Vaccine movements on social media: a visual and network analysis

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Abstract

Vaccines are considered one of the most effective public health interventions, but they have been subject to opposition since they were first proposed. Anti-vaccine activists disseminate and sensationalise objections to vaccinations through various channels, including the internet and social media outlets, such as Twitter. These means allow them to reach the public directly and potentially influence their intention to vaccinate. Twitter allows users to share short textual messages and images. Although, images have strong communicative power, there is a lack of research on the networks and actors sharing vaccine images. Moreover, there are no studies on the messages conveyed by these images. Therefore, this study aimed to investigate the dissemination, content, and messages of anti- and pro-vaccine images in relation to their respective Twitter networks. A mixed methods approach was used to address the research aims, comprising social network analysis and visual analysis. Anti-vaccine users re-shared images with each other; they provided support and strengthened their anti-vaccination beliefs. Some key actors, primarily activists and parents, influenced the information flow within the community. Anti-vaccine images claimed that vaccines are not safe, advocated against mandatory vaccinations and promoted vaccine conspiracy theories. They also provided alternative sources of information or pseudoscientific evidence supporting their messages while increasing distrust in traditional experts. The pro-vaccine users form loose connections that favour the dissemination of new vaccine information and networking. In this network, Non-Governmental Organisations (NGOs) and public health organisations influenced the dissemination of images, and the images mostly featured NGO campaigns and achievements in developing countries or promoted the flu vaccine in Western countries. In conclusion, anti- and pro-vaccine networks are insular and share different images in different ways; they use different visual communication strategies to reach their audiences. This resulted in a lack of a middle ground in visual communication of vaccines on Twitter. Addressing this gap could be an opportunity for future immunisation campaigns.

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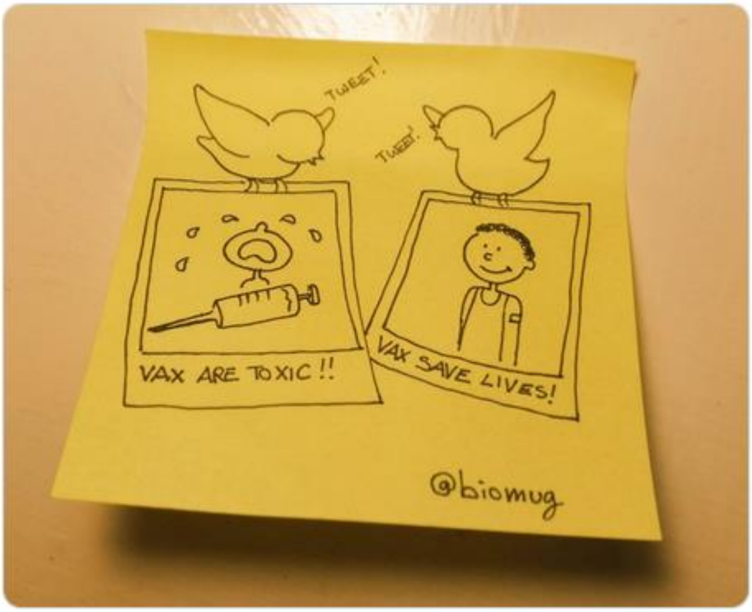
My PhD in a #PostItNoteScience - analysis of anti- and pro-vaccine Twitter images and networks #vaccineswork



12:29 AM · Jan 19, 2017 · Twitter for Android

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Glossary

***Ad hoc* publics.** Audiences formed around topical hashtags (e.g. #VaccinesWork). Users tweeting about the same topic tend to use specific hashtags to converse with each other. These aggregated conversations can eventually develop into hashtag communities and *ad hoc* publics where a user can reach the other members of the group virtually immediately by including a topical hashtag in a tweet (e.g. #vaxxed). See Sections 2.2.3.

Average Geodesic Distance. The average of the short paths (i.e. number of retweets) that connects two users in the network. See Section 4.4.2.

Betweenness centrality. This measures how many users an actor connects that belong to the same or different groups. An actor with high betweenness centrality can be a broker who dominates the information flow, and if s/he is removed from the network, the network will be disrupted. See Section 4.5.1.

Broker. Key actors that link users or groups of users otherwise not connected. These actors can access new information from some users within a network and control its flow to other users or groups. See Section 2.3.1.

Centrality. This indicates how central an actor is within a network; i.e. which actors can potentially influence or control the information flow within a group or the whole network. See Section 4.4.

Clusters. Groups of users positioned closely together. See Section 4.4.2

Connected Components. A group of users connected to each other and isolated from outsiders. See Section 4.4.2.

Density. This indicates how cohesive a network is. Density is the ratio between the number of observed retweets and the number of possible retweets in the network. It may not give a good estimate of connectivity in large-size networks (its value tends to decrease for these networks). See Section 4.4.2.

Diameter. Also called Maximum Geodesic Distance. It provides an estimate of the maximum distance between users in a network or cluster, but it is not precise. It is the maximum number of retweets that connects two users farther apart in the network. See Section 4.4.2.

Engaged user. Users who were mentioned in tweets from their counterpart (e.g. pro-vaccine users mentioned in anti-vaccine tweets) and replied/engaged with them.

Favourite. Liking someone's tweet. This is not considered an endorsement.

Followee. The user who is subscribed to, followed, by another user.

Follower. The user who subscribes to (follow) the updates of another user.

Gatekeeper. In this research, gatekeepers are defined as Twitter actors that could potentially control the access to and dissemination of information in a network.

Graph metrics. Set of parameters used to analyse the connectivity and distribution of a network (i.e. number of users, number of retweets, geodesic distance, diameter, density, modularity, number of connected components).

Hashtag. Hashtags are keywords that label specific discussions on Twitter. They are formed by one or more words preceded by a hash sign (#). For example, #vaccines, #CDCWhistleBlower or #vaccineswork. See Section 2.2.

> **Generic hashtags.** Hashtags that do not label conversations, but highlight specific words. For example #win, #study
>
> **Topical hashtags.** Hashtags that label specific topics and conversations. For example #VaccinesWork, #HearUs, #vaccinations

Hub. Key actors that broadcast their messages to their audiences. These actors are highly retweeted, but rarely retweet, and they can act as gatekeepers or sources of information for their network/group. See Section 2.3.1.

In-degree centrality. This measures how many times a user's messages were retweeted up to the date of data collection. An actor with high in-degree centrality could be a hub. See Section 4.5.1

Image. An image is a visual representation of objects, people, phenomena, concepts or ideas. In this research, an image includes both the tweet and the embedded picture(s).

Key Actor. Actors that occupy a strategic/central position within a network. These actors can be hubs or brokers; they can potentially influence the information flow within a network or group, and even the access of new members to the network or group. See Section 2.3.1.

Maximum number of Nodes in a Connected Component. This indicates the largest number of users that are members of the same isolated group. See Section 4.4.2.

Maximum number of Edges in a Connected Component. This indicates the largest number of retweets that connect the users of the same isolated group. It provides an insight into the connectivity of the biggest component in a network when compared with the maximum number of users. See Section 4.4.2.

Mention. A user can mention another user by adding his/her Twitter handle (e.g. @user) in the tweet. This practice can be used to notify a user about a specific message or to attribute the content to him/her (e.g. a picture, an article).

Mentioned user. Users who were mentioned in tweets, but did not participate in the conversation or did not tweet at all during the data collection period.

Modularity. This indicates how partitioned, segmented into clusters, a network is. Its value ranges from 0 (unified network) to 1 (fragmented network). Modularity, combined with density, can explain the connectivity of a network. See Section 4.4.2.

Out-degree centrality. This measures how many retweets a user has made up to the date of data collection. See Section 4.5.1.

Personal publics. Audiences of followers. Instead of reaching a broad but unknown public, Twitter users share their content and tailor their messages to their direct followers (i.e. personal publics). See Sections 2.2.1 and 2.2.2.

Picture. A graphical item, such as a photo, drawing, chart, or infographic. In this research, the term "picture" defines the visual element embedded in a tweet.

Quote. Sharing someone's tweet with a personal comment added. The original tweet can be re-contextualised or targeted to a different audience by adding a comment.

Reply. A reply to someone's tweet which also starts a direct conversation with the user.

Retweet. Sharing someone's tweet as it is, without adding any comment. Retweets are sometimes considered endorsements.

Size of a network. It indicates how wide a network is; i.e. how far apart the users of a network are. The size can be estimated by measuring its diameter or geodesic distance. See Sections 4.4.1 and 4.4.2.

Standard. In this study, a standard is defined as a social convention, shared norm or practice that enables external users to become part of a network and internal members to access each other (Grewal, 2009). A standard can be a shared language (e.g. English) or a digital media outlet (e.g. Twitter).

User. Generic Twitter users (either people or institutions) and/or members of a Twitter network.

User with high out-degree. These users do not influence the information flow within a network but they can amplify the visibility of other users' messages by frequently retweeting them. Their retweeting can sometime be seen as endorsement. See Section 2.3.1.

1. Introduction

Vaccines have eradicated or significantly reduced vaccine-preventable diseases and are considered one of the most effective public health interventions (Andre *et al.*, 2008). Nevertheless, they have aroused public concerns about their safety and effectiveness; as early as the 19th century this led to the formation of anti-vaccine leagues in the UK and the US (Wolfe and Sharp, 2002). The anti-vaccine sentiment flourished in particular after the 1970s, when the risk of outbreaks of infectious diseases was greatly reduced by high immunisation rates, and more vaccines were developed and integrated into the vaccine schedule (Poland and Jacobson, 2011).

News media coverage of vaccine-related events and anti-vaccine arguments have also influenced public perception of vaccinations (Gollust *et al.*, 2015; Speers and Lewis, 2004). Towards the end of the 20th century, the media's interest in arguments against vaccinations increased in relation to a surge of anti-vaccine activity (Wolfe and Sharp, 2002). Leask and Chapman (1998) analysed the Australian print media coverage of vaccines from 1993 to 1998, and they found that 4.7% out of 2,440 articles contained anti-vaccine claims. These arguments were often introduced by healthcare professionals in their attempts to debunk them. However, the authors observed that these attempts may backfire by "amplifying public awareness of anti-immunisation arguments" (Leask and Chapman, 1998, p.23).

The political frame of media coverage of vaccines seem to be main factor that affects public perception of vaccinations. Casciotti, Smith and Klassen (2014) found that the US coverage of the political controversy of the HPV vaccine occurred especially around 2007, during the FDA approval and when first legislations were introduced (e.g. school mandates). Whereas after these events the political controversy was less reported. Gollust *et al.* (2015) confirmed that this same media coverage mostly focused on the political controversies around the vaccine (e.g. school mandates, anti-vaccine messages) rather than on its public health benefits. The authors also claimed that this focus affected the public support of HPV vaccinations and increased public distrust in traditional authorities (e.g. healthcare professionals).

Similarly, the coverage of the MMR vaccine-autism controversy in the British print media was also presented as a political controversy, and politicians were quoted more often than healthcare professionals (Guillaume and Bath, 2008). Moreover, the British media did not provide a rigorous examination and critique of the MMR vaccine-autism link, and created instead the perception of a lack of scientific consensus about MMR vaccine safety. This affected public perception of the risks associated with MMR vaccination and increased vaccine hesitancy (Speers and Lewis, 2004). Clarke (2008) further investigated the British and US newspaper coverage of the MMR vaccine controversy, and observed that the health officials interviewed emphasised that the vaccine does not cause autism. However, they missed to address other public concerns, such as the government efforts to guarantee the vaccine safety or the reasons behind the unavailability of single vaccines instead of the trivalent. Holton *et al.* (2012) found that journalists often did not offer solutions to the explore issue, for example they did not say where to find medical and public health resources. All of these factors could have an impact on public perception of vaccines and vaccine hesitancy. Speers and Lewis (2004) observed a direct link between media coverage and vaccine hesitancy. However, Smith *et al.* (2008) found that in the US, a decline in the uptake of the MMR vaccine began two years before media coverage of the MMR-autism controversy. The authors hypothesised that parents may have consulted other sources of information, such as healthcare professionals, who had access to the original academic publication. The authors also hypothesised that the Internet could have been an alternative source of information (Smith *et al.*, 2008). Other researchers have suggested that internet played a major role in spreading anti-vaccine sentiment and misinformation (Betsch *et al.*, 2012).

In his work, Clarke (2008) advocated the importance of monitoring the media coverage of vaccines to identify the public concerns regarding vaccinations that should be addressed. Public concerns about vaccines can be surveyed by monitoring the internet and social media as well (Larson *et al.*, 2013). This is particularly important since with the advent of the Internet and social media, anti-vaccine movements have been able to sensationalise objections to vaccinations by emphasising a range of factors, such as the occurrence of vaccine side effects, perceptions of the business motives of the vaccine industry, and scepticism about or non-acceptance of scientific evidence (Larson *et al.*, 2011). Through these new media, anti-vaccine activists can disseminate misinformation about vaccines to a broad audience, reaching out to other like-minded people and those who are not anti-vaccine but are seeking information about vaccinations (Kata, 2010). Their content, though scientifically inaccurate, can be highly visible online (Ninkov and Vaughan, 2017) and may affect the intention to vaccinate of concerned parents (Dubé, Vivion and MacDonald, 2015; Ołpiński, 2012). Though anti-vaccine activists do not have the same scientific and medical expertise as scientists and healthcare practitioners, they may be acknowledged as 'experts' by their community (Kata, 2012).

Anti-vaccine communication online exemplifies several of the challenges to science communication caused by the rise of digital media. Digital media have blurred the distinction between producer (e.g. journalist) and consumer (i.e. audience) of information and have provided Internet users with direct access to scientific content, thus bypassing traditional mediators (Schmidt, 2014; Bruns, 2008). In fact, any Internet user can both access scientific information online and upload, curate, re-contextualise, edit and share scientific content with different audiences. Digital media have opened up scientific debates to the lay public (Bucchi, 2017), but at the same time, they have facilitated the dissemination of scientific misinformation (ALL Europe Academies, 2019). As anyone can produce and share content online, anyone can potentially become a source of information. However, not everyone can easily discriminate between reliable and unreliable sources (ALL Europe Academies, 2019). Moreover, the Internet has allowed like-minded individuals, geographically distant, to meet in a digital space and form their own communities. The formation of online communities has posed other challenges to science communication: they can polarise opinions online (Witteman and Zikmund-Fisher, 2012), facilitate the spread of misinformation (Del Vicario *et al.*, 2016), and reinforce previous misconceptions and beliefs (Southwell, 2013). Therefore, targeting anti-vaccine communities may not be a successful strategy for engagement (Lutkenhaus, Jansz and Bouman, 2019).

To improve the communication of scientific evidence about vaccination online, it is necessary to understand the communities and actors discussing this topic. This is not limited to their vaccine concerns and socio-economic demographics, but includes the content of the messages they share (Lutkenhaus, Jansz and Bouman, 2019). Therefore, understanding how anti- and pro-vaccination communities share information with their members and outsiders online could provide insights into their communication dynamics and potential gaps. It could also allow identification of actors that play a key role in access to the community and communication among members (Lutkenhaus, Jansz and Bouman, 2019; Grewal, 2009). To contribute to this understanding, this research investigated vaccine communities on Twitter.

Twitter is a newsfeed and information network where users follow content rather than personal contacts (Ackland, 2013). Twitter users can join topical conversations and do not need to establish a reciprocal relationship to access each other's newsfeeds (Kwak *et al.*, 2010). Twitter is one of the social media platforms used by anti-vaccine movements, where users share not only short textual messages, but also pictures (Chen and Dredze, 2018). Pictures can increase the visibility of the tweets (Yoon and Chung, 2013) and they have a strong communicative and persuasive power (Indira Ganesh *et al.*, 2014). By studying vaccine images, this research seeks to shed light on the visual communication techniques adopted by anti- and pro-vaccine movements.

Vaccine communication online includes images as well as text. Images can facilitate public understanding of and adherence to health interventions (Houts *et al.*, 2006), and affect public intentions to vaccinate (Guidry *et al.*, 2018). Though previous studies investigated the content of vaccine images shared on social media (Chen and Dredze, 2018; Lama *et al.*, 2018; Guidry *et al.*, 2015), none explored the messages conveyed by these visuals or their dissemination within and among social media communities. Therefore, this research aimed to analyse the messages of vaccine images and the networks and key actors sharing them on Twitter. Understanding how images combine different figurative elements to convey anti- and pro-vaccination messages could provide insights into the differences and similarities between anti- and pro-immunisation visual communication (Lester, 2014). Overall, this knowledge could be used to improve visual communication of vaccinations online.

The next chapter of this thesis, Chapter 2, provides a literature review of the communication dynamics on digital media, especially Twitter, and on how grassroots activists and anti-vaccine movements use social media for advocacy campaigns. It also discusses visual communication of science in the digital age. Chapter 3 provides the conceptual framework adopted in this research and the aims and objectives of the project. Chapters 4 and 5 focus on the methodology applied to investigate the dissemination of pro- and anti-vaccine images on Twitter and the results obtained, respectively. Chapters 6, 7 and 8 focus on the visual analysis. Chapter 6 explains the methodology applied, while the 7th and 8th chapters discuss the results of the content and image analyses, respectively. Finally, Chapter 9 provides a discussion of the research results and Chapter 10 outlines the practical implication of this study.

2. Literature review

2.1 Digital and social media communication

The rise of the Internet and social media outlets is facilitating access to new and old information from all over the world, but at the same time it is changing the way in which information is communicated and shared. On the Internet, information is not simply transmitted by the media, governmental agencies, or Non-Governmental Organisations (NGOs) to target publics, and from the target publics to a broader audience. Instead, information is often processed by the receivers before being shared: it is personally interpreted, edited, reviewed, and/or related to other topics (Hodkinson, 2016). For example, Twitter users engaged in political discussions do not share the original news as it is, but they frame it by providing alternative background information (e.g. blog articles), personal experiences, opinions, and interpretations. News and information are not communicated in a linear pattern, but they are produced, elaborated and consumed in networks. Through networks, users can access news from different sources of information, integrate it, and discuss it with other members (Maireder and Ausserhofer, 2014).

Baym (2010) argues that digital communication differs from traditional communication, in the following aspects:

- Interactivity – digital media platforms allow individuals to interact and engage with different content, sources of information and groups of users; hence, individuals can comment, share and re-contextualise content posted by others (media outlets, journalists, general online users, etc.);
- Temporal structure – digital media are asynchronous, which means that there is a delay between the first message and a reply; however, the delay can be very short since it takes only a few seconds for a message to arrive (it depends on the speed of the Internet connection). In this case, online communication can mimic synchronous communication

(e.g. a phone), making users feel closer even though they may be geographically far apart;

- Social cues – digital media platforms may exclude nonverbal cues, such as visual and auditory ones, which individuals use to interpret and contextualise a message; for example, an email offers only written cues, making it difficult to understand irony or emotional content. Though social media platforms may provide fewer social cues than traditional conversations, they also provide new cues to compensate for this lack, such as emoticons, emojis, and gifs;
- Storage – digital media allow users to retrieve content they shared or saved whenever they want. They can save pictures, screenshots, audios and videos on storage devices, such as smartphones, but they can also backup all their private conversations in apps such as WhatsApp, or access the content they shared on social media platforms. Outlets such as Facebook will also retrieve content for users automatically, reminding them of past events they shared in their timeline ('Facebook memories');
- Replicability – online users can share the same content across different platforms (e.g. a photo on Instagram, Tumblr and Facebook), and other users can re-share it;
- Reach – through digital media platforms, individuals and media outlets could potentially reach an enormous audience, but they are limited by several factors; for example, they have to compete with similar shared content and similar users (referred to as an economy of attention). The interface and technical affordances of platforms can also restrict users' access to a broad audience (e.g. Facebook privileges paid content, making it more visible than free content);
- Mobility – laptops and especially mobile phones and smartphones allow individuals to communicate with their friends, relatives and online communities wherever and whenever they want (they only need access to a Wi-Fi hotspot or a network connection).

Digital media have facilitated communication among individuals: Internet users that are geographically distant can cluster in conversations and/or join communities (Murthy, 2012; Castells, 2009). Moreover, they can bypass the traditional system of information gatekeeping and directly access new or alternative, institutional or individual sources of information (Schmidt, 2014; Murthy, 2012). Furthermore, digital media have blurred the roles of producer and consumer of information (Bruns, 2008). Internet users are not passive audiences who consume information published online, but they also share it (as it is, modified or re-contextualised) to different audiences and on different platforms (e.g. Twitter, Facebook). They can also produce their own content; for example, they can write an article for their blog, curate a content collection on Pinterest, or participate in a Twitter chat. These online users are defined as 'prosumers' since they both produce and consume information. Prosumers can produce or curate information individually, but they can also produce knowledge with other members of a community. For example, Wikipedia members actively participate in the creation of knowledge, editing and reviewing each entry on the platform (Bruns, 2008).

Bruns (2018a) investigated prosumer communities and claimed that they have changed traditional knowledge production by making it an ongoing an open process. He observed that the production of information and knowledge is not supposed to end in a finished product (e.g. a book), but it is edited, reviewed and updated continuously, and it is accessible to everybody on the net. Furthermore, whilst traditional knowledge production is based on a hierarchical system where experts (e.g. scientists, journalists, editors) decide what information to produce, publish and share, prosumer communities work as a heterarchical system (Bruns, 2008). In this case, every member can contribute to content production and curation, and the leaders of the community are selected by the community based on the number and quality of their contributions. Leaders do not have fixed positions in the community, and they may lose their position if their participation diminishes (Bruns, 2008).

2.1.1 Online communities and polarisation

Online, users can communicate and bond with strangers independently of their social status and geographical location. They can cluster in online communities around shared interests, hobbies, projects (e.g. Wikipedia, open source software), or purposes, and form weak ties (Castells, 2009). Weak ties are limited relationships without commitment (Hodkinson, 2016) and they favour access to people, information and opportunities that are geographically distant from users at relatively low cost (Castells, 2009). Users can also form strong ties, which are sustained and committed relationships[1] (Hodkinson, 2016). In online communities, users form mostly weak ties; these ties can turn into strong ties if interactions, engagement and commitment between users increase and are sustained overtime. Whilst weak ties can favour the dissemination of information, strong ties can increase the sense of support in a community (Kadushin, 2011).

In an online community, users share more than a common interest, they also share values, norms, and a collective identity (Ackland, 2013). Baym (2010) defined online communities by:

- A sense of space – for example a Facebook group, a Twitter hashtag, a geographic location;
- A shared practice – the members of a community must follow a shared set of norms and values that regulate interactions and behaviour inside the group; the presence of these norms indicates the existence of a hierarchy in the community, though it may not be evident;
- Shared resources and support – for example, the members of a cancer patients' community may seek emotional support, provide advice and guidance, and also share information and personal experience about treatments options and health clinics;
- Shared identities – for example, the members may share the same gender, sexual orientation, ethnicity, or profession;
- Interpersonal relationships – for example, the members may be relatives, colleagues or classmates.

[1] An example of a weak tie is a relationship between acquaintances, whereas a strong tie is a relationship between two friends.

Online communities tend to be highly specialised on a topic or a cause and be homogenous: their members share similar interests, political opinions, and views (Baym, 2010). However, being part of a community may reduce exposure to different perspectives and information (Kadushin, 2011); for example, members of a pro-vaccine community would not share anti-vaccine information. Therefore, though new media may facilitate interactions among users, they also promote the formation of insular groups and increase social division online (Baym, 2010).

2.1.2 Dissemination of mis/information online

Since any Internet user can share science information online, there are several types of science and scientific content (e.g. blog articles, reports) and sources of information (scientists, companies, advocacy groups) available on the web (ALL Europe Academies, 2019). These sources have different scientific authority and expertise and may have different purposes; hence, being able to discriminate between them is essential when seeking to evaluate the reliability of the scientific information shared. However, if Internet users do not have the required skills or literacy to make this differentiation, they may not be able to distinguish accurate information from misinformation (ALL Europe Academies, 2019). Actually, even accurate information could lead to misunderstanding or misinterpretation of scientific information since to understand scientific content (e.g. Open Access academic publications) a certain level of science literacy is required (Trench, 2008).

The type of information a user consults online can vary depending on the community to which they belong. For example, Meadows, Tang and Liu, (2019) found that anti-vaccine users tend to share links to alternative or emerging news websites, whereas pro-vaccine users share information from health organisations' and traditional news media websites. Southwell (2013) argued that members of a polarised community share selective pieces of information that confirm their shared beliefs and discard information offering a different perspective, thus making their shared knowledge biased and increasing the negative perception of outsiders. This confirmation bias could reinforce misconceptions or misunderstandings of scientific content, and the scepticism of individuals holding sceptical views towards science (ALL Europe Academies, 2019; Frey, 1986). For example, anti-vaccine communities may only share information and news supporting a relationship between vaccines and autism while excluding any scientific evidence claiming the opposite (Kata, 2012). Furthermore, polarised communities have been shown to facilitate the dissemination of misinformation and conspiracy theories among their members (Bessi *et al.*, 2015).

In online communities, experts and gatekeepers of information tend to be chosen by members based on the quality and quantity of their contribution (Schmidt, 2014; Bruns, 2008). For example, in communities of prosumers, expertise is recognised based on the number and quality of a participant's contributions, which are peer-reviewed by the other members (Bruns, 2008). Other communities also judge the quality of contributions internally, but the content may be valued because it aligns with members' opinions rather than for its scientific accuracy (Southwell, 2013). Since expertise is defined internally, these communities may not acknowledge external traditional authorities whose expertise is defined by the academic system (e.g. degrees, doctorates) (Bruns, 2008).

2.1.3 Science communication on digital media

Digital media are increasingly used to seek news and information on science and healthcare topics by lay audiences. Moreover, digital media enables scientists to communicate directly with the general public, bypassing mediators such as journalists (Peters *et al.*, 2014), and "lay audiences themselves can participate in the production of science communication content" (Brossard, 2013, p.14096). However, even though digital media, such as Twitter, can facilitate dialogue between researchers and the public, they are still used as one-way communication media (Smith, 2015). Smith (2015) reported that scientists valued Twitter as a means for engaging lay audiences, but use it more for disseminating information than for engagement. Government science agencies also use social media to broadcast information, "suggesting an adherence to deficit-model thinking with almost no implementation of dialogic strategies” (Lee and VanDyke, 2015, p.538). However, Su *et al.* (2017) found that even though scientific organisations use Twitter mostly to inform their audiences, they have begun to use this outlet for community-building.

Science communication research, like those aforementioned, often focused on scientists, scientific organisations and news media as producers of science information, and explored how social media and Twitter are utilised by these actors. However, online, science content is not passively consumed by the audiences, but it is shared and further enriched with opinions, contexts and perspectives by those publics (Brossard, 2013). As Büchi (2017, p.964) argues, digital media such as Twitter “extends public science communication by providing additional voices and contexts as well as recommending content and directing attention”. Weitkamp *et al.* (Under review) identified some of these new voices in the digital ecosystem of climate change and healthy diets. For example, they found that NGOs, activists, industries, governments, policy makers and non-professionals are as visible as scientists, journalists, media and scientific organisations in the climate change discourse online. In the case of vaccine discourse on Twitter, there is little knowledge on the diversity of actors contributing to the debate.

Therefore, this research, aims to investigate the vaccination debate on Twitter by considering not only traditional sources of vaccine information (e.g. scientists, academic organisations, healthcare professionals, the media), but also the new voices (e.g. laypeople, activists) that contribute to the curation of vaccination information and knowledge. Moreover, instead of interpreting science communication as a process divided into production and consumption of information, this research adopts the concept of *produsage* of information (i.e. the same individual both produces and consumes information, Bruns, 2008). This study considers the members of the Twitter anti- and pro-vaccine communities as prosumers, independently of their expertise, and explores how they disseminate, integrate, contextualise and contribute to vaccine visual information.

2.2 Twitter as a communication platform

Twitter is a popular platform that was founded in 2006; it is projected to reach 269.6 million users worldwide in 2019 (Statista, 2017). On Twitter, users post messages of 280 characters[2] (called tweets) that can embed web links, pictures, YouTube videos, and other media (see Figure 2.1). Twitter is used for a range of purposes, such as networking, following news, and advocacy campaigns.

Twitter is not a social network site like Facebook: most of the accounts are public, not private, and users can subscribe to other users' updates and interact with them without having a reciprocal relationship. Twitter is often defined as an information network (Ackland, 2013) and a news feed (Kwak *et al.*, 2010). It is also referred as a microblogging site and is event-driven: users can share short updates in real time, and they contribute to the coverage of events (e.g. protests, earthquakes) (Murthy, 2012).

There are several ways to interact on Twitter, such as:

- Follow – subscribe to a user's updates;
- Reply – reply to someone's tweet and start a direct conversation with the user;
- Mention – mention a user by adding his/her Twitter handle (e.g. @user); this practice can be used to notify a user about a specific tweet or to attribute credit for a work (e.g. a picture, an article);
- Retweet – share someone's tweet as it is;
- Quote – share someone's tweet and add a personal comment to it;
- Favourite – Like a tweet.

Replies are visible only to the users involved in the conversations; they can be made visible to everybody if there is a dot '.' in front of the mentioned user's name (e.g. '.@user'). Retweeting and favouring a tweet will likely increase its visibility across the audiences of the users who retweeted/favoured the post: by retweeting, users can forward a someone's tweet to their followers (Murthy,

[2] Twitter.com extended the tweet character limit from 140 to 280 in 2017. In this research data were collected in 2016; therefore, all the tweets were 140 characters or less.

2012). For this reason, retweets facilitate spread of news and rumours to new audiences (Boyd, Golder and Lotan, 2010). There are factors that can increase the likelihood that a tweet will be retweeted; for example, tweets shared by users with many followers are more retweeted than others, as are tweets with pictures, YouTube videos, web links and hashtags (Suh *et al.*, 2010)[3].

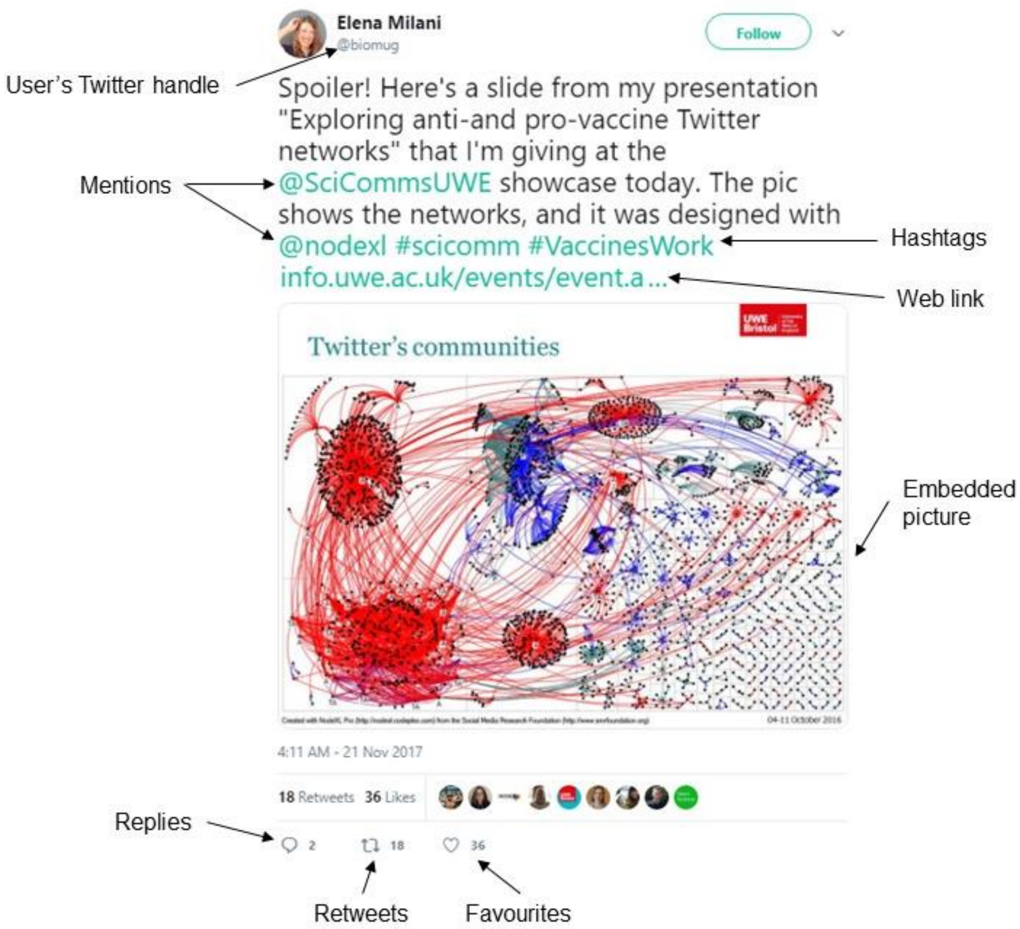

Figure 2.1 Anatomy of a tweet.

One of the most important functions of Twitter is the hashtag. Hashtags are keywords formed by words or sentences with a '#' sign in front of them. Hashtags work as aggregators of tweets on a specific topic; for example, #vaccines, #VaccinesWork, #WakeUpAmerica are topical hashtags used in discussions about vaccinations. Searching for hashtags on Twitter allows users to find all the published tweets with that keyword, without needing to follow those who shared them. Users can also add topical hashtags to their

[3] The authors found that the most recurrent URL domain was twitpic.com, which is generated by uploading a picture on Twitter.

tweets if they want to join the respective conversations. Hashtags are not moderated, and they make tweets easier to discover.

2.2.1 Personal publics and opinion leaders

Twitter is a platform for exchanging information and news with or without the mediation of gatekeepers (e.g. journalists, editors)(Schmidt, 2014). Schmidt (2014) discussed how Twitter users, such as companies, celebrities, scientists, scholars, activists, political parties, and brands, can reach their 'personal publics' (i.e. their followers) directly and can tailor their content to them. For example, a researcher can tweet about his/her research directly to his/her followers without needing a journalist to write about it. The audience can also bypass the gatekeeping system by selecting sources of information to follow on Twitter (e.g. media outlets, friends, commentators, politicians, etc.) (Schmidt, 2014).

News media can still reach Twitter audiences either directly or indirectly. In the first case, news media outlets can share updates with their followers, whereas in the second case information from news media passes through opinion leaders to their publics (Wu *et al.*, 2011). Opinion leaders are users with many followers and strategic connections that are able to control the information flow in their network (Schmidt, 2014). Murthy (2012) observed that opinion leaders may be considered as experts on a topic by their public, and though they can help news media to reach new audiences, they are not obliged to share information. Therefore, opinion leaders may act as new gatekeepers that influence information flow and potentially their public's opinions, though their actual influence may be relatively limited[4] (Murthy, 2012). This phenomenon is not limited to Twitter, and applies across online platforms (Southwell, 2013).

[4] As in the case of expertise in online communities (see Section 2.1.2), influence can be temporary and dynamic. Depending on the quality and number of contributions made by an opinion leader, his/her influence may change.

2.2.2 Three structural layers of communication

Bruns and Moe (2014) identified three different layers of communication on Twitter:

- **Micro-layer** – involves **interpersonal communications** between two or a few users, such as replies and mentions;
- **Meso-layer** – regards **personal publics** and is formed by follower-followee relationships;
- **Macro-layer** – describes ***ad hoc*** **publics** and is formed by conversations aggregated by topical hashtags.

In macro-layer communication, users include topical hashtags (e.g. #vaccines) in their tweets to reach audiences that are interested in the topic but that are not necessarily their followers (Bruns and Moe, 2014). Hashtags can facilitate the creation of organic conversations on Twitter, but that does not imply that all the users tweeting the same hashtag are actually conversing with each other. Hashtag streams are not direct conversations, rather, they look like bricolages of different tweets on the same topic (Murthy, 2012).

Bruns and Moe (2014) observed that the three layers are not isolated from each other, they are interconnected vertically and horizontally. For example, an individual can re-share a tweet to a specific user by mentioning him/her and starting a conversation, thus moving the communication from macro- to micro-layer. A user can retweet a post from a followee thereby forwarding it to his/her personal public of followers, hence moving the information from one meso-layer to another. A user can also modify a tweet by adding a hashtag moving the conversion from the meso-layer to the macro one.

2.2.3 Hashtag communities and *ad hoc* publics

Twitter hashtags can coordinate and distribute discussion among large numbers of users: they can create ephemeral audiences, but they can also form long-standing communities (Bruns and Moe, 2014). The group of users conversing around a hashtag may develop into an online community if it satisfies the requirements mentioned in Section 2.1.1; hence, if they share values, resources and identities. Moreover, the number of users tweeting about a topical hashtag does not indicate a community. It is the number of interactions (replies, mentions and retweets) among these users that prove they are following each other's updates on the topic and forming ties as in a community (Bruns and Burgess, 2015). Bruns and Moe (2014) suggested that the creation of hashtag communities is possible only around topical hashtags, such as #VaccinesWork; it is not possible for communities to form around generic hashtags such as #fail or #win. Topical hashtags are used to join conversations and seek for information, whereas generic hashtags can enhanced the message of a tweet in the meso-layer of communication, but they will not drive users to form a community (Bruns and Moe, 2014).

Bruns and Burgess (2015) stated that hashtag communities can be *ad hoc* publics. These publics "form virtually *ad hoc*, the moment they are needed" around a particular hashtag (Bruns and Burgess, 2015, p.7); they form and dissolve rapidly to discuss a particular topic. For example, hashtags related to specific events, such as political elections, can trigger the formation of a public discussing poll results (Bruns and Burgess, 2015; Bruns and Moe, 2014). When an *ad hoc* public forms, a user can reach the other members of the group virtually immediately by including the relevant topical hashtag. This can happen in cases of emergency, for example, during a riot, an outbreak, a natural disaster, a terrorist attack. All the users following the event hashtag will read the updates shared by others and interact with them in real-time (Bruns and Burgess, 2015). Not all hashtags generate *ad hoc* publics, and the communication dynamics within these publics differ depending on their size and composition and on the event (Bruns and Burgess, 2015). In this thesis, the term *ad hoc* publics will include hashtag communities, since they form around specific hashtags.

2.3 Social media networks analysis

Social network analysis can be used to investigate information flow in a domain, such as Twitter conversations, and quantify the distribution of connections between users (Himelboim, 2017; Kumar, Morstatter and Liu, 2013). Therefore, this type of analysis can provide further insights about the communication between and within pro- and anti-vaccine communities on Twitter. As discussed in Section 2.2, Twitter users use topical hashtags to join or follow a conversation, and by interacting with each other they can form a network (Kumar, Morstatter and Liu, 2013). Networks are formed by users and the connections between them; in this research study, they are constituted of Twitter users and the vaccine information they retweet. The connections between users can be reciprocal or not, and their distribution determines the information flow within and between communities (Kumar, Morstatter and Liu, 2013). For example, when users retweet each other frequently, they form a highly connected network (Smith *et al.*, 2014). The distribution of connections in this group may indicate that the users are highly engaged in the topic of discussion and value the information shared by other members (Kadushin, 2011). In another example, users may cluster in discrete groups that do not interact with each other but only with their own members (Himelboim *et al.*, 2017). These groups are polarised and they probably discuss the same topic from opposite perspectives; for example, in favour or against vaccinations (Salathé and Khandelwal, 2011).

When analysing social networks, it is vital to consider both the distribution of connections and their directions. A network may be formed by many users retweeting one actor or being retweeted by that actor (Smith *et al.*, 2014). In the first case, the message of the actor is broadcast to a wide audience and highly shared, as in the case of a news media outlet. In the second case, a bot may be programmed to retweet every message containing a specific hashtag (see Figure 2.2). The networks' connectivity can also provide insights on their members' attitudes (Kadushin, 2011). Kadushin (2011) discussed how highly connected networks have a tendency to be efficient at spreading information from the centre to the periphery, but this information can also become increasingly redundant if there are only few connections with non-members. Dense networks can also give a sense of trust, safety, and support to the members (Kadushin, 2011) but at the same time they can reinforce the common beliefs held by the community and promote a negative perception of those outside the group (Southwell, 2013). A loose network, where different clusters are not tightly connected with each other, can facilitate access to and diffusion of new information among users (Kadushin, 2011).

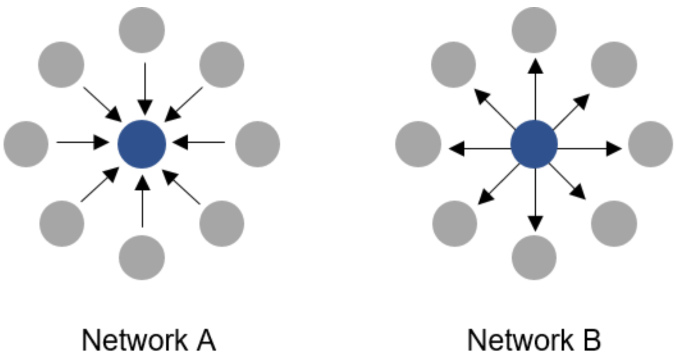

Figure 2.2 Examples of directionality of connections in a network.
In Network A the blue actor is retweeted by the other users (in grey), i.e. the blue actor's message is broadcasted to the others in the network. In Network B, the blue actor retweeted the other users (in grey) but the retweets may not be re-shared.

When analysing social networks, considering how individuals access the network is also relevant. Grewal (2009) suggested that individuals can access a network via 'standards'. He defined 'standards' as the social conventions, shared norms or practices that enable external users to become part of a network and allow internal members to access each other. A standard could be a language, such as English, or even a topical hashtag. For example, to access the anti-vaccine community and communicate with the other members, a user may use the hashtags #CDCWhistleBlower or #vaxxed. Without including or following these hashtags, a user could not access the anti-vaccine network. Understanding how users access a network could provide more information on its structure and communication dynamics (Grewal, 2009).

2.3.1 Key actors: hubs and brokers

Social network analysis also allows identification of those actors that act as 'hubs' or 'brokers' of information in the network or community (Kumar, Morstatter and Liu, 2013). The connections with members and outsiders allow this type of actors to potentially control the information flow within the network

(Himelboim, 2017)[5]. These actors are sometimes called influencers since they can influence the information that reaches their networks. However, defining influence on social media is not an easy task, since scholars cannot measure it directly: researchers can see the flow of tweets in a community as well as their follower/followee relationships, but they cannot determine if an actor changed others' perception or opinions (Himelboim, 2017). For this reason, this research did not seek to identify 'influencers' and 'opinion leaders' but 'key actors', who were defined as users occupying strategic or central positions within the network from where they can potentially control and influence the information flow (Grewal, 2009).

This study identified key actors based on a ranking by number of retweets rather than by number of followers, because highly retweeted messages gain high visibility even if they are shared by actors with less than a thousand followers (Kwak *et al.*, 2010). Moreover, the likelihood of a tweet being shared does not depend strictly on the number of followers, but also on the content of the messages itself (Suh *et al.*, 2010). In this research, key actors were categorised as hubs and brokers. Himelboim (2017) described hubs are actors whose content is highly shared by others and they occupy a central position in the network. These actors are highly connected to other users, but their relationships are unidirectional: they do not retweet the members of their wide audience (Himelboim, 2017). Brokers, instead, are actors who connect other users or groups of users that otherwise would not be linked (Himelboim, 2017). These actors can access new information and control its flow within the network (Kadushin, 2011). Both hubs and brokers can influence the information flow in the network by selecting the information to share with their public. In this study, a third type of actor was also analysed. These actors highly retweet other users but they are hardly retweeted themselves; hence, they do not control the dissemination of information in a network like brokers and hubs (Himelboim, 2017). However, by retweeting they amplify the visibility of other people's messages (Harrigan, Achananuparp and Lim, 2012).

[5] Chapter 4 provides a detailed explanation of social network analysis.

2.4 Activism and social media

The Internet and social media outlets have not only provided alternative means for communication and networking, but also for activism: advocacy groups and non-profit organisation use social media, especially Facebook and Twitter, for civic engagement (educating and informing the public) and collective action (Obar, Zube and Lampe, 2012). Advocacy groups perceive social media as an effective tool for accomplishing their organizational and advocacy goals, for sharing information on the organisation and the cause they support, building a community, and calling for action (e.g. donation, protest) (Auger, 2013; Obar, Zube and Lampe, 2012). Obar, Zube and Lampe (2012) found that through social media, these organisations can reach citizens that are not engaged in the cause as well as reaching local and global audiences, communicating and interacting with citizens, and engaging the public in collective actions at relatively low cost and high speed. Moreover, the two-way communication enabled by social media allows advocacy groups to engage individuals effectively in their cause, create and maintain a sense of unity with their members and followers (i.e. community building), and connect with their networks strategically thus facilitating collective action (Obar, Zube and Lampe, 2012). However, though in Obar, Zube and Lampe's study (2012) advocacy groups claim social media outlets act as two-way communication tools, Auger (2013) found that these types of organisations mostly use social media platforms for one-way communication and persuasion.

Advocacy groups use different platforms depending on what purpose they want to achieve. For example, non-profit organisations use Twitter for community building, while they prefer Facebook for sharing information and mobilisation (Auger, 2013). However, Guo and Saxton (2014) found that Twitter can be used effectively to raise awareness of issues, form an online community and call for collective action. On Twitter, advocacy groups can share information about their cause strategically to reach and educate the target audience (Guo and Saxton, 2014). By engaging with the public and reinforcing their ties, advocacy groups can create a community that shares their values. Building a community is a fundamental step for a successful online advocacy campaign, because as a community the members strongly support the advocacy group and they are more likely to join a collective action when the group calls for it (Guo and Saxton, 2014).

2.4.1 Online grassroots activism

Castells (2009) theorised that an online social movement is defined by the values and practices shared by its members, its self-definition, its adversary (the principal enemy it identified) and its societal goal. The societal goal is the movement's vision of social order, of what it wants to achieve through social action. For example, adherents to the anti-vaccine movement do not vaccinate their children (shared practice and self-definition), as such, this movement is reacting to governmental vaccination policies, healthcare services, healthcare professionals and pharmaceutical companies that make vaccines (adversary) and they want to stop mandatory vaccinations (societal goal). Moreover, Castells (2019) stated that an online social movement:

- Develops as a reaction[6] to the prevailing social trends or adversaries;
- Is defensive and offers solidarity and protection from the outside world;
- Is organised around a specific set of values, shared by all members (i.e. users identify themselves with values and practices shared with the rest of the community).

Online social movements and online communities (see Section 2.1.1) share a common aspect: they both have a collective identity shared by their members, which they express through values, practices and activities (Castells, 2009; Baym, 2010). This means that activists do not only promote social change, but they also put their collective ideals into practice in their everyday lives to contribute to this transformation (Lievrouw, 2011). For example, an anti-vaccine activist would not vaccinate his/her children and would promote this position inside and outside the movement as an example to follow to bring about social change (i.e. stop mandatory vaccinations). Moreover, digital platforms contributed to the shift from strictly defined activists groups (e.g.

[6] A reactive community does not accept social trends or established systems, but it does not have any alternative plan to the existing ones.

advocacy groups, NGOs), which have centralised and hierarchical structures, to loosely defined movements (i.e. grassroots activism) (Vegh, 2003). These movements have a decentralised and heterarchical organisational structure (Lievrouw, 2011; Castells, 2009), like the online communities of prosumers (Bruns, 2008).

A heterarchical organisation does not completely exclude the presence of leaders in online activist movements, and Gerbaudo (2012) identified these roles in Twitter influencers and the administrators of Facebook groups and pages. These participants contribute to the internal and external communication of the movement's cause, and to the organisation of offline protests; however, they do not acknowledge themselves as leaders. Instead, leadership and authority within the movement is defined by the activists' number and quality of contributions to the campaign and can be dynamic (Gerbaudo, 2012), as in the case of the prosumers' communities (Bruns, 2008). Gerbaudo (2012) found that leaders give coherence to their online activist movement by coordinating the information sharing inside and outside the group, and organising and coordinating the group's resources and protests. Moreover, leaders set the scene for collective action by creating emotional tension and attraction before demonstrations. Through social media informal communication, they can generate in individuals a sense of indignation, frustration and anger against the adversary, and aggregate these feelings together. This aggregation leads to the construction of an emotional digital space and of a collective identity that encourages participants to share a sense of unity against a common adversary (Gerbaudo, 2012). Forming a collective identity is fundamental for online movements since it allows them to bring and keep together highly geographically dispersed individuals, and therefore it facilitates their physical assembling and mobilisation during a protest (Gerbaudo, 2012; Castells, 2009). Gerbaudo (2012) defined the leaders of online movements as 'choreographers' who set the scene for collective action: they create a symbolic and emotional public space on social media where dispersed individuals interested in the same cause gather and interact, and they eventually mobilise these participants into a protest.

Vegh (2003) claimed that online activism includes more than mobilisation and collective action. The author defined three categories of online activism: awareness/advocacy, organisation/mobilisation, and action/reaction. In the first case, activists use the Internet and social media outlets as an alternative means to spread information, raise public awareness on a particular topic, and create a network that can be used for mobilisation. Mobilisation can occur offline or online: for example, the activist movement can organise a protest on the street (offline action), or ask its network to sign a petition (offline action that is more efficient online), or ask its members to spam the adversary's website (online action). The third category, action/reaction, is related to the proactive and aggressive use of the Internet (e.g. hacking) (Vegh, 2003).

There are many concerns about the effectiveness of social media in driving revolutions and social mobilisations, because it is not possible to have a definite measure of social media influence on public opinion (Murthy, 2012). Moreover, social media users do not represent the whole target public, but only the part that has access to an Internet connection and uses these communication tools (Fuchs, 2013). For example, in the case of the Arab Spring, social media were used only by a small part of the population and they contributed mainly to spread information about the revolution, while interpersonal communication and traditional media were the most important sources of information and tools of communication (Fuchs, 2013). In the Egyptian revolution, activists used social media outlets to raise awareness and organise the protest, but they also engaged the lower classes (which did not use online platforms) by face to face interactions, street communication, TV channels, newspapers, flyers and posters (Gerbaudo, 2012).

Another limitation of social media is that activists may reach only users who already support their cause because there is a tendency for clusters of like-minded people to form (Baym, 2010). Social movements may not be able to raise awareness outside their group because they have insufficient visibility and popularity on social media in comparison with corporates, politicians and celebrities (Fuchs, 2013). Another factor that can limit the use of social media in driving social mobilisation is 'slacktivism'. Slacktivism occurs when users support the cause by liking and sharing the activists' content but they do not commit to offline protests (Baym, 2010). Even when social movements succeed in mobilising people and protesting on the streets, they often collapse afterwards instead of creating long term campaigns. This happens when the movements' organisers are not interested in transforming them into formal organisations (Gerbaudo, 2012).

2.4.2 Twitter activism

Twitter is used for online activism. For example, the Black Lives Matter movement used Twitter extensively, especially to raise awareness about their cause. This movement has used Twitter to create and support a community around the cause, posting calls for action as well as sharing information (Edrington and Lee, 2018). Twitter can also facilitate activists' discussion and engagement with organisations, news media and the public, and support mobilisations that are happening on the streets (Theocharis *et al.*, 2015). Gleason (2013) found that this outlet can also increase users' learning and understanding of activist movements by facilitating the dissemination of news and user-generated content about these groups, especially through hashtags. For example, users following the stream #OWS were exposed to different news, perspectives, information, and user-generated videos and pictures about the Occupy Wall Street movement. Hence, these users had a better understanding of the movement and its cause (Gleason, 2013).

As mentioned in Section 2.2, on Twitter social movements can bypass information gatekeeping (held by media outlets and corporates) and reach their target audiences directly. They can also build up their personal publics of supporters, and raise awareness of the cause among non-followers by tweeting specific topical hashtags (Schmidt, 2014; Bruns and Moe, 2014). Moreover, online communities can form around topical hashtags and they can develop into social movements (Murthy, 2012). Murthy (2012) observed that these movements do not necessarily develop from centralised networks of strong ties, but they can start as large-scale networks of weak ties. However, to increase their efficiency, movements often combine networks of strong/offline ties and of weak/online ties. For example, the Occupy movement used its weak-ties networks on Twitter to spread real time updates about the movement and recruit participants. In the Arab Spring, Twitter was mainly used to communicate real-time information and personal experiences of the revolution to journalists from Western countries, thus spreading information around the world and bypassing the official governmental communication channels (Murthy, 2012).

What differentiates Twitter from other social media outlets used for advocacy are hashtags (see Section 2.2). Hashtags have a fundamental role for both advocacy organisations and grassroots movements (Guo and Saxton, 2014; Murthy, 2012). NGOs, non-profit organisations and social movements can use topical hashtags to aggregate knowledge on specific issues or situations, and tweet *ad hoc* hashtags (related to the campaign) to disseminate updates and information, and to organise and mobilise street protests (Guo and Saxton, 2014). In the case of grassroots movements, hashtags offer a space for emotional support and solidarity, which can spontaneously develop into a social movement (Murthy, 2012). For example, Clark (2016) found that the hashtag #WhyIStayed[7] started as a place where victims of domestic abuse seek emotional support and share their personal stories and outrage about the limitations of gender justice. The hashtag gradually obtained more and more participants and transformed into an online collective protest that raised awareness of the reality of domestic abuse and the limitations of current legislation. The movement's campaign was able to reach media's attention (Clark, 2016). Twitter is used by a wide range of social movements (e.g. #BlackLivesMatters, #WhyIStayed, #BringBackOurGirls, #MeToo), including anti-vaccine groups. The next section provides an overview of anti-vaccine activism on digital media.

[7] In 2014, the media released a video showing a celebrity punching his fiancée, which started a public debate on domestic abuse. Then, the domestic abuse survivor and activist Beverly Gooden launched #WhyIStayed to continue the debate on Twitter.

2.4.3 Online anti-vaccine activism

Anti-vaccine activists use different digital media for advocacy, and their online campaigns can potentially influence public risk perception about vaccines (Ołpiński, 2012). For example, previous research demonstrated that consulting anti-vaccination websites can increase the perception of the risk of vaccine side effects and decrease the perception of the risk of vaccine-preventable diseases (e.g. measles) and the intention to vaccinate (Betsch *et al.*, 2010). The dissemination of anti-vaccine conspiracy theories seems to be particularly effective, as they raise concerns about vaccine safety and mistrust in medical authorities (Jolley and Douglas, 2014).

Though anti- and pro-immunisation websites have the same visibility online, there are more web domains against vaccination than in favour (Ninkov and Vaughan, 2017). Pro-vaccine websites appear in online search results more often when users search for terms such as "immunis(z)ation" (Wolfe and Sharp, 2005), and they focus on the dissemination of correct scientific information about vaccination, especially that endorsed by governmental and medical authorities (Grant *et al.*, 2015). Anti-vaccine websites, instead, appear more often among online search results when users search common keywords, such as "vaccine" or "vaccination" (Wolfe and Sharp, 2005). They disseminate concerns about vaccine safety and effectiveness, and campaign against mandatory vaccines and for the right to decide whether to vaccinate themselves or their children. They also spread conspiracy theories about vaccination and call for searching for the truth about vaccines, which includes consulting alternative sources of information (Kata, 2010; Davies, Chapman and Leask, 2002). To make their claims persuasive, anti-vaccination websites share personal stories and testimonials, but they also use experts' opinions and (pseudo)science (Moran *et al.*, 2016).

Similar anti-vaccination arguments and persuasion techniques were found on Facebook (Hoffman *et al.*, 2019), YouTube (Yiannakoulias, Slavik and Chase, 2019; Briones *et al.*, 2012) and Twitter (Love *et al.*, 2013). On Twitter, anti-vaccination messages mainly claim that vaccines are dangerous and encourage vaccine refusal by sharing personal stories, anecdotes, opinions and misinformation (Dunn *et al.*, 2015; Love *et al.*, 2013). Moreover, anti-vaccine users tend to promote and believe conspiracy theories related to vaccination (Mitra, Counts and Pennebaker, 2016). Previous studies of the vaccine debate on Twitter found that most of the tweets shared are neutral, and there are more pro-immunisation posts than anti-vaccination posts (Love *et al.*, 2013; Salathé and Khandelwal, 2011). Moreover, since 2015 the volume of pro-vaccine tweets has increased, especially alongside seasonal surges, whereas that of anti-vaccine tweets have decreased though the number of users sharing them has doubled (Gunaratne, Coomes and Haghbayan, 2019).

Pro- and anti-vaccine users form two polarised communities on Twitter which rarely interact with each other (Bello-Orgaz, Hernandez-Castro and Camacho, 2017; Dunn *et al.*, 2015; Salathé and Khandelwal, 2011). The pro-immunisation group tends to be more open to outsiders than the anti-vaccine one, and its members are better connected. The anti-vaccination users, instead, form a structural community that does not interact with outsiders, and rather than engaging in discussion, like those in favour of vaccination, they only re-share each other's content (Himelboim *et al.*, 2019; Yuan, Schuchard and Crooks, 2018; Bello-Orgaz, Hernandez-Castro and Camacho, 2017). The users of the anti-vaccination community are often non-traditional sources of information and they share negative and angry messages about vaccines and/or links to emerging/alternative news websites. The pro-vaccine ones, instead, are usually more credible sources (e.g. health organisations) and tend to share positive messages about immunisations and/or links to news from mainstream media (Himelboim *et al.*, 2019; Meadows, Tang and Liu, 2019). The tendency of anti-vaccine users to believe and share conspiracy theories could explain why they seek alternative knowledge about vaccinations and refuse to interact with pro-vaccination users (Mitra, Counts and Pennebaker, 2016).

Though there are extensive studies on the relationships within and between anti- and pro-vaccine communities and the content they share, especially on Twitter, there is little research on the images posted by these groups. Guidry et al. (2015) found that most of the vaccine images shared on Pinterest are anti-vaccine and convey information through narratives, rather than statistical information, whereas the pro-immunisation images do the opposite. Moreover, the authors found that anti-vaccine images frequently express concerns about the safety of vaccines and accuse governmental organisations and pharmaceutical companies of promoting vaccination for financial gain. Considering that anti-vaccine images on Pinterest display narratives, Western cultural stereotypes and symbols (e.g. white children, syringes), and strong emotions (Guidry *et al.*, 2015; Milani, 2015), they could potentially increase the perceived risk of vaccinating amongst Western viewers (Betsch *et al.*, 2011). Chen and Dredze (2018) found similar imagery on Twitter – they reported that injections and babies are the most common visual elements among vaccine images. Moreover, vaccine pictures increase the sharing rate of tweets, especially if they show a positive or negative sentiment (Chen and Dredze, 2018).

Though there are several studies of vaccine networks on Twitter (Bello-Orgaz, Hernandez-Castro and Camacho, 2017; Salathé and Khandelwal, 2011) and vaccination images affect the visibility of tweets (Chen and Dredze, 2018) and can be potentially persuasive (Guidry *et al.*, 2015), there are no studies that link the content and messages of these images to the Twitter communities sharing them. Moreover, none of the previous studies on vaccine images considered the context where these images were shared, even though context can change the meaning of social media images (Rigutto, 2017; Geboers and Van De Wiele, 2020)

2.5 Visual communication

The rapid development of digital devices and the rise of the Internet and social media outlets have affected picture production, dissemination and consumption, making them more and more rapid. Therefore, digital images have become common and pervasive in the postmodern society, contributing to the formation of visual culture (Mirzoeff, 2009). Using a camera, a smartphone, or a laptop, anyone can create, modify, re-contextualise and share images online quickly, showing their personal views of the world. Thus, images are visual representations of the world made by society; they depict the world depending on what and how each cultural group in society sees it (Mirzoeff, 2009).

Viewing and posting images is a popular activity on social media (Cooper, 2019). On Twitter, embedded pictures can increase the visibility and sharing rate of tweets (Suh *et al.*, 2010). Furthermore, embedding pictures allow users to overcome the tweets character limit and further explain their opinions and thoughts (Giglietto and Lee, 2017). Thelwall *et al.* (2016) found that Twitter users regularly post personal photographs to update relatives and acquaintances. However, images are tweeted for other reasons too. For example, Twitter users post pictures to document events in real-time and share their feelings and thoughts during a crisis, like the 2011 UK riots (Vis *et al.*, 2013). The type of images shared to document a social movement or a revolution may differ depending on the political views of the Twitter users (Seo, 2014) or the stage of the revolt (Kharroub and Bas, 2015). For example, Kharroub and Bas (2015) found that the type of images posted on Twitter during the Egyptian revolution in 2011 varied with the revolutionary phases. While before and during the revolt there were more photos about crowds and protests, at the end there were more images depicting national and religious symbols. The authors hypothesised these symbols aimed at uniting the population around shared identities (Kharroub and Bas, 2015).

Images are interpreted differently depending on who produces them, what they depict and how, and their audience (Rose, 2012). Harris and Lester (2001) stressed the importance of considering the audience's visual literacy when communicating visually. They emphasised how individuals interpret an image based on their visual perception, cognitive processes, individual experience, culture and society. Therefore, two people are not likely to read an image in the same way. Moreover, audiences need a certain visual literacy to identify and interpret the figurative elements of an image (i.e. people, animals, objects, buildings represented). Figure 2.3 provides an example of these dynamics; the image resembles those used to represent vaccines and vaccinations on Twitter and on print media (Chen and Dredze, 2018; Catalan-Matamoros and Peñafiel-Saiz, 2019). If the audience have never seen a syringe before, they may not recognise it. If they know what it is, they may not interpret it as representing vaccines or vaccinations, but could misread it as referring to blood tests or drugs and drug addiction, depending on their experience and cultural background. To avoid this problem, Harris and Lester (2001) suggested including text that contextualises the picture and guides its interpretation. However, online images are often stripped from their original context and they can acquire new meanings and interpretations (Rigutto, 2017).

Figure 2.3 Example of photos about vaccines.
Photo via Pixabay.

The figurative elements of an image can be conventional signs used to represent objects and convey meanings in a specific community or network (Lester, 2014). If the community members recognise those elements and their interpretations, they likely use them to communicate with each other. Therefore, figurative elements can be like words of a language, a visual language that acts as a 'standard' through which access to certain networks (Grewal, 2009). For example, anti-vaccine users may share images with specific figurative elements that are commonly recognised and used by the members of the community.

2.5.1 Images used for advocacy

To convey their message effectively, images used for advocacy and advertisements use rhetorical figures, semiotic signs, and stereotypes tailored on their audience. These tailored elements recall the views of the world of the target public (Lester, 2014). Therefore, these figurative elements differ depending on who produced the image, which message they intend to convey, their target audience, and the medium in which the image is shared (Indira Ganesh *et al.*, 2014). For example, images diffused through the traditional media depict a topic differently from those disseminated by NGOs because they convey different message to the same public (i.e. sharing news vs. persuading donation, respectively) (Ali, James and Vultee, 2013).

Target audience, medium, design and message are all factors that contribute to the persuasiveness of an image (Indira Ganesh *et al.*, 2014). For example, different messages had a different impact on public attitudes towards smoking; anti-tobacco advertisings about industry manipulation and second hand smoke were found to be more effective than those about addiction and cessation (Goldman and Glantz, 1998). There are other factors that contribute to the capability of an image to influence public perception or behaviour, such as the type of hazard and the emotional intensity of the image (Xie *et al.*, 2011). For example, anti-tobacco advertisements that elicit strong negative emotions can influence public attitudes toward smoking (Goldman and Glantz, 1998). The efficacy of negative advertising has been criticized by scholars, but it was effective in an anti-tobacco “Truth” campaign (Apollonio and Malone, 2009) as well as in a campaign against the animal food-processing industry launched by People for the Ethical Treatment of Animals (PETA) (Scudder and Bishop Mills, 2009). In the latter case, highly emotional negative advertisements further reduced the public perceived credibility of farming, whereas it increased the perceived credibility of PETA (Scudder and Bishop Mills, 2009).

Fearful images used for advocacy are not always effective. For example, they have not been able to engage audiences with climate change (O’Neill and Nicholson-Cole, 2009). Braasch (2013) claimed that images used for advocacy about climate change are barely effective in both educating and engaging the public, mostly because the public do not perceive the effects of climate change. However, a visual campaign promoted by Greenpeace was able to bring public attention to the climate change issue using photographs that depicted melting glaciers (Doyle, 2007). Chapman *et al.* (2016) conducted a study to understand what type of images are more effective at engaging the public about climate change issues. For example, the authors observed that images showing serious local impact of climate change were more persuasive than those representing global impact (Chapman *et al.*, 2016).

Similar studies are needed to understand what images should be used to communicate about vaccines and persuade the public to vaccinate. Images are not all equally effective at advocating in favour of vaccination; for example, Guidry *et al.* (2018) found that images with positive messages were more effective than those with negative messages at increasing Zika vaccine uptake. Moreover, Nyhan *et al.* (2014) observed that images showing children affected by vaccine-preventable diseases do not reduce vaccine hesitancy. As mentioned at the beginning of this Section, images used for advocacy can convey messages effectively if they have figurative elements tailored to the target audience (Indira Ganesh *et al.*, 2014). If the target audiences are online communities and networks, it is possible to find out what figurative elements they recognise and use by analysing the images they share (Lutkenhaus, Jansz and Bouman, 2019). Therefore, this research aims to investigate the images shared by pro- and anti-vaccine networks to understand what figurative elements and what visual communication strategies they use to persuade their audiences.

2.5.2 Science and health images

As discussed in the previous Section, images can be used for advocacy, for example, to persuade the public to adopt a certain behaviour (e.g. to vaccinate or not) (Lester, 2014). Images can also be used to facilitate public understanding of a health intervention (Katz, Kripalani and Weiss, 2006) or a scientific concept (Bucchi, 2005). Katz, Kripalani and Weiss (2006) emphasised that pictorial aids in medical labels increase comprehension and adherence to medical instructions. However, images are most effective at facilitating patients' understanding of health information when they are combined with lay written or oral instructions, rather than alone (Katz, Kripalani and Weiss, 2006). Houts *et al.* (2006) observed that pictures associated with text can increase attention and recall of health information as well, and adherence to medical instructions. Moreover, the authors claimed that images particularly help patients with low literacy skills to understand health information. However, not all images are effective at communicating health information. Houts *et al.* (2006) emphasised that images should represent the target audience. For example, if the health intervention targets patients from an African country, the images should depict people, objects and environments from that that country, which the patients find familiar and can recognise easily.

There is also variability in the effectiveness of communicating science through visuals. Smith *et al.* (2011) found that the science literacy of viewers affects their understanding of astronomical images. Experts and non-experts elaborate colours, scale and explanations of astronomical pictures differently. For example, experts focus on the scientific aspects of astronomical images and need short, technical captions to understand them. Non-experts, instead, are captured by the aesthetic and emotional aspects of the images (Smith *et al.*, 2011). Trumbo (1999) emphasised that science literacy is not the only factor that influences the comprehension of scientific images; visual science literacy also plays an essential role. Viewers may not recognise the scientific objects depicted in the pictures or understand the scientific concepts that the images convey (Trumbo, 1999). For example, to recognise and understand that Figure 2.4 shows a model for a prototype of a universal flu vaccine, viewers need both a biology background and high visual science literacy. Visual science literacy can help to identify the helixes as proteins, and to interpret the different colours as two different types of protein forming the whole complex. Depending on the level of visual science literacy, viewers can understand how the structure of each protein helps them bind in a complex and how they may work together as a vaccine. Without biological visual literacy, viewers cannot understand what Figure 2.4 represents and means. Some scientific images can be easily recognised by viewers, almost independently of their level of visual science literacy. Bucchi and Saracino (2016) found that the DNA double helix and Einstein's face were familiar to most interviewees, though the scientific concepts or scientific relevance they represent may not be clear to the viewers. These scientific images could work as a hook to catch the audience’s attention, leading them to more substantial scientific information (Bucchi and Saracino, 2016).

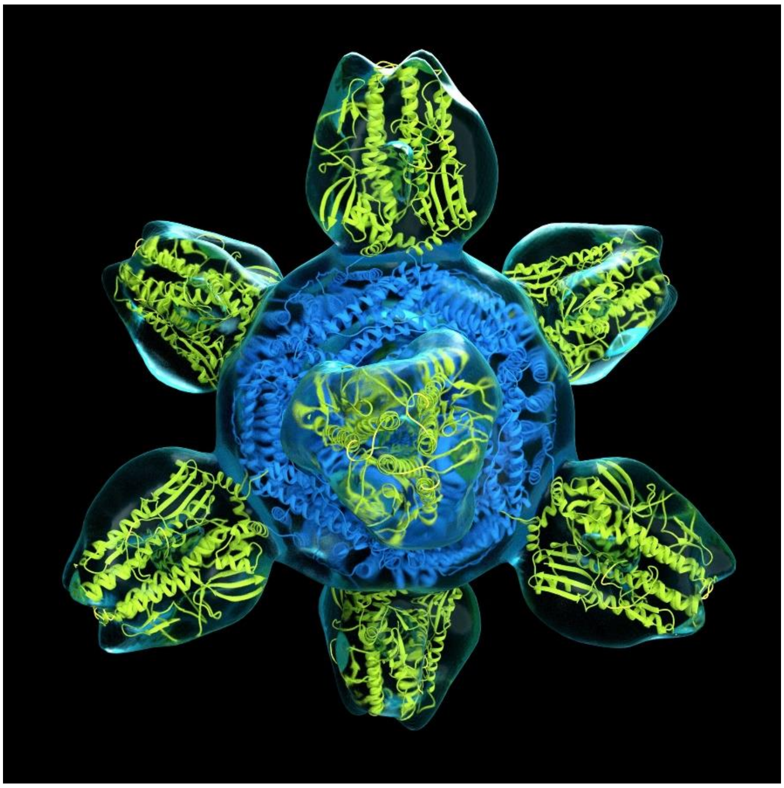

Figure 2.4 Example of a picture that requires high science and visual literacy skills.
“Prototype for a Universal Flu Vaccine” by NIH Image Library is licensed CC BY-NC 2.0.

