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Emotions during the Pandemic's First Wave: The Case of Greek Tweets

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Abstract: While most published research on COVID-19 focused on a few countries and especially on the second wave of the pandemic and the vaccination period, we turn to the first wave (March–May 2020) to examine the sentiments and emotions expressed by Twitter users in Greece. Using deep-learning techniques, the analysis reveals a complex interplay of surprise, anger, fear, and sadness. Initially, surprise was dominant, reflecting the shock and uncertainty accompanying the sudden onset of the pandemic. Anger replaced surprise as individuals struggled with isolation and social distancing. Despite these challenges, positive sentiments of hope, resilience and solidarity were also expressed. The COVID-19 pandemic had a strong imprint upon the emotional landscape worldwide and in Greece. This calls for appealing to emotions as well as to reason when crafting effective public health strategies.

Keywords: COVID-19; pandemic; social network analysis SNA; emotion; sentiment; Greece

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Citation: Skarpelos, Y.; Messini, S.; Roinioti, E.; Karpouzis, K.; Kaperonis, S.; Marazoti, M.-G. Emotions during the Pandemic's First Wave: The Case of Greek Tweets. *Digital* **2024**, *4*, 126–151. https://doi.org/10.3390/digital4010006

Academic Editor: Phivos Mylonas

Received: 13 November 2023
Revised: 29 December 2023
Accepted: 4 January 2024
Published: 8 January 2024

1. Introduction

Research on social and emotional reactions to COVID-19 is already quite extensive, although for the most part it is descriptive and geographically limited. Even more descriptive, focused and lacking depth are the publications concerning the first wave of the pandemic, until the end of spring 2020, which tried to capture the concerns rather than to articulate a substantial scientific discourse. In contrast, publications dealing with fall 2020 or attitudes toward vaccination are more mature, both in terms of content and methodology.

The SERP 19 project aimed to understand the social and emotional effects of the pandemic and the first lockdown period in Greece, and to compare them with the corresponding effects in two more member countries of the European Union, namely Italy and Germany. These countries were chosen because of the significant differences they presented to the Greek case: while Greece came out of the first wave of the pandemic successfully, and was considered a role model, Italy was among the countries that suffered the most in cases and death toll. Germany did not suffer as much, but its citizens expressed higher trust to public authorities compared to Greek citizens.

To achieve this goal we had to turn to the discourse of the subjects, as it emerged spontaneously in the period we were interested in, motivated either by the news about the evolution of the pandemic, or by the public discourses and measures imposed by governments, from the fears created by the above but also from the illness of relatives, friends and acquaintances, or from the discussion on social media, given that face-to-face discussions could not take place outside the household.

During the first year of the pandemic (January 2020–January 2021) the number of social media users worldwide increased by 13.2%, (or by 490 million users). The most popular platforms at the end of 2020 were Facebook, YouTube, WhatsApp, Messenger and Instagram. Twitter ranked 16th in popularity with 353 million users worldwide. The number of social media users in Greece during 2020 increased by 9.7% (+650,000 users), in part due to the containment measures limiting mobility during the lockdown; movement restrictions turned the global public towards telecommuting teleworking and online entertainment. The transfer of most activities online was boosted, boosting activity on social media. Twitter was the only popular social medium allowing mass data collection from public accounts.

In this paper, we present the evolution of the characteristics of the collected tweets from Greece during the three months of the first wave of the COVID-19 pandemic (March–May 2020), which covers the spread of the pandemic in the European countries, the World Health Organization declaration of COVID-19 as a pandemic (11 March 2020), the gradual imposition of measures and restrictions on movement (lockdown), to their gradual lifting during May 2020. Our aim is manyfold: on the one hand, we turn to the fluctuation of sentiments and emotions, looking for what may impact the emotional status of users during a crisis. We realize that it is the anticipation of a looming crisis as well as the insecurity when it is announced that the crisis is over that has a major impact upon negative sentiment, while secondary or irrelevant events during the crisis may trigger a surge in negativity. On the other hand, we analyze the volume of the tweets produced to realize a law of diminishing returns, or, to put it simply, that people get used to the critical situation and are less prone to discuss it, turning their interest to other issues. In the following, we present a review of the publications related to the debate about the pandemic on Twitter, including the sentiments and emotions expressed by the users, as well as the spread of disinformation—which the World Health Organization warned about from the beginning, characterizing it as a pandemic of misinformation (infodemic)—and conspiracy theories. The third section is dedicated to the presentation of the research methodology. It covers the choices we made for data collection (data mining) and its limitations, ethical issues, and the methodology adopted based on social network analysis, sentiment analysis, and discourse analysis. The fourth section presents the analysis for Greece. It presents a concise timeline of the most important events, the evolution of the volume of tweets and retweets, the analysis of the network of users per month, the presentation of the main topics and the evolution of emotion.

While timely publication of such research may seem important, and indeed a lot has been published in almost 'real time,' since academic journals published with priority COVID-19-related research, much of what has been published was ephemeral and lacked a critical lens, which comes with temporal distance. Thus, we expect that our findings may still be useful in planning communicational interventions for future crises, as well as understanding the impact of emotions in behavioral patterns complying or diverging from governmental guidelines.

2. Literature Review

Publications on the relation between social media and their use during the pandemic highlighted their role as a means of disseminating (dis)information and fake news, as well as a means of shaping public opinion, education, direct communication between the public, the state, institutions and stakeholders, along with surveillance [1]. The first wave of the pandemic caught both national and international governments as well as the scientific world off guard. Research into the analysis of sentiments on Twitter is quite limited, while published papers are mostly about India and the USA, and only one out of four adopts a global perspective. Although the countries suffering most during the first two months of the pandemic were Italy, France, Germany and Spain [2], published research did not follow the epidemiological map at the time. During the second wave, the second lockdown, the emergence of new mutations of COVID-19 and vaccination, the interest of the scientific community on the relation between Twitter and sentiments about the pandemic heightened and became more internationally oriented.

We analyzed 141 papers found in a Scopus search, combining sentiments and emotions or disinformation during the pandemic on Twitter. The network of keyword co-occurrence (Figure 1) captures the distinction between papers emphasizing computational techniques (the left, red and purple part of the graph) and those focusing on social issues (the right, green and blue part of the graph). Most of the papers were focusing on the second wave and the vaccination, leaving aside the first wave. On the other hand, most papers used corpuses with English tweets, or tweets in other languages machine-translated to English, thus discarding cultural and national differences.

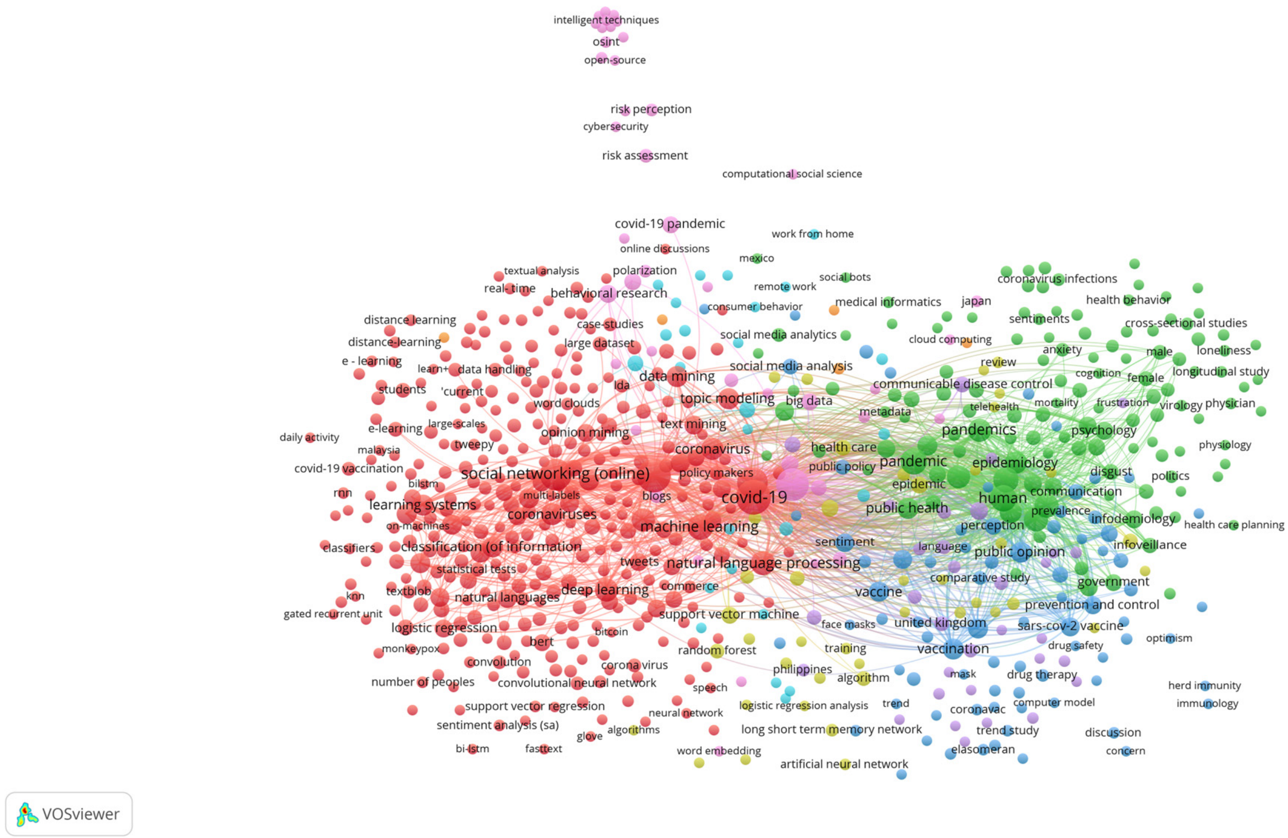

Figure 1. The network of keyword co-occurrence of papers included in Scopus examining the relation between the pandemic and sentiments/emotions.

The study of sentiments highlighted the negativity during the first wave, attributed to the gravity of the pandemic combined with the lack of medication [3]. On the other hand, the study of the trauma accompanying such stressful situations reveals that people were initially negatively disposed towards the new and threatening situation, prone to focus on negative events and reinforcing existing negative emotions [4,5]. In the case of Italy, the first period was marked by high levels of negative emotions and fear, due to growing anxiety and uncertainty, but after that and despite the strict measures, sentiments were back to normal, even reporting emotions such as boredom [4].

