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RESEARCH ARTICLE

Geo-sentiment trends analysis of tweets in context of economy and employment during COVID-19

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Abstract

To effectively design policies and implement measures for addressing problems faced by people during these difficult times of pandemic, it is critical to have a clear vision of the problems people are freely talking about. One of the ways is to analyze social media feeds e.g., tweets, which has become one of the primary ways people express their views on various socioeconomic issues and on-ground effectiveness of measures adopted to address these issues. In this work, we attempt to uncover various socioeconomic issues, which are giving rise to negative and positive sentiments and their trends across geographies over a course of one year of the pandemic. We also try identifying similarities and differences in opinions as they vary across gender as the time passes through the crisis. Many previous works have analyzed sentiments in context of vaccines, fatalities, and lockdowns; however, socioeconomic issues did not receive full attention. We found that sentiments of people with respect to economy are negative across geographies during starting of pandemic. Thereafter, gradually sentiments lift towards positive direction reflecting a sense of improvement in situation. Females appeared to have slightly different concerns and hopes in comparison to males and especially across globe people expressed positive sentiments during new year time. Finally, this work, together with many other similar works on social media analysis gives ground for wide scale adoption of geo-temporal sentiments trend analysis of social media as a tool for uncovering key concerns and effectiveness of measures.

Keywords Tweet analytics · Geo-temporal trend mining · Sentiment analysis · Gender opinion analysis

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Introduction

COVID-19 Pandemic, which started in early 2020, has major transformative impact on individual as well as a societal levels [11, 25, 28, 30]. Naturally, during 2020 and thereafter, it has been a highly discussed topic in various media platforms including social media [7].

Wider access of social media platforms like Twitter through mobiles has made them one of the most popular platforms for expressing views, opinions, feelings, and sharing information by individuals, organizations, media, and government agencies. Consequently, there has been significant efforts towards identifying patterns of individual expressions on various topics of interest by analyzing social media contents, which are often available freely (albeit under certain constraints) to researchers [6, 9, 15, 16].

There are significant number of published studies based on analysis of social media, including Twitter, to uncover various population level trends related to COVID1-19 pandemic [7, 13, 17, 27, 29, 31]. Most of these social media analyses based research is focused on topics like pandemic impact on economy and markets, pandemic spread, treatments and vaccines, and governments response [5]. For example, authors in [23] analyzed how trend of topics are changing over the course of time for the countries like Iran, Vietnam, South Korea, and India. They showed that the pandemic phases by governments do not match well with the what is expressed in tweets about information on COVID-19.

Sentiment analysis has particularly been applied on large number these studies, in particular on Twitter data [20, 22]. For example, authors in [14] introduce a tool for temporal sentiment analysis along with geographical distribution of tweets within USA using Wordcloud representation to know how people felt during the pandemic. Similarly, [3] has analyzed sentiment and interaction rate with respect to the origin of COVID-19, source of novel coronavirus, impact of COVID-19 on people and countries, and methods for decreasing COVID-19 spread. [4, 8] focus on learning how people are expressing their sentiments on COVID-19 and frequency of tweets over the symptoms during the pandemic and how can it help in understanding to which phase they are into.

However, only couple of published studies use Twitter for extracting information on people's sentiments on economy [5, 10, 19]. Other studies [2] have analyzed how people sentiments change to being less negative with reopening of economy. The research in [19] has showed that the frequency of economic impact from tweets is high and that fear is maximally expressed in the context of economy. In their analysis, authors in [10] have similarly noticed an increase in the volume of messages on proliferation, care, and widening economic gap. In their study, authors analyzed public sentiment using Twitter Data and time-aligned to the COVID-19 to identify dominant sentiment trends associated with the push to reopen the economy while people showed extreme fear, confusion and volatile sentiments, mixed along with trust and anticipation. In [5], authors reported that many Twitter users posted information about their job loss and unemployment.

This paper presents analysis of Twitter data related to economy during COVID-19 outbreak. From Jan, 2020 till Mar, 2021, we retrieved tweets mentioning keywords related to economy, business, investment, finance, unemployment, and jobs. These tweets were analyzed to identify how underlying sentiments had varied with respect to time, gender, and geographies before and during pandemic in terms economy, employment, money, and jobs.

Rest of the paper is organized as follows: "Methodology" presents methodology of data collection and analysis followed by "Tool design" on prototype tool used for the analysis."Top themes in the context of economy and employment" presents month-wise top themes found across all these tweets. " Temporal sentiment trends" presents temporal sentiment trends whereas "Positive sentiments on economy" summaries positive sentiments related to economy. Next "Geo-Sentiment trends" presents detailed analysis of Geo-Sentiment Trends on Economy and Unemployment followed by "Organizations vs individuals", which covers how tweets from organizations differed in focus from individuals. Finally, "Gender differences on economy and employment" presents a summarized view on how males and females aligned and differed on their views on Economy and Employment. "Discussion" presents overall discussion and reaches conclusion in the "Conclusion".

Methodology

Data collection

The data was collected from two different sources for the time-period between Jan 2020 and Mar 2021:

1. Using IDs from IEEE data-set provided by [18]. Around 544,584 tweets were extracted using Python library Tweepy and Twitter API V1.1 using terms related to economy as search: 'economy', 'economics', 'business', 'goods', 'investment', 'finance', 'financial', 'employ', 'unemployment', 'jobs', 'job'.
2. Next, we collected 30,635,135 tweets using Twinc python package with the same economy and employment related keywords.

After combining both these data-sets, however, we limited analysis to randomly selected 26685 tweets such that day wise frequency distribution of tweets is kept same as in the sampled data as was in the original data. Primary reason for limiting analysis to only small fraction of collected tweets is to be able to manage computational load as even with a system having 128 GB of RAM and dual GPUs (NVIDIA Quadro RTX 500 GPU with 16GB RAM and Intel UHD Graphics 630), managing higher number of tweets was getting difficult.

Table 1 Total statistics of collected data (Jan 2020–Mar 2021)

	Positive tweets	Negative tweets	Company tweets	Individual tweets	Male tweets	Female tweets
Number of tweets (2020)	11772	8372	490	24036	18405	5631
Before pandemic (Jan–Feb 2020)	206	443	3	649	596	53
During pandemic (Mar–May 2020)	3040	2404	124	6566	4956	1610
Pandemic recovery (June–Oct 2020)	7749	5342	320	15687	11884	3803
Recovery (Nov–Mar 2021)	777	183	43	1134	969	165

Tweets with neutral sentiment score are not counted

The Statistics of total collected tweets with distribution across time-zones, sentiments, and gender appear in the Table 1.

Data preprocessing

Non-English tweets were identified and removed from the collected data using Twitter metadata and *detect lang* API. Next, tool identifies duplicates tweets by mapping each tweet to a neural embedding space using Glove [24] and estimating cosine similarity with threshold of 0.9. Remaining tweets were preprocessed further to remove stop words, numbers, symbols, URLs, and references to other users.

Fake tweet detection

After preprocessing Tweets, tool aims to identify tweets, which could have potentially been from Bots using Botometer API [33], which takes usernames as inputs and generates five different scores as indicators of how similar a Twitter account is to different types of bots:

1. Fake follower: Indicates that account might have purchased bots as its followers.
2. Echo-chamber: Indicates that an account is similar to political bots, which are designed to share and delete content.
3. Self-declared: Indicates that it is a bot from botwiki.org
4. Spammer: Indicates that an account is labeled as spambot in different datasets.
5. Financial: Indicates that an account is similar to bots, which post using cashtags and currency related information.
6. Other: Indicates that account has been identified as bot through manual annotations and user feedback.

By combining above raw scores overall bot score is determined in the range of [0, 1] using both English language specific or Universal (language-independent) features. If a Tweet is in the English, English Language score is given, else universal score is given by the tool. Next, threshold conditional probability (CAP) is used so that accounts with a score equal to or greater than CAP are considered as bots else genuine.

