Supplementary Material for: Large-scale digital signatures of emotional response to the Covid-19 Vaccination Campaign

1 Data

We collected social media data about the large massive Vaccination Campaign against Covid-19 through special Twitter's endpoint dedicated to COVID-19 research between August 31, 2020 and July 15, 2021, from the announcement of the availability of the first Covid-19 vaccines up to the peak of the vaccine campaign in Europe and in the United States. Our dataset consists of 9.6 million of messages posted on Twitter from 3 million of unique users. We focused our attention on data captured by the filter of the Twitter Firehose on Covid-19 in 18 among the most represented languages on Twitter. More specifically, we focused on terms related to the vaccination, anti-vax campaigns but also to the most known vaccine brands, such as Pfizer, Astrazeneca, Johnson&Johnson, Moderna, Sputnik V.

Language	Subjects		Verbs	Participes	Root	Anti-vax
English	vaccine(s)	vaccination(s)	vaccine	vaccinated	vaccin	anti-vax
Italian	vaccino(i)	vaccinazione(i)	vaccinare	vaccinato	vaccin	no-vax
Spanish	vacuna(s)	vacunaciòn/vacunas	vacunar	vacunado	vacun	anti-vacunas
Catalan	vacuna(s)	vacunaciò/vacunes	vacunar	vacunat	vacun	
Portuguese	vacina(s)	vacinação/ões	vacinar	vacinado	vacin	anti-vacinas
French	vaccin (s)	vaccination(s)	vacciner	vacciné	vaccin	anti-vaccins
German	Impfstoff (e)	Impfung(en)	impfen	geimpft/ geimpften	impf	anti-impf
Russian	вакцина	Вакцинация/прививки	вакцинировать	вакцинированный	вакцина	антивакс
Polish	szczepionka/i	szczepienie	szczepić	szczepione	szczepi	Anty-szczepionki
Danish	vaccine (r)	vaccination (er)	vaccinere	vaccineret	vaccin	
Swedish	vaccin(er)	vaccinering	vaccinera	vaccinerad	vacciner	Vaccinationsmotstånd
Turkish	aşı(lar)	aşılama	aşılamak	aşılanmış	aşı	aşı karşıtı
Indonesian	vaksin	vaksinasi	divaksinasi	divaksinasi	vaksin	
Japanese	ワクチン	予防接種	予防接種	予防接種		
Thai	วัคซีน	การฉีดวัคซีน	ฉีดวัคซีน	ฉีดวัคซีน		
Korean	백신	백신 접종	예방 접종	예방 접종		안티 백스
Arabic	مصل	تلقيح	لقح	تطعيم		
Hindi	टीका (टीके)	टीका (टीकाकरण)	टीका लगाना	टीका		एंटी टीका लगाना

Figure 1: **Terms about vaccine discourse.** Terms from the 18 most used language on Twitter, used to filter the Twitter Firehose on Covid-19 for this analysis. The terms are related to vaccination. Additionally, we considered also the following terms related to the vaccine names: astrazeneca, moderna, johnson & johnson, sputnik, pfizer, biontech.

We collected online discussions where non specific contentious topic dominates consisting of more than 10 million of messages posted on Twitter from 6 million of unique users. This dataset covers only few days, from the 21/4/2021 to the 24/4/2021, since our interest was to capture any message on Twitter without filtering for specific keywords. In this way, we collected social media posts that represent a sort of baseline sample of the ordinary discussion found on Twitter. Thus, we have compared our analysis about a specific polarizing issue, such as the massive pharmaceutical intervention campaign against Covid-19 with a baseline sample taken as a benchmark of online discussions.