Uncertainty and fear were not the only factors behind negative emotions. Socio-political developments and the unprecedented 'violent' subversion of the social contract caused a widespread social discomfort. Despite national differences, a correlation was found between socio-economic events and negative emotions, as well as between the containment measures taken by the governments and an increasingly obvious social discontent. The increasing expression of negative emotions, mostly of isolation and depression, was related to government practices, as well as to economic consequences, as, e.g., in Mexico [6].

In the latter case, negative emotions were associated with positive concepts such as rescue and recovery, attributing greater intensity to social discomfort. Similar were the findings in Korea and Japan, with an emphasis upon the impact of containment measures upon everyday life, or the cancellation of the Olympic Games in Japan [7].

At the micro level, the problems faced in European countries, despite horizontal measures adopted by the EU, caused negative emotions such as rage, anger and fear. Research in Arabic-speaking countries [8] also found emotions of rage, anger and fear, followed by disgust and sadness. In other cases, anger was found to be related to social isolation, and many Twitter users reported that being isolated in hotels without institutional support made them feel like criminals [9]. Such findings indicate a crisis of trust towards political authorities and institutions [10], which was quite loud when vaccination was around the corner. While diffuse emotions of fear, anxiety and anger remained relatively stable since the beginning of the pandemic, the center of gravity shifted towards certain sectors of politics, economy and specific practices in the management of the pandemic.

Research regarding the expression of emotions on Twitter in Greece during the first wave of the pandemic is extremely limited. According to Kydros, Argyropoulou and Vrana [11], tweets using Greek and international hashtags on coronavirus were associated with positive emotions during the first wave of the pandemic. Official campaigns such as #menoume_spiti (i.e., 'we stay at home') were instrumental, highlighting a high level of compliance and trust shown by Greek citizens towards the government and EODDY (the Greek Organization for Public Health). This situation was gradually overthrown when the discussion shifted to topics such as the opening of markets and schools, the restart of the economy and the official announcement of the tourist season. The fluctuation of sentiments followed a different path than other countries. The initial optimistic attitude was replaced by negative emotions such as fear and anxiety, which were also expressed through practices such as the uncontrollable hoarding of goods. Especially during the first wave, there was a strong tendency to help each other with an exhortation for social distancing, compliance with the containment measures and personal responsibility. Geronikolou, Drosatos and Chrousos [12] also studied emotions on Twitter during the first wave of the pandemic, but their focus was on English tweets by Greek users. Using the Paul Ekman classification, they found that the most frequent emotions were surprise at the emerging contagion and anger over the imposed isolation, leading to a "fear versus anger" response. Samaras, García-Barriocanal and Sicilia [13] focused on the second wave, and they aimed at evaluating the accuracy of existing sentiment and emotion lexicons. They found a diminishing interest in tweeting about COVID-19, a lower positive polarity than in other countries, while the dominant emotions were surprise, disgust and anger. Other papers discuss sentiments related to long COVID [14] and vaccination [15].

Our research complements these studies in providing an in-depth analysis of tweets posted during the first wave, using a wider spectrum of country-specific COVID-related hashtags, as described in the following section. It diverges from published research in adopting a complex theory of emotions, involving eight basic, twenty-four combinations or dyads, and four opposite emotions. Finally, it makes use of social network analysis to examine the emotions expressed by different groups with divergent or opposing interests.

3. Materials and Methods

In this section, we detail data mining and compliance to ethics in Twitter use. We then proceed to the description of the data, and the criteria for choosing tweets and enhancing our corpus. A concise presentation of Plutchik's theory of emotions and its operationalization in Natural Language Processing and opinion mining with the use of NRC Word-Emotion Lexicon is followed by social network analysis basics, focusing on the metrics used in our research.

3.1. Data Mining

Data mining is a complex process, especially at the scale attempted for this project. The project covers an extensive period, and our goal was to sample data from all tweets shared throughout this period. Data acquisition had to follow a uniform policy for the entire period, to limit bias. Therefore, we examined available datasets in academic repositories, covering the first wave of the pandemic (March–May 2020). We chose to use the "COVID-19 Twitter Dataset" [16], which, according to its description

> *. . .contains 237M Tweet IDs for Twitter posts that mentioned "COVID" as a keyword or as part of a hashtag (e.g., COVID-19, COVID19) between March and July of 2020. Sampling Method: hourly requests sent to Twitter Search API using Social Feed Manager, an open-source software that harvests social media data and related content from Twitter and other platforms. NOTE: (1) In accordance with Twitter API Terms, only Tweet IDs are provided as part of this dataset. (2) To recollect tweets based on the list of Tweet IDs contained in these datasets, you will need to use tweet 'rehydration' programs like Hydrator (. . .) or Python library Twarc (. . .). (3) This dataset, like most datasets collected via the Twitter Search API, is a sample of the available tweets on this topic and is not meant to be comprehensive. Some COVID-related tweets might not be included in the dataset either because the tweets were collected using a standardized but intermittent (hourly) sampling protocol or because tweets used hashtags/keywords other than COVID (e.g., Coronavirus or #nCoV). (4) To broaden this sample, consider comparing/merging this dataset with other COVID-19 related public datasets. . .*

As noted in the description, the data is presented in a 'dehydrated' format; that is, it is a list of the unique identifiers (ID) of the tweets. This is generally accepted as the ethical way to disseminate Twitter datasets, as it ensures that any subsequent researcher will repeat the data collection, leaving aside tweets deleted, turned private, or posted by a deleted account. Such a procedure also complies with Twitter's guidelines during the data collection period. Data 'hydration' was completed using the twarc2 library for the Python programming language.

3.2. The Enrichment of the Greek Corpus

The corpus of Greek tweets was limited, due to the use of English-only hashtags during the original data collection procedure. This posed obstacles to mining tweets from countries using hashtags in non-Latin alphabets or country-specific hashtags (such as #covid19gr). Such a limited corpus also meant limitations to its scope, possibly excluding significant topics of national importance or even niche subjects and fake news or conspiracy theories. We took the following steps to enrich the corpus:

1. A selection of tweets identified as using the Greek language. The reconstruction of the network of hashtags used in those tweets;
2. Hashtag network analysis: This network is an undirected graph capturing the co-occurrence of hashtags in the same tweet, creating an edge for each pair of hashtags (Figure 2). We identified groups of hashtags appearing together more often, algorithmically organized into clusters (modularity classes) of strongly interconnected hashtags, shown in Figure 2 under different colors. Different attitudes towards the pandemic or containment policies are expected to use different hashtags. The nodes were ranked according to PageRank algorithm [17], which calculates both the degree of a node (i.e., the number of its connections to other nodes) and the connection to important nodes (highly influential nodes) [18].
3. We selected hashtags with the highest PageRank, excluding those non-country-specific and including hashtags from various groups (modularity classes), to ensure diversity. This resulted to a list of 50–75 hashtags per month (Appendix A, Table A2).
4. A search was conducted via Twitter API using the twarc2 library for the Python programming language querying for those hashtags to produce the final corpus of Greek tweets.

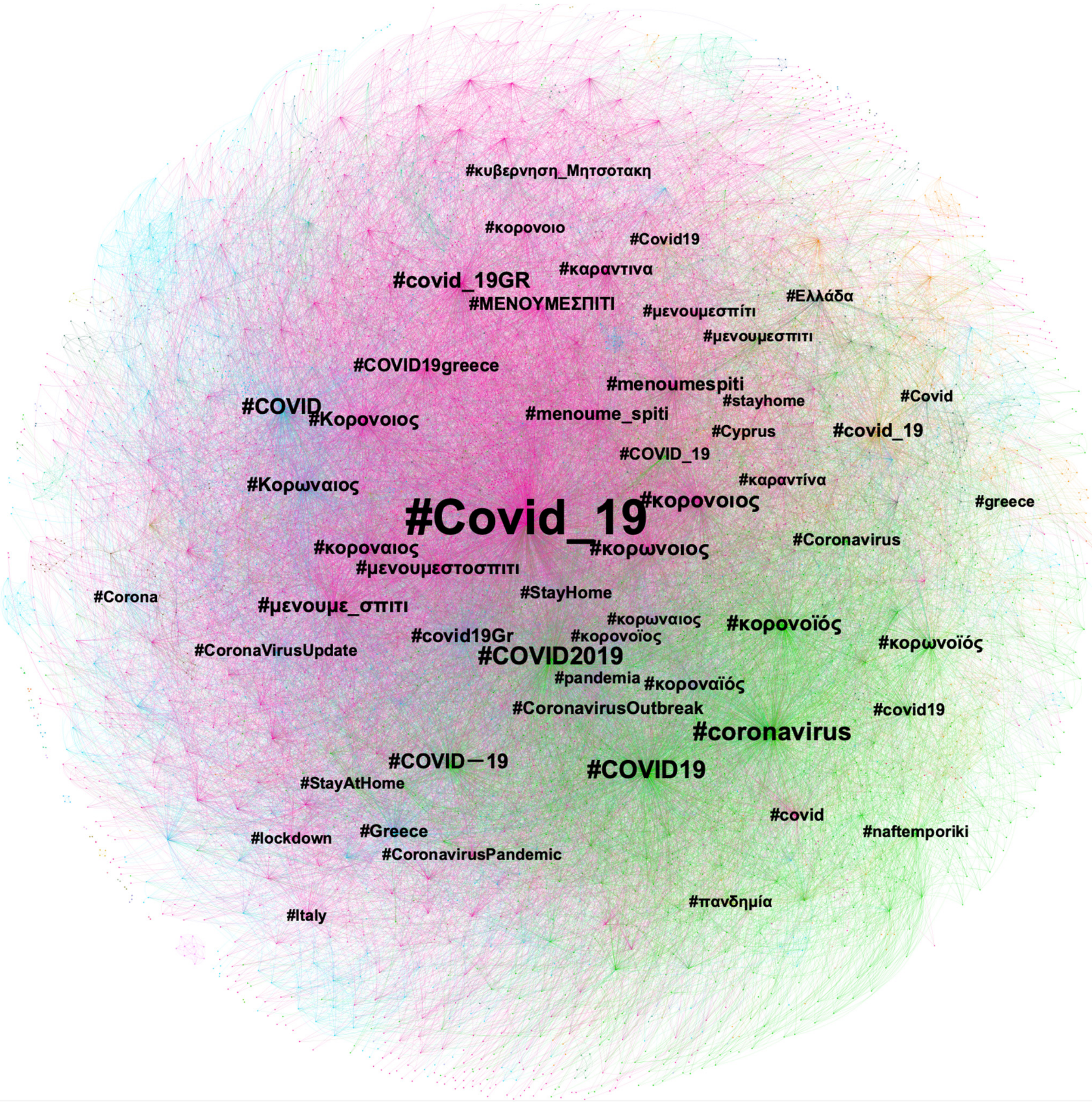

Figure 2. Hashtag network of Greek tweets in March 2020. The network included 3263 nodes (hashtags) connected to 25,010 edges. The 53 nodes with the highest PageRank are named. Colors indicate modularity class. Layout algorithm: Force Atlas2.