Social and cultural contexts also play a role in how viewers interpret and make sense of scientific images (Davies and Horst, 2016). “Scientific images are produced within specific scientific cultures” and they have a certain meaning within these; however, “their meaning may be lost as they travel into different contexts” (Davies and Horst, 2016, p.163). This is particularly problematic in the digital space. Digital media may introduce another factor that influences understanding and even the functionality of science images: its integration within digital platforms (Rigutto, 2017). Rigutto (2017) suggests that scientific images may lose their original aim and meaning as images are frequently de-contextualised, manipulated and shared in platforms and to audiences different from the intended ones. Hence, scientific images explaining or simplifying scientific concepts may become ineffective or even misinforming in a new context. She further claims that online scientific images should be tailored for digital media and online audiences/communities, and focus on attracting attention and being accessible rather than just simplifying scientific concepts (Rigutto, 2017).

3. About this research study

Images have an essential role in science communication; they facilitate understanding of scientific concepts and phenomena (Davies and Horst, 2016; Pauwels, 2005) and of health interventions (Houts *et al.*, 2006), such as vaccination. However, in the digital environment images are often shared, modified and re-contextualised across different platforms and networks; hence their original function and message may change (Rigutto, 2017). In this study, the term *message* includes the piece of information that is communicated and everything around this piece of information. For example, if the information communicated is “vaccines are not safe”, the *message* also includes the visual, textual and contextual elements representing this information. Hence, the *message* is how a piece of information is illustrated, adapted and contextualised by an individual for an audience.

3.1 Framing visual communication

Indira Ganesh *et al.* (2014, p.15) said that, to design effective images, it is essential “to know how best to use the available technology, in order to deliver the necessary information in its appropriate form or design, to the relevant networks of people”. The authors claimed that the combination of information, technology, design and networks determines the communicative power of images and the efficacy of their relative campaigns. They defined design as the form in which information is conveyed to the public visually. The design should be compelling for and tailored to the audience. Indira Ganesh *et al.* (2014) conceptualise audiences as networks of people linked by cultural, social and political interactions, and as groups sharing cultural, social and/or political values. To access these networks of people, the authors recommended using the technology they use. Digital technologies include any tool for manipulating and/or sharing information, such as social media outlets and mobile devices.

Indira Ganesh *et al.* (2014) presented these guidelines for improving the design of images used for advocacy, but they can also be used as a framework to investigate visual communication strategies applied by specific individuals or groups. Therefore, this research studied anti- and pro-vaccine images disseminated on Twitter by considering the networks sharing them, the technology where they are shared, the information they convey and their design. Pauwels (2005) designed a framework for assessing scientific images specifically, which considered the levels of image production, such as the portrayed scientific concept or object, the message, the technology and means used to create the picture, the target audience, and the communicative aim. However, this framework is not suited for images shared on digital media, because online images are often re-shared losing their original context, hence their original aim, message and meaning (Rigutto, 2017). Figure 3.1 shows several of the factors that influence the message and communicative power of vaccine images shared on Twitter. These factors were considered when developing the methodology for this research study.

3.1.1 Networks and technology

Rigutto (2017) highlights the importance of understanding how digital media technologies work before researching the images that are shared on them. Technology and networks are interlinked; to study a specific group (e.g. anti-vaccine movements) is fundamental to know what technology they use and how. For example, previous research found that Twitter is used to communicate and share information about vaccines (Love *et al.*, 2013), including images (Chen and Dredze, 2018). Therefore, researching Twitter could provide insights into the communication of pro- and anti-vaccine networks.

As discussed in Section 2.2, Twitter is an information network where users follow interests and news updates (Ackland, 2013). Users can follow individuals who share similar interests and share updates with the people who follow them. In addition, users can use hashtags to follow topics and share posts related to their interests (Bruns and Moe, 2014). This means that anti- and pro-vaccine movements can advocate against or in favour of vaccination with their followers (personal publics) or with new audiences (*ad hoc* publics, through use of hashtags). Hence, they can reach like-minded users and/or those who seeking information about vaccination. Investigating whether anti- and pro-vaccine users use hashtags and what hashtags they use, can provide insights into how they use Twitter to reach their audiences, and what audiences they target.

These target audiences could also be members of a community formed around hashtags. Online communities, as well as online movements, have a heterarchical organisation and acknowledge their leaders or experts based on their contributions to the group (see Section 2.4.1). These movements/communities share information and news about the issue to raise awareness (Vegh, 2003), which means they produce their own knowledge on the topic. Depending on the relationships among members and the structure of the community, the knowledge produced may be more or less biased. For example, the members of a polarised community may share messages that reinforce their beliefs and exclude any information that supports a different perspective (Southwell, 2013). On the other hand, the members of an open network may want to enrich their knowledge on the topic by reaching out for outsiders (Southwell, 2013).

Analysing how information is shared within a network gives insights into whether the network is polarised, closed or open to outsiders (Kadushin, 2011). Moreover, by analysing the dynamics with which images are shared and re-shared within and between the anti- and pro-vaccine networks, it is possible to gain insights into their communication, relationships, and knowledge exchange/production. It is also possible to identify the actors who have a key role in the diffusion of information within the network; hence, it allows identification of potential leaders or gatekeepers (Murthy, 2011) within the network. These key actors may be traditional experts (e.g. healthcare practitioners) or alternative sources of information (e.g. parents) trusted by their community.

3.1.2 Information and design

Images are visual interpretations of the world (Rose, 2012); therefore, images shared by the pro- and anti-vaccine networks are their visual interpretations of vaccination. Moreover, these networks likely use a set of conventions to communicate with their members (e.g. words, hashtags) (Grewal, 2009). These become a set of figurative elements in the images they post. In this study, figurative elements are defined as objects, people, animals, buildings, plants, etc. depicted in an image that can be interpreted in several ways. For example, a person wearing a white coat could be interpreted by the viewer as such, or could be interpreted as a researcher. Knowing how pro- and anti-vaccine images use specific figurative elements to represent vaccination could provide insights into the culture and understanding of the users sharing them, and their intended audiences (Ledin and Machin, 2018; Lester, 2014; Pauwels, 2011).

Understanding the function and potential interpretation of the figurative elements of an image facilitates understanding the message it conveys (Penn, 2000). The design of an image, hence its figurative elements, are decided by the author. However, online images are often shared and re-shared in different contexts by users other than the original author. Chen and Dredze (2018) found that several vaccine pictures shared on Twitter were not original but they were taken from the Internet (e.g. other social media or image archives). Therefore, the original message of the image may change, depending on the new context and manipulation (Rigutto, 2017). The tweet and addition of text overlay can provide this new context (Pennington, 2016). Therefore, it is fundamental to consider not only the figurative elements of the images studied but their relationship with text and context (Pennington, 2016; Indira Ganesh *et al.*, 2014). Pictures can also be manipulated and become fakes, as happened during hurricane Sandy in the US (Gupta *et al.*, 2013). These manipulated pictures showed unnatural storms or even sharks swimming in flooded streets. Thus, they may pretend to show real events, when they do not. The same could happen with anti-vaccine images: they may be altered photos or show pseudoscientific evidence or experts' statements to support their claims.

Context (tweet), text overlay, manipulation, figurative elements and emotions (e.g. positive or negative) are all factors that can influence the interpretation of the information conveyed by an image. This interpretation is further influenced by how the network perceives the user who shares it (i.e. member of the network or outsider) and by the existing beliefs and values of the network (e.g. against vaccination or in favour) (Indira Ganesh *et al.*, 2014).

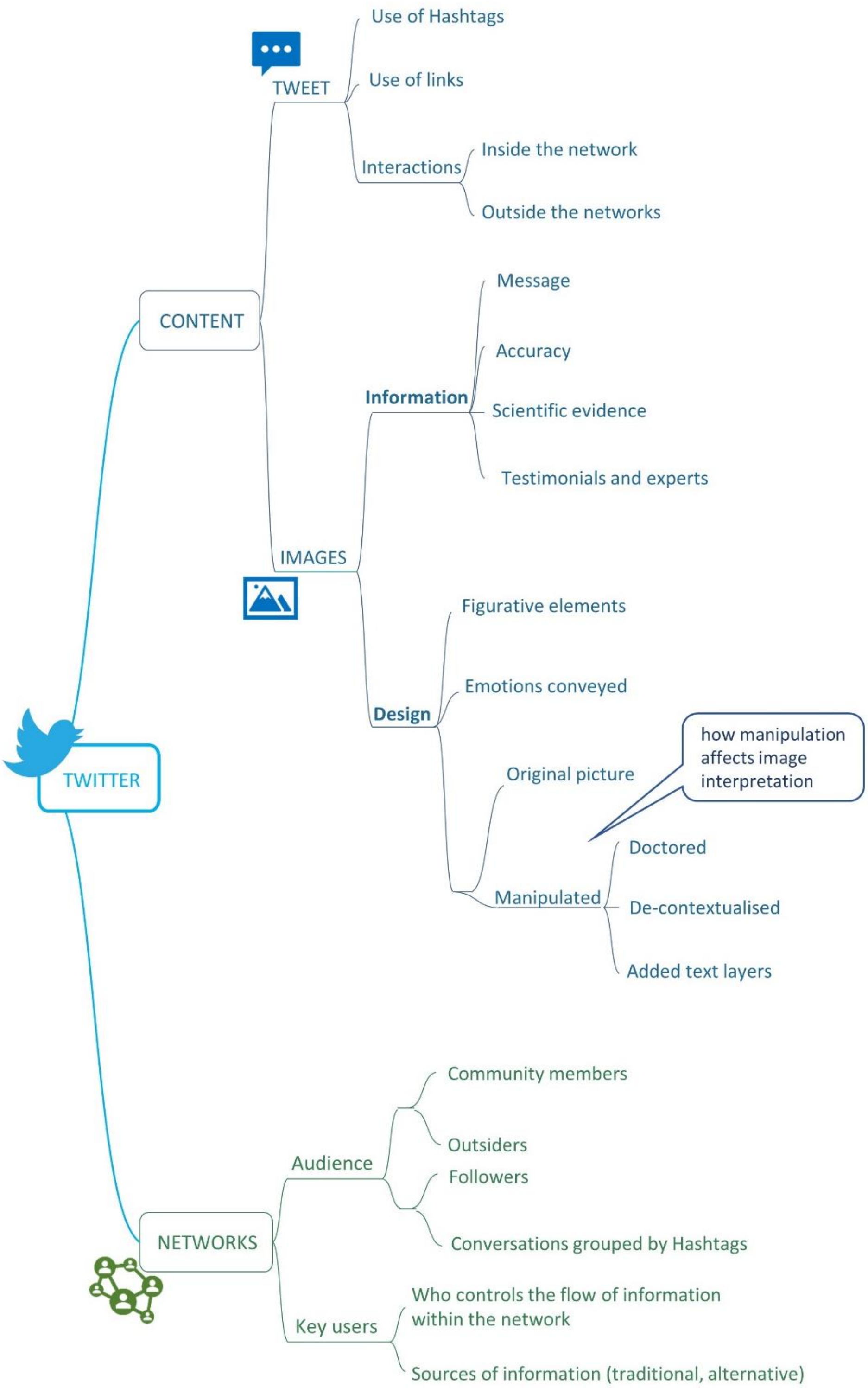

Figure 3.1 Factors influencing the interpretation and communicative power of an image shared on Twitter.

3.2 Aims and objectives

This research aimed to investigate anti- and pro-vaccine images shared on Twitter and the networks sharing them. It studied the content, messages, and dissemination of the images. Understanding how anti- and pro-vaccine images spread on Twitter can provide insights into the networks sharing them; for example, whether these networks are polarised or engaging with each other (Smith *et al.*, 2014). It can also provide information about the relationships between the members of the same network and their implications for vaccine communication campaigns on Twitter (Lutkenhaus, Jansz and Bouman, 2019). Therefore, the first research question of this study is:

RQ1) How are anti- and pro-vaccine images disseminated on Twitter?

As shown by Weitkamp *et al.* (Under review), the visible actors communicating about science topics in the digital ecosystem are diverse and beyond traditional scientific experts (see Section 2.1.3). In the case of the vaccine ecosystem on Twitter, however, previous studies focused only on specific influencers (Bello-Orgaz, Hernandez-Castro and Camacho, 2017). Therefore, the variety of key actors involved in the anti- and pro-vaccine networks was omitted. To fill this knowledge gap, the second research question is:

RQ2) How do the key actors differ between these networks?

When this research started, there were fewer studies on online vaccine images and they focused on Pinterest (Guidry *et al.*, 2015; Milani, 2015). Later studies investigated the content of vaccine images shared on Twitter but did not relate the content to the networks sharing them (Chen and Dredze, 2018; Lama *et al.*, 2018). Therefore, they did not unveil the full picture (see Section 2.4.3). By analysing the topics and the content of the images within the context of the networks sharing them, this research aimed to gain deeper insights into the anti- and pro-vaccine claims, and the figurative elements they use to convey messages to their members. Therefore, the next research question is:

RQ3) What do networks say about vaccines through the images they share?

The combination of figurative elements contributes to the message associated with images (Lester, 2014). However, many vaccine images on Twitter are not original but modified or re-contextualised versions (Chen and Dredze, 2018). Thus, to understand how anti- and pro-vaccine images convey their messages it is necessary to analyse not only their figurative elements, but their new context and transformation as well (see Section 2.5). Even so, previous studies on vaccine images did not consider how the context could influence the interpretation of these images (Chen and Dredze, 2018; Guidry *et al.*, 2015). Therefore, to fill this gap of knowledge, the final research question is:

RQ4) How do context and content combine in creating the images' messages?

3.3 A pragmatic approach

This research study applied a pragmatic approach to the methodology and interpretation of the results. Pragmatism was chosen since it accepts the coexistence of multiple realities and focuses on how to best answer the research questions (Feilzer, 2010). Morgan (2014) explained that pragmatism does not focus on the nature of truth and reality: it considers the world as both real and socially constructed, and knowledge as based on experience. Morgan highlights that pragmatism focuses on what knowledge (based on experience) is useful to provide the answers to the research questions; hence what methods would provide those answers. As Feilzer said (2010, p.13), pragmatism "aims to interrogate a particular question, theory, or phenomenon with the most appropriate research method".

By applying a pragmatic approach, this research focused on what methods would best answer the research questions. Several methods were studied and evaluated before deciding on the final research design. Social network analysis was chosen to investigate the dissemination of images within and between vaccine networks and to identify potential key actors. This method was applied in previous studies (Himelboim *et al.*, 2019; Bello-Orgaz, Hernandez-Castro and Camacho, 2017); it was used to address the first and second research questions (Section 3.2).

Finding the most suitable methods to answer the third and fourth research questions (Section 3.2) was more challenging. Visual content analysis was chosen in relation to the third research question as it provides insights into the recurrent figurative elements and topics included in vaccine images. To answer the fourth research question, an image analysis that focuses on deeper understanding of the messages conveyed by the images was applied (Ledin and Machin, 2018). However, most visual research methods analyse images from the perspective of a producer (author), product (image) or consumer (audience) (Rose, 2012), but online images are regularly shared by 'prosumers'. The roles of consumer and producer are blurred online (Bruns, 2008a), and images are often modified and/or de-contextualised (Rigutto, 2017). Therefore, the chosen methods were adapted in order to include the factors mentioned in Section 3.1 in the analyses (e.g. text, tweet, networks, and manipulation).

Once the methods were designed, they were applied first in a pilot study. The pilot study was conducted to verify whether the methods produced results that answered the research questions (Morgan, 2014). After the pilot study, the methods were adjusted and improved to find more satisfying answers to the research questions (Morgan, 2014). A main study was then conducted. Chapter 4 discusses the methods related to the social network analysis in detail, and Chapter 6 provides a detailed explanation of the methods applied to the visual analysis.

4. Social network analysis methodology

This chapter discusses the methods used to address the first two research questions: 1) How are anti- and pro-vaccine images disseminated on Twitter? 2) How do the key actors differ between these networks? To answer these questions, this research applied a pragmatic approach (see Section 3.3) and selected social network analysis as the most appropriate method. Social network analysis can provide insights into the dissemination of information in an online space, such as a Twitter conversation or community (Kumar, Morstatter and Liu, 2013; Kadushin, 2011), and into the actors that affect the information flow in that space (Grewal, 2009).

The reason why this research focused on the dissemination of the images and not just on their content, is because this can provide insights into the relationships among members of the same vaccine community and how they interact with outsiders (Kadushin, 2011). Hence, whether they only seek stories that confirm their beliefs or are open to new, alternative information (Southwell, 2013). Moreover, by analysing how vaccine images are shared, it is also possible to identify who influences their dissemination within a network. These actors act as gatekeepers of information: they control what information (or misinformation) enters the community (Murthy, 2012). Their position is not obtained by academic titles, but is based on the quality and quantity of their contribution to the community as judged by its members (Bruns, 2008a).

A pilot study was conducted to explore the visual vaccine debate on Twitter, and test and refine the methodology. The pilot study focused only on vaccine hashtags (Section 4.1.1) to explore ephemeral *ad hoc* audiences and potential long-standing communities that formed around these hashtags (Bruns and Burgess, (2015), see Section 2.2.3). As this is the first research on the dissemination of vaccine images on Twitter, the pilot study investigated the dynamics of the visual vaccine debate and explored whether these dynamics were recurrent (as in an established community) or not. Once the pilot data were analysed and the methodology was finalised, a main study was conducted. The main study was more inclusive than the pilot one, and explored *ad hoc* publics, vaccine communities formed around hashtags, and personal publics (Bruns and Moe, 2014; see also Sections 2.2). In this way, it was possible to compare the two studies and gain a deeper understanding of the use of hashtags by the anti- and pro-vaccine and news-related networks (see Section 4.1.2). The following sections will discuss the methodology in details and show the changes made for the main study.

4.1 Data collection

Data gathering and network analysis were conducted using the software NodeXL Pro, developed by the Social Media Research Foundation (Social Media Research Foundation, 2020). The software retrieves a maximum of 18,000 tweets, a limit determined by Twitter policy, or for a maximum of 7-8 days retrospectively, depending on how many posts were shared during that period. The software gathers data from Twitter based on criteria set by the researcher, such as keywords and filters, which have to be established carefully beforehand. The choice of criteria can have a significant influence on the data gathered and hence the research outcomes - for example, depending on the keywords selected, the collection will be either more inclusive or exclusive. Because the pilot study was exploratory whereas the main study was a deeper investigation of the dissemination of vaccine images, they applied different inclusion criteria. These differences are detailed below.

4.1.1 Pilot study data collection

For the pilot research, Twitter data were collected three times: on 30th June, 13th September, and 11th October 2016. The data collections periods were chosen at random. The tweets gathered had been posted from the 26th to the 30th of June, from the 9th to the 13th of September, and from 4th to the 11th of October. Each time a limit of 4,000 tweets was set, as the aim of this pilot was to explore the Twitter conversations about vaccines and polish the methodology. Metadata such as following-follower relationship were not collected because the focus of this study was on networks based on retweet relations.

4.1.1.1 Collection criteria - Keywords

Previous studies of Twitter conversations about vaccines used generic keywords such as vaccination(s), vaccine(s), vaccinate, and immunis(z)ation (Love *et al.*, 2013; Salathé and Khandelwal, 2011). However, this pilot study aimed to explore the macro-layer communication of vaccinations on Twitter, where users tweet topical hashtags (e.g. #vaccines) to join vaccine conversations and reach new audiences (i.e. non-followers) (Bruns and Moe, 2014). Therefore, instead of including words in the collection criteria, the pilot study considered Twitter hashtags about vaccines. To do this, first the keywords used by Love et al. (2013) and Salathé and Khandelwal, (2011) were converted into hashtags (e.g. #vaccine(s)). Then these hashtags were searched on Twitter to verify whether they were used to talk about vaccinations. Since Twitter users could include other vaccine-related hashtags in their tweets other than those, two online tools were used to find additional keywords: Symplur (Symplur LLC., 2020) and Hashtagify.me (CyBranding Ltd., 2020). Symplur offered a free database of Twitter hashtags about health-related topics, whereas Hashtagify.me provides Twitter hashtags correlated to the keywords of interest (e.g. #autism, #fluvaccine) and the strength of the correlation. Examples of the keywords and hashtags found are listed in Table 4.

Searched Hashtags	Hashtagify.me	Symplur
Vaccine(s)	#vaccines	#vaccines
Vaccination(s)	#CDCwhisteblower	#vaccineswork
Immuniz(s)ation	#autism	#vaccination
Vaccinate	#vaccineswork	#vaccine
	#CDCtruth	#immunization

Table 4.1 Examples of keywords searched and their corresponding hashtags as found using Hashtagify.me and Symplur.
The first column includes keywords adapted from Love et al. (2013) that were searched on the two tools.

After identifying the potential vaccine hashtags in Symplur and Hashtgify.me, each hashtag was searched on Twitter to check whether it was relevant to vaccination, how often it was used, and with which other hashtags it was associated. Different types of hashtags were found (see full list in Appendix A):

some of them were used to talk about vaccination in general, others were related to specific immunisation campaigns or specific vaccines or diseases. There were also hashtags that were not strictly linked to vaccinations, such as #BigPharma, #health, #parents...

Since the relevancy, frequency and co-occurrence were highly variable among hashtags, a sample of them was selected for the data collection. The choice was based on:

- High Frequency – hashtags tweeted many times a day for consecutive days for more than a month were selected;
- High Relevancy – hashtags labelling conversation about vaccinations were chosen, for example, #vaccinations was selected while #health was excluded;
- Generality – hashtags labelling generic conversations about vaccines were chosen, for example, #vaccine(s) was selected while #gardasil and #fluvaccine were excluded;
- Vaccine perspective – hashtag used in anti-vaccine or pro-vaccine conversations specifically were included, for example, #CDCwhistleblower and #vaccineswork.

Following these criteria, the final sample of hashtags used in the pilot included: #vaccine(s), #vaccination(s), #immunization, #vaccineswork, #vaccineinjury, #antivax, #whyIvax, #CDCwhistleblower. Before starting the pilot data collection, the selected hashtags were tested as criteria for the data collection. The research collected a small sample of tweets (less than 1,000 posts) written in English, having at least one of the hashtags mentioned above and an embedded picture. The recurrent hashtags were analysed to confirm that they were used to discuss vaccine topics. Through this procedure, a new hashtag was identified, #vaxxed, which was a new trending keyword, highly used and very relevant to the topic. Moreover, the hashtag #hearus was reconsidered since it turned out to be highly relevant in the preliminary dataset. By analysing the tweet sample, it was also possible to assess the vaccine perspective of the conversations labelled by the new hashtags, and select a final sample that included an equal number of frequently used anti-, pro- and neutral hashtags (see Table 4.2). The full process of keywords selection for the collection criteria is illustrate in Figure 4.1.

Hashtag	Sentiment	Description
#vaccine	Neutral	Used in either pro- or anti-vaccine conversations
#vaccines	Neutral	Used in either pro- or anti-vaccine conversations
#vaccination	Neutral	Used in either pro- or anti-vaccine conversations
#vaccinations	Neutral	Used in either pro- or anti-vaccine conversations
#vaxxed	Anti-vaccine	Launched in relation to *Vaxxed the movie*[8], it became a trending hashtag
#CDCwhistleblower	Anti-vaccine	About supposed fraud and conspiracy at the Centre for Disease Control and Prevention (CDC)
#VaccineInjury	Anti-vaccine	About vaccines' side effects
#HearUs	Anti-vaccine	Call to action
#VaccinesWork	Pro-vaccine	Used mainly by scholars and NGOs
#immunization	Pro-vaccine	Immunisation is not as popular as the American immunization
#WhyIVax	Pro-vaccine	CDC campaign
#AntiVax	Pro-vaccine	About the anti-vaccine movement and their claims

Table 4.2 Final sample of hashtags used for data collection.

[8] *Vaxxed the movie* is a documentary about Andrew Wakefield, which support the existence of a link between MMR vaccine and autism, and of a conspiracy against him.

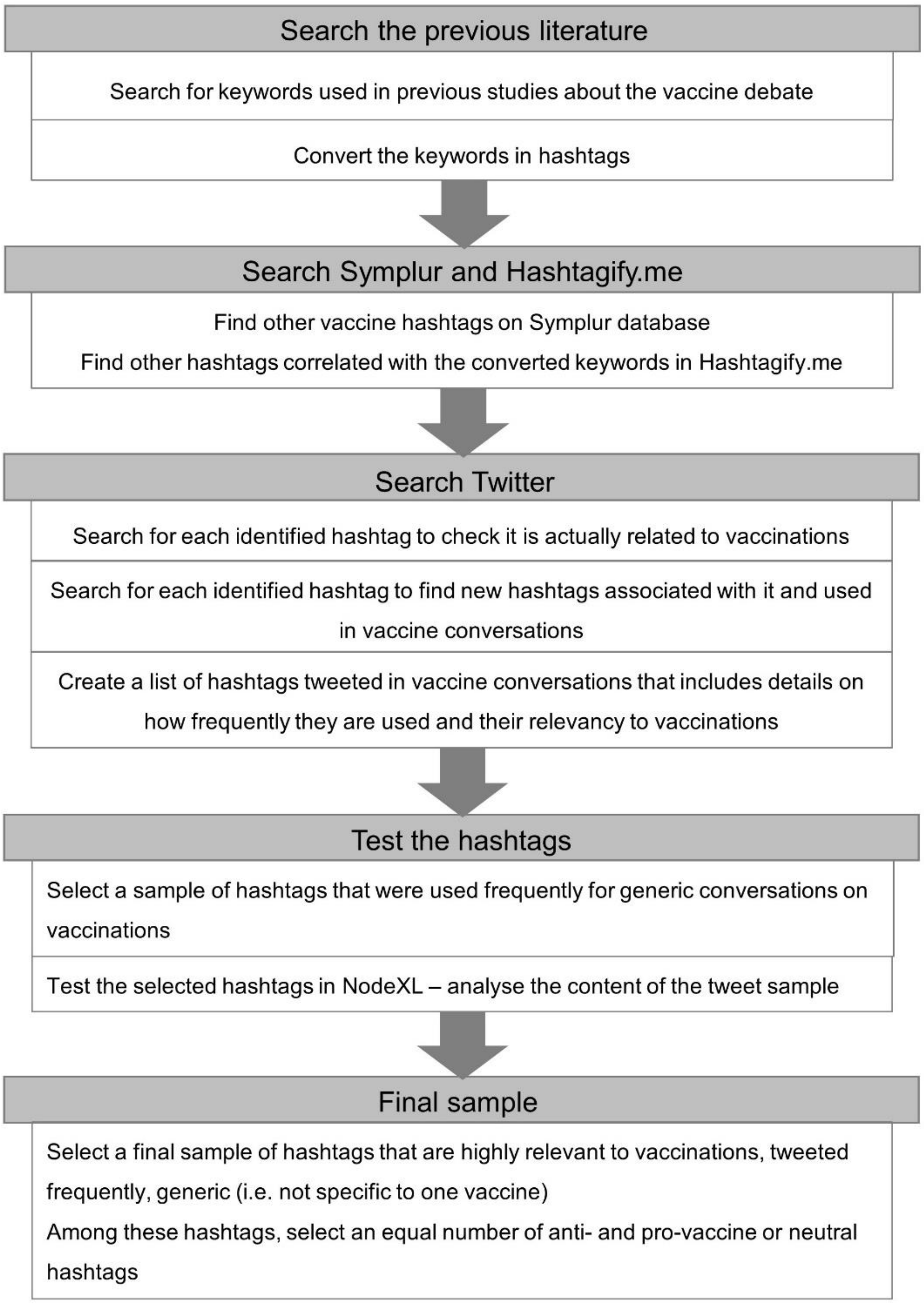

Figure 4.1 Hashtag selection process.
The diagram above shows the steps taken in selecting the keywords for the collection criteria of the pilot study.

4.1.1.2 Collection criteria – Advanced search operators

The software NodeXL imports a Twitter search network based on specific criteria given in the query box (Figure 4.2) – it uses the query to build up the API[9] and returns the tweets that match the criteria. NodeXL accesses and retrieves data from Twitter through the Representational State Transfer API (REST API) (Twitter, Inc., 2018a; Hansen, Shneiderman and Smith, 2010). The query was defined using the advanced Twitter search operators (Twitter, Inc., 2018b). These operators set the criteria for an advanced search on Twitter, for example filtering only the tweets containing a certain word or hashtag or shared by a specific user.

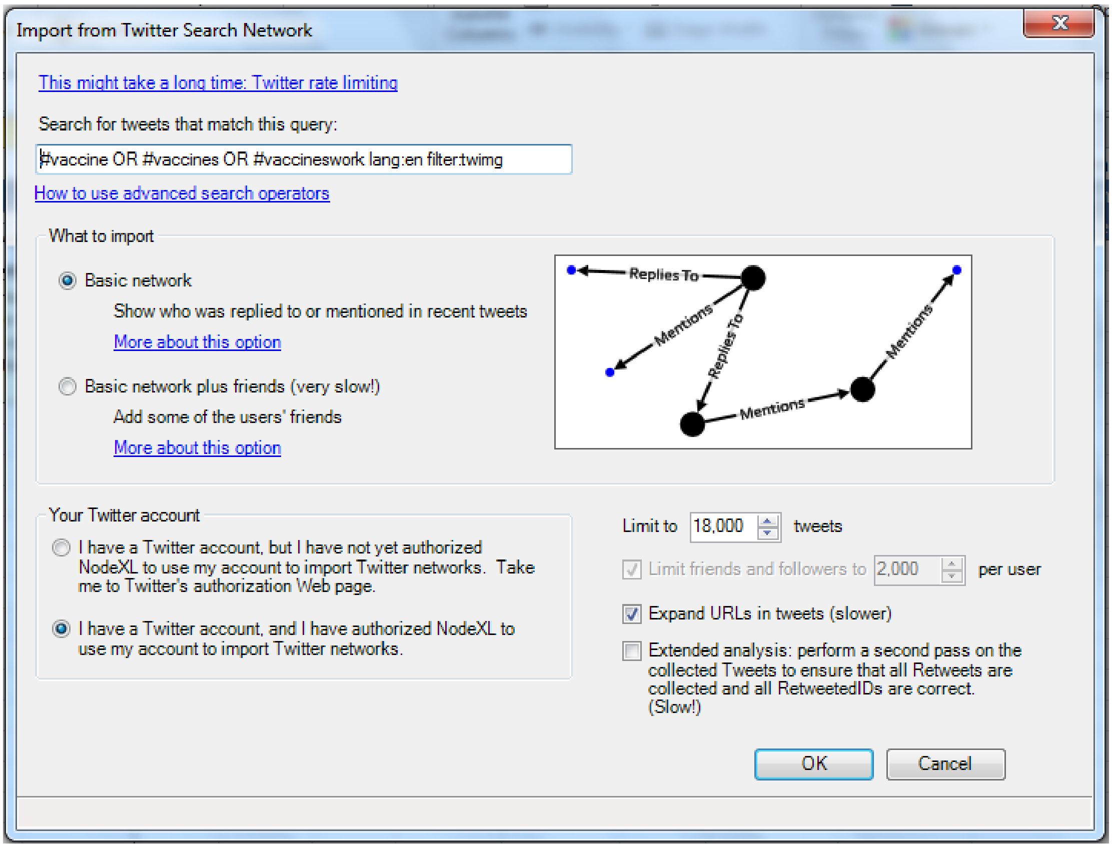

Figure 4.2 NodeXL Pro query box.
The inclusion criteria were added to the query box.

[9] Application Programming Interfaces (APIs) are "a way of communicating with a particular computer program or internet service" (Cambridge Advanced Learner's Dictionary & Thesaurus, 2019)

In the query, the keywords were separated by the Boolean operator "OR" to gather tweets that contained at least one of the hashtags, and they were followed by the two search operators lang:en and filter:twimg (Twitter, Inc., 2018b). The first operator ensures tweets are written in English – it was selected because the main anti-vaccine debate has been happening in the US and English is used as an international language. The second operator filtered tweets embedding links under the domain pic.twitter.com[10], ensuring that only those having a picture that had been upload on Twitter originally were collected. This operator excluded tweets where the picture had been imported from another digital outlet, such as Instagram or Facebook. Imported pictures are not visualised on Twitter, but they appear as an URL link and may not enhance the visibility of the tweets in the stream.

4.1.2 Main study data collection

As mentioned before, the pilot study was conducted to test the social network analysis methods and explore the vaccine debate. This method enabled exploration of *ad hoc* publics and potential vaccine communities formed around hashtags (Bruns and Burgess, 2015; Bruns and Moe, 2014); it was also effective at comparing relatively small tweet samples collected at different times. However, it could limit a bigger study for the following reasons:

- Only tweets having specific hashtags were collected, thus excluding those without any or with alternative ones. This decision was suited to the aim of the pilot, which focused on vaccine *ad hoc* publics, but excluded tweets and users targeting personal publics, such as news media outlets, which likely contribute to debate;
- The same set of hashtags was used for each data collection, even though hashtag usage varies over time, i.e. a hashtag may be highly tweeted during a specific period whereas it may be not tweeted at all another time;

[10] Uploading a picture on Twitter generates a link ending in 'pic/twitter.com''.

- The collection periods were chosen randomly; therefore, the number of tweets gathered was not predictable, and may have been affected by an unexpected event, or there may have been unusually low activity on Twitter during the collection period.

To address these limitations, the collection criteria were modified for the main study. First, both hashtags and words related to vaccinations were included in the criteria: this allowed the study to consider both *ad hoc* and personal publics, i.e. those users conversing around specific hashtags as well as those targeting followers and known audiences. This change also allowed investigation of the use of hashtags across different networks by comparing the pilot data with the main data. Second, the sample of hashtags was updated to include only those frequently used during the collection period (see Section 4.1.2.1). Third, the data collection was conducted in relation to a specific event (i.e. US presidential elections, because Donald Trump was known to support the anti-vaccine community) that could trigger a wider discussion about vaccines (see Section 4.1.2.2).

4.1.2.1 Collection criteria – Keywords

Keywords for the data collection were searched again in November 2016, but during that period the hashtag collection in Symplur (Symplur LLC., 2020) was temporarily only available for a fee and therefore not widely accessible. As a consequence, alternative software or databases were considered, such as RiteTag (Maintop Businesses s.r.o., 2017). This tool was chosen as an alternative means of gathering hashtags since it displays the time trends of a hashtag (i.e. how often that hashtag was used over a month or week), the correlated hashtags, the main countries that use that hashtag, and the language in which the hashtag is tweeted. Therefore, by combining the results obtained using RiteTag with those provided by Hashtagify.me, and then following the same procedure used in the Pilot data collection (Section 4.1.1.1), the keywords listed in Table 4.3 were identified. These hashtags were highly tweeted during the collection period, between the 7th and 13th November 2016.

Hashtag	Sentiment	Description
#vaccine	Neutral	Used in either pro- or anti-vaccine conversations
#vaccines	Neutral	Used in either pro- or anti-vaccine conversations
#vaccinations	Neutral	Used in either pro- or anti-vaccine conversations
#vaxxed	Anti-vaccine	Launched in relation to *Vaxxed the movie*, it became a trending hashtag
#CDCwhistleblower	Anti-vaccine	About supposed fraud and conspiracy at the Centre for Disease Control and Prevention (CDC)
#vaxwithme	Anti-vaccine	Sarcastic, related to #vaxxed
#HearUs	Anti-vaccine	Call to action
#VaccinesWork	Pro-vaccine	Used mainly by scholars and NGOs
#immunization	Pro-vaccine	Used mainly by scholars and NGOs
#immunizations	Pro-vaccine	Used mainly by scholars and NGOs
#vaccinate	Pro-vaccine	Call to action

Table 4.3 Hashtags selected as inclusion criteria for the main data collection.

On the 14th of November 2017, tweets were gathered setting as inclusion criteria the hashtags mentioned above, and the two filters lang:en and filter:twimg explained in Section 4.1.1.2. The collection was limited to 18,000 tweets, but less than 4,000 tweets were collected. However, when the collection was repeated applying the same criteria but including the words "vaccine(s)" and "vaccinations" as well, more than 15,000 tweets were gathered. This difference in numbers supports the decision to consider both *ad hoc* and personal publics in the main study. This larger number of tweets with embedded pictures could provide deeper insights into the actors and networks involved in the vaccine debate. By adding the words "vaccine(s)" and "vaccination(s)" in the inclusion criteria in NodeXL, it was possible to gather tweets with either hashtags or words embedded in the hashtag (e.g. #vaccinesinjury).

4.1.2.2 Collection criteria – Advance search operators

For the main data collection, a temporal range that included a specific event was chosen to gather as many tweets as possible that were posted in relation to the event. The chosen event was the US presidential election for the following reasons:

- The hashtags #Trump #TrumpTrain, #Trump2016 and #elections appeared in all three pilot study data collections, and they were tweeted especially by the anti-vaccine community. Moreover, Donald J. Trump was occasionally mentioned;
- Donald Trump is very active on Twitter, and he publicly declaimed his beliefs and concerns that vaccines cause autism and are dangerous (see Figure 4.3);
- On RiteTag, the hashtags #vaccine(s), #vaccinations, #immunizations, #immunisation, #vaccineswork, #vaxxed, #hearus, and #CDCwhistleblower were recorded as highly tweeted during that period.

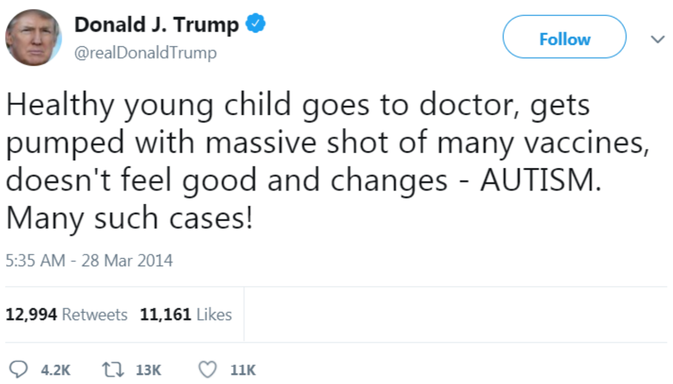

Figure 4.3 Public tweet posted by Donald Trump claiming that there is a correlation between vaccinations and autism.
This tweet was posted in 2014.

To collect only the tweets shared during the elections week, the Advanced Search Operator "until:2016-11-12" was applied (Twitter, Inc., 2018b), which limited the data collection to tweets that were sent seven sequential days before "2016-11-12" (year, month, day). This operator was used because the data were collected on 14th November 2016, and without it the software could not gather tweets sent the previous week. The Advance Search Operators applied in the pilot study also were used for this collection, to gather only tweets posted in English and having a picture uploaded on Twitter originally (see Section 4.1.1.2).

4.2 Preparing data

The data for the pilot and main studies were prepared in the same manner. Given that users may post the same message several times, duplicate tweets were considered as one; therefore, before analysing data, duplicate tweets were merged while retaining their information (Hansen, Shneiderman and Smith, 2010). Afterwards, data were filtered to include unique tweets and mentions (i.e. etiher tweets that mention a user or retweets) while excluding replies. Unique tweets and mentions were considered because they contributed to vaccine conversations; for example, mentions can endorse someone else's content or share it to other audiences (e.g. other users' followers). Replies were not included since they may be fragments of an ongoing conversation among individuals, rather than the whole community, and they may be visible only to those participating in that discussion[11]. Sections 5.1 and 5.2 show how many tweets were collected and how many were analysed after removing duplicates and replies in the pilot and main study, respectively.

4.3 Tweet classification

After preparing the data, the tweets were classified based on their perspective on vaccination (e.g. anti-vaccine). The coding strategy was developed and polished during the pilot study, and applied to the main research. During the pilot study, initially the tweets were categorised by sentiment such as anti-vaccine, pro-vaccine and neutral as in previous studies (Love *et al.*, 2013;

[11] Replies are shown in a user's profile stream if the handle of the person mentioned is not included at the beginning or it is preceded by a dot; for example, .@usershandle

Salathé and Khandelwal, 2011). However, classifying neutral tweets posed several challenges since many of them were either news or related to conferences and could be interpreted as in favour of vaccination[12]. For this reason, instead of classifying tweets by sentiment, they were categorised by content, and the code 'neutral' was avoided.

To code the tweets, both their content and context were considered. These were assessed using the following features:

- The posts' textual content
- Hashtags included (e.g. #vaxxed, #vaccineswork)
- Content of the shared picture(s)
- Sources and content of the embedded links
- User's biography (who posted the original tweet)
- Occasionally, the conversation where the tweets were posted[13].

The tweets from the June pilot dataset were analysed to develop a codebook. Once the codebook was finalised, the same dataset was re-coded and the other two pilot collections were coded; then, the same codebook was applied to the main dataset.

The tweets were classified into the groups below:

- Anti-vaccine tweets – e.g. 'vaccines are a crime against humanity', 'the government wants to cover up the MMR vaccine-autism link'
- Pro-vaccine tweets – e.g. 'get your flu vaccine', 'immunisation is the best form of prevention'
- Pro-safe vaccines tweets – e.g. 'the price of vaccines is too high to make them accessible for developing countries', 'why can't we say no to just one vaccine?'[14]

[12] For example, a tweet saying 'The new flu vaccine has showed promising results' could be interpreted as in favour of vaccinations due to its positive tone, but it may not be pro-immunisation if it is related to a news article simply reporting the finding of a recent study.
[13] Some tweets were posted as replies to other posts, but since they were retweeted the software showed them as mentions instead of replies.
[14] These two statements emphasise existing issues related to vaccinations. In the first case, the high price of vaccines may make them unaffordable for countries that need them the most. In the second case, wanting to avoid one single vaccine does not mean being against all of them, and there may be concerns about the safety or efficacy only for that specific vaccine.

- News tweets – e.g. ‘Haiti is launching a cholera immunisation campaign’, ‘the flu vaccine spray is not effective’ (these tweets usually have an external link to a news article)
- Academic tweets ‘Presenting the latest data from our study on the HPV vaccine at the conference’, ‘We are organising a webinar on recent immunisation practices’
- Not Relevant ‘e-cigarettes are a vaccine against smoking’.

Anti- and pro-vaccine tweets had a strong sentiment towards vaccination, whereas pro-safe vaccine tweets emphasised some limitations or concerns about vaccines, but were not strongly anti-vaccine. Academic tweets were related to conferences and journal papers, whereas those coded as news also embedded an external link to a newspaper article. Posts classified as not relevant mentioned the words ‘vaccines’ or ‘immunisation’ but were not about vaccinations. The full codebook and the criteria for each category are available in the Appendix B.

4.4 Network analysis

The connections among users were studied by applying social network analysis. First, the distribution of these ties (i.e. retweets) was observed and described, graphic metrics were then used to investigate the connections further (see Section 4.4.2). Graphic metrics are a set of parameters used to analyse the distribution and connectivity of a network and can be calculated in NodeXL (Hansen, Shneiderman and Smith, 2010). For example:

- Centrality – which actors can potentially influence or control the information flow within a group or the whole network;
- Size – how far apart the users of a network are; the size of a network can be estimated by measuring its diameter or geodesic distance (see Section 4.4.2);
- Density – how cohesive a network is;
- Modularity – how partitioned or segmented a network is.

By investigating these features, it was possible to observe whether the members of the network formed one highly connected community or two polarised groups having opposite opinions. It was also possible to identify actors controlling the exchange of information within the network, hence acting as gatekeepers (Himelboim, 2017; Smith *et al.*, 2014; Kumar, Morstatter and Liu, 2013; Kadushin, 2011). The following sections describe the methodology used for the social network analysis in detail.

4.4.1 Description of networks

The first step of the analysis included plotting of the networks and description of the distribution of their users and connections (retweets). The method applied in the pilot study slightly differed from that of the main research, hence they are discussed in two separate sections.

4.4.1.1 Pilot study network description

In each dataset, the network was plotted as a readable graph by applying the Harel-Koren Fast Multiscale algorithm[15] and eventually rearranging the disposition of its nodes (users). Thus, it was possible to isolate the different connected components (i.e. groups of users that are connected to each other but not with other groups) and to separate the anti-vaccine group from the pro-vaccine one. This provided insights into the relationships between and within anti- and pro-vaccine networks (see Figure 5.1 for example).

Afterwards, the anti-vaccine and pro-vaccine networks were plotted separately applying the same algorithm and rearranging the distribution of retweets and users to make them more visible. The anti-vaccine network contained pro-safe vaccine and anti-vaccine tweets only, whereas the pro-vaccine network had pro-immunisation, academic and news messages. This decision was taken after observing the overall network graphs, which were divided into two

[15] The Haren-Koren Fast Multiscale algorithm is provided by NodeXL. Applying this algorithm to the data, produces a graph having all the edges the same length, and minimises edge crossing, thus the graph is easier to read (Hansen, Shneiderman and Smith, 2010).

polarised groups. These two groups, one anti- and one pro-vaccine, shared different types of tweets, hence, could be analysed separately.

In each dataset, the networks appeared to be divided into groups and subgroups, therefore they were plotted again by applying the Clauset-Newman-Moore algorithm[16], which identified the networks' clusters (i.e. groups of users positioned closely together). Then, the Harel-Koren Fast Multiscale and the Treemap[17] algorithms were applied to lay out each graph's cluster in its own box (see Figure 5.2 for an example). In this way, it was possible to distinguish the different clusters within the pro- and the anti-vaccine communities and to isolate all the small components (i.e. groups formed by 2-20 users). The clusters' shape (e.g. star-shape network) and the connections among them were also studied since they could provide insights into the ways that information flowed within the anti- and the pro-vaccine groups (Smith *et al.*, 2014).

4.4.1.2 Main study network description

NodeXL works at its best with 7,000 tweets (Hansen, Shneiderman and Smith, 2010), but the main dataset included more than 15,000 tweets. Hence, it was not possible to discriminate between the distributions of connections with the Harel-Koren Fast Multiscale algorithm. However, this issue did not occur when the network was first divided in clusters using the Clauset-Newman-Moore algorithm. Therefore, the whole network was clustered and then plotted with the Harel-Koren Fast Multiscale and Treemap algorithms. The same method was applied to the anti- and pro-vaccine network graphs.

[16] The Clauset-Newman-Moore algorithm is used for detecting community structure in large networks (Clauset, Newman and Moore, 2004).
[17] The Treemap algorithm is used for visualising community structures and hierarchies in rectangular space in a space-filling manner (Hansen, Shneiderman and Smith, 2010).

The pro-vaccine network comprised more than 9,000 posts, presenting the same plotting issue for the overall network (Hansen, Shneiderman and Smith, 2010). Therefore, the dataset was divided into three groups instead of two:

- Anti-vaccine group – included anti-vaccine tweets and some pro-safe vaccine tweets;
- Pro-vaccine group – included pro-vaccine and academic tweets and some pro-safe vaccine tweets;
- News – included only tweets about news.

This time, pro-safe vaccine tweets were not only shared by anti-vaccine users, but they were distributed between the pro- and the anti-vaccination communities. These tweets, though belonging to the same category, presented some slight differences, such as the users and the clusters that shared them. Therefore, when the pro-safe vaccine messages were retweeted only by anti-vaccine users or cluster, they were considered as belonging to the anti-vaccine community. When the pro-safe vaccine tweets were shared only by pro-vaccine users or clusters, they were considered as belonging to the pro-vaccine group. There were no pro-safe vaccine tweets shared by both pro- and anti-vaccine users. The news-related tweets were analysed separately because they were often shared by news media outlets rather than NGOs or other types of actors.

4.4.2 Graph metrics analysis

In both the pilot and main study, the graph metrics were calculated for each data collection and group (e.g. anti-vaccine). By comparing the graphs and these metrics for each network and group, it was possible to identify similarities and differences in their distribution patterns; for example, whether they were highly connected in support communities or fragmented in parallel ongoing conversations.

The following graph metrics were calculated in NodeXL:

- Number of edges – how many retweets/mentions connect the users to each network or group;
- Number of nodes – how many users participate or are involved in each network or group;
- Connected Components – how many disconnected groups of users are present in the network or group (these groups are not connected to any other group);
- Maximum number of Nodes in a Connected Component – how many users form the biggest component in a network or group;
- Maximum number of Edges in a Connected Component – how many retweets form the most connected component in a network or group. Since the component with the highest number of nodes may not have the highest number of edges, these two values were considered together and in relation to the plotted graphs;
- Diameter (Maximum Geodesic Distance) – provides an estimate of the maximum distance between nodes in a network, but is imprecise;
- Average Geodesic Distance – the number of edges in the shortest path connecting two nodes (e.g. the smallest number of tweets that connects two users);
- Density – the ratio between the number of direct edges (retweets) and the number of possible edges in the network. This provides insight into a network's cohesion. Its value decreases for large-size networks, and it may differ among groups (anti-vaccine, pro-vaccine…) or clusters within the same network;
- Modularity – defines the extent to which a network is divided into disconnected clusters. It ranges from 0 (unified network) to 1 (fragmented network). Modularity, combined with density, explains the connectivity of a network better – a network formed by a few highly connected clusters may have high density, but if these clusters are disconnected the modularity will be high as well, indicating that the network is not unified (Himelboim, 2017; Hansen, Shneiderman and Smith, 2010).

4.4.3 Cluster analysis

After analysing the anti- and pro-vaccine groups in each pilot dataset, it emerged that some clusters had the same distribution and key actors each time; these were investigated further. Three anti-vaccine and two pro-vaccine clusters were identified as recurrent, and each of them was isolated to calculate its metrics. In this way, it was possible to compare their connectivity and number of users, and to study their variation across datasets. The same method was applied to the main data collection, but the clusters were selected based on their size and key actors. Three anti-vaccine clusters (the same of the pilot study) and three pro-vaccine clusters were further investigated.

4.5 Analysis of the key actors

Key actors were not identified based on their number of followers but on how many times they were retweeted. The number of followers does not contribute to tweet visibility as much as the number of retweets (Kwak *et al.*, 2010). The strategic position of key actors in the network was also considered because it can allow them to influence information flow (Grewal, 2009) (See Section 2.3.1). To identify these key actors, the centrality of each user in the network was calculated in NodeXL. Different centrality measures were considered:

- Betweenness centrality – measures how many users an actor connects that belong to the same or different groups. An actor with high betweenness centrality dominates the information flow, and if s/he is removed from the network, the network will be disrupted; hence, s/he occupies a strategic position within the network;
- In-Degree centrality – measures how many times an actor's messages were retweeted and/or how many times s/he was mentioned; hence, it measures the visibility of an actor's tweets;
- Out-Degree – measures how many retweets a user made (Himelboim, 2017; Newman, 2010).

There are other types of centrality, such as PageRank and eigenvector centrality, that were not considered in this study. PageRank measures centrality based on the in-degree centrality of an actor and that of the other users that retweet his/her messages, i.e. if they retweet the content of many other users or if they are retweeted (Newman, 2010). In this study, betweenness centrality was preferred since it allows identification of anti- and pro-vaccine users engaged in discussion. Eigenvector centrality measures the centrality of an actor based on the numbers of connections of the users linked to him/her, but it does not consider the direction of these connections (i.e. whether they retweet or are retweeted) (Newman, 2010). Eigenvector centrality is appropriate for analysis of indirect networks, but in the case of Twitter, the directionality of the connections is particularly important because it distinguishes key actors (high in-degree) from those that frequently retweet others (high out-degree) (Kumar, Morstatter and Liu, 2013). Therefore, Eigenvector centrality was not considered in this study.

By comparing the values of centralities with the network graphs it was possible to identify and distinguish some users that had high betweenness centrality but were not key actors. These users had low or null in-degree and out-degree centralities; hence, they were unlikely to influence the information flow in the network or increase the visibility of tweets. Three other types of users were found in both the pilot and main study that are of interest in the context of vaccine image sharing:

- Users who were mentioned in the conversation but did not participate in it (e.g. Donald Trump);
- Users who retweeted both anti- and pro-vaccine messages;
- Users who engaged in conversations with other users having a different point of view about vaccinations (e.g. pro-vaccine user communicating with anti-vaccine ones).

Betweenees, in-degree and out-degree centralities were used to identify key actors in both the pilot and main research. Key actors were ranked slighlty differently in these two studies due to the different sizes of the datasets, as further explained in the two following sections.

4.5.1 Pilot study key actors

The three centrality measures were calculated for every user in each dataset. Then, the top 50 users with highest betweenness centrality and in-degree different from zero were selected for further analysis. Users having high betweenness centrality but null in-degree were excluded from the ranking because their messages would be unlikely to be visible. Users having an in-degree higher than 20 retweets were also included in the analysis. The threshold was arbitrarily set at 20 but it included most key actors, who had an in-degree centrality of at least 30. Many ranked users had both high betweenness and in-degree centralities, hence they were counted only once. However, some of the ranked users were not key actors but mentioned or engaged users, or they re-shared both pro- and anti-vaccine messages without being retweeted (see Section 4.5); therefore, they were removed from the analysis.

Afterwards, users were ranked for out-degree centrality, to find those who potentially increase the visibility of vaccine images. Only the users retweeting at least 10 posts were considered, and some of them were also included for their high in-degree and/or betweenness centrality. Table 4.4 shows how many users were identified at the various stages.

	June	*September*	*October*
Key actors (high ID and/or BC)	48	47	51
Users with high OD only	12	1	11
Engaged users	4	3	7
Mentioned users	1	7	8
Users who retweeted both anti- and pro-vaccine posts	4	0	1
Total users	69	58	79

Table 4.4 Number of users included and excluded from the analysis.
Key actors with high betweenness centrality (BC) and/or in-degree centrality (ID) were included in the analysis as well as those with high out-degree (OD). Some users with high out-degree had high BC or ID, too. Users unlikely to exert power over the information flow of the network, such as engaged users, mentioned users, and users who retweeted a few (1-2) anti- and pro-vaccine posts, were excluded.

4.5.2 Main study key actors

Key actors could be recognised as gatekeepers, direct sources of information or experts by the members of their community, though they may not be recognised as such by every Twitter user in their community (Bruns, 2008a). Therefore, to identify the hubs and brokers that could influence the pro-vaccine, anti-vaccine and news-related groups, key actors were identified within each group, instead of the whole network.

In each group, 20 users that had the highest betweenness centrality and an in-degree centrality higher than 80 retweets were selected, and none of them was classified as engaged or mentioned. A total of 59 actors was identified - one actor met the criteria for both the pro-vaccine and news-related groups. This actor was considered in the analysis of key actors of both groups since s/he occupied a strategic position in each of them.

Users with high out-degree centrality were selected within each group as well, to see how many of them contributed to increasing the visibility of their community's tweets. The identified users had an out-degree centrality of at least 10 retweets, high betweenness centrality and low in-degree centrality (less than 80 retweets). These criteria allowed identification of users that retweeted messages from different clusters, bridging the whole community, but who are not key actors. Table 4.5 shows how many key actors, mentioned/engaged users, and users with high out-degree were identified in each group.

	Anti-vaccine	*Pro-vaccine*	*News-related*
Key actors (high ID and/or BC)	20	20	20
Users with high OD	6	7	0
Engaged users	0	0	0
Mentioned users	4	4	4
Users who retweeted both anti- and pro-vaccine posts	0	0	0
Total users	69	58	79

Table 4.5 Number of users included and excluded from the analysis.
Key actors with high betweenness centrality (BC) and/or in-degree centrality (ID) were included in the analysis as well as those with high out-degree (OD). Users unlikely to exert power over the information flow of the network, such as engaged users, mentioned users, and users who retweeted a few (1-2) anti- and pro-vaccine posts, were excluded.

4.5.3 Classification of key actors

Once the key actors were identified and selected, they were classified based on their opinion on vaccination and type of user (e.g. activist, parent, journalist, physician, NGOs...) based on how they had defined themselves in their Twitter biography, on their names and handles, the web page links they had provided, their profile and/or background pictures, tweets, and hashtags used.

Some actors may not have been honest in their biography, for example, they may falsely claim to be journalists. A different approach might have defined actors based on the researcher's personal opinion and perception, but this may have introduced other biases. The key actors were categorised into the following groups:

- Anti-vaccine – actors that clearly define themselves as anti-vaccine, claim vaccines injured themselves or their children, and/or retweet many posts against vaccinations;
- Tendentially anti-vaccine – actors that tweet or retweet messages against vaccines occasionally;
- Pro-vaccine – actors that define themselves as pro-vaccine, run immunisation campaigns (e.g. health organisations), and/or retweet many posts in favour of vaccination;
- Tendentially pro-vaccine – actors that tweet or retweet messages in favour of vaccines occasionally;
- Pro-safe vaccine – actors that retweet anti-vaccine, pro-vaccine and pro-safe vaccine posts;
- Neutral – actors such as media outlets that have a neutral perspective on the topic of vaccination and post mainly (if not only) news;

The actors were further classified into the following types: activists, parents, non-governmental organisations (NGOs), public health services, healthcare institutes, healthcare practitioners, academics, chief executives of NGOs, journalists, media outlets, writers and uncategorised (the full list is available in Appendix C). These categories were not exclusive; for example, some actors were classified as activists and parents. The frequency of types and vaccine opinions of the key actors were compared across groups (e.g. anti-vaccine, pro-vaccine) and datasets, to investigate whether there were emerging alternative experts in the anti- and pro-vaccine groups.

5. Results of the social network analysis

This chapter discusses the results of the social network analysis, and addresses the first two research questions of this study: How are anti- and pro-vaccine images disseminated on Twitter? How do the key actors differ between these networks?

A pilot study was designed to test the methods and to explore the dynamics of the visual vaccine debate on Twitter. Once the methods were improved and confirmed, the main study was conducted. Though the pilot and the main research adopted slightly different methods, they provided similar results: the pro- and anti-vaccine communities did not engage with each other in constructive discussions about vaccinations, and they shared images differently. While the anti-vaccine community was relatively cohesive and closed to external information, the pro-vaccine network was more fragmented but suited for networking and spreading new information between its clusters. Moreover, the pro-vaccine key actors were mainly NGOs, healthcare professionals and public health services, whereas most of the anti-vaccine key actors defined themselves as activists and/or parents.

The applied methods showed to be a reliable and suitable process to investigate vaccine networks on Twitter. This study demonstrated that there were some established pro- and anti-vaccine communities and key actors in 2016. The following paragraphs provide a detailed description of the vaccine networks and their influential actors. The findings of the pilot study are discussed first, followed by those of the main research.

5.1 Pilot data

In June, September, and October 2016, 4480, 2658, and 5262 tweets having embedded pictures were collected respectively. Following the removal of duplicates of these messages (i.e. reposted tweets) and of the posts that were not relevant to vaccinations[18], the final samples comprised 3,573 tweets and 1,987 users, 1,932 tweets and 1,390 users, and 3,778 tweets and 2,510 users, respectively (Table 5.1).

	June	*September*	*November*
All collected tweets	4480	2658	5262
Unique tweets (including not relevant tweets)	3655	1955	3799
Final tweets (unique tweets relevant to vaccines)	3573	1932	3778
Final users	1987	1390	2510

Table 5.1 Number of collected and selected tweets and the final users in the Pilot study.
Tweets were filtered automatically to obtain a sample of unique tweets, which excluded duplicates. Then, this sample was manually screened to exclude any irrelevant tweets. The number of final users only included unique users who shared relevant tweets.

In each collection, most of the tweets were anti-vaccine, whereas only a few posts reported news, and even fewer tweets were pro-safe vaccines (Table 5.2, see Section 4.3 and Appendix B for a detailed description of the tweets categories). The pro-safe vaccine messages appeared only in the October dataset when one pro-safe vaccine user engaged with pro- and anti-vaccine ones. This user joined an ongoing fight about vaccinations and emphasised that vaccines need stricter testing and control.

The number of pro-vaccine and academic tweets varied tremendously across datasets, ranging from 323 to 1298 tweets, and from 98 to 699 tweets, respectively (Table 5.2). This is likely related to the occurrence of specific events, such as conferences, immunisation campaigns... For example, in the

[18] Tweets classified as not relevant to vaccinations had the hashtags or the words *vaccine(s)* and *vaccination(s)* used in an unrelated context. For example, one tweet, stating that “e-cigarettes are the best vaccine against smoking”, was categorised as irrelevant since this research does not focus on e-cigarettes nor on the use of vaccination as an analogy.

June dataset, 42.2% of the pro-vaccine retweets (548 out of 1298) were of a photo about a measles vaccination campaign in Ethiopia.

	All	*Anti-vaccine*	*Pro-vaccine*	*Pro-safe vaccines*	*Academic*	*News*
June	3573	1896	1298	0	247	132
September	1932	1394	323	3	98	114
October	3778	2061	691	80	699	247

Table 5.2 Number of tweets for each data collection and each category.
Data from the Pilot study.

These results differ from those of previous studies, which found that most of the tweets were neutral and those against vaccination were a minority (Love *et al.*, 2013; Salathé and Khandelwal, 2011). In this research, tweets were classified by topic rather than by sentiment[19] (see Section 4.3); hence, the category *neutral* was substituted with *news* and *academic.* However, even when news-related and academic tweets were considered together, they were always fewer than the anti-vaccine tweets, making it unlikely that the discrepancies between this and previous studies were related to the different tweet categories. It is more likely that the inclusion criteria used in this research, which limited the collection to tweets having pictures and specific hashtags, and excluded posts having words such as "vaccines" but no hashtags, is responsible for the difference from previous research. The difference in findings could also be caused by the coding criteria, which unlike other studies considered the embedded pictures, web links and context (e.g. a conversation in which the tweet was shared) as well as the textual content of the tweet. For example, some tweets had a neutral tone and could be categories as news-related, but also included a web link to an anti-vaccine website.

[19] In sentiment analysis, tweets can be classified as positive, negative and neutral based on their tone and message.

5.1.1 Social network analysis

In each collection, the overall network was relatively wide, and the diameter, the geodesic distance and the density reflected its size (see Glossary for definitions). The modularity varied between 0.76 and 0.80 across the three datasets (Table 5.3), indicating that the network was fragmented into groups and clusters that are poorly connected or not linked with each other (Himelboim, 2017). The number of connected components – which are groups of users not connected to any other group – also reflected the size and fragmentation of the network across the collections (Table 5.3). This segmentation implies that different parallel conversations were ongoing when the data were collected (Kadushin, 2011).

Overall network's metrics	*June*	*September*	*October*
Users	1987	1390	2510
Tweets	3573	1932	3778
Diameter	12	14	15
Geodesic Distance	4.51	4.02	5.00
Density	0.0009	0.0010	0.0006
Modularity	0.76	0.81	0.80
Connected components	83	93	129
Maximum users in a component	1703	935	2026
Maximum tweets in a component	3341	1434	3311

Table 5.3 Metrics of the overall network across the three datasets.
Data from the pilot study.

In each dataset, the network looked to be formed of two groups: one retweeting pro-vaccine, academic, and news-related tweets, and another one sharing anti-vaccine and pro-safe vaccines messages (Figure 5.2). Therefore, the first group was named the pro-vaccine network, and the second named the anti-vaccine network. These two groups did not engage with each other, but formed two separate insulated networks. As shown in Figure 5.1, there were only a few interactions between the two groups that linked them into one big connected component. However, these interactions were not constructive, they were often tweets supporting users' opinions on vaccinations, or they were messages against users having a different perspective. In each collection, a pro-vaccine user, which was uncategorised[20], was always engaged by anti-vaccine users in these arguments.

The two groups were also connected through a few users who shared both anti- and pro-vaccine messages. Sometimes these users were anti-vaccine and shared news or academic tweets that stated the limitations of vaccines, at other times they were pro-safe vaccine users who retweeted objections to some aspects of vaccination but at the same time re-shared posts about immunisation campaigns. The users that linked the pro- and anti-vaccine groups, as in the cases just mentioned, were identified through their high value of betweenness centrality. However, this type of centrality does not consider the directionality of the connections (i.e. whether these users retweeted or were retweeted by different groups); hence, these users were not considered as key actors.

The pro- and anti-vaccine groups resembled the polarised crowds defined by Smith et al. (2014), which are two insular networks that do not interact with each other but only with their members who share similar opinions and beliefs. The polarisation of the pro- and anti-vaccine groups was found by Salathé and Khandelwal as well (2011). However, two polarised crowds should be centred on a few hubs[21] (Himelboim *et al.*, 2017), whereas the two communities found in this study were formed by various clusters (Figure 5.2). Knowing the distribution of connections among and within clusters might provide insights into how images were shared, and therefore on the relationships among members of the same cluster and of the same community. Smith et al. (2014) identified six different types of networks, patterns of information sharing, and this research used these as a framework.

When the overall networks were grouped into clusters, the pro- and anti-vaccine communities showed a different pattern of image sharing (Figure 5.2).

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[20] This user did not describe themselves as a parent, activist, healthcare practitioner, etc.; hence it was not possible to categorised them.
[21] Hubs are key actors with high in-degree and betweenness centralities (see Glossary for the definition).

The anti-vaccine community looked highly connected and was formed by most of the actors with high out-degree centrality, whereas the pro-vaccine network seemed divided into connected groups. The pro-vaccine network also had many small connected components (i.e. disconnected groups of two/three users) while the anti-vaccine community had only a few of them. Since the two communities differed in the distribution of tweets and actors, they were further analysed by comparison.

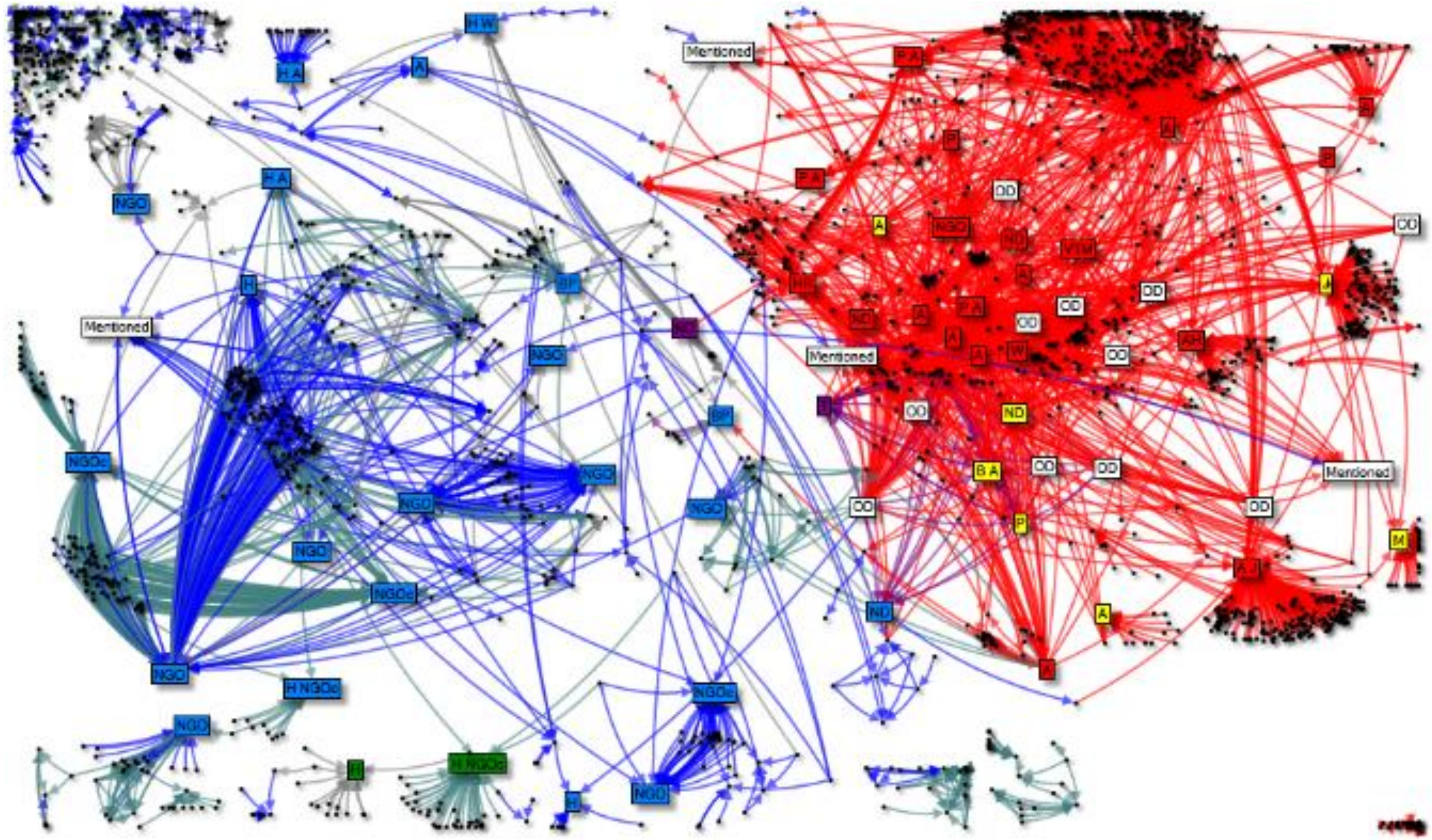


Figure 5.1 Vaccine networks in October 2016.

Legend: black dots – Twitter users; labels – potential key users; arrows – retweets, from who retweeted to who was retweeted. Colour code: blue – pro-vaccine; red – anti-vaccine; grey – news; petrol green – academic; purple – pro-safe vaccine; yellow – tendentially anti-vaccine; green – tendentially pro-vaccine. Label legend: NGO – Non-governmental organisations; NGOc – Chief executives, managers or advisors of an NGO; H – health professionals or scholars; AH –alternative health professionals; HR – hospitals, research centres, universities; A – activists; P – parents; VTM – related to Vaxxed the Movie; ND – uncategorised users; BP – pharmaceutical companies; M – news media outlets; J – journalists; W – writers; B – bloggers; T – teachers; OD – users with high out-degree centrality (who made more than 10 retweets); Mentioned – users who were mentioned in the discussion but did not participate. The categories in the labels are not exclusive; for example, a user can be both a parent and an activist (P A).

