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Social mood during the Covid-19 vaccination process in Spain. A sentiment analysis of tweets and social network leaders

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ABSTRACT

In accordance with the cognitive orientation contemplated in the resolution of complex problems posed in public decision-making using decision support systems and social networks, this work studies the possibility of identifying the state of mind of society through the state of mind of network leaders. Using sentiment and emotion analysis as research techniques and *Twitter* as a representative social network, the study corpus considers tweets and retweets in Spanish about COVID-19 in the period from February 27, 2020 to December 31, 2021. As cognitive orientation claims, the proposed techniques will allow us to extract the arguments that support the different positions and decisions from the analysis of the tweets issued exclusively by social leaders. In the case study considered, the COVID-19 vaccination process in Spain, the reduction in the number of tweets′ authors (more than 8,000) to the network leaders (just 8) was greater than 99 %; and the subsequent reduction in the number of associated tweets was greater than 88 % from the 18,193 tweets in society to the 2,145 tweets of the eight social leaders. The impressive degree of information compression achieved may be useful to establish new directions of social mood analysis applied to healthcare and business management.

1. Introduction

Decision-making is one of the essential and most distinctive human traits, reflecting the degree of development and evolution of the species. Much has been discussed about the dilemma between the two types of decisions traditionally associated with human behaviour: intuitive and analytical.

Intuitive or emotional decisions, predominantly made with the right side of the brain, reflect the evolution of living systems into today's *Homo sapiens sapiens*. They tend to be quick to make and carry out because: (i) they address urgent decisions made in the very short term; (ii) they are often made in critical situations that require immediate responses; and (iii) they reflect the evolutionary innate patterns of the human species.

Analytical or rational decisions, made with the left side of the brain, reflect the characteristics of the prevailing scientific method of the time. They tend to be slow to make and carry out because: (i) they systematically analyze existing information (internal and external), alternatives and their consequences according to different indicators; (ii) they establish one or more criteria to guide the decision; (iii) they determine the resolution process followed for each type of problem considered. In the decision-making context, the problems can be formally described [1–3] as: choice of the best alternative (P.α), or of the k best alternatives (P.α[k]); identification of

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groups (P.β), which would include segmentation and classification issues; ranking of alternatives (P.γ); problem description (P.δ) and knowledge extraction (P.κ); and (iv) the formal model is validated and calibrated before its practical application.

The construction of appropriate formal models requires a better understanding of the interaction between the two hemispheres of the brain. It seems [4] that humans use the traditional scientific method (analytical and rational) for a better understanding of the problem under consideration (providing light to darkness) and eliminating undesirable alternatives according to a set of tangible criteria. On the other hand, intuition (the emotional part) is used to identify, within the set of alternatives that have passed the previous rational filtering, the preferred alternatives, using for the moment intangible and subjective criteria [5–7].

If the traditional scientific method is characterized by objectivity (neutrality of values), rationality (logical and coherent developments), causality (construction of causal explanatory models) and verifiability (reproducible and testable), the new scientific method, which basically aims to provide an objective treatment of the subjective, is characterized by its publicity, accessibility, and rigor [2]. This new method is not limited to selecting the optimal decision (the P of Product) in situations in which a single decision-maker and criterion are used, nor even to knowing how the decision-making process works (the P of Process). Based on evolutionary paradigms [8,9] and in accordance with the 4Ps approach [10], the new scientific approaches focus on the P of Person; specifically, on their continuous training in scientific decision-making within a global framework, delimited in a Universal context by the P of Planet, and aligned with a holistic vision of reality [11,12].

In the Knowledge Society, it is not enough to make informed decisions (where information is understood as the objective contextualization of data); it is necessary to make cognitive decisions (where knowledge is understood as the subjective contextualization of information) which are oriented to the continuous education of individuals and systems in the scientific resolution of problems. Education is associated with the extraction and dissemination of the arguments that support the different positions and decisions. This requires analysing numerical data (data mining) and texts (text mining) to see the evolution (polarity evaluated by valence) of the state of mind and the most important emotions, both of society and of its individuals, especially of social leaders. Furthermore, and associated with feelings and emotions, a series of words can be identified, generally n-grams, which will be the basis of the arguments sought.

The evaluation of polarity or valence in emotional contexts becomes an essential factor. Currently, the main psychological and neurophysiological theories on emotions highlight the importance of polarity [13–17]. *Joseph LeDoux* contemplates that in all the cognitive processes of the nervous system, from the most abstract and rational to the most instinctive and emotional, a "movement" of either approach or rejection is generated with respect to the object or thought considered [18].

When the object of thought under consideration is related to "social cohesion", the role of this polarity or valence in emotions becomes a fundamental token in collective judgment. As Joseph Henrich [19] points out, given the eminently social nature of the human species, synchronizing polarity in reactions to different situations is of outmost importance for the cohesion of the social body itself. This author argues that "the success of our species" is based to a large extent on processes of emotional cohesion, via inherited cultural values, which generate a rapid, practically unconscious consensus on the value of different situations.

Achieving social cohesion continues to be an innate aspiration, which nowadays is most frequently brought about through communication exchanges in social networks [20]. Thereafter, the object of this work, the extraction and dissemination of arguments that justify different positions and decisions on COVID-19 vaccination, according to the evolution of the state of mind and emotions of society as reflected in social networks (*Twitter* in our case), appears perfectly aligned with the previously mentioned processes of social cohesion.

In recent years there has been a vast development of methodologies based on Decision Support Systems (DSS) that aid in the resolution process of complex problems [10], as well as a great adaptability of Natural Language Processing (NLP) techniques that help computers to understand human language input in the form of text or speech applied to sentiment analysis. Therefore, the number of works dedicated to mining opinions expressed on social networks has considerably grown, despite the great diversity of formats in which they are presented, constituting an efficient procedure to analyze opinions and, in general, the behavior of people in unforeseen situations that affect public opinion [21]. In particular, in recent years, sentiment analysis in social networks has been applied to the study of very diverse phenomena: the Syrian refugee crisis [22], the US presidential elections [23,24], the Russian campaign [25], the impact of Brexit [26], natural disasters [21], sentiment towards racial/ethnic minorities [27] or the very recent COVID-19 outbreak [28–33].

This work has been based on the social network *Twitter* (currently called *X*). The reasons for this choice are diverse: mainly, that it is an open network, in which the entire debate is public and accessible to all of society. But also because of the large number of people who use it to express and debate their ideas and opinions, which makes it easier to obtain sufficiently large and significant samples of public opinion. These two reasons make *Twitter* the favorite social network when carrying out studies of this type [34–38]. In particular, there are numerous studies on the effects of COVID-19 on society [28,39–42].