Table 2, presents manually verified results of Botometer for a random sample of 100 different usernames. Further, distribution of different types of fake users is listed in Table 3.

Number of tweets after different stages of collection and pre-processing can be summarized as:

- Initial Tweets: 30,635,135
- English Language Tweets: 61,769,05
- Sample Tweets for Analysis: 26,685
- Tweets after Removing Tweets, which are either Duplicates or are from Fake User Accounts: 24,526

Data transformation

Extracting location data

Since, only small fraction of available tweets (3%) had geo-location information of the user, we used other techniques to extract location data:

- Reverse Geo coding from Coordinates: For tweets containing latitude and longitude details, Python *reverse geocode API* helps in getting details like place, state, and country details.
- Reverse Geo Coding from Text: We collected location data such as place, state and country details from dataset [26] and compare it with text present in tweets. Python google geocoding API is then used to obtain latitude and longitude using these collected location details.

Gender recognition

To get the gender details we have used the usernames from the collected data of Twitter API and extracted gender details. Using Gender-Predictor API from the GitHub [21], male-female classifier is constructed using names dataset from the U.S. Social Security.

Table 2 Distribution of genuine and fake user accounts in a sample size of 100

	Genuine	Fake (i.e., Bot)	Total tweets	Language
Economy	81	16	97	English
	2	1	3	Non-English

Table 3 Different types of fake user accounts identified from a sample of 100 (ref. Table 2)

Fake follower	Self-declared	Echo-chamber	Spammer	Financial	Other
3	3	3	1	1	6

Organization versus individual

We further categorize tweet users into organization vs individual based on the username and profile name. Username of an account and can be mentioned as reference in other tweets, while profile name is used for search.

To identify organizations, list of names are collected from below sources:

- Company names [1] from Kaggle.
- New channels [32] from Wikipedia.
- Common suffixes in the company names such as Ltd, limited, inc, org, creations, company, jobs, software, solutions.

Using the above three data-sets each username and profile name is classified as an Organizational user or an Individual user.

Sentiment analysis

We used VADER (Valence Aware Dictionary and Sentiment Reasoner) Sentiment Analyzer [12] to determine sentiment score for each tweet. VADER has been specifically designed for sentiment analysis of social media text and has evolved over last couple of years. It is available as a library in NLTK and gives positive, negative, as well as neutral sentiment score for each tweet.

Tool design

In order to perform the analysis, we designed a prototype tool, which takes prepossessed tweet data as input and allows exploration of these tweets using its search functionality as shown in Fig. 1.

The basic search will give the analysis with sentiment, frequency, and geographical bubble maps. This search has filters such as gender and category (Individual/Organizations/Media). We can also filter search outcomes with respect to geographical information like country, state, and place names.

In contrast, comparative search as shown in Fig. 2 allows users to compare the sentiments, frequency, and geographical trends between two terms (words or phrases) refined by geographical filters if country, state, and place names. Elasticsearch was used for building index model towards enabling filtered search.

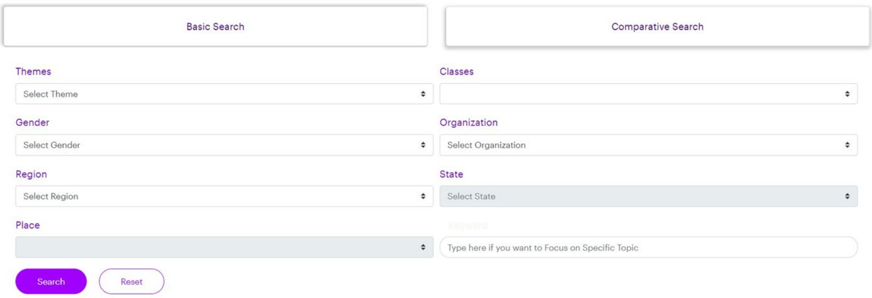


Fig. 1 Basic search

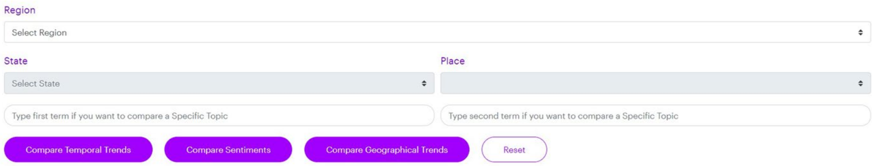


Fig. 2 Comparative search

Top themes in the context of economy and employment

Pandemic has created major concerns over the economy and employment. Figure 3 shows the most frequent words present in the tweets, wherein numbers in the parenthesis are the fraction (in %) of tweets which are related to corresponding term. Most frequent unigrams for each month seem to indicate that in Mar'20, concern is mainly over life of people, money for meeting essential needs, and job safety. During later months, people have expressed their concerns on the need of money and loss of jobs from April to August. Loss and hardship was expressed right from Apr to Nov until things came under control with vaccination. Then during months Dec'20 till Mar'21, jobs referring or government adding of more jobs became trending topics, with concern over money gone down and there is also good support from people for giving benefits to poor became a trend in Twitter.

Geographical distribution of data

Table 4 presents geographical distribution of tweets for major time-frames (before start of the Pandemic, during pandemic, during months of recovery, and post recovery period) for top Eight countries: USA, UK, India, Canada, Poland, South Africa, Kenya, and Ireland.

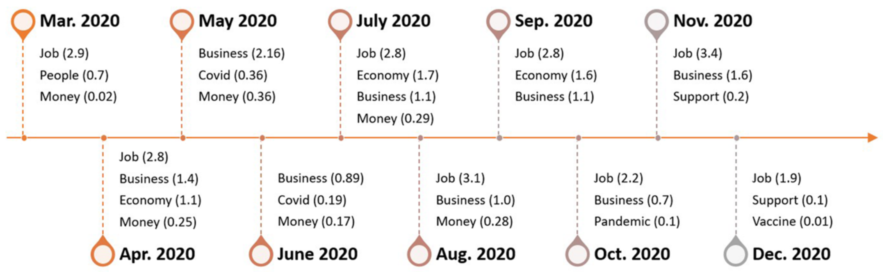


Fig. 3 Most frequent uni-grams from word cloud (Mar 2020–Dec 2020)

Table 4 Geographical distribution of data during (Jan 2020–Mar 2021)

Country (Frequency of tweets)	Before pandemic (355)	During pandemic (1918)	Pandemic recovery (8193)	Recovery (1171)
USA	161	861	4061	629
UK	91	231	1459	272
India	3	125	440	17
Canada	43	216	700	141
Poland	8	30	80	18
South Africa	4	26	140	10
Kenya	3	12	42	4
Ireland	2	18	139	13

Temporal sentiment trends

Sentiment trends before pandemic (Jan 2020–Feb 2020)

Sentiment trends in relation to economy were negative even before the pademic could start as shown in Fig. 4. During months of Jan’20 and Feb’20, people mostly expressed negative sentiments stating that even economy is high, they still have to do multiples jobs to meet their needs.

As can be noticed from Fig. 4 people are expressing their most worrisome sentiments often at the start of the months. During January people showed negative sentiments for economy owing to low employment and many having smaller jobs. They were mentioning about jobs of cabs which give at least them some hope, otherwise they are mostly unemployed. Another frequently discussed topic during late Jan’20 was that crime rate is going higher and pay is less.

For example: “.. economy has a fatal flaw, income stagnation and low employment .. when you are working 2 or 3 jobs just to survive..”

Let’s check how people are expressing during months of Jan and Feb using tweet summarizer in Fig. 5

1. During Jan’20, most of the people are showing negative sentiments on having low unemployment, but, unable to get good pay from the jobs or quality of jobs are not suitable. They have mostly expressed about economy bloom, less quality index Jobs.
2. While in month of Feb’20, most of the people struggled with multiple jobs for getting enough needs and without any job security. People have tweeted about new jobs, but at the end they are expressing concern that data does not match with they perceive as ground reality. Some stated that they were laid off and planning to move to other geographies to get jobs. Overall, users stated that while economy may still be high, there is looming unemployment.