2 Emotional Analysis

We wanted to investigate how emotional responses change during the large-scale Covid-19 vaccination campaign with respect to a baseline sample where no contentious topic dominates. For this reason, we tested different algorithms able to capture the emotional responses of the messages posted on Twitter. Initially, we focused on the well-known Valence- Arousal-Dominance model [5]. This algorithm does not perform particularly well on our dataset, since the three dimension of emotions are highly correlated among them. We decided to adopt another algorithm that classifies the emotions in eight categories; four of which with a positive valence (Joy, Trust, Anticipation, Surprise) and four with a negative valence (Fear, Disgust, Anger, Sadness). This allows us to better capture the variability and differences between each emotion in our case study. In some of our analysis, we decided to show the emotional distribution normalized in a range between -1 (completely negative valence) and +1 (completely positive valence). In order to do so, we found the total emotional value of the messages posted on Twitter by summing each singular emotion. Then, we divided each emotion by the total emotional value found and we grouped the positive emotions (Anticipation, Surprise, Joy and Trust) and the negative emotions (Sadness, Anger, Fear, Disgust) into two different categories (positive vs negative emotions) and finally we normalized the data in a range between -1 and +1.

3 Type of Users Accounts

In our research, we were also interested in the emotional response compared to the baseline, especially when we take into account characteristics of the users and the type of information shared in the online platform. In particular, a dimension that might elicit different emotional response is the public status of the accounts (verified vs unverified accounts). Figure 6 shows the emotional distribution of verified and unverified accounts (A) and the emotional responses of the verified and unverified users as distinguished between bots and humans. Discerning bots from humans is usually carried out by observing the social behaviour of the users in online social systems. In particular, to distinguish a bot from a human, we chose the criteria proposed by [1]. More specifically, automated accounts are usually associated to some forms of unusual behavior, either for the great amount of contents created or the frequency at which it created, as discussed in the supplementary material of [3] and also in [4] and [2]. However, in this case study, we are not mainly interested in the differences between bot and human behaviours, but rather in the differences between verified and unverified users within each category.

4 Statistical Analysis

For this work, we used several statistical Python libraries in order to perform our analysis. In particular, we used the *Scipy* python library that provides several algorithms for optimization, integration, interpolation, statistics and many other classes of problems. Among all the analysis that we performed, the Figure 4 might need a more precise and deeper research material. To find the distribution of messages across the emotional range, we use a joint probability distribution function, in order to quantify the distribution of tweets across the emotional range (-1, +1), when we consider the political leaning associated with the link shared and the type of users (verified, unverified). In particular, we grouped the data into 11 bins, which represent the emotional range (-1, +1). For the purpose of simplicity, we also multiplied each value for 100 in the panels related to our two samples in order to round our results, but we have shown the original values in each colorbar. The last panel shows the percentage difference between the vaccine and baseline sample.

References

[1] Carlotta Dotto and Seb Cubbon. How to spot a bot (or not): The main indicators of online automation, co-ordination and inauthentic activity. https://firstdraftnews.org/articles/activity/how-to-spot-a-bot-or-not-the-main-indicators-of-online-automation-co-ordination-and-inauthentic-2019.