As a result of this procedure, 920,002 tweets of any sort were collected, out of which 300,003 were original tweets, 602,376 were retweets and were 17,593 replies (see Appendix A, Table A1).

3.3. Restrictions

The data collected through Twitter Search API is a fraction of the total volume of the actual tweets. This fraction is determined by the content selection and delivery algorithm, while an exact percentage is not mentioned. Data aggregation of the original corpus was completed in certain time frames, thus tweets posted outside these time frames were ignored not collected. Finally, as the search was made with a generic hashtag, tweets using other hashtags were also ignored. This led to a limited representation of languages where the use of English hashtags is not common practice.

On the other hand, such restrictions are relevant when considering gaps at the 'fringe' of the debate, where fake news, conspiracy theories and misinformation are spreading. When they use unconventional hashtags, they go 'under the radar.' A different data-collection strategy should have been employed, were we looking for such tweets, as described for example in [19–22].

3.4. Sentiment Analysis

The idea of sentiment analysis is not particularly new. It can be traced, for example, to the analysis of sentiment as reflected in newspaper texts at the beginning of World War II [23]; however, it is flourishing with the application of computational methods in Digital Humanities. Pang and Lee [24] attribute this sudden 'explosion' of interest to the development of new systems for opinion expression and evaluation of products, services, etc. Indeed, the participatory Web 2.0 enabled users of services and products to rate them and describe their experience justifying their ratings. Upon realizing that "consumer voices can wield enormous influence in shaping the opinions of other consumers—and, ultimately, their brand loyalties, their purchase decisions, and their own brand advocacy" [24] (p. 4), sentiment-aware applications were developed.

The use of lexicons matching specific words with positive, negative or neutral sentiment is widespread in Digital Humanities. This technique compares each word within a document (a tweet in our case) with the words in the lexicon and applies the term frequency inverse document frequency (TF-IDF) statistic as a means of weighting the positive, negative and neutral words in relation to the total number of words in the text. We used the NRC Word-Emotion Association Lexicon (EmoLex) [25,26], providing annotations for two sentiments—positive and negative—and eight emotions—anger, anticipation, disgust, fear, joy, sadness, surprise and trust. They are related to Plutchik's evolutionary theory [27–30], which conceives emotions as "a complex chain of loosely connected events that begins with a stimulus and includes feelings, psychological changes, impulses to action and specific, goal-directed behavior" [30] (pp. 345–346). He argues that emotions such as fear and anger are common to all living organisms, while pairs of emotions produce complex feelings (dyads and opposites) more compatible with human nature. The outcome of sentiment analysis is presented in the form of 'Plutchik's wheel' (Figure 3). The Python library pyplutchik [31] was used to produce emotion wheels according to our research.

The EmoLex lexicon has been used by several authors [32–38] in the analysis of emotions during COVID-19.

Previous research has shown that the automatic translation of the English lexicon into other languages, along with its linguistic limitations [39] and field specific deficiency [40], should be amended to achieve better outcomes. In our analysis, an amended version of the Emolex dictionary has been used, produced by Sofia Messini for her doctoral thesis.

The preprocessing performed to cope with word inflection and lemmatization was based on spaCy NLP library for the Python programming language, and the el_core_news_lg pipeline.

3.5. Social Network Analysis

In its basic form, a social network describes the interaction between social actors. The actors are represented as 'nodes' or 'vertices,' while the interactions are represented as 'edges' connecting the nodes. The more intense the interactions between two nodes, the stronger the edge between them. Social networks may be quite complex, and social network analysis (SNA) may be used in very diverse contexts ranging from predicting political behavior and election outcomes to the spread of epidemics [41–43].

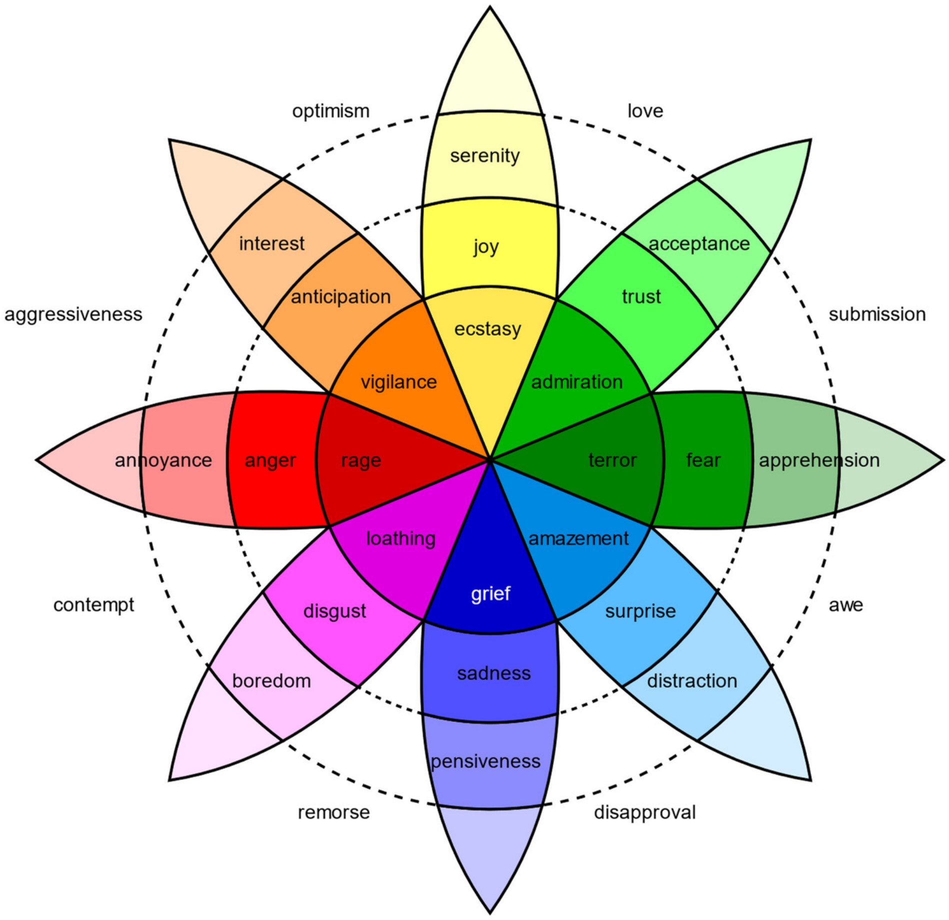

Figure 3. Emotional Wheel by Robert Plutchik. Source: https://commons.wikimedia.org/wiki/File:Plutchik-wheel.svg (accessed on 3 January 2024).

Despite its widespread use in social media analysis, only few publications used SNA on Twitter data during the COVID-19 pandemic. In most cases, their aim was to figure out opinion leaders, guiding the polemics between mainstream positions and partisan opinions, which were sometimes prone to misinformation and conspiracy theories [44–50]. Though such approaches involve recognizing discrete communities within the network, only Boucher et al. [51] emphasized the search of such communities or "clusters expressing mistrustful opinions on COVID-19 vaccination."

In this paper, we reconstruct the networks of reactions between Twitter users, including mentioning, replying, retweeting, quoting or liking. We employ SNA algorithms to discern communities within the network and locate opinion leaders or 'significant others' expressing the opinions and attitudes of each community. "A community is a locally dense connected subgraph in a network. (...) all members of a community must be reached through other members of the same community. At the same time, we expect that nodes that belong to a community have a higher probability to link to the other members of that community than to nodes that do not belong to the same community" [41]. Communities are pivotal in network dynamics, by supporting co-operation within and promoting diversity in the complete network [52]. The idea that communities display some degree of conformity, by sharing common interests, perceptions and ideologies, has been the foundation for recognizing the feature of homophily in networks [41,53,54]. To compute communities within our networks, we used a modularity algorithm [55]. To locate important nodes within each network, we employed centrality measures, based either on the number of connections (degree centrality) or on influence through being close to well-connected neighbors (closeness centrality) or being connected to the most influential nodes (eigenvector centrality) [18]. We utilized the old sociological concept of "significant others", i.e., "those persons who exercise major influence over the attitudes of individuals" [56]. As a proxy to such influence, we used the number of connections leading to certain users (in-degree centrality) who may otherwise have low contributions to content production: the prime minister or a party leader may use Twitter sparingly, while supporters and party members tend to "speak" to them by @mentions, express their consent to their opinions by repeating ('retweeting'), 'liking' or 'quoting' them. In the networks constructed by the tweet reactions in our corpus, a few users with high in-degree centrality (usually politicians, other public figures, or journalists) were a gauge of the political orientation and ideas held by the users 'belonging' to the same community (modularity class). We found that not only are content and ideas within each community are shared, but also the emotions expressed vis à vis the pandemic and the containment measures taken by the government.

In SNA (network analysis, clustering, centrality measures) and network visualization, we used the open-source software Gephi ver. 0.10.1 [57]. During visualization, we used Force Atlas 2 [58], OpenOrd [59], Yifan Hu [60] and Circle Pack [61] layout algorithms.

4. Results

The first case of the COVID-19 pandemic in Greece was detected on 26 February 2020 and the first ICU hospitalizations were announced on 4 March, while the first death occurred on 12 March.

The tweets we collected from March to May 2020 (Figure 4) display an overall declining trend after peaking on 13–15 March, when the first deaths from COVID-19 were announced, and a smaller peak a few days later (19–21 March) when the 10th death was announced. During the lockdown period (23 March–4 May), COVID-19-related tweets were significantly fewer, with a peak on April 17 as the Greek-Orthodox Easter was approaching and the churches were closed to the public, and smaller ones on 22 April and 1 May. From then on, interest decreased, and at the end of May, the tweets per day in our corpus did not exceed 5000.

