

Article

A Content and Sentiment Analysis of Greek Tweets during the Pandemic

Dimitrios Kydros ¹, Maria Argyropoulou ² and Vasiliki Vrana ^{3,*}
¹ Department of Economic Sciences, School of Economics and Administration, Campus of Serres, International Hellenic University, 62124 Serres, Greece; dkydros@ihu.gr

² University Center of International Programmes of Studies, International Hellenic University, 57001 Nea Moudania, Greece; maria.argyropoulou@gmail.com

³ Department of Business Administration, School of Economics and Administration, Campus of Serres, International Hellenic University, 62124 Serres, Greece

* Correspondence: vrana@ihu.gr

Abstract: During the time of the coronavirus, strict prevention policies, social distancing, and limited contact with others were enforced in Greece. As a result, Twitter and other social media became an important place of interaction, and conversation became online. The aim of this study is to examine Twitter discussions around COVID-19 in Greece. Twitter was chosen because of the critical role it played during the global health crisis. Tweets were recorded over four time periods. NodeXL Pro was used to identify word pairs, create semantic networks, and analyze them. A lexicon-based sentiment analysis was also performed. The main topics of conversation were extracted. “New cases” are heavily discussed throughout, showing fear of transmission of the virus in the community. Mood analysis showed fluctuations in mood over time. Positive emotions weakened and negative emotions increased. Fear is the dominant sentiment. Timely knowledge of people’s sentiment can be valuable for government agencies to develop efficient strategies to better manage the situation and use efficient communication guidelines in Twitter to disseminate accurate, reliable information and control panic.

Keywords: COVID-19; coronavirus; pandemic; discussion; Twitter; social network analysis; sentiment analysis



Citation: Kydros, D.; Argyropoulou, M.; Vrana, V. A Content and Sentiment Analysis of Greek Tweets during the Pandemic. *Sustainability* **2021**, *13*, 6150. <https://doi.org/10.3390/su13116150>

Academic Editor: Androniki Kavoura

Received: 19 April 2021

Accepted: 26 May 2021

Published: 30 May 2021

Publisher’s Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

On 11 March 2020, the World Health Organization declared COVID-19 a pandemic. The virus first appeared in the Chinese province of Wuhan but spread quickly to the rest of the world changing radically our way of life. Countries around the world responded to the outbreak with different measures, but most of them enforced strict policies, such as closing external borders, social distancing measures, and national or area-wide lockdown [1,2]. At the time of this study, most European countries are still implementing restriction measures to combat new peaks in infections and deaths [3]. These measures are mainly focused on remote work, suspension of economic, educational and cultural activities, and restriction of citizens’ mobility. With the measures still in place in most countries, European governments are trying to find ways to provide relief to the citizens and sectors that are particularly impacted [4]. The pandemic had many consequences on people’s lives due to the prolonged stress and uncertainty.

Due to confinement and limited activity outside the home, people turned to social media to stay connected with family and friends sharing their emotions, stress, as well as fear. The use of social media brought a new dimension to the pandemic by providing alternative ways of information sharing and communication [5]. Social networks provide Big Data on various topics, and researchers can use data mining techniques to analyze the underlined relationships between the data [6]. Moreover, such Big Data analysis has the

potential to solve overarching challenges, such as monitoring public opinion. Twitter can become a powerful public health tool for sharing real-time information about COVID-19 [7]. Building upon this argument, it is worth examining how social media had been used as an outlet during the pandemic. This became the focal point of this study which analyzes pandemic-related network data from Twitter in Greece. The first coronavirus case was identified in Greece on 26 February 2020, and the first death occurred on 12 March 2020. All educational establishments, stores, and leisure facilities were immediately closed by the authorities. Beginning on 4 May the government gradually lifted the restrictions to restore normalcy and fiscal measures were also put in place to help badly affected companies and individuals [8]. However, pandemics come in waves. The second lockdown started on 7 November 2020, and is still in force, at the time of writing this paper in April 2021. The data used for this study were collected during the first wave from 15 March 2020 until 17 June 2020.

The aim of this paper is to explore and analyze the textual content of social media using the Twitter comments to obtain information about people's feelings during the first wave of the pandemic.

The following research questions are framed:

RQ1: To what extent did the Greek Twitter sphere react during the first wave of the Covid-19 pandemic?

RQ2: What are the main topics discussed and which are the most important keywords that emerged through these discussions?

RQ3: What was the general sentiment of the people during this period?

Sentiment analysis, also called opinion mining was used to help us understand how people expressed their opinions, attitudes, and emotions toward the pandemic and the ensuing restriction measures [9]. Ten years ago, Manyika et al.'s. [10] report for McKinsey digital, enthusiastically described the growing power of Big Data and the resulting implications for executives across industries. Today, Big Data analytics techniques are used across industries and include statistics, predictive modelling, Natural Language Processing, the recently developed Hyperbolic Data Analytics [11] and the top-N recommender system/framework [12]. However, for the purposes of this study, sentiment analysis was deemed most appropriate to provide further insight into previous academic research with a similar methodological approach to the use of social media during the pandemic.

The paper is organized as follows. The next section discusses the role of social media during the pandemic. Next sentiment analysis and emotion understanding during the pandemic is presented. In section four, the processes of data collection and the limitations of collection are discussed. This is followed by the methodology used to form word pairs and the visualization of the networks. A content analysis was conducted to analyze the structure and meaning of the tweets. Conclusions and recommendations for future research are given at the end of the paper.

2. Social Media and Discussion Topics during the Pandemic

Nowadays, millions of people use social media to express their feelings, emotions, opinions, and disclose their everyday lives [13,14]. With the onset of the pandemic, however, social media use has accelerated connecting individuals in need for communication and/or information generation. During the lockdown, people spent more time on social media to be informed, communicate, and post their thoughts and feelings [15]. For social media users, this means of communication with the outside world reduced isolation, boredom, or even their anxiety [16]). Social media platforms played and keep playing an important role in disseminating information at regional and national level [17].

Social media platforms, especially Twitter that have long served as an important source of data [18,19] for social science research, provided researchers with different motives for academic research. For example, Marzouki et al. [20] tested a theoretical framework to understand the development of buffer mechanisms of social media use because of collective resilience. The abundance on data in social media motivated a stream of research to explore

people's feelings and sentiments during the pandemic. Using SentiOne Social Listening, Burzyńska [21] analyzed data collected in Poland from 24 February 2020 to 25 March 2020. The author found a total of 1,415,750 mentions related to COVID-19, resulting in an average of 47,192 mentions per day.

Abd-Alrazaq et al. [22], examined topics shared on Twitter related to COVID-19 and found that mentions and sharing links were the most common actions indicating that users were interested in warning or informing their followers about COVID-19. They identified 12 topics and grouped them into four themes: the origin of COVID-19, the source of a novel coronavirus, the impact of COVID-19 on people and countries, and methods to reduce the spread of COVID-19. In the same stream of research, Xue et al. [23] claimed that the following topics were consistently dominant on Twitter: *"Confirmed cases and death rates, government policies, health authorities and prevention measures, COVID-19 stigma, and negative psychological reactions."*

In another study, Xue et al. [24] identified 11 concepts and grouped them into ten themes: "Updates on confirmed cases, COVID-19 associated deaths, cases outside China (worldwide), COVID-19 outbreak in South Korea, initial signs of the outbreak in New York, Diamond Princess cruise, economic impact, preventive measures, authorities and supply chain." The authors emphasized that fear of the unfamiliarity of coronavirus is prevalent in all topics. Similar to this study, Su et al. [25] also concluded that tweets try to give as much information as possible and that fear is the dominant emotion. However, over time, the topics focused on local cases and events, testing, quarantine activities, and dissemination of public health information. The research arguments agree that Twitter has been effective in disseminating information and understanding public opinion, a fact that was reinforced by the research of Boon-Itt & Skunkan [26] who examined the trends and topics of concern posted by Twitter users. In the same research, they found that the topics of discussion fell into three broad categories: the COVID-19 pandemic emergency, how to control COVID-19, and reports of COVID-19.

Sciandra [27] collected tweets from Italian Twitter users to monitor discussions from 14 February to 14 April 2020. The sentiment analysis revealed captured changes in the tweets that were related to the different government measures that made an impact on people's lives [27]. Sentiment analysis of tweets has been employed by many other researchers, see [28,29], and for this reason, the next paragraph provides a detailed analysis of the method as well as its application during the pandemic.

3. Sentiment Analysis and Emotion Understanding during the Pandemic

3.1. Sentiment Analysis in the Literature

Sentiment analysis is the study of people's opinions [30] as well as sentiments, assessments, appraisals, attitudes, and emotions toward entities [31]. Nasukava and Yi [32] coined the term as *"A technique used to detect favorable and unfavorable opinions toward specific subjects, such as organizations and their products within large numbers of documents that offer enormous opportunities for various applications."* Sentiment analysis focuses on subjectivity analysis and/or polarity classification. Subjectivity analysis refers to classification into objective or subjective and separates facts from feelings [33]. Polarity classification is a binary classification task in which feelings are labeled as expressing either an overall positive or an overall negative sentiment [30,34]. Liu et al. [34] claim that sentiment analysis is a three-way classification problem as sentiment can be positive, negative, or neutral. Liu [35] defined a sentiment as a quintuple consisting of the following: a target object, a feature of the object, the sentiment value of the opinion holder's opinion, the opinion holder, and the timing of the opinion expression. According to Kaushik and Mishra [36], sentiment analysis can be phrase-based, sentence-based or document-based depending on what is considered in categorizing the sentiment as positive, negative, or neutral.

Various techniques have been used for sentiment analysis. They fall into two main categories: machine learning and lexicon-based techniques. Machine learning techniques are used in sentiment analysis due to their ability to "learn" from a training dataset to support

or even predict decisions with relatively high accuracy [37] and perform very well, better than human classifiers [38]. Naive Bayes [39–43], Support Vector Machines [44–46], Maximum Entropy [47,48] and their combinations [49–51] have been widely used in sentiment analysis. Lexicon-based approaches use dictionaries of words or multi-word terms labeled as positive, neutral, or negative [52]. Existing sentiment dictionaries can be used [53] or created in a context-sensitive manner [54,55]. Dictionaries can be developed manually [56], semi-automatically derive sentiment values from resources [57], or use “seed words,” word associations, to expand the list of words [58,59]. What these techniques have in common is bag-of-words. The bag-of-words representation of text treats words as independent entities [60].

3.2. Twitter Sentiment Analysis

Nakov et al. [61] introduced Sentiment Analysis to Twitter, although there was notable work before [62–64]. Sentiment analysis in Twitter is challenging due to the limited amount of contextual data in this type of small texts [65], unstructured nature, abbreviations, misspellings, and slangs [66]. In one of the first approaches to sentiment analysis in Twitter, Pappu and Victor [67] performed sentiment analysis on a per-tweet basis regarding stock prices. They used a machine learning technique that compares the words of tweets with other tweets previously labeled as “positive” or “negative,” and the overall sentiment for each item was determined by calculating the weighted average for all sentiments in the text data. Saif et al. [68] created an evaluation dataset that enables the evaluation of sentiment classification models at both the tweet and entity level. Thus, the sentiment of a tweet and the sentiment of the entities mentioned in it were distinguished. To perform Tweet-based sentiment analysis, Ribeiro et al. [69] proposed a four-module approach: (i) data collection, (ii) refinement-noise reduction, (iii) sentiment lexicon generation, and (iv) sentiment classification, and four algorithms were used to implement the modules. A five-module approach was proposed by Sahayak et al. [70] (i) data collection—retrieval of tweets, (ii) pre-processing of extracted data (filtering, tokenization, removal of stop words, construction of n-grams), (iii) parallel processing (model construction, model usage), (iv) sentiment scoring module, (v) sentiment output. Most approaches to Twitter sentiment analysis involve a preprocessing step [71], as the language used is often informal and different from traditional text types [72].