Furthermore, public health communication from official sources means a cost-effective communication strategy for public health promotion [43] as their retweets can reach far more people that are not following the official accounts. During the COVID-19 pandemic, most international political leaders turned to social networks to broadcast information about the pandemics, response plans, public health measures, and connection with citizens [44]. Identifying and monitoring those social leaders whose opinions most closely reflect the needs or demands of society will contribute to make more realistic and effective public health decisions [33,45,46].

In a previous paper [33], we had developed a new approach based on the combination of sentiment analysis using lexicons and multivariate statistical methods to assess the evolution of social mood through the COVID-19 vaccination process in Spain. In the present study we have used that approach with a different goal: to identify the state of mind of society through the state of mind of network leaders. Thus, the focus of this paper is analyzing the tweets issued exclusively by social leaders (and the communities that emerged around them), who are identified based on their influence on the other participants in the debate. The state of mind of an author and the extent in which this state of mind influences the community is characterized by the author's emotional valence, and word clouds are created to find out the main terms used as argumentation. Besides, the variation in the number of tweets between the two studies is significant (98,197 versus 41,669), this is due to the fact that in the present study we have improved the network (rate speed) and the computational capability for downloading through the *Twitter* API v2. This permitted us to reduce the reconnection failures of the *Twitter* API, already reported by several users (https://twittercommunity.com/t/rate-limit-on-tweets-stream-api/144389) and therefore we could download a greater number of tweets and improve the global analysis.

Therefore, in this study on the evolution of collective and individual moods during the COVID-19 vaccination process, two different tools will be combined. Firstly, a sentiment analysis of the tweets collected in a fixed period will be carried out for a specific problem. This will allow us to analyze the evolution of mood and emotions in the different stages considered for the problem. Next, also using sentiment analysis, a study similar to that done with tweets will be carried out with the authors of the tweets. This parallelism between tweets and authors will make it possible to confirm whether the evolution of the social mood and emotions coincides with that of network leaders.

2. Vaccination process in Spain

The aim of the international vaccination campaign was to prevent the disease and reduce its severity and mortality, as well as to reduce the impact of the pandemic on health care systems and the economy, providing special protection to the most vulnerable groups vaccination [47].

Given that the first COVID-19 vaccines were available in limited quantities, and were delivered progressively, it was necessary to prioritize the population groups to be vaccinated. To do this, an ethical framework was established in which the principles of equality and dignity of rights, necessity, equity, protection of disability, social benefit and reciprocity prevailed –additionally considering participation, transparency, and accountability– as well as the importance of information and education, on which the evaluation of the different population groups was based, also considering the applicable legal norms and international recommendations [47].

The vaccination strategy in Spain was published on December 2, 2020, with 11 updates by the end of the analysis reference period [48]. Four phases were defined according to available doses with different priority population groups (see Fig. 1).

Throughout these different phases of the vaccination process, it is important to know the evolution of the collective and individual moods and emotions. To do this, as we have already mentioned, two different tools were combined. On the one hand, sentiment analysis of the tweets, and on the other, the study of relational networks between the authors of the tweets.

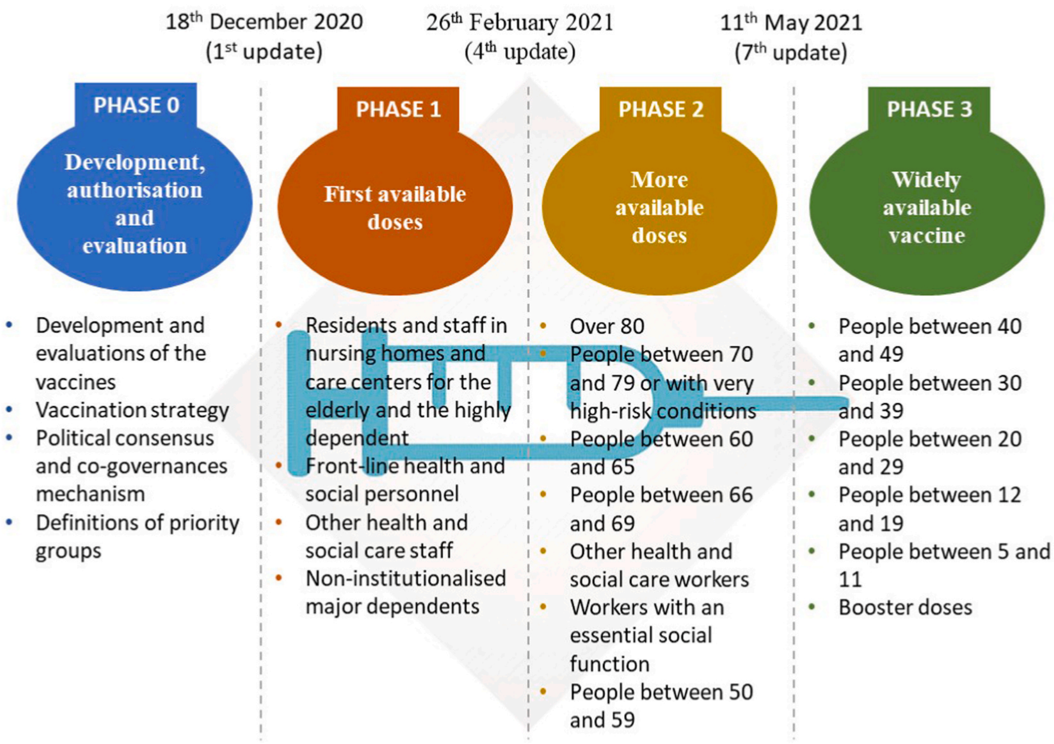

Fig. 1. Spanish vaccination phases and priority groups.

3. Materials and methods

3.1. Data

Data was collected from the full historical *Twitter* database using the *Twitter* Application Programming Interface (API) v2, an access point to the *Twitter* data by means of a computer application. The search period covered from 27 to 02–2020 to 31-12-2021, that is, from the beginning of the pandemic until the end of the main stage of the vaccination process in Spain. The search key was built from the following Spanish hashtags: *#covid*; *#covid19*; *#Yomevacuno* (I'm getting vaccinated); *#Yonomevacuno* (I'm not getting vaccinated); *#Negacionista* (denialist). The key string used to query the database was:

(*covid* OR *covid19*) AND (*Yomevacuno* OR *Yonomevacuno* OR *negacionista*) respectively referring to COVID and vaccination, and to the pro- and anti-vaccine positions. Only tweets written in Spanish were added. By doing this, a dataset of 772,070 tweets was collected, written by 302,521 different users.

The search key was constructed through a preliminary search in the *Twitter* search engine, and the terms were selected because they were the most widely used in the tweets that clearly referred to a position in favor of vaccination, against it, or neutral (but in no case necessarily identifying with it). Since the scope of the work refers to the opinion on the COVID-19 vaccination process in Spain, it was necessary to identify which of the authors of these tweets resided in Spain, and not in other Spanish-speaking countries.

