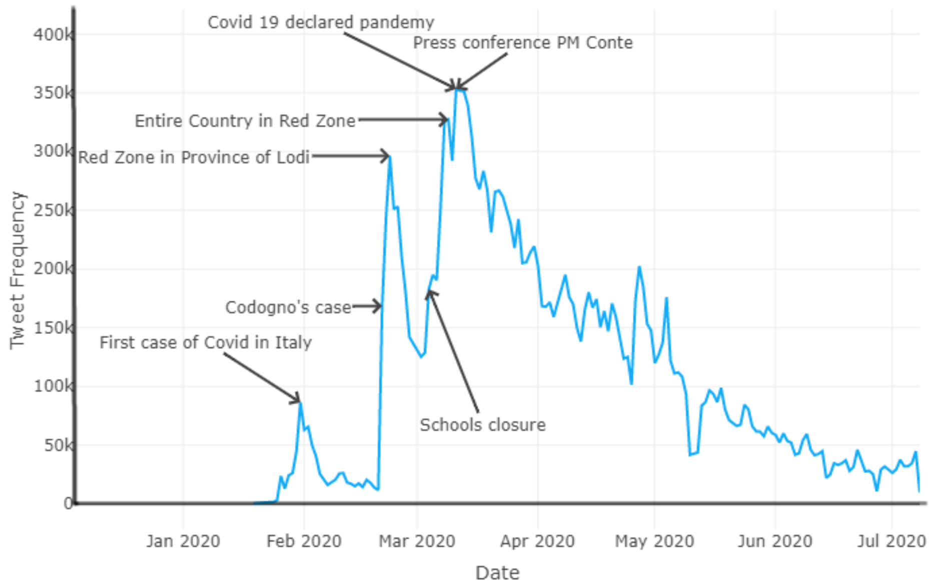


Figure 3.1: *Daily tweet frequency with most important events*

- March 11, 2020, WHO declares COVID-19 pandemic [13]. Entire Italy is Red Zone, the country enters in lockdown [14].
- April 27, 2020, press conference of Italy's PM in view about the partial reopening.
- May 4, 2020, beginning of the so-called "phase 2" with the partial reopening of some non-essential activities and release of restrictions.

After an initial period of highly triggering events, which start between end of January and half of March, we can appreciate a similar trend between the number of tweets (scaled for visibility in the Figure 3.2 and Figure 3.3) and the real COVID-19 cases in the period mentioned, we appreciate that the peak of the tweets anticipate by ten days the peak of COVID cases reported. This is clearer if we look these time series after smoothing with seven days moving average (Figure 3.3). Seven days is the standard measure used to smooth the data due to the variability of testing (during the weekends private laboratories are closed and the number of swabs analysed decreases).