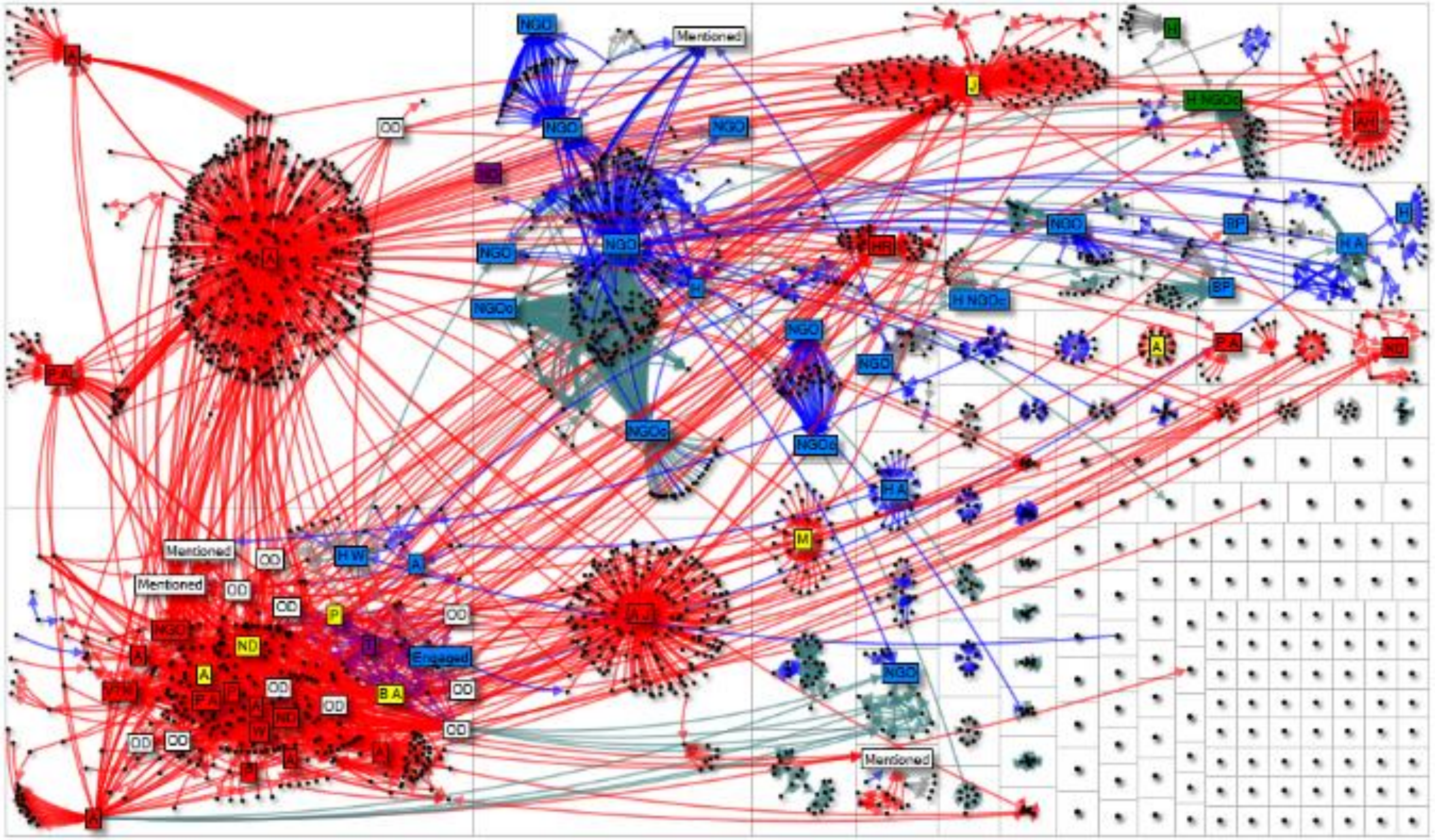


Figure 5.2 Vaccine networks divided into clusters, October 2016.
The network was divided into clusters using the Clauset-Newman-Moore algorithm (Clauset, Newman and Moore, 2004). See legend in Figure 5.1.

5.1.1.1 Comparing the anti- and the pro-vaccine networks

The anti-vaccine community shared most of the tweets, even when it had fewer users than the pro-vaccine network, as in the collection from June (Figure 5.2 and Table 5.5). The anti-vaccination group was always highly connected, and it was slightly less cohesive only in September. Even when it had a similar size to the pro-vaccine network, this community was formed by fewer connected components and had a smaller diameter and geodesic distance (except in June, when the geodesic distance was slightly higher in the anti-vaccine network); hence, it was more cohesive than the pro-vaccine network. The pro-vaccine network was very fragmented, especially in September (see Table 5.5), and had fewer connections linking the clusters. This segmentation could be emphasised by the news-related tweets, which were shared by many isolated groups of 2-5 nodes each. The different degree and distribution of the connections within the anti- and pro-vaccine networks reflected their different attitudes (Kadushin, 2011). While the high connectivity of the anti-vaccine community may reinforce the ties between members and their own beliefs about vaccinations, the fragmentation of the pro-vaccine group may reflect parallel conversations happening at the same time, and the few links among them favoured networking and exchanging of new information (Southwell, 2013).

Anti-vaccine community	*June*	*September*	*October*
Users	944	925	1393
Tweets	1896	1397	2141
Diameter	9	8	9
Geodesic Distance	3.62	3.71	3.56
Density	0.0021	0.0016	0.0011
Modularity	0.49	0.71	0.66
Connected Components	10	23	20
Maximum users in a component	919	860	1348
Maximum tweets in a component	1880	1350	2115

Table 5.4 Metrics of the anti-vaccine community across the three datasets.
It includes anti-vaccine tweets and pro-safe vaccines tweets. Data from the pilot study.

Pro-vaccine network	*June*	*September*	*October*
Users	1056	469	1135
Tweets	1677	535	1637
Diameter	11	14	15
Geodesic Distance	3.50	4.84	5.15
Density	0.0015	0.0024	0.0013
Modularity	0.72	0.92	0.80
Connected Components	78	72	115
Maximum users in a component	746	120	681
Maximum tweets in a component	1413	157	1186

Table 5.5 Metrics of the pro-vaccine network across the three datasets.
It includes pro-vaccine tweets, academic tweets, and news-related tweets. Data from the pilot study.

5.1.1.2 The anti-vaccine community

Though the anti-vaccine community was more connected than the pro-vaccine network, it was partitioned into clusters as well. The modularity of the community ranged from 0.49 to 0.71 across the three datasets, indicating that the community was not highly cohesive. This division was also evident when looking at the plotted network (Figure 5.3): most of the clusters looked like broadcast networks, in which one actor was highly retweeted by the others and therefore broadcasted his/her message to the audience (Himelboim *et al.*, 2017). One cluster of this community did not act as a broadcasting hub, nor as any other type of network defined by Smith et al. (2014). The users of this group re-shared the content posted from other members, but also from other groups, hence connecting the whole anti-vaccine network (Figure 5.3). Three clusters (named aC1, aC2 and aC3) were recurrent in all three datasets and were relatively broad, therefore they were investigated further.

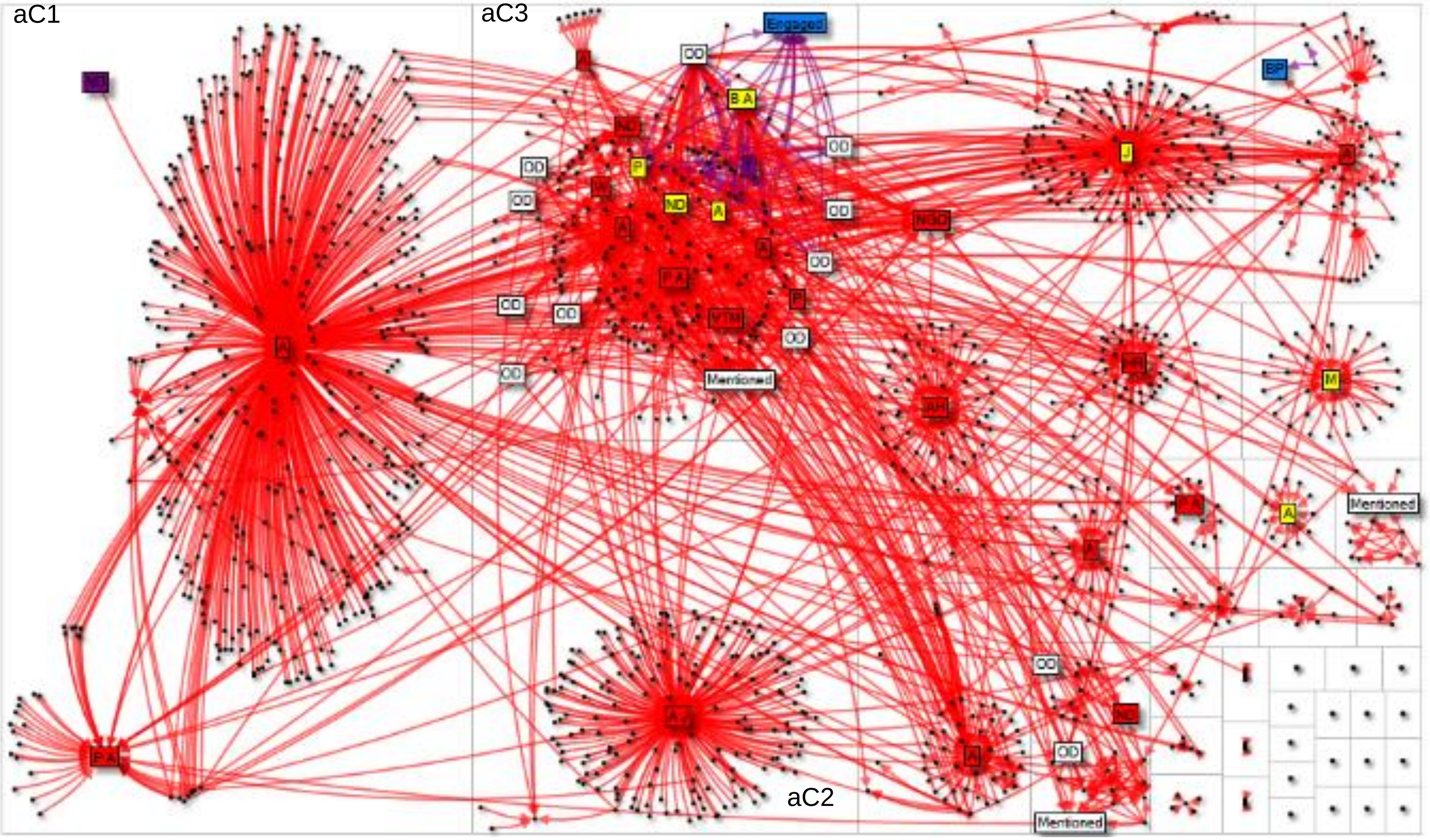


Figure 5.3 Anti-vaccine community in October 2016.
Only pro-safe vaccines and anti-vaccine tweets were considered in this network. The network was divided into clusters. Label legend: NGO – Non-governmental organisations; AH – alternative health professionals; HR – hospitals, research centres, universities; A – activists; P – parents; VTM – related to Vaxxed the Movie; ND – uncategorised users; BP – pharmaceutical companies; M – news media outlets; J – journalists; T - teachers; B – blogger; OD – users with high out-degree centrality (who made more than 10 retweets); Mentioned – users who were mentioned in the discussion but did not participate; Engaged – pro-vaccine users engaged by anti-vaccine actors.

The cluster aC1 was formed by one key actor, an activist, and his/her audience (left quadrant Figure 5.3). This cluster was well connected: the modularity was low, the farthest users of the cluster could be linked by three to four retweets, and the smallest number of retweets connecting two users was two on average (Table 5.6). However, the density was also low because the activist's messages were retweeted, but this actor did not retweet his/her audience[22]. Therefore, this cluster was a broadcasting network, where the images shared by the hub were broadcast, or diffused, to his/her audience (Smith *et al.*, 2014).

	June	*September*	*October*
Users	136	222	462
Tweets	123	240	493
Diameter	3	4	4
Geodesic Distance	2.00	2.01	2.06
Density	0.0075	0.0049	0.0023
Modularity	0.11	0.00	0.00

Table 5.6 Metrics of the anti-vaccine cluster aC1 across the three datasets.
Data from the pilot study.

The cluster aC2 was smaller and more dispersed than the previous one, and was star-shaped: it had a key actor, a journalist-activist, surrounded by a crowd of users (second quadrant on the left, bottom, Figure 5.3). As with the cluster aC1, its pattern and its metrics (Table 5.7) resemble a broadcasting network (Smith *et al.*, 2014), where the key actor has no interest in engaging with his/her audience but focuses on getting his/her messages out.

	June	*September*	*October*
Users	86	115	179
Tweets	76	114	178
Diameter	5	5	4
Geodesic Distance	2.19	2.07	2.03
Density	0.0116	0.0087	0.0056
Modularity	0.12	0.00	0.00

Table 5.7 Metrics of the anti-vaccine cluster aC2 across the three datasets.
Data from the pilot study.

[22] The density is given by the ratio between the possible maximum number of tweets and the number of observed tweets.

The third cluster, aC3, was the one that connected all the others in the network (second quadrant on the left, top, Figure 5.3). It was the largest: six to seven retweets connected the farthest users, and the smallest average number of tweets linking two users was three (Table 5.8). However, it had a higher density than the other two clusters, and its modularity was low, meaning that this group was cohesive and its members formed more reciprocal connections. The connectivity among the members could potentially form friendship relations and strong ties (Huberman, Romero and Wu, 2008). However, as mentioned before, these users did not retweet only each other, but also messages from other clusters, especially from the two broadcasting networks. Therefore, though this cluster looked like an in-group, where the members are highly connected (Himelboim *et al.*, 2017), it was not isolated from the rest of the community. Instead, it actively made the whole community cohesive.

	June	*September*	*October*
Users	160	144	200
Tweets	466	402	586
Diameter	7	6	6
Geodesic Distance	2.77	3.01	2.98
Density	0.0211	0.0195	0.0147
Modularity	0.16	0.05	0.05

Table 5.8 Metrics of the anti-vaccine cluster aC3 across the three datasets.
Data from the pilot study.

The cluster aC3 was formed by a group of recurrent key actors, who were mostly activists, parent-activists, and uncategorised users[23]. These actors often retweeted each other, potentially strengthening their ties. They also mentioned each other in the tweets occasionally, calling for attention to specific discussions. Moreover, many users with high out-degree (i.e. users who often retweeted others) were also part of this cluster and increased the visibility and popularity of its messages. While the key actors of the clusters aC1 and aC2 acted as information hubs, those of the cluster aC3 behaved as both hubs and

[23] Uncategorised users did not identify their profession or family role in their biography, but they described themselves using quotes or sentences such as “God will save us”, “I have cats”. Therefore, it was not possible to include these actors in any of the categories listed in Appendix C.

brokers[24], controlling the flow of visual information within the community (Grewal, 2009).

5.1.1.3 The pro-vaccine network

The pro-vaccine network looked more divided than the anti-vaccine community (Figure 5.4), especially in the dataset from September; its high number of disconnected components and high modularity confirmed this fragmentation. This network was formed of community clusters even more than the anti-vaccine group since its clusters were not well connected, and it had more isolated groups (Smith *et al.*, 2014). The distribution of users and tweets in the pro-vaccine group varied hugely across the three collections, maybe due to the occurrence of breaking news, conferences, or the launch of a new immunisation campaign. For example, in October, the number of academic retweets was higher than in the other collections, likely due to the occurrence of several academic conferences. Nevertheless, two clusters were recurrent in all the datasets, and they linked most of the prominent groups in the network. These two groups were always centred on the same two brokers, and in the October collection, they melted in one single cluster (Figure 5.4).

One of the clusters was named pC1 (Figure 5.4, left). At least 2-3 retweets could connect two users of this group on average, and the farthest members could be linked by 5-6 retweets (Table 5.9). This cluster was slightly bigger than the anti-vaccine ones regarding the number of users, but it had fewer reciprocal connections than aC3 (i.e. lower density), and it was less cohesive. Many NGOs and foundations were hubs in this group, and they were connected, especially through another NGO that acted as a broker. This broker retweeted the content shared by the hubs and was retweeted as well, introducing different types of information within the network. The actors of the cluster pC1 did not only retweet each other, but also users of other clusters (Figure 5.4). This brokerage allowed the creation of effective networking

[24] Hubs are actors whose content is highly shared by others and they occupy a central position in the network. Brokers are actors that connect clusters otherwise separated. See Glossary for the definitions.

among NGOs and the introduction of new information into the pro-vaccine group (Kadushin, 2011).

	June	*September*	*October*
Users	248	39	286
Tweets	262	64	587
Diameter	6	5	6
Geodesic Distance	2.55	2.32	2.56
Density	0.0047	0.0432	0.0072
Modularity	0.13	0.02	0.01

Table 5.9 Metrics of the pro-vaccine cluster pC1 across the three datasets.
Data from the pilot study.

The second cluster, pC2, was highly variable across the datasets (Table 5.10) but it was always loosely connected in comparison to pC1. This cluster was centred on the chief executive of the broker NGO identified in the previous cluster, and in October it formed one single cluster with pC1. Both these two pro-vaccine clusters acted as a bridge among the other groups of the pro-vaccine network, hence they likely facilitated the exchange of new information and networking within the wider pro-vaccine community (Kadushin, 2011).

	June	*September*	*October*
Users	243	41	286
Tweets	72	48	587
Diameter	8	7	6
Geodesic Distance	3.06	2.81	2.56
Density	0.0014	0.0293	0.0072
Modularity	0.11	0.00	0.01

Table 5.10 Metrics of the pro-vaccine cluster pC2 across the three datasets.
Data from the pilot study.

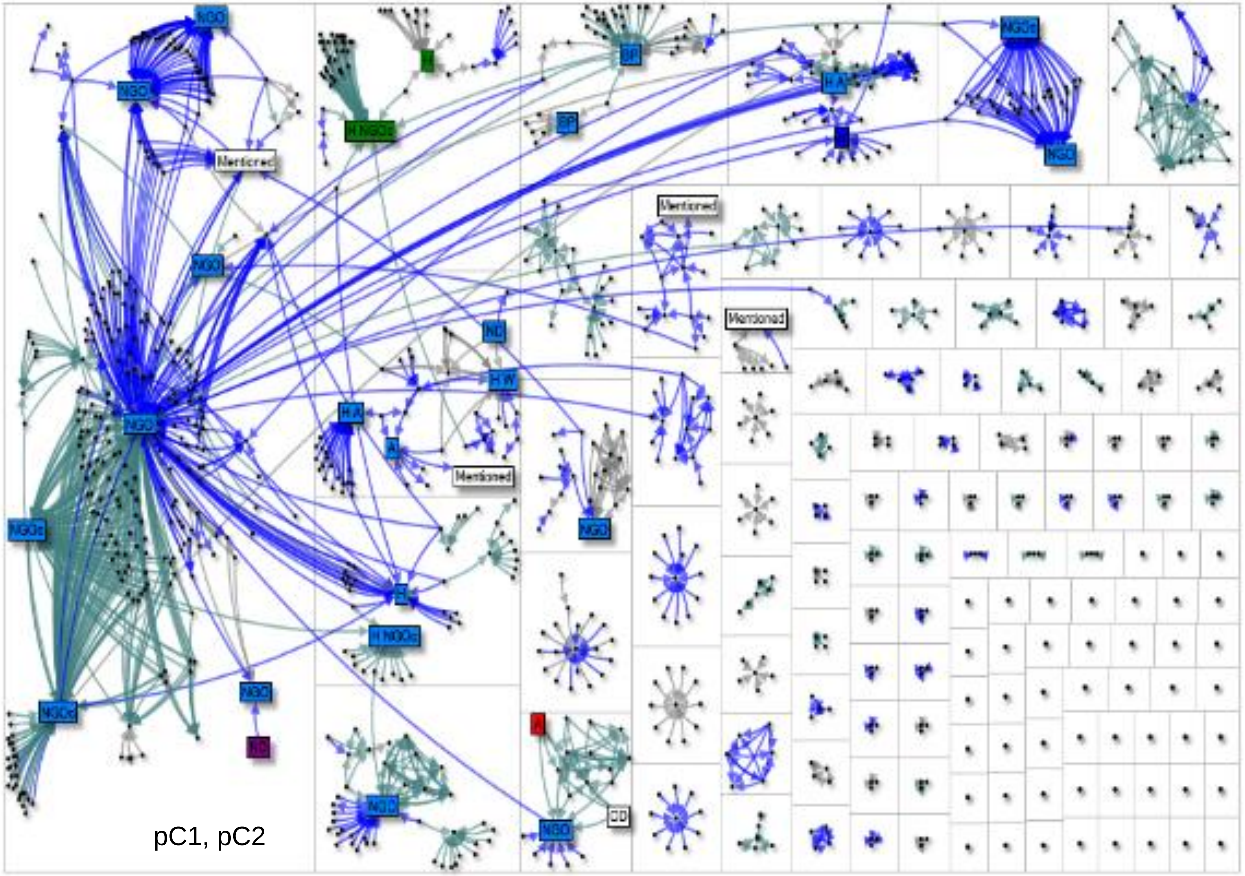


Figure 5.4 Pro-vaccine network in October 2016.
Only pro-vaccine, academic and news-related tweets were considered in this network. The network was divided into clusters. Label legend: NGO – Non-governmental organisations; NGOc – Chief executives or managers of an NGO; H – health professionals or scholars; A – activists; ND – uncategorised users; BP – pharmaceutical companies; M – news media outlets; W – writers; OD – users with high out-degree centrality; Mentioned – users who were mentioned in the discussion but did not participate.

5.1.2 Key actors: hubs and brokers

Based on their betweenness centrality and in-degree centrality, 48 key actors have been identified in June, 47 in September and 51 in October. In the datasets of June and September, most of these actors were anti-vaccine, whereas, in October, they were primarily pro-vaccine (Figure 5.5). This was surprising, because the larger size of the anti-vaccine community, suggested that they should have most of the key actors. However, it is possible that the number of pro-vaccine key actors increased in October due to the high number of academic tweets, which coincided with the occurrence of specific events, such as conferences and a meeting between an NGO, the Islamic Development Bank and a representative of the Kingdom of Saudi Arabia.

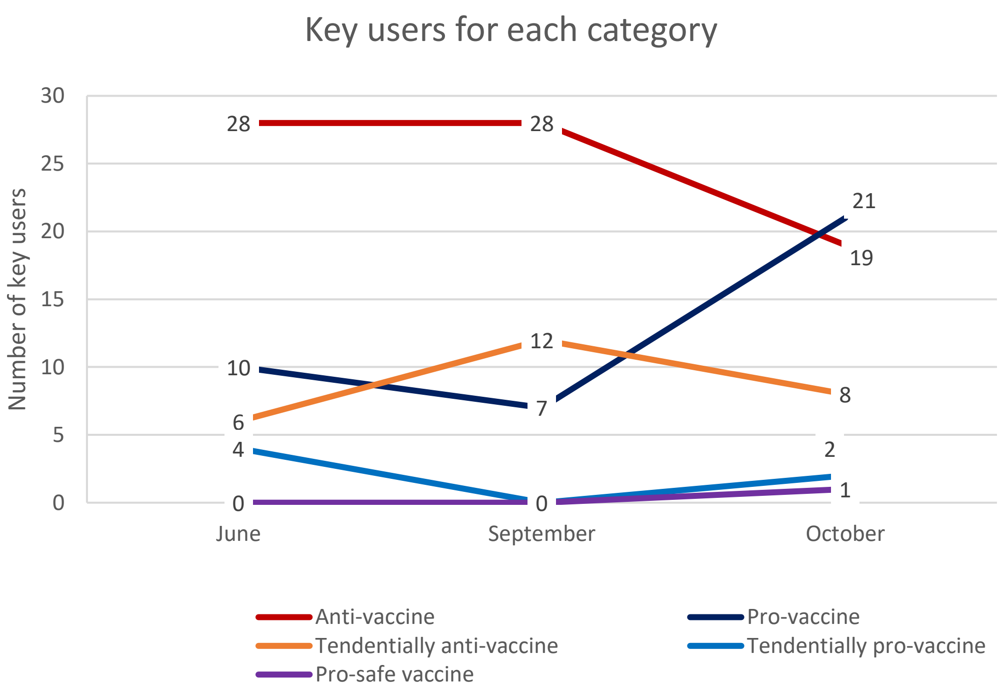


Figure 5.5 Key users classified by vaccine sentiment.
Data shown for June, September, and October 2016 (see Appendix D). These categories are exclusive.

Some key actors did not consistently campaign against or in favour of vaccinations, therefore they were defined as tendentially anti-vaccine or tendentially pro-vaccine, respectively. The tendentially anti-vaccine key actors were found in each collection, whereas there were only a few tendentially pro-vaccine key actors in June and October and none in September. Pro-safe vaccines key actors were even rarer: only one of them was identified in October, a teacher.

5.1.2.1 The key actors of the anti-vaccine community

In June and September, 28 anti-vaccine key actors were identified, whereas, in October, 19 of them were found. In each collection, most of these actors were activists or parent-activists or could not be categorised. A few of these actors were parents only, alternative health practitioners, or journalists who advocated against vaccination (Table 5.11).

	June	*September*	*October*
Activists	9	8	6
Parents	2	2	1
Parent-Activists	5	4	4
Journalist-Activists	2	2	1
Alternative Health practitioners	1	2	1
Research Centre	1	1	1
Uncategorised	6	4	2
Other	2	5	3
Total	28	28	19

Table 5.11 Anti-vaccine key actors classified by type of user.
The frequency of anti-vaccine key actors for each type of user are shown for June, September, and October 2016. These categories are exclusive. The category 'Other' includes types of user that appeared only occasionally and not in all three collections. In June, the category 'Other' included an online tool and a politician; in September, it included an online tool, a physician, a media outlet, a writer, and an account on *Vaxxed the movie*; in October it included an NGO, a physician and an account of *Vaxxed the movie*. Data from the pilot study.

Two activists, one journalist-activist, and a research centre always had both high betweenness centrality and in-degree centralities, therefore they were hubs of information considerably retweeted by their audience. One of these activists and the journalist-activist were also at the centre of the two broadcasting networks mentioned in the previous section, aC1 and aC2 respectively. Another interesting anti-vaccine actor was a parent-activist who had high in-degree, betweenness and out-degree centralities in the three data collections[25]. This actor was a potential hub and broker for anti-vaccine information since s/he retweeted messages from the same cluster, aC3, but also other clusters. This actor was also mentioned regularly by the members of the anti-vaccine community to engage him/her in ongoing conversations or flag a tweet.

There were fewer tendentially anti-vaccine key actors than anti-vaccine ones, and they were mainly uncategorised, activists or parents (Table 5.12). Several anti-vaccine and tendentially anti-vaccine key actors were members of the cluster aC3 (Figure 5.3), and they were well-connected with each other and with other groups. This high connectivity, especially within aC3, may reinforce the ties between the key actors and the other members as well as confirm their own beliefs against vaccination (Southwell, 2013). Moreover, since activists and parents influenced the information shared in this community, they may become a popular alternative source of vaccine information on Twitter (Harrigan, Achananuparp and Lim, 2012).

	June	*September*	*October*
Activists	2	1	3
Parents	2	1	1
Media outlets	1	1	1
Uncategorised	1	5	2
Other	0	3	1
Total	6	11	8

Table 5.12 Tendentially anti-vaccine key actors classified by type of user.
The frequency of tendentially anti-vaccine key actors for each type of user are shown for June, September, and October 2016. These categories are exclusive. The category 'Other' includes types of user that appeared only occasionally and not in all three collections. In September, the category 'Other' included two writers and a parent's association; in October it comprised a journalist. Data from the pilot study.

[25] This actor had high betweenness centrality and in-degree centrality in all datasets, and high out-degree centrality in June and September. In October, this actor retweeted 9 posts shared from others, instead of 10 (the chosen threshold for out-degree centrality).

5.1.2.2 The key actors of the pro-vaccine network

The number of pro-vaccine key actors were 10, 7 and 21 in June, September, and October, respectively. Most of them were NGOs or healthcare professionals and academics, whereas a few of them were chief executives or managers of NGOs and foundations (Table 5.13). One NGO and one of the chief executives were key actors in the clusters pC1 and pC2, respectively. These two actors acted as brokers by connecting different large clusters in the pro-vaccine network and facilitating networking among different NGOs and foundations (Kadushin, 2011). There were very few tendentially pro-vaccine key actors: four were identified in June and only two in October. These actors were mainly academics or healthcare professionals (Table 5.14).

	June	*September*	*October*
NGOs	5	1	9
CEOs	1	1	3
Healthcare professionals or scholars	1	4	6
Other	3	1	3
Total	10	7	21

Table 5.13 Pro-vaccine key actors classified by type of user.
The frequency of pro-vaccine key actors for each type of user are shown for June, September, and October 2016. These categories are exclusive. The category 'Other' includes types of user that appeared only occasionally and not in all three collections. In June, the category 'Other' included a public health service, a rotational curation account, and a science supporter; in September, it included a research centre; in October it included an activist and two pharmaceutical companies.

	June	*September*	*October*
NGOs	1	0	0
Healthcare professionals or scholars	2	0	2
Students and Bloggers	1	0	0
Total	4	0	2

Table 5.14 Tendentially pro-vaccine key actors classified by type of user.
The frequency of tendentially pro-vaccine key actors for each type of user are shown for June, September, and October 2016. In June, one of the scholars was also a parent; In October, one of the scholars was also the chief executive of an NGO.

The reason why many pro-vaccine and tendentially pro-vaccine key actors were NGOs and healthcare professionals may be related to the way these actors use Twitter. NGOs use this outlet for one-way communication and building a community supporting their cause (Guo and Saxton, 2014; Auger, 2013), but they may have used it for reaching out and collaborating with other organisations as well since they are slightly connected (see Figure 5.4). Healthcare practitioners use Twitter for professional development, for connecting and collaborating with other colleagues and professionals, for following online real-time coverage of conferences and for educating the lay public on health issues (Hart *et al.*, 2017a, 2017b). The types of tweets shared by the healthcare professionals (academic and pro-vaccine messages) and the strategic connectivity of these actors with other clusters (shown by the high betweenness centrality) were in line with the findings of Hart et al. (2017a, 2017b).

5.1.3 Users that retweet

The users with high out-degree increase the visibility of the tweets they re-share: the more a post is retweeted, the more frequently it will appear in the stream of followers, and it will be ranked higher on hashtags streams. None of the users with high out-degree was tendentially pro-vaccine, and only a few were pro-vaccine or pro-safe vaccine (Figure 5.6). The pro-vaccine users with high out-degree were a science enthusiast in June and an NGO in October. The NGO had high betweenness and in-degree centralities as well, and was the main actor at the centre of the cluster pC1. This actor not only broadcasted its information but also others' and linked several NGOs and foundations. Hence, it exerted an important influence and control over the information flowing in and out of the pro-vaccine network (Grewal, 2009).

The only pro-safe vaccine user was also identified as a potential key actor in October. S/he was a teacher whose tweets linked pro-vaccine and anti-vaccine users in the same conversation on the importance of testing vaccines rigorously. This actor was not only retweeted but also retweeted some anti-vaccine messages (though his/her personal stream was characterised by both anti-vaccination and pro-safe vaccine messages). However, s/he had an impact only on that one occasion, therefore s/he is unlikely a broker or hub of the anti-vaccine community.

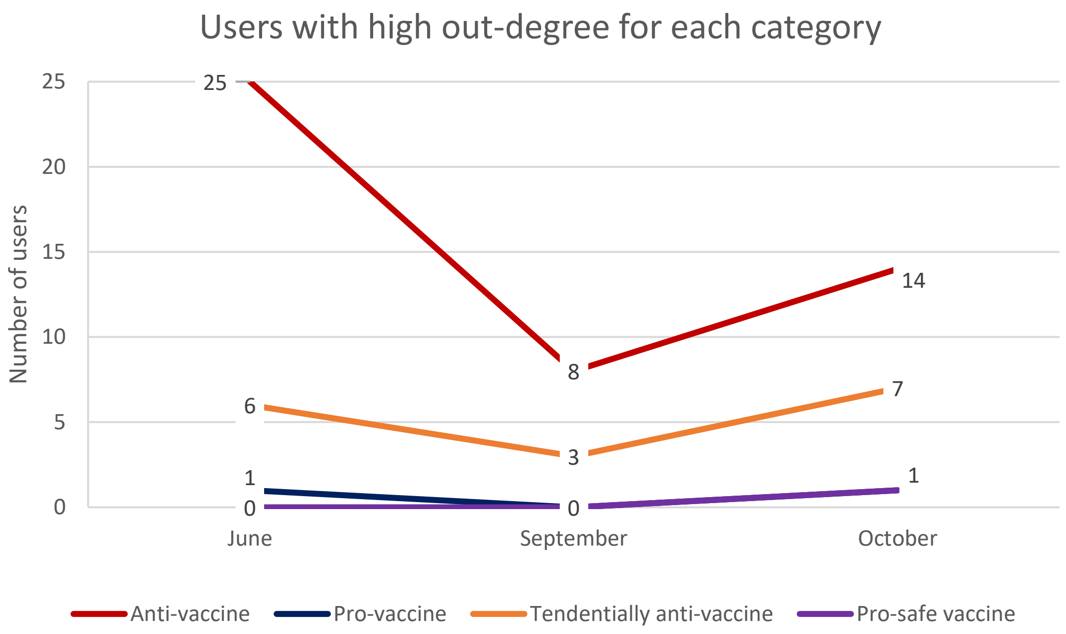


Figure 5.6 Types of users with high out-degree.
Data shown for June, September and October 2016. There were no tendentially pro-vaccine users with high out-degree, therefore this category was excluded from the graph.

Most of the users with high out-degree centrality were anti-vaccine or tendentially anti-vaccine, and many were part of the cluster aC3 (Figure 5.3 and Figure 5.6). Their retweeting not only made the anti-vaccine messages more visible and popular, but also contributed to making the information redundant within their community, reinforcing their anti-vaccine opinions (Southwell, 2013; Kadushin, 2011). The anti-vaccine users that retweeted others the most were mainly activists, uncategorised, or parents. Among those who defined themselves as activists, some claimed to be parents, healthcare professionals, or journalists as well. In the case of the tendentially anti-vaccine users, most of them were uncategorised or parents, and a few were activists (Table 5.15). Interestingly, these users occupied similar categories as hubs and brokers of the anti-vaccine community, though they were not as popular.

	Anti-vaccine			*Tendentially anti-vaccine*		
	June	September	October	June	September	October
Uncategorised	6	2	2	3	2	2
Activists	8	1	5	1	0	2
Parent-Activists	5	1	3	0	0	0
Journalist-Activists	1	1	0	0	0	0
Activist Healthcare professionals	1	0	0	0	0	0
Healthcare professionals	0	1	1	0	0	1
Parents	4	2	2	2	1	1
Bloggers	0	0	1	0	0	0
Writers	0	0	1	0	0	0
Total	25	8	15	6	3	7

Table 5.15 Type of anti-vaccine and tendentially anti-vaccine users with high out-degree across the three datasets.
Data from the pilot study.

Some of these anti-vaccine and tendentially anti-vaccine users had been identified as key actors previously (see Appendix D). Therefore, unlike the pro-vaccine network, the members of the anti-vaccine community (and in particular of cluster aC3) often retweeted each other and formed reciprocal connections, which could potentially become strong ties (Kadushin, 2011). Three users were particularly interesting: a parent-activist, an activist and a journalist-activist. These users appeared in at least two datasets and were not only retweeted but also re-shared other members' messages, hence acting as nodes of information exchange in the anti-vaccine community, and potentially as an alternative source of vaccine information on Twitter (Szomszor, Kostkova and Louis, 2011).

5.1.4 Engaged and mentioned users

The number of users engaged by their counterparts was quite variable across datasets, but all of them were in favour of vaccination. These users had a high betweenness centrality due to their interactions with anti-vaccine users – they linked two groups that otherwise would not have been connected. However, they were not key actors since they were not retweeted often by others (i.e.

they did not have high in-degree centrality) and their interactions with the anti-vaccine users were never constructive.

One uncategorised pro-vaccine user argued with the anti-vaccine users in every dataset. In June, three science supporters[26] and one biology laboratory were also involved in different arguments with anti-vaccine users, whereas in September, a science supporter and a scientific laboratory were engaged in these discussions. None of these occasions could be described as a dialogue, rather they were quarrels.

Some users never participated in debate during the data collection periods, but they were mentioned in highly shared tweets. As a result, they gained high in-degree centrality, even without taking part in the conversation. For example, Donald Trump was mentioned in anti-vaccine, pro-vaccine and news-related conversations in October, but he never tweeted or replied. Mentioned users were labelled as such in Figure 5.1-5.4 to discriminate them from the key actors, but they were not considered further in the analysis.

[26] The actors named “science supporters” defined themselves as rationalists or people interested in sciences; they did not state their scientific backgrounds in their biography.

5.1.5 Summary

The pilot study showed common trends across the three datasets. First, there were more anti-vaccine tweets than pro-vaccine or academic ones, and there were only a few news-related posts. This may be due to the collection criteria, which focused on capturing *ad hoc* publics and potential communities forming around topical hashtags (Bruns and Burgess, 2015). Second, the anti-vaccine community and the pro-vaccine network formed two polarised groups connected only by a few users that argued with each other. Third, these two groups had a different distribution of connections among their members, and third, they had different types of key actors.

The anti-vaccine community was highly connected, indicating that its members were engaged in discussion and likely valued the information shared by the other members (Himelboim, 2017). Moreover, due to this connectivity, the community could provide a sense of trust, safety and support to its members (Kadushin, 2011). One cluster was particularly responsible of the degree of connections within the network since its users frequently retweeted each other as well as other key actors and clusters. These users not only strengthened their ties, but they also made the information redundant within the network, thus reinforcing their anti-vaccination beliefs and their negative perception of outsiders (i.e. pro-vaccine users) (Southwell, 2013). Due to its insulation and recurrent pattern of connections, the anti-vaccine community may be an established network on Twitter, which can be accessed only through specific hashtags or keywords (i.e. standards, see Section 2.3) (Grewal, 2009).

The key actors of the anti-vaccine community were often parents, activists, parent-activists, activist-journalists or uncategorised: they were all alternative and non-academic sources of vaccine information (Himelboim *et al.*, 2019). In particular, one activist and one journalist-activist were the most influential hubs of the network and broadcast anti-vaccine messages to the audiences of their respective clusters (Himelboim, 2017). Many of the other key actors were part of the highly connected cluster instead, and they acted as both hubs and brokers, thus exerting power on the flow of information by choosing what to retweet from other clusters to their audience (Grewal, 2009). The users with high out-degree centrality were also part of this cluster, and though they did not influence the information sharing directly, they increased the visibility and redundancy of anti-vaccine messages by retweeting frequently (Himelboim, 2017).

The pro-vaccine network was segmented in several clusters loosely connected to each other, thus facilitating the access to and diffusion of news among its members and avoiding information redundancy. The distribution of ties favoured networking as well, especially between NGOs and foundations (Kadushin, 2011). Though the network's type of connectivity was recurrent across the datasets, with the exception of two clusters, its clusters were often different. These two clusters were centred on two brokers – an NGO and its chief executive – which connected the other groups and key actors, thus controlling the information flow within the network and promoting networking among them. Without these two brokers, the pro-vaccine network would have been even more fragmented into parallel conversations (Grewal, 2009). Most of the pro-vaccine hubs were NGOs or healthcare professionals. The NGOs broadcasted their messages to their audiences, promoting immunisation campaigns (Guo and Saxton, 2014). The healthcare professionals, instead, used Twitter likely for following or covering academic conferences or for educating the lay public on health issues (Hart *et al.*, 2017a).

5.2 Main data

The collection criteria applied to gather the main data differed slightly from those applied to the pilot study, as described in Section 4.1.2. In November 2016, 15,672 posts embedding pictures were collected from Twitter. Of these, only 13,170 were unique mentions and retweets, and 12,417 were relevant to vaccination. Most of the tweets were in favour of vaccination (45.4%) whereas the anti-vaccine and the news-related posts constituted 20.9% and 21.3% of the dataset, respectively (Table 5.16). The academic tweets formed 11.2% of the collection, and there were some pro-safe vaccine messages (1.2%).

	Tweets (n)	*Tweets (%)*
Anti-vaccine	2600	20.9
Pro-vaccine	5634	45.5
Pro-safe vaccines	143	1.2
Academic	1394	11.2
News	2646	21.3
Overall network	12417	100.0

Table 5.16 Frequency and percentage of anti-vaccine, pro-vaccine, pro-safe vaccines, academic and news-related tweets in November 2016.

These results are in line with previous studies, which found that pro-vaccine tweets formed the majority of the vaccine debate on Twitter (Bello-Orgaz, Hernandez-Castro and Camacho, 2017; Love *et al.*, 2013; Salathé and Khandelwal, 2011). However, these results differ from the pilot findings, which found a majority of tweets were anti-vaccine. This discrepancy could be due to the presence of many pro-vaccine and news-related tweets that were not labelled by hashtags such as #vaccines, #vaccinations or any other hashtags used as keywords for data collection in the pilot study (see Section 4.1.2). To check this hypothesis, the number of retweets with and without hashtags was counted for each group. As shown in Figure 5.7, the anti-vaccine users used hashtags more often than any other category: 91.4% of their tweets had at least one hashtag. The percentage of tweets with hashtags was high for pro-vaccine (68.2%) and academic tweets (63.1%) as well and reached 50.3% in the case of the pro-safe vaccine messages. Only 32.0% of news tweets had a hashtag. It is possible that anti-vaccine users included topical hashtags to reach *ad hoc* publics or to engage with an online community formed around specific hashtags (e.g. #vaxxed or #CDCwhistleblower), whereas users sharing pro-vaccine, academic, and news-related messages may target both *ad hoc* and personal publics (i.e. their followers) (Bruns and Moe, 2014).

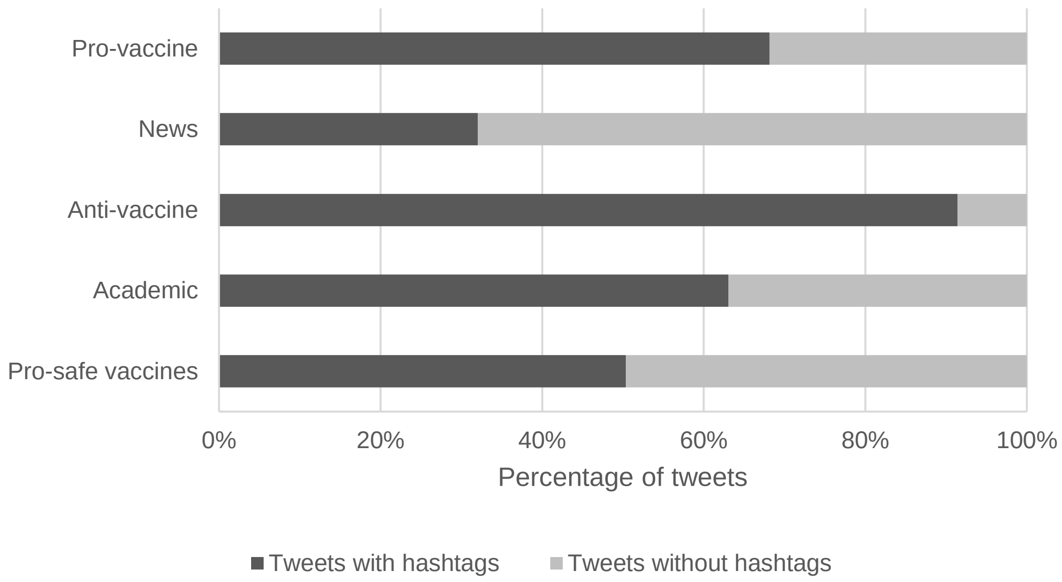


Figure 5.7 Percentages of tweets with and without hashtags in each category.
Data collected in November 2016. The frequencies of these tweets for each category are available in the Appendix D.

The overall network was formed by 9,377 users, and, as in the pilot collection, it looked polarised into two groups (Figure 5.8, Figure 5.9). The pro-vaccine group retweeted posts in favour of vaccination, news and academic messages, but they also shared some pro-safe vaccine tweets. The anti-vaccine group mainly shared anti-vaccination tweets or tweets arguing for pro-safe vaccines, but they also retweeted a few news and academic tweets, which, for example, stated the scientific limitations of specific vaccines. The pro-safe vaccine tweets shared by the anti-vaccine community differed from those shared by the pro-vaccine network. In the first case, the tweets highlighted that some schools and states would not provide exemptions from certain vaccines. The second case, tweets expressed concerns about the cost of vaccines, particularly for developing countries.

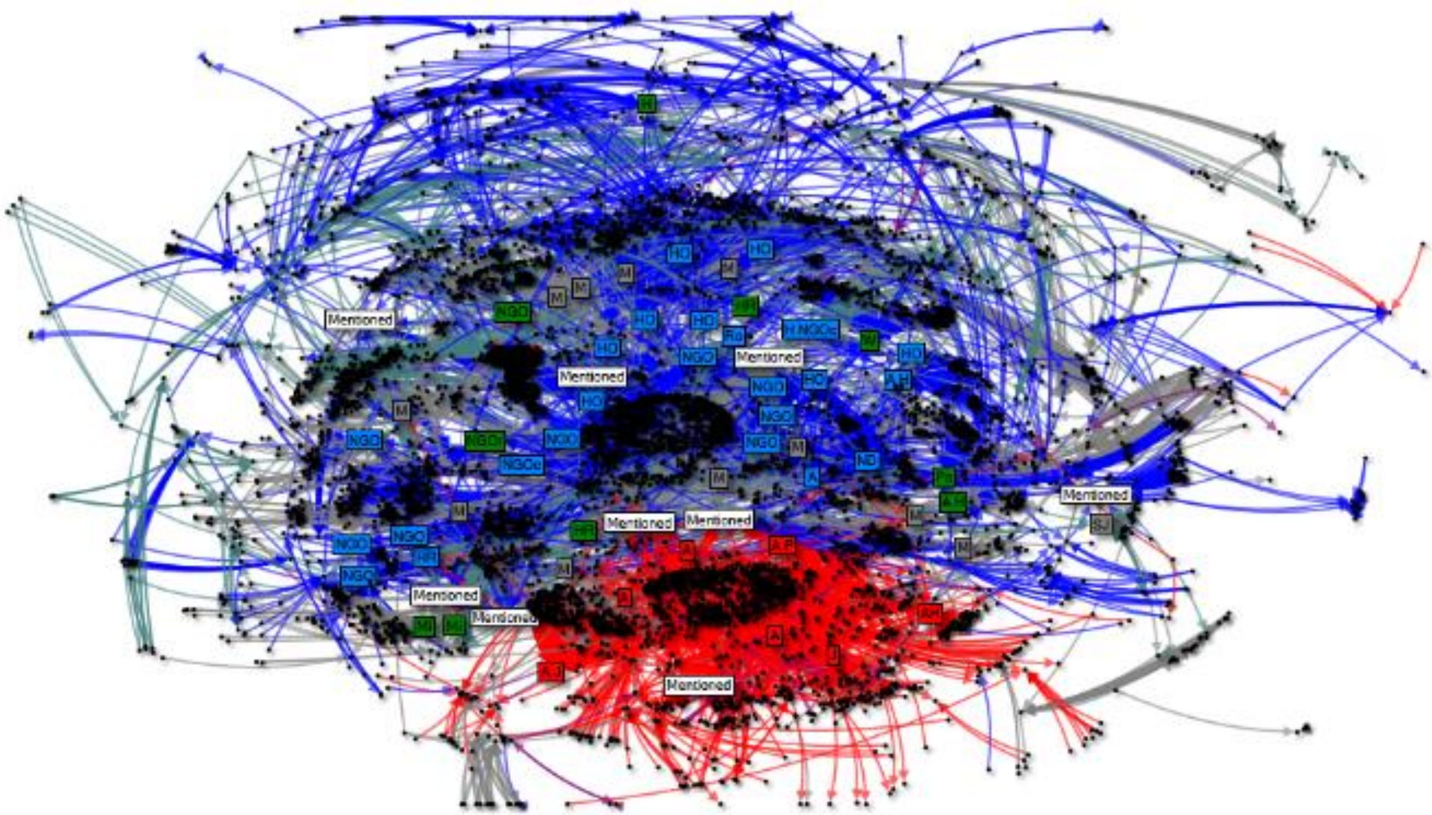


Figure 5.8 Vaccine networks in November 2016.

The anti-vaccine group (in red) and the pro-vaccine group (in blue and petrol green) form two poles of the same component. Label legend: NGO – Non-governmental organisations; NGOc – Chief executives or managers of an NGO; HO – public health services; H – health professionals or scholars; HR – hospitals, research centres, universities; AH – alternative health professionals; A – activists; P – parents; ND – uncategorised users; M – news media outlets; J – journalists; W – writers; Ro – Rotational curation accounts; Po – politicians; SJ – scientific journals; Mentioned – users who were mentioned in the discussion but did not participate.

5.2.1 Social network analysis

The overall network was formed by one big main component that included 9,377 users and 12,417 tweets, and 601 small components of various sizes (Table 5.17). The main component included both anti- and pro-vaccine networks since users from both sides shared a few tweets (e.g. academic tweets discussing vaccines limitations) or mentioned the same accounts (e.g. that of the US president Donald Trump). The network was broad: 16 retweets connected the farthest users, and 5.7 tweets formed the shortest paths linking two users on average. Since the network was wide, the density was low (Kadushin, 2011). The modularity was 0.89, therefore, the network was fragmented into several clusters and was not cohesive.

Overall network's metrics	
Users	9377
Tweets	12417
Diameter	16
Geodesic Distance	5.70
Density	0.0001
Modularity	0.89
Connected components	601
Maximum users in a component	6930
Maximum tweets in a component	10203

Table 5.17 Metrics of the overall network in November.

This fragmentation is also evident in Figure 5.9, which shows the network plotted in clusters. Some users were mentioned by both the anti-vaccine and the pro-vaccine groups, but, unlike the networks of the pilot study, there were no interactions between the two communities. The anti-vaccine users mentioned two news media and a research centre in their conversations, attacking them or their claims, but these users did not reply.

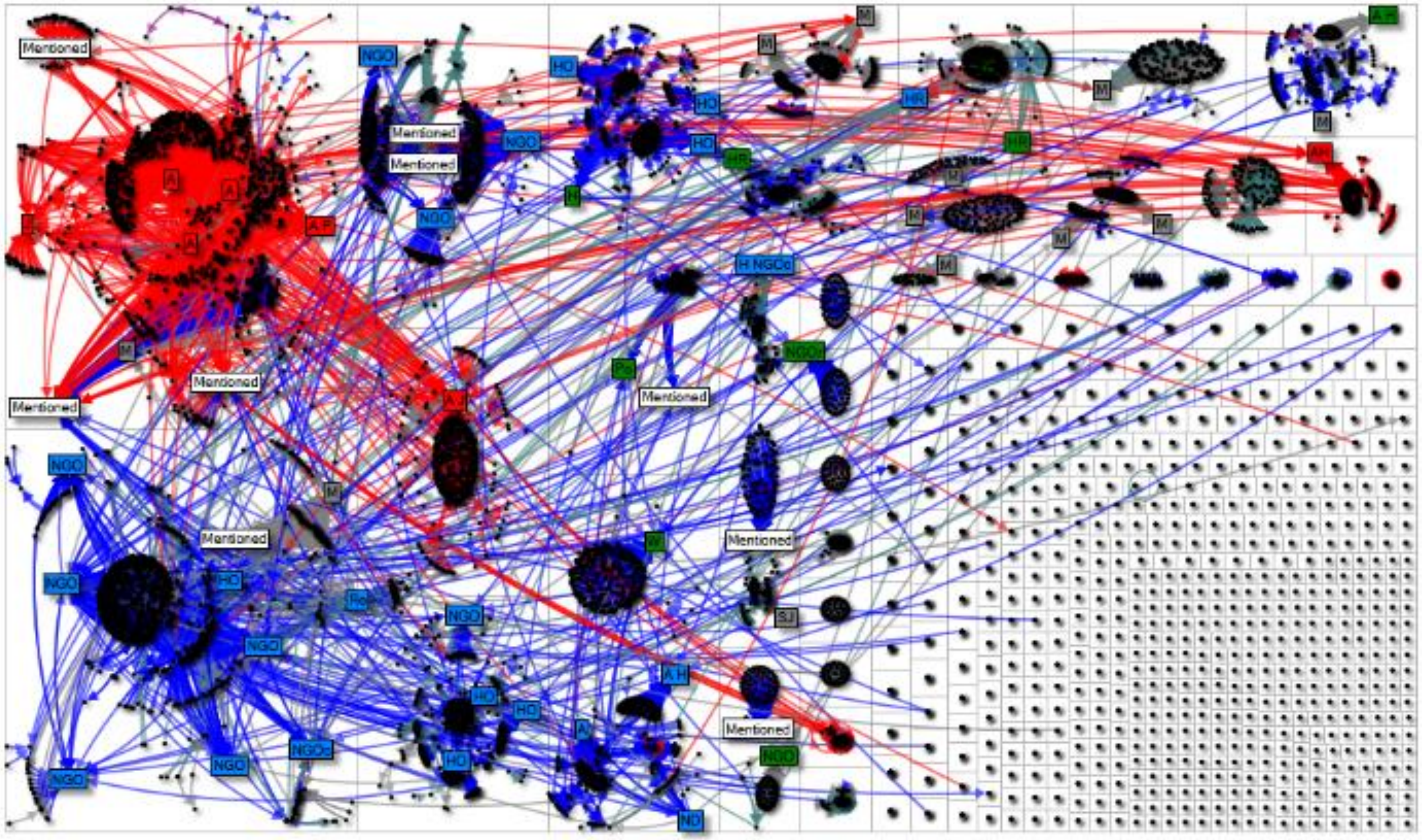


Figure 5.9 Vaccine networks divided into clusters, November 2016.

Data from November 2016. Label legend: NGO – Non-governmental organisations; NGOc – Chief executives or managers of an NGO; HO – public health services; H – health professionals or scholars; HR – hospitals, research centres, universities; AH – alternative health professionals; A – activists; P – parents; ND – uncategorised users; M – news media outlets; J – journalists; W – writers; Ro – rotational curation accounts; Po – politicians; SJ – scientific journals; Mentioned – users who were mentioned in the discussion but did not participate.

In this dataset, since there were many news-related tweets, the network was further analysed by splitting it into three groups instead of two. The anti-vaccine community included anti-vaccine tweets and some pro-safe vaccines posts; the pro-vaccine network was formed by pro-vaccine and academic tweets and some pro-safe vaccines messages; the news-related group had only news. Some users were included in more than one group since they retweeted different kinds of messages. The high number of news-related tweets in this collection might be due to the inclusion criteria, which included both words and hashtags as search keywords. As mentioned before, 68.0% of news did not have a hashtag (Figure 5.7).

	Anti-vaccine community	*Pro-vaccine network*	*News related group*
Users	1884	5377	2260
Tweets	2706	6931	2647
Diameter	10	16	20
Geodesic Distance	3.55	5.26	7.19
Density	0.0008	0.0002	0.0005
Modularity	0.70	0.90	0.95
Connected components	58	416	232
Maximum users in a component	1654	3611	1103
Maximum tweets in a component	2523	5252	1501

Table 5.18 Metrics of the anti-vaccine community, pro-vaccine network and news-related group, in November collection.

The pro-vaccine network included 6,931 tweets and 5,377 users, whereas the anti-vaccine community was formed only by 2,706 tweets and 1,884 users. The news-related group was slightly bigger than the anti-vaccine group, but it was also sparser and more fragmented than the pro-vaccine network: it included 2,647 tweets and 2,260 users, and its farthest members were linked by 20 retweets (Table 5.18). The three groups had a different distribution and partitioning of connections (see Figure 5.10 and Figure 5.12), which also emerged from the metrics related to the parallel conversations occurring at the same time (i.e. connected components). For example, the anti-vaccine community had the smallest number of components, 57, whereas the news-related group, which had a similar size, had 232 components.

5.2.1.1 The anti-vaccine community

The anti-vaccine community was similar to that found in the pilot study. The community was formed by several broadcasting networks (the star-shaped groups in Figure 5.10), and a highly connected cluster. This last cluster and two broadcasting groups were also identified in the pilot research, and they included the same key actors; therefore, they were called aC1m, aC2m, aC3m. All three clusters were bigger in this collection than in the pilot datasets.

The cluster aC1m (on the left of Figure 5.10) was a broadcasting network that included 528 users tweeting 559 posts, mostly shared by the activist hub. The cluster aC2m was also a broadcasting network (top-centre of Figure 5.10), and was formed by 320 users sharing tweets posted by a hub, a journalist-activist. This cluster was smaller and slightly wider in diameter than aC1m, but in both cases, their members were connected by two tweets on average (Table 5.19). These metrics were coherent with the clusters' distribution: most of the members could access the hubs' messages almost directly, in two retweets, and retweeted them at least once. However, these actors hardly ever re-shared posts from their audience, and their audiences rarely retweeted messages from other members. Therefore, both key actors dominated the conversations in their clusters as main sources of vaccine information (Southwell, 2013; Grewal, 2009).

The cluster aC3m (bottom-centre of Figure 5.10) had 266 users sharing 653 tweets and a density higher than aC1m and aC2m (Table 5.19); hence its users often retweeted each other and were highly connected. The cluster aC3m included various key actors who were mainly activists, parent-activists and users with high out-degree (i.e. they frequently retweeted other users). These key actors often retweeted and mentioned each other, increasing the connectivity and cohesiveness of the cluster, and facilitating the formation of strong ties among them (Huberman, Romero and Wu, 2008). Though this cluster resembled an in-group because of its high connectivity (Himelboim *et al.*, 2017), its users and actors not only retweeted other members but also outsiders, thus linking the different groups of the community. Therefore, the cluster aC3m and its key actors played an essential role in bridging the different groups creating a cohesive anti-vaccine community and diffusing information among them (Southwell, 2013; Kadushin, 2011).

	aC1m	*aC2m*	*aC3m*
Users	528	321	266
Tweets	559	320	653
Diameter	4	6	7
Geodesic Distance	2.02	2.09	3.25
Density	0.0020	0.0031	0.0093
Modularity	0.00	0.00	0.01

Table 5.19 Metrics of the anti-vaccine clusters aC1m, aC2m and aC3m in November 2016.

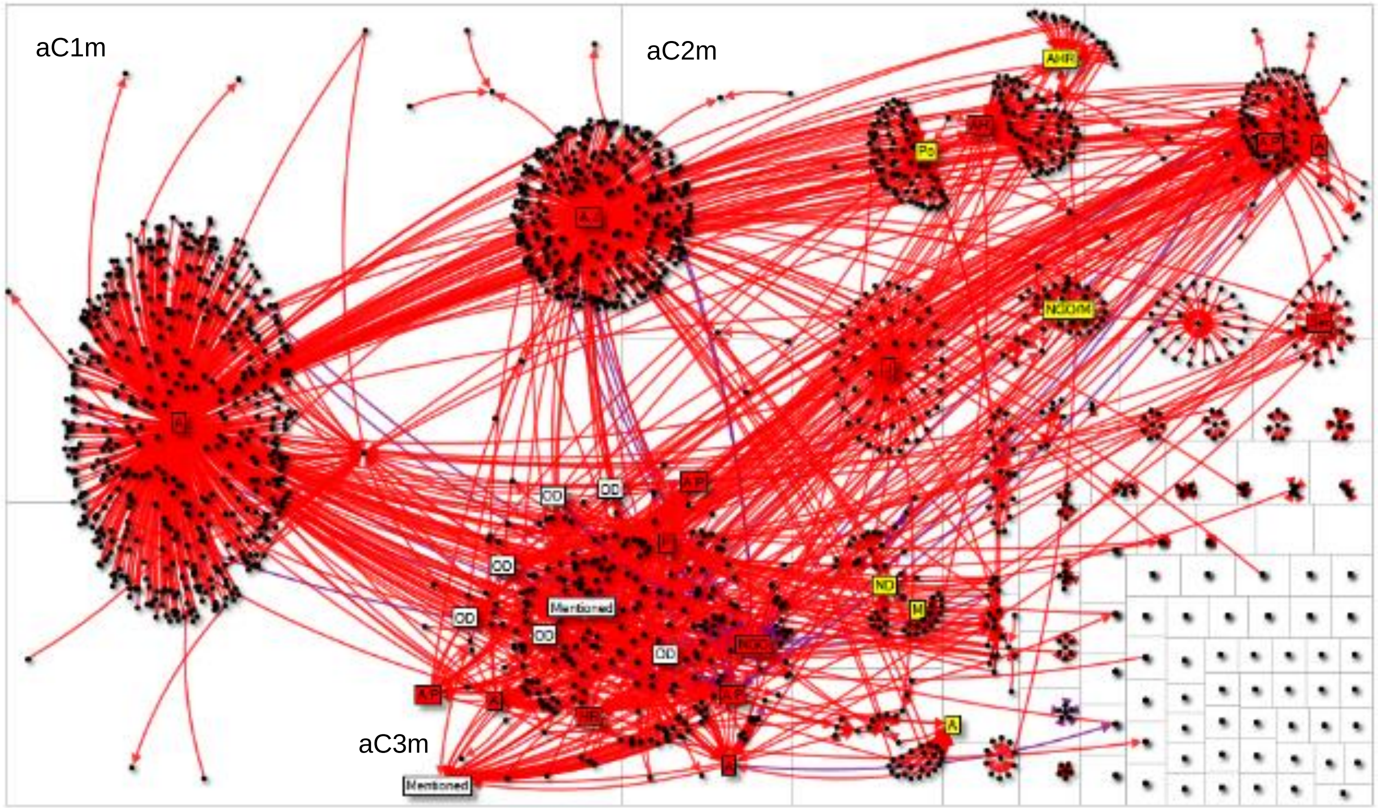


Figure 5.10 Anti-vaccine community in November 2016.

The network was divided into clusters. Label legend: NGO – non-governmental organisations; AH – alternative health professionals; HR – hospitals, research centres, universities; AHR – alternative health clinics; A – activists; P – parents; ND – uncategorised users; M – media outlets; J – journalists; Ser – online tools or software; OD – users with high out-degree centrality; Mentioned – users who were mentioned in the discussion but did not participate.

5.2.1.2 The pro-vaccine network

The pro-vaccine network resembled a community cluster since it was fragmented into various clusters which were not highly connected (Smith *et al.*, 2014), and many of its clusters looked like broadcasting networks with one or two central actors (Figure 5.11). The main cluster and two of its actors, an NGO and its chief executive, appeared in the pilot datasets as well and was named pC1m.

The cluster pC1m (second top quadrant from the left, Figure 5.11) included 358 users and 634 tweets, and it had the largest diameter (i.e. number of tweets connecting the farthest users) and geodesic distance (i.e. the average shortest path of tweets connecting two users) across the four clusters, though it was not the biggest (Table 5.20). These values may indicate that the cluster and its members tended to reach out to other groups, and seek new information to share, and its pattern in Figure 5.11 seems to support this observation. Moreover, the NGO that was noticed in the pilot datasets previously was identified as a key actor here as well and acted as an information hub and a broker linking the various NGOs in the pro-vaccine networks (Kadushin, 2011).

	pC1m	*pC2m*	*pC3m*	*pC4m*
Users	358	664	462	255
Tweets	634	695	803	254
Diameter	9	7	6	6
Geodesic Distance	3.46	2.29	2.97	2.09
Density	0.0050	0.0016	0.0038	0.0039
Modularity	0.02	0.00	0.00	0.00

Table 5.20 Metrics of the pro-vaccine clusters pC1m, pC2m, pC3m and pC4m in November 2016.

The clusters pC2m and pC4m (top-left and second central-left quadrants in Figure 5.11, respectively) were broadcasting networks with a healthcare organisation and a writer at their centres, respectively (Himelboim *et al.*, 2017).

The writer became a key actor due to one tweet s/he published, which suggested that Donald Trump was unsuitable as president of the United States due to his beliefs and claims that vaccines cause autism. In both clusters, the key actors were highly retweeted, but they did not re-share their audiences' posts, thus acting as information hubs (Himelboim, 2017).

The cluster pC3m (first bottom-left quadrant in Figure 5.11) had fewer users but more tweets than pC2m (Table 5.20), due to the reciprocal interactions among some of its members. In this cluster, three accounts linked to the same NGO tweeted about the same campaign which targeted two pharmaceutical companies (mentioned in the posts). These companies were called out to reduce the price of the pneumonia vaccine and make it affordable for developing countries. Though pC3m did not show a star shape, it was closer to a broadcasting network than to other types of clusters. The three NGOs accounts were connected through the two companies they mentioned, but they were retweeted by separated audiences, thus acting as hubs rather than as brokers (Himelboim, 2017). The clusters of the pro-vaccine group were not as highly connected as those of the anti-vaccine community. However, several NGOs, foundations, healthcare organisations and public health services reached out to each other, forming connections that facilitated networking and the exchange of new information (Kadushin, 2011).

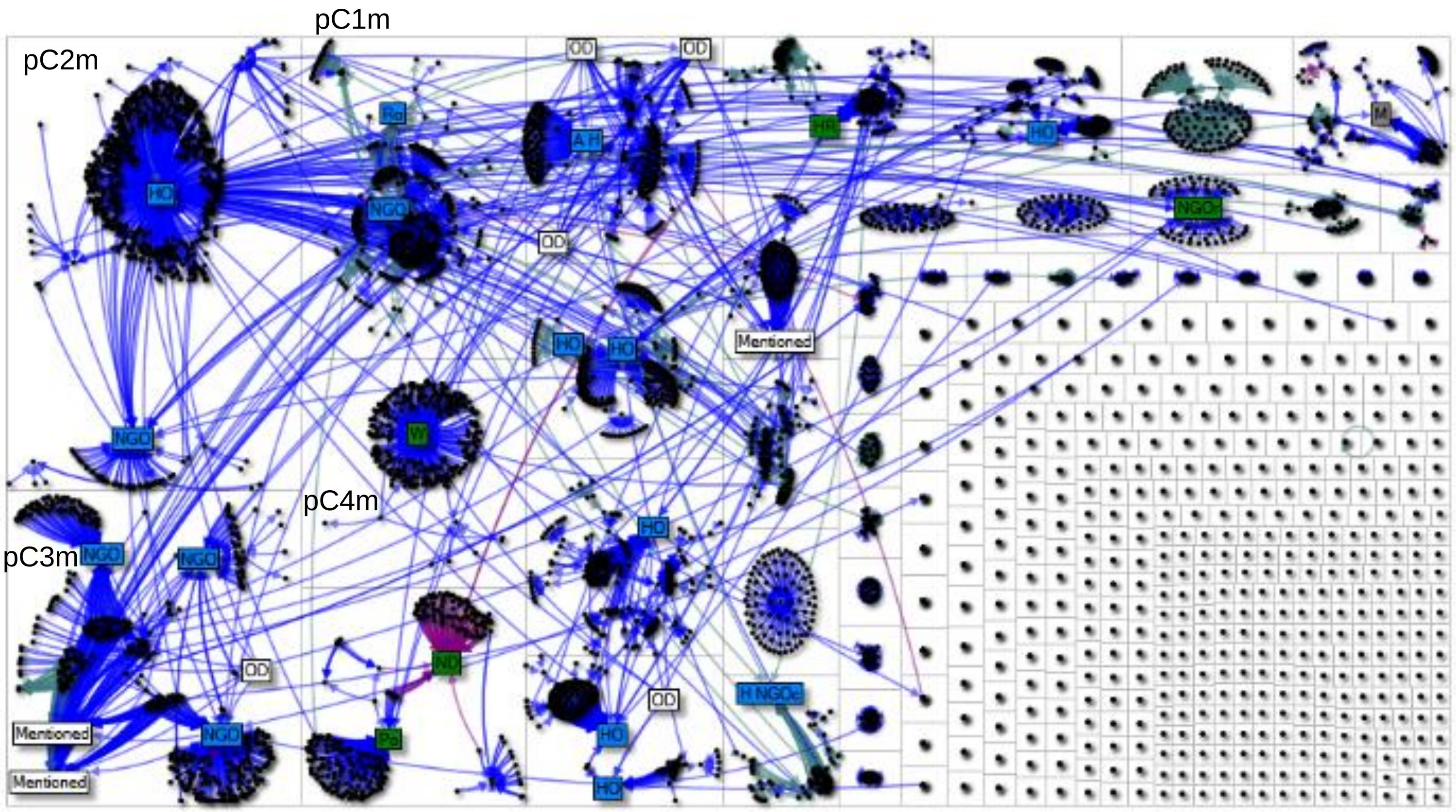


Figure 5.11 Pro-vaccine network in November 2016.
The network was divided into clusters. Label legend: NGO – non-governmental organisations; NGOc – chief executives or managers of an NGO; HO – public health services; H – healthcare professionals or scholars; HR – hospitals, research centres, universities; ND – uncategorised users; M – media outlets; W – writers; Ro – rotational curation accounts; Po – politicians; OD – users with high out-degree centrality; Mentioned – users who were mentioned in the discussion but did not participate.

5.2.1.3 The news-related group

The news-related group was formed by many clusters that discussed vaccination but only with their members. All these clusters were broadcasting networks with mainly news media outlets at their centres (Figure 5.12). As shown in Table 5.18, this group was highly fragmented: it had high modularity, a high diameter and geodesic distance, and many connected components. This fragmentation is evident in Figure 5.12 as well, which shows how the different clusters are poorly connected.

This observation was not surprising since most of the news-related tweets had no hashtags and were likely targeting the media outlets' followers (see Section 5.2.1). It is possible that the key influencers in this group were more interested in reaching their personal publics (i.e. direct followers) rather than *ad hoc* publics or communities that form around hashtag conversations (Bruns and Burgess, 2015; Bruns and Moe, 2014).