The following attributes were extracted from each message, some of them referring to the tweet itself and others to its author.

- Tweets: id, author_id, created_at, text, hashtags, retweeted_id.
- Users: id, name, username, created_at, location, description.

To select the tweets written by Spanish users, their geographical location was identified, whenever possible, from the information contained in the location field. This was done by calling the Nominatim geocoding service, an Open Data project of OpenStreetMap [49].

309,855 tweets (40.13 % of the total) that provided useful information in this field were posted by 82,292 users (27.20 % of the total). For these users, Nominatim obtained a location determined by its latitude, longitude, and country, and in some cases, it was also able to determine the user's region, city, or postcode. Once the geolocation information was obtained and stored in the database, it was shown that 33,127 users (10.95 % of the total) sent tweets from Spain and written in Spanish. This study considered the tweets sent by these 33,127 Spanish users. In total there were 98,197 tweets (12.72 % of the total) that constituted the corpus of the study (see Table 1); most of them, 80,004 (81.47 %) being retweets from other authors, 5,113 (5.21 %) responses to previous tweets, 1,114 (1.13 %) were tweets containing quotes from other tweets, and the remaining 11,966 (12.19 %) were original tweets. For the purposes of this study, we considered *users* to be all *Twitter* users who posted their own messages or quoted, replied, or retweeted messages from other users, and we will only call *authors* those who posted messages written by themselves (responses, quotes, and original tweets). The number of authors geolocated in Spain was 8,137 (12.96 % of all authors), and they posted 18,193 original messages (2.36 % of the total tweets).

Regarding participation, 229,147 tweets (73.95 % of all tweets geolocated) corresponded to retweets from users who did not write anything of their own. It can also be seen from Table 1 that, on the one hand, the average number of tweets per user is 3.77 for those geolocated and 2.96 for those geolocated in Spain, and the average number of tweets per author is 4.35 for those geolocated and 2.24 for those geolocated in Spain. On the other hand, the percentage of geolocated authors over geolocated users who write in Spanish about COVID-19 is 22.52 %. In contrast, that percentage in Spain is less than a third; only 24.56 %. The total number of users is 302,521, of which 62,775 (20.75 %) where authors.

Table 1
Filters for corpus determination.

Filter	#	%
Users	302,521	100.00
Users geolocated	82,292	27.20
Users geolocated in Spain	33,127	10.95
Authors	62,775	100.00
Authors geolocated	18,534	29.52
Authors geolocated in Spain	8,137	12.96
Tweets from users collected in Spanish	772,070	100.00
Tweets from users geolocated	309,855	40.13
Tweets from users geolocated in Spain	98,197	12.72
Tweets from authors in Spanish	140,678	18.22
Tweets from authors geolocated	80,708	10.45
Tweets from authors geolocated in Spain	18,193	2.36
Retweets[a] collected in Spanish	631,392	100.00
Retweets[a] from users geolocated	229,147	36.29
Retweets[a] from users geolocated in Spain	80,004	12.67

[a] Original tweets, replies and quotes are not included.

3.2. Methodology

The methodological approach was based on Social Web Mining complemented with NLP and Social Network Analysis (SNA). Messages were collected from social networks, pre-processed, and then their features were extracted to perform an analysis on society's changing opinion and mood regarding that critical event, and the way people related to each other and exchanged information on that event on *Twitter*.

The flow chart in Fig. 2 shows the methodological procedure that consists of 3 steps [33]: i) Corpus determination, ii) Authors and social mood evolution and iii) Authors and social mood comparison.

First of all, the tweets were pre-processed to eliminate all elements of the data that were susceptible to inconsistency or ambiguity, or unnecessary in the subsequent analysis (punctuation marks, symbols or numbers, words that do not provide meaning, etc.). This pre-processing was carried out using the *stringr R* package (https://cran.r-project.org/package=stringr).

Further, the tweets were analyzed applying text mining by means of the *Syuzhet* 1.0.6 package [50] and *RStudio* 1.1.419, according to the general procedure already shown in Fig. 2. The sentiment was evaluated with *NRC Word-Emotion Association Lexicon Version 0.92* [51–53]. This lexicon provides a list of English words and their associations with three sentiment values (negative, positive, and neutral).

3.2.1. Retweet network

Step 1 of the methodology aimed to obtain the Data Corpus described above. The goal of Step 2 was, on the one hand, to analyze the tweets written by the users geolocated in Spain to determine which sentiments were expressed in those texts and what the evolution of social mood was, plus the valence or overall feeling (neutral, positive, or negative) of the authors when writing them. The sum of the valences of a group of texts written in a timestamp transmits the mood of authors in that instant of time. From the valences at different moments of time throughout the period under study, the narrative structure is built, which gives an idea of the positive/negative evolution of mood over time [33,54].

On the other hand, SNA techniques were applied to determine which users of the *Twitter* network had aroused the most interest among Spanish users due to their comments about the vaccination process in Spain, how they related to each other by constituting communities or clusters, and which users of each of these communities had received the most attention from others.

When modelling the influence of some users over others, it was considered that the act of retweeting a previous message implies agreeing with the content of this message and seeking maximum dissemination by sharing it with one's own followers.

As the retweet was the majority action, this action was considered an indicator of influence, that is, an actor A influences another actor B if B retweets any message from A. Based on this relationship, we built the network of retweets based on the following methodological considerations.

- The network is a directed graph; the origin of each arc is the node corresponding to the author who retweeted a message and destination is the node that represented the author of the original tweet.
- The nodes were the users who had published tweets and retweets.
- The size of a node is proportional to the in-degree, that is, the number of arcs directed to the node, representing the volume of retweets that has been made of their tweets (leaderships or influential actors).

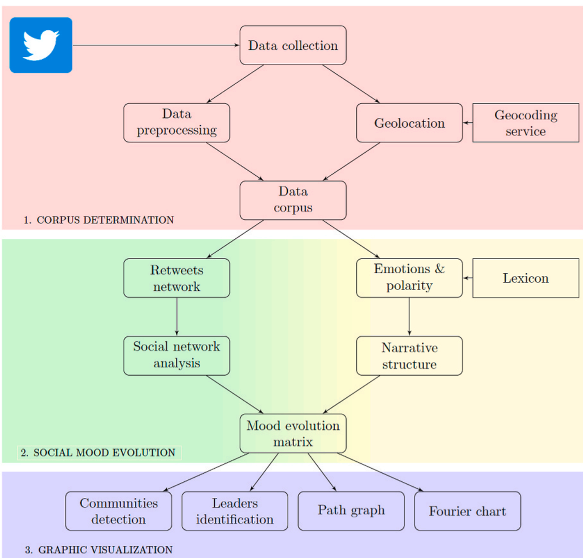

Fig. 2. Methodology flow chart.