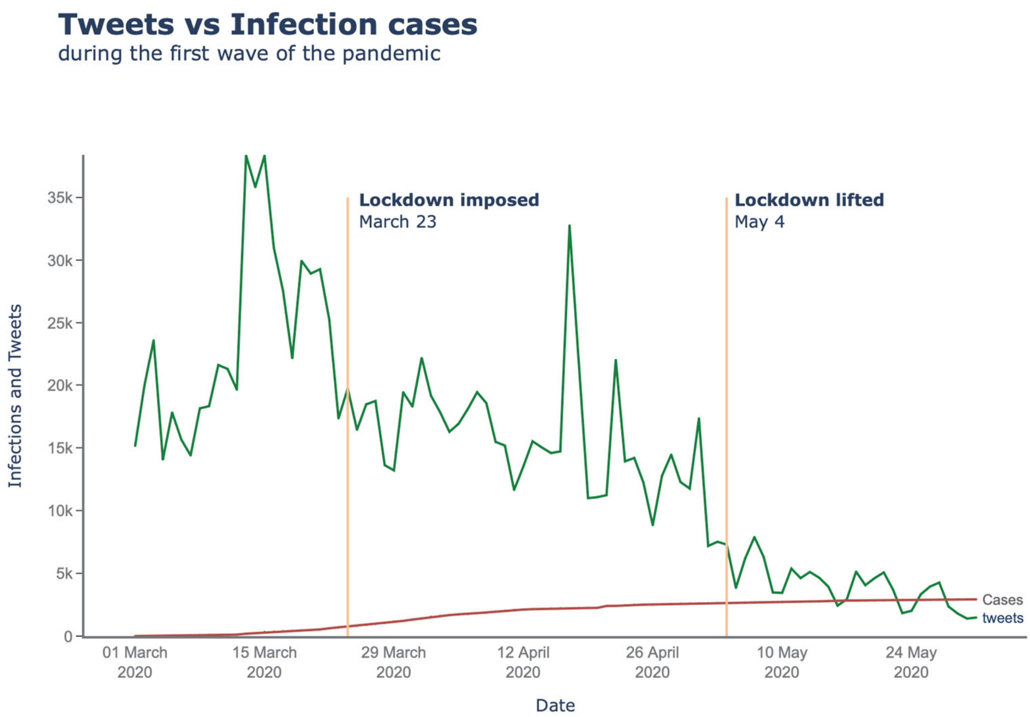

Figure 4. The evolution of the volume of Greek tweets in the research corpus, compared to the number of cases (infections) per day.

The sentiment expressed was mostly negative (Figure 5). It seems that since April 1st, and until the end of the quarantine, the expression of negative emotions became less intense. After the announcement of shifting travel restrictions (28 April) and the gradual opening of shops, accompanied with the mandatory use of masks (4 May), the negative sentiment intensified, because it was considered that such decisions were premature, taken only to facilitate tourism.

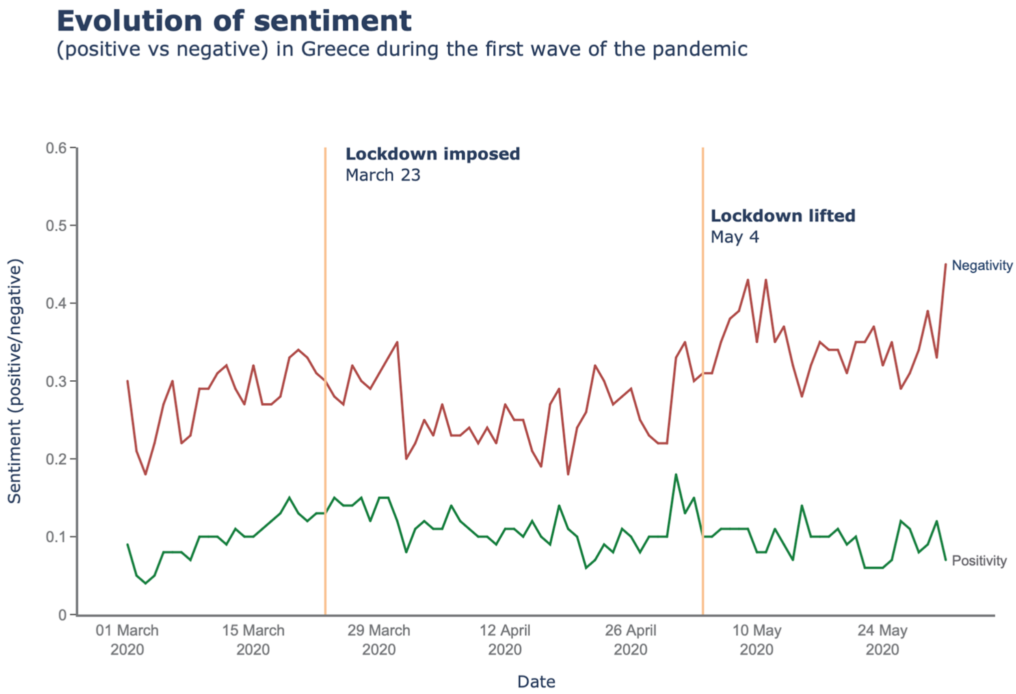

Figure 5. The evolution of sentiment (negative–positive) between 1 March 1 and 31 May 2020.

4.1. March 2020

The strongest emotions in Greek tweets during March were *Anger*, *Disgust*, *Fear* and *Sadness* (Figures A1 and A2). As mentioned, *Anger* is aimed at persons, while *Fear* is related to situations. Tweets posted during March 2020 scoring high in *Anger* mentioned governments, enemies, institutions, politicians or restrictions involving exclusions by decisions made by governments. At the same time, they were referring to deaths and outbreaks, both in Greece and in other countries:

- The French government has banned public gatherings of more than 5000 people indoors because of the new coronavirus, the health minister announced.
- Hey, don't terrorize the Greeks, dumbasses!
- I have been through Measles, Chickenpox, Rubella, Lice, Chernobyl, Anthrax, Avian Influenza, Pig Influenza, Mad Cows, Ebola, Coxsackie, H1N1, economic crisis with 3–4 Memoranda, Referendum, two Mitsotakis, two Karamanlis, two Papandreou, one [Varoufakis]
- Arrests under the antiterrorism law for a publication. This is how you fight a pandemic when you hire cops instead of nurses and doctors.
- After the notorious 'personal responsibility,' today we learned that the government has done all right with the medical equipment in hospitals, but it is the fault of the workers who waste it. #Καλοφάγωτο #COVID_19.

On the other hand, tweets scoring high in *Fear* (sometimes scoring high both in *Fear* and *Anger*) focus on the casualties and risks, sometimes supported with far-right rhetoric:

- COVID-19-Italy: The victims of the coronet in Bergamo are more than the victims of World War II. The authorities are talking about a catastrophe, according to France 2's correspondent in Rome.
- Who is afraid of "Makelio" [newspaper]? We're dying, do you understand, you miserable bastards?
- Coronavirus: high risk for COVID-19 in Europe #OpenNews #OraEllados7 It has now hit 1/3 of the world's countries and worldwide the number of victims has reached 3117 and the number of infections 90,912.
- during curfew staying at home is an order of the welfare state... and needless moving around entails a fine and maybe soon a prison sentence... so we either "#MENUMESPITI [i.e., Stay at home] or #PAMEPHILACY [i.e., We go to prison], therefore home and prison became identical...for our sake of course.
- #Government_Mitsotakis speaks about an 'invisible war,' but will we go mad? The #coronavirus or other VIRUS is the WEAPON the enemy is behind the weapon e.g., weapon #illegalimmigrants ENEMY #erdogan, everything has its origin why not refer to the origin or creation of the #coronavirus? Responsible = THEM.

The latter case points at persons, but in a vague and collective manner (e.g., "illegal immigrants") or beyond the immediate environment affecting the individuals. Though many of those tweets adopt xenophobic and far-right positions, *Fear* is not exclusive to xenophobic and far-right users.

Disgust also took several forms, often linking politics with the pandemic. Words like "contamination," "prohibition" or "fraud" are prominent in the vocabulary of *Disgust*:

- [An untranslatable derogatory term is used to describe the supporters of the Left party of major opposition] heckle the govt for delay (!!!) in taking measures for #COVID_19. When it banned carnivals 12 days ago, they were down on it for its "undemocratic" decision 😂. Decide exactly what the hell you want, you ideological opportunists!!!!
- When was the last time there was a curfew in Greece??? Um....During [German] OCCUPATION???? #Coronavirus, #Greece, #KyriakosMitsotakis, #HOAX, #Cases, #Scam, #Masons, #COVID
- The Turk is waiting for the right time to strike. That time is approaching. In 20 days, there will be queues outside hospitals waiting for hospitalization, people will be in panic. Then he will strike. Watch and pray #coronavirus #Evros #migration #Greece_under_attack.
- #Coronavirus epidemic of WORLDWIDE PSYCHOPATHS terrorizing, committing crimes with the DIRT of soul and body excretions!
- I can deal with #menume_spiti [i.e., We stay at home] for as long as it takes, but I can't fight dumbass, indifference, selfishness and the criminal incompetence of the government and all politicians #coronavirus.

Grief is also expressed in a variety of ways, ranging from regret for the news about the pandemic, to frustration at the attitude of politicians or society at large, sometimes adopting an aggressive rhetoric:

- It is smelling... death in Europe, as deaths from the new coronavirus are rising rapidly, with Spain surpassing China in the number of deaths.
- #Tsiodoras [i.e., the head of the Greek National Public Health Agency] "PLEASE keep what we tell you!" what a plea! curse the idiots who don't #MENUMESPITI [i.e., We stay at home] #we_are_homeless! pleas are too weak! Use a whip!!!!
- #Coronavirus here is Balkans but the nudity of the 'prosperous' Europe who entangled our countries in memorandums, wars, and 69 innocent souls are considered as a detail, without underestimating the tragedy of death in the face of ethnic cleansing in Italy for example!

- These days that we are delaying the compulsory closure of the country at home—because that will happen eventually—bring more deaths. In a country where the very enforcement of the law is optional, the recommendation to stay home and a video add with Spyros Papadopoulos is not enough. #MENUMESPITI

In Figure 6 the dominance of *Anger* throughout the month is clear, as well as the decrease in *Fear* after the first few days and its replacement by *Disgust*. After mid-March, *Sadness* gained impetus, alternating in third position with *Fear*.