Sentiment trends during pandemic (Mar 2020–Dec 2020)

Starting Mar’20 onward most people have expressed negative or neutral sentiments as shown in the Fig. 6 and it is clear from sentiment graph that people were getting increasingly unhappy about it. Due to possible reasons such as they must work two or more jobs, people mention that underemployment rates are higher even when unemployment rate is low. For example:

– “The economy isn’t that strong. The unemployment rate is low, but the underemployment rate is high - people have part time jobs or need to work for 2 jobs to get by. There have been some troubling economic indicators lately."

As can be seen in Fig. 7, sentiments on unemployment are often negative and only occasionally neutral. While using Search term “Job” as shown in Fig. 8, there is a significant rise in the positive sentiments due to increase in opportunities.

At the beginning of month of March, when outbreak of COVID-19 started, people expressed negative sentiments as many lost their jobs. Later on, during month of June, even after many tweets talk about losing jobs, small companies and secondary jobs have created a little positive sentiment. While in the month of November, people expressed happiness with work from home and thanksgiving brought positive sentiments. During December, people showed happiness as there are more job openings, Christmas, and free testing appeared to have made Dec’20 a bit positive.

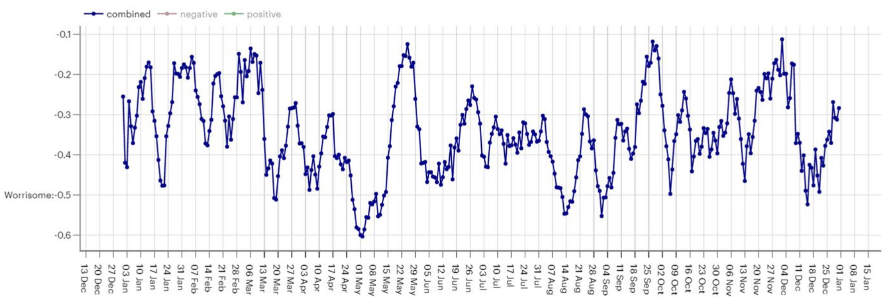


Fig. 4 Sentiment trends with respect to economy (Jan 2020–Dec 2020)

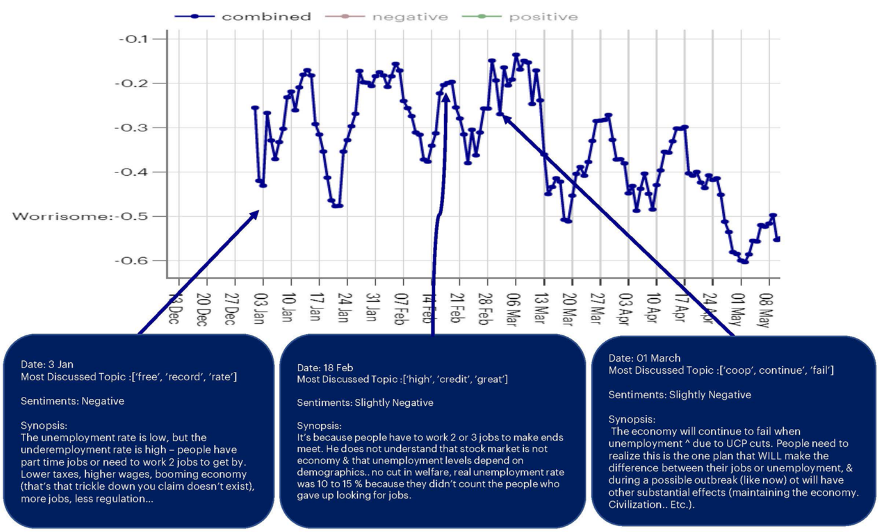


Fig. 5 Sentiment on economy (Jan 2020–Feb 2020)

Positive sentiments on economy

The Table 5 summarizes positive sentiments as expressed in tweets during pandemic situations. Figure 9, on the other hand, depicts temporal frequency trends across positive, negative, and neutral sentiments over a course of Jan 2020 to Jan 2021. As can be seen, positive sentiments are growing albeit gradually as the months passed and negative tweets have decreased slightly over the same period, especially during last few months. The news of vaccine, thanksgiving and Christmas have made a positive impact on sentiments of as days passed by through the pandemic.

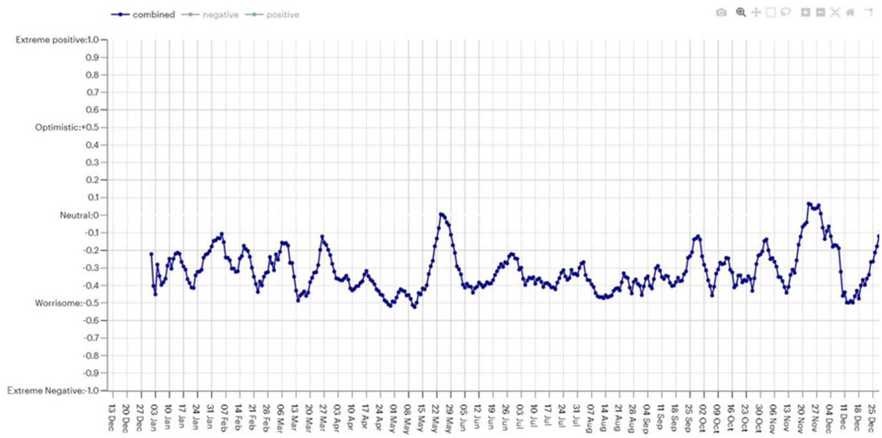


Fig. 6 Sentiments of unemployment (Feb 2020–Dec 2020)

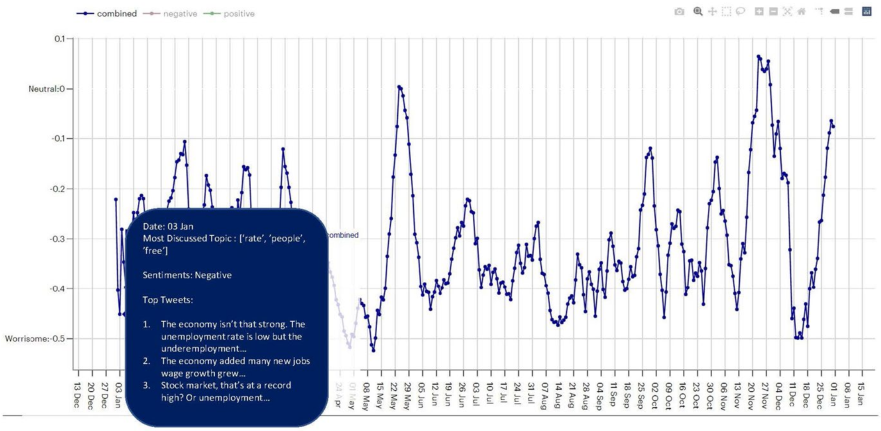


Fig. 7 Sentiments of unemployment before the outbreak (Jan 2020–Feb 2020)