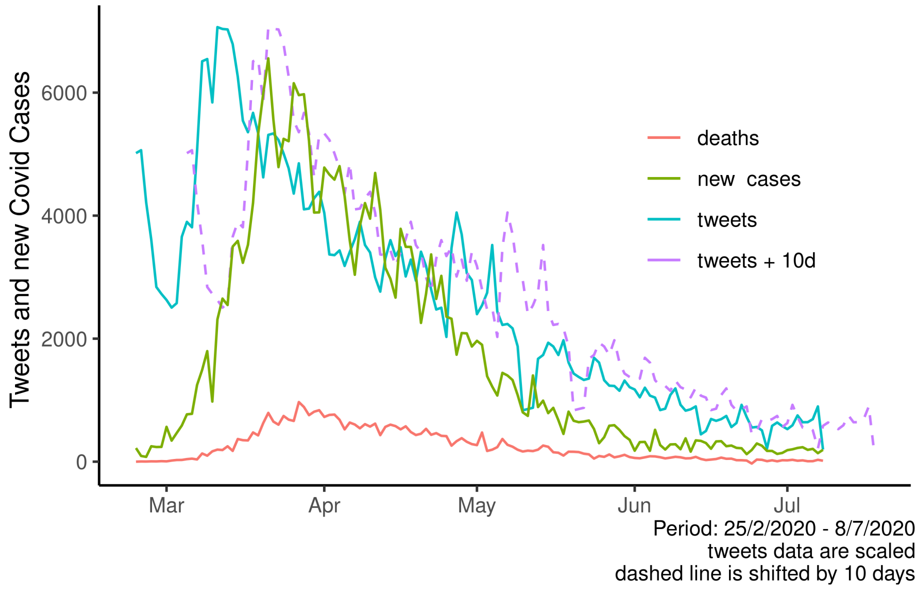


Figure 3.2: *Tweets, Covid cases, Deaths, and Tweets shifted by 10 days in Italy Tweets data are scaled by 50 times*

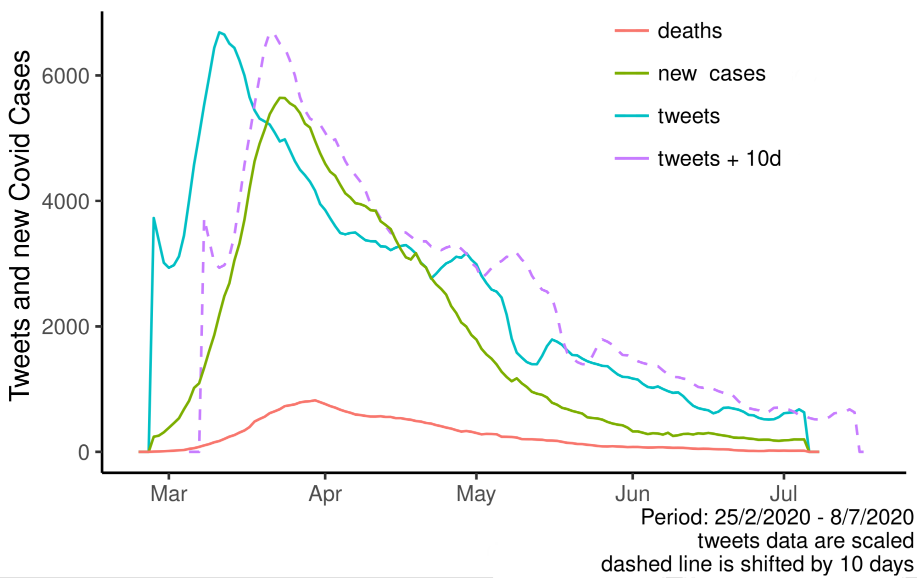


Figure 3.3: *Moving Average of Tweets, Covid cases, Deaths, and Tweets shifted by 10 days in Italy Tweets data scaled by 50 times*

In (Figure 3.3), we report in log-log scale the monthly distribution of the daily COVID cases reported in the first day of the bulletins [148] and the tweets. Each number represent the month of the year. We have a trend clearly visible as in the previous time series, again - after the period between 24 February and half of March - a trend in the following days.


Figure 3.4: *Monthly distribution of reported Covid cases and Tweets in log-log scale. Numbers represent the month of the year.*

## Correlation at regional and province level between cases and tweets

After this, we investigated the correlation between the flow of the tweets and the COVID-19 cases per region and province. (Figure 3.5 and Figure 3.6).

The two charts show the Pearson correlation between the tweets generated in the period February 24, 2020 - July 8, 2020, and the Covid cases reported by bulletins, both at the province and regional level. At the regional level, the highest values are Marche and Lom-

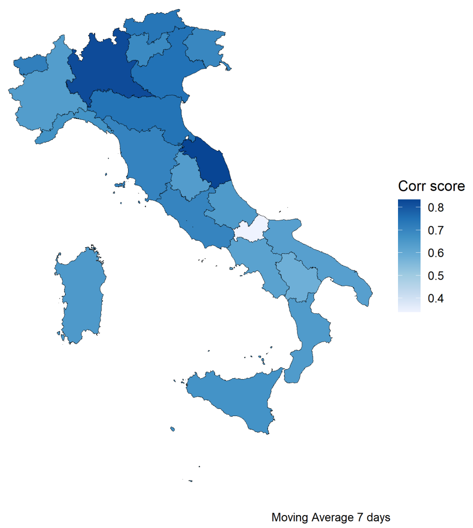


Figure 3.5: *Correlation between Tweets and Covid Cases By Region*

bardy. Marche is the first non-northern region particularly involved in the pandemic. Lombardy, on the other side, is the most hit region by COVID-19 in terms of deaths and infected. All correlations are statistically significant since all p-values are $< 0.001$.