Summarising, the three groups – anti-vaccine, pro-vaccine and news-related –differed in the density and distribution of their connections. The anti-vaccine community was the most cohesive, and its users retweeted each other, strengthening their ties and their vaccination opinions (Southwell, 2013). The pro-vaccine network was more fragmented, but its clusters formed effective connections that facilitated networking and information exchange (Kadushin, 2011). Finally, the news-related group was formed by ongoing parallel conversations, poorly connected to each other, in which the central actors broadcast messages to their personal publics (Bruns and Moe, 2014). These three groups not only differed in their connectivity, but also in the types of key actors.

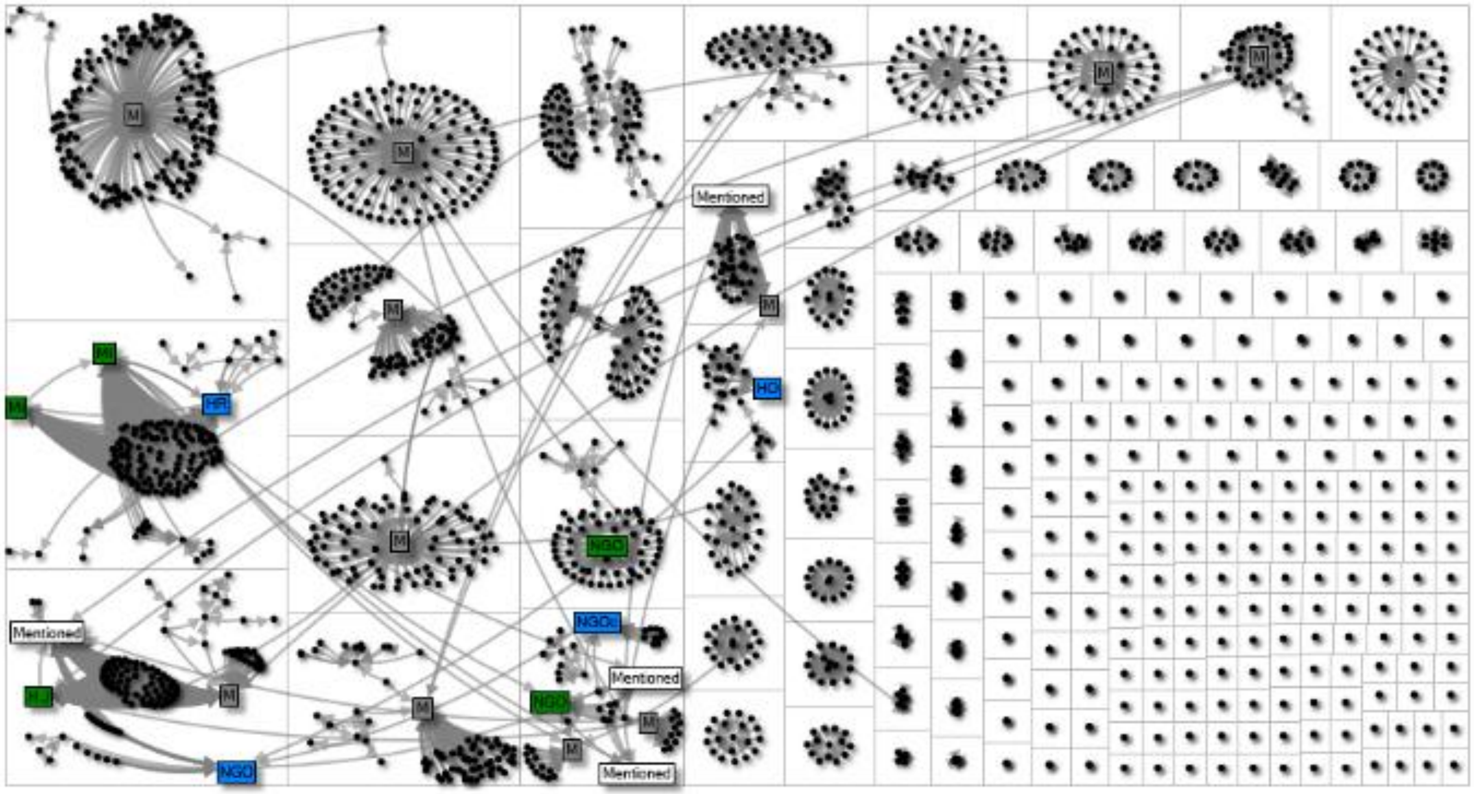


Figure 5.12 News-related network inNovember 2016.

The network was divided into clusters. Label legend: M – media outlets; NGO – non-governmental organisations; NGOc – chief executives or managers of an NGO; HO – public health services; H – healthcare professionals or scholars; HR – hospitals, research centres, universities; J – journalists; Mi – military accounts; Mentioned – users who were mentioned in the discussion but did not participate.

5.2.2 Key actors: hubs and brokers

Since the anti-vaccine, pro-vaccine and news-related groups had different patterns of information sharing, it was likely that they had different key actors influencing their information flow (Grewal, 2009). Therefore, the key actors were not identified for the overall network, as in the pilot study, but for each group (See Section 4.5.2). Fifty-nine unique key actors were found in total (one appeared both in the pro-vaccine network and in the news-related group). Overall, 46% of these actors were in favour of vaccinations (31% pro-vaccine and 15% tendentially pro-vaccine) whereas 34% were against vaccination (25% anti-vaccine and 9% tendentially anti-vaccine) and 20% were neutral (See Figure 5.13). There were no pro-safe vaccine key actors. In contrast to the pilot datasets, there were more tendentially pro-vaccine influential actors than tendentially anti-vaccine ones. This difference most likely arose as a result of the collection criteria, which included words as well as hashtags, and the consequent higher number of pro-vaccine, academic and news-related tweets in the sample. The distribution of these key actors differed among communities; hence, the three following sections discuss them in relation to their specific group.

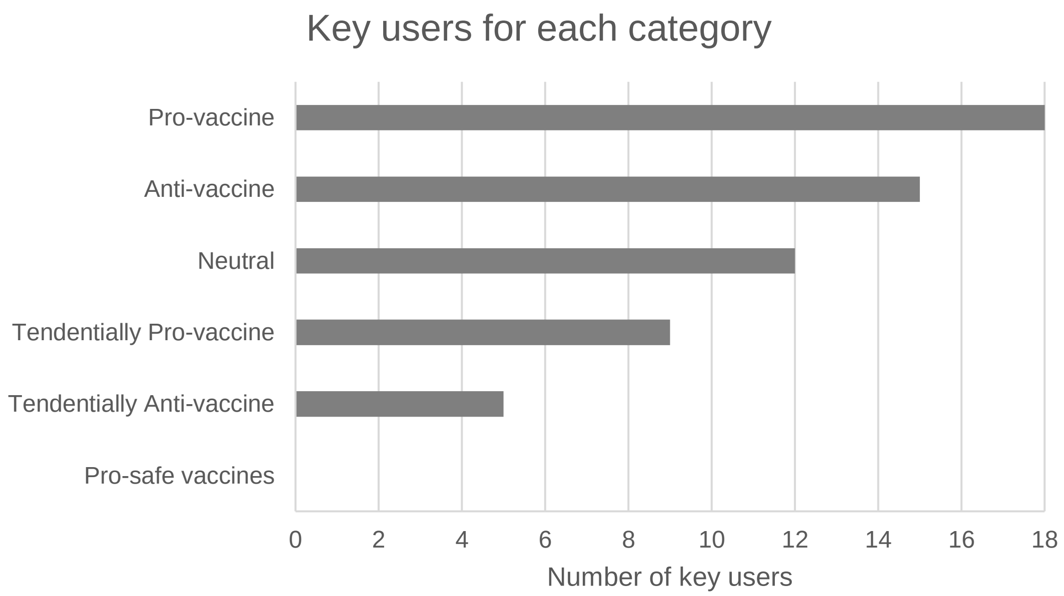


Figure 5.13 Key users classified by vaccine sentiment.
These categories are exclusive. In this graph, key users are not separated into networks (i.e. pro-vaccine, anti-vaccine and news-related group), but are considered all together. Data from November 2016.

Some users had high betweenness and/or in-degree centralities, but they did not share any tweets: they were only mentioned in highly shared messages and did not exert any influence on the network. Among these, the official account of Donald Trump obtained the highest level of centralities since it was often mentioned by anti- and pro-vaccine users and even media outlets, in relation to his anti-vaccination claims.

5.2.2.1 Key actors of the anti-vaccine community

The anti-vaccine key actors were mainly activists or parent-activists (Table 5.21), and all of them also appeared at least once in the pilot datasets, suggesting that they may have a certain influence within the community. Most of the tendentially anti-vaccine key actors also appeared in more than one pilot dataset, and two of them were related to anti-vaccine actors. For example, the news media outlet was a webzine administered by the journalist-activist, whereas the healthcare centre was also managed by the alternative health practitioner (Table 5.21).

The journalist-activist and one activist were hubs dominating the two main clusters (aC1m and aC2m). These two actors held the same strategic position in the pilot datasets as well, hence they were likely sources of information, experts acknowledged by the members of the anti-vaccine community (Bruns, 2008a). However, the information shared by these two hubs would not have been as influential without the aid of other anti-vaccine key actors, who were members of the cohesive cluster aC3m. These actors acted as hubs and brokers, interacting with members of the same cluster and, at the same time, retweeting the other clusters, thus controlling the information shared within the community (Grewal, 2009).

	Anti-vaccine	Tendentially anti-vaccine
Activists	4	1
Parent-Activists	4	0
Parents	1	0
Journalist-Activists	1	0
Alternative Health practitioners	1	0
Alternative Health centre	0	1
Research Centres	1	0
NGOs	1	1
Journalists	1	0
News media outlet	0	1
Uncategorised	0	1
Service	1	0
Total	15	5

Table 5.21 Anti-vaccine and tendentially anti-vaccine key actors within the anti-vaccine community classified by type of user.
Data from November 2016.

5.2.2.2 Key actors of the pro-vaccine network

In the pro-vaccine network, there were fifteen pro-vaccination key actors, four tendentially pro-vaccine key actors and one classified as neutral since it was a media organisation[27] (Table 5.22). Many of the pro-vaccine key actors found in this collection also appeared in the pilot datasets, and most of them were either NGOs and foundations or healthcare services and organisations. Among these recurrent actors there was an activist and healthcare professional that acted as a hub and advocated for vaccination.

All the NGOs were hubs, but they were also well connected to each other thanks to another NGO, which acted as a broker in the pilot datasets as well (see Section 5.1.2.2). The healthcare organisations, instead, looked more interested in disseminating their content than building relationships (Park,

[27] This media organisation shared mainly news, but it appeared in the pro-vaccine network because of one of it tweets campaigned against Donald Trump as president and his position on vaccination.

Reber and Chon, 2016). The tendentially pro-vaccine key actors identified in this collection were not present in the pilot, and they might have acquired a high in-degree centrality on this occasion by sharing particular tweets. For example, the writer (Table 5.22) posted a tweet against Donald Trump and his anti-vaccination position that became viral.

Pro-vaccine key actors	*Pro-vaccine*	*Tendentially pro-vaccine*	*Neutral*
NGOs	6	0	0
Public Health Services	6	0	0
Activists and Healthcare professionals	1	0	0
Rotation curation accounts	1	0	0
Healthcare practitioners	1	0	0
Writers	0	1	0
Politicians	0	1	0
Hospital/Research centres	0	1	0
CEO/managers of NGOs	0	1	0
News Media outlets			1
Total	15	4	1

Table 5.22 Pro-vaccine and tendentially pro-vaccine key actors within the pro-vaccine network classified by type of user.
Data from November 2016. CEO – Chief executive or manager of an NGO. Rotation curation account – every week a different individual manages the account.

Unlike the NGOs, the healthcare organisations were identified as key actors only in this collection and not in the pilot study. It is possible that these actors used keywords other than #vaccines or #vaccinations or #immunisation, hence they were not found in the pilot study. These actors might use hashtags tailored to specific immunisation campaigns, such as #FluFighters, or not use hashtags at all.

5.2.2.3 Key actors of the news-related group

In the news-related group, there were eleven neutral key actors, four pro-vaccine and five tendentially pro-vaccine (Table 5.23). All these actors were hubs loosely connected to each other if at all (Figure 5.12), and most of them were media outlets broadcasting their messages to their personal publics (i.e. followers) rather than *ad hoc* audiences (Bruns and Burgess, 2015). Moreover, these key actors likely monopolised the information flows within their clusters (Grewal, 2009).

The pro-vaccine and tendentially pro-vaccine key actors shared academic tweets and/or posts in favour of vaccination as well, but only the news posts were highly retweeted. Among these actors, the chief executive was of particular interest because s/he was also a key actor in the pilot datasets (see Section 5.1.2.2). His/her NGO was a broker of the pro-vaccine network, but both of them were in the same cluster in the overall network (Figure 5.12). It is possible that while the NGO bridged the cluster and key actors of the pro-vaccine network, the chief executive contributed to disseminating pro-vaccination messages and news about immunisation.

News related key actors	*Neutral*	*Pro-vaccine*	*Tendentially pro-vaccine*
NGOs	0	2	2
Chief executive of NGO	0	1	0
Research Centres	0	1	0
News Media outlets	11	0	0
Army related	0	0	2
Healthcare practitioners and Journalists	0	0	1
Total	11	4	5

Table 5.23 Key actors within the news-related group classified by type of user and sentiment.
Data from November 2016.

5.2.3 Users that retweet

Some users were neither hubs nor brokers, but retweeted the messages of their networks, thus increasing their visibility. Among these users, six were identified for the anti-vaccine community and seven for the pro-vaccine network, whereas the news-related group had none that satisfied the criteria stated in Section 4.5.2 (Figure 5.14). In this group, there were only two actors with raised values of out-degree centrality: a physician and an anti-vaccine activist[28] who appeared in the datasets of the pilot as well.

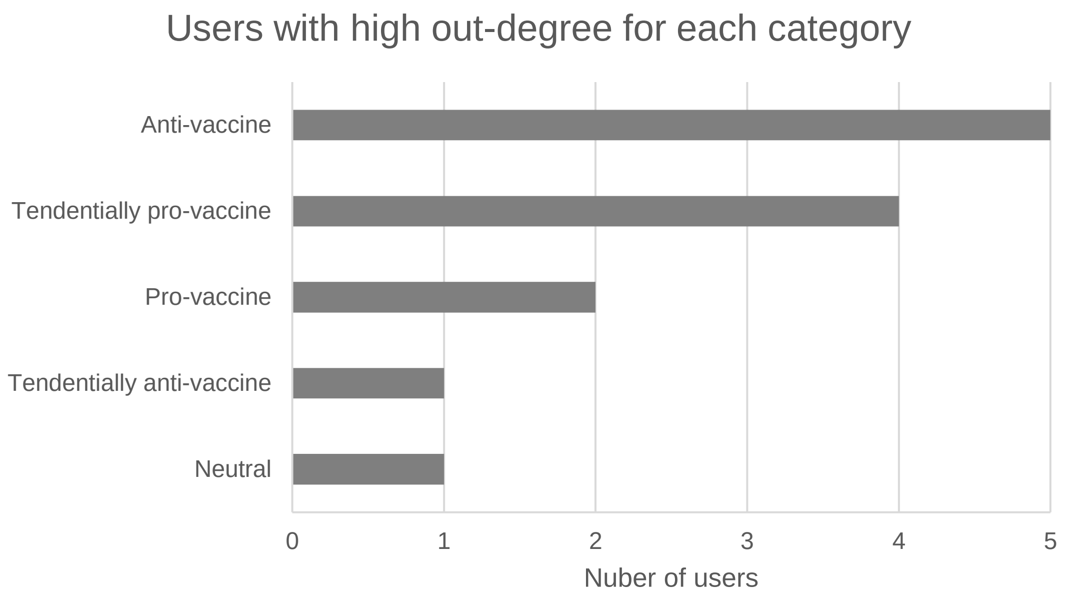


Figure 5.14 Users with high out-degree centrality classified based on their opinion of vaccines. Only the users identified in the anti-vaccine community and the pro-vaccine network are shown since there was none in the news-related group. Data from November 2016.

In the anti-vaccine community, most of the users with high out-degree were anti-vaccine, and only one was tendentially anti-vaccine. These users were parent-activists, uncategorised, activists or healthcare professionals (Table 5.24), and all of them appeared in the pilot datasets. Moreover, these users were members of cluster aC3m, which controlled information flow within the community; hence by retweeting they contributed to increasing the visibility and redundancy of the anti-vaccine information (Harrigan, Achananuparp and Lim, 2012; Kadushin, 2011).

In the pro-vaccine network, most of the users with high out-degree were tendentially pro-vaccine, and they were healthcare professionals or scholars

[28] The physician retweeted nine pieces of news, and the activist retweeted eight.

and/or activists (Table 5.24). The pro-vaccine users were a manager of an NGO and an uncategorised user, who also appeared in the pilot data as a user engaged by the anti-vaccine ones (see Section 5.1.4). In the pro-vaccine network, there was a neutral user as well, which was a bot retweeting vaccine information. Unlike the users with high out-degree from the anti-vaccine community, the pro-vaccine ones were not members of the same cluster. Only three of them were in the same group, but like the others, they retweeted members of several different clusters. Therefore, these users did not make the pro-vaccine messages redundant, but they increased their visibility and facilitated the exchange of new information within the pro-vaccine network (Kadushin, 2011).

	Anti-vaccine	*Pro-vaccine*	*Tendentially anti-vaccine*	*Tendentially pro-vaccine*	*Neutral*
Uncategorised	1	1	1	0	0
Activists	1	0	0	1	0
Activists and Parents	2	0	0	0	0
Activists and Healthcare professionals	0	0	0	1	0
CEOs of NGO	0	1	0	0	0
Healthcare professionals	1	0	0	2	0
Bot accounts	0	0	0	0	1
Total	5	2	1	4	1

Table 5.24 Types of users with high out-degree for each group.
The different types of anti-vaccine, pro-vaccine, tendentially anti-vaccine, tendentially pro-vaccine and neutral users with high out-degree are shown. Data from November 2016.

5.2.4 Summary

The results of the main study were similar to those of the pilot: the anti- and pro-vaccine users formed two insular networks and had a recurrent sharing pattern and key actors. However, while in the pilot study the anti-vaccine tweets and key actors were often the majority, in this research there were more pro-vaccine and news-related tweets and more key actors in favour of immunisation. These results were consistent with previous research (Bello-Orgaz, Hernandez-Castro and Camacho, 2017; Love *et al.*, 2013; Salathé and Khandelwal, 2011), even though only tweets embedding pictures were considered in this study. Therefore, the discrepancy between the results of the pilot and the main study is likely due to the exclusion/inclusion of words in the collection criteria. While the pilot research focused on *ad hoc* publics, the main study considered potential personal publics as well by including both hashtags and words in the criteria (Bruns and Moe, 2014).

Though the anti-vaccine community was smaller than the pro-vaccine one in this study than in the pilot, it presented the same key actors and distribution of connections. For example, most of the anti-vaccine key actors were either activists or parent-activists, and there were two main broadcasting clusters linked to the rest of the community especially through a third highly connected cluster. The members of this group frequently retweeted each other and other clusters, thus making the information redundant and reinforcing their own anti-vaccine beliefs within the community. Moreover, by doing so they strengthened their ties and likely increased the sense of safety, support and trust among them as well as their distrust towards outsiders (Southwell, 2013; Kadushin, 2011). Many key actors were part of this cluster as well as all the users with high out-degree, which increased the visibility and redundancy of the anti-vaccine messages (Himelboim, 2017). The two main hubs, an activist and a journalist-activist, and the key actors of the cohesive cluster occupied strategic positions within the community that allowed them to control the information flow by selecting the information to tweet and retweet with the other members. Therefore, these actors could exert power over the community acting as gatekeepers of information (Schmidt, 2014; Grewal, 2009). Moreover, since these actors contributed to the vaccine debate regularly and were frequently retweeted, they were likely seen as alternative sources of vaccine information and acknowledged as experts or authorities, by the other members of the anti-vaccine community (ALL Europe Academies, 2019; Bruns, 2008a).

The pro-vaccine network was more fragmented than the anti-vaccine community, though its clusters were more connected in the main study than in the pilot. The loose ties among clusters favoured information exchange and networking, thus facilitating access to news and potential collaborators but discouraging the formation of a close community. Several groups were linked to each other especially through a recurrent cluster dominated by an NGO, which also acted as a broker in the pilot study. This NGO connected clusters and hubs thus controlling the flow of tweets within the network and becoming an indispensable gatekeeper of information for most of the other members, especially other NGOs and foundations (Schmidt, 2014; Grewal, 2009). The other clusters formed around hubs such as NGOs or healthcare organisations; the first ones were focused on promoting their campaigns as well as building a community supporting their cause (Guo and Saxton, 2014; Auger, 2013), whereas the second were interested in disseminating organisational information and health messages to their personal publics (Park, Reber and Chon, 2016). Alternative sources of information were missing from the pro-vaccine network, which comprised primarily those recognised by the traditional expertise system, such as healthcare professionals, healthcare organisations, and journalists.

The news-related group was the most fragmented: several parallel conversations occurred in the same period and most of them were centred on a media outlet. These outlets rarely interacted with other users or networked, and they focused only on broadcasting their messages to their personal publics, likely their followers since they often did not include hashtags in their tweets (Bruns and Moe, 2014). It is possible that these actors aimed to augment their reach by cascading their images through their followers' followers instead of directly targeting conversations around hashtags. While the hubs in this group were mainly interested in their personal publics, the anti-vaccine key actors used Twitter in a fundamentally different way. They reached out to *ad hoc* publics by including either generic or anti-vaccination hashtags in their posts (e.g. #vaccines or #vaxxed, respectively). In this way, they could join different conversations about immunisation and disseminate their messages more broadly within Twitter groups interested in the topic. Moreover, this high use of hashtags may have gone beyond reaching users with similar beliefs and had become a way to engage with an established online community (Bruns and Burgess, 2015; Bruns and Moe, 2014). If so, the anti-vaccination hashtags were standards that regulated access to the anti-vaccine community: without including them it would not be possible to interact with the other members, or access the information they shared and obtain their support (Grewal, 2009). The pro-vaccine hashtags also granted access to the network, but they were not always necessary. In fact, the pro-vaccine users did not use hashtags as often as anti-vaccine users, especially the generic ones, and they targeted both their existing audience and *ad hoc* publics by combining keywords (e.g. vaccines) with either vaccine hashtags or those tailored on their immunisation campaigns (Bruns and Burgess, 2015; Bruns and Moe, 2014). News-related, pro-vaccine and anti-vaccine networks use Twitter in three different ways.

6. Visual analysis methodology

Objects, people and actions depicted in an image can require a certain cultural background to be understood. For example, two people exchanging rings can mean a ‘wedding’ as well as ‘loyalty’, but only in countries where wedding rings are a common tradition. Anti- and pro-vaccine networks on Twitter may have their own visual language, they may use images representing specific objects or a combination of figurative elements to communicate with other members. Knowing how figurative elements (e.g. objects, people) are used could facilitate communication with the community (Lester, 2014) as well as understanding how the members interpret and represent vaccination (Rose, 2012). Moreover, images “may offer a gateway to the culture of the producer and that of the implied audience” (Pauwels, 2011, p.6). As mentioned in Section 3.3, this research adopted a pragmatic approach, hence it chose the methods that were more appropriate to answer the research questions. These methods were quantitative and qualitative content analyses and image analysis (see below).

To understand how pro- and anti-vaccine communities communicate visually, the pictures collected during the social network analysis were investigated (i.e. pictures embedded in the tweets). A content analysis (quantitative and qualitative) was conducted to explore the recurrent topics and figurative elements of the images shared by these communities (Pennington, 2016); hence the potential visual conventions used by their members to communicate (Grewal, 2009). The content analysis was also used to identify image characteristics that should be considered for the selection of a smaller sample for a qualitative image analysis. This analysis was conducted to further interpret and understand the messages conveyed by the images in relation to their context. Hence, this analysis investigated the relationships between visual and textual elements, the tweet, hyperlinks, users and their potential Twitter audiences (Ledin and Machin, 2018; Pennington, 2016; Jewitt and Oyama, 2001). All these details were studied because social media images are often modified, cropped, re-contextualised and shared to an audience and with a purpose that can be different from those of the original picture. Moreover, vaccine images shared on Twitter are often not produced by those posting them (Chen and Dredze, 2018). Therefore, the contextual information and the text accompanying these images could influence their meaning and interpretation (Hand, 2016; Pennington, 2016).

Two samples of images collected during the pilot study (see Section 6.1) were first investigated by applying the content analysis to explore their figurative elements and test the method. The content analysis was then refined and applied to the images collected during the main study (see Section 6.2). The image analysis was applied in the same manner to a small sample from both datasets.

6.1 Image selection

Images were selected based on their tweets' textual content. On a few occasions, the same picture was embedded in different tweets thus acquiring different interpretations. Therefore, images with the same pictures were considered as different items if their tweets were different. A list of images was created for the anti- and pro-vaccine communities, separately, and for each dataset of the pilot and main study (which included a news-related group). The list for the anti-vaccine community included anti-vaccination and pro-safe vaccine tweets, whereas the one for the pro-vaccine community included pro-vaccination, academic and news-related posts (see Section 5.1.1.1). The frequency of the images (i.e. number of retweets during the collection period) was calculated within each dataset.

The images collected during the pilot study were analysed first to decide the sample to investigate in the main study. A sample of images selected at random provides insights into the recurrent figurative elements and topics shared by a community, independently on the visibility or popularity[29] of the

[29] The visibility of an image can be related to its number of retweets (Kwak *et al.*, 2010), whereas the popularity of an image can be related to its content but also to the number of followers of the user that shared or re-shared it (Chen and Dredze, 2018).

images and the users that tweet them. A sample of highly retweeted images shows the recurrent content of images that the members of a community perceive as representative of their values and themselves. These two sampling approaches may yield similar or different recurrent elements; therefore, both of them were analysed in the pilot study. In the main study, only highly retweeted images were considered for two reasons:

1) In the pilot study, images selected at random and highly shared images were found to have the same recurrent combination of elements and topics; hence, it was likely that they would yield similar results in the main study[30].
2) Highly shared images were more likely to be supported or valued by the community since retweeting implies amplifying a message to new audiences, sharing it to entertain or inform the followers, publicly agree with the message, or express friendship or loyalty (Boyd, Golder and Lotan, 2010).

For the pilot study, the three datasets obtained in June, September and October 2016 were used (see Section 5.1). Fifty images were selected for each group (anti- and pro-vaccine) and the same proportion was collected from each of the three datasets[31]. The images collected in each dataset were analysed together, thus there were two groups of items instead of six: one pro-vaccine and one anti-vaccine. Following these rules, 100 images were selected at random and 100 were selected for their high frequency within the datasets (see Table 6.1).

[30] In the social network analysis (see Section 5.2.4), the pilot and main study produced similar results. Hence, it is likely that this would also occur in the visual analysis.

[31] This proportion varies between anti- and pro-vaccine groups (5% and 7%, respectively) but the final number of images is the same (50).

	Images selected at random		*Highly retweeted images*	
	Anti-vaccine	*Pro-vaccine*	*Anti-vaccine*	*Pro-vaccine*
June	18 (out of 351)	16 (out of 237)	18 (out of 351)	16 (out of 237)
September	14 (out of 265)	11 (out of 152)	14 (out of 265)	11 (out of 152)
October	18 (out of 350)	23 (out of 344)	18 (out of 350)	23 (out of 344)
Total	50	50	50	50

Table 6.1 Number of images (i.e. tweets embedding pictures) selected for each dataset (June, September and October), group (anti- and pro-vaccine) and sample (at random vs highly retweeted).

The images selected at random were chosen by rolling two dice. Counting started from two instead of one, so the first tweet could be selected, and the image corresponding to the combined number of dots was picked. For each subsequent throw of the dice, counting began from the image next to the last selected. The highest frequency of retweeted images was selected for the highly retweeted group. As mentioned above, in the case of the main study only the highly shared images were selected but for three groups – anti-vaccine, pro-vaccine and news related. Fifty images were selected for each group.

The 200 images in the pilot and the 150 images in the main study were used for the content analysis. Content analysis allows identification of recurrent combinations of topics and figurative elements among the images. Combinations of figurative elements were then used as selection criteria for the image analysis (see details in Section 6.3). This ensured that images analysed would be representative of the highly retweeted images (Penn, 2000).

6.2 Content analysis

Quantitative and qualitative content analysis was conducted to study recurrent combinations of figurative elements and topics in anti- and pro-vaccine images, and explore how these combinations contribute to the images' messages. By combining quantitative and qualitative approaches, it was possible, for example, to see how frequently anti-vaccine images mentioned vaccine safety and how they talked about vaccine safety in different contexts and with different figurative elements.

The quantitative content analysis allowed for the complexity of the images to be reduced by dissembling them into categories (Bell, 2011). The items fitting these categories[32] can then be systematically quantified and compared between anti- and pro-vaccine images and news-related images (Bell, 2011). By quantifying figurative elements and topics, it was possible to identify those that were recurrent; hence, those that could be potential signs or social conventions used by the anti-vaccine and pro-vaccine networks to represent vaccinations.

Quantitative content analysis, however, is not sufficient to interpret vaccine images, as it does not provide information on what the images say. Instead, it answers the question of what is in the images (Bell, 2011). To understand how recurrent figurative elements and topics combine to represent vaccines, a qualitative approach is necessary. Therefore, a qualitative content analysis was conducted to complement the quantitative analysis. This qualitative approach sheds light on how recurrent figurative elements and topics are combined into themes - representations of vaccines - and how these themes differed between anti-, pro-vaccine, and news-related images (Pennington, 2016).

The unit of analysis included the picture as well as the text and the hashtags within the tweet embedding the picture, since they could contextualise the image and contribute to its meaning (Hand, 2016; Bock, Isermann and

[32] An example of category is *Objects*, and example of item of this category is *Syringe*.

Knieper, 2011). The units were processed following Marion and Crowder's guidelines (2013) and Braun and Clarke's coding method. First, the units were explored to decide what aspects to investigate, including contextual information (e.g. users sharing the images) and find potential codes for each aspect (Marion and Crowder, 2013). The data were analysed again to refine and identify additional codes. Once the codebook was established, the units were analysed again applying the same coding criteria to all of them and checking for mistakes (Braun and Clarke, 2013). The content of the images was categorised into the following aspects:

- Vaccine perspective– e.g. anti-vaccine, academic, news
- Topics – e.g. vaccine safety, immunisation campaigns
- Location of the topic – e.g. in the picture, in the text of the tweet
- Presence of text in the picture
- Picture format – e.g. photo, infographic
- Objects – e.g. syringes, vaccine vials
- People – e.g. ethnicity, gender of the people depicted in the picture
- Type of user sharing the item – e.g. activist, NGO, healthcare practitioner

This method was applied to the pilot data collection. In the main study, the codes found in the pilot were used with slight adaptions (see Section 6.2.7). New codes and categories were added, following the same procedure explained above. In both the pilot and main study, once all images were coded, the co-occurrence of codes was analysed to identify how specific topics were represented in anti- and pro-vaccine pictures and respective tweets. The software package Nvivo Pro 11 was used for the coding and content analysis. Figure 6.1 shows an example of how the content analysis was conducted.

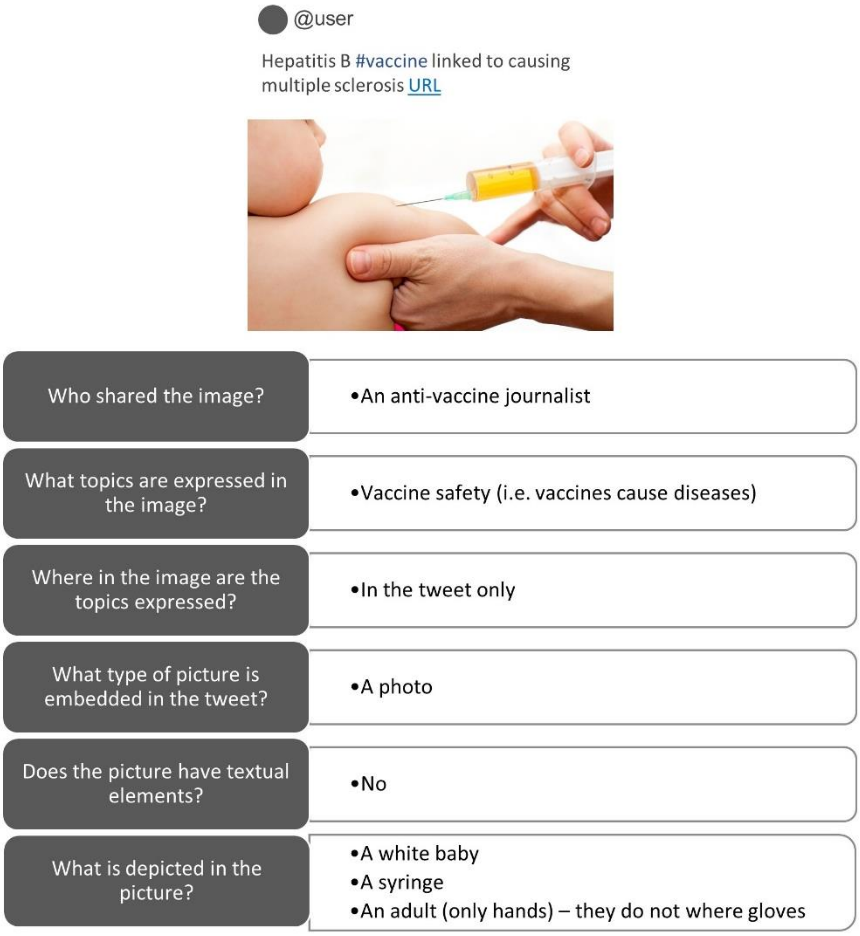


Figure 6.1 Example of how the content analysis process was applied.
Photo on top via Shutterstock, modified by adding text on the top.

In the following sections, the categories used to analyse the pilot images are explained in detail. The changes made in the coding and categorisation for the main data collection are discussed in Section 6.2.7.

6.2.1 Topics

Kata (2010) found that anti-vaccine websites shared content about the safety and effectiveness of vaccines, civil liberties (especially parental rights), conspiracy theories, alternative medicine, misrepresented studies about vaccines, personal testimonies, and information on legal vaccine exemptions and reporting adverse reactions. Conspiracy theories and concerns for civil liberties were two popular topics in anti-vaccine images shared on Pinterest

(Guidry *et al.*, 2015). Since these topics seem to be recurrent across platforms, this study investigated whether they were common among the anti-vaccine images shared on Twitter. Moreover, this research explored whether there were any other anti-vaccine claims and what topics the pro-vaccine network shared. Analysing topics could provide insights into the differences between anti- and pro-vaccine communication: what aspects of vaccinations their messages focus on, what are their claims and what vaccine information is missing.

As mentioned in Section 6.2, the unit of analysis included the textual content of the tweet, its hashtags and embedded pictures. Therefore, topics were coded in all three locations (see Section 6.2.2 for details) based on the messages they conveyed. For example, the hashtag '#vaxxed' was coded as related to *Vaxxed the movie*. A tweet text stating 'vaccines kill children' was classified as related to *vaccine safety*, and a picture stating 'get your flu shot' was coded as *immunisation campaign.* The full list of topics and their details are available in Appendix E. The coding strategy applied in the pilot and main study was similar; in the main study, more topics were considered as explained in Section 6.2.7.

6.2.2 Location of topics

As mentioned in Section 6.2, the unit of analysis included the tweet text and the hashtags as well as the picture, since they contribute to image's message (Bock, Isermann and Knieper, 2011). For example, the textual content of a tweet could complement, reinforce or contradict the message conveyed by the embedded picture, thus influencing its interpretation. The opposite could happen too: a picture could influence the interpretation of the message in the text of the tweet (Leeuwen, 2011). Hashtags could also contribute to the message since they could be used to emphasise the text of the tweet (e.g. #Fail) or convey a message (e.g. #VaccinesCauseAutism) (Giglietto and Lee, 2017; Bruns and Moe, 2014). Therefore, since the text, hashtags and pictures of a tweet could convey different messages and topics, this study considered whether and what topics were expressed in these three different locations.

6.2.3 Picture format

Previous studies on visual vaccine communication on Pinterest found that users share various picture formats, such as photos and infographics, but also charts, drawings and cartoons (Guidry *et al.*, 2015; Milani, 2015). These formats can convey different messages; for example, a chart or an infographic can show statistical information on the risk of vaccine side effects or vaccine-preventable diseases, whereas a photo can represent personal experiences of vaccination. Moreover, even charts and infographics differ in the way they present statistical information, and drawings and photos can target different audiences (Lester, 2014). Therefore, since the picture format could influence the interpretation of an image and pro- and anti-vaccine users could use different formats to communicate about vaccination, this study considered the picture formats and classified them as follow:

- Photos
- Text-only pictures
- Infographics
- Charts and tables
- Cartoons and drawings
- Screenshots – e.g. of social media posts
- Gifs
- Leaflets
- Mix pictures – collages of different photos, cartoons, and text.

The full description of these categories is available in Appendix E.

6.2.4 Presence of text

This category regards the presence or absence of text in the embedded pictures; it does not include the textual content of the tweet itself (which is considered in Section 6.2.1). Guidry *et al.* classified vaccine pictures into three categories: 'primarily text', 'primarily image', and 'a mix of image and text' (2015). Chen and Dredze (2018) also considered the presence/absence of text in vaccine pictures on Twitter. Text can have an important role in the interpretation of the images: it can provide the key to read the image or the context (Penn, 2000). Therefore, the presence of text inside the picture was considered in this study. Text was considered as present when the picture had text overlays, captions, or titles.

6.2.5 Figurative elements

Anti- and pro-vaccine images may show different figurative elements, i.e. different types of objects or people to represent vaccination or a particular aspect of vaccines. For example, Milani (2015) found that anti-vaccine images on Pinterest depicted mainly white children and syringes. Syringes and people were found by Chen and Dredze (2018) as well, in their study of vaccine images shared on Twitter. Objects and people are like words of a language: they are conventional elements used to communicate with other members of a community (Grewal, 2009). Therefore, pictures showing specific objects and/or people (i.e. their gender, ethnicity) could also be indicative of the cultural background of the user sharing them or the audience/community s/he wants to reach. For example, to recognise a syringe and its uses and link it to the concept of vaccination, individuals need to know about the object and its possible connotations (Lester, 2014; Rose, 2012). To gain insights into the elements of the visual language used by anti- and pro-vaccine users, this study coded the objects depicted in the pictures (e.g. syringes, vials, hospital/laboratory white coats or disposable gloves). The full lists of codes is available in Appendix E.

People' characteristics, such as gender and ethnicity, were also coded to explore ethnical and gender representation in anti- and pro-vaccine communication. People were also categorised as children or adults since Milani (2015) found a predominance of white children in anti-vaccination images. When the ethnicity or gender of the person depicted was not clear, due to the brightness or the frame of the picture (e.g. dark pictures, pictures cropped to show only the hands of a person but not the body or the face), no codes were applied. The list of codes is provided in Appendix E. The same coding strategy was applied to the pilot and main study, though in the second more codes were considered (see Section 6.2.7).

6.2.6 Users and groups

The users were considered because they had selected the images to share and had interpreted them within a particular context (Bock, Isermann and Knieper, 2011). Moreover, knowing who the users were provides additional context to the analysis of the images (Newbold, 2015). The users were analysed and coded using the same classification applied to the key actors in the social network analysis (see Section 4.5). Since the anti- and the pro-vaccine communities shared more than one type of tweet (academic, news, pro-vaccine, anti-vaccine and pro-safe vaccine), this information was also considered to contextualise the images. The type of tweet was coded during the social network analysis (Section 4.3).

6.2.7 Adjustments for main study

For the main data collection, minor adjustments were made to the content analysis following the pilot study. In particular, some categories of topics, objects and people were redefined to be more explicit, and new categories were introduced to make the analysis more exhaustive. The complete list of categories and subcategories applied to the content analysis of the main collection is available in the Appendix F.

In the case of topics, the category *immunisation campaigns* did not distinguish between mentions of a campaign and advocacy messages. Therefore, this category was divided into:

- Immunisation campaigns – news or messages about the launch of immunisation campaigns, on a new bill for increasing immunisation rate…
- Pro-immunisation messages – advocacy messages promoting vaccinations that are not related to the official launch of a campaign (e.g. "get your flu shot").

Moreover, new categories were introduced for topics that appeared only in the main study, such as *vaccine generic information* (i.e. generic information about vaccination), or for capturing more aspects of the vaccine debate, such as *vaccine schedule* (i.e. messages about the schedule of mandatory or recommended vaccinations). Some of these new topics were also about politicians and celebrities (e.g. *Donald Trump* or *Bill Gates*) and vaccine-preventable diseases (e.g. *Measles*).

In the case of people, one new category was added, named *Hands*. This category coded human figures whose body and face were not visible, but only their arms or hands were depicted in the picture, and it helped to identify the presence of an adult in a picture that could not be coded as male or female. The objects classification underwent more substantial change, and new categories were added to provide a better description of the visual content. The new categories included laboratory equipment, scientific signs, and organisms, such as chemical formulas, microscopes, test tubes, Petri dishes, mice, cells, and mosquitos. The code *Cells* was applied to human or animal cells, unicellular organisms, microbes, viruses. The category *Mosquitos* was introduced because some images depicted a mosquito to represent either Zika virus or malaria.

Many other new codes were defined to describe the content of the pictures better. These codes appeared in at least two pictures, and comprised: buildings, maps, newspapers, books, pharmaceutical companies' logos, cardboard boxes, phone icons, superheroes, and wheelchairs. Last, two new codes related to Donald Trump were added: one to identify photos depicting the US president, and one for screenshots of his tweets. These two types of content appeared a few times in both anti- and pro-vaccine pictures.

6.3 Image analysis

Images have social meanings built into them, which differ depending on how they represent the same topic and the context (Pennington, 2016). For example, vaccines can be represented by an image depicting a black child being administered an oral vaccine, which may imply the need for affordable polio vaccines in African countries. However, vaccines can also be represented by a photo of an older white man receiving a flu shot, which may represent a campaign promoting flu vaccinations in Western countries. By applying quantitative and qualitative content analysis, it was possible to identify these differences in content and vaccine representation (Bell, 2011; Pennington, 2016). However, the context can also influence the message of the same picture (Ledin and Machin, 2018). The photo of the black child may be shared in an immunisation campaign launched by an NGO, or it may be used by an anti-vaccine activist to show the victims of a vaccine used to 'control the African population'. The objects represented, the relationships amongst them, the image-text relationship, and the context in which they are shared (i.e. the user sharing the image, the platform used, the intended audiences) all influence the message of an image (Ledin and Machin, 2018; Hand, 2016; Leeuwen, 2011). However, all of these elements cannot be captured by applying a content analysis alone. For this reason, an additional image analysis was conducted.

The image analysis considered the relationships between content and context, and it was built upon the guidelines designed by Indira Ganesh *et al.* (2014) (see also Chapter 3). Therefore, it considered:

- The information conveyed by the images;

- The design of the images (e.g. format, figurative elements, settings visual-textual relationships, editing);
- The network where the image was shared (e.g. broad audience, close supporters);
- The technology used (Twitter and its affordances, use of hyperlinks).

These four elements all contribute to the message conveyed by an image; hence, they were analysed to interpret the images.

An image can be interpreted differently depending on the visual literacy of the viewer, hence on their culture, knowledge about vaccines and opinions (Lester, 2014). In this image analysis, the researcher placed herself as a Twitter user searching for information, without a strong opinion either in favour or against vaccination. This approach minimised the risk of adopting a narrow-minded, judgemental attitude towards anti-vaccine claims and favoured a sceptical attitude towards pro-vaccine statements. Hence, the researcher sought to verify whether both anti- and pro-vaccine information were supported by scientific evidence. The researcher also considered that her European cultural background and her higher education might influence her interpretation of the images and her capability of recognising figurative elements, metaphors, and statements. This means that metaphors or signs from a non-Western culture, for example, may have been missed while analysing the images. To mitigate this risk and increase her understanding of the images, the researcher further searched certain symbols or settings within the images on the Internet, whenever possible.

Because this method included both content and context in the analysis, it was suited to study and interpret social media images, such as Twitter images, which are dynamically transformed, and re-contextualised and shared to different audiences in different manners (e.g. via hashtags). Other methods, such as content analysis, multimodality and semiotics, are unlikely to be suitable for capturing the relationships between context (within and outside the Twitter space) and visual and textual content, and how these influence the message conveyed by online vaccine images. The image analysis was informed by these methods though, especially when interpreting the content of the picture and the relationships between textual and visual elements in the image.

Four anti-vaccine and four pro-vaccine images were selected from the pilot dataset, and four anti-vaccine, four pro-vaccine, and four news-related images were chosen from the main dataset. These images were selected based on the results of the content analysis (see Section 6.1); they had combinations of figurative elements and topics that were recurrent in the pilot datasets and main dataset. Only highly shared images were considered since these images were more likely to be supported and valued by their community (Boyd, Golder and Lotan, 2010). The same method was applied to the images from the pilot and main datasets. The signs represented in these pictures, their relationships, and their relations with text and hashtags were all studied as explained below. Figure 6.2, at the end of the chapter, shows a simplified diagram of the analysis process.

6.3.1 Analysis of the content

Social conventions determine the relationship between a signifier and a signified (Penn, 2000); for example, when we see the image of a syringe, the figure that depicts the syringe is the signifier, whereas the signified is the concept of “syringe”. However, “syringe” is a conventional term determined by language and can be understood only by those who have seen a syringe before and know that the tool is called a syringe.

Signs can be icons, indexes, or symbols, depending on how arbitrary and conventional the relationship between their signifiers and their signifieds is. In an icon, the signifier is related to a signified by resemblance rather than by convention - a photograph of a child depicts him/her realistically, and the viewer can recognise it as a child easily. In an index, the signifier and the signified are related by contiguity or causality; for example, smoke can be the index of fire, a syringe can be the index of injection. In a symbol, the signifier and the signified are linked by social conventions and cultural knowledge – a syringe can be a symbol of vaccination as well as heroin addiction (Penn, 2000).

To better analyse how the signs of the images and their relationships contribute to the message, the following aspects of the pictures were investigated:

- Objects
  - What the objects depicted in the picture resemble;
  - What these objects might have represented as indexes and symbols was assessed (Nöth, 2011; Penn, 2000);
- Setting
  - How the objects were distributed in the picture (Jewitt and Oyama, 2001):
    - In a right-left polarisation, the elements on the left of the picture communicate familiar, already known information (*Given*), while those on the right show new information (*New*)[33]
    - In a top-bottom polarisation, the elements on the top communicate an idealised or generalised essence of the message (*Ideal*), whereas those on the bottom present factual information or practical consequences (*Real*)
    - In a centralised composition, the centre unifies the elements of a picture thus providing a common meaning or purpose to those elements in the margins as well
  - Whether the picture has a background and how this and the composition could contextualise the depicted objects and their signs was considered (Ledin and Machin, 2018);
- People were investigated from four perspectives (Ledin and Machin, 2018)

[33] This is valid for Western cultures, where it is common to read and write from left to right.

    - Individualisation or collectivisation – individualisation occurs when a photo focuses on a specific individual and make it salient by depicting only him/her or making a close-up of him/her. Collectivisation occurs when a group of people is shown, depersonalised, or when the focus is on the generic features shared by the group (e.g. a white coat);
    - Categorisation can be cultural – based on the type of dress, ornaments, hairstyle… – or biological – based on stereotyped physical characteristics such as gender, age and ethnicity;
    - Generic or specific – people depicted in photos can be generic (e.g. a white man can be any white man) or they can represent a specific person, such as a celebrity or a politician (e.g. Donald Trump);
    - Non-representation – when no people are represented, it is important to question why they are absent and what objects and settings can take their place
- Actions and behaviours can be interpreted as indexes because they can cause an effect or be the result of an event; actions can be interpreted by analysing body movements, facial expressions and the setting (Ledin and Machin, 2018)
    - Emotional processes – emotional states;
    - Mental processes – a person who is thinking, pondering;
    - Verbal processes – a person who is speaking, talking, shouting;
    - Material processes – a person interacting with objects;
- Positioning the viewer – the perspective and frame of a photo can change the interpretation of its signs (Ledin and Machin, 2018)
    - Vertical angle – looking at a scene from below gives an impression of superiority or strength, looking at it from above, gives an impression of inferiority or vulnerability;
    - Horizontal angle – looking at a scene from the front engages the viewer more than looking at it from the side;

- Proximity and distance – a close-up photo of a scene gives a sense of intimacy, whereas a photo taken far from a scene gives a sense of isolation;
- Gaze – when the participant looks at the viewer, the viewer feels engaged in the picture; when the participant looks out of a picture and does not engage the viewer, the feelings conveyed can differ depending on the angle of his/her gaze.

As mentioned before, this analysis considered not only the signs in the images and their relationships but also the textual elements and the context accompanying these images. To interpret the images about vaccines required, not only cultural knowledge, but also knowledge of the vaccine debate on Twitter and its dynamics (Hand, 2016; Rose, 2012).

6.3.2 Analysis of text-image relationships

Text-image relationships were also investigated. These relationships define whether the image and the text convey either the same or different content, and whether they are equally important or not at delivering the message. In equal image-text relationships, the text and the image can be independent of each other or complementary, whereas in unequal relationships an image can relate only to part of the text or vice versa (Leeuwen, 2011). These relationships were considered between the picture and the text of the tweet as well as between the picture and textual elements in it.

When the picture and the text convey the same content, they are equal and independent of each other, and their relationship can be either illustration or anchorage. In an illustration, the text is primary whereas the picture contextualises the text for a particular audience, exemplifies it or adds details. In an anchorage, the picture offers a representation of the world whereas the text works as a caption to clarify or generalise the picture. When the picture and the text convey different but complementary content, they are equal and dependent on each other, and their relationship is called relay. In a relay, picture and text cannot convey content separately, but they need to be considered together to understand the whole message (Leeuwen, 2011; Penn, 2000).

6.3.3 Analysis of the context

Images shared on social media are often decontextualised or even modified, hence knowing their author and their original purpose may not be possible, and their message may be changed by the user who shares them. Therefore, it is essential to analyse these images within their old and new contexts, considering for exmaple their origin, potential manipulations (Newbold, 2015), the users sharing them and the Twitter conversations they reach via hashtags (Hand, 2016). Knowing how an image was manipulated, framed or re-contextualised could provide insights into the new messages acquired by the image (Pennington, 2016; Pauwels, 2011). To provide context to the images, the 5Ws (Who, What, Where, When, Why) were investigated:

- Who
  - Which type of user posted the image (activists, NGOs, physicians)?
  - What was the user's opinion towards vaccination? Were they anti-vaccine, tendentially anti-vaccine, pro-vaccine, tendentially pro-vaccine, pro-safe vaccine or neutral?

  Understanding who shared the image could provide context that would enable interpretation of the image.
- What
  - What type of picture was shared (photo, cartoon, mixed picture…)?
  - Was the image anti-vaccine, pro-vaccine, pro-safe vaccine, academic or news?
- Where
  - Where was the original picture from? Was it from an online photo database, from a website?
  - In what Twitter streams did the image appear?

To find the original picture, Tineye.com and Google Image Search were used; Tineye.com is an online tool that can do a reverse image search and find where an image appears on the Internet.

To identify in which Twitter streams the image was shared, the hashtags in the tweet embedding it were considered. Hashtags label a picture and its tweet and show them in specific Twitter conversations.

- When
  - When was the image posted?
  - Was the image shared in relation to a specific event?
  - Was the image shared in reply to a conversation?

  This information could provide insights on the communicative purpose of the image.

- Why
  - Was the image shared to provide information about vaccines?
  - Was the image shared to campaign either in favour or against vaccines?
  - Was the picture just decorative? (Newbold, 2015).

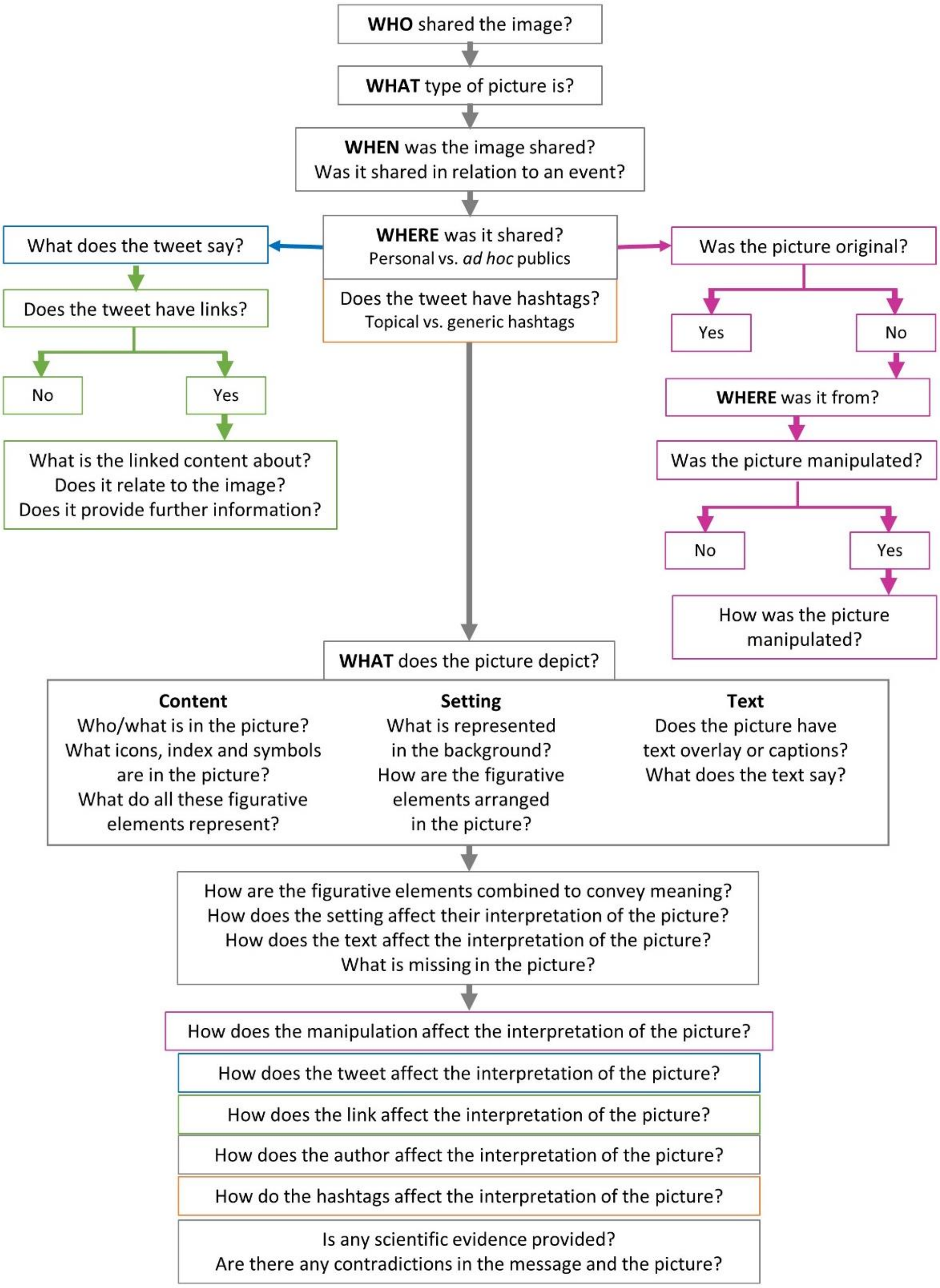


Figure 6.2 Simplified diagram of the image analysis.

7. Results of the content analysis

This chapter answers the third research question: What do networks say about vaccines through the images they share? A content analysis was first applied to the images collected during the pilot research to define the methodology and decide whether to focus the analysis on a random sample of images or on the most popular ones (i.e. most re-shared). The refined methodology was then applied to the most retweeted images from the main data collection.

In this chapter, the term ‘image’ indicates an item that contains both a tweet and at least one picture, whereas the term ‘picture’ defines the visual element embedded in a tweet. The content analysis considered the whole image and was conducted to identify recurrent combinations of topics (e.g. safety of vaccines), signs (e.g. syringes), people depicted (e.g. white babies), types of pictures (e.g. photo), and presence of textual content in the pictures (e.g. text overlay).

Identifying content differences and similarities between the images shared by the anti- and pro-vaccine communities provides insights into how these two groups represent and communicate about vaccination visually. For example, anti-vaccine images could express concerns that were not addressed by the pro-vaccine network but could potentially influence Twitter users holding doubts about vaccination. Moreover, a vaccine could be represented with a vial, a syringe, a package or a plaster on an arm, but it is likely that only one of these signs is used most frequently to represent vaccines and vaccination, though this might differ between pro and anti-vaccine groups. Therefore, a recurrent sign could be a convention adopted by the community to discuss vaccines (Grewal, 2009).

7.1 Pilot research

In the pilot research, fifty anti-vaccine images and fifty pro-vaccine images were selected at random across the three datasets. Then, another fifty anti-vaccine images and fifty pro-vaccine images were selected based on their popularity across the three collections. The popularity of these images was defined based on their frequency in each dataset, i.e. on their number of retweets within the dataset. Section 6.1 provides further details on the image selection. In the following paragraphs, the analysis of the images selected at random will be discussed before that of the most retweeted images.

7.1.1 Anti-vaccine tweeted images selected at random

At least half of the anti-vaccine pictures were photos (n=50), while the others varied in type: 16% were screenshots of website pages, social media posts or accounts, 12% were mixed pictures (i.e. collages of text, photographs and drawings), 8% had only textual elements and another 8% were charts or tables (Figure 7.1). Most of these pictures (78%, n=50) had text overlays or captions, except ten photos and one mixed picture.

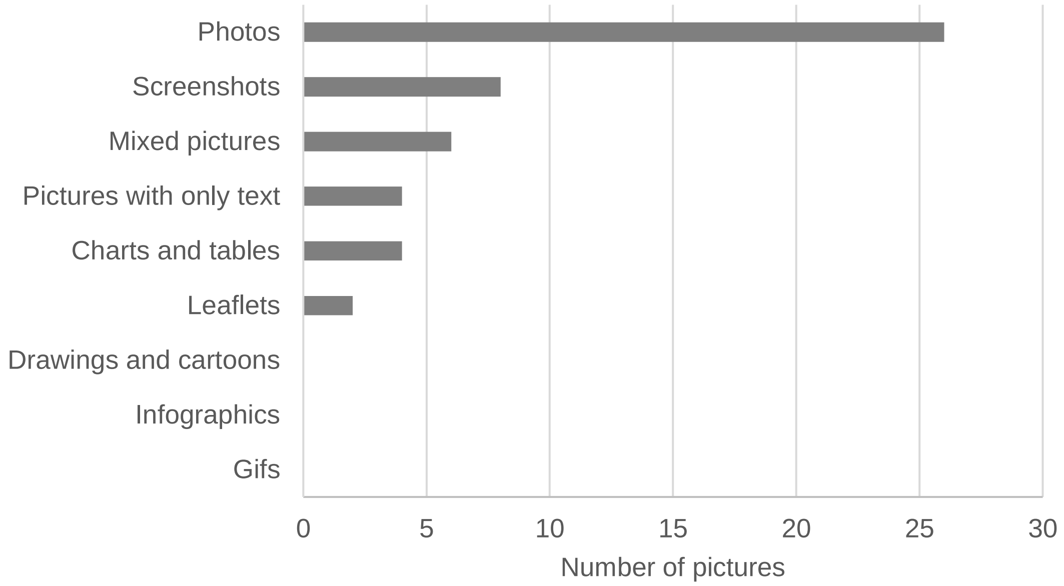


Figure 7.1 Frequency of the types of pictures among the anti-vaccine images selected at random. These 50 images were collected in June, September and October 2016. The related table is available in Appendix G.

The most common topics were *vaccine safety* (e.g. “vaccines are toxic”) and *conspiracy theories* (e.g. “vaccines are a tool to control the masses”), but some images also mentioned *Vaxxed* (*Vaxxed the movie*) and *vaccine development* (e.g. “vaccines contain mercury” or “vaccines have never been tested”) (Figure 7.2). However, the anti-vaccine images often conveyed more than one topic and combined them together in one message; for example, *vaccine safety*, *conspiracy theories*, and *vaccine development* were often linked together to convey messages such as “Never vaccinate again! The public health organisation admits 98 million Americans were given a cancer virus via the polio vaccine” (Tweet15 Oct16).

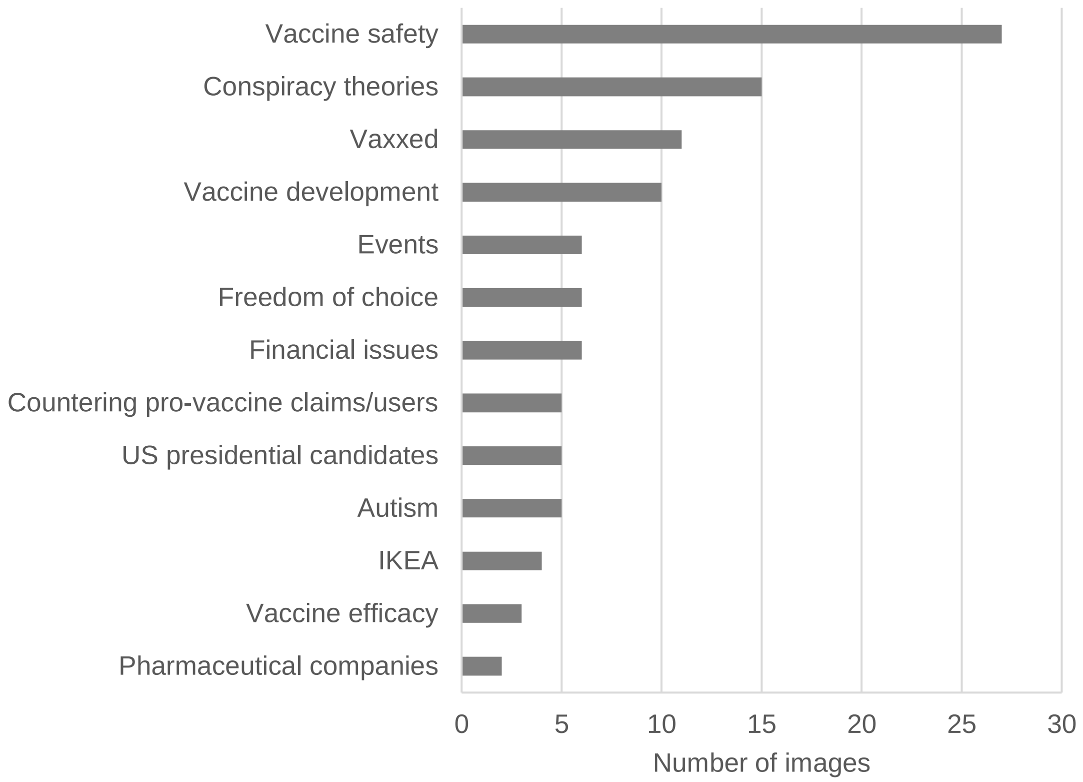


Figure 7.2 Frequency of topics that appeared in the anti-vaccine images selected at random.
One image could show more than one topic. These images were collected in June, September and October 2016.

The topics could appear in three parts of the images: the tweet text, the embedded picture and/or the hashtags (see example in Figure 7.3). Almost all images expressed topics in the tweet text (90%, n=50) and many of them in the pictures as well (70%, n=50). Sixteen images out of fifty expressed topics in the hashtags (32%). Pictures, tweet text and hashtags shared different topics, and some topics were more recurrent in one part of the image than in others; for example, the topic *Vaxxed* appeared in the hashtag of several images (16%, n=50), though rather than mentioning the movie it labelled anti-vaccine conversations on Twitter (as a hashtag).

Vaccines cause sudden infant deaths! #LearnTheRisk, watch #Vaxxed

Figure 7.3 Example of an image where the tweet text and the picture express the topic 'vaccine safety', while the hashtag conveys the topic 'Vaxxed'.
Photo via Pixabay, modified by adding a text box on the right.

The anti-vaccine pictures depicted some figurative elements more often than others, and in specific combinations. Moreover, some signs occurred more often in association with certain topics; for example, white babies and children and syringes were recurrent in images about *vaccine safety* and *conspiracy theories*. White people appeared more often in these pictures than members of other ethnicities (26 and 3 pictures, respectively), whereas the frequencies of children, men and women did not differ strikingly (12, 12 and 14 pictures, respectively). The most common sign was the syringe (13 pictures), followed by the logo of *Vaxxed the movie* and laboratory coats and disposable gloves (e.g. accoutrements used by physicians, nurses and researchers) (Figure 7.4).

Figure 7.5 shows an example of a picture having some of these recurrent signs.

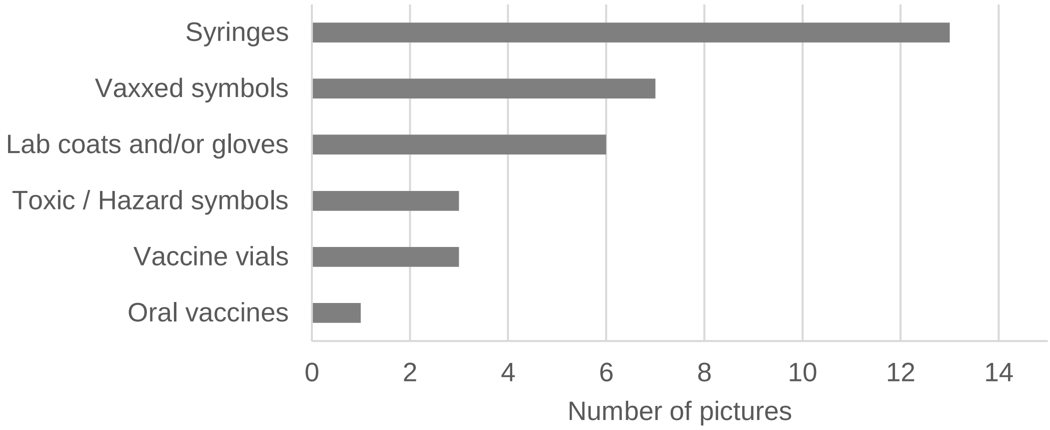


Figure 7.4 Number of pictures containing signs (e.g. syringes) among the anti-vaccine images selected at random.
These pictures were collected in June, September and October 2016. Some pictures, such as those with only textual elements or tables, did not have any figurative elements.

Figure 7.5 Example of picture containing the following signs: Caucasian child, syringe, disposable gloves.
Photo via Pixnio.

Four types of users shared images more frequently: activists (13 images), parent-activists (11 images), uncategorised users[34] (7 images), and journalist-

[34] These users did not provide a clear description of themselves in their Twitter biography.

activists (5 images); other types of users shared fewer than 3 images each, often only one. The four recurrent types shared different types of images; for example, the activists shared many photos and a few tables, whereas the parent-activists posted many screenshots (see Appendix G), which were often challenging pro-vaccine users or messages. In some of these screenshots, the parent-activists showed the accounts of pro-vaccine users who had blocked them on Twitter to demonstrate that these users were not open to a dialogue with those who have concerns about vaccines. The anti-vaccine images had some recurrent combinations of types of pictures, topics, figurative elements and sometimes users. Therefore, the next paragraphs will discuss four common combinations of figurative elements and topics found in these images.

7.1.1.1 The conspiracy behind vaccines

Most of the tweets embedding photos mentioned *conspiracy theories*, *vaccine safety* and *vaccine development* together. These images claimed that vaccines are not safe because they contain toxins (e.g. mercury, thimerosal) or they have never been tested. Moreover, they stated that public health services know about the harm caused by vaccines, but cover it up; they also claimed that governments are using vaccinations for evil purposes. Examples of these messages were “Baby-murdering public health organisation conspired to bury evidence of vaccine-induced deaths” (Tweet3 Jun16) or “The White House admits staging fake vaccinations to gather DNA from the public” (Tweet7 Sep16).

To emphasise these messages, the photos showed white children exposed to a syringe. Sometimes these children were accompanied by adults, who could be parents, or paediatricians and nurses wearing hospital uniforms (a white or green coat) or just disposable gloves. Sometimes nurses and doctors were depicted alone, holding a syringe and a vaccine vial. The syringes and the vials occasionally had a symbol of poison or death on them.

Activists, uncategorised users and journalist-activists shared this kind of photo, but only parent-activists combined it with the topics *financial issues* and *pharmaceutical companies*. These users emphasised that vaccines are dangerous because the pharmaceutical companies are not interested in children's health, only in profit. They might also claim that pharmaceutical companies seek to corrupt governments and public health services in order to profit from vaccines. For example, a common message was "Big pharma does not care about your safety, it is interested only in money", and it was accompanied by pictures of white men rather than women and children.

7.1.1.2 *Vaxxed the movie*

The topic *Vaxxed* appeared in tweets embedding photos, mixed pictures and even leaflets, and it was shared mainly by parent-activists and uncategorised users. The leaflets were used to promote the screening of *Vaxxed the movie* in specific cities of the US, whereas the photos showed attendants at *Vaxxed*-related events (mainly white women). *Vaxxed the movie* is a documentary about a supposed conspiracy behind vaccines, and is narrated by Andrew Wakefield (Wakefield and Bigtree, 2016). However, *Vaxxed* became viral on Twitter and #*Vaxxed* turned into a conventional hashtag used by the anti-vaccine community to label their conversations. In some images the topic *Vaxxed* appeared in the hashtag rather than in the tweet's text or in the picture, it has been used to the access anti-vaccine conversation instead of discussing the movie (Grewal, 2009).

Vaxxed appeared with other topics, such as *vaccine safety*, *vaccine development*, *conspiracy theories*, and *autism*. This combination of topics is not surprising since it is present in the movie as well, which suggests a cover-up of the link between the MMR vaccine and autism. The pictures about *Vaxxed* often depicted white children and syringes, occasionally with healthcare professionals.