- The colors of the nodes (see Fig. 3) indicate communities. These communities have been calculated with the Gephi software [55], which uses the algorithm described in [56].
- The color of the arcs is the same as in the origin node, while their size is proportional to the number of messages from the destination node that the origin node has retweeted.
- The position of each node in the graph has been calculated using the Force Atlas 2 algorithm [57], an energy model for network spatialization so that the more retweets a node has, the more focused it will be with respect to the nodes connected to it.

According to this, we consider that the *influence* of an actor is the number of retweets that get their messages.

The number of nodes considered in the study, those associated with the 80,004 retweets from users geolocated in Spain, is 33,127. After removing the 9,068 nodes that belonged to clusters with a very low number of nodes (less than 5 % of the total nodes), the 459 isolates (nodes that have not retweeted any messages and whose messages have not been retweeted) and the 17,267 arcs between those nodes, the resulting network (see Fig. 3) contained 23,600 nodes and 62,737 arcs (retweets), which represents a very low density (arcs present in the graph/maximum number of arcs the graph can contain), practically zero. Also, the average degree (average number of arcs directed to each node) of the network is 2.66.

The analysis reveals who are the most influential authors, due to the size of their node and their position within the cluster which they belong to (the more centered, the larger its size is, and the more compact a community is, the more relationships appear between its members). Besides, the different communities are closer to each other depending on how many nodes of each one is related to the other. The more relationships there are between two communities, the closer they would be. The different clusters therefore appear in positions of similarity based on the relationships they have in common.

This representation allows us to identify some similarity in the opinion about the vaccination process between members of the same community or nearby communities, determining the position of the Spanish community on *Twitter* with respect to the vaccination process.

3.2.2. Identification of users' communities in the retweet network

In Fig. 3, only seven clusters or communities with more than 5 % of the total nodes can be distinguished. These seven communities represent 71.24 % (23,600/33,127) of the total users considered and 23.85 % (23,416/98,197) of the users' tweets. Within each cluster, those nodes with the highest number of retweets have been distinguished (leaders), appearing as the largest nodes in the graph.

The first striking result is that two well-differentiated nuclei emerged, with very few interconnections between them. Other small, almost isolated nuclei gravitated around them. This agrees with similar results in other countries [58]. In Spain, the most numerous community (in orange) corresponds to the one grouped around the official accounts of the Spanish Ministry of Health (@sanidadgob) or the Health Departments of the Spanish Autonomous Communities. These accounts have been used during the pandemic to disseminate informative messages about the health plans of the Spanish central government or the regional governments. The most prominent account is @sanidadgob (see Table 2).

Four other communities very close to the previous one are characterized by their position clearly in favor of the vaccination process: the accounts around the Spanish Government and the Presidency (fuchsia), the accounts grouped around the media that are more openly positioned in favor of the process (pink color), a core of users who seem to be professionally related to the world of health and medicine (olive color), and another less centralized group of users without any particularly prominent node (blue color).

These five communities are very cohesive and highly interrelated with each other (a modularity coefficient of 0.712 was obtained by applying the algorithm of [57]), indicating a high degree of similarity in the messages they transmit. The other two communities,

Fig. 3. Retweet network.

Table 2
Most retweeted authors in each community.

Community	# of members	% members	# of retweets	% of retweets	Username	# of retweets	% of retweets	% of retweets Community
Orange	7,805	33.07	24,080	30.10	@sanidadgob	10,403	13.00	43.20
Olive	1,755	7.44	2,704	3.38	@sefh_	265	0.33	9.80
Fuchsia	1,359	5.76	2,400	3.00	@policia	630	0.79	26.25
Blue	1,493	6.33	2,202	2.75	@jmmulet	216	0.27	9.81
Pink	5,699	24.15	10,315	12.89	@elpais_es	590	0.74	5.72
Green	2,969	12.58	15,602	19.50	@ImTheResistance	10,407	13.01	66.70
Red	2,520	10.68	5,434	6.79	@HuhConH	907	1.13	16.69
Total	23,600	100.00	62,737	78.42		23,418	29.27	

clearly separated from the supernucleus formed by the previous communities, have a significant number of connections between them. The largest community (green color) is organized almost exclusively around a single node, @ImTheResistance, which issues messages positioned against vaccination. The remaining community (red color) also stands for the anti-vaccination discourse but is made up of users who are more interconnected with each other and less hierarchical. Both communities are also very cohesive with each other and with a high degree of relationships between their members, which also indicates high affinity in the dominant opinion against vaccination.

3.2.3. Authors' emotional valence

According to the definition of the retweet network given above, the leaders of each community are the authors whose tweets have been retweeted most, so in the network are represented by the nodes with the highest degree of entry. To characterize their state of mind, we will consider the *emotional valence,* which is a summary of the author's state of mind, weighted by the number of tweeters who have retweeted their messages.

Sentiment analysis has assigned tweets a positive or negative valence. If an author A_i has published n_i tweets, let $a_{ik}^{+}, a_{ik}^{-}, k = 1, \ldots, n_i$ the positive and negative valences, respectively, of each tweet. Since the valence of a tweet must be positive, negative, or neutral, necessarily $a_{ik}^{+} \bullet a_{ik}^{-} = 0$ must hold. The emotional valence v_i of author A_i is defined as $v_i = \sum_{k=1}^{n_i} w_{ik}(a_{ik}^{+} - a_{ik}^{-})$, where w_{ik} is the number

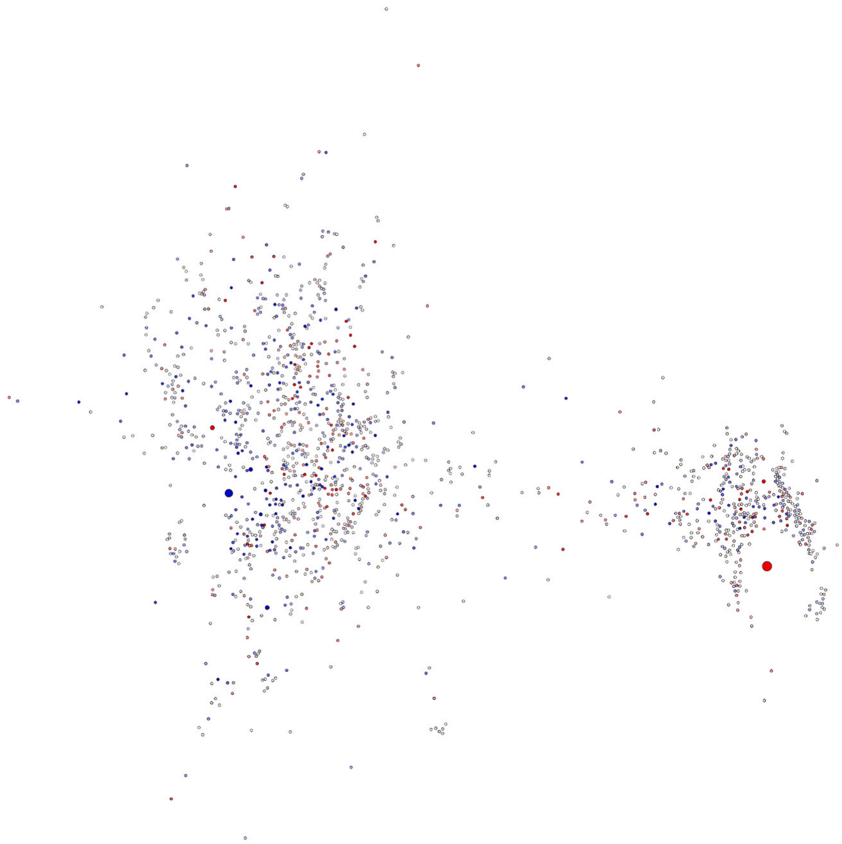

Fig. 4. Authors' emotional valences.

of times tweet k of author A_i has been retweeted.