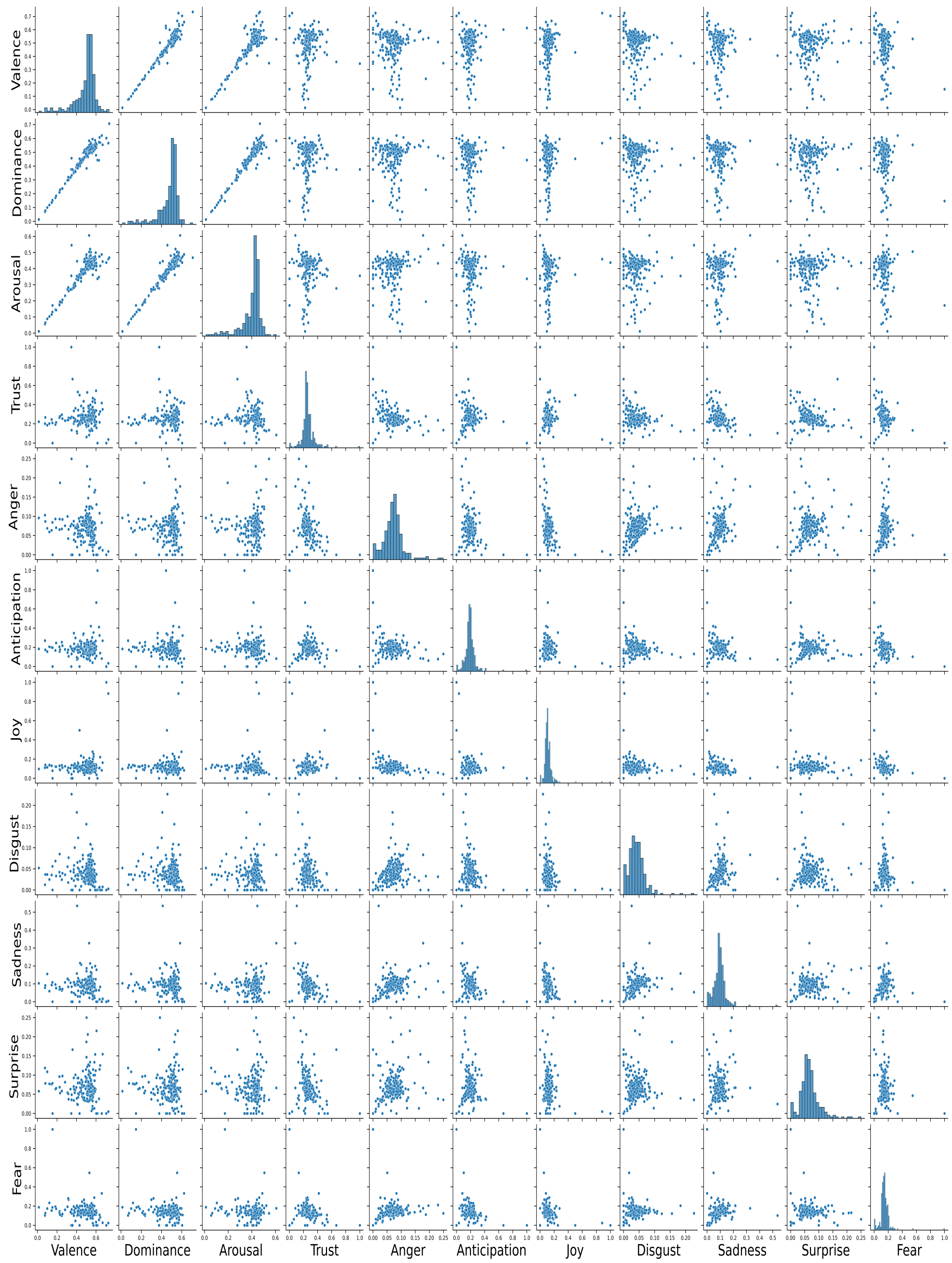

Figure 2: **Correlation among Valence-Arousal-Dominance emotional dimension and the eight emotions.** For each emotions, we calculated the Spearman correlation, finding that the three VAD emotions are highly correlated among them, while the four positive and four negative emotions are not correlated with respect to each singular emotion.

[2] Sandra González-Bailón and Manlio De Domenico. Bots are less central than verified accounts during contentious political events. *Proceedings of the National Academy of Sciences*, 118(11):e2013443118, 2021.

[3] Pier Luigi Sacco, Riccardo Gallotti, Federico Pilati, Nicola Castaldo, and Manlio De Domenico. Emergence of knowledge communities and information centralization during the covid-19 pandemic. *Social Science & Medicine*, 285:114215, 2021.