Machine learning techniques [73–75] and lexicon-based approaches [76,77] have been used in previous studies for Twitter sentiment analysis. Jianqiang et al. [78] proposed semantic feature for sentiment analysis to capture the implicit semantic relation information in the words of tweets.

3.3. Sentiment Analysis of COVID-19 Tweets

During the pandemic, a large amount of information about COVID-19 was shared on Twitter and other social media and received a great deal of public attention. The spread of the virus originated from China, and in one of the first studies, Zhao and Xu [79] investigated the public attention given to COVID-19 on Sina Weibo, the popular Chinese Microblog, analyzed topics related to COVID-19, and conducted sentiment analysis. They used ROST CM6.0 software to conduct word frequency statistics and sentiment analysis. Emotions evolved over time. The first stage of emotions was negative, as the public had a strong need for information about the disease that could not be satisfied. In the second and third stages, public sentiment became neutral as more news was reported and objective events attracted people’s attention.

Wang et al. [80] also analyzed 999,978 randomly selected COVID-19-related posts on Sina Weibo. They used the unsupervised Bidirectional Encoder Representations from Transformers model to classify posts to positive, neutral, and negative and term frequency-inverse document, to summarize the topics of the posts. The analysis focused on posts with negative sentiment to understand the experience of Chinese people during the outbreak of

COVID-19. Concerns about the origin, symptom, Production Activity and Public Health Control are interwoven with public sentiment.

The evolution of public sentiment in Austrian social media during COVID-19 was studied by Pellert et al. [81] who retrieved data from a news platform, Twitter, and a student chat platform. According to their results, anxiety decreased over time and can be linked to different events and media reports. "Saying goodbye" often appeared as an expression of sadness. The expression of admiration "aww*" and "hugs" suggests that people send virtual hugs to each other expressing positive feelings. Evidence from Twitter posts in India shows that Indians were positive about the fight against COVID-19 and agreed with their government's decision to go on lockdown. However, many people were upset that the lockdown came too late. Concern for passengers from abroad flying into the country was also registered [82]. Prastyo et al. [83] used Twitter data to examine the general sentiment and economic sentiment regarding COVID-19 in Indonesia. The tweet data were divided into two data sets: The first set consisted of two classes (positive and negative) and the second set consisted of three classes (positive, neutral, and negative). Indonesians were satisfied and agreed with the government's policy in dealing with COVID-19 in terms of economic aspects, but they were not satisfied with the government's policy in dealing with COVID-19. The reactions of people in Nepal varied from day to day by posting their feelings on Twitter. They adopted a positive and hopeful attitude. However, expressions such as fear, sadness and disgust were also shown [84]. In the U.S., the public sentiment determined from tweets reflected deep concern about COVID-19, fearful sentiment, and negative sentiment. A rapid spread of the fear-panic-despair trio related to coronavirus and COVID-19 was also recorded [85]. Emotions and sentiments in Spain were studied by de las Heras-Perdosa et al. [86]. The research results showed that government organizations mostly post tweets with a positive tone, while a lot of mixed sentiments were recorded. News and information generated spikes in different emotions and these were mixed between sadness, disgust, anger, and fear.

Tweets on the topic of #coronavirus posted around the world were studied by Kaila and Prasad [87] using sentiment analysis. The sentences of the tweets contain both panicky and comforting words that are closely associated with negative and positive sentiments. Fear is the predominant sentiment; sadness related to the disease outbreak and deaths was also recorded. Anger was also prevalent and mostly related to quarantine. These sentiments are followed by trust in the authorities and expectation that necessary steps and precautions will be taken. Chakraborty [88] claimed that people mostly tweet positive sentiments related to COVID-19, but they can also re-tweet negative feelings. Mansoor et al. [89] also presented a global sentiment analysis of tweets related to coronavirus. The authors opine that people's feelings changed over time, but fear remained consistently higher than confidence during the pandemic. Bangladesh, Pakistan, Mali, and South Africa are the countries where greater positive sentiment was recorded, while Australia, India, Canada, USA, Turkey, UK and Brazil are the countries where greater negative sentiment was recorded. The highest trust scores were recorded in Oman, Syria, and Kazakhstan. A sentiment analysis of Twitter data related to global coronavirus outbreaks was also conducted by Mangury et al. [90]. Most responses were calm and relaxed. The feelings of contentment, hope and relieved mood were also recorded in smaller percentages. It was found that people's reactions and feelings varied from day to day. Negative opinions played an important role in conditioning public mood, claimed Naseem et al. [91]. Initially, people were in favor of the lockdown and the order to stay home, but their opinions changed later, possibly due to misinformation spread through Twitter and other social media platforms. Using Natural Language Processing and Sentiment Classification Recurrent Neural Network, Nemes et al. [92] classified emotions in tweets about covid and coronavirus. They classified the different texts into classes of emotional strength: weakly positive/negative, strongly positive/negative. The results showed that positive emotions were strengthened over time, while there was a stronger negative array. The theme remained positive sometimes with a lower proportion and sometimes with a higher propor-

tion. Kruspe et al. [93] collected tweets during the first months of the pandemic in Europe. They recorded a general downward trend in sentiment in most countries, with dips at times when lockdowns were announced and a slow recovery in the following weeks. Sentiment was initially very negative and became more positive over time. In all countries except Germany, it remained well below the average sentiment.

4. Methodology

For the purposes of this research, Twitter was chosen as a data source for several reasons. This platform was instrumental in the COVID-19 pandemic through the rapid exchange of personal opinions, feelings, and information [94]. Not only ordinary users were involved, but also medical personnel to share information, observations, professional comments, and ideas. Finally, and importantly, Twitter has actively worked to curb Fake News by removing certain views that do not conform to the guidelines of global organizations such as the World Health Organization or other local authorities [95]. The term COVID-19 received the highest presence during the early stages of the pandemic, followed a decreasing tendency [96], thus the paper studies tweets from March to June 2020. In Sections 4 and 5, we discuss the data collection processes and associated limitations. We present the way word networks are formed and provide them with appropriate visualizations. Furthermore, certain macroscopic properties of the formed networks are presented and discussed. This is followed by a discussion of semantic insights hidden in the texts through a form of content analysis. We also deal with some more detailed levels related to important words, through the computation of relevant network metrics, such as betweenness and closeness centrality.

To create our networks, we used NodeXL Pro [97], an Excel-based template that offers many possibilities not only to import network data, but also to create corresponding visualizations. The same software was also used to create word networks and calculate our metrics. The process begins with identifying a set of keywords to be used as search terms. We decided to use the keywords “Κορωνοϊός,” “κορωνοϊός,” “κορωνοϊος,” “Κορωνοϊός,” “Κορωνοϊος,” all different forms of coronavirus with the same meaning in Greek (COVID-19) but with different orthography. All these key words were transformed using percent spelling to overcome the software’s inability to use non-Western character sets. Twitter’s API allows us to query a maximum of 20,000 tweets. In our case, we performed the search in four different time periods, creating four sets of approximately 20,000 tweets. In all cases, the time span covered about seven to ten days into the past, starting from the day of the search. The fact that in all cases the search was aborted due to the limitation of the API proves that quite a large volume of views and opinions were circulated. To capture the most relevant results, we chose 17 March 2020 (first impact of the store closure), 20 April 2020 (quarantine measures during Orthodox Easter), 24 May 2020 (partial lifting of quarantine measures), and 15 June 2020 (resumption of tourism measures). Thus, four different sets of tweets were collected, all during the first wave of COVID-19 in Greece. There are different types of tweets: simple tweets, retweets, and mentions contain important original content. Retweets and MentionsInRetweet were also retrieved, although it is known that no original information is conveyed through them [98]. Table 1 and Figure 1 list and plot the types of imported tweets.

Table 1. Types of tweets.

Tweets’ Type	17 March 2020	20 April 2020	24 May 2020	15 June 2020
Mentions	747	805	875	671
MentionsInRetweet	711	493	453	502
Replies to	363	334	478	321
Retweet	8475	6967	7275	9925
Tweet	9056	10,814	10,207	7809
Total	19,352	19,413	19,288	19,228

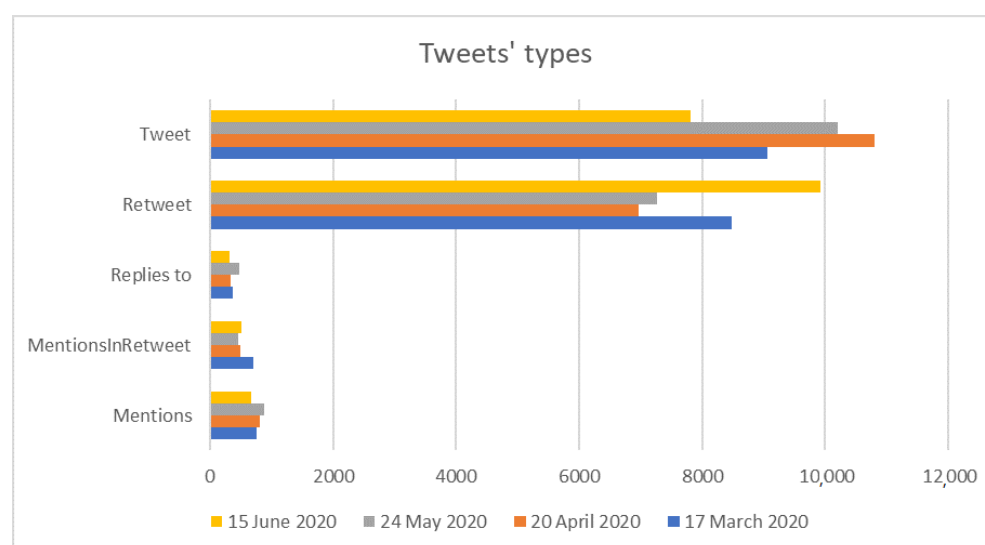


Figure 1. Chart of types of tweets.