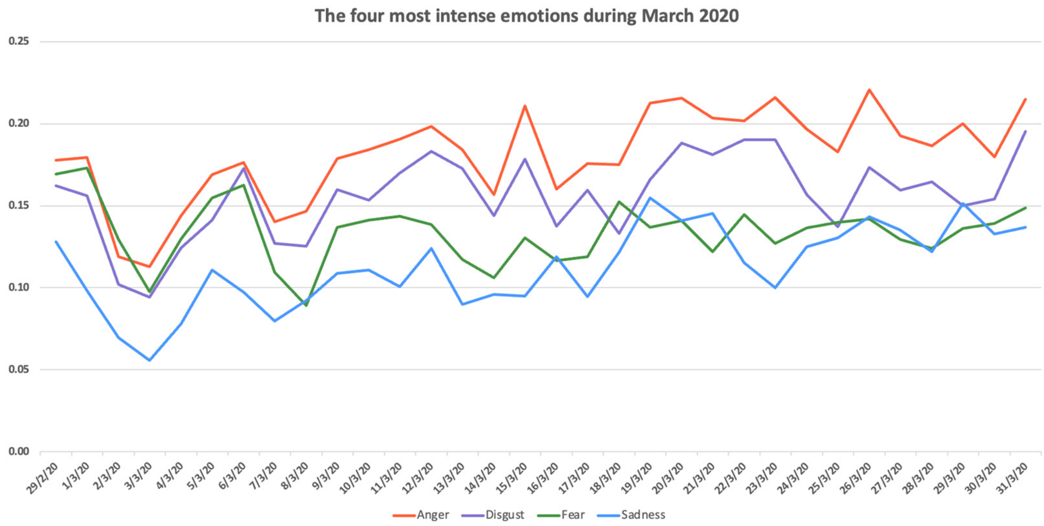

Figure 6. The fluctuation of the four most intense emotions expressed in Greek tweets during March 2020.

Turning from the big picture to the larger groups (modularity classes) of users, the differences among the emotions expressed become illuminating: the larger group was quite involved in the debate on the Greek–Turkish crisis before turning to the discussion on the pandemic, as the last days of February were marked by a sudden opening of the Turkish–Greek border by Turkish authorities so that some thousands of refugees or immigrants could enter Greece, despite a previous EU–Turkish agreement [62]. In the first week of March, the crisis was active, and the news about the pandemic paved the way to a xenophobic discourse connecting refugees with a potential threat to diffuse COVID-19 in Greece [63,64]. This group hosted both the xenophobic and the xenophilic voices. It expressed *Anger* and *Disgust* from 13 March onwards, feelings which became more systematic and intense from 20 March onwards, along with *Fear* and *Sadness*. After the lockdown was imposed, *Trust* was also expressed by the users in this group, peaking between 27 and 29 March. The less partisan second group, humoristic accounts such as "Undertaker Boukouras" and journalists were among the most mentioned. Tweets in this group sometimes expressed left-wing criticism of the government or displayed photos with beaches. During the first half of March, users in this group expressed stronger emotions of *Anger*, *Disgust*, *Fear* and *Sadness*. Later, positive emotions of *Joy*, *Trust* and *Surprise* intensified to above average. The third group was created around mentions to the Right. In early March, users in this group expressed *Anticipation*, *Fear, Sadness* and *Surprise*. In fact, on 1 March, *Fear* reached the highest value recorded for any group during this month. Then, *Anger* and *Disgust* intensified, while *Sadness* and *Surprise* receded. *Anticipation* was intense until the first containment measures were announced. Afterwards, it was replaced by *Trust*. A more "institutional" group, with tweets mentioning the Prime Minister, the Minister of Health and the National Public Health Agency, presented a neutral emotional footprint. It was only in the last three days of March that they scored high in *Anger*, *Disgust* and *Fear*. As neutral was the emotional footprint of the fifth group, associated with SYRIZA or the broader Left.

4.2. April 2020

In April, a daily update on the pandemic became part of a nationwide ritual. On some days, massive outbreaks were discovered in shelters for refugees, elderly people, neighborhoods, health units, etc. The most important dates in April were the following:

- On 8 April, control over violating containment measures and mobility restrictions was upgraded, fines were doubled and churches were announced to remain closed until 28 April, in view of the Easter celebrations (19 April);
- On 14 April, the death toll exceeded one hundred deceased persons in Greece;
- On April 17, a decision to provide lifelong learning aiming at freelancers and professionals in fields like medicine or engineering, as a means to provide financial aid to them due to lockdown, was uncovered as a scandal when the content was proved to be machine-translated and of dubious quality;
- On 28 April, the end of the lockdown and the phasing out of the containment measures was announced.

The strongest emotions expressed in Greek tweets during April were still *Anger*, *Disgust*, *Fear* and *Sadness*, but their scores were slightly lower than in March (Figures A3 and A4). The implementation of the lockdown followed a series of measures, establishing a clear framework that—despite reactions–provided security for citizens. Tweets posted during April 2020 scoring high in *Anger* were aimed at the government, politicians, the media and people who allegedly ignored protective measures and got sick. Some exemplar tweets were the following:

- #antireport #COVID_19gr #curfew The following example shows how TV channels are presenting their shots so that the burden of responsibility continues to fall on the "undisciplined" people who are walking on beaches and parks...
- I don't know about you, but I haven't seen anyone from SYRIZA uploading proof of deposit of 50% of their salary, unlike the members of the New Democracy party..... It's probably a coincidence 😎 #SYRIZA_exploiters #curfew #carantine #Covid_19 #StayHome #lockdown
- We won't die at home... Strengthen the National Health System... You are potential murderers @PrimeministerGR @Vkikilias #curfew #COVID_19 #MENUMESPITI

Fear in April's tweets was taking concrete forms as well: the fear of a bleak future, fear of the consequences from the collapse of the health system and conspiracy theories suggesting that COVID-19 and the pandemic were a means of political management through mobility restriction and fear. Typical tweets scoring high on *Fear* included the following:

- What will be left after the "pandemic"? A new memorandum, massive unemployment and poverty, suicide attacks from fundamentalist Muslims and State terrorism with repeated quarantines.
- Tragic images from Ecuador under total collapse of the health system: woman whose husband died in her home and stayed there for two days, "I'm not afraid of death, but I don't want to die like this" #COVID_19 #we_stay_at_home.
- The "scientific décor" of the Stalinist Junta #ND_deceptions should (1) release DEATH CERTIFICATES and (2) DO NECROPSY. Scammers with the FAKE #coronoius you are destroying the ECONOMY and SETTLE DOWN millions of baboon assassins #GoAway.
- For everyone else, political management is (a) fear mongering (b) incarceration (c) disappearance of any reaction to the Legislative Acts (d) broken health care system -⟶ regime incompetence. #Covid19gr.

High scores on *Disgust* or *Sadness* were in most cases combined with *Anger* and *Fear*. In Figure 7, the continued dominance of *Anger* throughout April is clear. *Disgust* maintained the second position, exceeded by *Fear* only on scarce occasions. *Sadness* and *Fear* were competing for the third position.

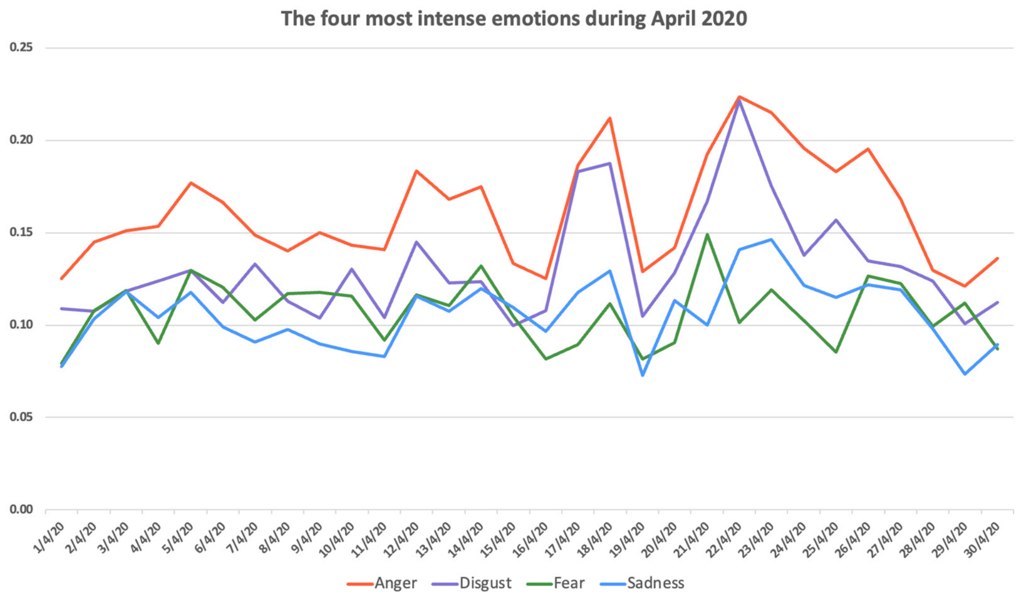

Figure 7. The fluctuation of the four most intense emotions expressed in Greek tweets during April 2020.

4.3. May 2020

The larger groups (modularity classes) of Twitter users were reconfigured during April. The first group was composed by those who mentioned the ruling party of New Democracy executives, Prime Minister Kyriakos Mitsotakis's personal account and Sotiris Tsiodras—the representative of the National Public Health Agency. Negative sentiments scored in this group higher than average. This is due mostly to the very high scores of *Anger* and *Disgust* and to a lesser extent to *Fear* and *Sadness*. Though, it should be noted that the tweets related to the aforementioned scandal were aimed both at the government, and at its critics. Thus, while mentioning the government officials and the ruling party, the negativity was not single-mindedly targeting them, but also it was targeting the ex-ruling opposition party. A second source of *Anger* expressed in the tweets of this group was the prohibition of liturgy in churches during the Greek Orthodox Easter. The second group was also a field of confrontation between users supporting the opposition party SYRIZA (mentioning its leader and party executives) and the 'Truth Group' (an account promoting the ideas and policy of New Democracy in a populist manner) or some of its most active supporters and journalists. This is reflected in the emotion scores, especially those of *Anger*, *Disgust*, *Fear* and *Sadness*, with a peak on April 1st, and again in the scores of a combination of *Anger* and *Disgust* between 18 and 24 April. The third group was populated by users supporting SYRIZA or the Left in general, but the emotion scores were close to the overall average. In general, they adopted a critical attitude towards the government and those who uncritically accept its decisions. The fourth group was populated by users who mentioned leftist accounts and collectives asking for organizing mutual support between citizens during the lockdown, promoting solidarity and supporting social and political mobilizations, such as the students' demonstrations and marches against the creation of University Police. Beyond the four dominant emotions, this group scored high in *Trust* and *Anticipation*.