7.1.1.3 Freedom from mandatory vaccines and the next US president

Some images combined the topics *freedom of choice*, *conspiracy theories*, and the *candidates for the US presidential elections*. Occasionally, these three topics were related to *vaccine safety* and *autism* as well, and their pictures showed white children, adults and syringes. These images stated that parents should have the right to decide whether to vaccinate their children or not since vaccines have side effects, such as autism[35]. Moreover, this right could be influenced by the next US president: Hillary Clinton or Donal Trump. Hillary Clinton was usually shown as an evil ambassador of mandatory vaccinations, whereas Donald Trump was depicted as the hero who would tell the truth about vaccines and stop mandatory vaccinations. However, Donald Trump never appeared in the photos, though Hillary Clinton did.

[35] Though scientific evidence says that vaccines do not cause autism, nor do any of their components (Taylor, Swerdfeger and Eslick, 2014).

7.1.2 Pro-vaccine, academic and news-related images selected at random

The pro-vaccine network shared images in favour of vaccinations, and academic and news-related images. Therefore, these images were analysed by considering their classification into pro-vaccine, academic and news-related tweets undertaken during the social network analysis (see Section 4.3). In this sample, pictures were not as varied as the anti-vaccine ones. Most were photos (72%, n=50), some were infographics (16%), and a few were leaflets, screenshots, charts or gifs (Figure 7.6). Unlike the anti-vaccine pictures, 54% did not have any textual element (n=50, 26 were photos, one was a gif).

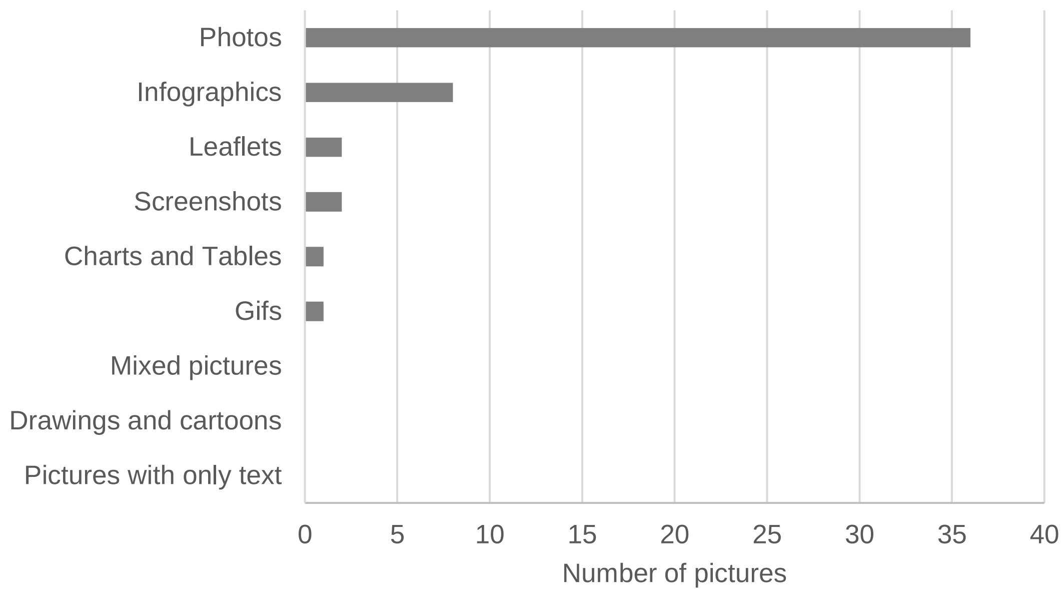


Figure 7.6 Frequency of the types of pictures among the pro-vaccine, academic and news-related images selected at random.
These 50 images were collected in June, September and October 2016. The related table is available in Appendix G.

Twenty-two images were classified as pro-vaccine, 15 as academic and 13 as news-related; these numbers were in line with the social network analysis findings, where most of tweets were coded as pro-vaccine and the fewest as news (see Section 5.1). In these three categories most of the pictures were photos, but the pro-vaccine images also included different types of picture, such as infographics, screenshots, charts, gifs, and leaflets, whereas the academic images comprised only photos and infographics, and a few news-related images included infographics.

The most recurrent topic was *immunisation campaigns*, followed by *vaccine development*, *vaccine efficacy*, *conferences* and *pro-vaccine statements* (Figure 7.7). Some of these topics, such as *pro-vaccine statements* and *vaccine confidence*, often appeared alone, while others, such as *vaccine development* and *conferences,* often occurred in combination with other topics.

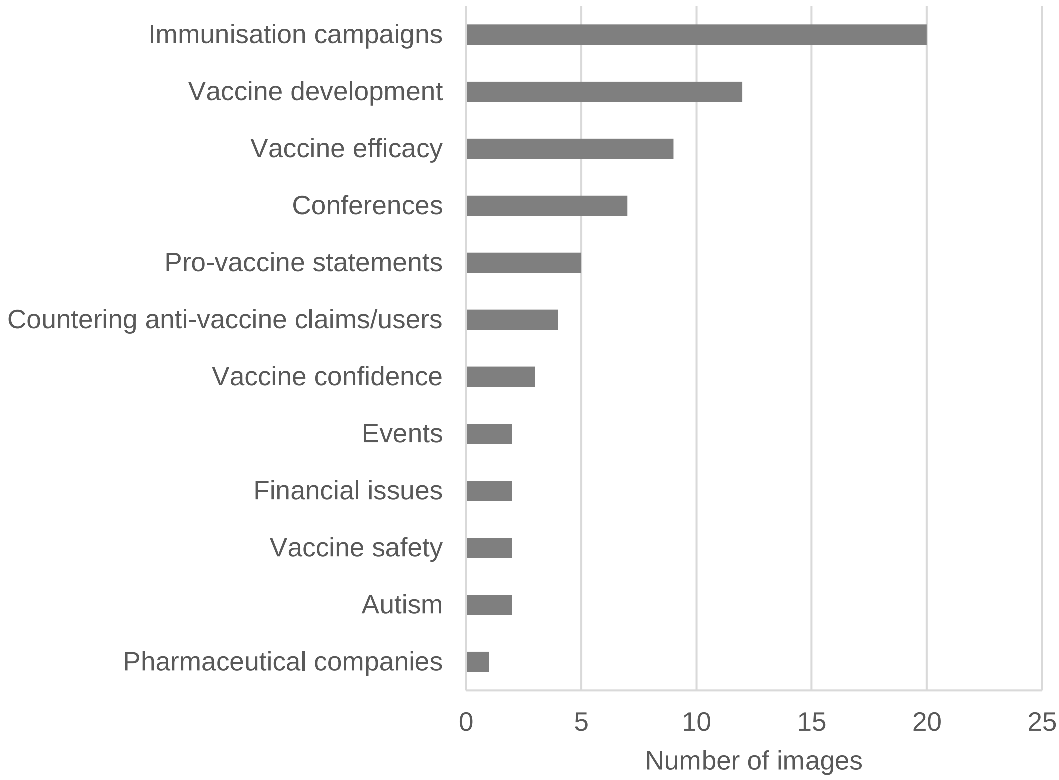


Figure 7.7 Frequency of topics that appeared in the pro-vaccine, academic and news-related images selected at random.
One image could show more than one topic. These images were collected in June, September and October 2016.

Many pro-vaccine images were about *immunisation campaigns* and *pro-vaccine statements*, and a few *countered anti-vaccine claims and users* or were about *vaccine efficacy*. *Pro-vaccine statements* emphasised the importance of vaccination by saying, for example, “I have just got my flu vaccine, you should do the same”; whereas *immunisation campaigns* images claimed: “We can fight pneumonia by vaccinating children” or “we should stand up for a world free from polio”. A few images about *immunisation campaigns* also emphasised topics such as *vaccine development* (e.g. “Improving the supply chain can close the immunisation gap”) or *vaccine efficacy* (e.g. “We can fight polio through vaccines, vaccines save lives”). Most of the academic images were about *conferences* (11 out of 15), and the photos depicted the speakers and/or their presentations. These images also mentioned the topics discussed at the conferences, such as recent research studies on vaccine production or delivery (*vaccine development*), or how a specific vaccine was in/effective (*vaccine efficacy*). Some news-related images were about *vaccine efficacy* (e.g. “malaria vaccine loses effectiveness over time”) or *vaccine development* (e.g. “found a vaccine for Lyme disease”). A few news-related images were about *vaccine confidence* due to a popular news article covering research on vaccine refusal, which was conducted in different countries around the world (5 images out of 13). This article was accompanied by the infographic of a map coloured in different shades of red, representing the degree of vaccine refusal.

The images shared by the pro-vaccine community conveyed the topics in the text of the tweets (98%, n=50) or sometimes in the pictures (42%). They rarely expressed the topics in the hashtags, except in the case of *immunisation campaigns*: NGOs and foundations used hashtags such as #FightPneumonia or #EndPolioNow to label their vaccination campaigns (see Appendix G). The most recurrent sign was the syringe, but laboratory coats and disposable gloves were also depicted (Figure 7.8). The syringe was not the only type of tool shown for the administration of vaccines: the pictures showed oral vaccines (e.g. against polio) and nasal sprays (for flu) as well. Other things, such as viruses, microbes or medical tests (e.g. blood test), appeared less frequently (in 3 and 1 picture, respectively). Viruses and microbes appeared in two leaflets promoting webinars or professional courses, and in one infographic about *vaccine efficacy*, which also depicted syringes and a healthcare practitioner (specifically a white adult wearing a laboratory coat).

Among these pictures, 18 depicted Caucasians, while 16 showed Africans or Asians. Though white people were not overrepresented as in the anti-vaccine pictures, the depicted children were often African or Asian (13 out of 17), while the adults were often white (25 out of 41).

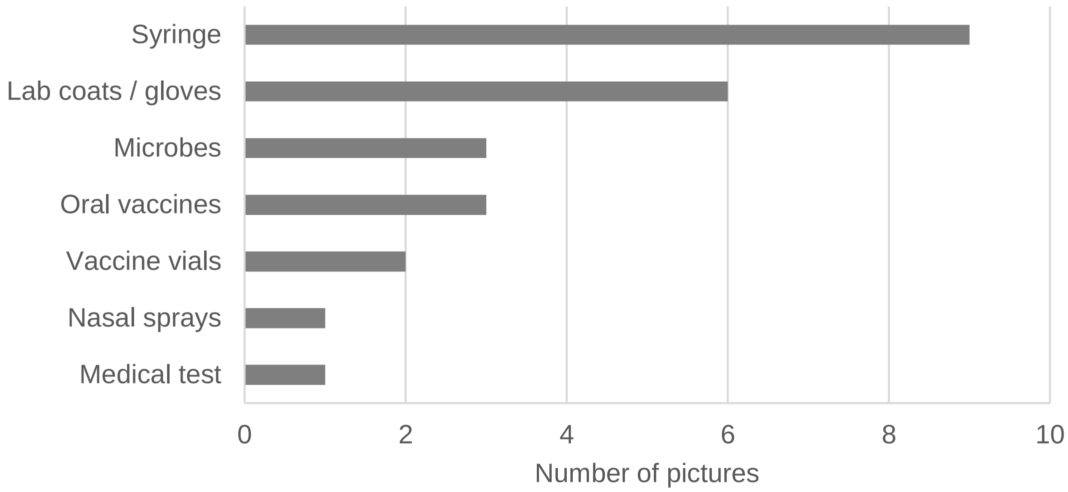


Figure 7.8 Number of pictures containing signs (e.g. syringes) among the pro-vaccine, academic and news-related images selected at random.
These pictures were collected in June, September and October 2016. Some pictures, such as those with only textual elements or tables, did not have any figurative elements.

These children might represent the target subjects of vaccine interventions, though they could also be interpreted through a colonial metaphor (Manzo, 2008). The depicted adults often wore laboratory coats or disposable gloves and held a syringe, especially in images about *vaccine development* or *pro-vaccine statements*. Children were shown while being vaccinated using either a syringe or an oral vaccine, and they appeared in images about *immunisation campaigns* and *vaccine efficacy*. African or Asian adults and children were shown in some images about *immunisation campaigns* as well, but these did not emphasise *vaccine efficacy*. Figure 7.9 shows an example of pro-vaccine picture.

Figure 7.9 Example of picture containing the following signs: Indian child and adults, oral vaccine.
Photo: "Polio immunization in Lucknow" by RIBI Image Library is licensed CC BY 2.0.

The most recurrent users were NGOs, healthcare practitioners/academics, and media outlets, which shared different types of pictures and topics (see Appendix G). NGOs shared photos about *immunisation campaigns* and *conferences*, and a few infographics. The healthcare practitioners/academics posted various types of pictures conveying *pro-vaccine statements,* and *vaccine confidence*, whereas media outlets shared photos on *vaccine efficacy*. *Immunisation campaigns*, academic *conferences* on *vaccine development* and news about *vaccine efficacy* were the most recurrent combinations of topics and figurative elements, therefore they were further analysed.

7.1.2.1 Immunisation campaigns

Images about *immunisation campaigns* embedded either photos or infographics. NGOs and foundations shared many of the photos, which often did not have any textual element and showed African or Asian children receiving the polio vaccine orally. Some of the images about *immunisation campaigns* mentioned either *vaccine development* or *vaccine efficacy* as well, but they depicted different figurative elements. When the topics *immunisation campaigns* and *vaccine development* were combined, the pictures showed healthcare professionals holding a syringe. These images often conveyed messages about the improvement of vaccine delivery in less economically developed countries. When *immunisation campaigns* and *vaccine efficacy* were combined, the photos depicted children while being vaccinated using a syringe or an oral vaccine. These images emphasised how vaccines can save lives.

7.1.2.2 Tweeting academic conferences

Seven images were about *conferences,* and this topic often appeared both in the text of the tweet and in the picture. These images differed from each other in the specific message they conveyed and the signs they used. Four images showed a presentation slide and a speaker, one depicted the participants of the conference, one represented the speakers of a panel, and the last promoted a webinar. Except the last one, they were all photos, likely taken on the spot. Four images of conferences also mentioned *vaccine development* in the tweet, but they addressed this topic differently; for example, one image emphasised how the outbreak of Ebola highlighted the need for further development of vaccines, whereas another one showed a map of organisations involved in vaccination during emergencies. Among the photos, there was one about *vaccine efficacy*, which discussed the challenges imposed by vaccines' limitations.

7.1.2.3 News about vaccine confidence and efficacy

News about vaccines covered two different topics: *vaccine confidence* and *vaccine efficacy*. The news-related images about *vaccine confidence* were all about the same article, which announced research on vaccine refusal conducted in different countries (Cohen, 2016), and they embedded an infographic. This infographic was the main picture of the linked news article.

The news-related images about *vaccine efficacy* were shared by news media outlets. They reported either how specific immunisation interventions had improved public health or the efficacy and limitations of specific vaccines. All these pictures were photos without any textual elements, and they showed syringes and vaccine vials, either alone or held by someone (only the hands were visible).

7.1.3 Most shared anti-vaccine images

The most retweeted anti-vaccine images had many similarities with those that were selected at random; for example, 78% of the pictures had textual elements (n=50). Again, most of the pictures were photos, but in this case, there were more drawings and cartoons, and fewer mixed pictures and screenshots. There were no infographics, and unlike the images selected at random, there were no charts or tables (Section 7.1.1) (Figure 7.10).

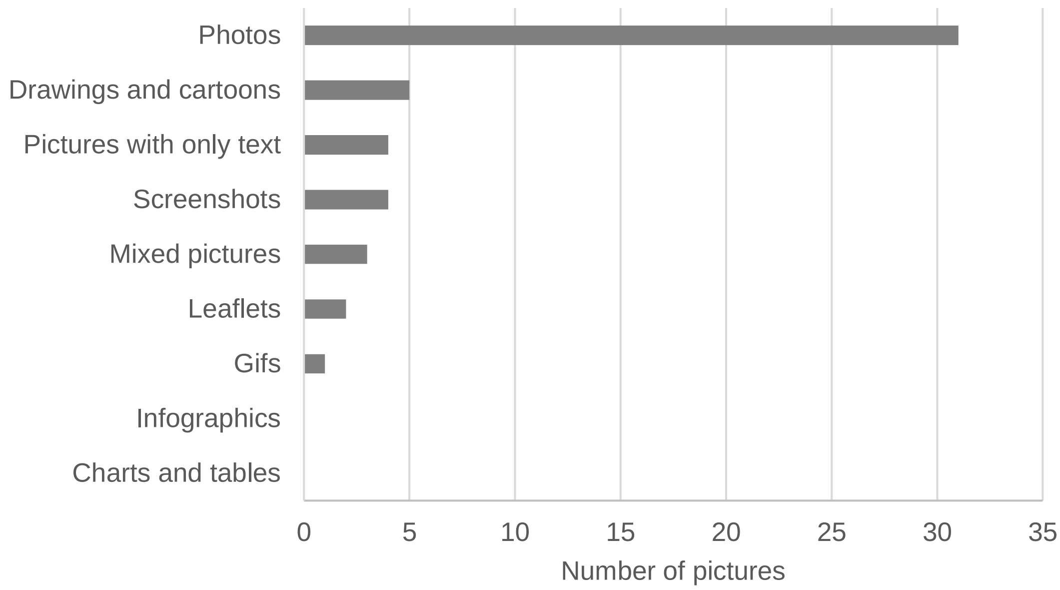


Figure 7.10 Frequency of the types of pictures among the most shared anti-vaccine images.
These 50 images were collected in June, September and October 2016. The related Table is in Appendix G.

The topics of the most shared anti-vaccine images were the same as those selected at random, but their recurrence was slightly different. For example, the topic *Vaxxed* was the most mentioned among the most shared images, even more than *vaccine safety* (Figure 7.11), whereas it appeared in only 11 of the images selected at random. *Vaccine safety*, *conspiracy theories* and *vaccine development* were again the most popular topics, and *freedom of choice* and *autism* also occurred frequently. There were few *events* related images, and only one image was *challenging pro-vaccine claims*.

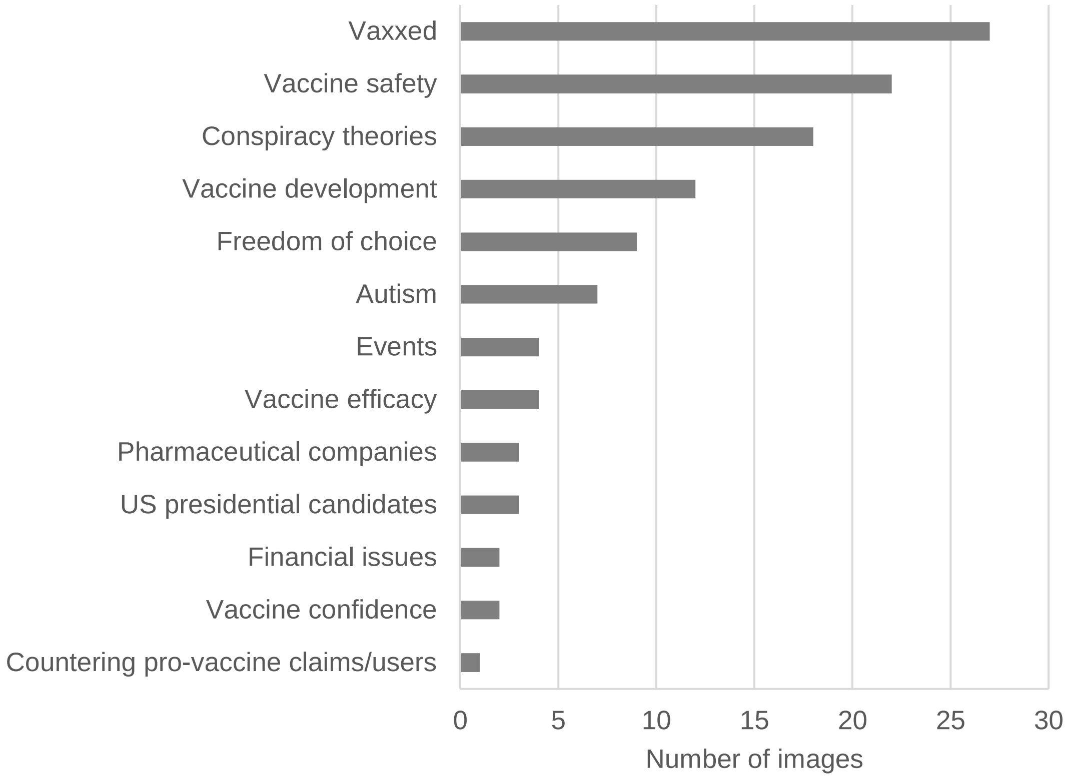


Figure 7.11 Frequency of topics that appeared in the most shared anti-vaccine images.
One image could show more than one topic. These images were collected in June, September and October 2016.

The topics *vaccine safety*, *conspiracy theories* and *Vaxxed* often appeared together, as well as *vaccine safety*, *conspiracy theories*, and *vaccine development*. The last three topics were combined in messages such as “Did you know that that vaccine is recommended but it contains neurotoxin?”. The topic *Vaxxed* was often shared in association with *freedom of choice* and *autism* as well: the movie *Vaxxed*, which was supposed to show the truth about vaccines and autism, was occasionally accompanied by a demand to stop mandatory vaccination. *Vaxxed* and *conspiracy theories* were also linked to *pharmaceutical companies*; for example, in messages claiming that a certain health organisation was not providing the true facts about vaccinations to parents.

Most of the images conveyed topics in the text of the tweet (90%, n=50), or in the picture (72%). 54% of the images showed topics in the hashtags (n=50). The distribution of the specific topics across tweet text, hashtag and picture within the image did not vary dramatically from that of the anti-vaccine images selected at random. *Vaxxed* was again popular as a hashtag, but unlike before, it was recurrent in the text of the tweets as well (see Appendix G).

Half of the pictures depicted white people, especially men (21 pictures), while 15 and 13 pictures portrayed women and children, respectively. However, in this sample there were slightly more pictures showing people with other ethnic backgrounds, in particular men and women (7 and 7 pictures). Among the signs, the most recurrent was the syringe, followed by laboratory coats and disposable gloves (Figure 7.12). *Vaxxed* symbols were also present but to a lesser extent than in the anti-vaccine images selected at random (8% and 14%, respectively; n=50). Topics like *conspiracy theories* were often associated with pictures of white adults wearing laboratory coats and holding syringes, whereas *vaccine safety* images depicted people belonging to different ethnicities, though many of them were white adults and children shown with syringes and laboratory coats.

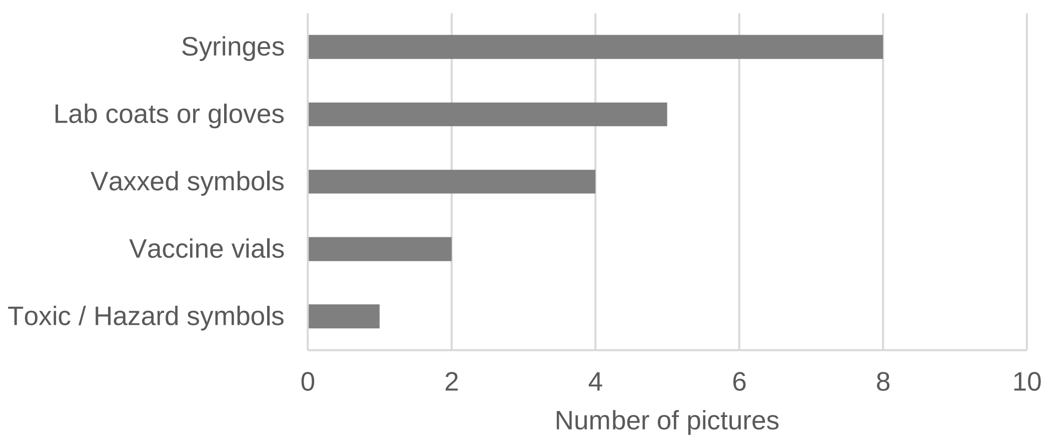


Figure 7.12 Number of pictures containing signs (e.g. syringes) among the most shared anti-vaccine images.
These pictures were collected in June, September and October 2016. Some pictures, such as those with only textual elements or tables, did not have any figurative elements.

The most retweeted images were posted primarily by four types of user: activists (18 images), journalist-activists (11 images), uncategorised users (6 images), and a parents' association (5 images). Only one parent-activist shared a popular image (i.e. frequently retweeted). The first three categories of users shared mainly photos, whereas the parent's association posted mixed pictures and drawings. Some images were posted by the same user – for example, a journalist-activist and an activist. These actors were important hubs within the anti-vaccine community[36]. Since a few users posted the majority of these images, they could have particularly affected the recurrent combinations of topics, types of pictures, and figurative elements identified in this analysis.

7.1.3.1 Educate yourself: vaccines are not safe

As in the anti-vaccine images selected at random, one of the most recurrent combinations of topics included *vaccine safety*, *conspiracy theories* and *vaccine development*. These images often claimed that vaccines contain thimerosal, mercury, and carcinogenic substances, which could cause diseases (e.g. multiple sclerosis, cancer) and even sudden death in children[37]. They also condemned public health services and healthcare practitioners who ignore or cover up the harm caused by vaccines. These pictures often depicted white children and men, and sometimes women, syringes and vaccine vials; at times, the adults were depicted as healthcare professionals. The two anti-vaccine hubs mentioned in Section 5.1.2.1 - the activist and the journalist-activist - shared this type of image. The activist occasionally introduced its tweets with "Study says" or "Doctor said", to attribute scientific validity to their claims. The journalist-activist, instead, shared more images supporting conspiracy theories. *Vaxxed* was often mentioned in these images, but as a hashtag to label them in anti-vaccine conversations. The movie was rarely mentioned.

[36] These two hubs were identified in the social network analysis (see Chapter 5), and they were at the centre of two recurrent clusters in the anti-vaccine community.
[37] These claims were not supported by scientific evidence, which instead states that vaccines are safe (Taylor, Swerdfeger and Eslick, 2014).

7.1.3.2 *Vaxxed* and the truth about vaccines

One popular trend combined *Vaxxed*, *vaccine safety* and *conspiracy theories*, and while stating that corrupt public health services and healthcare practitioners are covering up the truth about vaccines, it also emphasised the importance of finding the real facts about vaccination. In this case, *Vaxxed* was not used as a hashtag, but as a label for anti-vaccine conversations. These images also implied that it was a reliable source of information (e.g. "educate yourself, watch *Vaxxed*").

The images having this combinations of topics and elements often included cartoons and mixed pictures shared by the parents' association. These pictures, especially the cartoons, showed humanised animals instead of people, and they depicted syringes as well.

7.1.3.3 *Vaxxed the movie* and the protest

Vaxxed, *vaccine safety* and *conspiracy theories* were also combined in images, which were shared by activists and journalist-activists. These images represented events associated with *Vaxxed the movie*, such as screenings. The photos depicted mainly white adults, but they showed white children when the topic *autism* was mentioned. In a few photos, Afro-American adults were present, but they were related to a specific event, a screening of *Vaxxed the movie* for a local black community.

The logo of *Vaxxed the movie* was frequent only among those images combining *Vaxxed*, *freedom of choice* and *autism*. As mentioned above, *Vaxxed the movie* claims that the MMR vaccine causes autism, and the users mentioning this movie demand a choice whether to vaccinate their children. However, images also referred to *Vaxxed* in a way that suggests it has become a movement, specifically a protest movement. For example, four photos showed protesters seeking to halt mandatory vaccinations or suggesting that there is a medical tyranny imposing unsafe vaccines. These images were shared especially by activists and uncategorised users, and some of them were shared by journalist-activists.

7.1.4 Most shared pro-vaccine, academic and news-related images

The most retweeted images shared by the pro-vaccine network included pro-vaccine, academic, and news-related images. These pictures were mostly photos (70%) and some infographics (10%), but there were drawings (8%) as well (n=50, Figure 7.13). More than half of the pictures had text overlays or captions (58%, n=50); those without any textual elements were photos.

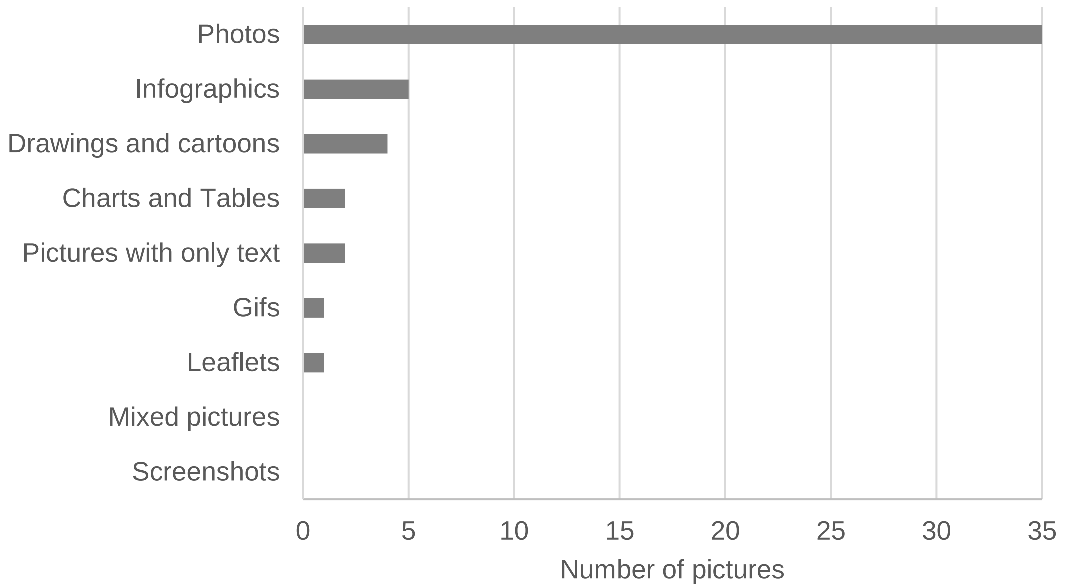


Figure 7.13 Frequency of the types of pictures among the most shared pro-vaccine, academic and news-related images.
These 50 images were collected in June, September and October 2016. The related Table is in Appendix G.

Thirty images were pro-vaccine, 14 were academic and nine were news-related. Twenty pro-vaccine pictures were photos, the remaining ten comprised a variety of types. The most shared academic images included eleven photos, and one infographic, one chart and one leaflet, whereas the news-related pictures comprised four photos and two infographics.

Most of the images showed *immunisation campaigns*. Other recurrent topics were *vaccine development*, *vaccine efficacy* and *conferences* (Figure 7.14). In the pro-vaccine photos, *immunisation campaigns* were sometimes associated with *vaccine development* and *financial issues* to emphasise how the development and administration of vaccines could reduce public health costs in the long term. Occasionally, *immunisation campaigns* and *vaccine efficacy* were combined as well. The *pro-vaccine statements* were sometimes related to *immunisation campaigns* or *vaccine development*.

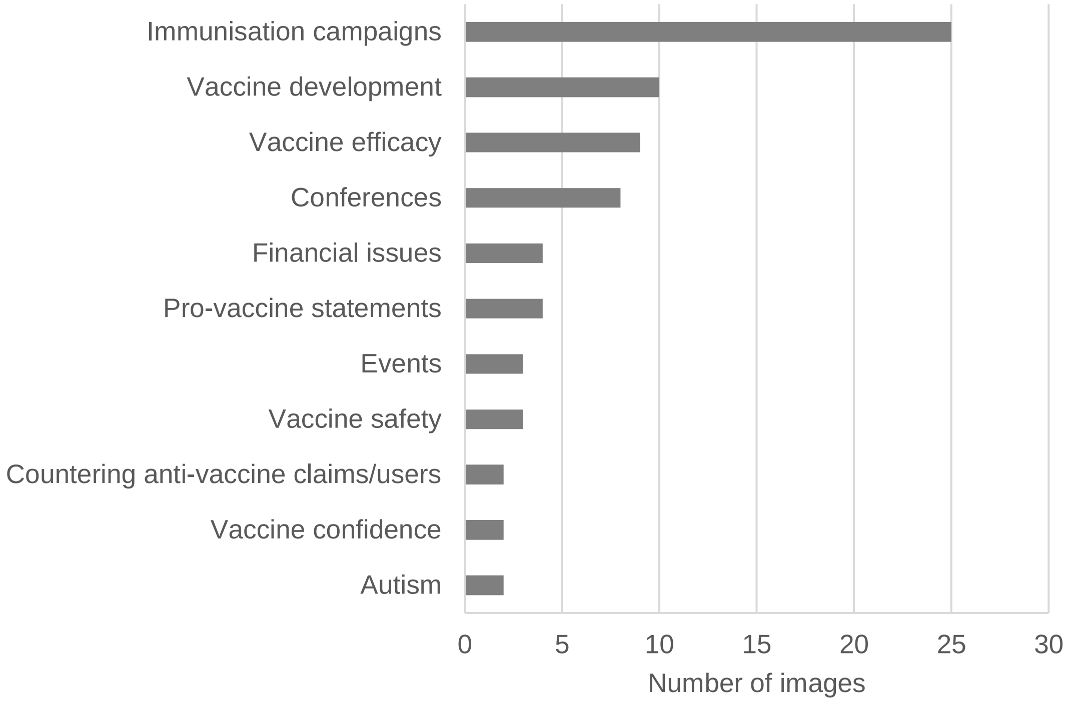


Figure 7.14 Frequency of topics that appeared in the most shared pro-vaccine, academic and news images.
One image could show more than one topic. These images were collected in June, September and October 2016.

Many academic images represented *conferences* in association with either *immunisation campaigns* or *vaccine development*. In the first case, they reported the launch or evaluation of immunisation campaigns at conferences; in the second case they showed a presentation about vaccine research. News-related images were about *vaccine confidence* and an article on research about vaccine refusal rates across countries (4 out of 6; see Section 7.1.2.3).

Other news-related images were related to *vaccine development*, and they reported news about the vaccine industry or research, or the launch of new immunisation campaigns.

Almost all images conveyed the topics in the text of the tweet (92%, n=50), many did in the pictures (60%). Only nine images conveyed the topics in the hashtags, of which eight were related to *immunisation campaigns* (see Appendix G). Many pictures showed Africans or Asians (44%, n=50), and only some showed Caucasians (20%, n=50). Moreover, these pictures depicted women (42%, n=50) and children (38%) slightly more often than men (26%). Among the most common signs there were oral vaccines, laboratory coats or disposable gloves, and syringes (Figure 7.15), but they appeared in association with different topics. For example, images combining *immunisation campaigns* and *financial issues*, which emphasised how vaccines could reduce public health expenses in the long term, portrayed African or Asian children and women. The children, in particular, were shown while taking an oral vaccine from someone wearing disposable gloves (a nurse or a volunteer). The images associating *immunisation campaigns* and *vaccine development* depicted African men, while those combining *immunisation campaigns* and *vaccine efficacy* showed African or Asian children, and those representing *vaccine efficacy* alone occasionally had pictures of microbes or viruses.

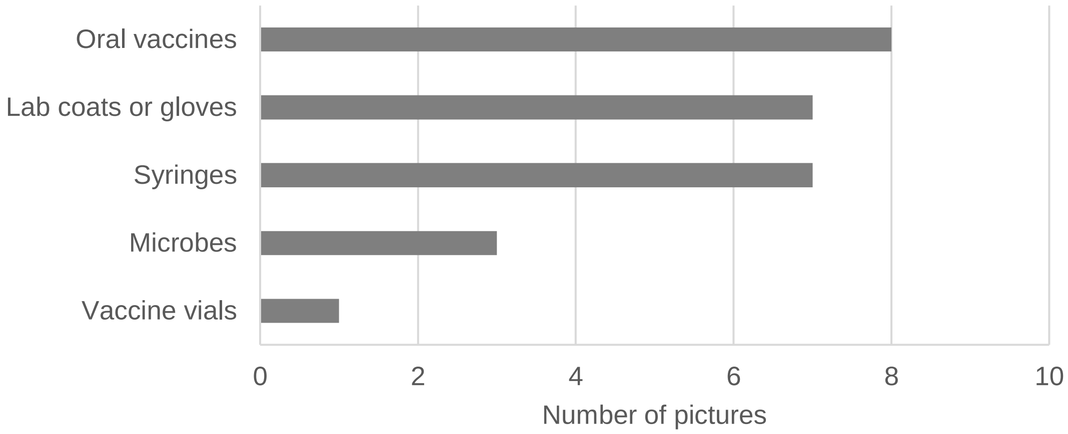


Figure 7.15 Number of pictures containing signs (e.g. syringes) among the most shared pro-vaccine, academic and news-related images.
These pictures were collected in June, September and October 2016. Some pictures, such as those with only textual elements or tables, did not have any figurative elements.

Three recurrent types of users shared the most retweeted images within the pro-vaccine network: NGOs, healthcare practitioners/academics, and chief executives/ managers/advisors of NGOs. A few users shared several images, especially an NGO and its chief executive that were identified as key actors in the social network analysis (see Section 5.1.2.2). The NGOs and the chief executives/managers shared mainly photos about *immunisation campaigns* and *conferences*, respectively. The healthcare practitioners/scholars posted different types of pictures and topics, including *conferences*, *vaccine development*, *messages countering anti-vaccine misinformation*, and *pro-vaccine statements*.

7.1.4.1 Immunisation campaigns as an investment

Most of the images promoting *immunisation campaigns* included photos, without any textual elements, and did not mention any other topic. For example, one tweet said: “We are delivering vaccines in Solomon Islands” or “This mother is smiling after her child was vaccinated”. These pictures portrayed African or Asian children and women, receiving vaccinations. Some images promoting *immunisation campaigns* mentioned the topic *financial issues* as well, and they included photos of African and Asian children and women with text overlay. These images claimed that *immunisation campaigns* were one of the best investments for future generations (in the text of the tweet), and also mentioned financial return from this investment (in the picture).

7.1.4.2 Vaccine efficacy and vaccine development in immunisation campaigns

The images promoting *immunisation campaigns* and *vaccine development* varied extensively. Some had photos depicting African men, likely volunteers or charity workers, and they explained the importance of effective supply chains for improving immunisation rates. Others had infographics and stressed the importance of increasing vaccination rates. In a few images, the topic *immunisation campaigns* was combined with *vaccine efficacy*. The pictures showed African children accompanied by a woman or during vaccination. These images emphasised how vaccines keep children healthy and have saved millions of lives.

7.1.4.3 Conferences and meetings

The images related to *conferences* were varied. Three of them showed photos of presentations: one discussed an immunisation campaign, one the efficacy of vaccines, and one the results of a study on a specific vaccine. Two images promoted specific academic events; for example, a public monthly meeting about vaccines with a group of physicians, and the World Vaccine Congress. Among the images about *conferences*, only three were visually similar and about the same topic: the representatives of an NGO and the Kingdom of Saudi Arabia met to agree financing for an immunisation programme in another country. These images mentioned the meeting and showed the participants while discussing or finalising the agreement. There was no mention of the content of the agreement in the tweets or in the pictures, nor an URL link to a web page providing more information[38]. Only the people and the parties involved in the agreement were mentioned. Two of these three images were shared by the NGO involved in the agreement, and one was tweeted by the chief executive of that NGO. These two users were classified as important key actors within the pro-vaccine network (see Section 5.1.2.2).

7.1.5 Summary

The anti- and pro-vaccine communities shared different images on different topics: while the first focused on *vaccine safety*, *conspiracy theories* and *Vaxxed the movie*, the second posted content on *immunisation campaigns*,

[38] The researcher found the information about the reason of this meeting by searching Google and the archive of the NGO’s website.

vaccine development and *efficacy*. The users sharing the images differed between the two groups, and they reflected the type of key actors identified in the social network analysis: activists, parent-activists, journalist-activists and uncategorised users shared most of the anti-vaccine images, whereas NGOs, healthcare professionals and chief executives/managers posted most of the pro-vaccine and academic images (see Section 5.1.2). Photos were the most common format in both groups, but only the pro-vaccine network shared infographics while the anti-vaccine community posted most of the screenshots, mixed pictures and pictures having textual elements only. Signs such as syringes and white lab coats were also common in both groups, though pro-vaccine pictures showed oral vaccines as well. Moreover, anti-vaccine pictures often showed white children and adults, whereas the pro-vaccine ones mostly portrayed African or Asian people.

Since some signs were more recurrent than others, they could be conventions, visual language standards, used by pro- and anti-vaccine users to talk about vaccinations (Grewal, 2009). The syringe, with or without the presence of a child, could express the concept of ‘vaccination’, whereas the lab coats and disposable gloves likely labelled a person as a healthcare practitioner or researcher. These signs were found in previous studies about vaccine images on social media (Chen and Dredze, 2018; Milani, 2015). In particular, the anti-vaccination images posted on Pinterest used the same figurative elements mentioned above (Milani, 2015), whereas the pro-vaccine images presented more statistical data (e.g. in form of infographics) than their counterparts (Guidry *et al.*, 2015) and depicted people representative of their immunisation campaigns.

The recurrent use of textual elements in vaccine pictures was also found by Chen and Dredze (2018), and they formed a shorthand for communication of topics and complex concepts, overcoming the character limit in the tweets (Giglietto and Lee, 2017). Topics were not expressed often in the hashtags, except for *Vaxxed* and immunisation campaigns. In the first case, #Vaxxed may be a topical hashtag used to access anti-vaccination conversations and the anti-vaccine community (Grewal, 2009), whereas in the second case

NGOs and foundations may use hashtags as catch phrases or labels for their advocacy campaigns.

There were few differences between images selected at random and the most retweeted ones. In the case of anti-vaccine images, the most re-shared ones had less text, showed fewer symbols of *Vaxxed* and more men than women or children than those selected at random. These differences were likely due to the fact that many of the most shared images were shared by the same users, often key actors (see Section 5.1.2), and were highly retweeted by their respective communities. For example, these actors did not give visibility to the campaign 'Boycott IKEA' or to the presidential elections (often mentioned in the random images shared by parent-activists, instead), but they focused on promoting *Vaxxed the movie* and disseminating misinformation about vaccine safety and efficacy (see Sections 7.1.3.1-3). In the case of the pro-vaccine images, African and Asian people were more frequent in the most shared images than those selected at random, the oral vaccine was also more common than the syringe, and text overlays appeared more often. Again, these differences depended on the key actors, such as NGOs and chief executives/managers, who shared many of the highly retweeted images.

In the main study (discussed below) only the most retweeted images were analysed for the following reasons:

- Both the most retweeted images and those selected at random showed similar combinations of topics, and figurative elements;
- The images that were most retweeted were likely more visible on Twitter than those selected at random;
- The most re-shared images are likely to be highly supported or endorsed by their respective community since retweeting implies sharing someone's content with your own followers, hence suggests agreement with, and value of the retweeted message.

7.2 Main research

The fifty most shared images were selected from the anti-vaccine community, the pro-vaccine network and the news-related group, for a total of one hundred fifty images. These images had the highest frequency in their respective groups. A qualitative content analysis was conducted to identify recurrent combinations of types of pictures, presence of textual content, topics, and figurative elements. However, in this research the analysis included additional signs and topics that were not considered in the pilot study (see Section 6.2.7). These new signs and topics were included to conduct a more thorough analysis.

7.2.1 Most shared anti-vaccine images

Half of the 50 most shared anti-vaccine images were photos, followed by mixed pictures and pictures having only textual elements (Figure 7.16). 32% of these pictures did not have any text overlay or captions (n=50), of which fifteen were photos and one was a drawing.

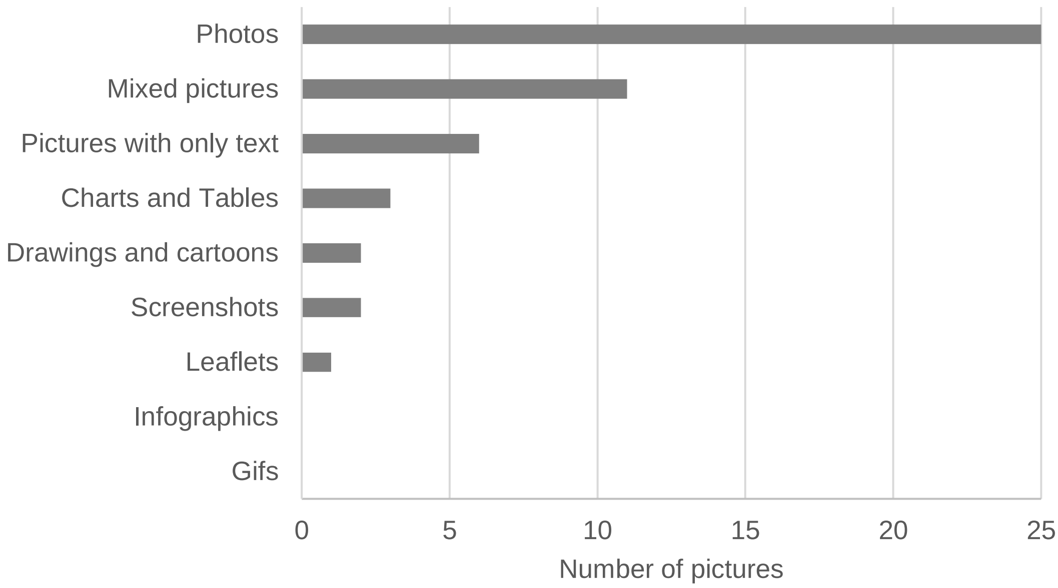


Figure 7.16 Frequency of the types of pictures among the most shared anti-vaccine images.
These 50 images were collected in November 2016.

Among the selected images there were two photos coded as pro-safe vaccines. These two pictures were among the most shared ones in the anti-vaccine community[39]. Whilst in the pilot study the most recurrent topic within the most shared anti-vaccine images was *Vaxxed*, in this dataset it was *vaccine safety*. *Conspiracy theories*, *autism* and *freedom of choice* were also common topics (Figure 7.17).

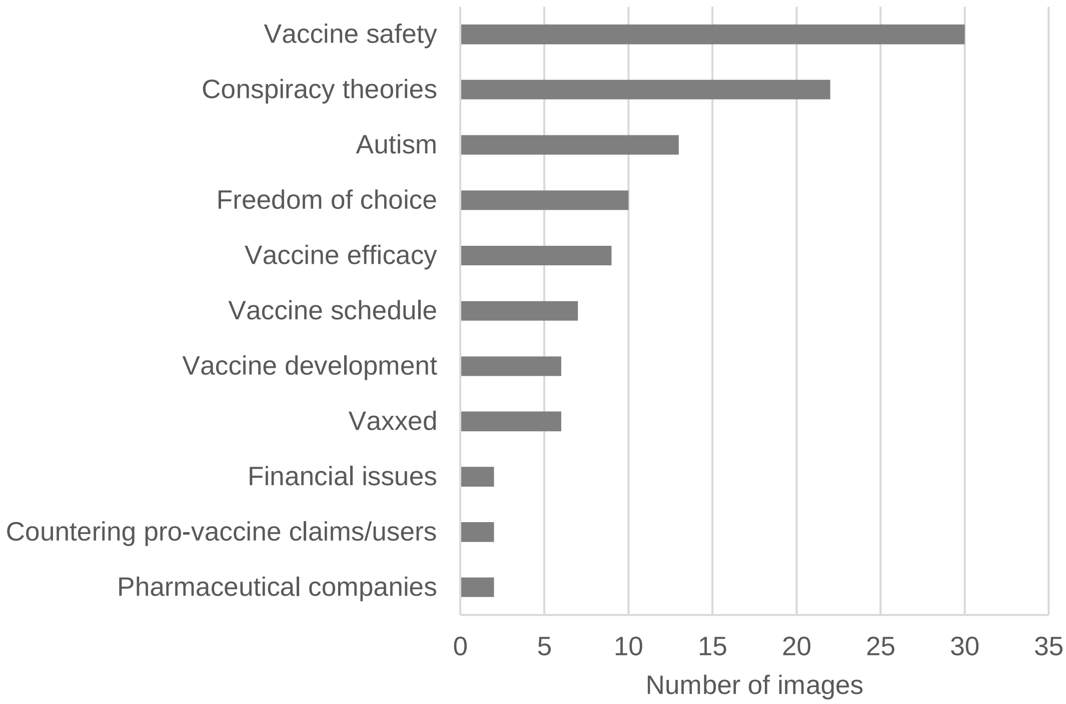


Figure 7.17 Frequency of topics that appeared in the most shared anti-vaccine images.
One image could show more than one topic. These images were collected in November 2016.

Vaxxed may be less prominent in this dataset because different coding criteria were applied. The code *Vaxxed* was assigned to images mentioning *Vaxxed the movie* or the protest, whereas the code #*vaxxed* was assigned to the hashtag #vaxxed when there was either no clear reference to the movie or the protest (see Section 6.2.7). *Conspiracy theories* and *vaccine safety* were often combined, occasionally with *Vaxxed*, in images that said, for example, "Whistle blower confirms the MMR vaccine is not safe" or "1 in 45 kids has autism. Learn

[39] The anti-vaccine community shared both anti-vaccine and pro-safe vaccine images (see Section 5.2.1).

the risk about vaccines: watch *Vaxxed*". *Vaccine safety* appeared frequently with either *vaccine development* or *vaccine schedule*, in messages claiming that the content of vaccines is toxic or that too many vaccinations can injure children. *Freedom of choice* was also associated with *vaccine safety*, especially in images questioning why it is not possible to refuse just one vaccine, or claiming that if there is a risk, there needs to be a choice.

Autism, *vaccine safety*, *freedom of choice* and *conspiracy theories* all occurred in images related to Donald Trump. Eleven of the most retweeted anti-vaccine images mentioned Donald Trump, of which three mentioned Hillary Clinton as well. These images claimed that Trump wanted to reduce the number of immunisations given at once, that he was against too many vaccines, he knew the truth about vaccines, and that a vote for Clinton was a vote for mandatory vaccination. Clinton appeared only in four images, and she was often depicted as a corrupt politician, standing up for pharmaceutical companies and multinationals like Monsanto. In the main research, specific diseases and vaccines were also considered. The anti-vaccine images mentioned once or twice the following diseases: measles, HPV, chickenpox, hepatitis, flu, and polio.

Almost all the images showed topics in the text of the tweets (49 out of 50), and many of them displayed topics in the pictures as well (33 out of 50). The images rarely used hashtags to convey topics (10 out of 50). *Vaxxed* as a topic appeared in the hashtag only in three images, while #*Vaxxed* as a label for anti-vaccine conversations appeared in seventeen of them (see Appendix G).

The anti-vaccine pictures depicted mainly white people (24 pictures), especially children (13 out of 24), rarely portraying other ethnicities (3 pictures). The white children appeared frequently alone (8 out of 15) or with someone wearing disposable gloves or a laboratory coat and holding a syringe (5 out 15; only the hands were visible). These two symbols, the syringe in particular, were the most recurrent signs (Figure 7.18). Syringes, laboratory coats and white children were common in images about *vaccine safety*, *vaccine development* and *vaccine schedule*. Syringes appeared often in images about *conspiracy theories* as well, together with white children and men.

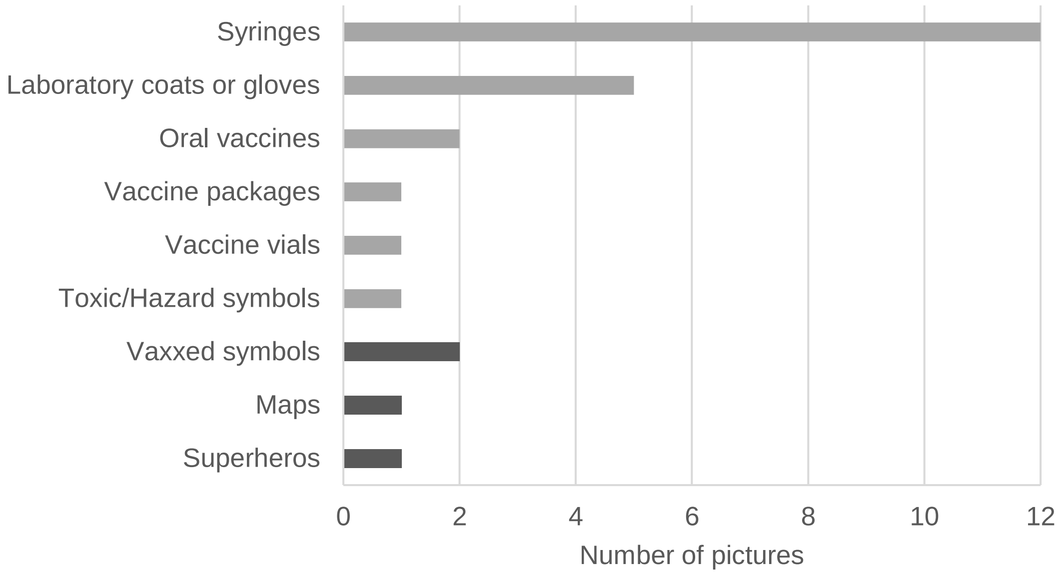


Figure 7.18 Number of pictures containing signs (e.g. syringes) among the most shared anti-vaccine images.
These pictures were collected in November 2016. Some pictures, such as those with only textual elements or tables, did not have any figurative elements. In light grey – signs related to vaccines, research laboratories and hospitals; in dark grey – signs not related to research and medical environments.

Twenty-one images were shared by activists, ten by journalist-activists, five by uncategorised users, four by parent-activists, and three by journalists. However, twelve of the images posted by activists were shared by the same user, and all the images tweeted by journalist-activists were shared by the same actor: these two individuals were the primary hubs of the anti-vaccine community (see Section 5.2.2.1). All the other users shared only one or two images each, except an activist who posted four most shared images. The journalist-activist shared photos about *conspiracy theories*, *vaccine safety*, and occasionally Donald Trump (see Appendix G). The activist, instead, posted photos and charts about *vaccine safety*, *vaccine efficacy*, *vaccine schedule* and *autism*, and claimed that scientific evidence showed how combined vaccines or specific vaccinations could be harmful or even cause autism.

7.2.2.1 Vaccines are not safe

Many images about *vaccine safety* showed photos of white babies and children, often while receiving the vaccine through a syringe. These children were alone or accompanied by an adult but only his/her arms or hands were visible. These images claimed that either the content (e.g. mercury, thimerosal and formaldehyde) or the large number of vaccines given in one session could cause injury. As well as autism, they accused vaccines of causing dementia, multiple sclerosis, shingles, paralysis, diabetes type 1, and sudden infant death. One of the biggest concerns was the mercury in vaccines, though level included has been proven not to be dangerous (Taylor, Swerdfeger and Eslick, 2014). The number of mandatory vaccinations was also an important concern for anti-vaccine users. The images claimed that receiving too many vaccines or specific combined vaccines could harm children, and they mentioned scientific publications or screenshots of tables and books that supported their statements. Both the activist and the journalist-activist shared these topics and signs. However, while the activist's images focused on the scientific evidence and the numbers of vaccine injuries, those posted by the journalist-activist mentioned the conspiracies behind vaccinations and/or supported Donald Trump.

7.2.2.2 Presidential candidate Donald Trump

22.0% of the most shared anti-vaccine images were about Donald Trump (n=50). Four of these images embedded photos of Trump and one showed a screenshot of his tweets, showing an anti-vaccine position. The other six images included a photo of Melania Trump, two pictures having only textual elements, and two photos and a drawing that did not depict Trump. In three pictures Andrew Wakefield appeared as well, especially in association with one of his quotes, which claimed that Donald Trump was the ideal candidate as president because he would stop mandatory vaccination. This quote also mentioned Hillary Clinton, saying that a vote for her would be a vote for mandatory vaccination. Donald Trump was often represented as the one who stands against vaccines and stands for the people (i.e. the anti-vaxxers, the *Vaxxed* supporters), and once he was even portrayed as a superhero. A few images also claimed that Trump knew the truth about vaccines and would challenge corrupt public health services.

7.2.1.3 Pro-safe vaccine images

As mentioned at the beginning of the section, three images reflected pro-safe vaccine positions. One of the images showed a photo of smiling women (including one or two men) at an NGO's event, during which it was proclaimed that the state of Virginia (US) would retain exemptions from vaccination. This NGO fights for freedom of choice as to whether to vaccinate, specifically for medical and religious vaccine exemptions.

Another image showed a happy white kid, it named him and demanded justice for him and awareness for future potential victims. This image claimed that the child died after he was denied treatment for a vaccine injury. These images were classified as pro-safe vaccines rather than anti-vaccine because they were not completely against vaccination. Instead, they raised ethical issues about vaccination: the right to ask for medical and religious vaccine exemptions, and the right to demand prompt treatment for a sick child (though the real cause of the illness might not be a vaccine).

7.2.2 Most shared pro-vaccine and academic images

The most retweeted images shared by the pro-vaccine network included 42 pro-vaccine, seven academic and one pro-safe vaccine images. 54% of the pictures were photos, while other recurrent types of pictures were infographics (12%), pictures having only text (10%) and screenshots (8%, Figure 7.19). Many pictures had text overlays or captions (76%).

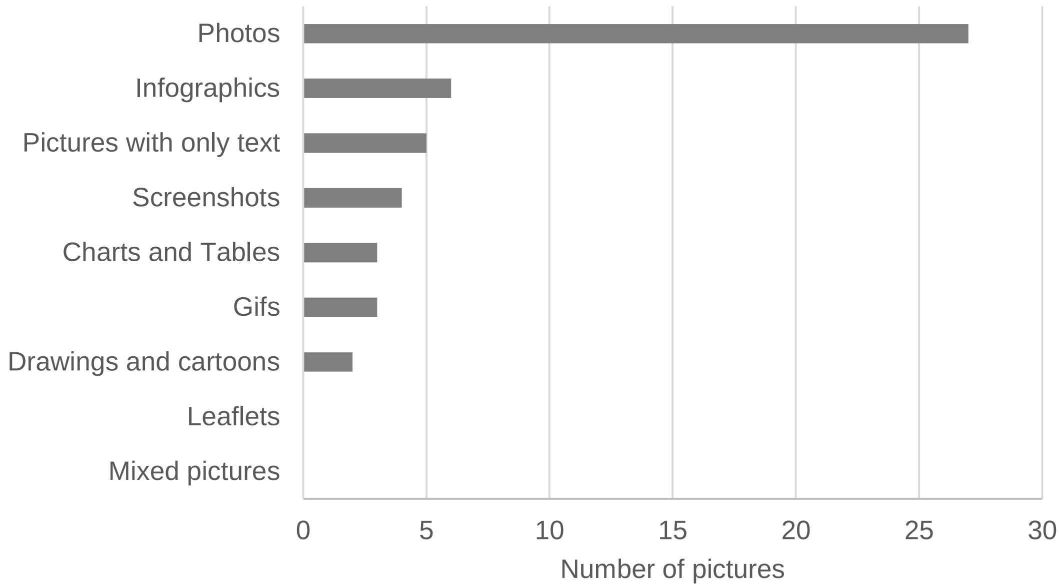


Figure 7.19 Frequency of the types of pictures among the most shared pro-vaccine and academic images.
These 50 images were collected in November 2016. The related table is in Appendix G.

The most popular topics were *vaccine development*, *pro-immunisation messages*, *vaccine efficacy* and *immunisation campaigns* (Figure 7.20). In this study there were slightly fewer images about *immunisation campaigns* than in the pilot research (17 and 25, respectively) because they were coded slightly differently (see Section 6.2.7). The images that mentioned vaccination campaigns were divided into those promoting a campaign (labelled *immunisation campaigns*) and those advocating for vaccination (labelled *pro-immunisation messages*). The category *immunisation campaigns* included messages about the launch, efficacy or backstage of a vaccination campaign; for example, “The immunisation campaign against cholera was just launched in Haiti", "Mass vaccination campaign saved millions of lives", or "Our volunteers are preparing for the cholera immunisation campaign". The topic *pro-immunisation messages*, instead, included messages seeking to persuade people to vaccinate; for example, "Get your flu shot" or "You can stop measles by making sure you and your family are fully vaccinated". These two topics were shared by NGOs and public health services, while *pro-vaccine statements* were messages in favour of vaccinations tweeted by other types of users (e.g. healthcare practitioners).

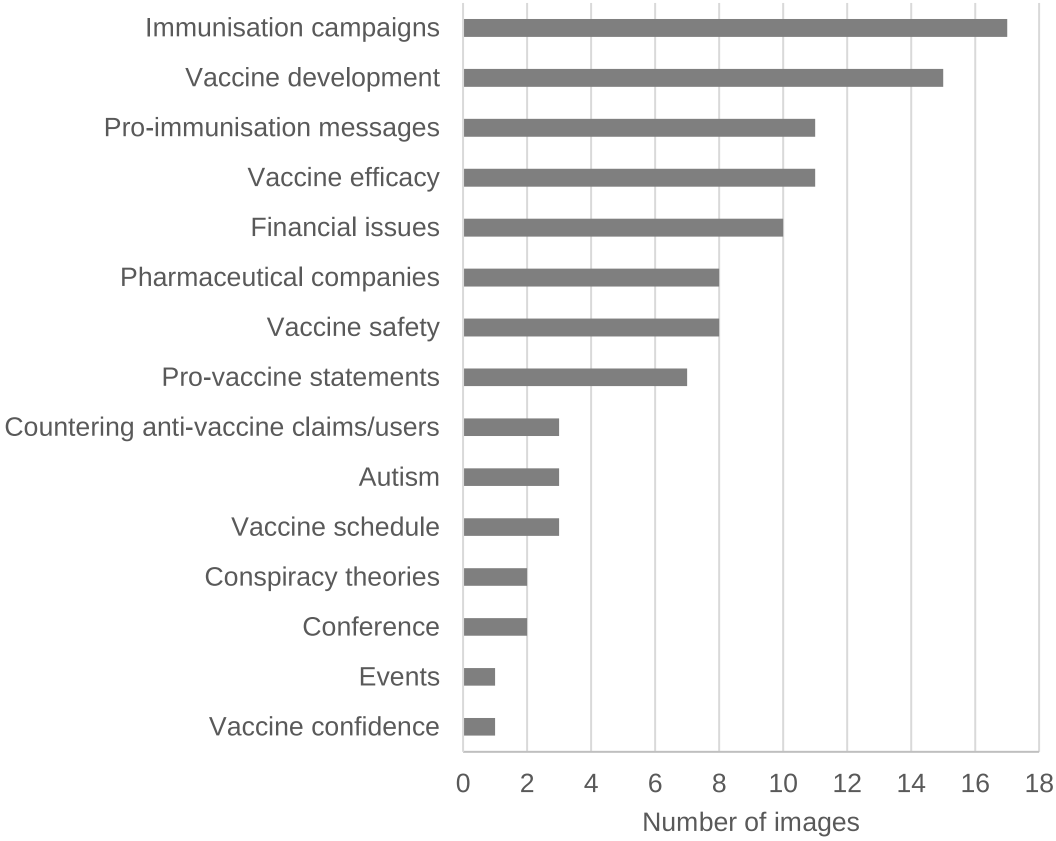


Figure 7.20 Frequency of topics that appeared in the most shared pro-vaccine and academic images. One image could show more than one topic. These images were collected in November 2016.

Seven images related to *immunisation campaigns* also talked about *vaccine development*, *financial issues*, *pharmaceutical companies* and *pneumonia* (the last one is discussed later in this section). These images were part of a campaign launched by an NGO, which asked two specific pharmaceutical companies (mentioned in the tweets) to reduce the price of the pneumonia vaccine to make it accessible to every country. Seven of the other eight images about *vaccine development* (that were not related to the NGO's campaign just mentioned) were academic.

Five images were about an *immunisation campaign* against *cholera* that was launched in Haiti after hurricane Matthew. The other images about *immunisation campaigns* regarded *measles*, *polio*, and *whooping cough*. The *pro-immunisation messages* were almost entirely about *flu* (19 out of 21), and two were about *measles*. Since the data were collected in November, it is likely that public health services were heavily promoting flu vaccinations to protect people over the winter. *Vaccine efficacy* was combined with different topics in different images. For example, it appeared in images about *immunisation campaigns*, *pro-vaccine statements*, and *pro-immunisation messages*. In general, these images emphasised the efficacy of vaccines and that they save lives. *Vaccine safety* also appeared in combination with various topics. For example, it was associated with *vaccine efficacy* in support of the MMR vaccine. The three most interesting images regarding *vaccine safety* included Donald Trump. These images showed Donald Trump's tweets or photos or the endorsement from Andrew Wakefield, and they contested Mr Trump's claims that there is a link between the MMR vaccine and *autism*, and that the *vaccine schedule* should be reduced if not abolished.

Among the academic images, two showed the same infographic about a study on the positive effect of breastfeeding on vaccination, and they were shared by the same research institute. Two other images embedded photos taken at conferences. The three remaining covered development of a Zika vaccine, a published study on a cure for HIV, and the vaccine market. Academic images were shared by healthcare practitioners, academics, a research institute, an NGO and a pharmaceutical company. The pro-safe vaccine image was shared by an uncategorised user, had only textual elements and complained about funding cuts by the Australian government which would reduce whooping cough vaccine coverage, and could increase the likelihood of outbreaks.

Some diseases/vaccines were more frequently mentioned than others (Figure 7.21). For example, flu was the most commonly mentioned vaccine, especially among *pro-immunisation messages*, and it was followed by pneumonia. The pneumonia vaccine was a particular focus in an NGO's campaign to reduce the price of this vaccine to make it more affordable. Cholera was mentioned in the immunisation campaigns related to Haiti, and measles was cited in different images, sometimes in relation to *immunisation campaigns*, as with polio, while at other times it was used in relation to *pro-immunisation messages* or *vaccine efficacy*. *Whooping cough* appeared only in images that mentioned the Australian government.

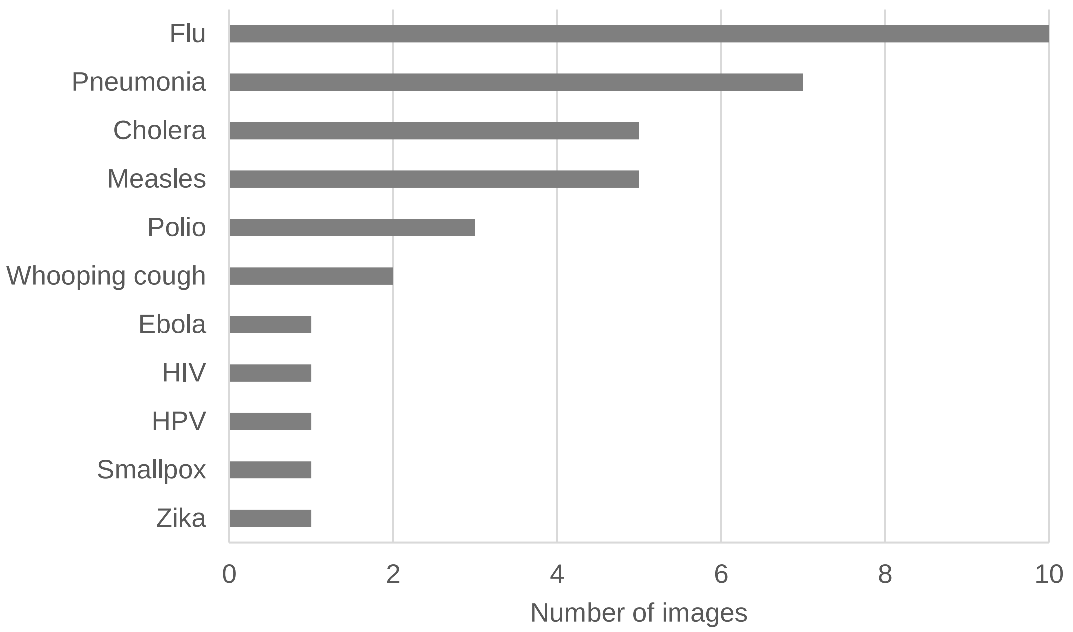


Figure 7.21 Frequency of the types of vaccines/diseases that appeared in the most shared pro-vaccine and academic images.
These images were collected in November 2016.

All the most shared pro-vaccine and academic images conveyed the topics in the text of the tweet; thirty-six also showed them in the pictures. Some images used a hashtag to convey a topic, especially those conveying *pro-immunisation messages* (see Appendix G). The most shared pro-vaccine pictures showed slightly more Caucasians (20 pictures) than any other ethnicity (14 pictures), but their distribution depended on the vaccination campaign. For example, pictures of the flu vaccination campaign showed more white adults than people belonging to ethnical minorities (8 and 4, respectively), while the campaign to reduce the price of the pneumonia vaccine had pictures depicting African children (4 out of 7). The most common signs were syringes, followed by laboratory coats or disposable gloves (Figure 7.22). There was only one picture of the oral vaccine. Different signs appeared in association with different topics; for example, images combining *immunisation campaigns* and *financial issues*, which emphasised how vaccines could reduce public health expenses in the long term, portrayed African or Asian children being vaccinated accompanied by women of the same ethnicity. The images associating *immunisation campaigns* and *vaccine development*, depicted African men, while those combining *immunisation campaigns* and *vaccine efficacy* showed black children, and those representing *vaccine efficacy* alone occasionally had pictures of microbes or viruses.