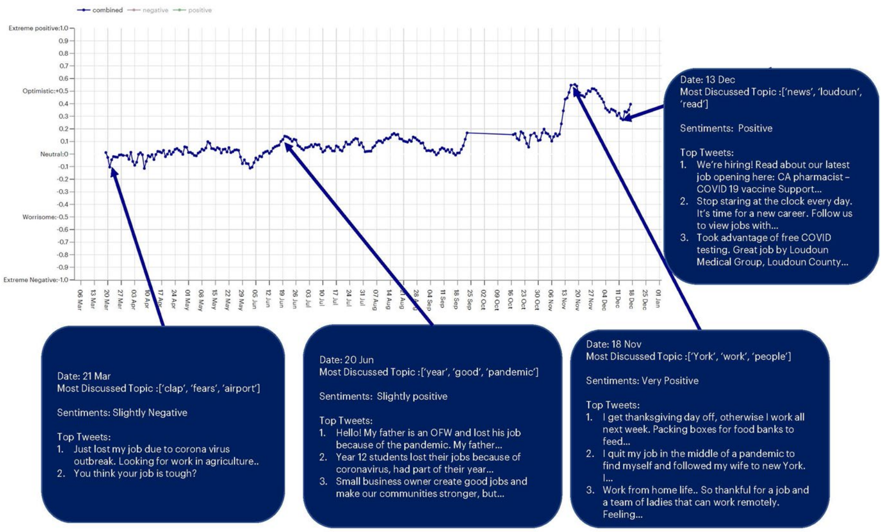


Fig. 8 Sentiments related to job (Jan 2020–Dec 2020). There were no tweets in the sample data-set during Sep 24 and Oct 17

Geo-sentiment trends

Next, let us present sentiment trends across various geographies related to economy and unemployment. These trends are identified during three different time-frames: During initial months of Mar–Aug 2020, during the period Sep–Oct 2020, and finally during Nov 2020–Mar 2021.

Geo-sentiment trends during (Mar 2020–Aug 2020)

Economy

Geographical details as listed in Table 6 depict how are people expressing their sentiments around USA & UK during the months of Mar to May 2020.

USA: Geographically males are reacting positively in USA, in cities like San Jose, Washington, Danville, Port Royal, Colorado Springs, Twain Harte as shown in Table 7. People are experiencing positive emotions during this period for various reason, specially the hope of reopening the business making people happy. In Washington and San Jose also, people are getting ready to reopen business with more strength after the COVID-19 pandemic. In a different discussion people are talking about helping each other to overcome this pandemic as many people already lost jobs and may not have savings to go through this situation.

Table 5 Key positive sentiments on economy (Jan 2020–Jan 2021)

Month	Positive sentiments in tweets
Jan 2020	Most of them express positively as there are new jobs, economy blooming, largest increase in manufacturing workers and low unemployment rate
Feb 2020	They express that unemployment rate is low temporary because of contract jobs. And mentioned that China and international trade increase in women # of jobs and salary
Mar 2020	Many people have expressed positive sentiments as sarcasm. For example: “In order to save his economy, now you are showing the trick to spread the corona virus across the world, boost your economy”
Apr 2020	People expressed the government as doing it best and it gave unemployment benefits for self-employed workers, independent contractors, economy workers. Then later after 15 April, they mostly express economy is growing and unemployment decades. jobs are growing, consumers are protected, and have all the testing they needed
May 2020	They are expressing that it will take a year to improve economy over the pandemic, they also suggest economy will be good for rich than others
Jun 2020	They express as Economy becoming good. Please, encourage people for shopping to boost economy. it will be back in swing. Most of them are expressing as there is a boost in the economy and China has turned to a street vendor economy encouraging people
Jul 2020	Most of the express that US economy gaining back by providing employment to its people.
Aug 2020	Small businesses were booming economy. Saving the U.S. economy with gain of 4.8 million jobs, some express as “economy is coming back, coming back strongly”
Sep 2020	Growing economy or making economy out of recession is possible. Some have expressed joy for government in bringing economy out of recession with low unemployment
Oct 2020	Some people tweet about government is promising of economy bloom with less unemployment. Stable and growing global economy
Nov 2020	U.S. adds 638,000 Jobs which are good to make an improved economy. Also, in this month, people suggest that government has improved the economy by adding more jobs
Dec 2020	Boost the economy and vaccine mitigate the effects of the pandemic on economy. People suggest of Care act to boost the economy
Jan 2021	Vaccine made a hope in month of January, and people are getting jobs with economy growth

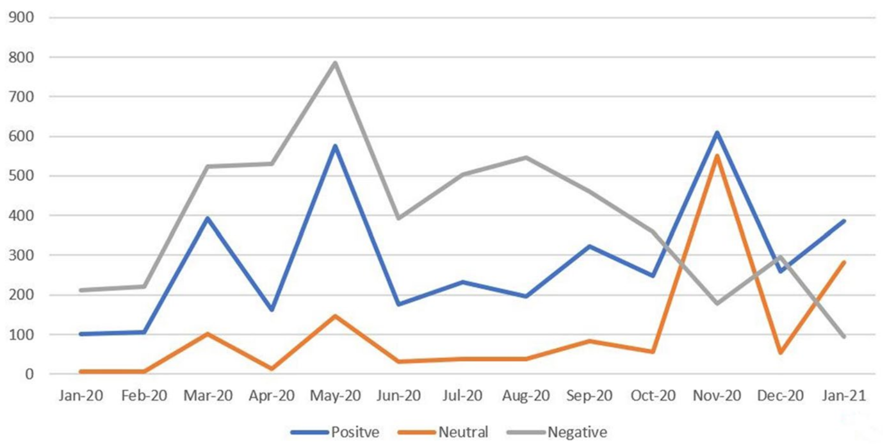


Fig. 9 Temporal sentiment frequency graph on economy (Jan 2020–Jan 2021)

Table 6 Geo-sentiment trend in US and UK during (Mar 2020–May 2020)

Country	Location	Main topics	Overall sentiments
USA	Vancouver	Cuts, S Korea, UTC	Slightly Negative
	San Jose	God, Good, Plans	Very Positive
	Livermore	Post, Corona, Government	Very Negative
	Rancho Palos Verdes	Strained, Month, Active	Highly Negative
	Colorado Springs	Knocked, Economy, Round	Very Positive
	Nebraska	Supports, Global, Partners	Positive
	Washington	Sake, Baby, Daughter	Very Positive
UK	City of London	COVID-19, Government, Consider	Negative
	South East	Data, Economy, Collapsing	Negative

However, in cities like Livermore, Rancho Palos Verdes males are not happy with govt's steps post COVID-19. People are expecting govt should invest in communities and the path to improve economy should work for all. Apart from this people are yet to get over from COVID-19 trauma as people are still dying with the disease, there are not enough medical equipment like PPE. In such a situation, people are also confused whether they should reopen business or not. As, downgraded economy forces people to reopen business but at the same time it is not safe enough to do same. Along with COVID-19 death and infection, people are facing consequences of falling economy, like increase in rate of crime and violence.

Females, on the other hand, are rather hopeful and encouraging others to take test for COVID-19 as they felt that for economic recovery people must test.

UK: Whereas, in UK as shown in Fig. 10, in cities like London, people are expressing distress over how COVID-19 has impacted economy. Industries like hospitality and aviation are highly impacted due to this pandemic.

Table 7 Geo-sentiment trends in US during (Mar 2020–May 2020)

Male	Female
	
Mostly Positive sentiments are concentrated	Mostly Positive in the center of USA.
Most of the negative sentiments are seen in cities like San Francisco, New York, Los Angeles.	There are very few negative sentiments from females in USA

Unemployment

When it comes to months of march and April as shown in Figs. 11 and 12, as the COVID-19 cases rise, sentiments become negative and people are mostly tweeting about unemployment and economy. Many are losing jobs or are on low paying jobs. And most discussed topics during Apr suggest that people are mostly concerned about financial risks and death.

In the starting of May'20 with reference to Fig. 12, in US, people are arguing about the work and health as they are forced to work and they were forced to lose benefits if they say no to the jobs to keep their health. And most discussed topics also shows terms such as "banks, manufacturing and work" in the context that people have to work even during Pandemic in certain sectors like manufacturing and banking.

In the month of June, people are also blaming economically well of sections of the society as they disregard unemployment and jobs losses. As on July, they are expressing negatively about handling of the Pandemic and that they are under pressure to return to the jobs. People express apprehension on reopening of schools for improving economy during high number of active cases of COVID-19.