The public discourse reflected the gradual lifting of restrictions from th^e 4th May onwards, the opening of secondary schools, and the optimistic forecasts from epidemiologists, in the optimistic belief that the pandemic would end soon. This belief was supported by the statements of epidemiologists who reported that the high temperatures during summer leave no room for the spread of COVID. The month started with controversy around a rally organized by trade unions related to the Communist Party, despite the measures taken and social distancing. The controversy would be kept alive as professionals affected by the containment measures went on protests. On 20 May, the Prime Minister announced measures of financial support to businesses. Finally, on 25 May, travel to the islands was allowed and the opening of restaurants was announced.

Anger, *Disgust*, *Fear* and *Sadness* remained the top scoring emotions, though *Disgust*, *Sadness* and *Fear* scored very close (Figures A5 and A6). *Anticipation* scored higher than the previous months, as restrictions were lifted and people were thinking about the future, often with concern. After a month with containment measures, which proved successful, a new uncertain situation was ahead, and the uncertainty was reflected in the dramatic increase in negative sentiments and the increasing gap between positive and negative sentiments.

Exemplar tweets scoring high in *Anger* during May 2020 included the following:

- Imagine them updating us every evening at 6 pm (those left alive) on the evolution of #Covid_19 in Greece. A Nightmare on Elm Street 🤣😂🤣😂🤣🤣😂🤣 And then you tell me there are no miracles 😎😂🤣.
- @Apotis4stis5 Brigand Davelis, Mitsotakis family and the "success story" with the masks #May_Day #coronavirus #mask #COVID19 #COVID_19 #Nordwest: The article...reads: "...behind all this is an effort to attract tourists..."
- So today I watched carefully the whole session of the Parliament, the briefing at six [. . .] Conclusion: those who don't have low income or a business of more than 200 people are screwed.
- "For flu we have a vaccine, for #covid_19GR we don't. Do you understand the difference?" All the years we've had a flu vaccine did deaths cease, you idiot??? #Parliament #corona #Covid_19.
- Twitter allows access to our coronavirus-related tweets, to scientists and public crisis management and civil protection officials! The purpose, is to investigate misinformation, they say...
- Prosecutors and police authorities closed their eyes. They only know how to persecute Greek Orthodox citizens! #May_Day #left #anti-Greeks #PAME #Government_Mitsotakis #quarantine #corona #banning_traffic #Orthodoxy [For the Communist trade union's May Day rally].

The return to an intermediate situation, with restrictions but no lockdown, has brought to the fore broader debates: from the continuing debate between restrictions on Easter celebrations (and therefore a form of 'imposition' on 'the people of the Church') and the Communist trade union's rally without imposing fines or other consequences, to conspiracy theories which were beginning to include vaccines, while users were concerned about access to their tweets, the partisan debate and the economic survival of the private sector. Such tweets combine *Anger* with the other high-scoring emotions, namely *Disgust*, *Sadness* and *Fear*.

As shown in Figure 8, *Anger* was no longer the highest scoring emotion throughout the month, since on some days it was overthrown by *Sadness*. *Sadness, Disgust* and *Fear* alternate positions throughout the month, indicating the emotional frustration and concern about what was to come, which is reflected in the increase in *Anticipation*.

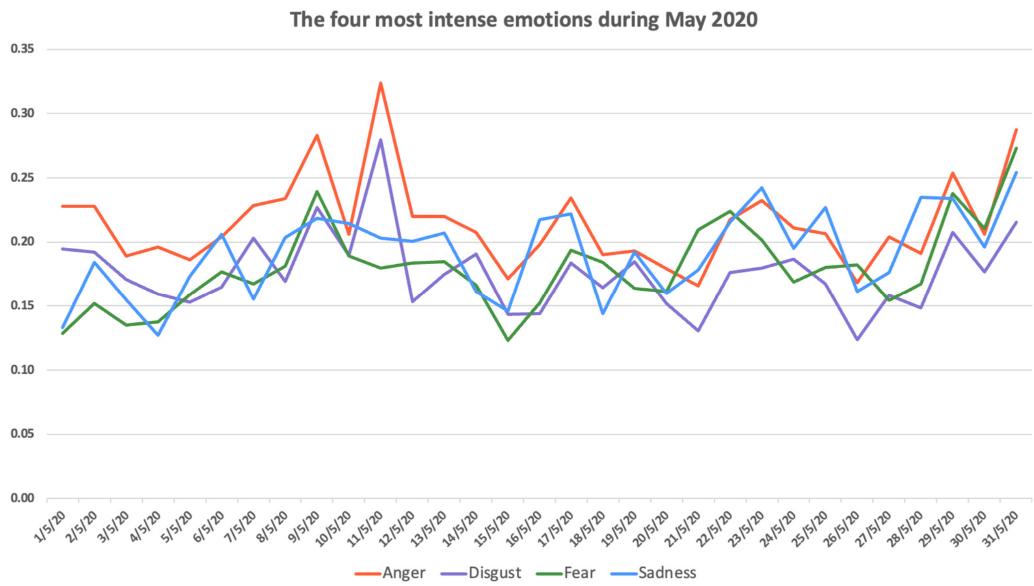

Figure 8. The fluctuation of the four most intense emotions expressed in Greek tweets during May 2020.

The larger groups (modularity classes) of Twitter users were reconfigured once again. The more populated group was affiliated to the opposition, joined by the hitherto independent group of a medical doctors, who had become a standard point of reference for the critical approach to the government's policy towards the pandemic. This group's tweets expressed *Anger* and *Disgust* well above average, directed to government's policies. Among the tweets combining *Anger* and *Disgust*, there are references to the May Day rally and rallies organized by the far (extra-parliamentary) Left, which are treated as a response to the deprivation of freedom. There is often a comparison between events approved by the government or its supporters and rallies in open spaces that the government attempt to disperse through police violence. The second group is close to the governing party of New Democracy, joined by the hitherto distinct group of partisan accounts. One more group was populated by users mentioning government officials, the Athenian–Macedonian News Agency and pro-government media. Here too, *Anger* and *Disgust* were the top scoring emotions, as it presents an aggressively anti-communist discourse, paired with racist and xenophobic utterances and the denial to using face masks. The fourth group mostly mentions humorist accounts such as Undertaker Boukouras, and many tweets reveal a light-hearted attitude, along with more serious concerns, such as questioning why in March the government officials discouraged the use of masks before making them mandatory in May. The most active accounts were broadcasting news and gossip about show business. It is, therefore, not surprising that the emotions expressed by the users participating in this group were close to the overall average scores. The fifth group mentioned mostly the accounts of anarchists and collectives raising demands for solidarity, support for lonely people during the period of quarantine and social distancing measures, but also collective political requests. Thus, this group lies at the opposite end of the previous groups, scoring very low in *Anger*, *Disgust*, *Sadness* and *Trust*, and lower than average in the remaining emotions. Thus, this group had the lowest negative sentiment index.

5. Discussion

During a period of uncertainty, it is expected that negative sentiments will prevail. Such knowledge is self-evident, and this has been documented in sociology since Émile Durkheim's treatise on suicide [65]: sudden changes in the socioeconomic situation cause anxiety—not only when change is for the worst but also when it is for the better. It is the pace of change, its rapidity rather than its direction that causes anxiety or negative sentiment in general. This would support our finding that not only the news about the spreading of the pandemic and the imposition of containment measures—with lockdowns being the most important—but also what was considered as a premature lifting of such measures, both intensified negative sentiments.

Monitoring user-generated content in social media provides valuable insights into popular sentiments in a non-intrusive, less biased manner than traditional methods such as polls or survey questionnaires. It allows for constructing time-series and examining the impact of external factors like information about the development of the pandemic, media content and policy measures upon popular sentiments.

In this paper, we investigated public opinions expressed during the COVID-19 pandemic through tweets in a publicly available database ("COVID-19 Twitter Dataset"), augmented with content in Greek, collected from Twitter; for the latter content, we also performed Social Network Analysis, in order identify potential central nodes and network characteristics pertinent to how public opinion is shaped and expressed. After processing and cleaning the data, we performed Sentiment Analysis, looking for emotional content usually found in online discourse, both in a discrete, label-based representation, as well as a dimensional one (i.e., Plutchik's). In the results presented in Section 4, we found a diminishing interest in the pandemic, per se, on behalf of Twitter users, which might imply that side-issues gained in popularity. It has been noted in previous research [4] that even in countries paying a high toll in deaths, people came to express boredom as new forms of everyday routine had been established. We found that in the period between imposing and lifting containment measures, the distance between recorded positive and negative sentiments was minimal in comparison to the preceding and following periods. In its own terms, though, this distance was important and had an impact upon media messages' success and obedience to policies and rules.

With the use of a modified emotion lexicon, we were able to follow the fluctuation of the most intense emotions throughout this period, thus going deeper into understanding the content of the prevailing negativity. For the most part of the three-month period, *Anger* was the prevailing emotion. By the end of May, though, it was superseded by *Sadness*. Indeed, though during March and April the hierarchy of the four most intense emotions (*Anger*, *Disgust*, *Fear* and *Sadness*) was rather stable, after lifting the containment measures, it was destabilized. This destabilization may have been due not only to uncertainty about the pandemic, but also to the realization of its economic impact upon personal income.

The application of computational methods and their triangulation allowed for the segmentation of the public and for following the emotional status of each segment. Greek Twitter users formed groups mostly based on political partisanship. For both the ruling party and the party of major opposition, two respective groups were formed: one was rather 'institutional' while the other was rather 'populist' or 'militant.' While the former group of each party adopted a mild emotional expression, closer to neutrality, the latter ones were 'louder' and participated in a mutual blame game. Besides those groups, though, we were able to locate other, either humoristic non-political, groups around accounts adopting a humoristic outlook to fight emotional stress, or groups at the fringe of the political spectrum prone to xenophobia and conspiracy theories.

Such findings propose an innovative methodology for monitoring popular sentiments during crisis, as well as the segmentation of national audiences, thus achieving a better understanding of overarching sentiments thanks to their breakdown into emotions. We have also shown that understanding popular sentiment as stable and monolithic does not inform communication campaigns in supporting containment policies or stress the need for diversity and flexibility. Finally, our findings may be applied in different contexts, beyond public health crises, to support reliable and truthful information and combat misinformation, fake news and the adoption of conspiracy theories.

Author Contributions: Conceptualization, Y.S.; methodology, Y.S., S.M. and K.K.; data curation, K.K.; writing—original draft preparation, literature review E.R., S.K. and M.-G.M., materials and methods Y.S., K.K. and S.M., results and discussion Y.S. and S.M.; writing—review and editing, E.R., Y.S. and S.M.; visualization, S.M.; supervision, Y.S.; funding acquisition, Y.S. and K.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Hellenic Foundation for Research and Innovation (HFRI), grant number 39161/9 September 2021.