The graph in Fig. 4 represents all the authors. The size of each node is, as in Fig. 3, proportional to the in-degree, and represents the influence of the author within the community. The color is blue if the emotional valence of the author is positive, and red if it is negative. The color intensity of each node represents the absolute value of the emotional valence. A logarithmic scale has been used to visualize lower intensities better.

As can be seen in the figure, there is a red node (negative valence) of large in-degree in the supernucleus on the left (positive valences). This is because it is an account of the ministry of health, specifically public health (@saludpublicaes), which addresses the negative messages about the future of the pandemic or effects of vaccination in different diseases (oncology, human immunodeficiency virus (HIV)…).

4. Results

This section presents the results corresponding to the issues described in Step 3 of the methodology. It also includes different illustrations about community detection, leader identification, author graphs, and social mood graphs.

4.1. Evolution of the retweet network along the process

Fig. 5 presents the evolution of the retweet network during the four phases of the process identified in [33]. As in Fig. 3, two clearly differentiated clusters are distinguished in each phase: on the left, pro-vaccines linked to the official sources of the Government and the health administrations of Spain, journalists, and media; on the right, accounts disseminating denialist and anti-vaccine messages. The remaining nodes correspond to users whose activity has been very low during the period studied and therefore appear isolated or forming dyads or triads. These individuals show no interest and have been suppressed.

Fig. 5 verifies the following facts.

- **Phase 0.** In this initial phase, two very compact groups with very few interconnections between them are clearly perceived (3,818 nodes and 6,137 arcs). The group on the left includes the official sources of the Spanish administration (in pink), journalists and the

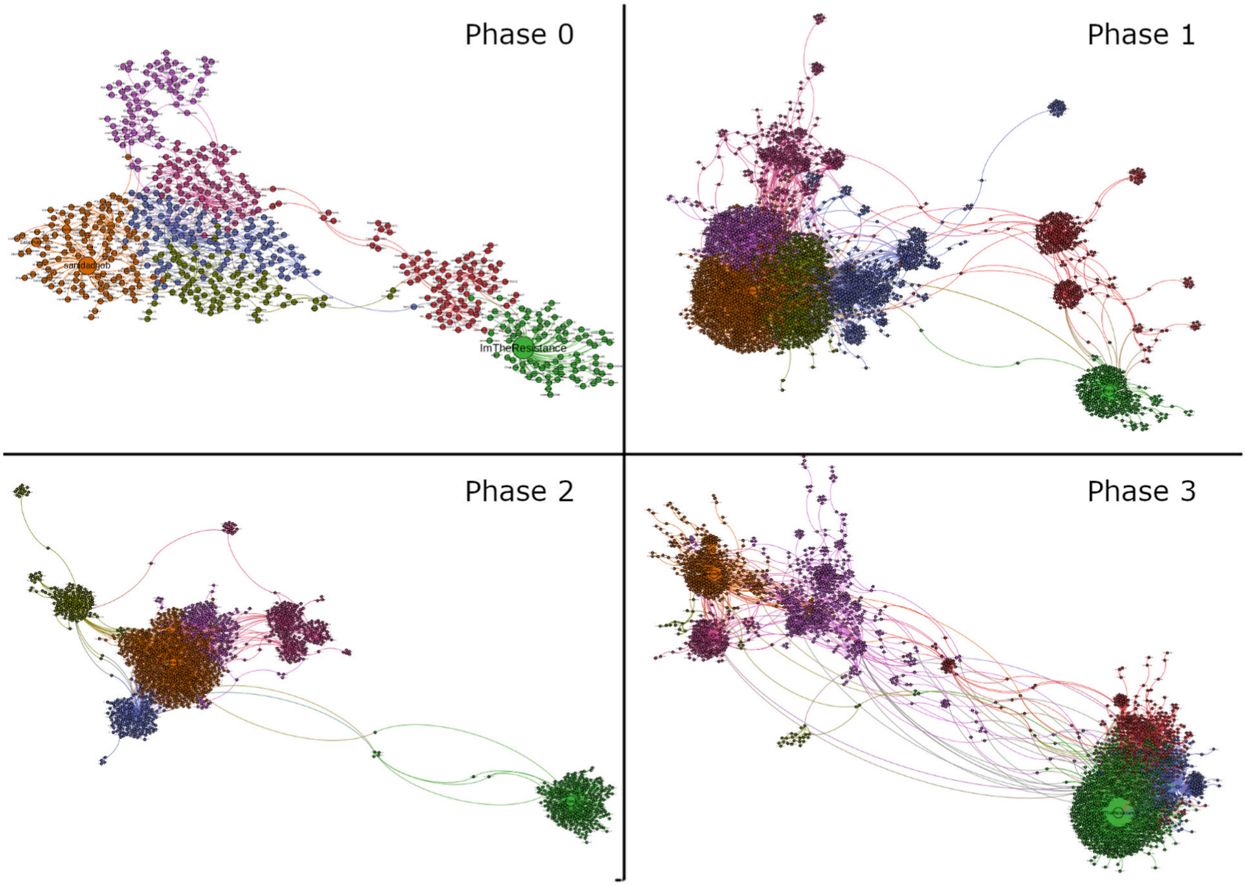

Fig. 5. Evolution of the retweet networks.

media (blue), and the official account of the Spanish National Police (orange). The group on the right appears centered around two accounts disseminating denialist and anti-vaccine messages, completely disconnected from the previous one, and another less numerous group whose messages follow the same trend but has a small percentage of arcs connecting this nucleus with the first one.