The extreme negative sentiments are near Washington, Miami and Mexico City as shown in Fig. 13 and a bit of positive sentiments near Los Angeles. The detailed list concerns of people during these times are listed in Table 8.

Let check how males and females reacted during the months of May to Aug 2020 in US from Table 9

There are relatively less instances where males are discussing anything positive about employment. In US, in a city like Manhattan, positive sentiments can be seen in people due to discussion of reopening businesses and people are trying to support local business which is closed for long time. In Bell city people are positive because of getting unemployment benefits from govt.

Fig. 10 Sntiments in UK during (Mar 2020–May 2020)

On the other hand, in cities like Washington, Hammond, Miami Palos Verdes people expressed their concerns on increasing number of unemployment, which apart from other consequences, also affected mental health, specially for those who lost jobs.

Females, in particular, expressed their views on how gun violence, unemployment, civil unrest, and political leadership occupied atmosphere during the pandemic.

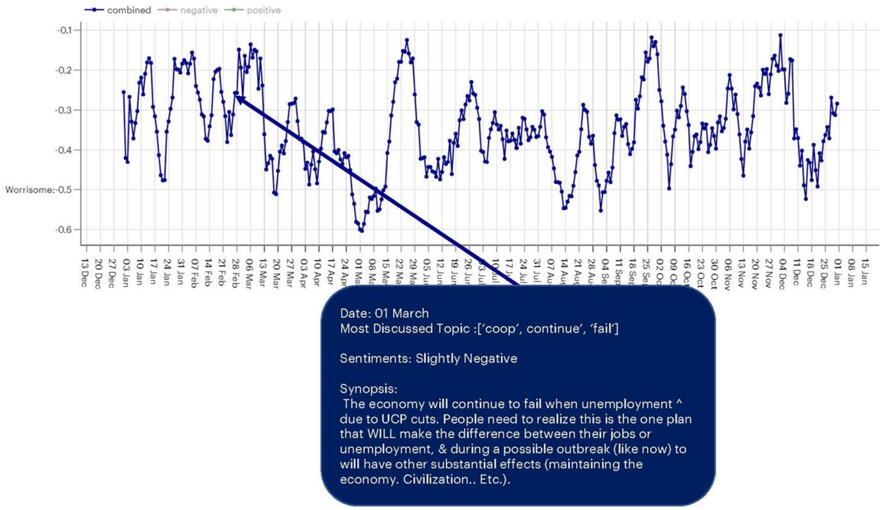


Fig. 11 Geo sentiments on unemployment during Mar 2020

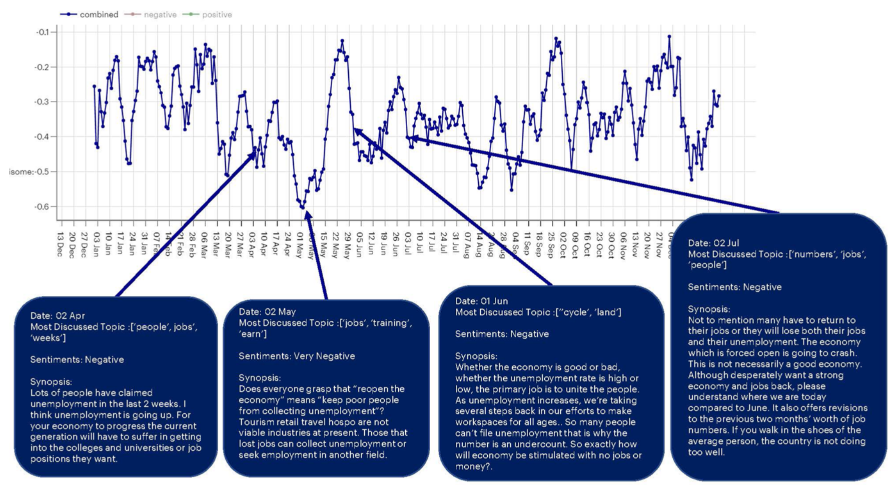


Fig. 12 Temporal sentiment trend during (Apr 2020–Jul 2020)

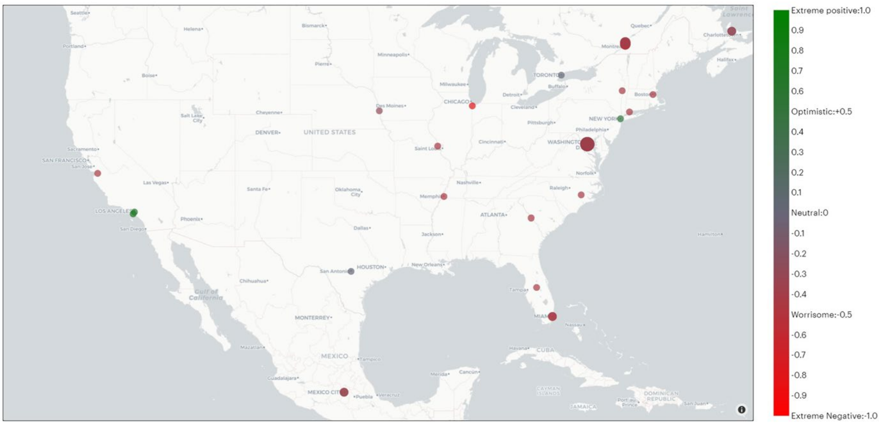


Fig. 13 Geo-sentiment spread on unemployment during (May 2020–Aug 2020)

Table 8 Geo-sentiment trend in US during (May 2020–Aug 2020)

Country	Location	Main topics	Overall sentiments
USA	Washington	Weeks, record	Negative
	Hammond	Washington, post, opinions	Highly negative
	Miami	Unemployment, Miami, evidentiary	Very negative
	Torrance	Insurance, COVID-19	Very positive
	Manhattan	Happy, light, pandemic	Very positive

Table 9 Geo-sentiment trends across gender in US during (May 2020–Aug 2020)

Male	Female
	
Males mostly tweeted negative sentiments in the USA. It is mostly concentrated east side of the country such as New York Washington, Boston and Toronto	There are a smaller number of tweets which are expressed during May to Aug month and most of them very negative sentiment

Globally, with reference to Fig. 14, frequency of male tweets is bit more than frequency of female tweets, however, females expressed relatively more positive sentiments than of male during pandemic.

Geo-sentiment trends during (Sep 2020–Oct 2020)

Economy

USA: During the month of Aug'20, as shown in Fig. 15, people are expressing negatively on policies as reason for down fall of economy and increase in COVID-19 cases. While, some of them also expressed positively that in order to improve economy, people must buy things. On the other hand, some have expressed fear of another lockdown resulting into downfall of economy. While, others expressed happiness that economy is recovering fast with drop in unemployment rate and addition of new jobs. In San Tan Valley people expressed concern that people are not wearing mask to control the spread and that even after many lost their jobs, they weren't scared of COVID-19. Table 10 summarizes differences in sentiments between male and female during Sep'20 and Oct'20.

UK: In reference to the Fig. 16, people in UK expressed negative sentiment on the media suggestion that work from is damaging economy, while others expressed positively as work from home made to save fossils fuels. Helping elderly people from COVID-19 could help economy was yet another point of discussion. Key themes of discussion among male and female are shown in Table 11.

India: Table 12 shows some of the points of focus of tweets by males and females in India during Aug to Oct 2020.

Unemployment

In reference to Fig. 17, globally negative sentiments were expressed more often. However, some positive tweets about unemployment do mention pandemic benefits, zoom meeting benefits, and other novel employment opportunities arising due to the Pandemic.

Example tweets:

- "I best not be out here catching no damn #COVID-1919 / #coronavirus! Cause I'd gladly #stayhome and #safe, with unemployment / #pandemic benefits! ..."
- "It's the COVID-19 Cash for Trash beach cleanup employment project in motion in the pouring rain..though fund raising ..."