Data Availability Statement: The data presented in this study are available (in dehydrated form) on request from the corresponding author due to legal and ethical restrictions.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Appendix A

Table A1. Tweets collected per month.

Month	Tweets	Retweets	Replies	Total
March	147,311	348,368	9416	505,095
April	100,671	202,331	6380	309,382
May	52,051	51,677	1797	105,525
Total	*300,033*	*602,376*	*17,593*	*920,002*

Table A2. Hashtags used to collect Greek tweets per month.

March 2020	April 2020	May 2020
#κορωναιος	#covid19gr	#κορωνοιος
#ειδήσεις	#covid_19gr	#μενουμε_ασφαλεις
#κορωνοιο	#menoumespiti	#κορονοϊός
#ελλάδα	#μενουμε_σπιτι	#κορονοιος
#μεταναστευτικό	#menoume_spiti	#πανδημια
#coronavirusgreece	#covid19greece	#μενουμεσπιτι
#νδ_απατεωνες	#κορονοϊός	#προσφυγικο
#καρναβαλι	#μενουμεσπιτι	#κρανιδι
#κορονοιος_movies	#απαγορευση_κυκλοφοριας	#koinoniamega
#κορονοιος_songs	#καραντινα	#the2nightshow
#koronaios	#κοροναιος	#κορωνοϊός
#κοροναιος	#κορονοιος	#πανδημία
#ιταλια	#κορωνοιος	#υγεία
#κορονοϊός	#μενουμεστοσπιτι	#ηπα
#κορωνοϊός	#θεσσαλονίκη	#οικονομία
#μένουμε_σπίτι	#καλοπασχα	#ειδήσεις
#πανδημία	#κορωνοΐος	#τουρισμός
#μένουμεσπίτι	#μετζη_του_νεουκτη	#πολιτική
#κορωναϊός	#πάσχα	#κίνα
#υγεία	#σκοιλ_ελικικου	#ηλιοθεραπεία
#κοροναϊος	#υπερβαση	#παραλία
#ιταλία	#υστερογραφα	#ξαπλώστρες
#πνευμονία	#apotis4stis5	#περιβαλλοντικά

Table A2. *Cont.*

March 2020	April 2020	May 2020
#επιδημία	#greek	#λουόμενοι
#κορονοϊού	#staypositive	#παθογόνοι
#κορωναϊος	#thessaloniki	#ιοί
#κορονοϊό	#ysterografa	#επιστημονική
#ηπα	#γερμανία	#ευρωπαϊκή
#τουρκία	#εε	#επιβράδυνση
#οικονομία	#ελλάδα	#υπερβαση
#κύπρος	#κοροναϊός	#εε
#κορονοιος	#κορωνοϊός	#elefantaki
#κορωνοιος	#δντ	#πρωτομαγια
#menoumespiti	#κορονοιός	#αγια_παρασκευη
#μενουμεστοσπιτι	#μεθ	#1μαη
#κοροναϊός	#κορωναϊός	#refugeesgr
#menoume_spiti	#ειδήσεις	#petralona
#κορονοϊος	#κυβέρνηση	#μερκούρη
#θεσσαλονικη	#ισπανία	#φιλοπάππου
#κυσεα	#σκαι	#ανοιξη
#refugeesgr	#απάτη	#μαπ
#greece_turkey_borders	#μασόνοι	#απαγόρευση_κυκλοφορίας
#τουρκια	#ηπα	#μένουμεασφαλείς
#λεσβο	#κρούσματα	#μένουμεσπίτι
#εβρο	#ευρώπη	#κορώναφόβος
#greeks	#υγεία	#κορονάϊος
#καθαραδευτερα	#οικονομία	#κοροδόϊος
#greekborders	#τεστ	#κορωναιος
#digitalsolidaritygr	#koronoios	#κοροναϊού
#συνορα	#covid19cy	#καναλάρχες
#greekborder	#κύπρος	#κλινικάρχες
	#κυπρος	#μένουμε_άνεργοι
	#θατακαταφέρουμε	#4_μαΐου
	#dimokritos	#μενουμεσπιτι
	#amarysia	#menoumeasfaleis
	#antireport	#ιβεαα
	#κορονοϊος	#ευχαριστώ
	#menoume_dynatoi	
	#κκε	
	#μμε	
	#μένουμεενεργοί	
	#κουκάκι	
	#στηριζουμετοεσυ	
	#εβρος	
	#ergnews	
	#αλληλεγγύη	
	#καη	
	#παραιτηθειτε_ειστε_ανικανοι	
	#μεταναστευτικό	
	#κέρκυρα	
	#κανενας_μονος	
	#καμια_μονη	
	#τωρα_λογαριαζομαστε	
	#κλειστε_τις_εκκλησιες_τωρα	
	#καμίαμόνη	

Appendix B

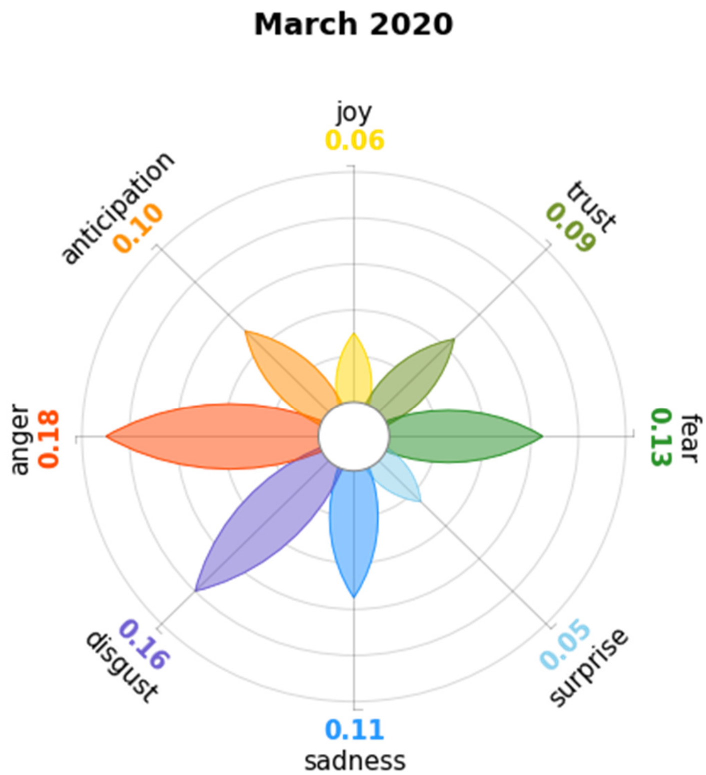

Figure A1. Emotions expressed in Greek Tweets on COVID-19 during March 2020.

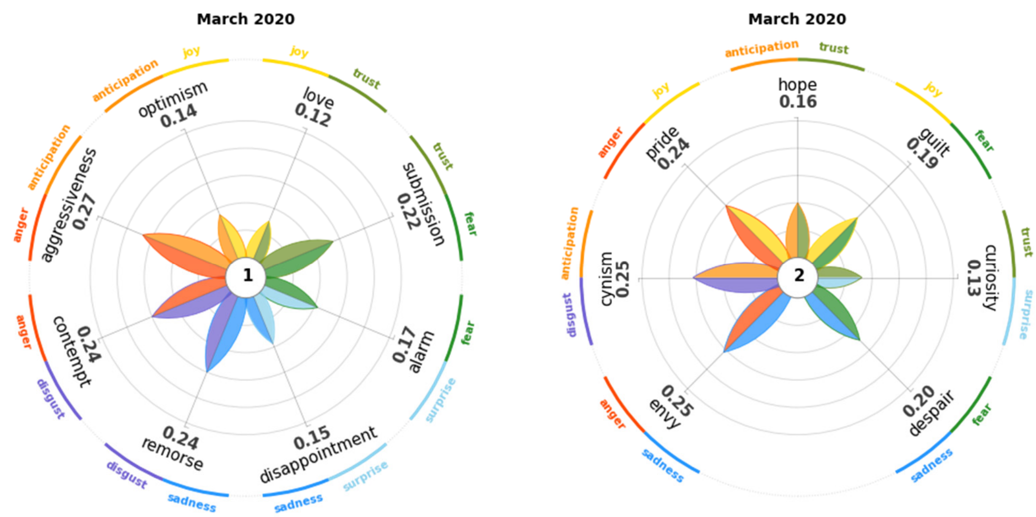

Figure A2. *Cont.*

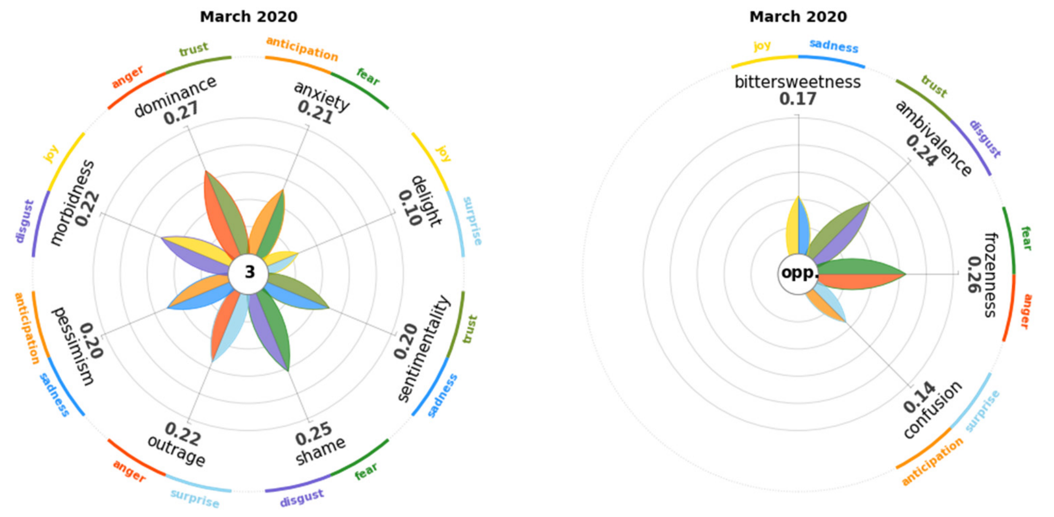

Figure A2. Complex feelings (dyads and opposites) expressed in Greek Tweets on COVID-19 during March 2020.