[4] Massimo Stella, Emilio Ferrara, and Manlio De Domenico. Bots increase exposure to negative and inflammatory content in online social systems. *Proceedings of the National Academy of Sciences*, 115(49):12435–

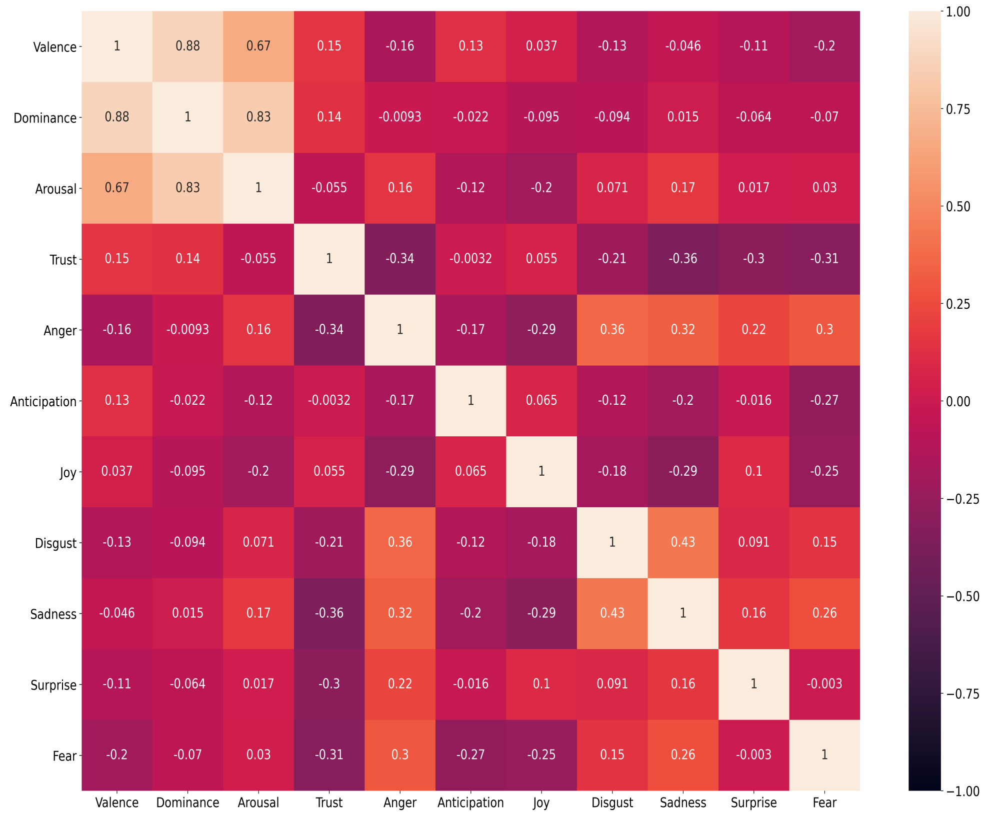

Figure 3: **Heatmap showing the Spearman Correlation among Valence-Arousal-Dominance emotional dimension and the eight emotions.** We show the Spearman Correlation against each singular emotions (Joy, Surprise, Trust, Anticipation, Fear, Anger, Disgust, Sadness) and the three VAD emotions. We find that the the VAD emotions are higly correlated among them with values of 0.88 among Dominance and Valence, 0.83 among Dominance and Arousal, 0.67 among Valence and Arousal.

12440, 2018.

[5] Amy Beth Warriner, Victor Kuperman, and Marc Brysbaert. Norms of valence, arousal, and dominance for 13,915 english lemmas. *Behavior research methods*, 45(4):1191–1207, 2013.