The balanced volume between information-bearing tweets and retweets shows that new content has indeed been created and disseminated (a disproportionately large volume of retweets would mean that there is too much information noise circulating). To avoid this “noise” nevertheless, all non-information-bearing types were removed from the subsequent processes. At this point, it is important to mention that networks of users have already formed to discuss the topics of the keywords. However, in this work we proceed with the formation of semantic and not user networks. The next step in the process involves identifying word pairs (pairs of consecutive words found within tweets). All word pairs in all tweets are identified and counted using NodeXL Pro after removing some “stop words” deemed unimportant, such as articles, particles, etc., although Twitter users unintentionally perform a kind of “stop word elimination” to comply with the 280-character length of tweets [99]. The lists of word pairs are then inserted into a new instance of NodeXL Pro along with their respective cardinalities. In this way, new networks are created where words are represented by nodes edges represent the existence of word pairs, and edge weight represents the frequency with which these word pairs were found in the tweets, resulting in four distinct word pair networks [98,99]. These networks are clearly semantic, in the sense that they can reveal thought patterns of meanings across the networks. For our sentiment analysis questions, we used a lexicon-based method. Gonçalves et al. [100] proved that such methods are excellent for sentiment analysis on microblogging platforms such as Twitter. Moreover, according to Khan et al. [101] that such methods can achieve high precision. Tsakalidis et al. [102] created two quite adequate lexicons for sentiment analysis on social media (“GrAFS”), which contain almost 32,000+ words. They created “Twitter-specific lexicons that have the potential to capture a larger portion of sentiment-related keywords as expressed on the social media, including misspellings, abbreviations, and slang” to overcome the informal nature of user-generated content. Existing sentiment lexicons have been enriched due to the lack of specific words for the coronavirus case. Words like virus, coronavirus, death, epidemic, pandemic were added to the fear category, a subcategory of negative sentiment, and words like vaccine, inoculation, tsiodras, etc., were added to the positive sentiment category. Again, Nodexl PRO was used for sentiment analysis. Sentiments were classified as positive or negative and anxiety sentiment was also recorded.

5. Results

5.1. Answering the Research Questions

From Table 1 and Figure 1, along with the relevant discussion of the previous section, a clear answer to our first research question emerges, as it is evident that genuine and

important discussions containing new information have taken place within Twitter. In this section, word adjacencies (word pairs) are used to address our RQ2, i.e., uncovering main discussion topics and unearthing new keywords. Recall that our methodology has already generated four different semantic networks, all carrying weights on their edges signifying the frequency of occurrence of each word pair. In Table 2, we present the relevant results.

Table 2. Word-pairs frequencies.

17 March 2020	20 April 2020	24 May 2020	15 June 2020	Classes
4775	6096	6112	4145	0–2
4372	6230	5173	3737	3–10
464	609	531	346	11–30
83	82	79	52	31–50
51	66	58	36	51–100
10	15	36	15	101–1500

In Table 2, the first four columns represent the total number of word pairs for each date, while the last column indicates their frequency class. For example, for the network created on 20 April 2020, 6230 word pairs appeared 3 to 10 times, 82 word pairs appeared 31 to 50 times, and so on. Obviously, small frequencies mean less important word pairs, or (alternatively) word pairs with larger frequencies are more important than word pairs that appear less often. For our purposes, after a series of tests, and in order to reduce unnecessary overloading of our networks, we decided to include only word pairs with frequencies greater than or equal to 10, i.e., we included only word pairs from the third row of Table 2. In Table 3, we list the most important (frequent) of these word pairs. Due to space constraints, not all of them are listed.

Table 3. Most frequent word-pairs.

17 March 2020			20 April 2020		
Νέα/New	Κρούσματα/Cases	267	Νέα/New	Κρούσματα/cases	663
Σούπερ/super	Μάρκετ/Market	182	Νέοι/New	Θάνατοι/deaths	312
Μέσο/average	Χρήστη/User	177	Νεκροί/Dead	Ελλάδα/Greece	272
#covid_19	#covid2019	130	108	Νεκροί//dead	169
Κορωνοϊός/coronavirys	Νέα/new	128	Τελευταίο/last	24ωρο/24 h	167
#covid2019	#κορονοϊός/#coronavirus	121	Κορωνοϊός/coronavirus	Νέα/new	159
#καραντιννα/#quarantine	#κορονοϊός/#coronavirus	117	#ysterografa/#ps	#υστερογραφα/#ps	135
Ελλάδα/greece	Κοσμος/world	107	Ελλάδα/Greece	Κοσμος/World	130
#menoume_spiti/#stayhome	#κορονοϊός/#coronavirus	98	Μέσο/Average	Χρήστη/user	124
#menoume_spiti	#stayhome	95	#κορονοϊός/#coronavirus	#μενουμε_σπιτι/#stay_home	119
24 May 2020			15 June 2020		
Νέα/new	Κρούσματα/cases	1137	Νέα/New	Κρούσματα/cases	1062
Κορωνοϊός/coronavirus	Νέα/new	284	Κορωνοϊός/Coronavirus	Νέα/new	342
Τελευταίο/last	24ωρο/24 h	275	Τελευταίο/last	24ωρο/24 h	315
#κορονοϊός/#coronavirus	#covid19 gr	267	Νέος/New	Θάνατος/Death	259
#covid19	#covid_19	265	Κρούσματα/Cases	Ελλάδα/Greece	182
#coronavirus	#κορονοϊός/#coronavirus	261	Κορονοϊός/coronavirus	Νέα/new	178
#μενουμεσπιτι/#stayhome	#menoumespiti/#stayhome	261	Κρούσματα/cases	Νέος/new	144
#covid_19	#μενουμεσπιτι/#stayhome	259	Κρούσματα/cases	Θάνατος/death	144
#menoumespiti/#stayhome	#menoume_spiti	259	Θάνατος/death	Τελευταίο/last	140
#menoume_spiti/#stay_home	#stay_safe	259	#ysterografa/#ps	#υστερογραφα/#ps	124

A close look at Table 3 shows that the most important word pair in all four cases is “new cases” (νέα κρούσματα). Obviously, Twitter users were quite worried at that time and the first information they tried to discuss was about the growing process of the epidemic. A similar pair of words is “coronavirus news” (κορονοϊός νέα), which is a more general aspect of news than new cases. Staying with the first network, we see that “supermarket” (σούπερ μάρκετ) is the second most frequent word pair. In the first few weeks of the pandemic, citizens were very insecure about food and other products of first necessity. “Supermarkets were very efficient in providing a lot of food for a lot of people

during this period” [103]. It was recorded that retail sales totaled €615 million in March 2020, much more than in the months before: shoppers began stocking products “from antibacterial wipes to toilet paper, which sold out quickly but were restocked almost as quickly after panic purchases” [104]. It is well-known that trending topics in social media (such as COVID-19 news) sometimes get lost in the news feeds [105]. To deal with this situation, hashtags are used by Twitter users because posts with hashtags are properly clustered and get more visibility.

During our first period, some of the words observed within word pairs were: #covid19, #covid2019, #κορονοϊος, #καραντινα (quarantine), #κορονοϊος. It is precisely during this period that the first hashtags that are highly positive can be found. Such hashtags are #menoume_spiti (#stay_at_home), a slogan introduced by the state in these first months. The fact that such a slogan appeared and was maintained for the first three periods shows that people in Greece were indeed convinced of the state’s regulations and tried to convince others to follow the quarantine measures. In the second period (around 20 April), the discussion of new cases continued (νέα κρούσματα), but a new issue emerged in that death rates were discussed. The incidence of “new deaths” (νέοι θάνατοι), dead Greeks (νεκροί Ελλάδα), and 108 dead (108 νεκροί) is now quite high, as people began to realize that it was a serious and real problem during this period. The discussion about the number of deaths and the search for information about the recent deaths is also here twenty-four hours (τελευταίο εικοσιτετράωρο). It is a surprise, however, that although Greece is considered a “highly religious” country (especially in the Eastern period), no such discussion was followed during this period. During the third period (24 May), some form of consensus and sense of purpose was already established. The most common tweets were #μενουμεσπιτι #menoumespiti (stayhome), #covid_19 #μενουμεσπιτι, #menoumespiti #menoume_spiti, #menoume_spiti #μένουμε_ασφαλείς (stay safe). At this point, the curve of the first pandemic wave showed signs of leveling off, and people continued to believe that maintaining quarantine measures could lead to positive results, despite the (mainly economic) problems with the lockdown. In the last period (just before 15 June), there were again discussions of new cases, which accounted for almost 50% of the total word pairs (νέα κρούσματα, κορωνοϊός νέα, κρούσματα ελλαδα, κορωνοϊός νέα, κρούσματα νέος). However, as the first wave was winding down (but not actually dying out), the discussion focused on somewhat different issues, mainly ending the lockdown, opening up the market, and education. Concerns were also expressed, especially about the opening of the tourist season, while the number of new deaths was still very worrying. In Figures 2–5, we present visualizations of our four networks. Each node represents a word and each edge between two words represents the existence of a word pair. Again, not all nodes and edges are drawn (in fact, there are more than 30) to avoid noise in the visualizations [106]. The size of the nodes corresponds to their relevant metric of betweenness centrality. Moreover, the nodes are clustered into groups according to the community structure of the networks. Figures 2–5 actually confirm the observations and discussion of this section. Moreover, a close inspection of these visualizations can detect not only word pairs, but actually small sentences (although this can only be true for speakers of Greek).

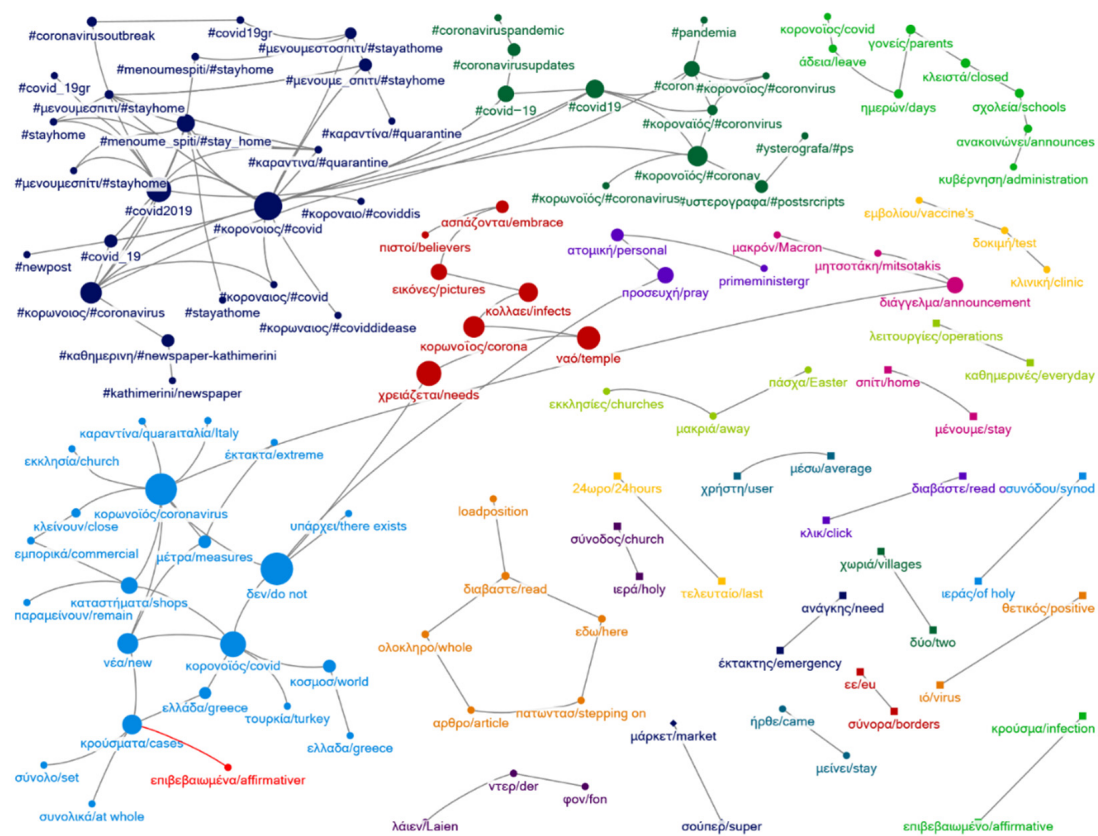


Figure 2. Network 17 March 2020.