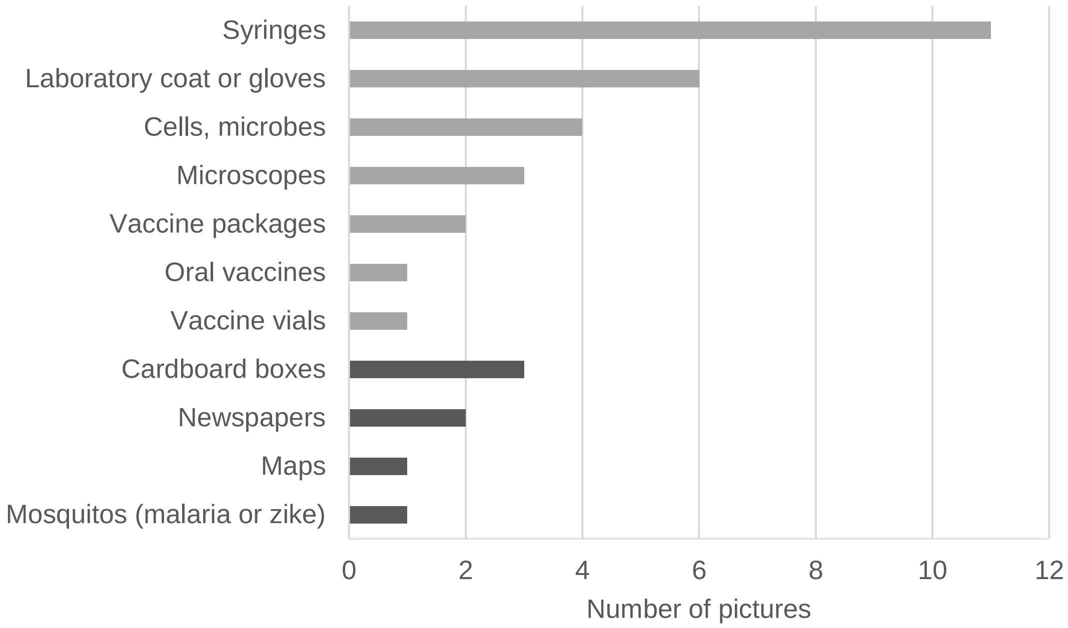


Figure 7.22 Number of pictures containing signs (e.g. syringes) among the most shared pro-vaccine and academic images.
These pictures were collected in November 2016. Some pictures, such as those with only textual elements or tables, did not have any figurative elements. In light grey – signs related to vaccines, research laboratories and hospitals; in dark grey – signs not related to research and medical environments.

Syringes, cells, microbes, viruses, and microscopes often appeared as icons in infographics. The syringe was also depicted in all the photos related to the campaign to reduce the price of the pneumonia vaccine. Laboratory coats or gloves were recurrent in images about *pro-immunisation messages*, and they also appeared in three images about the pneumonia vaccine campaign. Cells, microbes and viruses appeared in three images related to *pro-immunisation messages* about flu. These three pictures were two gifs and an infographic talking about myths and facts behind the flu vaccine. Some of the pro-vaccine pictures showed unusual signs, such as cardboard boxes and newspapers. The cardboard boxes contained cholera vaccines and they appeared in three images related to the campaign in Haiti. Two images included photos of articles from newspapers (the print version), and one showed a map as infographic.

Thirty-nine different users posted the most shared pro-vaccine and academic images. Most of these users posted only one or two images, whereas two NGOs shared three and five images. Overall, NGOs and foundations shared eighteen images, public health organisations tweeted ten images, healthcare practitioners and academics posted four images, and hospital and research centres shared three of them. None of the users was a parent.

7.2.2.1 A call for an affordable pneumonia vaccine

Four different Twitter accounts from the same NGO posted the same two images three times. These images called for a lower price for the pneumonia vaccine and asked for support from around the world. The seventh image thanked everyone who joined the campaign and celebrated its success. In these images, the NGO mentioned two pharmaceutical companies asking them directly to reduce the price of the vaccine. The two re-posted pictures were both photos and had text overlay. One used the photo as a background, which showed people walking on a street, and put the text in the foreground, which said “give this pharmaceutical company a call! Ask them to reduce the price of the pneumonia vaccine”. The other image had photos and text on the same level, and showed a black child receiving a vaccine through a syringe.

The text overlay mentioned the number of pneumonia victims each year and emphasised the need of a more affordable vaccine for developing countries.

7.2.2.2 Get your flu shot

The *pro-immunisation messages* about *flu* focused on the importance of vaccinating against flu, but they conveyed this messages in two different ways: suggesting the flu nasal spray for children and the flu jab for pregnant women, or debunking flu vaccine myths. In the first case, the pictures were photos of nurses and had text overlay, and they were shared by the same health organisation. In the second case, the pictures were infographics or gifs showing icons of viruses and contrasting real facts about flu vaccination against false claims. These images were shared by two health organisations. The other images about *pro-vaccination messages* were shared by other public health institutes, and they comprised a gif, a comic, a picture having only text and a photo. Their messages differed from the other flu images either suggesting General Practitioners encourage their patients to get the flu jab, explaining how the vaccine can stop flu epidemics and protect family and friends.

7.2.2.3 The cholera vaccination campaign in Haiti

After hurricane Matthew hit Haiti in October 2016, a cholera vaccination campaign was launched, and it received support from various NGOs and governments. The pictures shared were all photos without any textual elements, and they showed different aspects of the campaign. For example, three pictures depicted cardboard boxes containing the cholera vaccine donated by an NGO to the Haitian government. They also depicted volunteers or workers helping with the delivery. Another image showed Red Cross volunteers preparing for the campaign. The last picture was slightly different; it depicted only black men, and it focused on one of them holding an oral vaccine. The message in the tweet's text was also different, it emphasised the importance of combining water sanitation with the vaccination campaign.

7.2.3 Most shared news-related images

78% of the most shared news-related pictures were photos (n=50), of which 84% did not have any text overlay or caption (n=39). The other news-related pictures were infographics, mixed pictures, screenshots, pictures having only text, drawings, and leaflets, and all of them had textual elements (Figure 7.23).

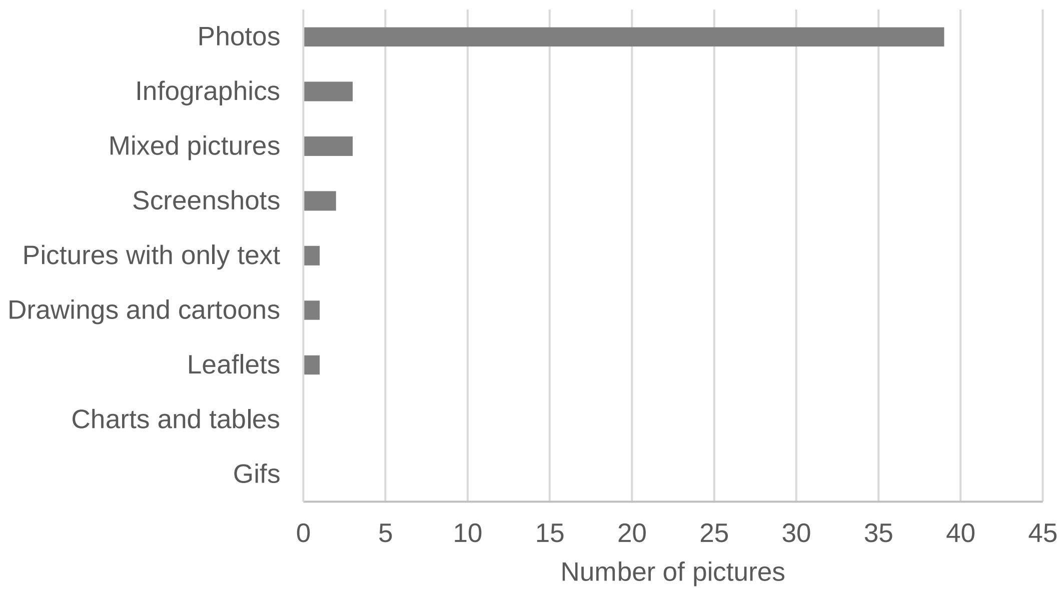


Figure 7.23 Frequency of the types of pictures among the most shared news-related images.
These 50 images were collected in November 2016. The related table is in Appendix G.

Most of the news-related images were about *vaccine development* (Figure 7.24), especially scientific achievements in the development of a vaccine against the Zika virus. Other news regarding *vaccine development* were about: a new vaccination technology based on skin patches; innovative technologies to track vaccine coverage or delivery; research studies aiming to find or test vaccines for HIV or flu. *Vaccine development* was combined with *financial issues* in a few images, which talked about charities and NGOs donating funding for vaccine research, or pharmaceutical companies reducing the price of the pneumonia vaccine to make it affordable.

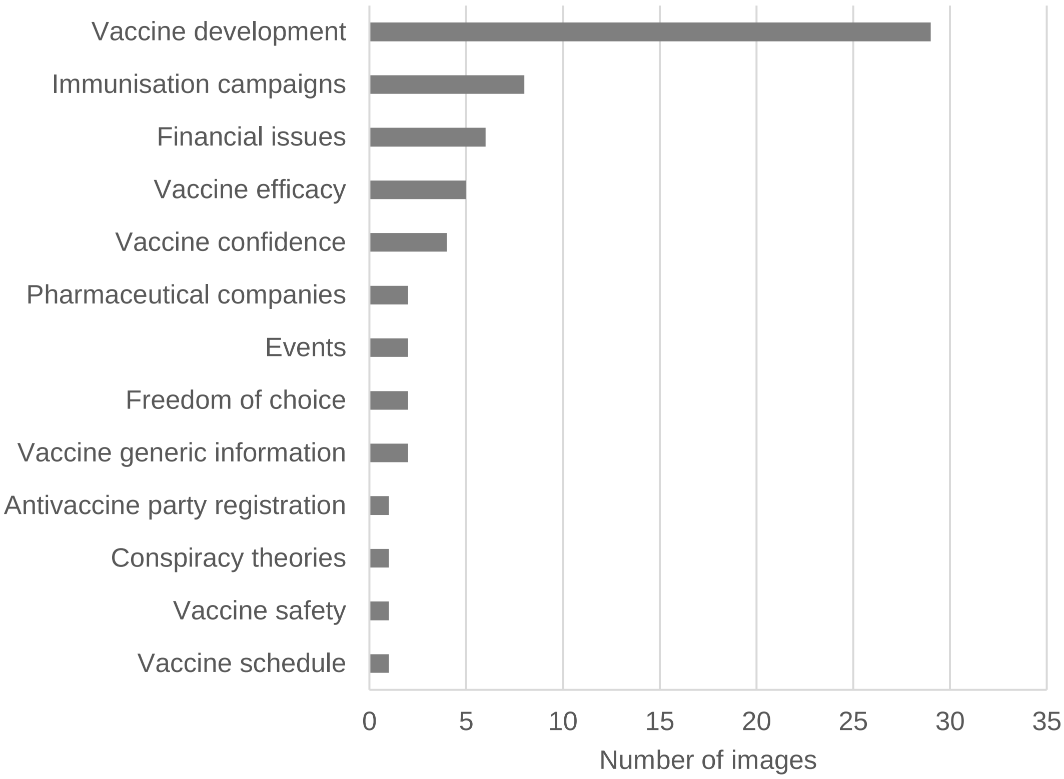


Figure 7.24 Frequency of topics that appeared in the most shared news-related images.
One image could show more than one topic. These images were collected in November 2016.

Other recurrent topics were *immunisation campaigns* and *vaccine efficacy*. Eight images mentioned the launch of specific *immunisation campaigns*, for example the cholera vaccination campaign in Haiti, or HPV immunisation in India. Five images were about the efficacy of vaccines, specifically the cholera vaccine, the HPV vaccine, a new malaria vaccine, and the MMR vaccine. Four images addressed *vaccine confidence*, two of which recalled the study about vaccine refusal conducted in several countries. This news item appeared in the pilot results as well (see Paragraph 7.1.2.3). Among the news-related images, two mentioned unusual topics. One was about the *registration of anti-vaccine parties*; this covered the approval of the registration of the Involuntary Medication Objectors (Vaccination/Fluoride) Party in Australia. This political party officially registered on the 26th October 2016, with a platform opposing mandatory vaccination and water fluoridation. A healthcare practitioner and journalist shared this image. The other topic was about *conspiracy theories*, though it was framed differently to the way this topic was framed in the anti-vaccine images. Amongst news-related images, *conspiracy theories* comprised reports of government politicians accused of stealing funding for immunisation. The image was shared by a parent-activist, also manager of a foundation. None of the news-related images mentioned autism or Donald Trump. The most recurrent types of vaccine in the news-related images were those against Zika virus, cholera, and HIV (Figure 7.25). As mentioned before, the Zika virus was mentioned in relation to *vaccine development* (10 out of 10), whereas cholera was combined with *immunisation campaigns* (5 out 7).

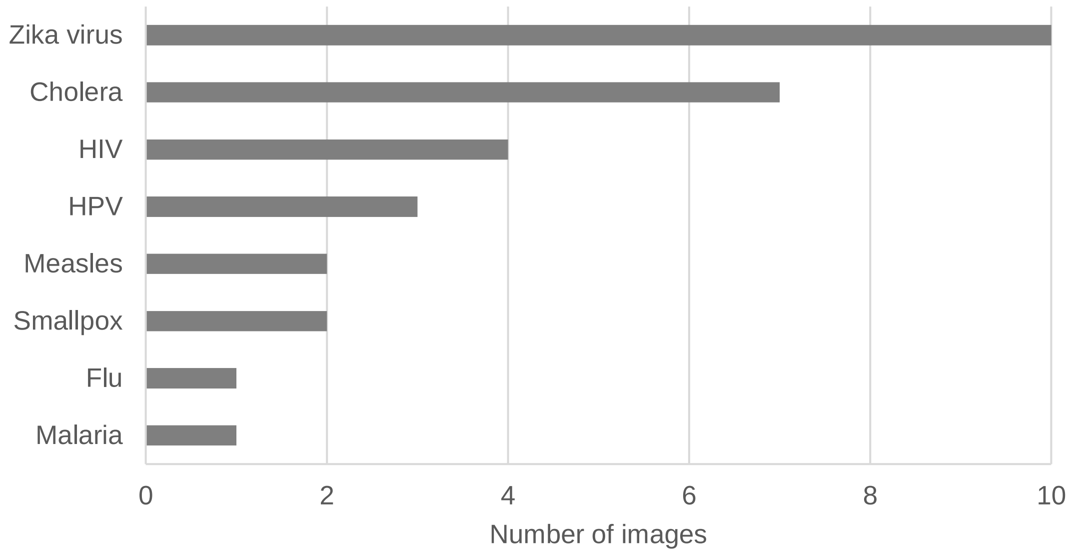


Figure 7.25 Frequency of types of vaccine mentioned in the most shared news-related images.
One image could show more than one type.

None of the images showed the topics in a hashtag, and almost all of them (49 out of 50) mentioned the topics in the text of the tweet. Only fifteen images expressed a topic in the picture (see Appendix G). Most of the signs in the news-related pictures were laboratory coats or gloves, followed by oral vaccines, syringes and cells or petri dishes[40]. Five photos showed buildings, for example headquarters or universities, four showed photos or infographics of maps, and four photos depicted mosquitos (Figure 7.26). In these pictures, Caucasians, Africans, Asians and other ethnicities were represented with similar frequency. However, white people appeared more often wearing laboratory coats and/or gloves or holding a syringe (6 and 4 pictures, respectively) than those belonging to ethnical minorities (1 and 0, respectively). Instead, this second group was often depicted with the oral vaccine (6 out of 6),

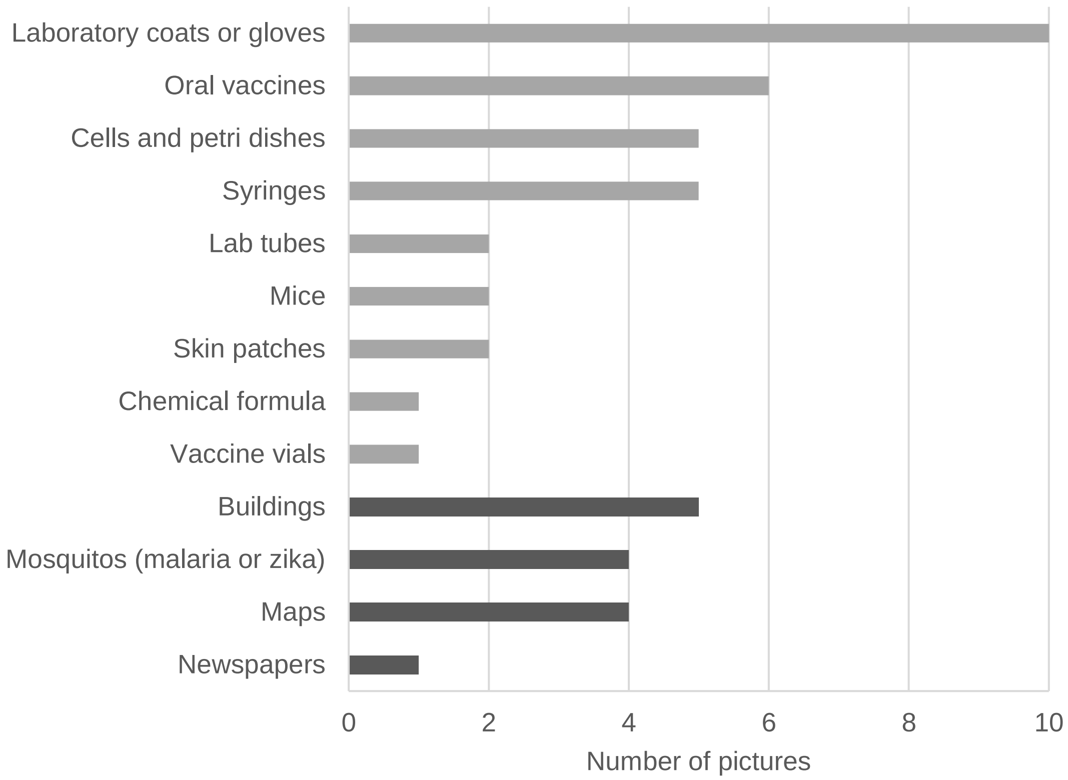


Figure 7.26 Number of pictures containing signs (e.g. syringes) among the most shared news-related images.
These pictures were collected in November 2016. Some pictures, such as those with only textual elements or tables, did not have any figurative elements. In light grey – signs related to vaccines, research laboratories and hospitals; in dark grey – signs not related to research and medical environments.

[40] The petri dish is a tool used to grow cells and bacteria in biological laboratories.

Some combinations of figurative elements were common for specific topics. For example, the images about *immunisation campaigns* against cholera showed black people, likely Haitians, receiving a vaccine administered orally. *Vaccine development*, instead, often portrayed white people wearing gloves or coats while managing laboratory equipment, such as cells, petri dishes and tubes. Other images about *vaccine development* showed vaccine skin patches, buildings or maps. Those talking about the development of a Zika vaccine depicted a mosquito (4 out of 10), mice in a cage (2) and cells (2).

News media outlets, NGOs and healthcare practitioners shared most of the images, whereas all other types of user tweeted only one image each. The news media outlets shared many images about *vaccine development*, and a few regarding *immunisation campaigns*, while the NGOs showed mainly images about *vaccine confidence*, and only two about *immunisation campaigns*. The healthcare practitioners and academics also posted images about *immunisation campaigns*, but also about the *registration of anti-vaccine parties*, and on *vaccine efficacy*. Thirty-four single users posted only one image each, and only seven tweeted more than one image. Among these, one news media outlet shared five images, four news media outlets shared four images each and two NGOs posted two images each.

7.2.3.1 A vaccine against the Zika virus

There were ten images about the Zika virus, four of which depicted a mosquito. The others varied broadly, from those showing healthcare practitioners or researchers to those showing mice or maps. Though these images were about the development of the Zika vaccine, they mentioned different research studies. For example, three of them regarded a clinical trial launched by the US army and they were shared by the army's accounts, whereas three other images mentioned a study in UK and were tweeted by news media outlets. Of the last four images, three were also shared by news media outlets and one by the chief executive of an NGO, but they were all about different pieces of news.

7.2.3.2 The cholera immunisation campaign

Five of the eight images about *immunisation campaigns* mentioned cholera, and they specifically reported the large cholera vaccination campaign that was launched in the areas of Haiti hit by hurricane Matthew in October 2016. These pictures were all photos, without any textual element, and they depicted black people. In four pictures, shared by news-media outlets, either a child or an adult was shown while taking the vaccine, administered orally. The fifth image, tweeted by a healthcare practitioner, depicted a woman standing in front of a microphone, as in an official press conference. The text in the tweet identified her as Haiti's Minister of Health.

7.2.4 Summary

The results of the main research were similar to those of the pilot study; their differences related to the occurrence of events during the collection period, such as the launch of new immunisation campaigns or new scientific discoveries. The pro-vaccine and academic images were most influenced by events; though they showed syringes, white or black adults, often healthcare professionals, and many African, Caribbean or Asians children, they combined these elements differently depending on the campaign they were discussing (Ali, James and Vultee, 2013). For example, they depicted a white female nurse and child to promote the flu vaccine in a Western country, and they showed an African child being vaccinated by a local healthcare practitioner when referring to the pneumonia vaccine.

Most of the pro-vaccine and academic pictures were photos and many of them were infographics, as also found in Pinterest by Guidry *et al*. (2015). These images were shared especially by NGOs, healthcare practitioners, hospitals, research centres and public health organisations – they were similar categories of users to those found in the pilot study (see Section 7.1.4) and the same key actors were identified in the social network analysis (see Section 5.2.2.2). These actors, especially NGOs and health organisations, shared images about *pro-immunisation messages* or *immunisation campaigns*. All the images conveyed their messages in the tweet but many of them used pictures too, which had textual elements. These pictures help to overcome the limit of 140 characters in a tweet, and facilitated communication of more than one message (e.g. more than a topic) or a complex concept (Chen and Dredze, 2018; Giglietto and Lee, 2017). The hashtags seldom conveyed topics, except for labelling specific advocacy campaigns.

The news-related images were shared mainly by news media outlets, but also by NGOs and healthcare practitioners and academics, which reflected the type of key actors found in the social network analysis (see Section 5.2.2.3). These images were mostly photos without any textual element and conveyed their messages through the tweets, never through hashtags. The pictures may have been decorative rather than informative, and used to attract attention or increase the number of retweets (Suh *et al.*, 2010). The content of the news-related pictures was time-sensitive, like the pro-vaccine ones. Though many of them were about the same topic, *vaccine development*, they used different signs depending on the news they disseminated. For example, they showed photos of mosquitos or white researchers for articles about the Zika vaccine, and pictures of locals and oral vaccines for news about the cholera immunisation campaign in Haiti. This type of selection of figurative elements, based on the themes of the articles, is also common for vaccine news published in printed newspapers (Catalan-Matamoros and Peñafiel-Saiz, 2019).

The anti-vaccine pictures varied in type of format, unlike the news-related and pro-vaccine ones. Though many were photos, there were also pictures having only textual elements, charts, screenshots, mixed pictures and so on. There were no infographics, and as found by Guidry *et al.* (2015) on Pinterest, most of the anti-vaccination images used narrative elements rather than statistical data. Narratives can be more persuasive and potentially reduce the intention to vaccinate (Betsch *et al.*, 2011). The anti-vaccine pictures often had textual elements, and as in the case of the pro-vaccine ones, this enriched the messages their tweets conveyed (Chen and Dredze, 2018; Giglietto and Lee, 2017). Occasionally, hashtags were used to express a topic. Moreover, the hashtag #Vaxxed had the same use it had in the images from the pilot study: it provided access to the anti-vaccine community and conversations (Grewal, 2009).

The anti-vaccine images were shared by activists, journalist-activist, uncategorised users, parent-activists and journalists – the same categories of key actors identified in the social network analysis (see Section 5.2.2.1). Furthermore, two of them were the most influential hubs of the community and shared specific messages: the activist emphasised the scientific evidence behind anti-vaccine claims, whereas the journalist-activist insisted on the existence of a vaccine conspiracy. These types of actors could be seen as alternative sources of information that competed with pro-vaccine experts, such as healthcare professionals (Harrigan, Achananuparp and Lim, 2012), and emphasised that vaccines are not safe nor effective. *Vaccine safety*, *conspiracy theories*, *autism* and *freedom of choice* were recurrent topics amongst these images as well as in anti-vaccine images shared on Pinterest (Guidry *et al.*, 2015) and anti-vaccination websites (Kata, 2010). Unlike the pro-vaccine, academic and news-related images, these visuals rarely differentiated their messages based on the type of vaccine and their content did not vary over time. As in the pilot study, vaccines in general were always depicted as an imposed and unjust danger. Even the signs and people depicted did not change: syringes and white children, and sometimes healthcare practitioners (identified as wearing lab coat or gloves), were recurrent elements. The same elements were found in anti-vaccine pictures on Pinterest (Milani, 2015). This recurrent combination of figurative elements, even across platforms, could indicate that these images were created, shared and re-shared by users from Western countries (Rose, 2012). If this is the case, these figurative elements might be visual language conventions adopted by the anti-vaccine community to represent vaccinations (Grewal, 2009).

8. Results of the image analysis

This chapter discusses how recurrent figurative elements and context contribute to the messages of vaccine images by presenting the results of the image analysis. Four highly retweeted images from each group (e.g. anti-vaccine) having a recurrent combination of topics and figurative elements were selected for these analyses (see Section 6.3 for details). When more than one image having the same combination was suitable, the most retweeted and liked was selected since this suggests it was more popular in the community and visible in the Twitter stream (Yoon and Chung, 2013). The same methodology was applied to analyse the images from the pilot and the main datasets.

By analysing the content of highly shared pictures, their framing, their context and manipulation, it is possible to gain insights into the ways that vaccines are represented and discussed by the anti- and pro-vaccine communities (Rose, 2012; Pauwels, 2011). It is also possible to understand how and what messages these images could potentially convey and how these messages could be interpreted by audiences (Ledin and Machin, 2018; Lester, 2014). It also helps explain how these users combine figurative elements, settings, tweet text and hashtags in a message, if and how they use scientific information to persuade their audiences, and what information or messages are missing from the Twitter discourse. Understanding the visual discourse on Twitter could facilitate the design of campaigns to counteract vaccine misinformation.

The following sections discuss the images from each group and dataset. In each figure shown in this Chapter, the text above the picture rephrases the original tweet text. This was done to protect the identity of the users who shared the tweet[41].

[41] By searching the text in a tweet on Google or Twitter it is possible to trace back the original tweet and the actor who posted it. To protect the anonymity of the actors, the tweet text was rephrased.

8.1 Anti-vaccine images from the pilot datasets

8.1.1 Study claims vaccines are not safe

The image in Figure 8.1 is representative of several images posted by the same key actor, an anti-vaccine activist, who regularly claimed vaccines are dangerous and provided (pseudo)scientific evidence to support these claims. This actor was an influential hub in the anti-vaccine community (see Section 5.1.2.1). The selected image reported that a '#study published in the Journal of American Physicians and Surgeons claimed that combining #vaccines in one visit is not safe', and it provided a link to the paper. Though the linked article had the same layout as an academic paper, it was written by a medical journalist, and it was published in a non-scientific journal curated by the Association of American Physicians and Surgeons, which is a non-profit association. The tweet text and the linked article made the image look like news rather than an anti-vaccine message, and provided (pseudo)scientific credibility[42]. Moreover, by adding the hashtag #vaccines, the key actor sharing this misleading image sought to reach *ad hoc* publics discussing vaccinations around a neutral hashtag as well as his/her followers. The hashtag #study is generic and does not label any particular topical conversation or community (Bruns and Moe, 2014). Though the article mentioned was published in the summer of 2016, the tweet was posted at the beginning of October 2016. This tweet and embedded picture have been shared by this actor more than once, and was also found among the most shared images collected in November 2016. This actor does not share event-related tweets and images, but reuses messages to convey their perspective.

[42] There is extensive research demonstrating combined vaccines are safe (DeStefano, Bodenstab and Offit, 2019)

#Study in the Journal American Physicians and Surgeons: it is not safe to combine **#vaccines** at one visit link

[Picture redacted]

Figure 8.1 Study claims vaccines are not safe.

The picture embedded in the tweet was likely made specifically to be shared on Twitter since it mentioned the study and link. The picture had five chunks of text in different formats and sizes and only one small photo on the top left. The text occupied most of the space and provided further information supporting the claims in the tweet, but also a clear anti-vaccine message targeting the vaccination schedule suggested by the US Centre for Disease Control and Prevention[43] (CDC).

The photo depicts a child held in front of a syringe. The blank background does not provide any information about the setting of the picture; therefore, the photo could have been taken in a photo studio or modified digitally. The child is

[43] The Centre for Disease Control and Prevention (CDC) is the national's health protection agency in the US. It is involved in vaccine development, control and determining the vaccine schedule.

Caucasian, but his/her gender is unclear because only the upper part of the naked body is visible and there are no clues about his/her identity or situation. Therefore, even though the child is the focus of the photo, s/he is depersonalised to the extent that s/he could represent any Caucasian baby of similar age, even the viewers' child. The child has a neutral expression, s/he does not show any negative emotion towards the syringe but rather looks focused on and curious about the needle. The baby is trying to touch the syringe with his/her hand, while s/he is being held by someone whose arms and blue shirt are the only visible parts. The syringe is held upright (not towards the baby) by another person in front of him/her. Only their hand is shown and it is covered by a white rubber glove. The glove may identify the hidden person as a nurse or a paediatrician. The blue shirt of the person holding the child could also define him/her as a nurse (nurses typically wear a blue or green uniform), but s/he could also be a parent. Both the two adults are excluded from the photo as if their categorisation (e.g. healthcare practitioner) is more relevant than their individuality for interpreting the photo.

In this picture, the syringe could be interpreted as an icon representing the actual object, and as an index of the act of injection. However, since the syringe is commonly used to administer several types of vaccines (e.g. measles, rubella, tetanus, flu, diphtheria…), it could also be a conventional symbol that represents vaccination. This last interpretation is heavily affected by the text overlay, the tweet and the hashtag #vaccines, because a syringe could be read as a symbol of a different type of medical treatment in a different context. The text plays a fundamental role in the picture, adding details to the tweet and contextualising the photo. On the top, it provides the generalised essence of the information – a list of the several combined vaccines recommended by the CDC, whilst on the bottom, it gives down-to-earth information – the claim that combined vaccines are not safe and a link to an article demonstrating this. At the centre of the picture, the most important text paragraph says: "this combination of eight vaccines [mentioned on the top of the picture] administered during a single physician visit was never tested for safety in clinical trials". This claim is supported by the (pseudo)scientific evidence provided at the bottom of the picture, and suggests that the CDC is unreliable, and combined vaccines are dangerous. The five text paragraphs also influence the interpretation of the photo. The photo is on the left of the picture, where the information already known by the viewer is shown – children are usually vaccinated at an early age, while the text on the right provides new information that the viewer may not know – children are injected with eight vaccines in the same session. This text, associated with the photo, gives the impression that all the listed vaccines are combined inside the syringe, and they will be administered to the child in one visit. The text below suggests that combining eight vaccines in one session is not safe, so the syringe and the imminent vaccination it represents can be perceived as a threat to the child. Moreover, the healthcare practitioners vaccinating the child may be associated with the CDC, which the text suggests is untrustworthy. Hence, the distrust towards the CDC could be extended to all healthcare practitioners providing vaccinations.

This anti-vaccine image conveys the same message in the tweet and the picture: combined vaccines are not safe. Moreover, it claims that the CDC, a medical authority, is wrong about vaccine safety and supplies ‘evidence’. However, this evidence is neither scientific nor reliable, though it could be perceived as both. The image adds detail to the statement in the tweet through the text overlays, while its photo emphasises the main claim that vaccines are not safe.

8.1.2 Do not trust the CDC

The second anti-vaccine image was shared by a tendentially anti-vaccine journalist-activist, who defined him/herself as investigative reporter. The mixed picture combined different drawings, photos, icons and texts of various fonts and sizes (Figure 8.2); it was originally uploaded to the web by Cancer Truth, which publishes alternative non-medical information about cancer. The image was tweeted in late June 2016, and it was not related to any articles posted on the website, nor to any vaccine event. The tweet and picture convey different but complementary messages. While the tweet reported the CDC to be more interested in pharmaceutical companies' profits than in public health, the picture suggests that the flu vaccine, recommended by the CDC, contains mercury and is not safe. Together, these two elements convey the message that the CDC promotes the flu shot for the sake of pharmaceutical companies' profit, even though the vaccine is toxic. Three hashtags, #vaccine, #VaccineInjury and #VaccinesWork, followed by two CDC Twitter accounts handles, are listed at the end of the tweet. The first hashtag is a generic tag for tweets about vaccines and vaccinations, while the second and the third hashtags label anti- and pro-vaccine messages, respectively. It is possible that the user tried to spread his/her message across different conversations about vaccinations by using three different topical hashtags (Bruns and Moe, 2014).

CDC does not care about your health but about pharmaceutical companies **#vaccines #vaccineinjury #vaccineswork** @CDC… @CDC…

[Picture redacted]

Figure 8.2 Do not trust the CDC.

The picture is a non-aesthetic collage of visual and textual elements on a white background. Moreover, the visual elements were likely taken from other pictures because their drawing style and shadows are all different. On the top left of the picture, there is the logo of the website, Cancer Truth, followed by the texts “presents:” and “Things that make you go “Hmmmmm””, which occupies the top centre. This could be an attempt to state the authorship of the whole picture and message. All these textual elements have a different font and format, and below them, there are two groups of visual items. On the left, there is a drawing of a nurse with the text “Get your flu shot” [44]. This nurse is a Caucasian woman and can be identified as a healthcare practitioner thanks to her uniform and the stethoscope around her neck. The nurse has her arms crossed, she is holding a syringe in one hand and is smiling while looking at the viewer. However, while she may look reassuring in her original context, she looks suspicious in this case, especially as there is a syringe and a vial with a poison symbol (a skull with crossed bones) next to her. The user seems to have made a collage of these elements to suggest vaccines are poisonous and dangerous, and that the syringe held by the nurse contains a poisonous flu shot.

The elements described above provide a generic message about the flu vaccine, whereas those below give specific information. The bottom of the picture shows a man and a call out with his thoughts. The man is Caucasian and wears a grey jacket and a tie that make him look like a businessman or a manager, someone belonging to a middle social class. This impression is also reinforced by his thoughts: “How can it be that the EPA[45] classifies a liquid with 200 parts per billion (ppb) of mercury as a ‘hazardous waste’… but the CDC says the flu shot, which contains 50,000 ppb of mercury, is safe?”. The technical terms used in this text shows that the man has extensive knowledge about substances regulations (EPA) and measures (ppb), and therefore he may have a high level of education. This man could represent the average anti-vaccine parent (middle class, high level of education) identified by Wei *et al.* (2009). The text in the callout shows a contradiction: the vaccine contains a

[44] This element was taken from an article posted on a news website that promotes a clinic providing free flu vaccines.
[45] EPA is the acronym of the United States Environmental Protection Agency

large quantity of mercury, enough to be classified as dangerous by the EPA, yet it is considered safe by the CDC. This contradiction is emphasised by the pose of the man: he has his head tilted and is scratching it with his left hand while looking towards the call out. Moreover, his expression looks perplexed and disconcerted. The call out, which occupies the centre and most salient part of the picture, influences the interpretation of the visual elements above it: the flu vaccine is poisonous because of the mercury it contains.

This picture, interpreted in this context, conveys a complex message: based on the EPA standards for toxic materials, the levels of mercury in the flu vaccine would be toxic. However, the CDC says it is safe because the CDC is more interested in pharmaceutical companies' profit than in citizens' health (see tweet in Figure 8.2). This suggests that the CDC and healthcare practitioners (i.e. medical authorities) are untrustworthy, and any sensible American should be sceptical of them and seek independent information. However, scientific evidence indicates that the amount of mercury in vaccines is not dangerous (Taylor, Swerdfeger and Eslick, 2014); hence this image provides vaccine misinformation.

8.1.3 Real facts on vaccines

An anti-vaccine parents' association shared a cartoon highlighting the need to find the real facts about vaccinations (Figure 8.3). The tweet embedding the picture said "Who are you listening to for vaccine information? Please don't let it be the elephant in the room for profit". This text had emojis and abbreviations (e.g. "R" for "are"), and it mentioned the Anglo-Saxon metaphor of the elephant in the room[46]. These elements require a certain knowledge of the English language and Anglo-Saxon culture (emojis) to be understood. The tweet also included two hashtags, #vaxxed and #FactsOnVax, and the Twitter handles of two anti-vaccine actors. It is possible that, by mentioning these two well-

[46] This metaphor means that there is an obvious problem that people do not want to discuss.

connected users[47], the user sharing the picture tried to attract their attention and encourage retweets. The hashtag #vaxxed helped the image to join the anti-vaccine community, though *Vaxxed the movie* was not mentioned directly (Bruns and Burgess, 2015; Grewal, 2009). The hashtag #FactsOnVax labels another anti-vaccine conversation, though smaller than #vaxxed, which is dominated by this parents' association.

Who are you listening to for vaccines information ❓ Please don't let it be the elephant in the room for profit 💰 ‼️
#vaxxed #factsonvax @user1 @user2

[Picture redacted]

Figure 8.3 Real facts on vaccines.

The image was posted at the end of June 2016, but it was not related to a specific event. Moreover, the picture was probably designed for the tweet: it appeared only on Twitter, it was not uploaded on any other online platform, and it completed the message in the tweet. Hence, the original message of the picture was not altered[48]. The tweet and the picture are structured as a dialogue about vaccine information between the user and the elephant in the

[47] These two users were identified in the social network analysis, and one of them was a parent-activist who acts as an important information hub in the anti-vaccine community.
[48] Online pictures that are re-contextualised or modified may lose their original message and acquire new ones. When the picture was created for a specific tweet, its message was original.

room. In the tweet, the viewer is warned not to listen to the elephant in the room, and in the picture, the figure of an elephant replies “What are you talking about? Vaccines are good for you – you’ll die without them!”. Then the user reinforces the message at the bottom of the cartoon, recommending “Don’t listen to the elephant in the room. Get the REAL #FACTSONVAX”.

The elephant wears a white coat with a red cross near the collar, which identifies the elephant as a physician, and the context provided by the tweet suggests that healthcare practitioners do not tell the truth about vaccinations. The elephant looks cute and friendly, but in its pocket, there is a syringe, a tube (those containing pills), and a green banknote with a dollar symbol on it. The money suggests a profit motive; hence, that healthcare practitioners do not tell patients about the ‘real facts on vaccines’ (the elephant in the room) not because they are ignorant, but because they are financially incentivised. The picture suggests hypocrisy by depicting the elephant smiling and with open arms, as if it was trustworthy and harmless.

The main message of the image is not to trust healthcare practitioners regarding vaccine information and to seek other sources of information. While it does not say where to find this information explicitly, it subtly suggests two alternative sources of information. The first one is the hashtag #FactsOnVax, mentioned in the tweet and recalled at the bottom of the picture; and the second is #vaxxed. These two hashtag streams are presented as a place where to find the vaccine information hidden by healthcare practitioners. These hashtag streams provide alternative vaccine information (or misinformation) and promote *Vaxxed the movie*, which is considered a reliable source by the anti-vaccine community. There is a noticeable contradiction in this image: the alternative source they encourage, *Vaxxed*, was directed by Andrew Wakefield, an ex-physician who falsified a research study on the MMR vaccine and autism link for financial gain (Deer, 2011).

8.1.4 *Vaxxed* the protest

An anti-vaccine activist shared Figure 8.4, a photo of a protest against vaccination. This key actor tweeted the image discussed in Section 8.1.1 as well. The activist tweeted the photo on the 28th of June 2016, but this picture was online in 2015. The tweet captioned the photo using the title of an article published on the Health Impact News website at the beginning of June 2016, and says: "Resistance to #Vaccine Medical Tyranny Growing in the U.S. as #VAXXED Film Gains Wider Audience". The tweet included the link to this article at the end. By using the hashtag #vaccine, the actor could reach conversations about vaccines that are not polarised (Bruns and Moe, 2014), whereas by adding #vaxxed, s/he also joins the anti-vaccine community (Bruns and Burgess, 2015) and discussions about *Vaxxed the movie*.

The resistance to **#vaccine** medical tyranny is growing in the US as the film **#vaxxed** gains broader audience link

[Picture redacted]

Figure 8.4 Vaxxed the protest.

The photo, also published in the article, shows a march on the street where people carried signs against vaccines and the SB 277[49]. The march occupies

[49] The California Senate Bill 277 (SB 277) made vaccination mandatory to enter primary and secondary schools in California in 2015.

2/3 of the photo horizontally, and on the top third skyscrapers are visible in the background. The viewers are positioned slightly to the left, on a horizontal angle, facing the head of the demonstration. The photo captures a moment of the protest, which was real and not staged. In fact, a little bit hidden in the middle of the crowd, there is a man with a video camera recording the event. The signs of the activists show messages such as “If there is a risk there should be a choice”, “No to SB 277”, “Vaccines are unsafe”, “Autism is rising, why?”, and even “Parents decide, not politicians”. Two signs also show the US flag. Most of the demonstrators are adults and Caucasians, but there are also a few children and a few people belonging to other ethnicities. The protesters are walking along a wide tree lined road, and some of them are shouting. The photo represents the demonstrators as a collective group of American men and women, likely parents, protesting for the health and life of their children.

Based on the context provided by the tweet, this photo is supposed to depict resistance to medical tyranny triggered by *Vaxxed the movie* in 2016. However, the photo actually shows a mass demonstration in California against the SB 277, which was organised by the movement, California Coalition for a Vaccine Choice in 2015. Though the picture shows a particular demonstration, those who do not know its origin could think it actually represents a march against mandatory vaccinations that is linked to *Vaxxed the movie*. Moreover, by re-contextualising the photo, this image promoted the success of *Vaxxed the movie* and suggested that mandatory vaccinations are dangerous, forced on people by a medical tyranny and deny parents’ right to decide whether to take the risk to vaccinate[50].

[50] Scientific evidence shows that vaccines are not dangerous (DeStefano, Bodenstab and Offit, 2019) and they effectively reduce the risk of vaccine-preventable disease outbreaks, especially through herd immunity (Andre *et al.*, 2008).

8.2 Anti-vaccine images from the main dataset

8.2.1 Experts against vaccines

The anti-vaccine activist and key actor that shared Figure 8.5 tweeted Figure 8.1 and Figure 8.4 as well (see Sections 8.1.1 and 8.1.4). In this image, the tweet claimed that the American College of Pediatricians[51] was alarmed about the Human Papilloma Virus (HPV) Gardasil vaccine, and it included the link to an official statement published on the College's website. The College statement was posted on January 2016, while the image was shared in November of the same year. The tweet integrated three hashtags: #HPV, #Gardasil and #LearnTheRisk. The first hashtag labels conversations about the disease and its related vaccine, whereas the second hashtag tags messages about the vaccine Gardasil, produced by the pharmaceutical company Merck. Thanks to these two keywords, the image could reach whoever was searching for information about HPV and the vaccine. The hashtag #LearnTheRisk labels tweets about different types of risk (e.g. health, environment…); hence, it might have been used as a call to action rather than as a tag to reach vaccine conversations (Bruns and Moe, 2014).

The tweet and embedded picture conveyed the same message, though the tweet added details that clarified the picture. Based only on the tweet, this image could have been classified as pro-safe vaccine; however, the embedded picture made it anti-vaccine by claiming that the American College of Pediatricians was not only concerned about the vaccine, but they even discourage parents from vaccinating their children. The embedded picture was not an original photo, it was modified by adding the text overlay[52].

[51] The American College of Pediatricians is an association of paediatricians, and they expressed concerns on some potential adverse effects of the Gardasil vaccine against HPV and called for more research studies about its safety. However, they are not against vaccines.
[52] The original photo was uploaded on an online image archive.

The American College of Pediatricians is alarmed about the **#HPV** vaccine **#Gardasil** link
#LearnTheRisk

Figure 8.5 Experts against vaccines.
Photo via Shutterstock, modified by adding text overlay.

The picture shows a white teenage girl receiving a vaccine by injection. Someone is administering the vaccine but only his/her hands and arms are visible; s/he is wearing disposable gloves that could identify him/her as a healthcare practitioner, and s/he does not have any other items that could describe his/her role or identity. The girl is looking at the needle piercing her arm; both her gaze and the healthcare practitioner's arms point towards the syringe, directing the viewers' attention to it. The syringe occupies the centre of the photo, making the vaccination the salient part of it, though its needle is not visible at all and it may even not be real. The picture looks like it was taken in a photography studio since the background does not show any clues about the setting. The medium shot and the horizontal angle of the photo increase the sense of proximity and familiarity with the girl, which could resemble any other American teenager receiving the HPV vaccine[53]. The text overlay is on the right side of the photo and it conveys new information to the viewers: the American College of Pediatricians warns them not to vaccinate their children

[53] The HPV vaccination is recommended to children age 9-15 years old in the US (CDC, 2019).

against HPV. The image warned parents against the Gardasil vaccine and suggested they learn the risk about vaccinations (as the hashtag mentioned). However, the image never mentioned why the College had concerns about the vaccine and what those concerns are; it only exploited the name and the statement of the College to provide scientific credibility to the anti-vaccine message. As in Image 1 (Section 8.1.1), this image used pseudo-scientific evidence and authority to support its claims that vaccines are not safe.

8.2.2 What is in a vaccine

Figure 8.6 was shared by an anti-vaccine NGO advocating cancer awareness and 'freedom' from traditional medical authorities. This organisation publishes information on alternative cancer treatments and against vaccinations. The image was posted on the 9th of November 2016, though not in relation to a specific event. The image warned against the content of vaccines and their safety, and its tweet even questioned how parents could vaccinate their children since it is like injecting toxins and carcinogens. It also called like-minded users to action, asking them to share the tweet and educate others about vaccine toxicity. The tweet did not include any link to further information, it had only emojis and hashtags, such as #vaccinate and #toxic. The hashtag #vaccinate can reach both neutral and polarised conversation about vaccinations, whereas #toxic is a generic tag and it was likely used to highlight the specific word (Bruns and Moe, 2014).

The original photo was from an online image archive, and it was slightly cropped, flipped horizontally and overlaid with text, including the prominent logo of the NGO. This modification allowed the picture to carry slightly different but complementary messages to the tweet, as in Image 3 (see Section 8.1.3). The tweet questioned vaccine safety, whereas the picture listed all the carcinogens and toxins supposed to be in a vaccine. Moreover, the tweet began by saying "Knowing this", which referred to the vaccine content explained in the picture.

Figure 8.6 What is in a vaccine?
Photo via [Shutterstock](), modified by rotating it horizontally and adding text overlay.

The picture depicts a Caucasian baby receiving an injection; there are no visual clues about identity or gender[54]. The baby lies on the lower half and centre of the picture, whilst someone pierces his/her arm with a syringe. Only one hand of this person is visible and is gloved, which could identify him/her as a healthcare practitioner. This figure and the blank setting are probably not important, whereas the baby is the salient element of the photo. The child looks anxiously at the viewer, as if these emotions were evoked by the text overlay on the top, which says “Known ingredients found in vaccines: Aluminium, Formaldehyde, MSG (Monosodium glutamate), Mercury, foetal cells, protein, and DNA”. The baby is represented as a powerless victim of vaccination: the syringe containing the vaccine is already injecting all the toxins and carcinogens mentioned in the text. Though alarming, the claim of the text overlay is false (DeStefano, Bodenstab and Offit, 2019; Taylor, Swerdfeger

[54] The baby is apparently a girl based on the description of the original photo, which says “Paediatrician giving a three-month baby girl intramuscular injection in arm. Child looking anxiously at a camera. Isolated on white background”.

and Eslick, 2014) and is an example of misunderstanding caused by a low scientific literacy[55]. Though this image is scientifically inaccurate, it still uses scientific information (i.e. the vaccines' components) for persuasion. Moreover, the child's lack of identity and gaze directed at the viewer, is designed to draw them into the scene and could make them identify the baby as their child.

8.2.3 Doctors' ignorance

Figure 8.7 was shared by an anti-vaccine activist on the 10th November 2016, but it was not related to specific events nor conversations. The tweet stated that most physicians "are taught that vaccines are safe and effective" but never about vaccines' side effects, and they follow the vaccination schedule without questioning it. The tweet included only the hashtag #doctors to highlight that specific word rather than to join a discussion, and mentioned the Californian senator who authorised California Senate Bill 277 (SB 277) in 2015[56]. The image could be an attack on the senator since the user has mentioned him in several tweets, protesting against vaccination and his political decision.

The tweet and the picture conveyed the same message, but the tweet provided slightly more information. Moreover, the picture might be made *ad hoc* for the tweet since it was modified by adding overlaid text against vaccinations. The original picture did not have any textual element, and has been used for designing memes on different topics.

The photo is a close-up of a Caucasian baby with a surprised but funny expression. The gender of the baby is not clear since the clothes are almost entirely excluded from the frame, and the only visible part is gender-neutral. There are some clothes and objects of different patterns in the background, and even though they are not clear, they give the impression that the photo was taken in a house, maybe by a parent or a relative of the baby, and then

[55] It is true that some of these components are present in vaccines, their amount is so small that is not dangerous for children or for adults (DeStefano, Bodenstab and Offit, 2019). Moreover, proteins in general and DNA are not dangerous. Though some proteins, such as albumin, could cause allergic reactions.
[56] SB 277 cancelled the Personal Belief Exemption from vaccination in California.

uploaded on the Internet. Hence, the setting makes the photo look authentic, rather than staged in a studio.

.@senator Most **#doctors** are taught that vaccines are safe & effective and the vaccine schedule to use. They have never been taught about the adverse reaction or ingredients

[Picture redacted]

Figure 8.7 Doctor's ignorance.

The salient part of the picture is the baby's expression. The baby looks directly at the viewer and communicates his/her thoughts through the text overlay: "So, you went to medical school, and you give vaccines, but you don't know how to diagnose a vaccine injury? You're kidding me, right?". The picture reported physicians' lack of knowledge about adverse reactions to vaccines and described it as shocking and ridiculous (through the child's expression and the text overlay). The image accuses physicians who vaccinate children of ignoring the potential for damage caused by vaccines because they accept what they are taught at medical school without question. Hence, the image rejects their authority as experts and suggests even a baby expects better. The style of the picture and of the tweet makes the picture accessible to a lay audience, but the text overlay seems to engage physicians rather than parents (i.e. “you went to medical school”). Moreover, the user mentioned a senator in the tweet, likely pointing the image to him to show how his decision on SB 277 was based on biased and ignorant advice given by physicians.

8.2.4 Donald Trump as anti-vaccine

Figure 8.8 was shared by a journalist-activist who was a key actor in the anti-vaccine community (see Section 5.2.2.1). This actor often posted tweets of news articles published in an alternative health news website of which s/he was the editor, and this image was no exception. The image was about Donald Trump and his position on the vaccine debate; it reported an article published in the actor’s website in November 2015 and related it to the US presidential elections occurring in 2016. The tweet copied the title of the web article, stating that a scientist from the CDC confirmed that Donald Trump was right about the link between vaccines and autism. The tweet did not name the scientist, who is a famous CDC whistleblower in the anti-vaccine community, but he is mentioned in the article[57].

#CDC researcher confirms that **#Donald #Trump**
is right about **#vaccines** and **#autism** link

Figure 8.8 Donald Trump as anti-vaccine.
Photo via Shutterstock, modified by cropping the upper and left side.

[57] The CDC whistle blower is William Thompson, a researcher at the CDC who claims the CDC covered-up the link between autism and vaccines. Thompson collaborated with Andrew Wakefield on more than one occasion, including *Vaxxed the movie.*

The tweet included a link to the article, and integrated many hashtags in the text, such as #CDC, #Donald, #Trump, #vaccines, and #autism. The hashtags #CDC labels tweets either against or in favour of the directives provided by the CDC, #autism relates to discussion about the disease and #vaccines tags various conversations about vaccinations. The hashtag #Trump labels messages about the US president, whereas #Donald is a generic tag. All these hashtags allowed the image to reach diverse audiences outside the circle of followers of the actor, but also highlighted specific words within the tweet. The tweet had a primary role in the interpretation of the image, whereas the embedded picture about Donald Trump seems decorative. The photo appeared in the linked article as well, but the original version was uploaded to an online image archive, and it was not related to the US presidential elections nor Trump's claim that vaccines cause autism[58]. Therefore, the photo was re-contextualised in both the article and the image.

The photo depicts Donald Trump standing behind a podium with a US flag in the background. The photo excluded any signs commonly used in anti-vaccine images: there are no syringes, children, healthcare practitioners, or researchers, even though the tweet mentions one of them. Instead, the picture focuses on Trump entirely. Though Donald Trump is the salient element in the picture, he does not occupy the centre of the photo but its right. Maybe the photographer opted for this frame to include part of the stars of the American flag in the background and make it recognisable. The photo is a medium-shot with a horizontal angle and a frontal point of view, which shows Donald Trump as someone at the same level as the viewers and relatively close to them. He is not depicted as an authoritative leader but as someone at the same level of his citizens (represented by the US flag), listening to them and acknowledging the link between vaccines and autism. As also emerged in the content analysis (see Section 7.2.1.3), this image represents Trump as a politician supporting the concerns of anti-vaccine parents. Moreover, this image claims that Trump's

[58] The original picture, available on Shutterstock.com, was described as "Donald Trump speaks at the First in the Nation Leadership Summit in Nashua, NH, on April 18, 2015".

belief that vaccines cause autism is right[59], and is confirmed by an expert (a scientist). Hence, the mention of the CDC researcher adds scientific credibility to the claim, and at the same time discredits the reputation of the CDC, which always denied any link between vaccines and the disease.

8.3 Pro-vaccine, academic and news-related images from the pilot datasets

8.3.1 A mother's smile

A pro-vaccine NGO and key actor shared a photo (Figure 8.9); this NGO works worldwide to improve the quality of life of children and their families. The image was posted on the 24th of June 2016, in relation to a vaccination campaign carried out in Ethiopia in April of the same year. The Ethiopian government launched this campaign to prevent measles outbreaks in the most drought affected areas of the country, and the NGO supported the cause by supplying vaccines. However, neither the tweet nor the photo of the image mentioned the campaign directly, and they did not provide any links to further details[60]. The tweet said "Merdiya smiles after her child was vaccinated against measles at a hospital in #Ethiopia", and it mentioned the Ethiopian branch of the NGO to attribute the ownership of the photo and/or notify the user's support for the campaign. The tweet also included two hashtags, #Ethiopia and #VaccinesWork. The first hashtag might reach Twitter users searching for information and updates about the country or it may be a generic tag (Bruns and Moe, 2014), whereas the second one is a topical hashtag regularly used by the pro-vaccine network, especially by charities, foundations, and healthcare practitioners.

[59] Several studies disproved the link between vaccines and autism (Taylor, Swerdfeger and Eslick, 2014)
[60] Two websites and a Flickr account of the NGO that showed the same photo provided information on the campaign, but not in the tweet or the embedded picture.

Merdiya smiles after her child was vaccinated against measles at a hospital in **#Ethiopia** @NGO **#vaccineswork**

Figure 8.9 A mother’s smile.
“Measles response in drought-affected areas” by UNICEF Ethiopia is licensed CC BY-NC-ND 4.0.

The image suggests the photo was taken during the measles immunisation campaign in Ethiopia, but does not make that clear. The picture does not show the child while being vaccinated nor the NGO’s volunteers at work, but it represents the joy of a mother after her son’s vaccination. The tweet captioned the photo, which looks generic and does not have any text overlay providing information on the depicted scene. The tweet even named the Ethiopian woman portrayed in the picture and explained the reason for her smile, making her a real person, not a model, and adding credibility and reality to the photo. The photo is a close-up of Merdiya carrying a child on her back, who the tweet identified as her son. Merdiya occupies the centre of the picture; she is smiling at the viewers, engaging them, and she directs their attention to her son by pointing at him with her right hand. With this gesture, Merdiya may indicate that the reason for her smile, her happiness, is her child. This interpretation is supported by the tweet, which explicitly says that Merdiya smiles after her child was vaccinated and hence he is protected from measles. The child is also engaging the viewers by looking at them; he looks healthy and lively, thus emphasising the effectiveness of vaccines at protecting children from certain diseases[61].

The woman and the child are both in focus against a slightly blurred outdoor environment in the background. This background contextualises the scene suggesting the photo was actually taken outside a facility, e.g. a hospital. The background, the clothes, the two figures' features all contribute to the reality and credibility of the picture and tweet. Merdiya is shown as a real, living person, and as proof that the NGO's contribution to the vaccination campaign in Ethiopia has a positive impact on Ethiopians (Moro, 1998). Moreover, Merdiya is shown as a testimonial of vaccines effectiveness and as a parent model to imitate; she is a mother who perceives measles as the real threat to her son's health, she considers vaccines safe and necessary to protect her child, and she is happy to vaccinate. Therefore, the message conveyed by this image is exactly the opposite of those shared by the anti-vaccine community.

8.3.2 Immunisation as investment

A key actor, a strategic communication advisor of an NGO, shared an image about the importance of vaccinations. The tweet claimed that "immunisation is one of the best investments to make for future generations", and it included hashtags such as #ForEveryChild and #VaccinesWork (Figure 8.10). The first hashtag is related to a specific campaign, whereas the second one is regularly used by the pro-vaccine network. The tweet also mentioned the NGO to attribute credit for the embedded photo.

The image was shared on the 28th of June 2016, and mentioned the NGO's campaign *For Every Child* in both the tweet and photo. This campaign was launched for the NGO's 70th anniversary, which occurred on the 11th of December 2016, and it ran throughout 2016. The photo also mentioned another campaign run by the NGO, called *Fight Unfair,* and it was originally

61 Scientific evidence proves that the MMR vaccine is effective against Measles (La Torre *et al.*, 2017)

included in an article posted on the NGO's website at the beginning of June 2016. This article reported that Iraqi families were leaving Fallujah to escape the fighting and how the NGO was helping them. However, the tweeted image did not provide any of these pieces of information, and it re-contextualised the picture. Therefore, the embedded photo conveyed a new message: there is a conspicuous return on money invested in vaccinations. This message complemented the tweet – the tweet claimed that immunisation is one of the best investments to make[62], and the photo showed the actual return on this investment.

Immunisation is one of the best investments to make for future generations **#foreverychild** @NGO **#vaccineswork**

[Picture redacted]

Figure 8.10 Immunisation as investment.

The embedded picture was modified from the original (that posted on the NGO's website); it was cropped and tilted, and enriched with text overlays and

[62] This claim is supported by scientific evidence (Rémy, Zöllner and Heckmann, 2015).

campaigns logos. It is a medium shot [63] of a girl receiving an oral vaccine from a health operator. The girl, an Afghan, stands on the left of the picture, just below the centre, with her chin lifted and her mouth open. The health operator, a woman, stands next to her on the right of the picture; she is wearing a white coat and a cap, which classify her role as a healthcare professional or volunteer, and a scarf around her head that identifies her as Muslim. The girl and the woman do not show any emotion and they do not look at the viewers, but they face each other and focus on the vaccination. Hence, unlike previous picture where the viewer is engaged by Merdyia in sharing her happiness, here the viewer is a passive spectator excluded from the scene.

The original picture included more figures than the tweeted one: it depicted a small crowd of other children and one more operator as it represented childhood vaccinations conducted at the Baghdad Al-Takya Al-Kasnazaniya Camp[64]. In Figure 8.10, these other figures are cropped out making the scene more intimate and emphasising the relationship between the girl and the health worker. Moreover, by excluding the other children from the setting, the picture makes the girl look as if she was the only child in the camp. The modified setting and arrangement are tailored for the campaign *For Every Child,* and show how the NGO is taking care of every single child, including the little girl in the refugee camp. The background (a blurred refugee camp), the figures and their features make the photo authentic and realistic, illustrating how the health operator and the NGO are helping and vaccinating the girl. The logos of both campaigns are shown at the bottom corners of the picture, to provide more information about the NGO's activities.

Though the child and the woman occupy most of the picture, its salient part is a text overlay at the centre, stating that "There's a $16 return on every $1 invested in immunisation". Therefore, the text adds additional context to the photo, which is linked to the message in the tweet: investing one dollar in immunisation will contribute greatly to help future generations, like the little girl

[63] Medium-shots show only bodies' upper part including heads of figures. They do not show the whole figure but they focus on more than just the face.
[64] This context was provided by the website article where the original picture was included.

and every other child in unfair situations. Since the photo emphasises the monetary return from vaccination and depicts how a donation would be used by the NGO, this image may be designed for fundraising (Moro, 1998). The image persuades the viewer to donate to the NGO, as it will use that money for the *For Every Child* campaign.

8.3.3 Vaccines save lives

The NGO strategic communication advisor described in the Section 8.3.2 shared a second image that was about the efficacy of vaccines (Figure 8.11). The tweet claimed that “Immunisation has saved millions of lives and contributed to reducing child mortality”, and it included the hashtags #immunisation and #VaccinesWork, which are both used to label pro-vaccine conservations (Bruns and Moe, 2014).

This image was shared in October 2016, but the same picture was also tweeted by the NGO in May 2016, to show the success of the measles and rubella vaccination campaign launched in April by the Islamic Republic of Gambia. However, the selected image did not mention the campaign, nor provide any link with more information; it only mentioned the NGO branch supporting the campaign.

The tweet captioned the photos and contextualised it. The picture does not have any text overlays and it depicts an African child, likely Gambian, while being vaccinated. The child wears a pink dress that could identify her as a little girl, and she is sitting on someone’s laps. This person could be an African woman, based on her colourful dress, but other clues about her identity, such as her head and chest, are excluded from the photo. The woman might be the child’s mother, and she is keeping her still during the vaccination. The picture also depicts another adult’s hands, the person who is doing the vaccination. This second person could be a health worker, but they do not wear any items that could classify them as such (e.g. disposable gloves).

#Immunisation has saved millions of lives and contributed to reduce child mortality **#vaccineswork** @NGOGambia

[Picture redacted]

Figure 8.11 Vaccines save lives.

The woman's body and the child occupy most of the picture, leaving little space to the background. What is visible places the scene as outdoors. The focus of the photo is on the vaccination taking place. The syringe occupies the centre of the picture, and the child's body and the four adult arms all point to the syringe as radii. The child is also looking at the needle piercing her arm – without showing any emotions – thus further directing the viewers' gaze towards the syringe. Moreover, the vertical angle of the photo positions the viewer as looking down on the scene, as if they were passively assisting to the event.

This photo could represent any vaccination event taking place in Africa if it was not attributed to the Gambian immunisation campaign by a previous tweet from the NGO. However, the tweet provides the picture with a different frame, which does not emphasise the effects of a specific campaign, but the success of all vaccination campaigns. Therefore, the photo does not show a Gambian child vaccinated against measles and rubella, but one of the millions of children saved by immunisation[65]. This image focuses on the efficacy of vaccines in reducing child mortality especially in Africa, and it could aim to promote the importance of immunisation campaigns in developing countries.

8.3.4 Celebrating a successful agreement

The news-related image in Figure 8.12 was shared by the chief executive of an NGO to celebrate the successful agreement between the NGO and the Kingdom of Saudi Arabia. At the beginning of October 2016, the Kingdom of Saudi Arabia contributed $25 million to support childhood immunisation programmes run by the NGO; however, there was no mention of the specifics of this agreement in the tweet nor in the photo. The actor did not share the image as a formal update, but made it personal by saying in the tweet: “I’m very happy to see that the agreement between the NGO and the Kingdom of Saudi Arabia has been signed”. In the tweet, the actor also thanked the NGO board chair who led the agreement, and included both her Twitter account and another one of the NGO. The actor, who was an important broker in the pro-vaccine network, added the hashtags #SaudiArabia and #VaccinesWork to the tweet. The first hashtag likely labels tweets related to the Kingdom of Saudi Arabia but it may also be used as a generic hashtag (Bruns and Moe, 2014), whereas the second one is regularly used by foundations, charities and healthcare practitioners in the pro-vaccine network. The second hashtag also contextualised the tweet and the photo by specifically mentioning the agreement.

The tweet did not include any link to provide more information about the agreement, though the NGO published an article about it on its website. However, the tweet was posted before the article; hence, it could have been

[65] There is scientific evidence supporting this claim (Orenstein and Ahmed, 2017).

part of social media coverage of the event. The photo seems to confirm this impression: it looks like it was taken on the spot.

I'm very happy to see that the agreement between @NGO and the Kingdom of **#SaudiArabia** has been signed. Thanks @NGOboardchair **#vaccineswork**

[Picture redacted]

Figure 8.12 Celebrating a successful agreement.

The photo does not have any text, and it was not taken by the actor[66]. It depicts four people standing in a room around a table. The water bottles, pens and folders neatly placed on the table indicate that a meeting took place in the room. The two men on the right wear Arabic clothes and they are probably representatives of the Kingdom of Saudi Arabia, as suggested by the tweet. On the left, there is a man wearing a suit and a woman, who is the NGO board chair, wearing a Nigerian dress. Since these two participants are on the same side of the table, they are both likely members of the NGO. The board chair and the Saudi Arabian man next to her are shaking hands, as if to confirm they have reached an agreement. The four participants are smiling, and they all

[66] The same photo was included in the NGO web article about the agreement, but its credits were attributed to another person.

look in different directions as if there were several photographers taking pictures of them. Only the board chair is looking at the viewer, making them part of the scene. The horizontal angle of the photo also contributes to this sense of proximity and involvement as if the viewer were in the room witnessing this important event.

This image captured an important moment for the NGO and celebrated the successful work of its board chair at achieving an important agreement with the Kingdom of Saudi Arabia. In particular, the chief executive of the NGO claimed his/her satisfaction with this agreement, though s/he did not specify of what the agreement consists; s/he only added the hashtag #VaccinesWork to indicate that this contract regards vaccines. Maybe, the image does not aim only to promote the NGO's efforts, but also its partnerships with other countries to raise immunisation rates across the world.

8.4 Pro-vaccine and academic images from the main dataset

8.4.1 #AskPharma campaign

This image was shared by an NGO as part of an advocacy campaign calling for more affordable pneumonia vaccines[67]. The image was posted on the 9th of November 2016 (Figure 8.13), three days before World Pneumonia Day; hence, it could have used this upcoming event to gain popularity. The embedded tweet asked the two pharmaceutical companies producing the pneumonia vaccine to reduce the vaccine's price. The tweet also claimed that a more affordable vaccine would make the eradication of pneumonia possible. The tweet integrated the hashtag used in the campaign, #AskPharma, and two

[67] The campaign was launched in 2014 to persuade two pharmaceutical companies to reduce the price of the pneumonia vaccine and make it affordable for developing countries. The campaign obtained its first big result on the 11th November 2016, when one of these companies reduced the price of the pneumonia vaccine. However, the NGO is still fighting to drop the cost to $5 per vial.

hashtags related to pneumonia, such as #KnowPneumonia and #NoPneumonia. These two hashtags could be related to campaigns run during World Pneumonia Day or they could be labels of conversations about pneumonia and pneumonia vaccines.

Hey @Pharma1 @Pharma2, we **#KnowPneumonia** and that your vaccine is too expensive! Reduce the price so that there will be **#NoPneumonia**! **#AskPharma**

[Picture redacted]

Figure 8.13 #AskPharma campaign.

The tweet and the embedded picture conveyed complementary messages; the tweet asked the pharmaceutical companies to drop the price of the pneumonia vaccine, whereas the picture emphasised how many children die of pneumonia because developing countries cannot afford the vaccine. The photo depicts an African child being vaccinated. The child is wearing a uniform with the logo of a school in Matam (Guinea) and the background shows a crowd of children and adults, maybe waiting for their vaccination; therefore, the photo might have been authentic and taken during a vaccination campaign in that country. An African volunteer or health worker is vaccinating the child, but only his/her hands are visible leaving out any other signs that could identify him/her role apart from the disposable gloves. The vaccine administrated could be against pneumonia since it was mentioned in the text overlay and in the tweet.

The original photo also included a third person, holding the child, but s/he was cropped out of this picture thus moving the child from the centre to the left and focusing on the vaccination. The text overlay was placed on the right, providing new information to the viewers: “Each year, 1 million kids die of pneumonia”. There is one more sentence at the bottom of the picture, which connects the first two elements further; it says: “There’s a vaccine, but it’s too expensive for many developing countries”. The relay relationship between text and picture conveys the message that the pneumonia vaccination is important and urgent, especially in developing countries, but it is not always affordable. The medium shot frame and the horizontal angle of the picture make the child close to the viewers: there are many children, like the one in the photo, that could benefit from the pneumonia vaccine, if it cost less. However, only the pharmaceutical companies that produce the pneumonia vaccine can drop the price, and for this reason, the NGO asks these companies to act in the tweet, and save one million children.

8.4.2 Flu vaccination for children

Figure 8.14 was part of a campaign run by the British public health service in the autumn/winter to promote flu vaccination. The image was shared by the English branch of the service in November 2016, and its tweet advises parents not to delay vaccination and to ask their General Practitioner (GP) about the nasal spray for kids[68]. The tweet included the hashtag of the campaign, “Stay Well This Winter”, and the generic hashtag #GP[69]. The tweet did not include hashtags such as #vaccines and #flu, which could reach audiences interested in these two topics. Hence, it is possible that the tweet was primarily aimed at the actor’s followers (Bruns and Moe, 2014).

[68] The flu nasal spray is a non-painful alternative to the flu vaccine administered via injection.
[69] #GP labels very different topics, such as General Practitioners, car racing and sports competitions.

Don't postpone getting the free flu vaccine. Ask your **#GP** about the nasal spray for children. **#StayWellThisWinter** @HealthInst.

[Picture redacted]

Figure 8.14 Flu vaccination for children.

The mixed picture shows text overlay on the left and a nurse holding a little boy in her arms on the right. There are two logos on the borders of the picture: one of the health service and one of the campaign "Stay Well This Winter". The text and the photo are juxtaposed to a background that has the same blue tone as the logo of the public health service. The series of circles act as a target to focus the eye on the nurse and child. The text overlay says: "Help protect children aged 2, 3 and 4 with the flu nasal spray".

The nurse is a Caucasian woman[70], she is wearing a uniform, and text in a small font size states her name and profession. Hence, this woman does not represent a generic British nurse but herself, and since she is supporting the flu vaccination by being in the picture, she might be a testimonial for the Stay Well This Winter campaign. The child is also Caucasian, but his identity is not shown, and he could be any 2-4 year old child mentioned in the text on the left. Both the nurse and the child are smiling and looking at the viewer, giving a sense of reassurance that the nasal spray flu vaccine is effective and protects

[70] In other pictures from the same campaign, Stay Well This Winter, the nurses or pharmacists were not only Caucasians but also representative of other ethnicities

young children. Moreover, since the nurse is a real person and she looks caring, she may add credibility to the message.