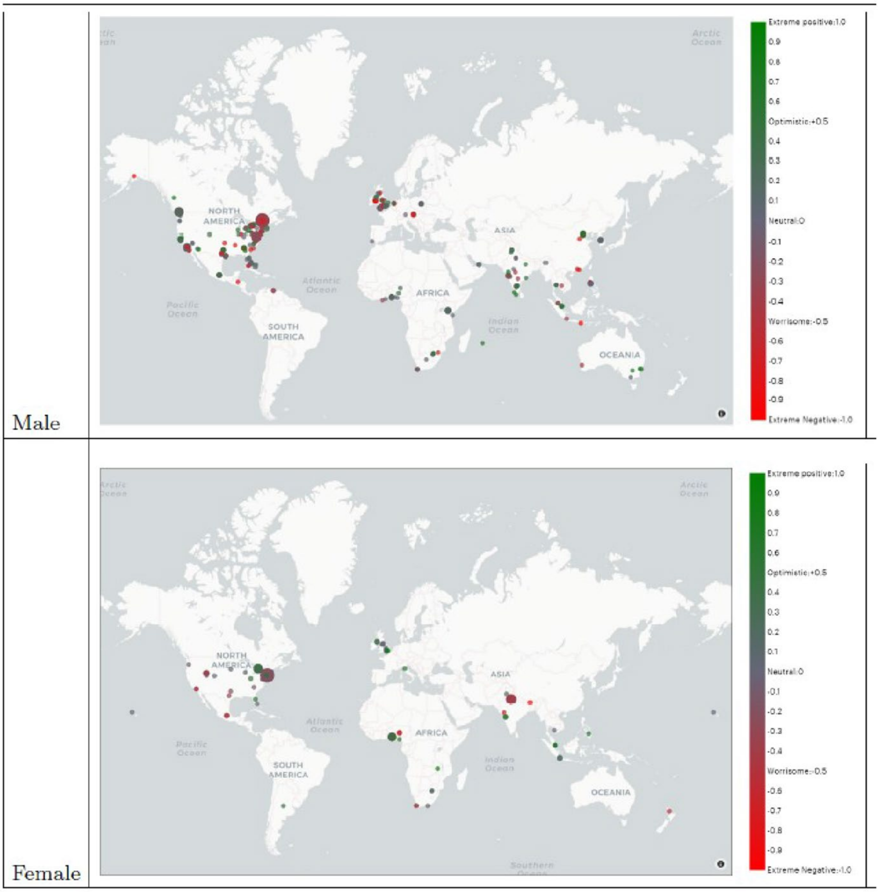


Fig. 14 Global geo-sentiment trends across gender during (May 2020–Aug 2020)

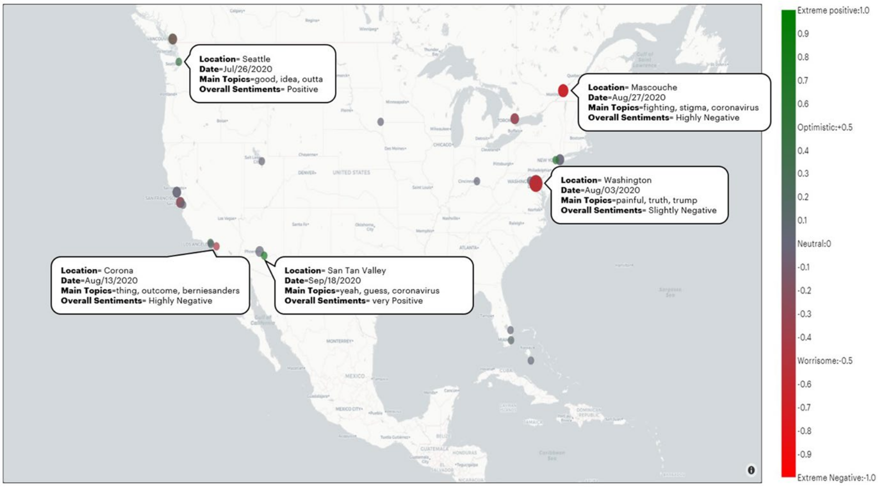


Fig. 15 Geo-sentiments in US during (Sep 2020–Oct 2020)

Figure 18 depicts how sentiments across the globe for both the genders appear, which is further elaborated for US and India in Tables 13 and 14 respectively.

Geo-sentiment trends during (Nov 2020–Mar 2021)

Economy

Negative sentiments are mostly concentrated in USA during the months of Nov 2020 to Mar 2021 and some places in Asia, which are shown in Fig. 19. Sentiment differences among gender appear in Fig. 20—females are mostly positive during the recovery period and indicating support which they provided, whereas males reacted both positively (on recovery) as well as negatively (about difficulty they observed during this period).

USA: Across both genders, primary concern appears related to vaccines and in turn sliding economy due to lockdowns as detailed in Table 15.

UK: In UK, people have positive sentiments during these months and also encouraged and suggested various ways to show ways to improve local economy as suggested in Table 16

People are expressing their concern that asymmetry in wealth distribution is increasing and economic policies may not be effective in creating more Jobs and improve finances and therefore many preferred to stay in home to keep them safe Fig. 21.

Table 10 Geo-sentiments of males and females in USA during (Sep 2020–Oct 2020)

Male	Female
	
Males showed positive sentiments in some areas and negative sentiments are mostly over cities	Females showed more negative sentiments as compared to positive sentiments
Positive sentiments could be seen in cities like San Francisco, Seattle, and Dallas	Females showed positive sentiments in Toronto
Negative sentiments are heavily concentrating in areas of cities like Los Angeles, New York, Washington dc	Females also shared negative sentiments in New York and Washington DC
Males expressed concerns over snap benefits negatively affecting the economy. While some expressed COVID-19 has financially devastated families that rely on businesses	They expressed negative sentiments on huge amount of money is being invested into the economy and many are worried about getting their investments back, they also expressed that economy is growing a record slow down

Unemployment

In North America, we see a little concentration of the negative tweets as shown in Fig. 22—most of these tweets talk about unemployment being severe and some pointed out challenges due to less wage and temporary employment. On the other hand, positive tweets often focused on encouraging each other for good recovery.

Fig. 16 Geo-sentiment trends across UK during (Aug 2020–Oct 2020)

Table 11 Geo-sentiment trends across males and females in UK during (Aug 2020–Oct 2020)

Male	Female
	
Males expressed positive, negative, as well as neutral sentiments	Females showed mostly positive and neutral sentiments
Males expressed negative sentiments that children sent to schools by re-opening even with high COVID-19 rate, while some suggest that economy may have shrank by 21% in April in Ireland is worst ever down. While some males showed positive sentiments expressing that they were happy about being able to go to a bar	Females expressed positive sentiments by suggesting that Business Support Scheme has helped businesses, which in turn helped them and they Supported local business post lockdown

The difference of sentiments in between male and females is shown in Fig. 23—females expressed negative sentiments over unemployment stated that they are spending many hours online to earn income for providing basic stuff to their household. Males too stated on the rise in unemployment and decline in subsidy during recovery period.

Table 12 Geo-sentiment trends for males and females in India during (Aug 2020–Oct 2020)

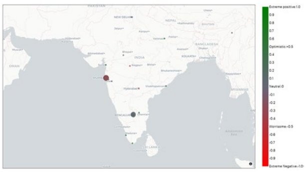
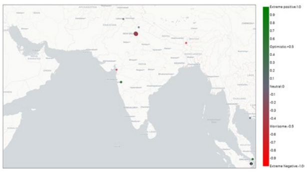
Male	Female
	
Males expressed negatively in larger cities where positivity rates were higher than normal. While other location witnessed mix of positive and negative sentiments	Females also often expressed negative sentiments
Males in India mostly suggested positively about fighting collectively with the virus and boosting the economy. While others emphasized that Indian economy lost jobs due to outbreak	Women expressed that they were negatively impacted due to job cuts cused by the pandemic, for example, in Tourism. They also expressed concerns over difficulties in enforcement of the lockdown and reopening when cases are still high.