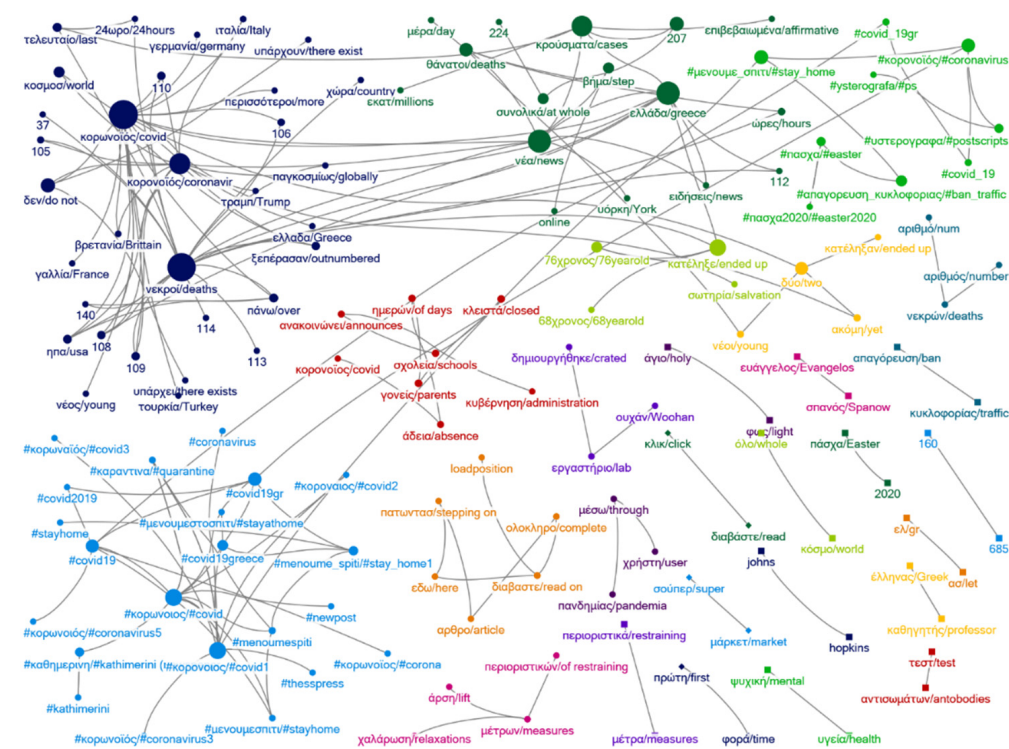


Figure 3. Network 20 April 2020.

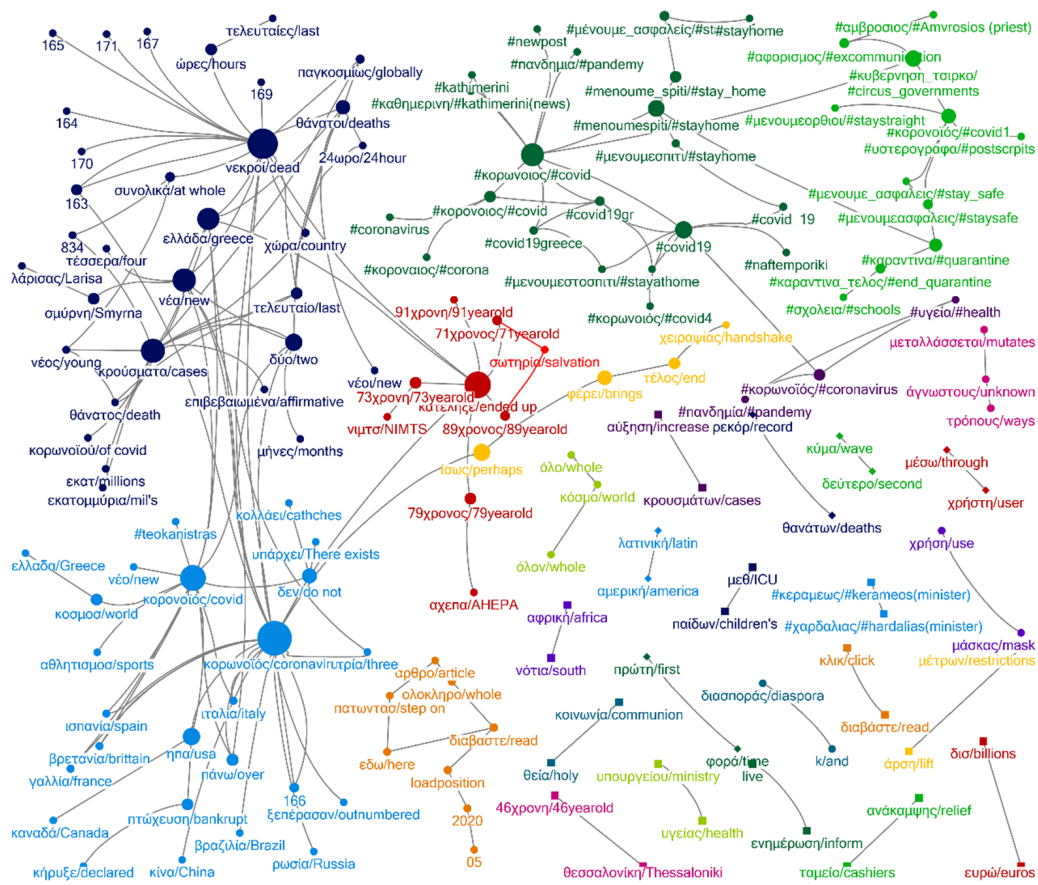


Figure 4. Network 24 May 2020.

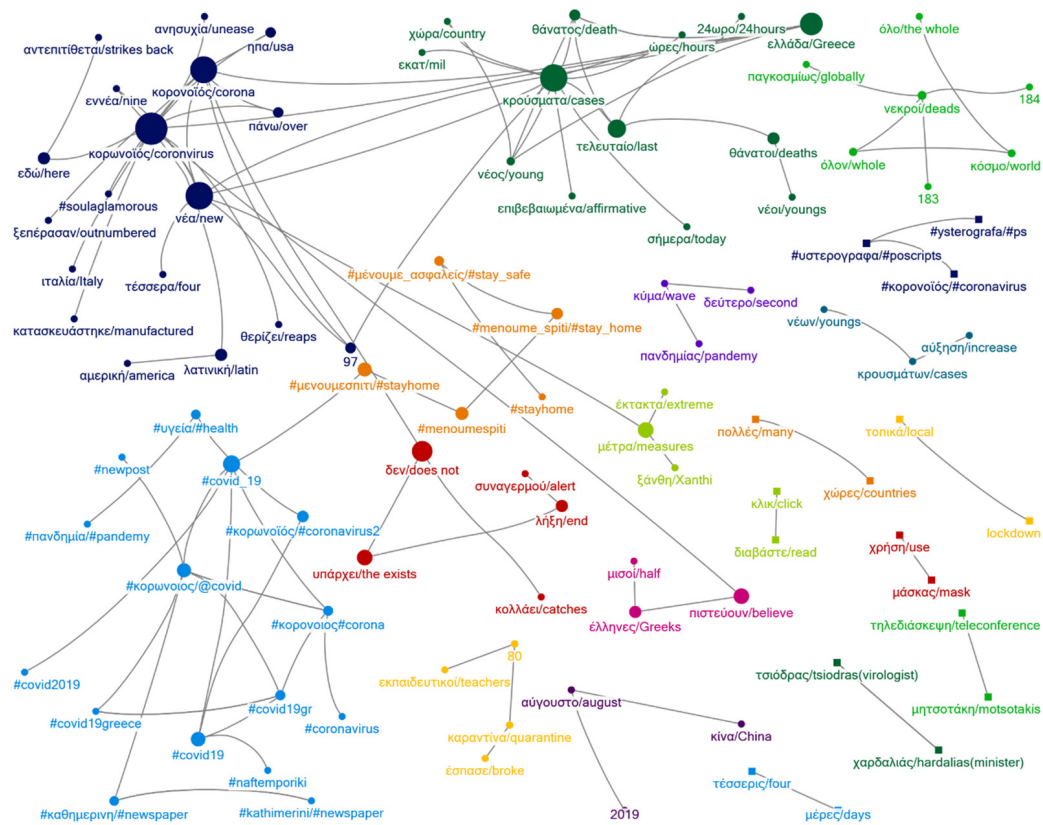


Figure 5. Network 15 June 2020.

5.2. Macroscopic Analysis

The macroscopic properties of the: 17 March 2020, 20 April 2020, 24 May 2020, and 13 June 2020 networks are shown in Table 4. In terms of nodes and links, the four networks are quite similar in terms of volume. All four networks have 99–144 nodes, so they are small networks according to Kenett et al. [107] with 10 unique words 1000. The users in the networks discuss few topics, which is evident from the small number of different linked components they contain.

Table 4. Macroscopic characteristics of the networks.

17 March 2020		20 April 2020		24 May 2020		15 June 2020	
Nodes	121	Nodes	144	Nodes	158	Nodes	99
Links	145	Links	172	Links	185	Links	106
Components	21	Components	23	Components	24	Components	15
Diameter	11	Diameter	7	Diameter	8	Diameter	9
Aver. Shortest Path	3.33	Aver. Shortest Path	2.9	Aver. Shortest Path	3.33	Aver. Shortest Path	3.37
Density	0.009	Density	0.016	Density	0.014	Density	0.02
Modularity	0.69	Modularity	0.7	Modularity	0.71	Modularity	0.73

The average shortest path length ranges from 2.9 to 3.37, indicating that any two words in the networks are separated by 2.9 to 3.37 associative steps. The diameter of the four networks is 11, 7, 8, and 9 respectively, indicating how separated are the nodes from one another in the networks. Density is the number of connections a word has divided by the total possible connections a word could have in the network. It ranges from 0.009 to 0.02 and it is considered normal for real-life networks [108]. Finally, modularity ranges from 0.59 to 0.73, indicating that the four networks contain many different cliques [109].

To continue the discussion on RQ2, the closeness centrality and betweenness centrality measures were calculated. These measures can be used to locate nodes representing semantic resources that have the most advantageous positions compared to other nodes in the network [110]. The influence of a word in a semantic network can be described using Betweenness centrality [111]. Table 5 shows the words with the highest overall betweenness centrality. The gatekeeping words of information in all networks are: Coronavirus (κορωνοϊός or κορωνοϊός), dead (νεκροί), new (νέα), cases (κρούσματα), died (κατέληξε), Greece (Ελλάδα). From Figures 1–4, it can be seen that these words have the ability to shape the network by activating or activating connections over topic communities [112].

Table 5. Betweenness centrality.