- **Phase 1:** the two groups from the previous phase are still clearly differentiated (7,758 nodes and 14,671 arcs), although the size of the former has increased and the roles of its components are more clearly outlined: one nucleus brings together official and government sources, another the mass media, and the third one sympathizers of the political parties that form the coalition government. It is also perceived how, in addition to the health authorities of the Government of Spain, those of the different Autonomous Communities have intervened in the debate.
- **Phase 2:** despite the different sizes, there are hardly any differences with respect to the previous phase (3,510 nodes and 7,933 arcs). The group critical of vaccination has been practically structured around the authority of a single tweeter. Some nodes of both groups are connected to each other, but a detailed analysis of the arcs shows that the authors do not belong to either of the two groups, but rather they show affinity with the first group and retweet messages from some authors of the second.
- **Phase 3:** the group critical of vaccination has increased in size and shows two small nuclei independent of the main cluster clearly distinguishable (5,637 nodes and 14,383 arcs). The ruling group maintains the structure of its own cluster. Nuclei of users have been established in intermediate positions and it can be seen that both main groups have gained interconnections, and in turn the intraconnections have weakened within the first group and have been strengthened within the second.

To summarize, during the evolution of the retweet networks throughout the vaccination progress, two groups of users were clearly differentiated. The first one retweeted positive messages mainly from official sources (pro-vaccine); while the second one retweeted negative messages, denials and criticisms of vaccination (anti-vaccine). As we discuss below, the composition and size of both groups appear clearly related to variations in social mood.

4.2. Leader identification

As can be seen in Table 3, the leaders of the different communities are: @sanidad_gob (official account of the Spanish Ministry of Health), @ImTheResistance (account positioned against the vaccination process), @policia (official account of the Spanish Police Force), @HuhConH (account positioned with the thesis of @ImTheResistance), @elpais_es (media positioned in favor of the process), @jmmulet (very heterogeneous community but with media presence with very low activity on the network) and @sefh_ (world of health and medicine). Clearly, the two most prominent leaders are the Government (10,403 retweets) and the deniers (10,407 retweets).

Table 3 shows the most outstanding authors, colored by community, ordered from highest to lowest by their influence, measured by the number of retweets. They are also the same authors that present the greater valence, although in a different order. These eleven authors will constitute the group of leaders of the discussion, as they are the most valued according to both indicators (influence and valence).

4.3. Mood authors

The emotional valence of the leaders is represented in Fig. 6. It can be seen that although the most influential leaders present the highest emotional valence, a very high value of valence also appears in other authors. It should be noted that the pro-vaccination group has positive emotional valences, and the opposite group (anti-vaccination) has negative emotional valences. However, as we have mentioned the @SaludPublicaEs node shows a high negative emotional valence, despite belonging to the favourable pro-vaccination group. A manual inspection of their messages shows that many of them are instructions related to vaccination for patients with specific pathologies (oncology and immune depressive patients…), messages that may have a negative valence due to their content but whose dissemination is of interest to tweeters who support vaccination.

Table 3
Influence and emotional valence (with number of tweets posted and sign, positive or negative, of the valence) of the 8 most influential leaders.

Author	Influence	Valence	Tweets	Sign
ImTheResistance	10,407	1,555	1,299	neg
sanidadgob	10,403	3,800	241	pos
SaludPublicaEs	2,391	230	269	neg
desdelamoncloa	2,381	786	108	pos
salvadorilla	1,892	372	27	pos
sanchezcastejon	1,458	350	10	pos
Covidiota8M	1,238	191	182	neg
HuhConH	907	298	9	neg

Let's note that the reduction in the number of tweets' authors (more than 8,000) to the network leaders (just 8) was greater than 99 %; and the subsequent reduction in the number of associated tweets was greater than 88 % from the 18,193 tweets in society to the 2,145 tweets of the eight social leaders.

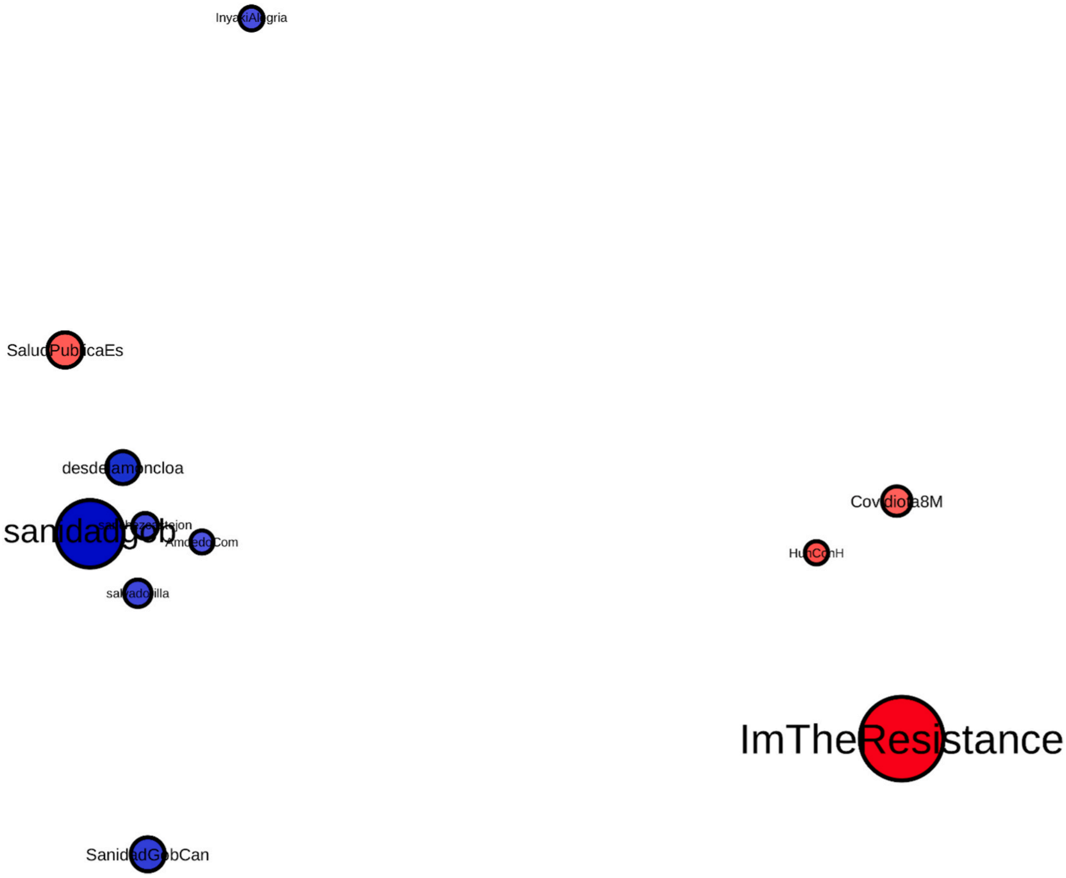

Fig. 6. Emotional valences of the leaders.