Visual social semiotics suggests that the text should be on the right side since it provides information that viewers may not know (Jewitt and Oyama, 2001; see Section 6.3.1), but in this picture it is presented on the left. It is possible that picture layout has different interpretations: 1) the background circles and shades move the viewers' attention to the nurse, and then to the text, which could be a projection of the nurse's recommendation; or 2) the text occupies two thirds of the space and could be the salient part of the picture, whereas the nurse, on the last third, reinforces the message in the text. In any case, this image seeks to persuade parents to vaccinate their children soon, and repeats the message in both the tweet (which also provides further information) and picture (which shows a testimonial). The nasal spray is mentioned both in the tweet and in the picture as well, and it may encourage parents to vaccinate their children since it is a non-painful alternative to injection.

8.4.3 Flu vaccination for health workers

This image was shared by an account of the British public health service related to a specific flu vaccine campaign, Flu Fighter, which targeted healthcare professionals (Figure 8.15). The image was part of the campaign run by this account, and it was shared on the 7th November 2016, during the recommended time for flu vaccinations (NHS UK, 2019). The tweet says the flu vaccine is the best protection against flu and recommends getting vaccinated. It also provided a link to the campaign website where it is possible to find further information about the flu vaccine. The tweet does not mention the campaign's target audience (i.e. health and social care workers) directly; this information is clear only in the linked webpage. The target public might be defined by the hashtag #FluFighter in the tweet, but it would not be evident without knowing the specifics of the campaign. The tweet also includes other hashtags, such as #flu and #FluMatters. The hashtag #flu labels conversation about the seasonal disease but it could also be used to highlight the word ‘flu’ in the text, whereas #FluMatters is used in the Flu Fighter campaign.

The **#flu** vaccine is the best protection against flu, make sure you get yours <u>link</u> **#flufighter #flumatters**

[Picture redacted]

Figure 8.15 Flu vaccination for health workers.

The tweet and the picture conveyed two different messages: the first advocated for early vaccination, while the second compared real facts and myths about flu and the flu vaccine. The picture is divided into two squares of different colours and each of them contains text within a thin frame to separate it from the logos on the margins of the picture. The left square shows information that the viewer already knows: if they are fit and healthy, they do not need the flu vaccine. However, the word “MYTH” in capitals is above this sentence, thus stating that the viewer’s belief that a healthy person does not need to be vaccinated against flu is as a myth. The right square displays new information, what the viewer does not know: being healthy does not protect you against flu, and you could be spreading it even if you have no symptoms. The title “FACT” stands above this text, thus reinforcing the message that being healthy does not protect against flu, and being vaccinated protects people around you. The logo #FluMatters occupies the top left of the picture; it represents the hashtag of the campaign as well as a general message: flu should not be underestimated. Two other logos occupy the bottom of the picture: the Flu Fighter logo and the public health service employers logo; these logos provide practical information, i.e. the names of the organisations that contributed to the campaign.

The image highlights the need for vaccination against flu to avoid spreading it. The tweet and the picture establish a relay relationship by showing a full message: flu vaccination is the best protection against the disease (as stated in the tweet), and it is particularly important to prevent other people from being infected (as shown in the picture). Hence, especially health and social care workers, who interact with patients daily, should be vaccinated. Though this image is targeted at health and social care staff, it does not do so explicitly, this information is only in the link provided and the campaign's hashtags and logos; hence its message could adopted by lay publics as well.

8.4.4 The NGO's contribution to the vaccination campaign in Haiti

In October 2016, hurricane Matthew hit Haiti, raising the risk of cholera outbreaks in some areas of the country; therefore, the Haitian government launched a cholera vaccination campaign in November 2016, which was supported by various NGOs. The chief executive of one of these NGOs (the same one who posted the image described in Section 8.3.4) shared Figure 8.16 on the 8th of November showing how his/her organisation contributed to the campaign. The embedded tweet specified that the immunisation campaign was set to begin, and it would use 1 million vaccine doses from the NGO's stockpile. The tweet mentioned the NGO and integrated the hashtags #Haiti, #cholera and #VaccinesWork. The hashtag #Haiti could have been used to link to discussions and updates about the country but also as a generic hashtag; #cholera labels conversations related to the disease and outbreaks; #VaccinesWork can reach NGOs, foundations and healthcare practitioners of the pro-vaccine network (Bruns and Moe, 2014).

#Haiti‘s **#cholera** vaccine campaign is set to begin soon, using 1 million doses coming from @NGO supported stockpile **#vaccineswork**

[Picture redacted]

Figure 8.16 The NGO’s contribution to the vaccination campaign in Haiti.

The picture combined five photos that look like they were taken at the same time and in the same place. The picture does not have any text overlay, and it was likely made *ad hoc* for the tweet: it shows the doses of cholera vaccine mentioned in the tweet are ready to be distributed in Haiti. Therefore, the tweet links the picture to the Haitian campaign. All five photos depict boxes containing cholera vaccines, and some show workers or a plane as well. The distribution of the photos is shown in Figure 8.17; each photo discussed below is named with the same number indicated in the Figure.

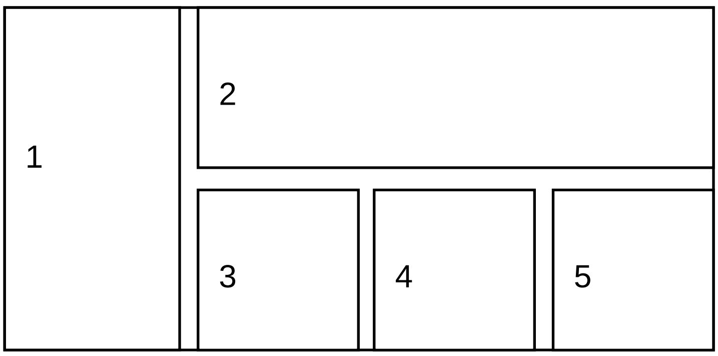


Figure 8.17 Layout of Figure 8.16.
The numbered squares represent the photos inside the picture.

Photo 1 was cropped and adapted for the picture; it focuses on the label on a big box that states it contains an urgent supply of vaccines for Haiti, and provides other technical information related to the delivery. This photo represents what the viewer already knows or has heard from the news: there was an urgent need for vaccines in Haiti due to a potential cholera outbreak. Photo 2 occupies the top of the picture, representing the most salient part: the one million doses of cholera vaccines ready to be used in the Haitian vaccination campaign. This photo depicts several packages of vaccines, just delivered from a plane or in the process of being unloaded by a group of workers in the background. This photo in itself could depict the loading of the plane, but the figurative elements of the other photos (especially Photo 3), taken in the same place, locate it in Haiti. Photo 3, 4 and 5 occupy the bottom half of the picture. Photo 3 shows Caucasian men, wearing World Health Organisation (WHO) gilets, and non-Caucasians, likely Haitians, working or talking to each other, maybe to organise unloading and distribution of the vaccines. Photo 4 depicts a lorry being loaded with the boxes of vaccines, which occupy the most salient part of the photo (the centre). The last photo, number 5, captures one of the WHO workers (recognisable from the logo on the gilet) showing two packages of cholera vaccine Euvichol that he is holding in his hands. Only his arms and upper part of the body are visible, hence the photo focuses on the vaccines just delivered rather than on the staff. These three photos and photo 2 provide the viewers with new information: the actual delivery of the NGO's cholera vaccines.

The mixed picture shows the different phases of the NGO's support to the Haitian government: the cholera vaccines in boxes from the stockpile, the plane delivering them, the unloading and distribution of the boxes, and the actual vaccine package that will arrive in areas of Haiti hit by the hurricane. The photos depicted a large number of boxes, recalling the 1 million doses of vaccine mentioned in the tweet. All of the photos provide elements or details that locate them in an airport in Haiti, and they were likely taken during the event. Hence, they are the visual proof that the NGO is actually helping the vaccination campaign in Haiti. Since the image showed the NGO's contribution to the Haitian campaign, it might aim to improve the reputation and public image of the NGO, hence to attract more funding and donations (Moro, 1998).

8.5 News-related images from the main dataset

8.5.1 Zika vaccine and mosquitos

One of the news-related images (Figure 8.18) was shared by a Twitter account affiliated with a country's army. The tweet announced that the Army would start clinical trials for a Zika vaccine they developed, and it included the link to a news article with further information about this research; it did not use any hashtags. The actor likely shared the image directly to followers (Bruns and Moe, 2014), but since it included the word "vaccines" in the tweet, it could reach users searching for conversations labelled with that word or correspondent hashtag[71] as well. The tweet copied the title of the web article and it was shared the day after publication, on the 10th of November 2016. The embedded photo also appeared in the article, as the main picture, but it was archived on the CDC website originally.

The photo depicts a mosquito and does not have any text overlays; without the context provided by the tweet it could represent an insect as well as any of the diseases that it can carry (e.g. of Malaria, Dengue, Nile fever…). The mosquito is in the centre of the picture and it looks vivid and very detailed, especially against the black background, but its link to the Zika virus and the Zika vaccine are not evident. Many news-related images showed a mosquito in relation to the Zika vaccine (see Section 7.2.3.1); hence, it is possible that this insect acquired different interepretations and visual language conventions. If so, the mosquito does not only represent the insect itself (an icon), but also the transmission of the Zika virus (an index), and it has become a symbol of

[71] When a user searches Twitter for the word "vaccines", Twitter returns posts that include either the word "vaccines" or the hashtag #vaccines. However, searching for #vaccines will return only tweets including that specific hashtag.

everything related to the Zika virus, including the vaccine. The mosquito may have become a visual convention for representing research studies about the Zika vaccine or the Zika virus (Grewal, 2009). Except for representing Zika transmission, hence research studies to stop this transmission, this picture does not convey any particular message, and it may have been chosen for quality so as to catch the followers' attention browsing their Twitter feeds (Suh *et al.*, 2010).

Human clinical trials begin for the Zika vaccine developed by the Army. @user link

Figure 8.18 Zika vaccine and mosquitos.
Via Public Health Image Library, photo ID "9920" by James Gathany.

8.5.2 Zika vaccine and laboratory equipment

The image was shared by the chief executive of an NGO (Figure 8.16), who also posted Figure 8.12 (Section 8.3.4). The tweet reported that “Researchers have found ZIKV-117, an antibody that could become the precursor to a vaccine against Zika” and provided a link to a news article at the end. The tweet also included two hashtags, #Zika and #GlobalHealth, which respectively label Twitter conversations about the Zika virus and the vaccine, and about global health more generally. The image was posted on the 9th November 2016, two days after article publication.

Researchers have found ZIKV-117, an antibody that could become the precursor to a vaccine against **#Zika**: link **#globalhealth**

[Picture redacted]

Figure 8.19 Zika vaccine and laboratory equipment.

The photo embedded in the tweet was also in the news article, and was provided by the research team who made the discovery. The photo shows someone, likely a scientist from the team, holding a six-well plate[72]. This figure

[72] A six-well plate is a tool for cell culture in laboratories. Using this tool, it is possible to grow colonies of eukaryote cells (i.e. human, animal and yeast cells) and test them for antibodies.

recalls the researchers mentioned at the beginning of the tweet; hence, the tweet provided a caption and a context to the picture, establishing an anchorage relationship. Most of the picture is occupied by a six-well plate, which is the salient part of the photo: it seems to show the results of the research experiment that identified the antibody ZIKV-117. However, without the context provided by the tweet, this plate could represent the scientific output of any biological experiment. Viewers without specialised knowledge would not recognise the six-well plate nor understand its function. To identify the tool and understand how it could be related to the discovery claimed in the tweet, the viewers would need a certain level of visual science literacy (Trumbo, 1999). Therefore, though the focus of the photo is on the output shown by the six-well plate, when combined with the text of the tweet the viewers could interpret it as a researcher showing experimental results that confirm his contribution to the development of a Zika vaccine. The identity of the scientist is not important – he is placed in the background and almost completely covered by the plate, even blurred. However, his presence provides scientific context and credibility to the discovery.

8.5.3 The Haitian vaccination campaign (1)

This image (Figure 8.20) was about a cholera vaccination campaign launched in Haiti and it was posted by a news media outlet on the 8th November 2016. This tweet emphasised that Haiti aimed to vaccinate 800,000 people against cholera, especially in areas of the country that were devastated by hurricane Matthew. The tweet did not include any hashtags or Twitter handles, only the link to a news article published on the user's website two days earlier. The actor likely shared the image to followers and was not seeking to reach a wider audience except organically through sharing (Bruns and Moe, 2014). The text of the tweet and the title of the article were different, while the photo embedded in the tweet and in the article was the same.

The Haitian government will try to vaccinate 800,000 people against cholera where the country was devastated by Hurricane Matthew link

[Picture redacted]

Figure 8.20 The Haitian vaccination campaign (1).

The photo depicts a Haitian girl receiving a medicine orally, likely the cholera vaccine mentioned in the tweet. Someone is administering the vaccine but only his/her bare hands are visible, on the right of the picture, and there are no elements that could categorise him/her as a health worker, a volunteer or a relative. Even the background provides little information and it only suggests an indoor setting. The girl is the salient figure in the scene: she occupies most of the space and the close-up frame and horizontal angle of the picture bring the viewers close to her. However, she does not engage with the viewers. She does not express any emotions as she is passively being vaccinated. Unlike the anti- and pro-vaccine pictures, this photo does not aim to persuade the viewer to take action, it simply illustrates the text of the tweet. It represents one of the 800,000 Haitians to be vaccinated during the cholera immunisation campaign.

This photo is not authentic as it does not depict any Haitian people vaccinated in 2016. The original picture was purchased from the online image archive Getty Images, and had been uploaded in September 2014[73]. The caption in the image archive links the photo with a cholera vaccination campaign

[73] The date of the uploaded picture is provided in the image archive.

launched in Haiti by the United Nations in 2014. Therefore, this photo was not taken during the immunisation campaign in 2016.It was probably chosen and shared by the news media outlet because it is high quality and has visual similarities with the 2016 campaign. It was a good illustration for the tweet and might promote sharing (Suh *et al.*, 2010).

8.5.4 The Haitian vaccination campaign (2)

The second image about the cholera vaccination campaign launched in Haiti was shared by a different news media outlet (Figure 8.21). The tweet copied the title of the linked news article, which reported that a big cholera vaccination campaign was underway in Haiti. Both the tweet and the article were published on the 10th November 2016, by the same actor. The tweet did not include any hashtags, nor Twitter handles; hence the image could reach only the actor's followers (Bruns and Moe, 2014) or users searching for the term "vaccination" on Twitter.

A cholera immunisation campaign is underway in Haiti link

[Picture redacted]

Figure 8.21 The Haitian vaccination campaign (2).

The photo embedded in the tweet was also copied from the web article, where it appeared as the first frame of a video. In the image, the photo illustrates the text of the tweet. The picture shows a Haitian man receiving an oral vaccine, which was identified as a cholera vaccine in the tweet. The man stands in the foreground, on the right side of the photo, and three Haitian men stand in the background. One of them, on the left, is administering the cholera vaccine to the main figure. The setting is outdoors but it is too blurred to provide any information on the scene. The three men in the back are also blurred and partially visible; their role is not clear since they are wearing only white t-shirts and no other element that could categorise them. They could be health workers, especially the one giving the vaccine, volunteers or Haitians waiting for their turn to be vaccinated.

The salient part of this scene is the vaccination taking place, which is represented by the hand of the volunteer, the man in the foreground and the vaccine vial, vividly and neatly depicted at the centre of the picture. The horizontal angle and the close-up to these three elements highlight the relevance of the vaccination and bring the scene closer to the viewer. The visual clues may place this picture in Haiti, but only the tweet contextualise it in relation to a campaign in 2016. Therefore, as in the case of the image described in Section 8.5.3, this picture exemplifies the message in the tweet, and it shows the cholera vaccination that was underway in Haiti, but does not convey any further meaning.

8.6 Summary

There were no striking differences between the images collected in the pilot dataset and those collected in the main dataset, but there were differences among the three groups: pro-vaccine, anti-vaccine and news. Appendix H provides tables of the characteristics of each image discussed in this chapter.

The anti-vaccine images claimed that vaccines are not safe, for different reasons (e.g. they contain mercury), and they encouraged distrust in medical authorities, such as healthcare practitioners and the CDC. However, these images also sought scientific legitimacy for their statements and sought to persuade viewers to consult alternative sources of information, such as *Vaxxed the movie*. These images were not shared in relation to specific events, even when they occasionally included links to web articles. In this case, the link was included only to provide further support for their claims (e.g. Sections 8.1.1, 8.2.1) or to promote new or old web articles (e.g. Sections 8.1.4, 8.2.4). The generic and time-unrelated messages of the anti-vaccine images made them looked like part of an ongoing grassroots advocacy campaign to spread misinformation and raise awareness about a 'vaccine conspiracy' (Vegh, 2003). Moreover, the anti-vaccine tweets often had hashtags related to different vaccines conversations and/or communities that could increase the dissemination of their visual messages. For example, many of them included #vaccine(s) and could reach parents seeking information about vaccination on Twitter; others had #vaxxed, which is highly used by the anti-vaccine community, and a few included #VaccinesWork, which characterised the pro-vaccine network (Bruns and Burgess, 2015).

The anti-vaccine pictures were often made *ad hoc*, modified, re-contextualised, or as a collage of visuals elements; their origin was either uncertain or from online image archives. This use and re-use of pictures and visual elements is common among individuals online, who act as prosumers of textual and visual information (Bruns, 2008b). The pictures from the image archives were often staged – white children received an injection of vaccine from a partially visible healthcare professional in a blank setting. Their gender and age were often not clear; they could represent any child at the age of vaccinations, including those of the viewer. These pictures were either neutral or negative, not positive; for example, they did not show any benefits or happiness of unvaccinated children, only the loneliness and almost victimisation of those being vaccinated. This choice of figurative elements (i.e. white child, syringe, healthcare professionals) and the mention of the CDC, Donald Trump, and SB 277 suggests they are targeting white parents from Western countries, especially from the US (Lester, 2014), or it may reflect the Western/American culture of the users and actors sharing these images (Rose, 2012; Pauwels, 2011). Moreover, these recurrent figurative elements could be part of a visual language shared by the anti-vaccine community (Baym, 2010; Grewal, 2009).

The messages conveyed by these images (both or either in the tweet and the picture) were recurrent on anti-vaccine websites and Pinterest images too (Guidry *et al.*, 2015; Kata, 2012). In particular, Kata (2010) found that anti-vaccination websites disseminated misinformation and misinterpretation of scientific studies while distrusting medical authorities; they also supported conspiracy theories, and called for an informed choice about vaccinations and a search for the truth about vaccines. These messages were conveyed by the anti-vaccine images analysed as well, which persuaded viewers not to listen to medical authorities – accused authorities of being motivated by financial interests or ineptitude (Sections 8.1.1-4, 8.2.1, 8.2.3) – and called for viewers to educate themselves by searching for alternative sources of information, especially *Vaxxed the movie*. The images themselves offered some alternative information, which was manipulated (Sections 8.1.1, 8.1.2, 8.2.1) or misinterpreted (8.2.2).

While the anti-vaccine images sought to engender distrust in medical experts and policies in Western countries, especially in the US, the pro-vaccine ones showed the importance or success of vaccinations campaigns. All of the pro-vaccine images from the pilot dataset were shared by NGOs or their advisors/chief executives, whereas half of those from the main dataset were shared by these actors and half by public health institutions. This difference could be related to the different collection criteria (see Section 4.1). For example, only tweets having specific hashtags were gathered in the pilot study and all four images included the hashtag #VaccinesWork. However, this keyword was not common among the images of the main study, which had hashtags related to the NGOs' and health services' campaigns (e.g. #AskPharma) and words such as vaccine(s). The hashtag #VaccinesWork was included in the images from both datasets to reach the pro-vaccine network of NGOs, foundations and healthcare practitioners (Bruns and Burgess, 2015). Some pro-vaccine tweets could also include generic hashtags related to the country where a specific intervention took place (e.g. #Ethiopia) or a disease (e.g. #flu), or hashtags related to advocacy/immunisation campaigns (e.g. #StayWellThisWinter) (Bruns and Moe, 2014).

The pro-vaccine images were shared in relation to vaccination campaigns or NGOs' activities, efforts and achievements, but many of them did not embed any link to external web pages to provide further information. Only one of the images share by the public health institutions included a link. Moreover, most of the images from the pilot dataset did not specify the campaign they promoted (e.g. Sections 8.3.1, 8.3.3). Even so, they were likely part of a campaign, and could aim to attract the attention of the viewer and raise awareness of their cause (Indira Ganesh *et al.*, 2014).

Most of the pro-vaccine pictures shared by NGOs and their advisors/executives did not portrayed children alone, distressed, dehumanised or as victims, like those used by non-profit organisations to campaign against childhood poverty in African countries (Ali, James and Vultee, 2013). They did not depict the situation before the NGOs' intervention to induce pity, but they portrayed positive or neutral moments during or after their campaign to promote its success, and hence, the NGOs running it (Moro, 1998). While pictures related to NGOs depicted African and Arab children and health workers, syringes and oral vaccines, those share by the public health services showed nurse uniforms, logos, and myths representative of the country where they were promoting the flu vaccination. In this way, they could draw the attention of their audiences, and potentially increase their adherence to and recall of the information (Houts *et al.*, 2006).

The pro-vaccine images conveyed their message not only in the tweets but in the pictures as well. These pictures looked like professional photos, and they were taken by photographers or staff members of the NGOs or made *ad hoc* by public health organisations or their subcontracted communication agencies. The photos were often taken for different campaigns, and re-contextualised or modified to convey a new message, but because they depicted real people, they could be perceived as authentic proof of the actors' claims. These real people represented those who benefitted from vaccinations or the NGOs' activities, and when they were named and identified (e.g. Sections 8.3.1, 8.4.2), they became testimonials of vaccine effectiveness and safety. While anti-vaccine images depicted healthcare professionals as untrustworthy sources of information (Sections 8.1.2, 8.1.3, 8.2.3), one of the pro-vaccine pictures represented a nurse as an expert and reliable testimonial (Section 8.4.2). The pro-vaccine images did not display scientific data or statistical information, unlike some of the anti-vaccine ones (e.g. Sections 8.1.1, 8.1.2), though a few of them made claims or narratives based on scientific evidence (e.g. Sections 8.3.2, 8.4.3).

The news-related images were always event-related and posted the same day or a few days after the publication of the news article they promoted. Their tweets embedded a link to the article and often copied its title, but they rarely included mentions or hashtags, suggesting that they sought to reach followers primarily (Bruns and Moe, 2014). The embedded photos were taken from the articles, and, originally they were provided by the authors to the media outlets or they were available on image archives. In the latter case, these pictures were not authentic, they did not portray the actual event but they were re-contextualised as if they did (e.g. Figure 8.20). These pictures did not convey a message, unlike the anti- and pro-vaccine pictures. Instead, they were usually decorative. Their main use could be to catch the viewer's attention and promote sharing of the tweet (Suh *et al.*, 2010). Moreover, these pictures used specific visual conventions (symbols) to represent the message in the tweet;

for example, Figure 8.18 associated the figure of a mosquito with the transmission of Zika virus and the related vaccine. Figure 8.19 depicted lab equipment to suggest researchers studying a vaccine. Similar vaccine pictures were found in printed news articles by Catalan-Matamoros and Peñafiel-Saiz (2019) as well.

In conclusion, anti-vaccine images warned Caucasian parents against vaccines because they are not safe, using representative images to convey their message. These pictures showed symbols, such as the syringe, that are likely recognised and associated to vaccines by Western audiences. In contrast, there are no highly shared representative images saying that vaccines are safe, or promoting vaccines (except for flu) in Western countries. Instead, NGOs campaigned for vaccinations in developing countries to save lives and shared pictures of local people and health workers. Public health services promoted flu immunisation in Western countries showing real healthcare professionals (not actors or models). Media outlets shared news on vaccines development using decorative pictures that depicted what the viewers' likely associate in relation to the news (e.g. a local in relation to the vaccine campaign in Haiti).

9. Discussion

This research is the first to investigate the content, message and dissemination of anti- and pro-vaccine images, in relation to the Twitter networks sharing them. The discussion is structured around the research questions, taking each in turn to explore how the data have addressed the question. The final section discusses potential interventions to counter vaccine misinformation based on the research findings.

9.1 How are anti- and pro-vaccine images disseminated on Twitter?

The study shows that vaccine images are shared by two polarised Twitter communities: one in favour of vaccination and one against. The two groups rarely interact with each other, and when they do, they attack their counterpart or aggressively defend their position. This polarisation and lack of interaction among the two groups was also found in previous studies on vaccine networks on Twitter (Bello-Orgaz, Hernandez-Castro and Camacho, 2017; Salathé and Khandelwal, 2011), and Yuan, Schuchard and Crooks (2018) further claimed that pro-immunisation messages do not reach the anti-vaccine community at all. Meyer *et al.* (2019) also found polarisation in forums; users tended to post comments that confirmed and reinforced their beliefs about vaccinations. My research deepens these findings, implying there is no middle ground, no space in which both anti- and pro-vaccine users engage with each other. Unlike the previous studies mentioned above, my research also further investigated how the pro- and anti-vaccine networks differ in their structure, i.e. in the ways images are disseminated among members.

I found that the pro-vaccine network was structured in several clusters that retweeted each other images relatively less often than the anti-vaccine group. Therefore, the pro-vaccine clusters were loosely connected, but this structure favoured the exchange of new vaccine information among them. The anti-vaccine network, instead, was formed by highly connected clusters and users, thus it was more cohesive. However, this cohesiveness combined with the polarisation of the network, increased the redundancy of the same anti-vaccine images and messages. Additionally, I found that the structure of the pro-vaccine group varied slightly across datasets. The size, number and composition of its clusters changed and reflected specific events (e.g. the launch of an immunisation campaign). As previous studies on vaccine Twitter networks (Yuan, Schuchard and Crooks, 2018; Bello-Orgaz, Hernandez-Castro and Camacho, 2017) focused on larger data collections over several months or even years and were treated as a single time point, they did not consider these subtle differences. Whilst in my study, I collected data on four different occasions, thus I could actually observe how networks changes over time. Unlike the pro-vaccine group, the anti-vaccine community retained the same clusters and sharing dynamics in all four datasets. The image sharing dynamics of the pro-vaccine network may reflect its members' attitude to exchange new information, which could be seen when new information and news become available. The anti-vaccine network appeared more rigid over time, reflecting a constant stream of similar information they shared. This difference between the two networks was also reflected in the images they share, as explained in Sections 9.3 and 9.4.

The anti-vaccine community appears to be more cohesive than the pro-vaccine network, a feature that Kadushin (2011) associated to support communities. This cohesiveness seems to be induced by the members of one cluster who regularly retweeted each other as well as other anti-vaccination clusters. By retweeting reciprocally and frequently, they strengthened their ties and made anti-vaccine images redundant within the community. This redundancy of messages can reinforce the community's anti-vaccine beliefs. Considering Southwell's (2013) and Kadushin's (2011) propositions, this type of behaviour can create a sense of trust, safety and support within the community. It can also increase the negative perception of outsiders and further limits access to and dissemination of messages holding a different perspective in the network. For example, Yuan, Schuchard and Crooks (2018) defined the anti-vaccine network as a ‘structural community’, where members only communicate between themselves and not with outsiders. Dunn *et al.* (2015) suggested that homophily and social contagion may play a role in this closure and polarisation, at least in the case of HPV vaccine conversations on Twitter. They found that users posted negative opinions about the HPV vaccine if they had been previously exposed to negative messages; they also found that these users were more connected to users sharing the same perspective. Homophily seems to affect the virality of misinformation as well. Bessi *et al.* (2015) demonstrated that in Facebook groups of like-minded users believing in and exposed to conspiracy theories misinformation spread faster. Considering the studies mentioned above, it is possible that homophily, polarisation and exposure to anti-vaccine messages increased the sharing of anti-vaccination images found in my research.

The pro-vaccine network had a different structure from the anti-vaccination community, and they were more open to outsiders, as also found by Yuan, Schuchard and Crooks (2018). In my research, the pro-immunisation network was fragmented with loosely connected clusters. According to Southwell's (2013) and Kadushin's (2011) concepts, the network structure I found in my study facilitated networking among users, and access to and diffusion of new information and collaborators. The pro-vaccine network was especially fragmented in the pilot datasets, while it was more cohesive in the main study. This may have resulted from the data collection strategy which included the words ‘vaccine(s)’ and ‘vaccination(s)’ in the main study. Pro-vaccine users, especially NGOs and health organisations, seemed to add these terms in their tweets as words rather than hashtags; therefore, many pro-vaccine and academic images were excluded from the pilot study, resulting in a smaller and less cohesive pro-immunisation network.

In my research, I did not use a neutral category. Instead, tweets were coded as anti-, pro-vaccine, news or academic (see Section 4.3). Previous studies classified vaccine tweets as positive, negative or neutral towards the intention to vaccinate, finding a majority of positive or neutral messages (Bello-Orgaz, Hernandez-Castro and Camacho, 2017; Love *et al.*, 2013). Though news-related and academic tweets may have a neutral content, during the coding process some were found to favour vaccination, thus partially losing their neutrality. For this reason, tweets that had news-related content or academic content, and that did not advocate either in favour or against vaccinations, were always classified as news or academic, respectively (see Section 4.3). As news and academic tweets can be targeted at different audiences and they require different science literacy to be interpreted, it is therefore relevant to distinguish them. By adding these two alternative categories, partially neutral tweets were not forced into a neutral content category. The exclusion of the neutral content category may make comparisons with previous studies difficult; even so, the coding of anti- and pro-vaccine messages was similar, and most of the analyses focused on those (Yuan, Schuchard and Crooks, 2018; Bello-Orgaz, Hernandez-Castro and Camacho, 2017; Love *et al.*, 2013).

During the pilot study, academic and news-related tweets were included in the pro-vaccine network as few were collected (see Section 4.4.1.1). This is likely due to the scarce use of hashtags from media outlets and some pro-vaccine users. In the main study, however, the different collection criteria resulted in more news-related images; this enabled them to be analysed separately (see Section 4.4.1.2). The news-related group was more fragmented than the pro-vaccine network. It had several broadcasting networks that were poorly connected or even unconnected. At the centre of most of these clusters was a news media outlet that disseminated posts to their personal publics. This research found that news media outlets rarely used topical hashtags in their tweets, suggesting that they target personal publics, i.e. their Twitter followers, and are not interested in reaching new audiences or *ad hoc* publics, though they may choose pictures that promote sharing as a way of generating broader reach (Schmidt, 2014; Bruns and Moe, 2014). It is likely that news media outlets rely on their followers to augment their reach by cascading their messages instead of targeting conversations around hashtags. Interestingly, my study also found that pro-vaccine actors seldom included the topical hashtags #vaccine(s) or #vaccination(s), instead healthcare practitioners and NGOs used #VaccinesWork, which has become the standard to access and join pro-vaccine conversations. NGOs and health organisations regularly used the words 'vaccine(s)' or 'vaccination(s)' combined with hashtags of the country where the immunisation intervention took place (e.g. #Ethiopia), the type of vaccine (e.g. #flushot), or the catchphrase of the vaccination campaign (e.g. #EndPolioNow). In this way, they promoted their campaigns to their followers or reached new audiences discussing a specific vaccine (Schmidt, 2014; Bruns and Moe, 2014). By using existing hashtags, NGOs can join conversations and increase their following (Guo and Saxton, 2018). However, by choosing to include mostly pro-vaccine hashtags, they only targeted and reached users already supporting vaccinations. Failing to include #vaccine(s) or #vaccination(s) limited their access to publics seeking information on vaccines in general, who may search for these hashtags on Twitter. Hence, even though the pro-vaccine is not a structural community like the anti-vaccine, it may act as an echo-chamber where users only talk to each other.

Anti-vaccine users may be more successful at reaching wider audiences by using the more general sounding #vaccine(s) and #vaccination(s), in addition to the anti-vaccination hashtags. This was noticeable when comparing the pilot datasets with the main dataset: when words were included in the collection criteria of the main study, the number of anti-vaccine images did not vary greatly, whereas the news-related and pro-vaccine images increased dramatically. Even though new keywords were added in the main data collection (see Section 4.1.2.1), this led to only a small increase in anti-vaccine tweets since most of the anti-vaccine tweets had hashtags that were also part of the pilot collection criteria. However, in the main data collection, a number of pro-vaccine tweets were identified without any hashtags. Addawood (2018) also found more anti-vaccine opinions than pro-vaccine ones when considering only tweets with vaccine-related hashtags. It is possible that, by including the #vaccine(s) and #vaccination(s) in the tweets, anti-vaccine users reach new audiences, especially those seeking and exchanging information about vaccines in general. By including the anti-vaccine hashtags (e.g. #Vaxxed), these users also reach members of their community (Bruns and Burgess, 2015; Bruns and Moe, 2014). Though anti-vaccine users form a closed polarised network, their choice of hashtags means they may reach audiences neglected by the pro-vaccine network. Moreover, since anti-vaccine users retweet each other frequently, their images may be seen by these audiences more often and influence their perception and understanding of vaccinations.

9.2 How do the key actors differ between these networks?

This study is the first study that explores the categories of individuals and institutions participating in the vaccine Twitter ecosystem. Bello-Orgaz, Hernandez-Castro and Camacho (2017) identified some of the actors involved in the debate, but not to the extent of the research presented here. Moreover, by collecting data in four different periods over 2016, I could identify those actors that were hubs or brokers over the year and not just at one moment in time.

Previous science communication studies often focused on scientists' or scientific organisations' communication on Twitter (Su *et al.*, 2017; Smith, 2015). Moreover, these studies applied a strict distinction between producers (scientists, journalists) and consumers (general public) of information (Peters *et al.*, 2014). My study, instead, focused on the *produsage* of vaccine information, thus identifying new players that contribute to the vaccination debate by posting content enriched with their opinions and context. These players do not necessarily produce their own content (e.g. articles), but they act as content curators and gatekeepers (similar to editors in traditional media). This positions them as alternative sources of information acknowledged by their community and considered on a par with traditional scientific knowledge experts.

This study found that anti-vaccination actors comprised activists, parents, parent-activists, journalist-activists and uncategorised users, whereas pro-immunisation actors comprised NGOs, foundations, healthcare practitioners or academics, and public health organisations. This distinction occurred in all four datasets, and in all datasets, several anti-vaccine and pro-vaccine key actors occupied the same role in their respective networks. As also stated by Weitkamp *et al.* (under review), the most visible actors in the digital ecosystem are diverse, comprising many actors who are not considered traditional scientific experts (e.g. parents), who have largely been ignored in science communication research.

The pro-vaccine key actors were mostly hubs. Most of the NGOs, foundations and public health organisations were hubs broadcasting pro-vaccination messages, covering conferences or promoting their immunisation campaigns. These results reflected those on use of Twitter by advocacy groups (Guo and Saxton, 2014) and public health organisations (Park, Reber and Chon, 2016). Moreover, in this research these actors used Twitter primarily as a one-way communication tool to persuade and educate their audiences, as also observed by Auger (2013). Health professionals and academics also acted as hubs, but they countered vaccine misinformation, posted their opinions in favour of vaccination, and covered scientific conferences. Hart *et al.* (2017) found similar findings in their study on health practitioners' use of Twitter.

Two pro-vaccine actors, an NGO and its CEO, acted as brokers by retweeting and being retweeted by NGOs and foundations; they had a key role in the pro-vaccination community in all four datasets. These two brokers enabled networking among organisations and disseminated messages about their immunisation campaigns and activities as well as those of others. Therefore, they acted as what Murthy (2012) called gatekeepers, controlling access to and flow of new information within the network. Though the NGO and its CEO had the same role, they may have slightly different audiences since in the June and September datasets they were members of different clusters.

While the pro-immunisation key actors were traditional sources of vaccine information, anti-vaccination activists comprised alternative sources of information. Two hubs in particular, an activist and a journalist-activist, were at the centre of the two biggest broadcasting networks of the anti-vaccine community in all four datasets. Their messages were retweeted within and outside their clusters, reaching a wide audience. This suggests that the two hubs acted as what Schmidt (2014) would define as opinion leaders in the anti-vaccine community; they selected what vaccine images to share (or not), thus potentially influencing the other members' opinion on vaccination. These actors could be potentially acknowledged as experts by the anti-vaccine community, which valued and re-shared their content.

Several brokers and hubs were members of the recurrent highly connected anti-vaccine cluster mentioned in Section 9.1. These actors frequently interacted with each other and users belonging to other anti-vaccine clusters. Hence, they formed what Huberman, Romero and Wu (2008) call strong ties and friendship relationships. At the same time, they acted as gatekeepers by controlling the visual information flowing among the clusters of the anti-vaccine community. Through high levels of retweeting, these actors also contributed to the redundancy of information within the anti-vaccine network and reinforced its polarisation, thus confirming its members' beliefs about vaccinations and excluding any information that might counter them. This statement is supported by Yardi and Boyd (2010), who concluded that the closure and polarisation of the anti-vaccine community on Twitter could reinforce their existing opinions.

Himelboim *et al.* (2019) also found that anti-vaccine actors shared alternative sources of information, whereas the pro-immunisation ones shared traditional sources or were traditional experts. Considering Southwell's theory about online health communities (2013), the polarisation I found between the two communities and the closure of the anti-vaccine network suggest that anti-vaccination users hold a negative perception of outsiders, and make it difficult for traditional experts to gain access. Anti-vaccine key actors may be acknowledged as experts within their community based on the quality and quantity of their contributions rather than on the scientific accuracy of their claims; as has been observed in prosumer communities (Bruns, 2008a). In line with Larson *et al.* (2011) findings, anti-vaccination users likely trust these key actors and the credibility of their messages as they are members of the same community. Anti-vaccine users may not accept messages from external sources of information or those that conflict with their beliefs. Moreover, as doctors and traditional experts could be considered adversaries of anti-vaccine users, it seems unlikely that anti-vaccine users would listen to them (Castells, 2009). Thus, the anti-vaccine community challenges the expert system. In his book, Gerbaudo (2012) showed how the actors acknowledged as leaders by an online social movement create a collective identity that encourages members to share a sense of unity against a common adversary. To create this identity, the leaders foment indignation, frustration and anger against the adversary, and aggregate these feelings together in a shared emotional digital space. It is possible that the anti-vaccine actors identified in my study are also acting as leaders, because their behaviour suggests they are creating a shared emotional space and collective identity for the members of the network (see also Section 9.3).

Unlike previous studies of vaccine networks on Twitter, (Himelboim *et al.*, 2019; Bello-Orgaz, Hernandez-Castro and Camacho, 2017) this study analysed users that were not hubs or brokers but had out-degree centrality. Even though these users were retweeted less often, they contributed to the network's discussion of vaccinations by re-sharing content they valued. This contribution is particularly relevant from a science communication perspective: thanks to them and their retweeting, it is possible to see what concerns, objections and beliefs are more visible and predominant among the anti- and pro-vaccine images. Some of these actors were in favour of vaccinations, and they were classified as health professionals, academics and/or activists. Anti-vaccine users with high out-degree centrality comprised parents, health professionals, uncategorised users and/or activists that appeared in all four datasets and were members of the highly connected cluster. Harrigan, Achananuparp and Lim (2012) suggested that by retweeting, Twitter users increase the visibility of certain messages and the redundancy of information within a network. The users with high out-degree found in my research increased the visibility of anti-vaccine images and made them redundant within the anti-vaccine community. Moreover, anti-vaccine users' out-degree centrality was higher than that of pro-vaccine users, meaning that they increased the dissemination of anti-vaccination messages in their followers' timelines and Twitter hashtag streams to a greater extent and potentially reached a broader audience than the pro-vaccine users.

9.3 What do networks say about vaccines through the images they share?

This research study found that anti- and pro-vaccination images conveyed different topics but shared a few figurative elements, such as syringes and laboratory coats or gloves. Among the anti-vaccine images the combination of topics and figurative elements did not vary across datasets, whereas among the pro-vaccination images these elements varied slightly depending on the occurrence of events (e.g. cholera vaccination campaign in Haiti). This phenomenon resembled the variability of the networks: the anti-vaccine community did not change its structure or its key actors over time, whereas the pro-vaccination network varied slightly across datasets (see Section 9.1).

Photos prevailed in both anti- and pro-vaccine images, 50-62% of anti-vaccine pictures (n=50) and 54-72% of pro-vaccine pictures were photos (n=50). Pro-vaccine users shared few other types of pictures with a focus on infographics (10-16%, n=50), whereas anti-vaccination users shared a variety of formats including screenshots (4-16%), mixed-pictures (12-22%), cartoons (4-10%) and pictures having only textual elements (8-12%, n=50). This last type of picture could have been used to overcome the tweet's character limit and/or convey a more complex message, as suggested by Giglietto and Lee (2017) in their study on #JeNeSuisPasCharlie. Unlike pro-vaccine users, anti-vaccine users did not post infographics; however, they shared statistical information in form of charts (6-8%, n=50). The variety of formats used, especially the mixed pictures and screenshots, emphasised the online prosumer attitude of anti-vaccine users; they use, re-use and mix visual content found online. This was substantially different from the pro-vaccine users, who mostly posted professional photos and infographics. Most of the pro- and anti-vaccine images analysed in this research had textual elements, which provided either context or additional detail to the pictures. Moreover, they had recurrent signs such as syringes, health carers' uniforms, laboratory coats and disposable gloves. Chen and Dredze (2018) obtained similar results in their quantitative content analysis of vaccine images on Twitter.

My study found that the anti-vaccine pictures were contextualised by the tweets, which carried the main message, and had further details in overlaid text. Sometimes the picture and the tweet complemented each other in conveying the message. The anti-vaccine messages claimed that vaccines are unsafe, they cause autism, contain toxic components and are not effective, though all these statements have been disproved[74]. They also campaigned against mandatory vaccination and promoted conspiracy theories and *Vaxxed the movie*. The images rarely specify a specific vaccine that is supposed to be dangerous and refer instead to vaccines in general.

The pictures associated with these messages often depicted syringes alone, held by someone, or white children being vaccinated with a needle. These children were often alone or with white adults wearing disposable gloves or a white coat (suggesting they are health professionals), though in many pictures only their hands were visible. Considering Lester's teachings about visual communications (2014), it is possible that these images target Western publics and/or are shared by Western users since they mostly represent white people. These figurative elements of anti-vaccine pictures were also common on Pinterest (Milani, 2015). These elements, especially the syringe, could be what Grewal (2009) define as 'standards': conventional figures used to represent and identify vaccination in the anti-vaccine community online. Anti-vaccine images on Pinterest also expressed conspiracy theories and concerns about vaccine safety (Guidry *et al.*, 2015). These topics, as well as parental rights and concerns about vaccine effectiveness, were also common tropes used in

[74] See study from DeStefano, Bodenstab and Offit (2019) for science evidence countering anti-vaccine claims.

anti-vaccine websites (Kata, 2010). The anti-vaccine images did not vary overtime. The redundancy of these images and lack of variety of figurative elements and topics recall (as discussed in Section 9.1) that the anti-vaccine network is a closed community where members re-share each other messages. However, the use generic vaccine hashtags may allow these redundant and highly visible messages to reach new audiences.

The pro-vaccine pictures shared by NGOs and foundations showed African or Asian children being vaccinated either by injection or orally by local health workers. Children are not only a common target of vaccination schedules, but also a common element of NGOs' imagery (Vasavada, 2016; Manzo, 2008). Unlike the anti-vaccine images, these children were often with other children or fully-visible adults. The ethnicity of the people represented, the setting and even the type of vaccine (e.g. polio vaccine) changed depending on the immunisation campaign or activity promoted, and intended message. NGOs and foundations shared these images to convey pro-immunisation messages or promote their campaigns; hence, they rarely talked about 'vaccines in general' and mentioned specific vaccines instead. They also emphasise the efficacy of vaccines but rarely discuss their safety. From these findings, it was noticeable that, though NGOs may target Western publics, they may have no interest in promoting vaccinations in Western countries. Moreover, these actors may take their audiences' vaccine acceptance for granted, as also seen in their use of pro-vaccine hashtags rather than generic ones. The public health organisations also shared images about pro-immunisation messages and specific vaccines, especially about the flu vaccination. However, their pictures depicted mostly white people and, again, did not address concerns around the safety of vaccines. These images did not include any evidence that supported their claims, and suggested to refer to doctors for further information (e.g. Section 8.4.2). These actors therefore may target audiences that already vaccinate or support vaccinations, thus missing those having concerns or being hesitant about vaccinations. These findings reinforce the previous observation that the pro-vaccine network may act as an echo chamber (see Section 9.1).

The pro-immunisation pictures were contextualised by the tweet: the tweet provided the main message and guided the interpretation of the picture. The text overlay in the pictures often added details to the main message and in some cases complemented the tweet. Without the text or the tweet, viewers could not read the image easily: they would see what is happening (e.g. a child drinking something from a vial) but they might not interpret it as an activity conducted by the NGO (e.g. vaccinating children against polio). Hand, (2016) observed that social media images in general need textual elements that facilitate or guide their interpretation.

The content of news-related pictures was time-related, like that of pro-vaccine visuals. The news-related images were about vaccine research or the launch of immunisation campaigns, such as the cholera one in Haiti. The pictures represented syringes, white adults in lab coats (possibly researchers), mosquitos or the people targeted by the campaigns (e.g. Haitians). Similar content was found in print news media by Catalan-Matamoros and Peñafiel-Saiz (2019). The similarity between print news pictures and Twitter news pictures suggests that news media outlets may choose the images for their articles and posts from images sets or online image archives. Moreover, in this study news-related pictures were mostly photos and did not have textual elements; rather than conveying or complementing a message, they looked decorative, and the message was entirely carried by the tweet. The tweet also contextualised the images; for example, the tweets associated photos of mosquitos with the Zika virus, hence to the development of a Zika vaccine. Without the tweet providing the key to interpret the photo, the mosquito could have been read as simply an insect or any disease carried by it (e.g. malaria).

The differences in content, messages, and aims between anti- and pro-vaccine images emphasised the lack of middle ground between the anti- and pro-vaccine communities. Though pro- and anti-vaccine images share similar figurative elements (e.g. syringes), they combined them differently. Moreover, these images communicated different aspects of vaccination: while anti-vaccine messages claimed vaccines are not safe, pro-vaccine ones said they are effective (see Figure 9.1). Therefore, the two communities were polarised in the content and dissemination of the images. Pro-vaccine users, especially NGOs and health organisations, did not address concerns about vaccines, they only promoted their organisations' activities in developing countries or told audiences to vaccinate against flu. Hence, they seemed to aim only at audiences already in favour of vaccination and who recognised their authority. In the case of anti-vaccine users, their choice of hashtags, their messages expressing concerns about vaccine safety, vaccine conspiracies and civil rights, suggest that they target both anti-vaccine audiences and individuals who remain undecided. This research suggests that these audiences that are not reached by the pro-vaccine network.

In the pro-vaccine and news-related images the combination of signs was time-related and varied with the messages conveyed; this resembled the attitude of the pro-vaccine network to seek new information and promote new or ongoing immunisation campaigns and activities. The anti-vaccine images, like the network itself, often conveyed the same claims and rarely changed over time. The lack of variety in the messages and signs may be related to the redundancy of information caused by the way the anti-vaccine users shared information, as described in Sections 9.1 and 9.2.

There were several elements missing in the pro- and anti-vaccine images. For example, the pro-immunisation images rarely addressed concerns around vaccine safety. Some users, especially individuals, countered vaccine misinformation or even mocked anti-vaccine claims, but they did not address parents' possible concerns about adverse reactions arising from the childhood vaccine schedule. This suggests that pro-vaccine users are targeting individuals who already support vaccinations, and do not take seriously the concerns expressed by the anti-vaccine publics. Thus, pro-vaccine users may be missing those publics who have doubts about vaccination or are not familiar with the polarisation of vaccine hashtags (e.g. #vaccineswork, #getyourflushot). Anti-vaccine images lacked ethnic representation, which means that audiences seeking vaccine information on Twitter would find either images promoting immunisation campaigns in developing countries or images claiming vaccines are not safe in Western countries. Anti-vaccine images also disseminated conspiracy theories about vaccines, which, as observed by Jolley and Douglas (2014) could raise concerns about vaccine safety and mistrust in medical authorities.

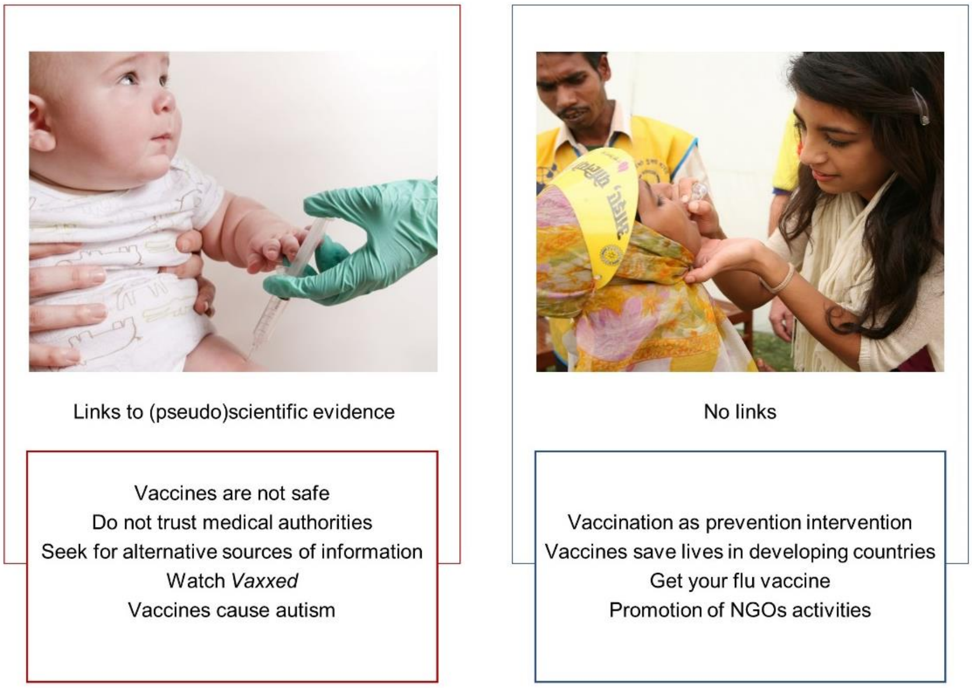


Figure 9.1 Visual content and messages of anti- and pro-vaccine images.
Photo on the left via Pixnio. Photo on the right: "Polio immunization in Lucknow" by RIBI Image Library is licensed CC BY 2.0.

There was another essential difference between anti- and pro-vaccine networks which was related to activism. The relatively closed and polarised nature of the anti-vaccine community resembles social movements that develop as a reaction to prevailing social trends (e.g. immunisation programmes) (Castells, 2009). Castells (2009) observed that reactive social movements are organised around values and practices shared by the group, its self-definition, its adversary and its societal goal. In the case of the anti-vaccine community, the shared images provided insights into these criteria. The choice of figurative elements and the messages conveyed defined the shared practices and values of the members of this community (e.g. do not vaccinate), and their accusations and conspiracy theories identified traditional experts (e.g. doctors) as their enemy. Their societal goal (i.e. what they want to achieve) is to stop mandatory vaccination. The anti-vaccination community may soon develop into a social movement; the anti-vaccine users used the hashtag #vaxxed regularly and promoted the related documentary as something every parent should watch. The website of *Vaxxed the movie* seems to be already set up to campaign against vaccination and even provides information on how to take action (Bennato, 2017).

Castells (2009) also stated that reactive social movements have a heterarchical structure and offer support and protection to their members. The anti-vaccine community had a similar structure, where a few members chosen by the community (hubs and brokers) controlled the visual information flow (see Section 9.2). Moreover, these actors shared repetitive messages (all vaccines are not safe, they are hiding the truth about vaccines, vaccines do not work) that could create a sense of indignation, frustration and anger against the traditional authorities among the anti-vaccine members. These emotions are fundamental for creating the collective identity necessary for a social movement online (Gerbaudo, 2012). The anti-vaccine community also had a structure that created a sense of trust, safety and support among the members (Southwell, 2013).

The pro-vaccine network also had a heterarchical structure, though some actors were more influential than others (i.e. the broker NGO). Moreover, it did not provide safety and closure, but favoured networking and exchange of new information, which did not necessarily confirm previous beliefs (i.e. some news or academic images reported the limitations of vaccines). Therefore, unlike the anti-vaccination community, the pro-vaccine network did not resemble a social movement as defined by Castells (2009) or Gerbaudo (2012). If the anti-vaccine community is close to being an organised social movement, engaging with its members and debunking their disinformation campaigns would be even more challenging.

9.4 How do context and content combine in creating the images' messages?

This is the first study that investigates images' messages considering the relationships between their content and context, i.e. among tweets, pictures, hashtags, hyperlinks, and users sharing them. While previous studies on vaccine images have explored the content of the pictures (Guidry *et al.*, 2015; Milani, 2015) or of the tweets and pictures (Chen and Dredze, 2018), none have looked at hashtags, users and networks sharing them. Including this contextual information in the image analysis is fundamental to understand the full message of social media images (Pennington, 2016), but it still often ignored in studies of science images online (Rigutto, 2017). My image analysis is the first to consider several contextual elements that could affect the interpretation of the images' messages (see Figure 6.2).

Even though the data were collected at different times or in relation to an event, anti-vaccination images were not triggered by specific events. For example, in some cases these images were posted several months after the publication of an article or an event, sometimes even years later. Moreover, they repeated the same messages over and over (see Section 9.3) and used figurative elements commonly known in Western countries (i.e. white people, laboratory coats, syringes). Lester (2014) showed how cultural visual elements tailored to the target audience increase the communication efficacy of the images. Considering these insights, the anti-vaccine images analysed in this study could be either (or both) shared by Western users and/or targeted at Western audiences. In particular, the mentions of *Vaxxed the movie*, the SB 277[75], the CDC and Donald Trump, link these images to users/audiences from the US. Anti-vaccination pictures were made *ad hoc* for Twitter and the message communicated in the tweet, or they were taken from the Internet and modified or re-contextualised (as also found by Chen and Dredze, (2018)). Anti-vaccine users acted as prosumers, because they used, mixed, and re-used visual

[75] The California Senate Bill 277 (SB 277) made vaccination mandatory to enter primary and secondary schools in California in 2015.

materials found online. This finding suggests that there are few boundaries between production and consumption of information within this group (see Section 2.2.3). The anti-vaccine users sharing images did not create the pictures, instead they used existing ones to convey or emphasise their messages. They also curated content, rather than producing it, by sharing articles (though old) that they valued with their network.

The modified/re-contextualised photos were Internet memes or pictures taken from image archives. Archive images were staged, showing children and/or adults with no cues about their identity nor the setting. By using models of children, parents may relate to them (see Ledin and Machin (2018) and Section 6.3.1). Moreover, these photos were neutral or negative and they emphasised loneliness and suggested victimisation of children as if they could not be protected from harm caused by vaccination. Betsch *et al.* (2011) observed that emotional content increases parents' perceptions of risk associated with vaccinating children; therefore, these images could potentially have a similar effect amongst viewers.

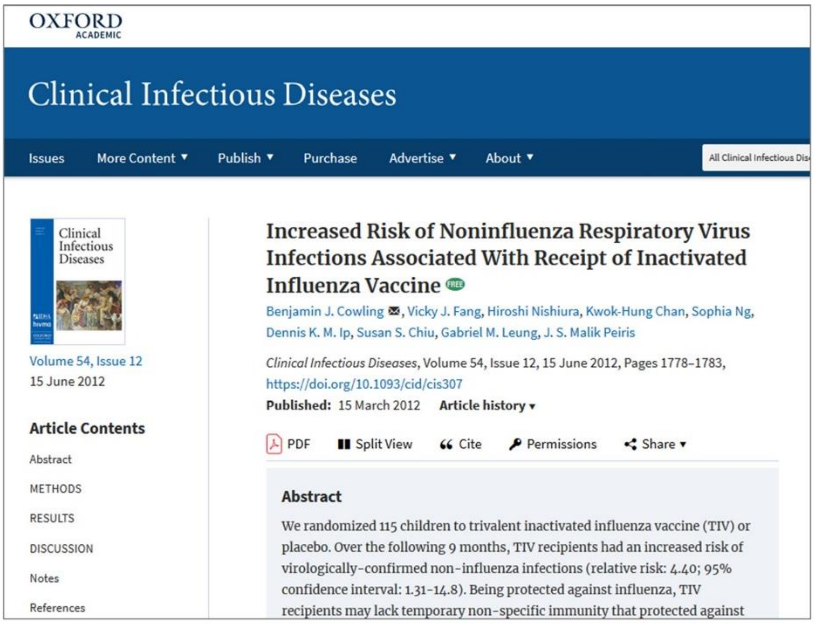
Health professionals (categorised by the presence of white coats or disposable gloves) were rarely fully visible, and their identity was often hidden in anti-vaccine images. Health professionals were sometimes fully shown in *ad hoc* images, as discussed in Section 8.1.2. In these images, they represented traditional experts and were accused of being motivated by financial interests. This accusation was contradictory since anti-vaccine images supported Andrew Wakefield, a former doctor, who was accused of making up the link between the MMR vaccine and autism to support a vested interest (Deer, 2011). Doctors, health organisations and pharmaceutical companies were depersonalised in anti-vaccine websites as well, and they were presented as conscious (or unconscious) members of a vaccine conspiracy is also found by Davies, Chapman and Leask (2002). Davies, Chapman and Leask (2002, p.22) found that these figures were presented as adversaries armed with "cold, analytical science", which was shown as weaker than the strong force of "parents' love and compassion". In other anti-vaccine images within my research, health professionals were accused of being incompetent or ignorant about adverse reactions to vaccines (see Section 8.2.3). Hoffman *et al.* (2019) found this same representation on Facebook posts as well as claims that parents were more informed than physicians about vaccines. By increasing distrust in medical authorities and providing alternative sources of information (e.g. *Vaxxed the movie*), anti-vaccine images may try to empower parents with (alternative) knowledge and claim back the right to decide whether to vaccinate their children or not. This technique was found first in anti-vaccine websites by Kata (2012). The closed nature of the anti-vaccine network, the role of activists and parents as trusted sources of information, the repetition and redundancy of the anti-vaccination messages, and the clear claims against medical authorities, are all factors that increase the distrust in medical authorities (Section 9.2 and 9.3). Moreover, by portraying doctors and health organisations as either corrupt or incompetent, key anti-vaccine actors depict them as the common adversary of the anti-vaccine movement (Castells, 2009).

Overall, the anti-vaccine images claimed that vaccines are not safe and have toxic components, they disseminated misinformation about vaccination, and spread vaccine conspiracy theories. At the same time, they encouraged distrust in medical authorities and advocated against mandatory vaccination. Many, if not all of these elements were also found in anti-vaccine images shared on Pinterest (Guidry *et al.*, 2015) and anti-vaccination websites (Moran *et al.*, 2016; Kata, 2010). Both this research and Kata's (2010) study found that conspiracy theories were often linked to calls for 'searching for the truth'. For example, some of the images I studied claimed that public health organisations covered-up the truth about vaccine safety while promoting alternative sources of information, such as *Vaxxed the movie*, and calling for an informed choice about vaccination. Anti-vaccine users share conspiracy theories on social media as a result of their mistrust in medical authorities (Hoffman *et al.*, 2019). By disseminating vaccine conspiracy theories, they raise concerns about vaccine safety and increase mistrust in doctors (Jolley and Douglas, 2014). Moreover, the belief in conspiracy theories may induce anti-vaccine users and their audiences to seek alternative vaccine information (Mitra, Counts and Pennebaker, 2016). In my research, anti-vaccine images provided links to alternative news websites and even pseudo-scientific journals (see Section 8.1.1). These alternative sources reached beyond the members of the anti-vaccine network, likely also reaching those users seeking vaccination information on Twitter (see Section 9.1).

While anti-vaccine users denigrate vaccine research and the scientific method, they also seek scientific legitimacy for their claims. This approach was also found in anti-vaccine websites (Kata, 2012). On YouTube, anti-vaccination users use medical language in their videos to gain scientific authority. By presenting themselves as experts in the medical field, they raise questions about the scientific consensus on immunisation (Yiannakoulias, Slavik and Chase, 2019). On websites, anti-vaccine activists also present themselves as scientific authorities or medical experts. Moreover, they cite health professionals speaking out against vaccination, thus implying that the medical community is divided on the topic (Davies, Chapman and Leask, 2002). Some anti-vaccine images identified in my study did this by mentioning the American College of Pediatricians or the CDC whistle-blower Dr William Thompson (see Sections 8.2.1 and 8.2.4). Many images also recalled *Vaxxed the movie*, hence Andrew Wakefield. Dixon and Clarke (2013) observed that showing scientific division over vaccination can reduce the intention to vaccinate even in people with neutral or slightly positive opinions about immunisation. This strategy could have been used by the anti-vaccine users investigated in this research to promote anti-vaccine views: the images they shared cited medical experts as well as ‘scientific’ studies against vaccination. These studies were pseudoscientific or fake. They were presented as academic papers (e.g. layout) but they were not published in scientific journals. However, Twitter users (including anti-vaccination ones) may not recognise the unreliability of these anti-vaccine studies as they may not have the level of education needed to discriminate them from academic ones. In other images, like that in Section 8.2.2, scientific information was misrepresented (e.g. proteins and DNA were labelled as carcinogenic vaccine components, Figure 8.6). As Trench (2008) observed, nowadays anyone can access scientific papers online thanks to Open Access, but they may not have the necessary scientific literacy to interpret them. Therefore, scientific information available online could be interpreted and understood in various ways, and instead of informing parents about vaccinations may misinform them (Kata, 2012). This could happen with scientific images as well, as they can be decontextualized and/or modified online (Rigutto, 2017). The anti-vaccine images investigated in this research reflected this problem, as the example in Figure 9.2 shows. Scientific content as well as scientific images were manipulated or re-contextualised to support anti-vaccine claims and claim there is a lack of scientific consensus over vaccines.

Themes such as conspiracy theories, distrust in medical authorities and concerns about vaccine safety were also recurrent in anti-vaccine images related to Donald Trump and the US presidential elections in 2016. In the main study, 22% (n=50) of the anti-vaccine images and three pro-vaccine images were about Donald Trump. In both cases, photos of Donald Trump, screenshots of his tweets about vaccination or endorsements from Andrew Wakefield were shown. The pro-vaccine images contested Mr Trump's claims that the MMR vaccine causes autism or the vaccine schedule should be reduced. The anti-vaccine images depicted Donald Trump as the presidential candidate against mandatory vaccination. These images portrayed him as a superhero, and as the candidate who knows truth about vaccines and would end corruption within public health services. Dredze *et al.* (2017) obtained similar results in their study of anti-vaccine tweets shared during the US presidential campaign. As in this research, they found that these tweets were positive towards Donald Trump (they even requested him to support *Vaxxed the movie*), and negative towards Hillary Clinton.

Original picture



Modified picture

Figure 9.2 Example of how a scientific image modified to convey a different message.

The original picture is a screenshot of a scientific paper. Without having a certain level of science literacy, it would not be possible to understand that the modifications to the picture changed the meaning of the paper.

Unlike anti-vaccination pictures, pro-vaccine ones were made *ad hoc* for the campaign and using professional design standards or they were taken by photographers working for the NGO. In the latter case, the photos were sometime re-contextualised or modified (e.g. by adding text overlay) to convey a new message. The pro-vaccine images used narratives to convey their messages, and they did not often show statistical information nor mention scientific evidence supporting their claims. Since these images were shared in a polarised network, it is possible that they were intended for audiences already in favour of vaccination and that trust traditional experts (e.g. GPs). The pro-vaccine images shared by NGOs were about their achievements, activities, efforts, and campaigns in developing countries. These images did not provide information about vaccinations in Western countries, and maybe it was not part of their agenda to do so. Their messages differed slightly and the design and combination of signs varied depending on the activity. The pro-vaccine images did not provide links to their respective vaccination campaigns, and they often did not mention the campaign specifically. Considering them through the perspective of Indira Ganesh *et al.* (2014), the main use of these images may have been to catch the audience's attention rather than to inform them.

Public health organisations targeting lay audiences also did not provide links, but directed viewers to their GPs for further information on the vaccination campaign or intervention. Their messages were of prevention, as those found by Park, Reber and Chon (2016), encouraging lay audiences to be vaccinated against seasonal flu. However, these messages can only reach users already trusting the health organisation and/or supporting vaccinations. Health organisations are missing the opportunity to reach users who do not have a polarised opinion about vaccines and are seeking information. They do not use generic vaccine hashtags to reach these audiences, and they do not address any concerns about vaccine safety. While it makes sense that NGOs do not promote vaccinations in Western countries (as they run immunisation campaigns in developing countries), it is disappointing that Western health organisations are only reaching those who are already convinced about vaccines. Since vaccinations are preventative and are the most efficient when most of the population is vaccinated (DeStefano, Bodenstab and Offit, 2019), health organisations cannot afford to ignore or miss parents who may be hesitant.

The pro-vaccine images were positive or neutral, and they depicted the activities run or supported by NGOs in developing countries. These photos were authentic, they depicted people from the country where the intervention was taking place (e.g. local health workers), and include cues about identity (e.g. a school uniform) or names. The photos were not distressing and they did not victimise the people they represented, as the anti-vaccine images did. Children were a common element in NGOs' images, which is not surprising since the visual representation of children is an effective persuasion strategy often employed by NGOs (Zarzycka, 2016; Dogra, 2007). These children were not depicted as victims, tough they were represented as passive and innocent. Previous research suggests audiences perceive images that victimise people as manipulated and this causes them to counter-argue thereby rejecting the message (Indira Ganesh *et al.*, 2014). In Section 8.3.2, for example, the photo was cropped in order to focus on only one child receiving a vaccine, thus giving a feeling of isolation. As Vasavada (2016, p.12) said in her study on UNICEF photographs: "children are still largely portrayed as passive, innocent, and primitive recipients of a Western benefactor's goodwill". Moreover, children are sometimes depicted with their mother, but never with their father. Dogra (2011) observed that NGOs often depict women from developing countries as vulnerable and somehow 'inferior' to Western men and women. Vasavada (2016, p.13) also noticed that NGOs portray women as "necessary but not sufficient to sustain a family", thus needing the intervention from the Western saviours. From the images analysed in my study it is unclear whether women are portrayed as victims. However, the absence of a paternal figure is evident and women are depicted as mothers who have a caring motherly attitude towards their children (as also found by Dogra, 2011). However, in my study they do not look needy or vulnerable. Nevertheless, these women are depicted as receiving help from the NGOs, and by inference, therefore from Western donors. In line with previous studies on NGOs imagery (Vasavada, 2016; Zarzycka, 2016; Manzo, 2008), the images I analysed still represent developing countries as places that need some financial support from Western countries. Ali, James and Vultee (2013) suggested that this type of image favours donations or support to the NGOs. Similarly, pro-vaccine images like that in Section 8.3.2, claiming that immunisation is a good investment, may call for financial support from Western countries indirectly. Public health organisations' pictures also depicted logos, signs, health professionals and children from their countries. These elements, as Houts *et al.* (2006) suggested, can increase adherence to the health intervention promoted (i.e. the flu vaccination). Moreover, these images provided the identity of the health professionals, proposing them as experts to trust.

News-related images were always event-related and provided a link to a web article. The embedded photos were the same as those in the linked article, and they were often taken from online image archives. Unlike the pro-vaccine images, these pictures were not authentic. Moreover, they depicted signs related to the topic of the linked article; for example, they showed a mosquito or laboratory equipment when the article talked about the development of a Zika vaccine, or Haitian people taking an oral vial when the article discussed a cholera vaccination campaign. These images seemed to have a decorative function and a role at attracting the viewers' attention and increasing the sharing rate of the tweet. In fact, the company, Buffer, reported that tweets embedding pictures receive more retweets, favourites and clicks than those without pictures (Cooper, 2013), and highly recommended the use of images on Twitter. From their decorative use of pictures, the absence of hashtags and fragmentation of their network, it is clear that news media have no interest in actively engaging in the vaccine debate. Instead, they broadcast their latest articles. This, however, does not mean that news media images will never affect the vaccine controversy. As found by Gollust *et al.* (2015) and Guillaume and Bath (2008), the news media coverage of the HPV vaccine and the MMR vaccine (respectively) focused on the political controversy of the vaccine instead of their benefits, and increase distrust in medical authorities. Therefore, even though I did not find this type of coverage in my sample, it does not mean it has not occurred.

The messages and interpretations of the anti- and pro-vaccine images again reflected the polarisations of the two communities sharing them. Anti-vaccine images warned parents against vaccines, suggesting they are not safe and provided links, alternative sources of information and experts' opinions supporting their claims. In contrast, pro-vaccine images promoted immunisation campaigns in developing countries or flu vaccination in Western countries; they rarely provided links or further information about vaccination or scientific evidence. Moreover, anti- and pro-vaccine images evoked different emotions. While anti-vaccine images enhanced individual risk perception of vaccines (e.g. claims against mandatory vaccinations, which are not safe), pro-vaccine images recalled altruistic emotions (e.g. campaign to make vaccines affordable to developing country). Though it is likely that both the pro-vaccine network and the anti-vaccine community target audiences from Western countries (see discussion above), their communication aims are clearly different as are their messages. This leads to a visual communication gap in the Twitter discussion about vaccines: there are not enough pro-vaccine images stating that vaccines are safe (not just effective) and providing access to evidence or further information. The polarisation between the two communities is also emphasised by the different presentation of scientific evidence and authority. While the pro-vaccine images took medical evidence for granted, anti-vaccination images provided alternative information and (pseudo)scientific experts. Hence, both these types of images might target like-minded audiences; pro-vaccination images may be tailored for those already supporting immunisation, whereas anti-vaccine images may target parents against or concerned about vaccinations (Indira Ganesh *et al.*, 2014; Lester, 2014).