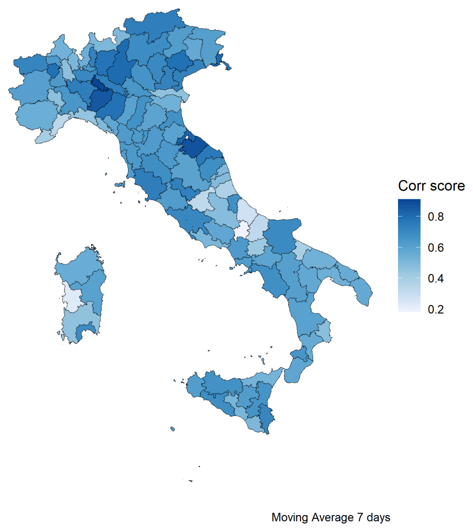


Figure 3.6: *Correlation between Tweets and Covid Cases by Province*

At province level, the highest correlation is present in the province of Piacenza, and Lodi, with the latter being highly involved in the

| Region Name | correlation - r | CI & p-value |
|---|---|---|
| Abruzzo | 0.645 | (0.581-0.685) - <0.001 |
| Basilicata | 0.582 | (0.489-0.652) - <0.001 |
| Calabria | 0.641 | (0.602-0.691) - <0.001 |
| Campania | 0.622 | (0.580-0.673) - <0.001 |
| Emilia-Romagna | 0.744 | (0.715-0.766) - <0.001 |
| Friuli-Venezia-Giulia | 0.695 | (0.647-0.736) - <0.001 |
| Lazio | 0.702 | (0.665-0.742) - <0.001 |
| Liguria | 0.666 | (0.610-0.711) - <0.001 |
| Lombardia | 0.821 | (0.806-0.837) - <0.001 |
| Marche | 0.833 | (0.808-0.855) - <0.001 |
| Molise | 0.338 | (0.220-0.435) - <0.001 |
| P.A. Bolzano | 0.739 | (0.651-0.808) - <0.001 |
| P.A. Trento | 0.687 | (0.586-0.768) - <0.001 |
| Piemonte | 0.636 | (0.601-0.672) - <0.001 |
| Puglia | 0.628 | (0.579-0.665) - <0.001 |
| Sardegna | 0.646 | (0.602-0.691) - <0.001 |
| Sicilia | 0.664 | (0.633-0.696) - <0.001 |
| Toscana | 0.704 | (0.675-0.729) - <0.001 |
| Umbria | 0.637 | (0.567-0.710) - <0.001 |
| Valle d'Aosta | 0.715 | (0.621-0.790) - <0.001 |
| Veneto | 0.748 | (0.715-0.773) - <0.001 |

Table 3.2: *Correlation Tweets and Covid cases per Region*

early phase of the pandemic in Italy. The highest correlations are in the northern region's provinces, we reported (Figure 3.7) the number of tweets and the number of cases in log scale and in moving average of 7days for the top three provinces and the last province in term of correlation: (a) Lodi (Lombardy) r = 0.910, (b) Pesaro e Urbino (Marche), r = 0.871, (c) Piacenza (Emilia-Romagna), r = 0.860, and (d) Isernia (Molise), r = 0.182. These results are coherent with the correlations per Region, moreover, Province of Piacenza borders with the Province of Lodi.

A similar result in the two most hit province of Bergamo and Brescia, as well as the Province of Padova, Vicenza, Treviso in the Region of Veneto. For all provinces, correlations are statistically significant since all p-values are <0.05. Amongst regions capitals, the highest correlation r is for Ancona (Marche) r = 0.76 and the lowest value is for Campobasso (Molise) r = 0.323.