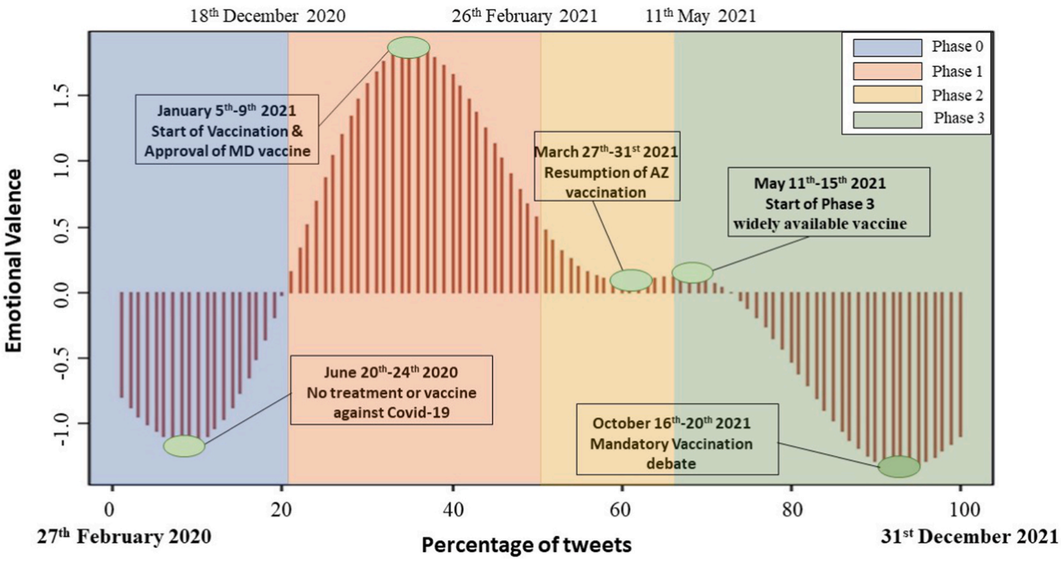

Fig. 7. Fourier plot trajectory with the 4 vaccination phases (differently colored).

4.4. Social mood

Fig. 7 shows the trajectory graph (Fourier plot) representing emotional valence versus date of tweets (percentage of tweets). Positive sentiments are on the upper side and negative ones are on the lower side. From this analysis of the tweets, we can see how the mental state or social mood of Spaniards changed at different phases of the vaccination process (in different colors). Local hotspots (green circles) were marked by analyzing the content of the tweets and relating them to relevant news and political decisions.

The highest value of valence is found at Phase 1 (orange), between January 4th and 6th 2021, corresponding with the start of vaccination in Spain with the Pfizer-BioNTech COVID-19 vaccine and the approval of the Moderna COVID-19 (MD) vaccine by the European Medicines Agency (EMA). While the lowest value of valence is found at Phase 3 (green), between August 4th and 6th 2021, corresponding with the announcement of the need for booster doses and the debate on compulsory vaccination. At an international scale, we can also detect a similar evolution of the global conversation and shifting social moods during the COVID-19 pandemic [59].

Fig. 7 shows five hotspots or critical points during the process, that is, five moments in time in which the state of mind of the citizens has undergone a notable change in trend. To analyze the reasons for these changes, it would be necessary to study the content of the messages published in the surroundings of each of these five points. What follows shows that there is a direct relationship between the mood of society and that of the leaders in the days before and after these changes; in this way, the arguments used in the debate that have led to these mood swings can be found simply by analyzing the speech of the leaders.

More precisely, the average emotional valences of the group of leaders and of society are calculated analyzing all tweets published during a period that goes from five days before to five days after each of those outstanding moments. The data obtained are shown in Table 4.

The Pearson correlation between the valence of society and the leaders, when considering tweets from 11 days (5 before and 5 after the marked date) is very high (0.9754), which justifies that the search for the arguments that support the different positions and decisions is carried out among the leaders and not among all the users. This simplification makes it possible to go from considering 1,197 tweets to 414 tweets (a reduction of 65.41 %). The % of leaders with respect to the total decreases notably when the number of days increases (from 3 to 11 days); however, the % of tweets increases slightly. The average number of tweets per author is considerably lower in society than among leaders (approximately 5–6 times lower for the critical periods considered), being the relationship between them not significant. The average valence per author is significantly lower in society than among leaders (approximately 7–19 times for the critical periods considered).

The analysis was done using a correlation test. The *p*-values were obtained by bootstrapping, obtaining 99,999 resamples of the original sample of tweets in each hotspot, using the software R.

Finally, although the identification of the arguments would require obtaining the relevant n-grams from the tweets, Fig. 8 shows the word clouds of the five hotspots of Fig. 7 for the leaders and for society in general.

As can be seen in Fig. 8, the comments of social networks leaders are influencing society, being especially evident in the 2nd and 3rd hotspots with the appearance of the first doubts with the Astra Zeneca vaccines and the words *Yonomevacuno* (I'm not getting vaccinated), and *Negacionista* (denialist); and in the 4th and 5th hotspots as well, reflecting the generalized dissatisfaction with the possible booster doses and the words *Yonomevacuno* (I'm not getting vaccinated), and *Plandemia* (plandemic). Conversely, in the hotspot 1 (coinciding with the start of vaccination) there is an ample difference between the comments of those leaders and society; for society uses words such as vaccination, vaccine, doses… related to the arrival of the first doses as the possible solution to stop or try to reduce the intensity of the virus. While leaders are using anti-vaccination words such as *Yonomevacuno* (I'm not getting vaccinated), and *Plandemia* (plandemic). This is due to the fact that the majority of tweets (65%) in these dates are coming from the anti-vaccination leader (@ImTheResistance) with a strong start to the anti-vaccination campaign, while the society was happy for the possible beginning of the end.

Comparing with Fig. 7, at hotspots 1, 3 and 5, when there is a downward change in mood, a predominance of negative emotional valences is observed. At hotspot 2, when the trend is reversed, it can be observed that the most intense emotional valences are positive. As for hotspot 4, there is a similar change in trend below the axis, indicating a general negative mood, which may correspond to the

Table 4
Emotional valences of leaders and society in the environment of overt mood swings.