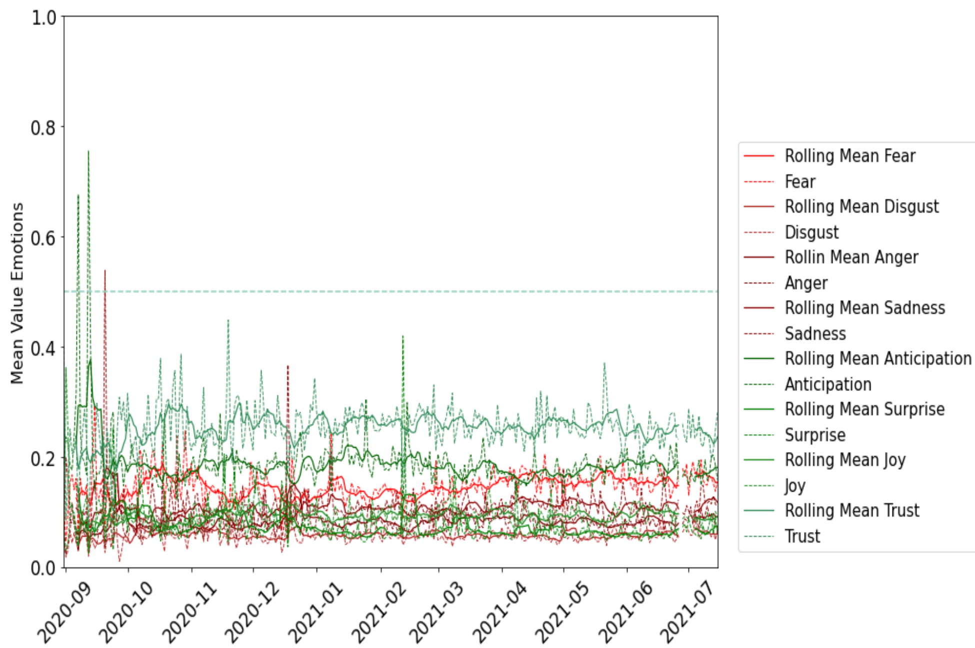

Figure 4: **Distribution of positive and negative emotions during the entire phase of Covid-19 Vaccination Campaign.** We show the average distribution per day of each emotions. In particular, the emotions with a positive valence (Joy, Trust, Anticipation, Surprise) are represented by different scale of green, whereas the emotions with a negative valence (Fear, Anger, Disgust, Sadness) are drawn by different scale of red. Based on this plot, we decided to normalize the data by summing the value of each emotion and then divided each singular emotion by the total emotional value. Separately, we summed the positive and the negative emotions and then we normalized each new category in a range between -1 to +1 in order to have a more comparable emotional value for each message posted on Twitter.