17 March 2020	20 April 2020	24 May 2020	15 June 2020
Δεν/do not	Κορωνοϊός/coronavirus	Κορωνοϊός/coronavirus	Κορωνοϊός/coronavirus
Κορωνοϊός/coronavirus	Νεκροί/dead	Νεκροί/dead	Νέα/new
#κορωνοϊός/#coronavirus	Ελλάδα/Greece	Κατέληξε/died	Κρούσματα/cases
Κορωνοϊός/corona	Νέα/New	Κορωνοϊός/covid	Κορωνοϊός/corona
Χρειάζεται/needs	Κορωνοϊός/covid	Κρούσματα/cases	Ελλάδα/Greece
#covid2019	Κρούσματα/cases	Νέα/new	Δεν/do not
Ναό/temple	#κορωνοϊός/#covid	#κορωνοϊός/#covid	Τελευταίο/last
#κορωνοϊός/#corona	#κορωνοϊός/#corona	Ελλάδα/Greece	#covid_19
Κορωνοϊός/#covid	Κατέληξε/died	ηπα/USA	Μέτρα/measures
Νέα/new	Δεν/de not	#covid19	Υπάρχει/there exists

Closeness centrality of a word in the network shows its average farness to the other words [112]. Table 6 presents the words with high values of closeness centrality. In the first two networks, the words super (σούπερ) market (μάρκετ) have the highest closeness centrality. These words are in favorable positions in the networks to acquire and control vital information and spread information in an efficient manner. In the third network, the words second (δεύτερο) wave (κύμα) are the more central words, thus they are closer to all other words. In the fourth network, the words local (τοπικά) and lockdown are only

a few links away from all other words. In all of the networks the words click (Κλικ) and read (διαβάστε) have high closeness centrality and only a few links must be traversed to get from that words to other words in these networks. These words urge people to read more, mostly from websites to which they redirect readers.

Table 6. Closeness centrality.

17 March 2020	20 April 2020	24 May 2020	15 June 2020
Σούπερ/super	Κλικ/click	Μέσο/average	Κλικ/click
Μάρκετ/market	Διαβάστε/read	Χρήστη/user	Διαβάστε/read
Μέσο/average	Σούπερ/super	Δεύτερο/second	Τοπικά/local
Χρήστη/user	Μάρκετ/market	Κύμα/wave	Lockdown
Κλικ/click	Πρώτη/first	Πρώτη/first	Πολλές/many
Διαβάστε/read	Φορά/time	Φορά/time	Χώρες/countries
Ιερά/holy	Απαγόρευση/prohibition	Λατινική/latin	Χρήση/use

5.3. Sentiment Analysis

For our RQ3, the results regarding sentiment analysis are discussed. Table 7 presents the overall community sentiment during the study period, using words by sentiment. It shows that the public had a highly positive sentiment in March and April. There was a slight drop in late May and a significant drop in June. This could be due to the increased number of confirmed cases from COVID-19. There were fluctuations in negative sentiment. The peak in negative sentiment was on 24 May, which could be due to the government's plan to gradually de-escalate emergency measures with the lifting of travel restrictions and the reopening of businesses, including schools, which took effect on 4 May. Elevated levels of anxiety were recorded in April, remained fairly stable in May, and declined in June. Anxiety is associated with deaths and panic caused by the pandemic. Figure 6 shows sentiments by category.

Table 8 presents sentiments per time period. We used R statistical language to compute sentiment scores, after proper tokenization, stop-words elimination and word-scores computation, applied on Greek LEXICON resources [102]. Polarity refers to the agreement on the emotion and ranges from -1.0 to 1.0. Values close to zero indicate a general agreement on the sentiment. Data from Table 8 are depicted in Figure 7 (the ribbon represents polarity).

Table 7. Words by sentiment.

Sentiment	17 March 2020	20 April 2020	24 May 2020	15 June 2020
Positive	21,329	21,326	20,461	15,496
Negative	23,070	21,326	26,309	19,566
Fear	20,385	24,431	23,871	18,073
Non-Categorized	125,805	144,649	136,004	100,143
Total words	158,956	177,753	171,503	126,992

Table 8. Sentiments per time period.

Date	Anger	Disgust	Fear	Happiness	Sadness	Surprise	Polarity
March-2020	0.131476	0.122283	4.487119	0.205658	0.043271	0.256531	0.031635
April-2020	0.100473	0.105995	4.605822	0.137242	0.037904	0.194033	0.018211
May-2020	0.098979	0.094727	4.579573	0.120884	0.037775	0.194678	0.017574
June-2020	0.123149	0.096447	4.609404	0.138101	0.050227	0.209887	0.016401

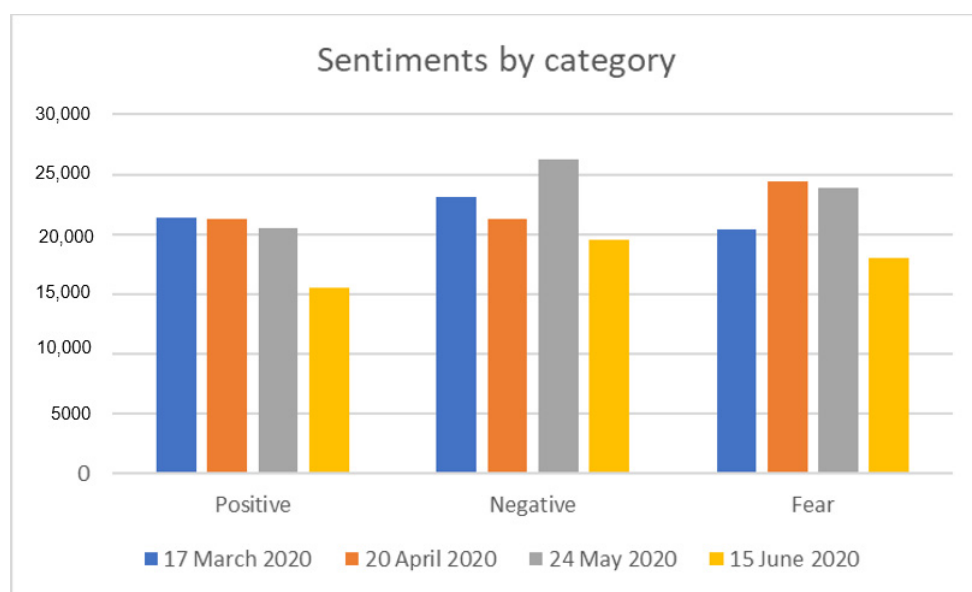


Figure 6. Sentiment by category.

What people think and how they react varied from day to day, as can be seen from the posted sentiments on Twitter. Thus, a fluctuation in moods (sentiments) has been recorded. Negative moods and fear dominate positive moods. Fear is extremely elevated, while Happiness shows diminishing curves. Anger also shows off a rise during the end of our period, probably because people have realized that this situation would be continued with subsequent pandemic waves. The continuation of the pandemic spreading around the world and the increasing number of confirmed cases and deaths seem to have stressed people who felt that the situation was getting worse and more serious than they had expected. The fear of the coronavirus and what might happen became overwhelming and caused strong negative moods.

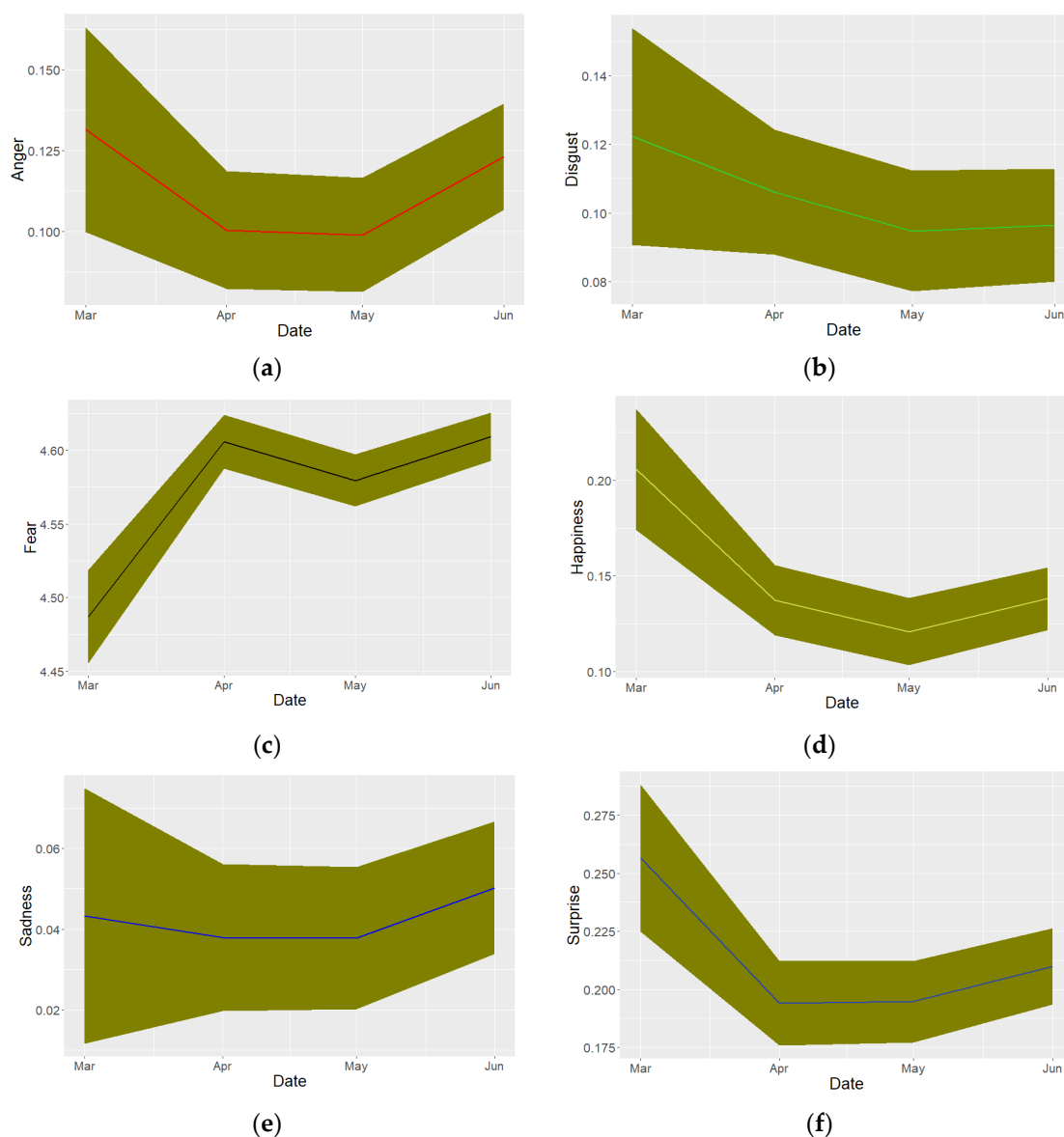


Figure 7. (a) Anger; (b) Disgust; (c) Fear; (d) Happiness; (e) Sadness; (f) Surprise. All sentiments are plotted together with their respective polarity.