9.5 Addressing the vaccine information gap

To counter vaccine misinformation on Twitter, targeting the anti-vaccine community directly may not be a successful strategy as medical authorities and traditional experts are not trusted. The World Health Organisation (WHO) also recommend against engaging with vaccine deniers, (though their guidelines apply to public debates) and to focus on lay audiences instead (WHO, 2017). In the case of Twitter, sharing more pro-vaccine images with the hashtags #vaccine(s) and #vaccination(s) could facilitate reaching lay publics, users that do not hold a strong opinion about vaccinations and may be more open to immunisation messages. This strategy could also help to reach 'silent audiences', i.e. those who read the tweets but may not actively contribute to the debate on Twitter. Using existing hashtags to reach new audiences is already recommended by previous studies (Guo and Saxton, 2018). As seen in my research, this is a strategy adopted by the anti-vaccine community; hence, using it to present pro-vaccine visuals could help counterbalance, if not reduce, the visibility of anti-vaccination images. A different approach could be targeting influencers and gatekeepers at the edge of the anti-vaccine community (Lutkenhaus, Jansz and Bouman, 2019). Lutkenhaus, Jansz and Bouman (2019) suggested mapping Twitter vaccine communities and identifying their key actors, especially those that are not completely against nor in favour of vaccination. By engaging with these users and providing them with scientific information and accurate information about vaccines, they argued it would be possible to reach closed communities such as the anti-vaccine one. However, I would argue that providing information to these actors may not be sufficient. Anti-vaccine users, especially parents, sometimes argued that pro-vaccine users are not open to dialogue (see Section 7.1.1). Therefore, a one-way communication approach may be insufficient to persuade key actors who are not completely in favour of vaccinations; rather a transparent dialogue with them may be more efficient.

Regarding how to improve visual communication of vaccination, some aspects of anti-vaccine images could be adapted to pro-immunisation visual messages. For example, anti-vaccination images use figurative elements that are likely recognised by the anti-vaccine community and their audiences (e.g. parents seeking vaccine information on Twitter). Therefore, using icons, indexes and symbols that can be understood and easily recognised by the target audience (e.g. health professionals' uniforms) could improve the communication efficacy of the pro-vaccine images (Indira Ganesh *et al.*, 2014; Lester, 2014). Moreover, these figurative elements should represent the audiences they target to be effective; if the publics do not recognise themselves or their situation or environment in the images (e.g. ethnicity, gender, culture), they may not understand or comply with the health intervention (Houts *et al.*, 2006). Though anti-vaccine pictures did not depict real people, their use of cultural symbols was designed to make them representative of their community and potential audience. Among the figurative elements, the syringe was predominant in anti-vaccine images as well as pro-vaccine and news-related visuals. Though the needle is a symbol for vaccination in all these three types of images, it may not be adequate for pro-immunisation visual messages. The syringe is unlikely to hold a positive connotation since it pierces the skin and causes pain and is often associated with drug misuse; hence, considering Indira Ganesh *et al.* (2014) guidelines, showing smiling children while being vaccinated may be provocative, whereas showing crying children being vaccinated may be distressing. In either case, these images may not be incentives to vaccinate. Depicting the syringe alone could be an alternative, but a needle could represent blood donation or drug addiction too, and the image could be de-contextualised online thus acquiring a different meaning (Pennington, 2016). This problem may be addressed by including text in the picture. As seen in this study, pictures often had text overlay or caption that contributed to the final message. More practical implications of the research results are provided in the next chapter.

10. Conclusions

This is the first research study to investigate in detail the visual vaccines discourse on Twitter, since it considered the messages *and* the content of vaccine images *within* the context of the networks and key actors sharing them. The research shows how the figurative elements and messages of the images reflect the structure of the networks sharing them (see Section 9.3) – that is how figurative elements and messages differ between anti and pro-vaccine networks and users. This suggests that networks and images are not separate entities, but inform each other through an iterative process of reinforcement. Previous studies on the vaccine debate on Twitter focused either on the networks (Bello-Orgaz, Hernandez-Castro and Camacho, 2017; Salathé and Khandelwal, 2011) or on the image content (Chen and Dredze, 2018) alone, and so they reflect only part of the phenomenon. By looking at both content and networks, it is possible to uncover not only the polarised nature of the visual vaccines discourse, but also the different ways in which pro- and anti-vaccine networks mobilise figurative elements and encode messages in images, and how the relationship between image and network reinforce different practices.

The pro-vaccine network contained several loosely connected clusters, and its structure favoured access to and sharing of new pro-vaccination, academic or news-related images. The images shared by the network contained a diversity of messages. Although the images contained similar figurative elements (e.g. vaccines vials, health care uniforms) to those seen in the anti-vaccine network, they were combined differently. Unlike anti-vaccine images, they showed positive messages and represented real people and authentic situations. The images represented the activities of NGOs and the results of their efforts, or real health professionals acting as testimonials for vaccination. Pro-vaccine hubs and brokers were either traditional sources of information or NGOs; perhaps because public health organisations and NGOs are recognised as authorities online and offline, they did not provide further information via hyperlinks or mention scientific evidence to support their claims. As they take their status and Twitter audiences' positive attitude towards vaccines for granted, they miss the opportunity to contribute to the wider discourse on vaccination, by supporting as yet undecided and hesitant Western publics who may be seeking information.

In contrast, the anti-vaccine community was highly connected and isolated. Based on Southwell's theories on health communities (2013), the high level of retweeting of the anti-vaccine members could increase the redundancy of anti-vaccination messages within the group, reinforcing existing beliefs. The images they shared were also redundant in content and messages: they often had the same combinations of figurative elements and topics, and they claimed that vaccines are not safe using pseudo-scientific evidence as support and promoting conspiracy theories. They recommended that members search for alternative vaccine information, such as *Vaxxed the movie*, and suggested that traditional authorities cannot be trusted. The design of the images and their emotional and narrative components could persuade parents not to vaccinate their children or themselves (Betsch *et al.*, 2011). This redundancy of messages and content reflected the closure of the community; any messages that did not support the community's beliefs were excluded as were outsiders and traditional experts. Only alternative sources of information, such as activists, parents and journalist-activists, were endorsed and retweeted by the community. The anti-vaccine network, in its structure and messages, showed a strong refusal of any information against their beliefs, prompting over-sharing of information confirming their opinions.

The anti-vaccine community has been defined previously as an echo chamber or a structural community (Yuan, Schuchard and Crooks, 2018; Salathé and Khandelwal, 2011). Altough it looked like an echo chamber in my study, the hashtags its members used suggest otherwise. I found that anti-vaccine users sought to reach beyond their community by tweeting and retweeting images using anti-vaccination and more general vaccine-related hashtags (e.g. #vaxxed and #vaccines, respectively). It is by looking beyond the network, at the use of Twitter affordances such as hashtags, that this outward looking or potentially campaigning approach can be seen. In contrast, the pro-vaccine network failed to make use of opportunities to reach beyond their existing followers or those already supportive of vaccination. This was evident from the polarisation between the communities, and from the use of pro-vaccine hashtags (#VaccinesWork) rather than more general vaccine-related hashtags (e.g. #vaccinations) by the pro-vaccine community. Thus, although the pro-vaccine network appears to broadcast messages, it does so ineffectively, instead becoming more of an echo chamber. It is only by looking at image, content and network that this failure to reach out, through the use of neutral hashtags, becomes evident.

Pro-vaccine NGOs and health organisations also appear to take for granted that they are trusted and believed by audiences. By assuming trust, they broadcast messages like “get your flu shot” or “vaccines save lives” without providing any explanation or hyperlink to further information (unlike the anti-vaccine users). However, on social media and on Twitter, trust, authority and expertise are acknowledged by the members of the network or community rather than rights acquired through status as traditional experts (e.g. healthcare workers) (Schmidt, 2014; Bruns, 2008a). Anti-vaccine actors, instead, provide hyperlinks to articles or papers – though unreliable – and mention pseudoscientific evidence and ‘experts’ to support their claims. Moreover, since it is activists and parents that uncover vaccine ‘cover-ups’ and corruption amongst medical authorities, they may be seen as resembling those audiences seeking information. Research by Farmer, McKay and Tsakiris (2014) suggests that this resemblance may increase the trust in these anti-vaccine actors and consequently their messages. Thus, my research suggests that anti-vaccine users are better at using Twitter affordances to reach and potentially persuade new audiences. This observation is supported by Gunaratne, Coomes and Haghbayan (2019), who found that even though the volume of anti-vaccine tweets decreased from 2015 to 2016, the number of anti-vaccine users doubled. It is clear that pro-vaccine actors are missing an opportunity to reach those who are unsure about vaccine safety and efficacy. These audiences may not be vocal, they may not tweet or retweet vaccination content, but could be silent observers of the vaccine debate.

This is the first study to explore the variety of actors characterising the vaccine communication ecosystem on Twitter. Previous science communication studies on Twitter focused on scientists or scientific institutions' communication about science topics (Su *et al.*, 2017; Lee and VanDyke, 2015; Smith, 2015) but Weitkamp *et al.* (Under review) showed how other actors, such activists, non-professionals and industries, also produce and share science-related content online. Regarding vaccinations, Bello-Orgaz, Hernandez-Castro and Camacho (2017) identified specific Twitter accounts involved in the discussion on Twitter, whereas my study had a more inclusive approach that found a broader spectrum of actors fitting in categories such as activists, parents, uncategorised users, bloggers, alternative healthcare practitioners, students, science enthusiasts, and policy makers (see Appendix C) contribute to the anti- and pro-vaccination knowledge on Twitter. This finding highlights that scientific knowledge and information about vaccines is not tightly controlled by traditional experts, such as scientists, healthcare practitioners, journalists, and media organisations, as previous studies suggest. Instead, this mixed ecology implies that there is an urgent need for traditional experts and gatekeepers to change the way that they communicate about vaccinations on Twitter, and in doing so, to adopt the practices used amongst the wider ecology of communicators in this discourse.

10.1 Practical implications

As discussed in the section above, the pro-vaccine visual discourse on Twitter despite operating in a broadcast fashion is failing to make use of the affordances offered by the Twitter platform. This research found that Twitter is an ecosystem where different voices contribute to the debate and knowledge about vaccinations. These voices contribute regardless of their academic expertise or healthcare background. If we are 'all experts now' (Collins, 2014), then it is important to understand how information flows and who is trusted by different communities within the ecosystem. My research shows that anti-vaccine actors make better use of Twitter affordances to reach beyond their communities; in contrast pro-vaccine users remain disconnected and make little use of affordances such as hashtags. My research identified several issues that could hinder the visual communication of vaccinations and immunisation campaigns by pro-vaccine actors:

- The anti-vaccine community
    - Distrust medical authorities
    - Is a closed community that does not accept messages from external sources of information or those that conflict with their beliefs
    - Disseminate images that promote conspiracy theories, and encourage distrust in traditional medical authorities and encourage viewers to seek alternative vaccine information
    - Disseminate images that provide alternative or (pseudo)scientific evidence and misrepresent science
    - Disseminate images that present ‘traditional experts’ who are against vaccination or mandatory vaccine schedules, thereby suggesting a lack of scientific consensus about vaccination
    - Reach outside of their community
- The pro-vaccine network
    - Engage with users already supporting vaccination
    - Trust traditional experts and medical authority
    - Do not provide external links with further information or scientific evidence that supports their claims
    - Health organisations and NGOs appear to take for granted that the audience they reach trust them already and are in favour of vaccination
- News-related group
    - News media outlets focus only on their followers
    - News media outlets do no interact with their audiences

These issues highlight the lack of a middle ground. The three networks form three bubbles that differ in the content and messages they share and in their communicative aims. Therefore, the question that follows is: How do we break the bubble?

Targeting the anti-vaccine community directly may not be a successful communication strategy as medical authorities and traditional experts are not trusted. Lutkenhaus, Jansz and Bouman (2019) suggested targeting gatekeepers and opinion leaders within anti-vaccine communities that are not completely against vaccination. This solution may be difficult to apply, though. The key actors identified in this research may not want to engage with traditional authorities or outsiders. An alternative solution could be providing the missing 'middle layer' instead (i.e. the missing information about vaccines, tailored for Western audiences); for example, by sharing:

- Images addressing anti-vaccine concerns (e.g. vaccines cause autism)
- Images that represent the target public (i.e. use of cultural symbols, settings and people tailored to the audience)
- Images providing scientific evidence and/or further information (e.g. links) supporting the pro-vaccine claims
- Tweets and images having generic vaccine hashtags (e.g. #vaccines) to reach *ad hoc* publics and new audiences

Sharing more pro-vaccine images with the hashtags #vaccine(s) and #vaccination(s) could facilitate reaching lay publics and users that do not hold a strong opinion about vaccination and may be more open to immunisation. These images could help counterbalance, if not reduce, the visibility of anti-vaccination images.

By proving this 'middle layer', there is the risk of increasing the impression that there is a scientific divide about vaccination. Countering vaccine misinformation and exposing anti-vaccine strategies could help overcome this problem. This suggestion I am making aligns with WHO guidelines for public debates about vaccination (WHO, 2017). Moreover, Larson *et al.* (2011)

advised considering broader issues (e.g. vaccine policies and new research findings), rather than focusing only on concerns about vaccine safety. My research highlighted three additional concerns that could be addressed: 1) vaccine safety and vaccine components (thimerosal, mercury), 2) mandatory vaccinations and the vaccine schedule, and 3) who to trust (medical authorities vs. alternative experts). When I conducted this research, these three issues were regularly discussed by the anti-vaccine community, whereas the pro-vaccine images barely mentioned them. Combined with Larson *et al.* (2011) directions, my study suggests that these concerns should be tackled by immunisation campaigns.

Finally, it may be important to avoid judging anti-vaccine concerns when countering misinformation. As mentioned in Sections 7.1.2, 7.1.4 and 7.2.2, some recurrent pro-vaccine images mock anti-vaccine claims. However, Meyer *et al.* (2019) observed that judgement, ridicule and sarcasm may negatively influence parents' intention to vaccinate. Therefore, I suggest a more open-minded approach and willingness to listen and discuss Twitter users concerns about vaccination may make vaccine communication more effective (see also Leask *et al.*, 2012).

10.2 Research strengths and limitations

This study combined three different methods to investigate the visual communication of vaccines on twitter in an extensive way: social network analysis, content analysis and image analysis. Each method had its strengths and limitations. For example, social network analysis enables an understanding of how images are disseminated within and between networks. Hence, it facilitated an understanding of the polarisation and closure of the networks. Social network analysis was also allowed identification of key actors that could influence or even control the dissemination of images within a network. However, social network analysis cannot identify users that do not actively participate to the debate (i.e. they do not tweet or retweet). This means it cannot provide access to the opinions and attitudes of these silent users, who could be the majority of Twitter users. For example, a study focusing on the US showed that the majority of adult users do not engage on Twitter often (Hughes and Wojcik, 2019).

As in previous studies (Chen and Dredze, 2018; Guidry *et al.*, 2015; Milani, 2015), a content analysis was conducted to investigate the content of the vaccine images. Content analysis was the most appropriate method for making comparisons between anti-, pro-vaccine and news-related images (Bell, 2011). My study combined a quantitative and a qualitative approach of this analysis. The quantitative approach was used to quantify the topics and figurative elements in the images, while the qualitative approach explored how these elements combine to represent vaccines. My content analysis considered visual and textual elements of the pictures, tweets' content and hashtags. Chen and Dredze (2018) only included pictures and tweets in their study, thus missing some contextual information (e.g. hashtags) that is necessary to interpret the images correctly.

Analysing the content of a tweet and its embedded picture is not sufficient to fully understand how vaccine images convey their messages, since social media images, including those about science, are often modified and re-contextualised thus acquiring new communicative aims and interpretations (Rigutto, 2017; Pennington, 2016). Therefore, I applied an image analysis to understand anti- and pro-vaccination messages within the context of the Twitter networks sharing them. Context had a fundamental role in shaping the message conveyed by the images, and in their understanding and interpretations (see Chapter 8). However, context is rarely considered in studies on science images online (Rigutto, 2017). Even though the image analysis allowed me to interpret vaccine images at a deeper level than the content analysis, my understanding of these images could be affected by my own education and cultural background (Lester, 2001; Trumbo, 1999).

There were additional constraints that may have limited this research. First, the coding of the tweets and images was done manually, potentially increasing the risk of miscoding. Previous studies used machine learning to code tweets or images, which may be more precise and less prone to human error (Chen and Dredze, 2018; Salathé and Khandelwal, 2011). However, the manual approach allowed consideration of more metadata in the coding process of the tweets (e.g. users' orientation, embedded hyperlinks, picture content), and the context in which the tweets were shared. In this way, it was possible to classify sarcastic tweets as well as posts that conveyed their full message in the embedded picture. The manual coding of the images for the content analysis also allowed the researcher to be fully immersed in the process and have a deeper understanding of the data (Braun and Clarke, 2013). The manual coding also allowed consideration of the context of the image (e.g. relationships with the tweet, hashtags, users), thus facilitating an understanding of how different elements of an image relate to each other to convey a topic and a message.

The research criteria excluded tweets without embedded pictures, making it challenging to compare the results with previous Twitter studies that did not focus on images (Bello-Orgaz, Hernandez-Castro and Camacho, 2017; Love *et al.*, 2013). However, limiting the data to tweets having pictures allowed this research to focus on images and the way they are shared within Twitter networks, an area previous unexplored. The research also focused on a limited number of keywords. Previous studies included either words only, such as 'vaccines' (Love *et al.*, 2013), or a large number of vaccine hashtags (Dredze *et al.*, 2017) in their search criteria. Since the pilot study was designed as an exploratory study and did not aim to analyse a large volume of data, a limited number of hashtags were included. Furthermore, words, such as vaccine(s), were excluded so that the study could focus on *ad hoc* publics and potential communities forming around topical hashtags (Bruns and Burgess, 2015). The main study was designed to have a deeper understanding of the dynamics and images found in the pilot study, and to include both *ad hoc* and personal publics of users and actors communicating about vaccines. Therefore, both hashtags and words were included in the collection criteria (Bruns and Moe, 2014). More hashtags could have been considered, as Dredze *et al.* (2017) did in their study, but some of these hashtags could have introduced more noise as not all of them are used to discuss vaccination exclusively (see Section 4.1.1.1 and Appendix A).

There was the potential risk that the intervention of Russian trolls during the US presidential campaign in November 2016 could have affected the data collected for the main study (Broniatowski *et al.*, 2018). However, Broniatowski *et al.* (2018) found that several of these trolls used the hashtag #VaccinateUS, which was not included in the collection criteria. Furthermore, even if they combined hashtags with words such as vaccine(s) or vaccination(s) (which were included in the criteria), their posts had no pictures; since tweets without pictures were excluded from the data collection there is little indication that the study was affected by these trolls. Although, it is possible that the data were contaminated by bots or trolls, the focus on tweets with pictures minimised this risk.

Even though there were some constraints that affected my research, the methodological decisions taken allowed an innovative and extensive approach to investigate vaccine images. This approach therefore considered and integrated networks, key actors, images' content and context. Thus, it enabled me to show how vaccine images' figurative elements and messages are intertwined with the networks and actors sharing them.

10.3 Future directions

This research analysed only vaccine images on Twitter, and future studies could focus on the differences and similarities between vaccine images and the community sharing them on other digital media outlets. Most of the previous studies on vaccine visual content focus on YouTube (Briones *et al.*, 2012; Keelan *et al.*, 2007), Twitter (Chen and Dredze, 2018; Lama *et al.*, 2018), and Pinterest (Guidry *et al.*, 2015; Milani, 2015) whereas there is a lack of research on what images are shared on popular platforms such as Instagram and Reddit. However, it is necessary to investigate the messages of images shared online as well. As this research demonstrated, analysing the messages of the images can provide insights into common vaccine concerns and communication strategies used by anti-vaccine activists (see Section 9.4). This information could inform future immunisation campaigns (Lutkenhaus, Jansz and Bouman, 2019; Larson *et al.*, 2011).

Future studies should also consider the content and interpretations of vaccine images in relation to the platforms where they are shared and the community and actors sharing them. As this research showed, the polarisation of anti- and pro-vaccine images reflected the polarisation of the respective communities (see Section 9.3). By analysing vaccine images within their context (e.g. platform, community, actors), this study gained a deeper understanding of the visual communication strategies of the anti- and pro-vaccine networks on Twitter. For example, it uncovered the ways in which anti- and pro-vaccine images used similar figurative elements (e.g. a syringe) to convey different messages (see Section 9.4). This highlights the need to consider the context (community and platform) of images when investigating their messages to avoid bias. Finally, there is little research on the actual impact of vaccine images shared online (Guidry *et al.*, 2018). There is a lack of knowledge on whether anti-vaccine images influence parents' intention to vaccinate and on whether pro-vaccine images are effective at improving vaccine uptake. Therefore, future studies should also investigate the impact of anti- and pro-vaccine images on online audiences.

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Appendix A

Hashtags selection

Vaccine-related hashtags found searching Hashtagify.me, Symplur and Twitter search in May–June 2016. There were no tweets with the following hashtags for several months: #VaccinationsSaveLife, #VaccineInjuries, #ReThinkVaccine.

Highly used hashtags	*Hashtags used often*	*Hashtags used sometime*	*Hashtags seldom used*
#AntiVax	#AntiVaxxer	#AntiVaxer	#Advocate2vaccinate
#CDCWhistleBlower	#CDCtruth	#AntiVaxx	#CDCCoverUp
#HearUs	#FactsOnVax	#AntiVaxxers	#CirqueDuSyringe
#Immunization	#GetVaccinated	#GetVax	#EducateBeforeYouVaccinate
#Vaccination	#IAmTheHerd	#Immunise	#HerdImmunity
#Vaccinations	#Immunisation	#Immunity	#VaccinationDanger
#Vaccine	#Immunize	#TeamVax	#VaccinationEducation
#VaccineInjury	#Vaccinate	#TX4VaxChoice	#VaccinationSavesLife
#Vaccines	#Vaccinated	#VaccinateYourKids	#VaccineChoice
#VaccinesWork	#VaxsHill	#Vaccinating	#VaccineCult
#Vaxxed		#VaccinesKill	#VaccineExempt
#WhyIVax		#VaxTruth	#VaccineFree
			#VaccineHarm
			#VaccineInducedAutism
			#VaccineInjuriesNotRare
			#VaccineJusticeOrElse
			#VaccinesArePoinson
			#VaccineWorks
			#VaxCause
			#VaxChoice
			#VaxDebate
			#VaxFraud
			#VaxPusher
			#VaxVote
			#VaxWithMe

Table A.1 Hashtags related to vaccines identified in June 2016.
Highly used hashtags: more than 10 tweets having that hashtag were posted every day; Hashtags used often: at least one tweet having that hashtag was posted every day; Hashtags used sometime: at least one tweet having that hashtag was posted every week; Hashtags seldom used: at least one tweet having that hashtag was posted in one month. Some hashtags were no longer used during the date of hashtag selection (June 2016).

Other vaccine-related hashtags appeared during May – June 2016. These hashtags were found when searching vaccine-related hashtags on Twitter.

Immunisation campaigns	*Specific vaccines*	*Diseases related*	*Co-occurrent hashtags*
#SpreadTheWordNotF lu	#FluVaccine	#Flu	#Health
#FluFighters	#Gardasil	#Autism	#BigPharma
#GetYourFluShot	#MMR	#Cancer	#BreakABillion
#GetYourFluShotToo		#Chickenpox	#CDC
#MeaslesTruth		#HPV	#Child, #Children
#WhyIVax		#Influenza	#ParentalChoice
#EndPolio		#Measles	#Parents
#EndPolioNow		#Pertussis	#PetCare, #Pet
#SpreadTheWordNotF lu		#Polio	#ProtectingKids
#FluFighters		#Typhoid	#PublicHealth
#GetYourFluShot		#WhoopingCou gh	Related to anti-vaccines claims (e.g.; #Freedom, #AskLoud, #JusticeOrElse)
#GetYourFluShotToo		#YellowFever	Related to call to action (e.g.; #WakeUpAmerica, #WeAreNotGoingAway #HearUs)
			Related to conferences
			Related to countries
			Related to healthcare professionals (e.g. #doctors)
			Related to people (e.g.; #DonaldTrump #JohnRoberts #JustinTimberlake)
			Related to TV programs (e.g.; #AHS or #AHShotel #GOpdebate #CNNdebate)
			#ScienceNotFear
			#Science or related to science

Table A.2 Hashtags related to vaccines identified in June 2016.
These hashtags were very specific: for example about immunisation campaigns, specific vaccines, or diseases, or they were not related to vaccinations but occurred together with vaccine hashtags (co-occurrent).

Appendix B

Categories of tweets

The collected tweets were classified into anti-vaccine, pro-vaccine, pro-safe vaccine, news-related and academic. The description of each category is provided below.

Anti-vaccine tweets

These tweets contained at least one of the following items:

- False information about vaccines – for example, vaccines cause autism or other diseases, vaccines cause sudden infant death
- Claims against vaccination – for example, vaccines are toxic, vaccines do not work, vaccines are #CrimesAgainstHumanity
- Conspiracy theories – for example, "Big Pharma's true story", "The White House use vaccinations to gather the population's DNA", "the truth the doctors will not tell you"
- Comments against pro-vaccine claims – for example, "you know nothing about vaccines (referred to a pro-vaccine user) educate yourself and watch *Vaxxed*"
- Hashtag such as #vaxxed, #CDCwhistleblower, #vaccinesinjury, #CDCtruth, and at least one of the characteristics mentioned above (a few pro-vaccine users might have mentioned these hashtags as well)
- Web links to anti-vaccine web and blog articles – for example, links to the website NaturalNews.com, which spreads misinformation about health issues
- Images with claims against vaccinations – for example, memes mocking vaccination campaigns, graphs demonstrating the correlation between the MMR vaccine and autism (though research demonstrated that there is no correlation between autism and vaccines).

Pro-vaccine tweets

These tweets contained at least one of the following items:

- Claims in favour of vaccination – for example, vaccines save lives, vaccines are safe and effective, "this baby is now protected from measles thanks to vaccinations"
- Messages about immunisation campaigns and calls to action – for example, "the measles vaccines campaign was a success". "fight flu, vaccinate", "let's end polio now", "get your flu shot"

- Comments or jokes against anti-vaccine claims – for example, “The anti-vaxxers fake the graphs to demonstrate they are right”, “Did you know vaccines can cause even stripping?!”
- Information debunking vaccine myths – for example, “the MMR vaccine does not cause autism, and this is why: web link”
- Information about clinics providing free vaccines, timetables of vaccinations, travel vaccinations
- Hashtags such as #VaccinesWork and #WhyIVax and at least one of the characteristics mentioned above (a few anti-vaccine users mention these hashtags as well)
- Web links to pro-vaccine web and blog articles – for example, links to physicians’ or academics blogs that debunk vaccine myths
- Images with claims in favour of vaccination – for example, memes mocking anti-vaccine parents, infographics showing how vaccines work

Pro-safe vaccines tweets

These tweets contained at least one of the following items:

- Claims about the need for safer vaccines and strict controls on vaccine production and administration
- Statements about the limitation of vaccines, but that do not claim vaccines are useless or harmful – for example, “this vaccine has the following limitations that should be addressed”
- Requests not to vaccinate only for one vaccine – for example, I want to vaccinate my child, but I also want to be able to choose what to vaccinate him/her against”
- Concerns about vaccine delivery or market – for example, an NGO refused a donation of vaccines from a pharmaceutical company because it would have increased the market price of those vaccines

News tweets

These tweets did not promote vaccinations and they had at least one of the following items:

- News about vaccinations, outbreaks, vaccine research and development – for example “scientists are developing a new vaccine against Zika”
- News on immunisation campaigns – for example, “the Haitian government launched a vaccine campaign against cholera”

- News related to vaccination – for example, news about politicians claiming they are not against vaccination
- Lay language or limited use of jargon – for example, “Scientists said the nasal flu spray is not effective”, “the human clinical trial for the Zika virus has started”
- A link to web articles published in online newspapers or webzines

Academic tweets

These tweets support vaccination but they do not promote vaccination specifically, unlike the pro-vaccine tweets. They contained at least one of the following items:

- Web links to academic papers, journals, job positions
- No web links to newspapers’ articles
- Patients recruitment messages – for example, “We are looking for subjects for this clinical trial”
- Scientific jargon
- Messages likely aimed at scientists, researchers, physicians, stakeholders – for example, promotion of research centres, academic conferences, university talks
- Hashtags of conferences or scientific events

Not Relevant tweets

These tweets were not about vaccines specifically, for example they were:

- About *The Vaccines*, and indie rock band
- Analogies using vaccines – for example, “e-cigarettes are a vaccine against smoking cigarettes”
- About vaccines for animals – these tweets were not considered because this research focused on images about vaccines for humans.

Appendix C

Categories of actors

Actors’ perspectives on vaccines

Anti-vaccine – these actors share anti-vaccine tweets regularly or declare themselves to be anti-vaccine in their biography. Though they may tweet about other topics as well, their stream focuses on vaccinations and other health topics.

Tendentially anti-vaccine – these actors share anti-vaccine tweets occasionally; their timeline is not entirely about vaccines and health.

Pro-vaccine – these actors share pro-vaccine tweets regularly or declare themselves to be in favour of vaccinations in their biography. Though they may tweet about other topics as well, their timeline focuses on vaccinations and other health topics.

Tendentially pro-vaccine – these actors share pro-vaccine, academic or news-related tweets occasionally. Their timeline is not entirely about vaccines and health.

Pro-safe vaccines – these actors share anti-vaccine, pro-vaccine and/or pro-safe vaccine tweets. Their biography may claim they are pro-safe vaccines or the tweets they share regularly are not completely against vaccinations. E.g. a tweet saying “vaccines should be tested before being administered” is not necessarily against vaccines, especially if supported by evidence (journal papers, vaccine leaflet, report…).

Neutral – these actors are official accounts of news media outlets and tweet mainly (if not only) news.

Type of users

The types of users are listed below. These categories were defined based on how actors defined themselves in their Twitter biography.

Types of users related to activism:

- Activists
- Activist Associations
- Non-governmental organisations (NGOs), foundations, charities, no-profit organisations
- Chief executives, managers, communication strategists, advisors, spokesmen of NGOs
- Vaxxed the Movie – the documentary *Vaxxed: From Cover-Up to Catastrophe* directed by Andrew Wakefield

Types of users related to healthcare and academia:

- Public Health Services – such as the National Health Service (in the UK) and the Centre for Disease Control and Prevention (in the US)
- Hospitals, Research Centres, Universities, Libraries, Laboratories
- Healthcare practitioners, researchers, scholars
- Allied Healthcare practitioners
- Alternative Health clinics
- Alternative Health professionals
- Pharmaceutical companies
- Pharmacies
- Medical Associations
- Students
- Science journals
- Published scientific/medicine books, the account of which is managed by the authors
- Science enthusiasts and supporters

Types of users related to parenting:

- Parents
- Parents Associations
- Forum – an online group of parents that is not established as association

Types of users related to news:

- Media outlets (e.g. newspapers, TV shows, webzines, etc.)
- Journalists (including editors) – journalists or editors working for news media organisations or news websites or as freelancers.
- Bloggers

Other types of users:

- Uncategorised – users who were not definable based on their profile information; for example, users defining themselves with quotes or sentences such as “I love cats”
- Official accounts of services – for example, social network sites, software packages, web services
- Politicians
- Writers
- Official accounts of celebrities
- Official accounts of the army or defence department
- Rotation Curation account – every week a new expert is invited to curate the account
- Artists
- Official accounts of corporates
- Teachers
- Bot account – these accounts state that they are bots retweeting posts about specific topics

Appendix D

Pilot data

Key actors

	June		September		October	
	n	%	N	%	N	%
Anti-vaccine	28	58	28	60	19	37
Pro-vaccine	10	21	7	15	21	41
Tendentially Anti-vaccine	6	13	12	25	8	16
Tendentially Pro-vaccine	4	8	0	0	2	4
Pro-safe vaccine	0	0	0	0	1	2
Total	48	100	47	100	51	100

Table D.1 Key actors classified by vaccine sentiment.
The frequency (n) and percentage (%) of key actors for each category (anti-vaccine, pro-vaccine, tendentially anti-vaccine, tendentially pro-vaccine, pro-safe vaccine) are shown for June, September, and October 2016. These categories are exclusive.

Anti-vaccine actors	June		September		October	
	n	%	N	%	n	%
Activists	9	32	8	29	6	32
Parents	2	7	2	7	1	5
Parent-Activists	5	18	4	14	4	21
Journalist-Activists	2	7	2	7	1	5
Alternative Health practitioners	1	4	2	7	1	5
Research Centres	1	4	1	4	1	5
Uncategorised	6	21	4	14	2	11
Other	2	7.	5	18	3	16
Total	28	100	28	100	19	100

Table D.2 Anti-vaccine key actors classified by type of user.
The frequency (n) and percentage (%) of anti-vaccine key actors for each type of user are shown for June, September, and October 2016. These categories are exclusive. The category ‘Other’ includes types of user that appeared only occasionally and not in all three collections. In June, the category ‘Other’ included an online tool and a politician; in September, it included an online tool, a physician, a media outlet, a writer, and an account on *Vaxxed the movie*; in October it included an NGO, a physician and an account of *Vaxxed the movie*.

Tendentially anti-vaccine actors	*June*		*September*		*October*	
	n	%	n	%	n	%
Activists	2	33	1	9	3	36
Parents	2	33	1	9	1	13
Media outlets	1	17	1	9	1	13
Uncategorised	1	17	5	46	2	25
Other	0	0.00	3	27	1	13
Total	6	100	11	100	8	100

Table D.3 Tendentially anti-vaccine key actors classified by type of user.
The frequency (n) and percentage (%) of tendentially anti-vaccine key actors for each type of user are shown for June, September, and October 2016. These categories are exclusive. The category 'Other' includes types of user that appeared only occasionally and not in all three collections. In September, the category 'Other' included two writers and a parents' association; in October it included a journalist.

Pro-vaccine actors	*June*		*September*		*October*	
	n	%	n	%	n	%
NGOs	5	50	1	14	9	43
CEOs	1	10	1	14	3	14
Healthcare professionals or scholars	1	10	4	58	6	29
Other	3	30	1	14	3	14
Total	10	100	7	100	21	100

Table D.4 Pro-vaccine key actors classified by type of user.
The frequency (n) and percentage (%) of pro-vaccine key actors for each type of user are shown for June, September, and October 2016. These categories are exclusive. The category 'Other' includes types of user that appeared only occasionally and not in all three collections. In June, the category 'Other' included a public health service, a rotation curation account, and a science supporter; in September, it included a research centre; in October it included an activist and two pharmaceutical companies.

Tendentially pro-vaccine actors	*June*		*September*		*October*	
	n	%	n	%	N	%
NGOs	1	25	0	0	0	0
Healthcare professionals or scholars	2	50	0	0	2	100
Students and Bloggers	1	25	0	0	0	0
Total	4	100	0	0	2	100

Table D.5 Tendentially pro-vaccine key actors classified by type of user.
The frequency (n) and percentage (%) of tendentially pro-vaccine key actors for each type of user are shown for June, September, and October 2016. In June one of the scholars was also a parent; in September there were no key actors of this category; in October one of the scholars was also the chief executive of an NGO.

Users with high out-degree

	June		September		October	
	n	%	n	%	n	%
Anti-vaccine	25	78	8	73	14	61
Pro-vaccine	1	3	0	0	1	4
Tendentially anti-vaccine	6	19	3	27	7	31
Tendentially pro-vaccine	0	0	0	0	0	0
Pro-safe vaccines	0	0	0	0	1	4
Total	32	100	11	100	23	100

Table D.6 Types of users with high out-degree.
The frequency (n) and percentage (%) of users with high out-degree for each category (anti-vaccine, pro-vaccine, tendentially anti-vaccine, tendentially pro-vaccine, pro-safe vaccine) are shown for June, September, and October 2016. These categories are exclusive.

Dataset	*Sentiment*	*Type of user*	*In-Degree*	*Out-Degree*
June	Anti-vaccine	Parent-Activist	43	43
	Anti-vaccine	Activist	20	10
	Anti-vaccine	Parent	7	20
	Anti-vaccine	Blogger	21	11
	Anti-vaccine	Writer	11	12
	Tendentially anti-vaccine	Parent	11	19
	Tendentially anti-vaccine	Uncategorised	13	22
	Tendentially anti-vaccine	Activist	7	16
September	Anti-vaccine	Activist	9	28
	Anti-vaccine	Journalist-Activist	40	13
	Tendentially anti-vaccine	Uncategorised	11	23
October	Anti-vaccine	Parent-Activist	73	35
	Anti-vaccine	Activist	34	17
	Anti-vaccine	Journalist-Activist	19	20
	Anti-vaccine	Activist-Healthcare professional	42	14
	Anti-vaccine	Activist	8	17
	Tendentially anti-vaccine	Parent	9	23

Table D.7 Types of anti-vaccine and tendentially anti-vaccine users that had high out-degree centrality and high or relatively high in-degree centrality.
The users were divided for each dataset of the pilot study.

Main data

Frequencies of tweets with or without hashtags collected in the main study.

	Tweets with hashtags (n)	*Tweets without hashtags (n)*	*Total tweets (n)*
Anti-vaccine	2377	223	2600
Pro-vaccine	3841	1793	5634
Pro-safe vaccines	72	71	143
Academic	879	515	1394
News	848	1798	2646
Overall network	8017	4400	12417

Table D.8 Frequency of anti-vaccine, pro-vaccine, pro-safe vaccine, academic and news-related tweets having hashtags or without hashtags.
Data collected in November 2016.

Key actors

Frequencies and percentages of key actors and users with high out-degree for each category (anti-vaccine, pro-vaccine, etc.) and type of actor.

	Frequency (n)	*Percentage (%)*
Anti-vaccine	15	25
Pro-vaccine	18	31
Tendentially Anti-vaccine	5	9
Tendentially Pro-vaccine	9	15
Pro-safe vaccines	0	0
Neutral	12	20
Total	59	100

Table D.9 Key actors classified by vaccine sentiment.
The frequency and percentage of key actors for each category (anti-vaccine, pro-vaccine, tendentially anti-vaccine, tendentially pro-vaccine, pro-safe vaccine, neutral) are shown for November 2016. These categories are exclusive. In this table, key actors are not separated in networks (i.e. pro-vaccine, anti-vaccine and news-related group), but are considered all together.

	Anti-vaccine		*Tendentially anti-vaccine*	
	n	%	n	%
Activists	4	26	1	20
Parent-Activists	4	26	0	0
Parents	1	7	0	0
Journalist-Activists	1	7	0	0
Alternative Health practitioners	1	7	0	0
Alternative Health clinics	0	0	1	20
Research Centres	1	7	0	0
NGOs	1	7	1	20
Journalists	1	7	0	0
News media outlets	0	0	1	20
Service	1	7	0	0
Uncategorised	0	0	1	20
Total	15	100	5	100

Table D.10 Key actors within the anti-vaccine community classified by sentiment type of user.
The frequency (n) and approximate percentage (%) of key actors for each type of actor and sentiment are shown for November 2016.The category 'Service' includes digital media platforms, software, and web tools.

	Pro-vaccine		*Tendentially pro-vaccine*	
	n	%	n	%
NGOs	6	40	0	0
Public Health Services	6	40	0	0
Activists and Healthcare professionals	1	7	0	0
CEO and Healthcare professionals	1	7	0	0
CEO/managers of NGOs	0	0	1	25
Hospital/Research centres	0	0	1	25
Rotational curation accounts	1	7	0	0
Writers	0	0	1	25
Politicians	0	0	1	25
Total	15	100	4	100

Table D.11 Key actors within the pro-vaccine network classified by sentiment and type of user.
The frequency (n) and approximate percentage (%) of key actors for each type of actor and sentiment are shown for November 2016. CEO – Chief executive or manager of an NGO.

	Neutral		Pro-vaccine		Tendentially pro-vaccine	
	n	%	n	%	n	%
NGOs	0	0	2	50	2	40
Chief executives of NGOs	0	0	1	25	0	0
Research Centres	0	0	1	25	0	0
News Media outlets	11	100	0	0	0	0
Army related	0	0	0	0	2	40
Healthcare professionals and Journalists	0	0	0	0	1	20
Total	11	100	4	100	5	100

Table D.12 Key actors within the news-related group classified by sentiment and type of user.
The frequency (n) and approximate percentage (%) of key actors for each type of actor and sentiment are shown for November 2016.

Users with high out-degree

	Frequency (n)	Percent (%)
Anti-vaccine users	5	38
Pro-vaccine users	2	15
Tendentially anti-vaccine users	1	8
Tendentially pro-vaccine users	4	31
Neutral users	1	8
Total	13	100

Table D.13 Users with high out-degree centrality.
Frequency (n) and percentage (%) of users with high out-degree centrality, classified on sentiment. Only the users identified in the anti-vaccine community and the pro-vaccine network are shown since there was none in the news-related group. Data from November 2016 collection.

	Anti-vaccine	*Pro-vaccine*	*Tendentially anti-vaccine*	*Tendentially pro-vaccine*	*Neutral*
Uncategorised	1	1	1	0	0
Activists	1	0	0	1	0
Activists and Parents	2	0	0	0	0
Activists and Healthcare prof.	0	0	0	1	0
CEOs of NGO	0	1	0	0	0
Healthcare professionals	1	0	0	2	0
Bot accounts	0	0	0	0	1
Total	5	2	1	4	1

Table D.14 Types of users with high out-degree for each group.

The different types of anti-vaccine, pro-vaccine, tendentially anti-vaccine, tendentially pro-vaccine and neutral users with high out-degree are shown. Data from November 2016.

Appendix E

Codebook for the content analysis of the images of the pilot research.

Picture format

- Photos – e.g. mobile camera photos, studio photos, advertising photos
- Text-only images
- Infographics
- Charts and tables
- Cartoons and drawings
- Screenshots – e.g. screenshots of social media profiles, posts, conversations, websites pages. They show a cropped picture or the apps icons of the smartphone screen on the top
- Gifs
- Leaflets – they are images promoting events, in which the text is dominant and the picture functions as background
- Mixed pictures – they are collages of different photos, cartoons, and/or text.

Presence of text

- With text – captions, titles, text overlay
- Without text

Where the topics are shown

- Text of the tweet
- Picture
- Hashtag

Topics

Vaccines related

- Vaccine safety – messages about side effects of vaccines, safety of vaccines, toxicity of vaccines, injuries induced by vaccines
- Autism – messages either supporting or rejecting the link between autism and vaccines
- Vaccine development – messages about vaccine production, delivery, administration, vaccine schedules, and components
- Vaccine efficacy – messages stating vaccine are either effective or ineffective
- Vaccine confidence – messages about vaccine coverage or vaccine hesitancy
- Immunisation campaigns – news, messages, call for action of immunisation campaigns
- Pro-vaccine statements - Statements supporting vaccinations, usually shared by users who are not organisations. These messages are generic claims about the importance of being vaccinated, but they do not mention vaccine efficacy or safety
- Countering anti-vaccine claims/users – messages attacking or mocking anti-vaccine users with memes, attacks, insults
- Countering pro-vaccine claims/users – messages attacking or mocking pro-vaccine users with memes, attacks, insults; protests about anti-vaccine users being bullied by pro-vaccine actors

Others

- Financial issues – messages about health care costs to cure vaccine-preventable diseases, corruption of health organisations and physicians, funding for research on vaccine development or immunisation campaigns. When these messages were combined with the topics “vaccine development”, they were related to the price of vaccines on the market (e.g. a pharmaceutical company reducing the price of vaccines) or on new funding for vaccine research
- Conspiracy – messages claiming health organisations or governments support vaccines because of vested interests, to control the masses; messages stating pharmaceutical companies or health organisations are hiding the truth about vaccine safety and efficacy
- Freedom of choice – messages related to civil liberties, contesting mandatory vaccinations, campaigning for the right to choose whether to vaccinate or not
- Vaxxed – messages related to the documentary *Vaxxed the movie* (Wakefield and Bigtree, 2016) or mentioning *Vaxxed*

- IKEA – messages related to the “Boycott IKEA” campaign, launched by the Vaxxed group when the IKEA staff asked them to move their bus from the customer car park
- Pharmaceutical companies – messages mentioning pharmaceutical companies
- US presidential candidates – messages mentioning the candidates for the US presidential elections, Hillary Clinton or Donald Trump
- Events – messages related to public events, showings of *Vaxxed the movie*
- Conferences – messages related to academic or stakeholder conferences, congresses, global meetings

Objects

Laboratory or hospital related

- Hospital/Laboratory coats or disposable gloves – they resembled those used in a laboratory or in a hospital
- Toxic, poison or biohazard signs
- Syringes
- Oral vaccines
- Nasal sprays
- Vaccine vials
- Vaccine packages

Other

- Vaxxed – logo or hashtag of *Vaxxed the documentary*
- Vaxxed bus – an icon used by the Vaxxed activist movement

People

- White skin – possibly Caucasian
- Black or Asian – belonging to any other ethnicity
- Men
- Women
- Children

Appendix F

Following the pilot study, minor changes were made to the codebook in order to make the analysis more extensive. No changes were made to the codes relating to picture format, presence of text, and where the topics were shown. However, minor changes, detailed below, were made to the topics, objects and people.

Topics

Vaccines related

- Vaccine generic information – messages related to history of vaccines or generic information about vaccines; these messages were neither against or in favour of vaccination
- Vaccine schedule – messages about the recommended vaccine schedule for babies and children
- Anti-vaccine party at the elections – the participation of a political party against vaccines at the federal elections in Australia, called the Involuntary Medication Objectors (Vaccination/Fluoride) Party
- Immunisation campaigns – news or messages on the launch of immunisation campaigns, on a new bill for increasing immunisation rates…
- Pro-immunisation messages – immunisation campaign messages that are not related to the official launch of the campaign (e.g. “get your flu shot”)

Others

- Vaxxed – messages related to the documentary *Vaxxed the movie* (Wakefield and Bigtree, 2016)
- Hashtag Vaxxed – the hashtag #Vaxxed was counted separately from the topic *Vaxxed*
- Team Daniel – messages related to a campaign supporting supposed victims of vaccine injuries, such a child called Daniel

Vaccine-preventable diseases

- Cholera
- Zika
- Flu

- Human Immunodeficiency Virus (HIV)
- Human Papilloma Virus (HPV)
- Measles
- Malaria
- Polio
- Smallpox
- Chickenpox
- Hepatitis
- Ebola
- Pneumonia
- Whooping cough

Objects

Lab related

- Hospital/Laboratory coats or disposable gloves
- Toxic, poison or biohazard signs
- Chemical formulas
- Microscopes
- Test tubes
- Petri dishes
- Mice
- Cells – human or animal cells, unicellular organism, microbes, viruses
- Mosquitos

Vaccines related

- Syringes
- Vaccine vials
- Oral vaccines
- Nasal sprays
- Skin patches
- Vaccine packages

Other

- Buildings
- Maps
- Newspapers
- Books
- Pharmaceutical company logo
- Boxes – delivery
- Phone icon
- Superheroes
- Wheelchairs

People

Generic features

- Hands – when the only arms or hands of a person are visible.

Politicians and celebrities

- Donald Trump
- Hillary Clinton
- Melania Trump
- Andrew Wakefield
- Bill Gates

Related to the US presidential candidate Donald J. Trump

- Photos of Donald Trump
- Donald Trump's tweets

Appendix G

Pilot Research content analysis

Anti-vaccine images selected at random

Types of pictures

	Frequency (n)	*Percentage (%)*
Photos	26	52
Screenshots	8	16
Mixed pictures	6	12
Pictures with only text	4	8
Charts and tables	4	8
Leaflets	2	4
Drawings and cartoons	0	0
Infographics	0	0
Gifs	0	0
Total	50	100

Table G.1 Frequency and percentage of the types of pictures among the anti-vaccine images selected at random.
These images were collected in June, September and October 2016.

Location of the topics

	Tweet	*Picture*	*Hashtag*
Countering pro-vaccine users/claims	5	0	2
Pharmaceutical companies	2	0	1
Conspiracy theories	12	5	2
Events	5	3	1
Freedom of choice	4	2	0
Financial issues	5	2	2
US presidential candidates	3	3	1
Vaccine development	2	8	0
Vaccine efficacy	3	1	1
Vaccine safety	21	16	6
Autism	3	1	3
Vaxxed	6	9	8
IKEA	2	3	4

Table G.2 Frequency of topics appearing in the tweet (text), picture or hashtag of the anti-vaccine images selected at random.

These images were collected in June, September and October 2016. One topic could appear in all three places (tweet. picture, and hashtag) as well as in only one or two of them. The tweet, picture, or hashtag of the same image could contain more than one topic. Moreover, a topic in a hashtag was also considered as included in the tweet when the hashtag was necessary to understand the text of the tweet (e.g. everybody should watch #Vaxxed).

Type of pictures shared by different types of users

User	*Photo*	*Mixed picture*	*Only text*	*Chart/ Table*	*Screenshot*	*Leaflet*	*Total*
Activist	6	0	1	3	2	1	13
Uncategorised	4	2	0	1	0	0	7
NGO	1	0	0	0	0	1	2
Parent-Activist	4	2	1	0	4	0	11
Journalist-Activist	3	1	1	0	0	0	5
Blogger	0	1	0	0	0	0	1
Service	0	0	1	0	0	0	1
Media	3	0	0	0	0	0	3
Healthcare Professional	1	0	0	0	1	0	2
Alternative Health professional	1	0	0	0	1	0	2
Research Institute	1	0	0	0	0	0	1
Parent	1	0	0	0	0	0	1
Parent association	1	0	0	0	0	0	1
Total	26	6	4	4	8	2	50

Table G.3 Frequency of type of the pictures shared by types of users in the sample of the anti-vaccine images selected at random.
These images were collected in June, September and October 2016.

Pro-vaccine images selected at random

Types of pictures

	Frequency (n)	*Percentage (%)*
Photos	36	72
Infographics	8	16
Leaflets	2	4
Screenshots	2	4
Charts and Tables	1	2
Gifs	1	2
Mixed pictures	0	0
Drawings and cartoons	0	0
Pictures with only text	0	0
Total	50	100

Table G.4 Frequency and percentage of the types of pictures among the pro-vaccine, academic and news-related images selected at random.
These images were collected in June, September and October 2016.

Location of the topics

	Tweet	*Picture*	*Hashtag*
Countering anti-vaccine claims/users	4	1	1
Pharmaceutical companies	1	0	0
Events	1	1	0
Conferences	6	7	2
Immunisation campaigns	19	4	6
Financial issues	2	1	0
Pro-vaccine statements	5	2	1
Vaccine confidence	3	2	0
Vaccine development	12	2	0
Vaccine efficacy	8	4	1
Vaccine safety	1	2	0
Autism	0	2	0

Table G.5 Frequency of topics appearing in the tweet (text), picture or hashtag of the pro-vaccine, academic and news-related images selected at random.
These images were collected in June, September and October 2016. One topic could appear in all three places (tweet. picture, and hashtag) as well as in only one or two of them. The tweet, picture, or hashtag of the same image could contain more than one topic. Moreover, a topic in a hashtag was also considered as included in the tweet when the hashtag was necessary to understand the text of the tweet (e.g. #vaccines save lives).

Type of pictures shared by different types of users

	Photo	*Chart /Table*	*Leaflet*	*Gif*	*Infographic*	*Screenshot*	*Total*
NGO	12	0	2	0	4	0	18
Media	7	0	0	0	1	0	8
Healthcare Professional	3	1	0	1	2	2	8
Rotation curator account	3	0	0	0	0	0	3
Service	2	0	0	0	0	0	2
Parent-Journalist	2	0	0	0	0	0	2
Parent-Activist	1	0	0	0	0	0	1
Research centre/University	2	0	0	0	0	0	1
NGO chief executive	1	0	0	0	1	0	2
Health Organisation	1	0	0	0	0	0	1
Pharmaceutical company	1	0	0	0	0	0	1
Blogger	1	0	0	0	0	0	1
Total	36	1	2	1	8	2	50

Table G.6 Frequency of type of the pictures shared by the most recurrent types of users in the sample of the pro-vaccine, academic and news-related images selected at random.
These images were collected in June, September and October 2016.

Most shared anti-vaccine images

Types of pictures

	Frequency (n)	*Percentage (%)*
Photos	31	62
Drawings and cartoons	5	10
Pictures with only text	4	8
Screenshots	4	8
Mixed pictures	3	6
Leaflets	2	4
Gifs	1	2
Infographics	0	0
Charts and tables	0	0
Total	50	100

Table G.7 Frequency and percentage of the types of pictures among the popular anti-vaccine images.
These images were collected in June, September and October 2016.

Location of the topics

	Tweet	*Picture*	*Hashtag*
Countering pro-vaccine users/claims	1	0	0
Pharmaceutical companies	3	2	0
Conspiracy theories	17	6	3
Events	2	3	2
Freedom of choice	7	5	4
Financial issues	1	2	0
US presidential candidates	1	3	0
Vaccine confidence	1	1	0
Vaccine development	5	9	0
Vaccine efficacy	2	4	1
Vaccine safety	12	20	1
Autism	4	5	1
Vaxxed	14	8	26
IKEA	1	0	3

Table G.8 Frequency of topics appearing in the tweet (text), picture or hashtag of the popular anti-vaccine images.
These images were collected in June, September and October 2016. One topic could appear in all three places (tweet. picture, and hashtag) as well as in only one or two of them. The tweet, picture, or hashtag of the same image could contain more than one topic. Moreover, a topic in a hashtag was also considered in the tweet when the hashtag was necessary to understand the text of the tweet (e.g. everybody should watch #Vaxxed).

Type of pictures shared by different types of users

	Photo	Mixed picture	Only text	Screenshot	Leaflet	Cartoon/ Drawing	Gif	Total
Activist	11		1	2	2	1	1	18
Uncategorised	4	1	0	1	0	0	0	6
Parent association	3	0	0	0	0	2	0	5
Journalist-activist	7	1	2	0	0	1	0	11
Journalist	1	0	0	0	0	0	0	1
Blogger	1	0	0	1	0	0	0	2
Alternative Health professional	1	0	0	0	0	0	0	1
Research Institute	1	0	0	0	0	0	0	1
Priest	1	0	0	0	0	0	0	1
Writer	1	0	0	0	0	0	0	1
Parent-activist	1	0	0	0	0	0	1	0
Service	0	0	1	0	0	1	0	2
Total	31	3	4	4	2	5	1	50

Table G.9 Frequency of type of the pictures shared by the most recurrent types of users in the sample of the most shared anti-vaccine images.
These images were collected in June, September and October 2016.

Most shared pro-vaccine images

Types of pictures

	Frequency (n)	Percentage (%)
Photos	35	70
Infographics	5	10
Drawings and cartoons	4	8
Charts and Tables	2	4
Pictures with only text	2	4
Gifs	1	2
Leaflets	1	2
Mixed pictures	0	0
Screenshots	0	0
Total	50	100

Table G.10 Frequency and percentage of the types of pictures among the popular pro-vaccine, academic and news-related images.
These images were collected in June, September and October 2016.

Location of the topics

	Tweet	Picture	Hashtag
Countering anti-vaccine claims/users	1	1	0
Events	3	1	0
Conferences	6	6	0
Immunisation campaigns	19	9	8
Financial issues	4	3	0
Pro-vaccine statements	3	1	0
Vaccine confidence	2	2	0
Vaccine development	8	6	0
Vaccine efficacy	8	4	1
Vaccine safety	3	0	0
Autism	1	2	0

Table G.11 Frequency of topics appearing in the tweet (text), picture or hashtag of the popular pro-vaccine, academic and news-related images.
These images were collected in June, September and October 2016. One topic could appear in all three places (tweet. picture, and hashtag) as well as in only one or two of them. The tweet, picture, or hashtag of the same image could contain more than one topic. Moreover, a topic in a hashtag was also considered in the tweet when the hashtag was necessary to understand the text of the tweet (e.g. #vaccines save lives).

Type of pictures shared by different types of users

	Photo	*Chart/ Table*	*Only text*	*Leaflet*	*Cartoon/ Drawing*	*Gif*	*Infographic*	*Total*
NGO	20	0	1	0	2	0	1	24
Media	3	0	0	0	0	0	0	3
NGO chief executive	3	1	0	0	0	0	1	5
Healthcare professional	6	1	1	0	2	1	3	14
Pharmaceutical company	1	0	0	0	0	0	0	1
Research Institute	0	0	0	1	0	0	0	1
University	1	0	0	0	0	0	0	1
Health organisation employee	1	0	0	0	0	0	0	1
Total	35	2	2	1	4	1	5	50

Table G.12 Frequency of type of the pictures shared by the most recurrent types of users in the sample of the most shared pro-vaccine, academic and news-related images.
These images were collected in June, September and October 2016.

Main Research

Most shared anti-vaccine images

Types of pictures

	Frequency (n)	Percentage (%)
Photos	25	50
Mixed pictures	11	22
Pictures with only text	6	12
Charts and Tables	3	6
Drawings and cartoons	2	4
Screenshots	2	4
Leaflets	1	2
Infographics	0	0
Gifs	0	0
Total	50	100

Table G.13 Frequency and percentage of the types of pictures among the popular anti-vaccine images.
These images were collected in November 2016.

Location of the topics

	Tweet	Picture	Hashtag
Countering anti-vaccine claims/users	1	1	0
Pharmaceutical companies	1	0	1
Conspiracy theories	14	10	2
Freedom of choice	8	7	0
Financial issues	1	1	0
Vaccine development	3	4	2
Vaccine efficacy	7	3	0
Vaccine safety	23	15	7
Vaccine schedule	6	9	4
Vaxxed	4	5	3
Autism	5	2	0

Table G.14 Frequency of topics appearing in the tweet (text), picture or hashtag of the popular anti-vaccine images.
These images were collected in November 2016. One topic could appear in all three places (tweet. picture, and hashtag) as well as in only one or two of them. The tweet, picture, or hashtag of the same image could contain more than one topic. Moreover, a topic in a hashtag was also considered in the tweet when the hashtag was necessary to understand the text of the tweet (e.g. everybody should watch *#Vaxxed the movie*).

<u>Type of pictures shared by different types of users</u>

	Photo	*Mixed picture*	*Only text*	*Chart/ Table*	*Screen shot*	*Leaflet*	*Cartoon/ Drawing*	*Total*
Activist	10	3	3	3	1	0	1	21
Journalist - Activist	9	0	1	0	0	0	0	10
Journalist	2	0	0	0	1	0	0	3
Parent-Activist	1	2	0	0	0	0	1	4
Uncategorised	1	2	1	0	0	1	0	5
NGO	1	1	0	0	0	0	0	2
Politician	1	0	0	0	0	0	0	1
Parent	0	0	1	0	0	0	0	1
Allied Healthcare professional	0	1	0	0	0	0	0	1
Allied Health Clinic	0	1	0	0	0	0	0	1
Forum	0	1	0	0	0	0	0	1
Total	25	11	6	3	2	1	2	50

Table G.15 Frequency of type of the anti-vaccine pictures shared by the most recurrent types of users. These images were collected in November 2016.

Most shared pro-vaccine and academic images

Types of pictures

	Frequency (n)	Percentage (%)
Photos	27	54
Infographics	6	12
Pictures with only text	5	10
Screenshots	4	8
Charts and Tables	3	6
Gifs	3	6
Drawings and cartoons	2	4
Leaflets	0	0
Mixed pictures	0	0
Total	50	100

Table G.1 Frequency and percentage of the types of pictures among the popular pro-vaccine and academic images.
These images were collected in November 2016.

Location of the topics

	Tweet	Picture	Hashtag
Countering anti-vaccine claims/users	3	1	0
Pharmaceutical companies	8	5	0
Conspiracy theories	2	0	0
Events	0	1	0
Conferences	2	2	2
Immunisation campaigns	9	1	2
Financial issues	10	9	0
Pro-immunisation messages	11	10	8
Pro-vaccine statements	6	1	0
Vaccine confidence	0	1	0
Vaccine development	14	10	0
Vaccine efficacy	9	6	1
Vaccine safety	7	7	0
Vaccine schedule	1	3	0
Autism	2	2	0

Table G.2 Frequency of topics appearing in the tweet (text), picture or hashtag of the popular pro-vaccine and academic images.
These images were collected in November 2016. One topic could appear in all three places (tweet. picture, and hashtag) as well as in only one or two of them. The tweet, picture, or hashtag of the same image could contain more than one topic. Moreover, a topic in a hashtag was also considered in the tweet when the hashtag was necessary to understand the text of the tweet (e.g. #vaccines save lives).

Type of pictures shared by different types of users

	Photo	*Mixed picture*	*Only text*	*Chart/*	*Screenshot*	*Leaflet*	*Cartoon/Drawing*	*Gif*	*Infographic*	*Total*
NGO	14	0	0	1	0	0	0	0	3	18
Activist	1	0	0	0	1	0	0	0	0	2
Healthcare professional	0	0	1	1	1	0	0	0	0	3
Corporate manager	0	0	0	0	0	0	1	0	0	1
Health Organization	4	0	1	1	0	0	1	3	1	11
Hospital, Research Centre, University, Library	0	0	0	0	1	0	0	0	2	3
Media	2	0	0	0	0	0	0	0	0	2
Uncategorised	1	0	1	0	0	0	0	0	0	2
NGO chief executive	2	0	0	0	0	0	0	0	0	2
Pharmaceutical company	1	0	0	0	0	0	0	0	0	1
Politician	1	0	1	0	0	0	0	0	0	2
Student	1	0	0	1	0	0	0	0	0	2
Writer	0	0	1	0	0	0	0	0	0	1
Total	27	0	5	4	3	0	2	3	6	50

Table G.3 Frequency of type of the pro-vaccine and academic pictures shared by the most recurrent types of users.
These images were collected in November 2016.

Most shared news-related images

Types of pictures

	Frequency (n)	*Percentage (%)*
Photos	39	78
Infographics	3	6
Mixed pictures	3	6
Screenshots	2	4
Pictures with only text	1	2
Drawings and cartoons	1	2
Leaflets	1	2
Charts and tables	0	0
Gifs	0	0
Total	50	100

Table G.4 Frequency and percentage of the types of pictures among the popular news-related images.
These images were collected in November 2016.

Location of the topics

	Tweet	*Picture*	*Hashtag*
Vaccine development	26	3	0
Vaccine efficacy	5	1	0
Vaccine confidence	4	3	0
Vaccine safety	1	0	0
Vaccine schedule	0	1	0
Generic information about vaccines	2	0	0
Immunisation campaigns	8	1	0
Financial issues	6	1	0
Freedom of choice	2	1	0
Pharmaceutical companies	2	1	0
Conspiracy theories	1	0	0
Anti-vaccine party at the elections	1	1	0
Events	0	2	0

Table G.20 Frequency of topics appearing in the tweet (text), picture or hashtag of the popular news-related images.
These images were collected in November 2016. One topic could appear in all three places (tweet. picture, and hashtag) as well as in only one or two of them. The tweet, picture, or hashtag of the same image could contain more than one topic. Moreover, a topic in a hashtag was also considered as included in the tweet when the hashtag was necessary to understand the text of the tweet (e.g. Researchers are developing a new #Zika vaccine).

Type of pictures shared by different types of users

	Photo	Mixed picture	Only text	Screenshot	Leaflet	Cartoon/ Drawing	Infographic	Total
Media	25	0	0	0	0	1	2	28
NGO	4	2	0	0	0	0	0	6
Healthcare professional	2	0	0	2	1	0	0	5
University, Research Centre	2	0	0	0	0	0	0	2
NGO chief executive	2	0	0	0	0	0	0	2
Writer	1	0	0	0	0	0	0	1
Military related	1	0	0	0	0	0	1	2
Political Party	1	0	0	0	0	0	0	1
Student	1	0	0	0	0	0	0	1
Uncategorised	0	0	1	0	0	0	0	1
Corporate manager	0	1	0	0	0	0	0	1
Total	39	3	1	2	1	1	3	50

Table G.21 Frequency of type of the news-related pictures shared by the most recurrent types of users. These images were collected in November 2016.

Appendix H

Anti-vaccine	*Hashtags*	*Link*	*Picture Content*	*Background*	*Picture type*	*Picture origin*	*Event related*	*Messages*	*Scientific information provided*
Figure 8.1 *(Pilot dataset)*	Topical and generic	Paper	White child receiving vaccine	Blank	Collage of visual and textual elements	Image archive	No	Combined vaccines are not safe Do not trust medical authorities (CDC)	Fake scientific evidence
Figure 8.2 *(Pilot dataset)*	Topical	No	White nurse, syringe with poison symbol, white man	Blank	Collage of visual and textual elements	Not clear	No	Flu vaccine is not safe Do not trust medical authorities (CDC, physicians)	Re-interpretation of scientific facts
Figure 8.3 *(Pilot dataset)*	Topical	No	Elephant healthcare professional	Blank	Original drawing	Not clear	No	Do not trust medical authorities (physicians) Seek alternative sources of information (Vaxxed)	//
Figure 8.4 *(Pilot dataset)*	Topical	News article	Protest	Room (empty)	Re-contextualised photo	Not clear	Yes?	Do not trust medical authorities (medical tyranny) Vaxxed as alternative and trusted source of information Vaccines are not safe	//
Figure 8.5 *(Main dataset)*	Topical and generic	State ment	White girl receiving vaccine	Blank	Modified photo	Image archive	No	HPV vaccine is not safe Do not trust medical authorities (CDC)	Fake scientific evidence

Anti-vaccine	***Hashtags***	***Link***	***Picture Content***	***Background***	***Picture type***	***Picture origin***	***Event related***	***Messages***	***Scientific information provided***
Figure 8.6 *(Main dataset)*	Topical and generic	No	White baby receiving vaccine	Blank	Modified photo	Image archive	No	Vaccines are not safe Seek alternative sources of information	Misunderstanding of scientific information
Figure 8.7 *(Main dataset)*	Generic	No	White child	Home environment	Modified photo	Online meme, not clear	No	Do not trust medical Vaccines cause autism authorities (physicians)	//
Figure 8.8 *(Main dataset)*	Topical and generic	News article	Donald Trump	US flag	Re-contextualised photo	Image archive	Yes	Donald Trump stand with anti-vaccine Vaccines cause autism	Researcher mentioned collaborated to *Vaxxed the movie*

Pro-vaccine	*Hashtags*	*Link*	*Picture Content*	*Background*	*Picture type*	*Picture origin*	*Event related*	*Messages*	*Scientific information provided*
Figure 8.9 *(Pilot dataset)*	Topical and generic	No	Ethiopian woman and child	Outdoor, blurred	Re-contextualised photo	NGO's photo	Not clear, possibly campaign-related	Vaccination as prevention intervention Vaccines protect lives	//
Figure 8.10 *(Pilot dataset)*	Campaign-related and topical	No	Afghan girl receiving oral vaccine from female healthcare professional	Refugee camp	Modified photo	NGO's photo	Yes	Vaccination as good investment for future generations Vaccinations as prevention intervention Vaccinations to help children in unfair situations (e.g. refugees)	Money return from investing in vaccinations – correct information but no evidence provided –
Figure 8.11 *(Pilot dataset)*	Topical	No	African child receiving vaccine	Not clear	Re-contextualised photo	NGO's photo	Not clear, possibly campaign-related	Vaccines save lives – in developing countries –	//
Figure 8.12 *(Pilot dataset)*	Topical and generic	No	Two Saudi men, NGO's chairwoman and another man concluding agreement	Meeting room	Re-contextualised photo	NGO's photo	Yes	Success of NGO in reaching agreement	//
Figure 8.13 *(Main dataset)*	Topical and campaign-related	No	African child receiving vaccine	Outdoor	Modified photo	NGO's photo	Yes	Pneumonia vaccine price is too high and developing countries cannot afford it Pneumonia vaccine can save 1 million lives each year	– correct information but no evidence provided –

								Call to convince pharmaceutical companies to reduce the vaccine price	
Pro-vaccine	***Hashtags***	***Link***	***Picture Content***	***Background***	***Picture type***	***Picture origin***	***Event related***	***Messages***	***Scientific information provided***
Figure 8.14 *(Main dataset)*	Generic and campaign-related	No	White nurse holding a child	Blue	*Ad hoc* photo	Health organisation's photo	Yes	Vaccinate children against flu Promotion of flu nasal spray for children	//
Figure 8.15 *(Main dataset)*	Topical and campaign-related	Yes	Text	Pink and purple	*Ad hoc* picture	Health organisation's picture	Yes	Promotion of flu vaccination Flu vaccination protects surrounding people	Debunking myths on flu vaccine
Figure 8.16 *(Main dataset)*	Generic and topical	No	Haitians and NGO workers unloading vaccines delivered	Airport	*Ad hoc* picture	NGO's picture	Yes	NGO's support to Haitian vaccination campaign	//

News	*Hashtags*	*Link*	*Picture Content*	*Background*	*Picture type*	*Picture origin*	*Event related*	*Messages*	*Scientific information provided*
Figure 8.18 *(Main dataset)*	None	Yes	Mosquito	Blank	Re-contextualised photo	Image archive	Yes	News on Zika vaccine development	//
Figure 8.19 *(Main dataset)*	Topical	Yes	Six-well plate	Research lab, blurred	Photo	Research lab (mentioned in the article)	Yes	News on Zika vaccine development	//
Figure 8.20 *(Main dataset)*	None	Yes	Haitian girl receiving oral vaccine	In-door, not clear	Re-contextualised photo	Image archive	Yes	News on Haitian cholera vaccination campaign	//
Figure 8.21 *(Main dataset)*	None	Yes	Haitian man receiving oral vaccines by male volunteers	Out-door	Video frame	News outlet's video	Yes	News on Haitian cholera vaccination campaign	//