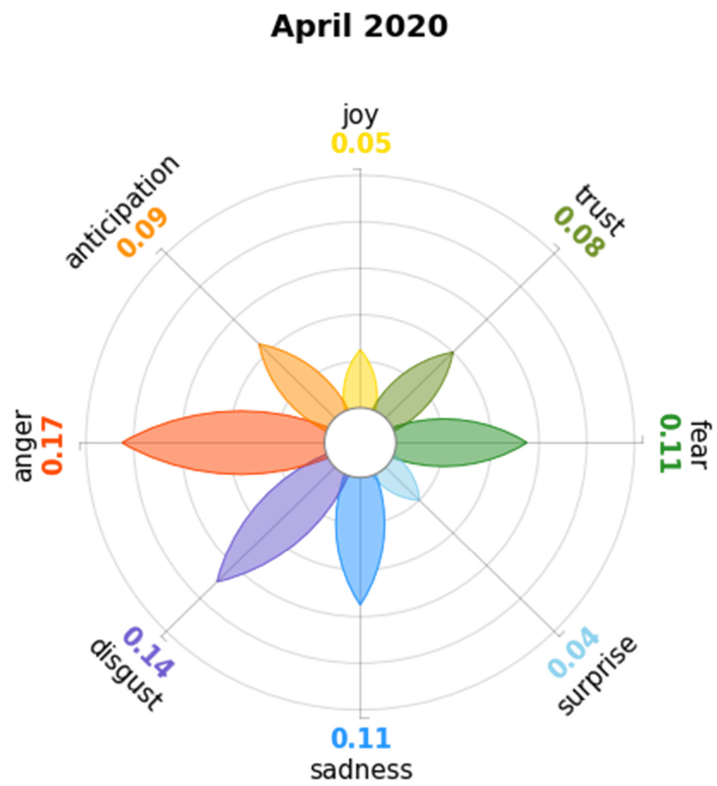

Figure A3. Emotions expressed in Greek Tweets on COVID-19 during April 2020.

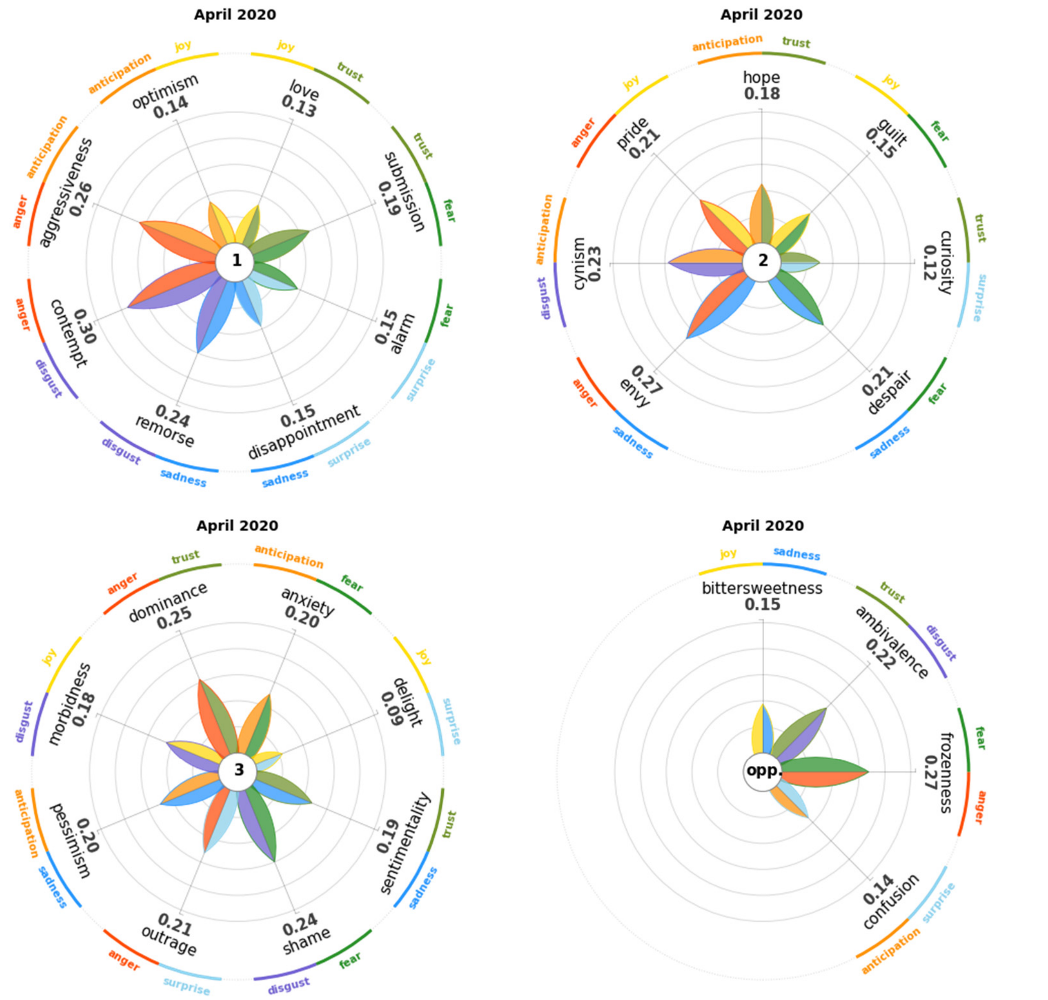

Figure A4. Complex feelings (dyads and opposites) expressed in Greek Tweets on COVID-19 during April 2020.

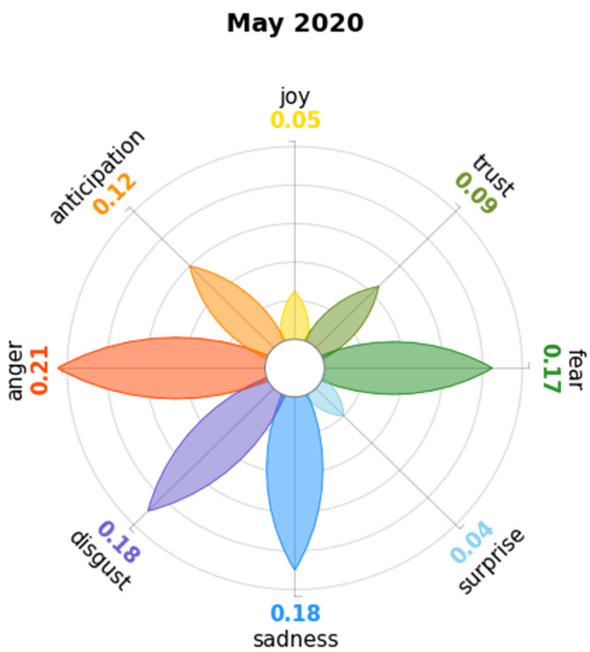

Figure A5. Emotions expressed in Greek Tweets on COVID-19 during May 2020.

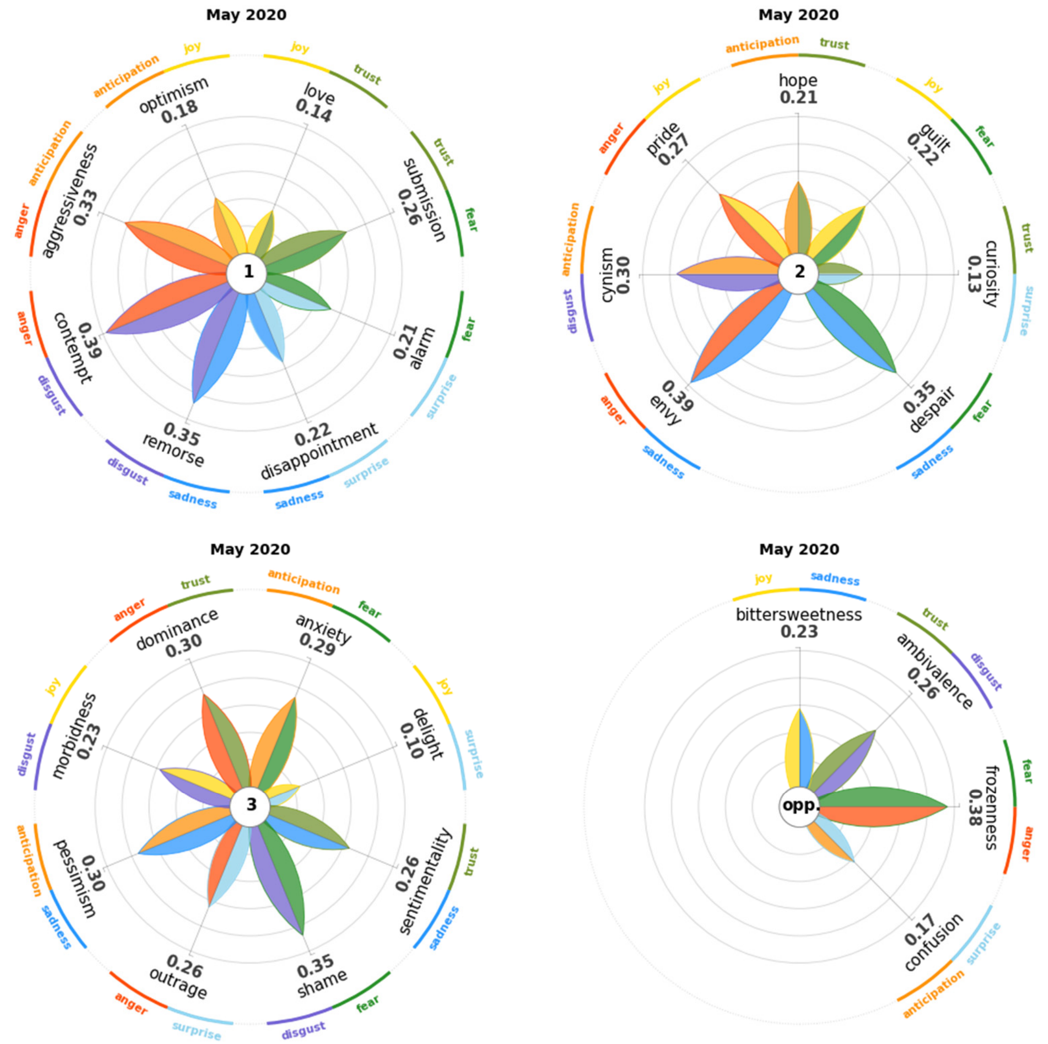

Figure A6. Complex feelings (dyads and opposites) expressed in Greek Tweets on COVID-19 during May 2020.

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