6. Discussion

As discussed in this paper, monitoring the spread of COVID-19 in a population has attracted the attention of many academics who tried to explore how social media may contribute to the understanding of people's feelings during the ongoing COVID-19 outbreak. This paper extends that concept, by performing semantic network analysis of Twitter posts to interpret what people felt during four key dates of the pandemic in Greece and content analysis [113]. To capture and evaluate tweets, NodeXL was used. We chose unique Greek keywords to collect data during these particular dates. Simple mainstream information about the pandemic such as "new outbreaks" and "new deaths," was posted on Twitter by users. Words that act as information gatekeepers and words that are similar to a large number of other words in the networks were identified, and major debates were visualized.

People responded by stocking up on food and other necessities before the lockdown, according to our key findings. Following the outbreak's spread and strict precautions, people used optimistic hashtags to encourage others to stay at home and battle against

the pandemic. The most important message was that social distancing was needed in order to save lives. Our results back up previous research [95] that found how Twitter played a crucial role in the spread of medical knowledge during the COVID-19 pandemic. In online communities users exchange knowledge [114], and in this case in Greece, Twitter users quickly exchanged knowledge and opinions about our duty to protect the community's health.

The results of the sentiment analysis showed fluctuations in sentiment over time, possibly due to the severity of the COVID-19 pandemic, the level of uncertainty, and quarantine or policy changes affecting people's daily lives. During the period studied, positive emotions weakened while negative emotions increased. The overall emotional polarity was negative, and fear seems to be the dominant emotion. These results are consistent with the findings of Pokharel [84], Samuel et al. [85], Kaila and Prasad [87]. Anxiety has been reported in similar studies in USA [85] and fear of death is a similar finding from previous studies [23,24,85]. Our results show a rotation between positive and negative feelings, which is perhaps the most common finding from relevant studies [83,88,90].

A general but important finding of this research is that the Twitter based analytics captured the feelings of the public, which shows the power of social media during a crisis. This may prove to be an effective tool for opinion leaders and public health professionals to monitor and respond to public sentiment and emotions and better respond to national emergencies. This is discussed in more detail in the subsequent section.

7. Conclusions—A View Ahead

This study reports the results of sentiment analysis conducted to determine the emotional tone of people's tweets during the first wave of the pandemic. What became clear from this as well as from previous similar studies is that people in Greece responded with the same reactions as in other countries, although governments responded independently to find out which response measures worked and which did not, considering not only the epidemiological but also the economic and social components [115]. We recommend that both governments and Health Care Organizations should engage in data analysis of social media content and Twitter in particular, to listen to the voice of the public and promote reassuring advice.

As COVID-19 is still evolving and changing, it would be interesting to capture people's discussions and feelings as recorded on Twitter in more countries and cultures. The COVID-19 crisis taught the planet a lesson. We were not adequately prepared to respond to disruptions of this magnitude. A recent McKinsey report by Craven et al. [116] points forcefully to the readiness of governments for future crises. Policymakers might consider surveillance mechanisms of public opinion to avoid chaos and panic. Twitter can be used for well-intentioned data. Timely knowledge of public sentiment can be valuable for all governments to develop an effective strategy to better manage the situation and develop an effective communication strategy to disseminate accurate and reliable information and engage the public in the necessary response actions.

Author Contributions: Conceptualization, V.V. and D.K.; methodology, D.K.; software, D.K.; validation, M.A., D.K., V.V.; writing—original draft preparation, M.A., D.K., V.V.; writing—review and editing, M.A., D.K., V.V.; visualization, D.K.; supervision, D.K.; project administration, M.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All data are available by emailing dkydros@ihu.gr.

Conflicts of Interest: The authors declare no conflict of interest.

References

- Alqurashi, S.; Alhindi, A.; Alanazi, E. Large Arabic Twitter Dataset on COVID-19. *arXiv* **2020**, arXiv:2004.04315.
- Chen, E.; Lerman, C.; Ferrara, E. Tracking Social Media Discourse About the COVID-19 Pandemic: Development of a Public Coronavirus Twitter Data Set. *JPHS* **2020**, *62*, e19273. [CrossRef] [PubMed]
- Covid: How Are European Countries Tackling the Pandemic? Available online: <https://www.bbc.com/news/explainers-53640249> (accessed on 7 March 2021).
- Jobs and Economy during the Coronavirus Pandemic. Available online: https://ec.europa.eu/info/live-work-travel-eu/coronavirus-response/jobs-and-economy-during-coronavirus-pandemic_en (accessed on 7 March 2021).
- Drouin, M.; McDaniel, B.T.; Pater, J.; Toscos, T. How Parents and Their Children Used Social Media and Technology at the Beginning of the COVID-19 Pandemic and Associations with Anxiety. *Cyberpsychol. Behav. Soc. Netw.* **2020**, *23*, 727–736. [CrossRef]
- Yan, Y.; Zhou, R.; Gao, X.; Chen, G. Predicting Content Popularity in Social Networks. In *Big Data in Complex and Social Networks*; Thai, M.T., Wu, W., Xiong, H., Eds.; CRC Press: Boca Raton, FL, USA, 2016.
- Rufai, S.R.; Bunce, C. World leaders' usage of Twitter in response to the COVID -19 pandemic: A content analysis. *J. Public Health* **2020**, *42*, 510–516. [CrossRef] [PubMed]
- European Commission. Policy Measures Taken against the Spread and Impact of the Coronavirus. 14 May 2020. Available online: https://ec.europa.eu/info/sites/info/files/coronavirus_policy_measures_14_may_1.pdf (accessed on 4 December 2020).
- Liu, B. Sentiment Analysis. In *Sentiment Analysis: Mining Opinions, Sentiments, and Emotions (Studies in Natural Language Processing)*; Cambridge University Press: Cambridge, UK, 2020.
- Manyika, J.; Chui, M.; Brown, B.; Bughin, J.; Dobbs, R.; Roxburgh, C.; Hung Byers, A. Big Data: The Next Frontier for Innovation, Competition, and Productivity. 1 May 2011. Available online: <https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/big-data-the-next-frontier-for-innovation#:~:text=The%20amount%20of%20data%20in%20our%20world%20has,research%20by%20MGI%20and%20McKinsey%27s%20Business%20Technology%20Office> (accessed on 29 May 2021).
- Stai, E.; Karyotis, V.; Katsinis, G.; Tsiropoulou, E.E.; Papavassiliou, S. Hyperbolic Big Data Analytics within Complex and Social Networks. In *Big Data in Complex and Social Networks*; Thai, M.T., Wu, W., Xiong, H., Eds.; CRC Press: Boca Raton, FL, USA, 2016.
- Stai, E.; Kafetzoglou, S.; Tsiropoulou, E.E.; Papavassiliou, S. A holistic approach for personalization, relevance feedback & recommendation in enriched multimedia content. *Multimed. Tools Appl.* **2018**, *77*, 283–326.
- Rambocas, M.; Gama, J. Marketing Research: The Role of Sentiment Analysis. In *The 5th SNA-KDD Workshop'11*; University of Porto: Porto, Portugal, 2013.
- Sarlan, A.; Basri, S. Twitter Sentiment Analysis. In Proceedings of the 2014 International Conference on Information Technology and Multimedia (ICIMU), Putrajaya, Malaysia, 18–20 November 2014.
- Yin, H.; Yang, S.; Li, J. Detecting Topic and Sentiment Dynamics Due to COVID-19 Pandemic Using Social Media. Cornell University. *arXiv* **2020**, arXiv:2007.02304.
- Brooks, S.K.; Webster, R.K.; Smith, L.E.; Woodland, L.; Wessely, S.; Greenberg, N.; Rubin, J.G. The psychological impact of quarantine and how to reduce it: Rapid review of the evidence. *Lancet* **2020**, *395*, 912–920. [CrossRef]
- Merchant, R.; Lurie, N. Social Media and Emergency Preparedness in Response to Novel Coronavirus. *JAMA* **2020**, *323*, 2011–2012. [CrossRef]
- Kavoura, A.; Patrikakis, C. Data Crowdsourcing. In *Encyclopedia of Tourism Management and Marketing*; Buhalis, D., Ed.; Edward Elgar: Cheltenham, UK, 2022.
- McCormick, T.; Lee, H.; Cesare, N.; Shojaie, A.; Spiro, E. Using Twitter for Demographic and Social Science Research: Tools for Data Collection and Processing. *Sociol. Methods Res.* **2015**, *46*, 390–421. [CrossRef]
- Marzouki, Y.; Aldossari, F.S.; Veltri, G.A. Understanding the buffering effect of social media use on anxiety during the COVID-19 pandemic lockdown. *Humanit. Soc. Sci. Commun.* **2021**, *8*, 1–10. [CrossRef]
- Burzyńska, J. The social life of COVID-19: Early insights from social media monitoring data collected in Poland. *Health Inform. J.* **2020**, *26*, 3056–3065. [CrossRef]
- Abd-Alrazaq, A.; Alhuwail, D.; Househ, M.; Hamdi, M.; Shah, Z. Top Concerns of Tweeters during the COVID-19 Pandemic: Infoveillance Study. *J. Med. Internet Res.* **2020**, *22*, e19016. [CrossRef]
- Xue, J.; Chen, J.; Hu, R.; Chen, C.; Zheng, C.; Su, Y.; Zhu, T. Twitter Discussions and Emotions About the COVID-19 Pandemic: Machine Learning Approach. *J. Med. Internet Res.* **2020**, *22*, e20550. [CrossRef] [PubMed]
- Xue, J.; Chen, J.; Chen, C.; Zheng, C.; Li, S.; Zhu, T. Public discourse and sentiment during the COVID 19 pandemic: Using Latent Dirichlet Allocation for topic modeling on Twitter. *PLoS ONE* **2020**, *15*, e0239441. [CrossRef] [PubMed]
- Su, Y.; Venkat, A.; Yadav, Y.; Puglisi, L.B.; Fodeh, S. Twitter-based analysis reveals differential COVID-19 concerns across areas with socioeconomic disparities. *Comput. Biol. Med.* **2021**, *132*, 104336. [CrossRef] [PubMed]
- Boon-Itt, S.; Skunkan, Y. Public Perception of the COVID-19 Pandemic on Twitter: Sentiment Analysis and Topic Modeling Study. *JMIR Public Health Surveill* **2020**, *6*, e21978. [CrossRef] [PubMed]
- Sciandra, A. COVID-19 Outbreak through Tweeters' Words: Monitoring Italian Social Media Communication about COVID-19 with Text Mining and Word Embeddings. In Proceedings of the 2020 IEEE Symposium on Computers and Communications (ISCC) Computers and Communications (ISCC), 2020 IEEE Symposium, Rennes, France, 1–6 July 2020. [CrossRef]