Fig. 17 Geo-sentiment trends on unemployment (Sep 2020–Oct 2020)

Fig. 18 Geo-sentiments globally for males and females during (Aug 2020–Oct 2020)

Table 13 Geo-sentiments in US for males and females during (Sep 2020–Oct 2020)

Male	Female
	
Males are expressing positive sentiments with strong hope for recovery and sharing motivational tweets to face 2020 by supporting healthcare, firefighters, police, and essential workers	Female are suggesting positive sentiments over support of government on access to small loans and unemployment benefits for the music community. Others expressed happiness on job creation and decrease in unemployment rates. Some are thankful to start working again and for economic recovery
Some have expressed very negatively on coming future while others suggested that unemployment benefit is the only thing that is giving them support they wanted an extension to it	Females in are expressing their negative sentiments by showing 12 million people who make live events have lost jobs due to pandemic. Some are expressing that lockdown have confined them to home and they experienced suicidal thoughts

Organizations vs individuals

Cooperate communication had often being in on neutral or slightly positive side in contrast to people sentiments. Often tweets from corporate accounts mentioned that many people are working in contract, from home, about Affordable Care Act, that many telework jobs were reduced due to Pandemic. Later during Dec, coorporate tweets emphasized that many new jobs were added adding to positive sentiment as shown in Fig. 24.

Table 14 Geo-sentiments in India for males and females during (Sep 2020–Oct 2020)

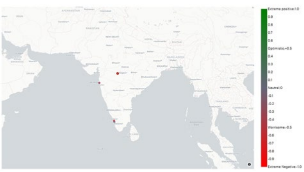
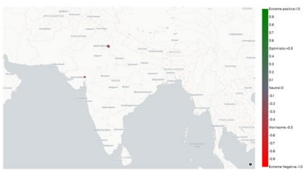
Male	Female
	
Increasing unemployment has been a major cause of concern for majority of males in larger cities in India	Some expressed concern that unemployment has affected women relatively harder as lockdowns has impacted informal job relatively more

Fig. 19 Sentiments trends on economy (Nov 2020–Mar 2021)

Gender differences on economy and employment

Let us summarize gender-based analysis of how males and females think about economy before and after COVID-19. During the months of Jan and Feb in 2020, both male and females expressed that people must work on more than one job to meet their basic needs and low unemployment data need not reflect all financial aspects. Males suggested shortcomings in the economy data, while female suggested that automation is replacing their jobs.

Then in the month of Mar, males talked about newly added jobs, while females suggested loss of jobs as work moving to other countries. During start of pandemic, both males and females expressed their concern over unemployment. During April, some suggested that economy is reopening but unemployment is still high. Males tweeted mostly about applying for unemployment insurance. While between the months of May to June, both male and female suggested higher unemployment even though economy is still recovering,

During August, males suggested that government is not helping small business, whereas females expressed their concern of forced labor and that they would not get unemployment benefits and will be not considered in unemployment. In between September to December, males talked about losing jobs and enhanced unemployment benefits, while females expressed that people are now getting into their normal jobs which are lost and jobs they lost to robots.

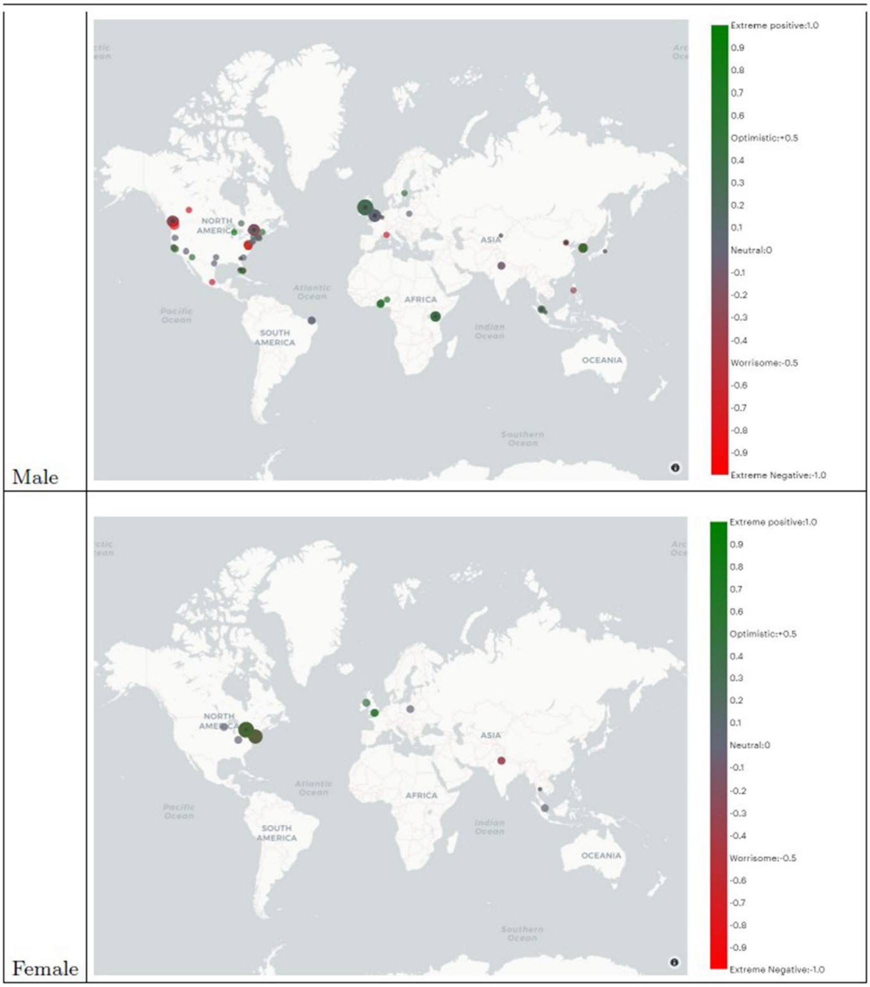


Fig. 20 Globally geo-sentiment trend for males and females during (Nov 2020–Mar 2021)

Discussion

Sentiments of people on economy before and after pandemic are both negative, individuals showed negative sentiments on employment as they had to work for more than one job and then they showed worry over losing jobs during the early stages

Table 15 Geo-sentiment trend in US for males and females during (Nov 2020–Mar 2021)

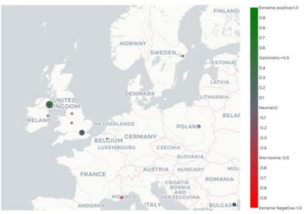
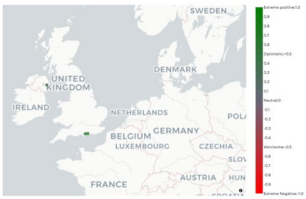
Male	Female
	
Males have expressed their concerns over vaccines and trade-off between open business as usual and spread of COVID-19	Females, on the other hand expressed concerns that measures to boost the economy by taking funds from the country may not be effective for long
In some other states, males positively expressed on improving job growth	Similarly, female expressed positive sentiments on political support to uplift the economy
Negative sentiments are concentrated over Washington, Los Angeles, and some places New York. While remaining places showed slightly negative or neutral sentiments	

of the COVID-19 outbreak. Later after few months of the pandemic, they expressed concerns over unemployment during pandemic situation. Some of the positive sentiments were shown during end of Nov and Dec as they were working from home, which helped in celebrating thanksgiving and Christmas with family. People have felt unhappy during start out of the outbreak. Eventually, they showed positive sentiment as economy re-opened with increasing job opportunities.