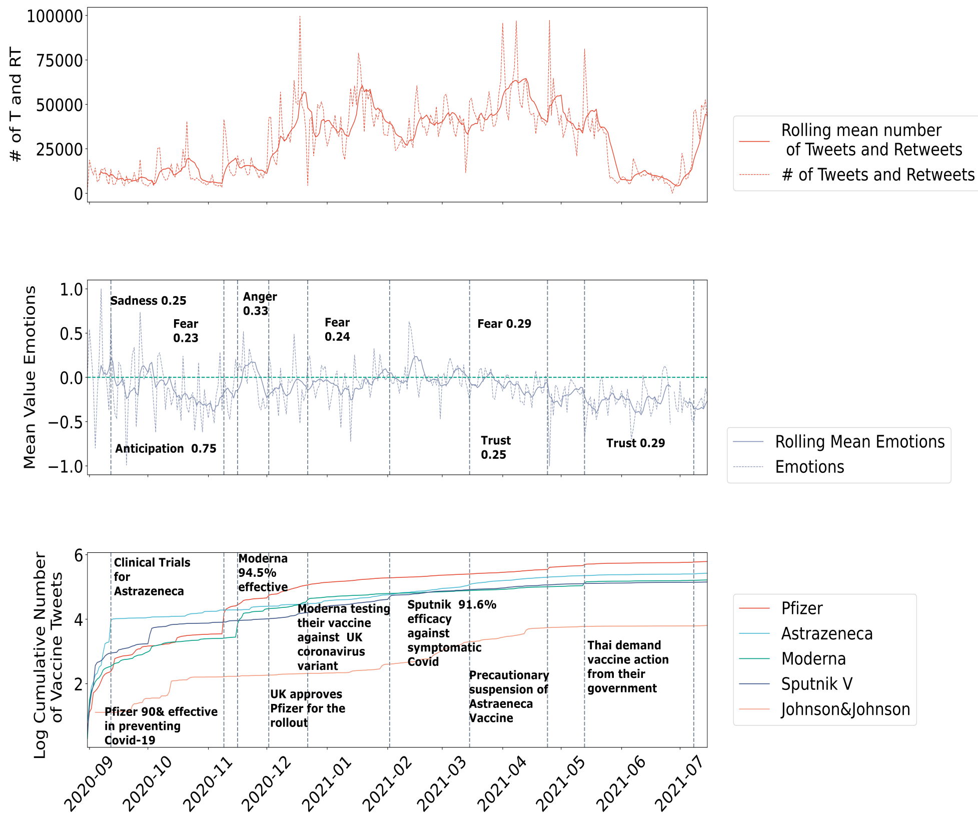

Figure 5: **Evolution of the messages, emotions and events during the Covid-19 Vaccination Campaign.** In the first panel, we quantified the distribution of tweets and retweets posted on Twitter during the entire phase of Covid-19 Vaccination Campaign. The second panel shows the distribution of emotions in a range between -1 (completely negative valence) and +1 (completely positive valence). We calculated the mean emotion for those emotional dimensions that have reach values higher than 0.25 in particular days. The third panel indicates the cumulative logarithmic number of messages with reference to particular vaccines names. Labels refer to manually inspected events about the massive COVID-19 vaccination campaign.

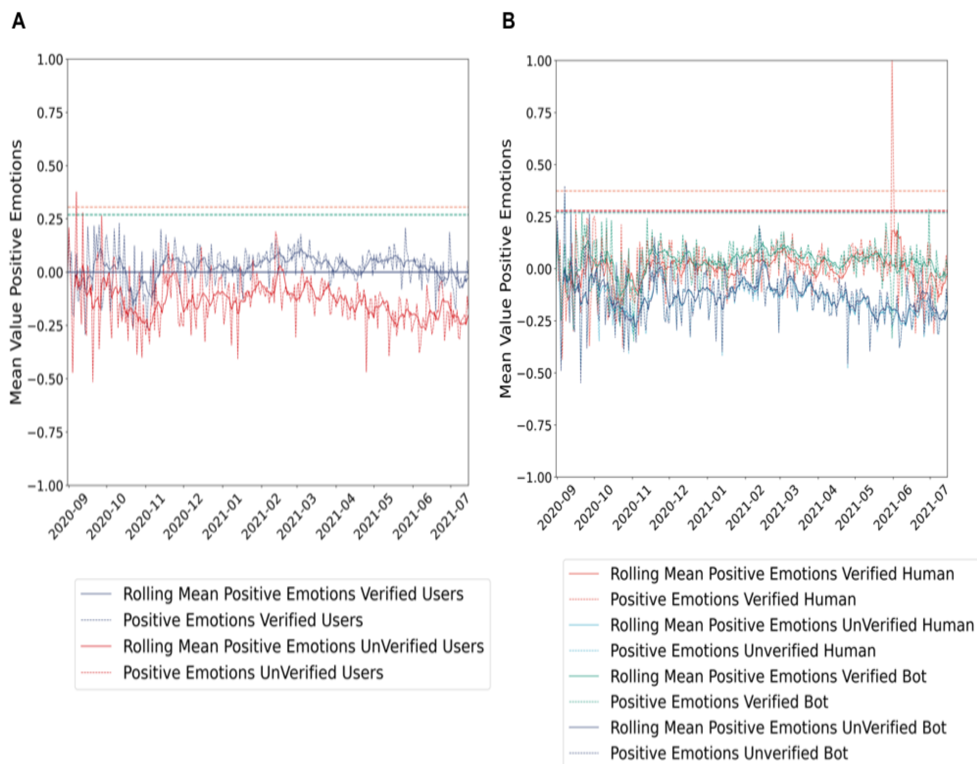

Figure 6: **Emotional Analysis for different type of users accounts.** We quantified (A) emotional trends from -1 to +1 for verified/unverified users, (B) for verified and unverified human, verified and unverified bot. We have shown both the mean distribution per day and the rolling mean emotions in order to better visualize the frequent variation of the emotional distribution with respect to each type of users accounts. Especially in the second panel, we observe that the differences between the four categories of users tend to stabilize as the vaccination campaign unfolds, whereas in the very first months the responses are less predictable.