28. Kumar, A.; Safi, U.K.; Ankur, K. COVID-19 pandemic: A sentiment analysis: A short review of the emotional effects produced by social media posts during this global crisis. *Eur. Heart J.* **2020**, *41*, 3782–3783. [CrossRef] [PubMed]
29. Asif, M.; Ishtiaq, A.; Ahmad, H.; Aljuaid, H.; Shah, J. Sentiment analysis of extremism in social media from textual information. *Telemat. Inform.* **2020**, *48*, 101345. [CrossRef]
30. Pang, B.; Lee, L. Opinion mining and sentiment analysis. *Found Trends Inf. Ret.* **2007**, *2*, 1–135.
31. Liu, B. *Sentiment Analysis and Opinion Mining*; Morgan & Claypool Publishers: San Rafael, CA, USA, 2012.
32. Nasukawa, T.; Yi, J. Sentiment analysis: Capturing favorability using natural language processing. In Proceedings of the KCAP-2003, 2nd International Conference on Knowledge Capture, Sanibel Island, FL, USA, 23–25 October 2003.
33. Carrillo-de-Albornoz, J.; Rodríguez Vidal, J.; Plaza, L. Feature engineering for sentiment analysis in e-health forums. *PLoS ONE* **2018**, *13*, e0207996. [CrossRef]
34. Liu, K.L.; Li, W.J.; Guo, M. Emotion Smoothed Language Models for Twitter Sentiment Analysis. In Proceedings of the 26th AAAI Conf. on Artificial Intelligence, Toronto, ON, Canada, 22–26 July 2012; pp. 1678–1684.
35. Liu, B. Sentiment Analysis and Subjectivity. In *Handbook of Natural Language Processing*, 2nd ed.; Indurkha, N.N., Damerau, F.J., Eds.; Taylor and Francis Group: Boca, FL, USA, 2010.
36. Kaushik, C.; Mishra, A.; Scalable, A. Lexicon Based Technique for sentiment analysis. *IJFCST* **2014**, *4*, 35–43. [CrossRef]
37. Liu, B.; Blasch, E.; Chen, Y.; Shen, D.; Chen, G. Scalable Sentiment Classification for Big Data Analysis Using Naive Bayes Classifier. In Proceedings of the 2013 IEEE International Conference on Big Data, Silicon Valley, CA, USA, 6–9 October 2013.
38. Pang, B.; Lee, L.; Vaithyanathan, S. Thumbs up? Sentiment classification using machine learning techniques. *EMNLP* **2002**, *2002*, 79–86.
39. Chesley, P.; Vincent, B.; Xu, L.; Srihari, R.K. Using verbs and adjectives to automatically classify blog sentiment. *Training* **2006**, *580*, 233.
40. Kennedy, A.; Inkpen, D. Sentiment classification of movie reviews using contextual valence shifters. *Comput. Intell.* **2006**, *22*, 110–125. [CrossRef]
41. Thomas, M.; Pang, B.; Lee, L. Get out the vote: Determining support or opposition from congressional floor-debate transcripts. In *Proceedings of the 2006 Conference on empirical Methods in Natural Language Processing*; Association for Computational Linguistics: Stroudsburg, PA, USA, 2006; Available online: <https://www.aclweb.org/anthology/W06-1639/> (accessed on 29 May 2021).
42. Mubarak, M.; Adiwijaya, S.; Aldhi, M.D. Aspect-based sentiment analysis to review products using Naïve Bayes. In Proceedings of the AIP Conference, Budapest, Hungary, 15–18 August 2017; pp. 1–8.
43. Song, J.; Kim, K.T.; Lee, B.; Kim, S.; Youn, H.Y. A novel classification approach based on Naïve Bayes for Twitter sentiment analysis. *KSII Trans. Internet Inf. Syst.* **2017**, *11*, 2996–3012.
44. Patil, G.; Galande, V.; Kekani, V.; Dan Dange, K. Sentiment Analysis using Support Vector Machine. *IJIRCCCE* **2014**, *2*, 2607–2612.
45. Povoda, L.; Burget, R.; Dutta, M.K. Sentiment analysis based on Support Vector Machine and Big Data 2016. In Proceedings of the 39th International Conference on Telecommunications and Signal Processing (TSP), Vienna, Austria, 27–29 June 2016; pp. 543–545.
46. Naz, S.; Sharan, A.; Malik, N. Sentiment Classification on Twitter Data Using Support Vector Machine. In Proceedings of the 2018 IEEE/WIC/ACM International Conference on Web Intelligence (WI), Santiago, Chile, 3–6 December 2018; pp. 676–679.
47. Xie, X.; Ge, S.; Hu, F.; Xie, M.; Jiang, N. An improved algorithm for sentiment analysis based on maximum entropy. *Soft. Comput.* **2019**, *23*, 599–611. [CrossRef]
48. Yan, X.; Huang, T. Tibetan Sentence Sentiment Analysis Based on the Maximum Entropy Model. In Proceedings of the 2015 10th International Conference on Broadband and Wireless Computing, Communication and Applications (BWCCA), Krakow, Poland, 4–6 November 2015; pp. 594–597.
49. Ficamos, P.; Liu, Y.; Chen, W. A Naive Bayes and Maximum Entropy approach to sentiment analysis: Capturing domain-specific data in Weibo. In Proceedings of the 2017 IEEE International Conference on Big Data and Smart Computing (BigComp), Jeju Island, Korea, 13–16 February 2017; pp. 336–339.
50. Neethu, M.S.; Rajasree, R. Sentiment analysis in Twitter using machine learning techniques. In Proceedings of the 2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT), Tiruchengode, India, 4–6 July 2013; pp. 1–5.
51. Shivaprasad, T.S.; Shetty, J. Sentiment analysis of product reviews: A review. In Proceedings of the 2017 International Conference on Inventive Communication and Computational Technologies (ICICCT), Coimbatore, India, 10–11 March 2017; pp. 298–301.
52. Khoo, C.; Johnkhan, S.B. Lexicon-Based Sentiment Analysis: Comparative Evaluation of Six Sentiment Lexicons. *J. Inf. Sci.* **2018**, *44*, 491–511. [CrossRef]
53. Kleinnijenhuis, J.; Schultz, F.; Oegema, D.; Van Atteveldt, W. Financial news and market panics in the age of high-frequency sentiment trading algorithms. *Journalism* **2013**, *14*, 271–291. [CrossRef]
54. Aaldering, L.; Vliegthart, R. Political leaders and the media. Can we measure political leadership images in newspapers using computer-assisted content analysis? *Qual. Quant.* **2016**, *50*, 1871–1905. [CrossRef]
55. Haselmayer, M.; Jenny, M. Sentiment analysis of political communication: Combining a dictionary approach with crowd coding. *Qual. Quant.* **2017**, *51*, 2623–2646. [CrossRef]
56. Taboada, M.; Brooke, J.; Tofiloski, M.; Voll, K.D. Lexicon based methods for sentiment analysis. *Comput. Linguist.* **2011**, *37*, 267–307. [CrossRef]

57. Esuli, A.; Sebastiani, F. SentiWordNet: A publicly available lexical resource for opinion mining. In Proceedings of the 5th International Conference on Language Resources and Evaluation, Genoa, Italy, 22–28 May 2006; pp. 417–422.
58. Hatzivassiloglou, V.; McKeown, K.R. Predicting the semantic orientation of adjectives. In Proceedings of the 35th Meeting of the Association for Computational Linguistics, Madrid, Spain, 7–11 July 1997; pp. 174–181.
59. Turney, P.; Littman, M. Measuring praise and criticism: Inference of semantic orientation from association. *ACM Trans. Inf. Syst.* **2003**, *21*, 315–346. [\[CrossRef\]](#)
60. Rudkowsky, E.; Haselmayer, M.; Wastian, M.; Jenny, M.; Emrich, Š.; Sedlmair, M. More than Bags of Words: Sentiment Analysis with Word Embeddings. *Commun. Methods Meas.* **2018**, *12*, 140–157. [\[CrossRef\]](#)
61. Nakov, P.; Kozareva, Z.; Ritter, A.; Rosenthal, S.; Stoyanov, V.; Wilson, T. SemEval-2013 Task 2: Sentiment Analysis in Twitter. In Proceedings of the Second Joint Conference on Lexical and Computational Semantics (*SEM), Seventh International Workshop on Semantic, Atlanta, Georgia, 14–15 June 2013; Volume 2, pp. 312–320.
62. Go, A.; Bhayani, R.; Huang, L. *Twitter Sentiment Classification Using Distant Supervision*; CS224N Project Report. Stanford, CA, USA, 2009. Available online: <https://www-cs.stanford.edu/people/alecmgo/papers/TwitterDistantSupervision09.pdf> (accessed on 29 May 2021).
63. Pak, A.; Paroubek, P. Twitter as a corpus for sentiment analysis and opinion mining. In Proceedings of the Seventh conference on International Language Resources and Evaluation (LREC'10), Valletta, Malta, 17–23 May 2010.
64. Barbosa, L.; Feng, J. Robust Sentiment Detection on Twitter from Biased and Noisy Data. In Proceedings of the Coling 2010, Beijing, China, 23–27 August 2010; pp. 36–44.
65. Dos Santos, C.N.; Gatti, M. Deep Convolutional Neural Networks for Sentiment Analysis of Short Texts Proceedings of COLING 2014. In *The 25th International Conference on Computational Linguistics*; Technical Papers; Dublin City University and Association for Computational Linguistics: Dublin, Ireland, 2014; pp. 69–78.
66. Nagarajan, S.; Gandhi, U.D. Classifying streaming of Twitter data based on sentiment analysis using hybridization. *Neural Comput. Appl.* **2018**, *31*, 1425–1433. [\[CrossRef\]](#)
67. Pappu Rajan, A.; Victor, S.P. Web Sentiment Analysis for Scoring Positive or Negative Words using Tweeter Data. *Int. J. Comput. Appl.* **2014**, *96*, 33–37.
68. Saif, H.; Fernandez, M.; He, Y.; Alani, H. Evaluation datasets for Twitter sentiment analysis: A survey and a new dataset, the STS-Gold. In Proceedings of the 1st International Workshop on Emotion and Sentiment in Social and Expressive Media: Approaches and Perspectives from AI (ESSEM 2013), Turin, Italy, 3 December 2013.
69. Ribeiro, P.L.; Weigang, L.; Li, T. A unified approach for domain-specific tweet sentiment analysis. In *Information Fusion (Fusion), 18th International Conference*; IEEE: New York, NY, USA, 2015; pp. 846–853.
70. Sahayak, V.; Shete, V.; Pathan, A. Sentiment Analysis on Twitter Data. *IJIRAE* **2015**, *1*, 178–183.
71. Narr, S.; Hulferhaus, M.; Albayrak, S. Language-Independent Twitter Sentiment Analysis. In Proceedings of the KDML, LWA 2012, Dortmund, Germany, 12–14 September 2012; pp. 12–14.
72. Han, B.; Baldwin, T. Lexical normalisation of short text messages: Makn sens a#twitter. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*; Association for Computational Linguistics: Stroudsburg, PA, USA, 2011.
73. Saif, H.; Fernandez, M.; He, Y.; Alani, H. Semantic sentiment analysis of twitter. In Proceedings of the Semantic Web-ISWC 2012, Boston, MA, USA, 11–15 November 2012; pp. 508–524.
74. Kiritchenko, S.; Zhu, X.; Mohammad, S.M. Sentiment analysis of short informal texts. *J. Artif. Intell. Res.* **2014**, *50*, 723–762. [\[CrossRef\]](#)
75. Da Silva, N.N.F.; Hruschka, E.; Hruschka, E.R. Tweet sentiment analysis with classier ensembles. *Decis. Support Syst.* **2014**, *66*, 170–179. [\[CrossRef\]](#)
76. Jianqiang, Z. Combing semantic and prior polarity features for boosting twitter sentiment analysis using ensemble learning. In Proceedings of the IEEE Int. Conf. Data Sci. Cyberspace (DSC), Changsha, China, 13–16 June 2016; pp. 709–714.
77. Paltoglou, G.; Thelwall, M. Twitter, MySpace, Digg: Unsupervised sentiment analysis in social media. *ACM Trans. Intell. Syst. Technol.* **2012**, *3*, 1–19. [\[CrossRef\]](#)
78. Jianqiang, Z.; Xiaolin, G.; Xiejun, Z. Deep Convolution Neural Networks for Twitter Sentiment Analysis. *IEEE Access.* **2018**, *6*, 23253–23260. [\[CrossRef\]](#)
79. Zhao, Y.; Xu, H. Chinese Public Attention to COVID-19 Epidemic: Based on Social Media. *medRxiv* **2020**. [\[CrossRef\]](#)
80. Wang, T.; Lu, K.; Chow, K.P.; Zhu, A.Q. COVID-19 Sensing: Negative Sentiment Analysis on Social Media in China via BERT Model. *IEEE Access.* **2020**, *8*, 138163. [\[CrossRef\]](#)
81. Pellerty, M.; Lasserre, J.; Metzler, H.; Garciay, D. Dashboard of sentiment in Austrian social media during COVID-19. *Front. Big Data* **2020**. [\[CrossRef\]](#)
82. Barkur, G.; Vibha, G.B.K. Sentiment analysis of nationwide lockdown due to COVID 19 outbreak: Evidence from India. *Asian J. Psychiatry* **2020**, *51*, 102089. [\[CrossRef\]](#) [\[PubMed\]](#)
83. Prastyo, P.H.; Sumi, A.S.; Dian, A.W.; Permanasari, A.E. Tweets Responding to the Indonesian Government's Handling of COVID-19: Sentiment Analysis Using SVM with Normalized Poly Kernel. *JISEBI* **2020**, *6*, 112–122. [\[CrossRef\]](#)
84. Pokharel, B.P. Twitter Sentiment analysis during COVID-19 Outbreak in Nepal. *SSRN* **2020**. [\[CrossRef\]](#)