Key positive themes discussed about economy:

1. People supporting local business to make economy back to normal.

Table 16 Geo-sentiment trend in UK for males and females during (Nov 2020–Mar 2021)

Male	Female
	
In UK, males mostly showed positive or neutral sentiments during this month	Females were in favor of growth of the local economy, appeared positive, and motivated others that they can get out of pandemic crisis

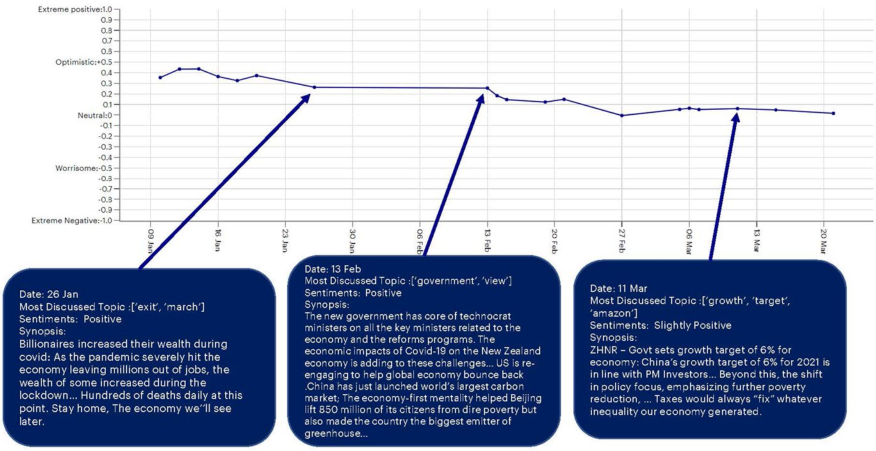


Fig. 21 Temporal sentiment trends during (Jan 2021–Mar 2021)

Fig. 22 Geo-sentiment trends related to unemployment during (Nov 2020–Mar 2021)

2. Government is adding jobs for economic growth.
3. People have expressed happiness for work from home as they were able to celebrate thanksgiving and Christmas with family.

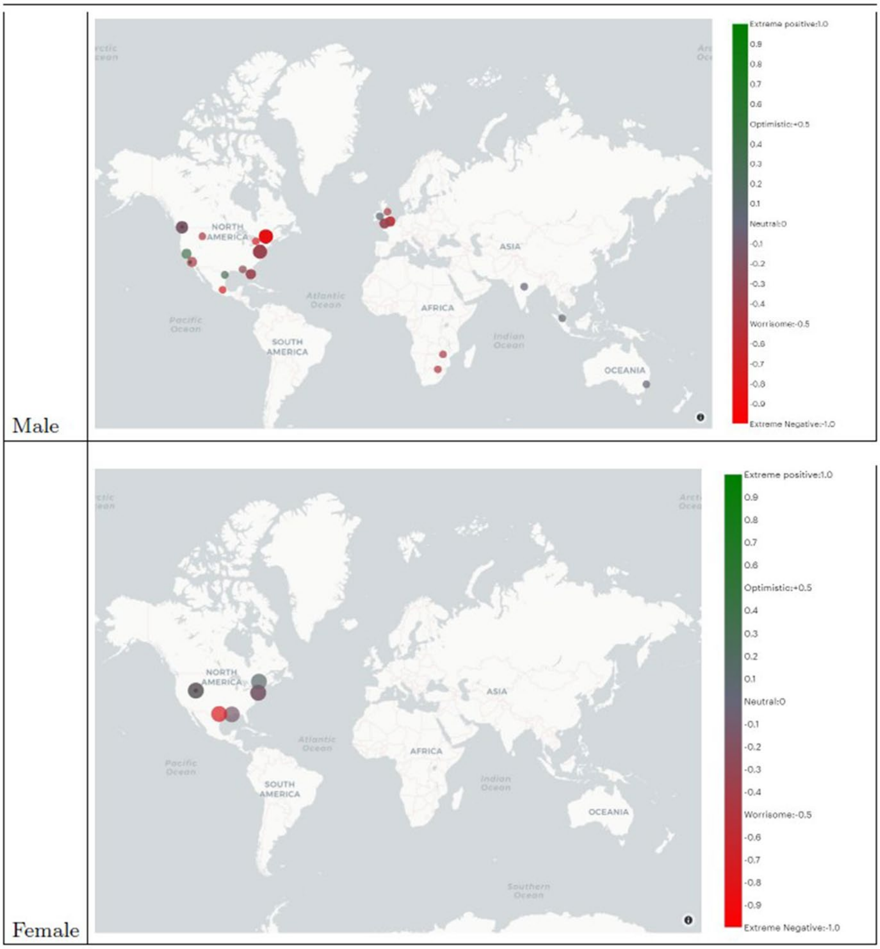


Fig. 23 Globally geo-sentiments of males and females during (Nov 2020–Mar 2021)

4. Vaccine mitigating effects of the pandemic on economy.

Key negative themes discussed about economy

1. Central banks are primarily focusing on financial economy and less of small businesses.
2. Some expresses that working from home is damaging economy.
3. People were forced to do jobs or else leave unemployment benefit even in pandemic situation to grow economy.

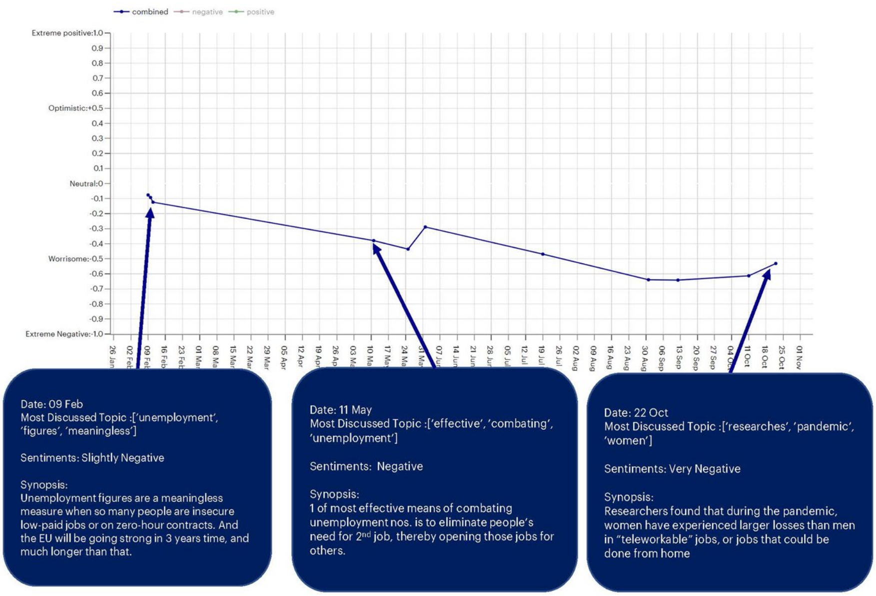


Fig. 24 Temporal sentiment graph for organizational tweets during Jan 2020–Jan 2021

Conclusion

In this work, we find that before pandemic outbreak, people had their economic concerns on having less paying jobs and doing multiple jobs to meet their needs. However, during pandemic intense negative sentiments were expressed on economic breakdown and job losses. In contrast, after pandemic started subsiding, sentiments started lifting on hope of economic recovery, governmental support for businesses, and job openings.

Geographical analysis of tweets indicated that people mostly showed negative sentiments near city areas as many lost their jobs. Further, overall analysis revealed differences in how individuals are reacting to the outbreak as against organizations. Gender analysis, on the other hand, revealed that women engaged more positively about support for improving local economy and businesses in contrast to men mostly tweeting positive sentiments on funding support for improving economy and referring people to jobs.

Data Availability The data that support the findings of this study are not publicly available because that may compromise data privacy of Twitter users. However, information on how to obtain it and reproduce the analysis is available from the corresponding author on reasonable request.

Declarations

Conflict of Interest All the authors state that there is no conflict of interest.

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