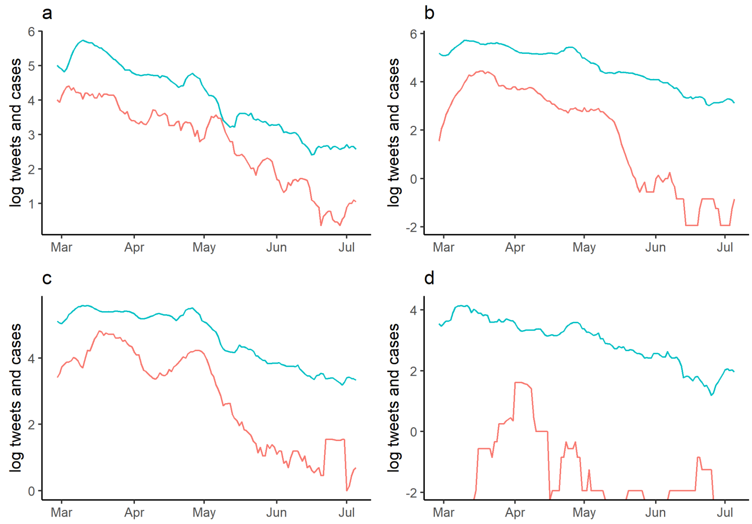


Figure 3.7: *Local correlation for Lodi(a), Pesaro e Urbino(b), Piacenza (c), and Isernia (d)*

## 3.4 Discussion

In this study we reported an analysis of distribution of tweets in Italy and the COVID-19 cases occurred in the period February 24 - June 8, 2020. We reported that exists a positive correlation between the flow of pandemic, i.e., daily COVID-19 cases at national, regional, and local level with social media flow, i.e., number of tweets posted daily at national, regional, and local level. We have found that apart from few days with high Twitter flow due to particular events (e.g., the press conference of Italian PM at end of April), there is a shift of around 10 days between the two outcomes, with Twitter data that anticipate the COVID-19 cases. Our results are consistent with other results obtained in similar studies [48]. We notice, although, that in the early stage of COVID-19 outbreak in Italy the patterns do not match even considering this shift. We believe that this happens for two reasons: i) objective, because of a very low number of cases at the early stage, with official counts starting only on February 24; ii) subjective, because of high responses from tweeters to "political" events rather than pandemic events.

Since a second wave of the pandemic is somewhat expected [155], it would be interesting to analyse if there is a matching trend in the two time-series during this period. A difficulty in this sense could be the update of the keywords in the streaming process since new terms such as "lockdown2" are coined by the users becoming a trending topic on Twitter.

It will be interesting the analysis of the penetration rate of COVID-19-related news on national and regional newscasts, to deeply understand if they are responsible in tweets' reactions, since most triggering events in tweets' peaks are press conference of the Italian PM broadcasted on TV, or new decrees, or "bad" results in daily bulletins. A limitation in province analysis is the lack of features in public daily bulletins.

The Italian Civil Protection for the "lowest" administrative level, releases only the total daily cases, while for regions we have much more info such as Intensive Care Unit occupied, number of hospitalized, number of deaths, number of recovered and swabs tested; this is because the healthcare is administrated in concurrency between state and regions, the latter communicate the data to the Italian Civil Protection.

Sentiment analysis, with a similar approach of chapter two, would be useful to analyse deeply the polarity and the perception of users, establishing if each tweet reflect an involved person in the disease or only scared of it, or as in [150]. In this analysis, we also included the retweet, that are tweets reposted by other users, representing in text analysis a noise, without new information generated, and we can only assume that it represents and endorsement.

The retweets are the majority of the tweets retrieved in the streaming, resulting in a first limitation, which will require a calibration in terms of cases. Twitter data can be useful to estimate also public health messages and campaigns during a pandemic. Detect a matching pattern from these data to estimate real illness data still remain a space that needs to be explored and not discarded, but at the same time need effort in calibration with the use of traditional statistical, epidemiological and econometric methods.

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