11 days From To	Hotspot 1 Dec 31, 2020 Jan 11, 2021	Hotspot 2 Feb 3, 2021 Feb 15, 2021	Hotspot 3 Mar 21, 2021 Apr 2, 2021	Hotspot 4 Jul 31, 2021 Aug 11, 2021	Hotspot 5 Oct 10, 2021 Oct 22, 2021	Correlation	*p*-value
# Tweets of Society	244	305	159	353	136		
# Tweets of Leaders	91	96	90	88	49	0.6219	0.0000***
# Authors of Society	92	99	32	90	32		
# Authors of Leaders	6	5	5	4	2	0.5488	0.3295
Valenc. of Society	995	660	179	−275	−104		
Valenc. of Leaders	965	435	101	−144	−83	**0.9754**	**0.0167***
Mean T/A of Society	2.6522	3.0808	4.9688	3.9222	4.2500		
Mean T/A of Leaders	15.1667	19.2	18	22	24.5000	0.4523	0.4404
Mean V/A of Society	10.8152	6.6667	5.5938	−3.0556	−3.2500		
Mean V/A of Leaders	160.8333	87	20.2	−36	−41.5	0.9474	0.0160*
% Tweets (L/S)	38.5246	35.4098	73.5849	32.8612	36.0294		
% Authors (L/S)	7.6087	8.0808	18.75	5.5556	6.25		

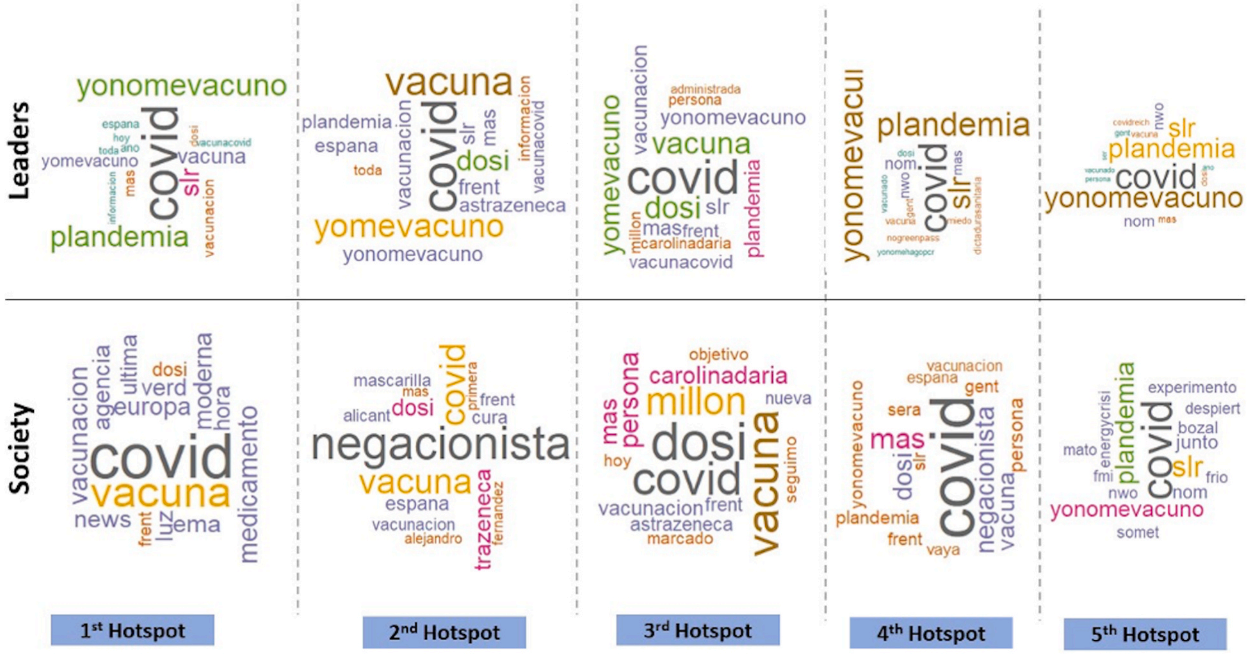

Fig. 8. Leaders and Society word clouds of the five hotspots from Fig. 7.

situation represented in the figure in which the most intense emotional valence node is negative but is counteracted with several weaker positive emotional valence nodes.

Overall, the results obtained are impressive regarding both the potential degree of information compression in tweets′ authorship and the strong emotional coupling between leaders and followers. As will be highlighted in the conclusion section, the proposed technique is framed within the cognitive orientation contemplated in the resolution of complex problems and opens the door to the extraction of the arguments that support the different positions and decisions, which will allow establishing new directions in the analysis of social mood.

About the limitations of this approach, it is necessary to ponder the existing complementarity between the technique of sentiment analysis using lexicons, as performed in this article, and supervised/unsupervised deep learning models [60]. Lexicon-based models are preferred when datasets are small and available computational resources are limited, subject to somewhat lower performance [61]. Supervised models perform well in the specific domain for which they have been trained; however, when working with other domains or entirely new topics, such as the current COVID19 pandemic, the specific training becomes a significant limitation. Approaches based on unsupervised learning are independent of the domain or topic of the training data, overcoming the difficulties of collecting and creating labelled training data, although they require a long training process and subsequent computational resources. The hybrid method is a combination of lexicon and deep learning. This combination improves the efficiency of classification, enables the detection and measurement of sentiment at the concept level, and ensures high accuracy of results [62].

5. Conclusions

This work has studied the possibility of identifying the state of mind of society through the state of mind of network leaders. It has been done by using sentiment and emotion analysis as research techniques and *Twitter* as a representative social network. The COVID-19 vaccination process in Spain has been considered as the Case Study.

From the analysis of the tweets issued by social leaders, the proposed techniques could allow us to extract the arguments that support the different positions and decisions, as the cognitive orientations claim. The reduction in the number of authors from the others present in society (more than 8,000) to the network leaders (8) was greater than 99 %; and the subsequent reduction in the number of associated tweets was greater than 88 % from the 18,193 tweets in society to the 2,145 tweets of the eight social leaders.

That means that an impressive degree of information compression has been achieved, which may be useful to establish new directions of social mood analysis. Considering tweets from 11 days (5 before and 5 after each hotspot), we have witnessed how the changes in emotional valence of leaders and of society was very high, 0.9754 (with a p-value of 0.0167). This justifies that the search for the arguments that support the different positions and decisions could be carried out among the leaders and not among all the users. It is impressive that we can so easily follow the evolution of social emotions (approval/rejection) regarding the main decisions and public policies adopted.

There is an imperative of social cohesion that encourages followers to be in agreement with the positions adopted by their leaders. And this is also evident in the real time dynamics of social networks. Our analysis of emotional valence during the whole period that was considered, and in the hotspots marked by political and public health decisions, has shown that emotions are always associated with the extraction and dissemination of arguments by the leaders who support the different positions and decisions.

In summary, our preliminary study suggests that the new scientific methods in DSS applied to public decision making (healthcare, economy, business …), which basically aim to provide an objective treatment of the subjective, may be a fruitful path to explore in order to contribute to solving the highly complex social problems of our times. So, the proposed technique is framed within the cognitive orientation contemplated in the resolution of complex problems and opens the door to the extraction of the arguments that support the different positions and decisions, which will allow establishing new directions in the analysis of social mood.

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Data availability

All data supporting this study was obtained from public sources (*Twitter*) using the *Twitter* API v2 (https://developer.twitter.com/en/docs/twitter-api). Information needed to replicate the data extraction is provided in the Materials and Methods section of the document.

Ethical approval

Review and/or approval by an ethics committee was not needed for this study because it does not contain any research with human participants performed by any of the authors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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