85. Samuel, J.; Ali, G.G.M.N.; Rahman, M.M.; Esawi, E.; Samuel, Y. COVID-19 Public Sentiment Insights and Machine Learning for Tweets Classification. *Information* **2020**, *11*, 314. [\[CrossRef\]](#)
86. De las Heras-Pedrosa, C.; Sánchez-Núñez, P.; Peláez, J.I. Sentiment Analysis and Emotion Understanding during the COVID-19 Pandemic in Spain and Its Impact on Digital Ecosystems. *Int. J. Environ. Res. Public Health* **2020**, *17*, 5542. [\[CrossRef\]](#) [\[PubMed\]](#)
87. Kaila, R.P.; Prasad, A.V.K. Information Flow on Twitter Corona Virus Outbreak—Topic Modelling Approach. *IJARET* **2020**, *11*, 128–134.
88. Chakraborty, K.; Bhatia, S.; Bhattacharyya, S.; Platos, J.; Bag, R.; Hassanien, A.E. Sentiment Analysis of COVID-19 tweets by Deep Learning Classifiers—A study to show how popularity is affecting accuracy in social media. *Appl. Soft. Comput.* **2020**, *97*, 106754. [\[CrossRef\]](#)
89. Mansoor, M.; Gurumurthy, K.; Anantharam, R.U.; Prasad, V.R.B. Global Sentiment Analysis of COVID-19 Tweets over Time. *arXiv* **2020**, arXiv:2010.14234v2.
90. Mangury, K.; Ramadhan, R.; Mohammed Amin, P. Twitter sentiment analysis on Worldwide Covid19 Outbreaks. *KJAR* **2020**, *5*, 54–65. [\[CrossRef\]](#)
91. Naseem, U.; Razzak, I.; Khushi, M.; Eklund, P.; Kim, J. COVIDSenti: A Large-Scale Benchmark Twitter Data Set for COVID-19 Sentiment Analysis. *IEEE Trans. Comput. Soc. Syst.* **2021**. [\[CrossRef\]](#)
92. Nemes, L.; Kiss, A. Social media sentiment analysis based on COVID-19. *J. Inf. Telecommun.* **2021**, *5*, 1–15.
93. Kruspe, A.; Häberle, M.; Kuhn, I.; Zhu, X.X. *Cross-Language Sentiment Analysis of European Twitter Messages during the COVID-19 Pandemic*; Association for Computational Linguistics: Stroudsburg, PA, USA, 2020.
94. Liang, H.; Fung, I.C.; Tse, Z.T.H.; Yin, J.; Chan, C.; Pechta, L.E.; Smith, B.J.; Marquez-Lameda, R.D.; Meltzer, M.I.; Lubell, K.M.; et al. How did Ebola information spread on twitter: Broadcasting or viral spreading? *BMC Public Health* **2019**, *19*, 438. [\[CrossRef\]](#) [\[PubMed\]](#)
95. Rosenberg, H.; Syed, S.; Rezaie, S. The Twitter pandemic: The critical role of Twitter in the dissemination of medical information and misinformation during the COVID-19 pandemic. *CJEM* **2020**, 1–4. [\[CrossRef\]](#)
96. Smith, M.; Ceni, A.; Milic-Frayling, N.; Shneiderman, B.; Mendes Rodrigues, E.; Leskovec, J.; Dunne, C. *NodeXL: A Free and Open Network Overview, Discovery and Exploration Add-In for Excel 2007/2010/2013/2016*; Social Media Research Foundation: Redwood City, CA, USA, 2010.
97. Kantrowitz, A. The Man Who Built the Retweet: We Handed A Loaded Weapon To 4-Year-Olds. 2019. Available online: <https://www.buzzfeednews.com/article/alexkantowitz/how-the-retweet-ruined-the-internet> (accessed on 7 October 2020).
98. Danowski, J.A.; Park, H.W. Arab spring effects on meanings for Islamist web terms and on web hyperlink networks among Muslim-majority nations: A naturalistic field experiment. *J. Contemp. East. Asia* **2014**, *13*, 15–39. [\[CrossRef\]](#)
99. Danowski, J.A.; Yan, B.; Riopelle, K. A semantic network approach to measuring sentiment. *Qual. Quant.* **2020**, *55*, 221–255. [\[CrossRef\]](#)
100. Gonçalves, P.; Araújo, M.; Benevenuto, F.; Cha, M. Comparing and Combining Sentiment Analysis Methods. In Proceedings of the First ACM Conference on Online Social Networks; 2013; pp. 27–38. Available online: <https://dl.acm.org/doi/abs/10.1145/2512938.2512951> (accessed on 28 May 2021).
101. Khan, A.Z.H.; Atique, M.; Thakare, V.M. Combining Lexicon-Based and Learning-Based Methods for Twitter Sentiment Analysis. *IJECSCSE* **2015**, *89*. Available online: <https://www.semanticscholar.org/paper/Combining-Lexicon-based-and-Learning-based-Methods-Z.H.KHAN-Thakare/871ec266e405be4ddeeb298505a0d1adde4a8be3> (accessed on 29 May 2021).
102. Tsakalidis, A.; Papadopoulos, S.; Voskaki, R.; Ioannidou, K.; Boididou, C.; Cristea, A.I.; Liakata, M.; Kompatsiaris, Y. Building and evaluating resources for sentiment analysis in the Greek language. *Lang. Resour. Eval.* **2018**, *52*, 1021–1044. [\[CrossRef\]](#)
103. Shveda, K. How Coronavirus Is Changing Grocery Shopping. 2020. Available online: <https://www.bbc.com/future/bespoke/follow-the-food/how-covid-19-is-changing-food-shopping.html> (accessed on 7 October 2020).
104. TornosNews.gr Greek Supermarket Sales Rise during Coronavirus Outbreak. 2020. Available online: <https://www.tornosnews.gr/en/greek-news/economy/39605-greek-supermarket-sales-rise-during-coronavirus-outbreak.html> (accessed on 7 July 2020).
105. Media Update Seven Trending Hashtags about COVID-19 on Social Media. 2020. Available online: <https://www.mediaupdate.co.za/social/148423/seven-trending-hashtags-about-covid-19-on-social-media> (accessed on 4 July 2020).
106. Kydros, D.; Vrana, V.; Kehris, E. Social Networks, Politics and Public Views: An Analysis of the Term “Macedonia” in Twitter. *Soc. Netw.* **2019**, *8*, 1–15. [\[CrossRef\]](#)
107. Kenett, Y.; Kenett, D.; Ben-Jacob, E.; Faust, M. Global and Local Features of Semantic Networks: Evidence from the Hebrew Mental Lexicon. *PLoS ONE* **2011**, *6*, e23912. [\[CrossRef\]](#) [\[PubMed\]](#)
108. Melançon, G. Just how dense are dense graphs in the real world? A methodological note. In Proceedings of the BELIV 2006: BEyond Time and Errors: Novel Evaluation Methods for Information Visualization (AVI Workshop), Venice, Italy, 23 May 2006; pp. 75–81.
109. Kulig, A.; Drozd, S.; Kwapien, J.; Oświęcimka, P. Modeling the average shortest-path length in growth of word-adjacency networks. *Phys. Rev. Stat. Nonlin. Soft Matter Phys.* **2015**, *91*, 032810. [\[CrossRef\]](#) [\[PubMed\]](#)
110. Čerba, O.; Jedlička, K.; Čada, V.; Charvát, K. Centrality as a Method for the Evaluation of Semantic Resources for Disaster Risk Reduction. *Int. J. Geo-Inf.* **2017**, *6*, 237. [\[CrossRef\]](#)
111. Hooper, C.J.; Marie, N.; Kalampokis, E. Dissecting the butterfly: Representation of disciplines publishing at the Web Science Conference series. In *WebSci*; ACM: New York, NY, USA, 2012; pp. 197–200.

-
112. Nerghes, A.; Lee, J.; Groenewegen, P.; Hellsten, L. Mapping discursive dynamics of the financial crisis: A structural perspective of concept roles in semantic networks. *Comput. Soc. Netw.* **2015**, *2*, 16. [\[CrossRef\]](#)
 113. Kavoura, A. Two to Tango: Entrepreneurs and Robots' Users in Hospitality Service Innovation. In *Service Excellence in Tourism and Hospitality. Tourism, Hospitality & Event Management*; Thirumaran, K., Klimkeit, D., Tang, C.M., Eds.; Springer: Cham, Switzerland, 2021; pp. 111–131.
 114. Kavoura, A.; Buhalis, D. Online communities. In *Encyclopedia of Tourism Management and Marketing*; Buhalis, D., Ed.; Edward Elgar: Cheltenham, UK, 2022.
 115. Rozanova, L.; Temerev, A.; Flahault, A. Comparing the Scope and Efficacy of COVID-19 Response Strategies in 16 Countries: An Overview. *Int. J. Environ. Res. Public Health* **2020**, *17*, 9421. [\[CrossRef\]](#)
 116. Craven, M.; Sabow, A.; Van der Veken, L.; Wilson, M. Not the Last Pandemic: Investing Now to Reimagine Public-Health Systems, McKinsey. 12 May 2021. Available online: <https://www.mckinsey.com/industries/public-and-social-sector/our-insights/not-the-last-pandemic-investing-now-to-reimagine-public-health-systems> (accessed on 28 May 2021).