Understanding Emotional Health Sustainability Amidst COVID-19 Imposed Lockdown

Shreya Dhingra, Rohan Arora, Piyush Katariya, Adarsh Kumar, Vedika Gupta, and Nikita Jain

Abstract Considering the COVID-19 outbreak, comprehending the psychological state is a major concern across the world. Sentiments and their emotions can be accessed via diverse social media platforms. Most prominently, Twitter plays a vital role in understanding the emotions of netizens, regardless of their origin. In this chapter, we study emotional health during the lockdown phases, taking India as a case study. Varied emotions over time derive their possible existence from the reported, deceased, and recovered cases, or a number of unanticipated situations. This study's empirical findings are based upon eight emotions: Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, and Trust. We also describe how every lockdown impacted the emotions among people in worst hit Indian states towards COVID-19 cases by analyzing how a particular lockdown comes to be associated with distress and relief. For better understanding, we developed an automated tool to pictorially represent emotions, URL: https://emotiontrackerindia.herokuapp.com/. Understanding the emotional and mental health of the masses makes the nations proactive and future-ready. Adoption of suitable sustainability measures at the right time mitigates such crisis-like situations. This chapter puts forth an emotion analysis mechanism using social media and recommendations for upcoming emergencies.

Keywords COVID-19 · Lockdown · Emotion analysis · Twitter · India

1 Introduction

Since the second half of the year 2019, COVID-19 has been sorely hitting the world. The seriousness of this pandemic can be determined by the uninterruptedly growing COVID-19 cases around the world. As per the current situation, countries like the USA, Russia, Brazil, and India have been severely affected by this virus [1]. Several lockdowns were imposed worldwide in different countries to minimize the outspread of the disease. Due to these unprecedented situations in the lives of all human beings

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alive today, the behavior and emotions of human beings have been greatly affected [2]. As one could expect at this time of total lockdown, it is but natural for a person to have different sorts of emotional swings. A lot was happening within a fraction of days, that there were mixed emotions [3]. The physical movement of people came to a halt to maintain social distancing. The sudden outbreak of the disease made the authorities put in a tough situation to handle the medical facilities for treating the deadly virus [4] as well as the psychological disorders that were caused by the imposed lockdown. Understanding the emotional and mental wellbeing of the citizens of the country plays a major role in sustaining these kinds of pandemic situations. The World Health Organisation (WHO) [5] also issued several guidelines to maintain the healthy mental state of people throughout the pandemic. While some people were dealing with the emotional trauma, fighting with the negative psychological effects while other people were finding ways to entertain themselves and getting more and more creative in these times of home confinement [6, 7]. To assist numerous administrations and organizations, it is extremely necessary to comprehend the emotional state of people of the country so that they can be helped in overcoming the psychological imbalance that has occurred throughout this time [8]. Moreover, technology has grown by leaps and bounds in today's modern world [9]. The whole tedious process of writing and publishing news articles has been simplified using social media [10]. Immense amount of data is produced every day every minute [11]. Nowadays, online social media websites are frequently used as a source of analyzing and investigating the emotional state of people. Social media platforms play a vital role in the time of trouble to evaluate the mental and emotional health of people around the world [12]. Particularly, social media platform Twitter provides a handy mechanism to express one's viewpoint in short and crisp messages. The challenge is to identify, process, and combine various data sources to reach intelligent decisions [13].

When it comes to highly populous[1] countries like India, COVID-19 cases have significantly escalated. Owing to the heterogeneous demographics of India, it took just three months for the number of cases to reach almost thousand times the cases that were at the commencement of the spread. Furthermore, living in the largest democracy [14], people are free to express their feelings and thoughts on all the incidents happening around them. Every individual has the right to convey their opinion on political, social, economic, and cultural matters.

Taking into account the seriousness of the pandemic, it is very essential to persuade the public to reduction of the spread of COVID-19 and adoption of sustainable measures. Several initiatives were taken, not only by the Government of India but also by the citizens. The government has set up helpline centers to help people (telephonically) with emotional issues during the pandemic. The adoption of these sustainable measures helps to mitigate such crisis situation and make the public future-ready. During COVID-19 also, people took healthy participation in spreading awareness about the disease not only in cities but also in village areas. In order to minimize the outbreak of the disease, the Indian government gave several instructions to people from wearing masks to maintaining social distancing among each other.

[1] https://www.worldometers.info/world-population/population-by-country/.

Table 1 shows the major events that caused a havoc of emotions amongst the people. These events played a key-role in triggering emotional outbursts on Twitter.

In this chapter, we present an internet portal visualizing the eight-pointer emotional spread amongst the people of different states of India during different phases of lockdown. Our application does real-time monitoring of tweets and displays the tweets of people related to various hashtags as mentioned. The internet portal

Table 1 Major events that took place in India during the lockdown period

Timeline	Major events
30th January	First reported case
6th March	International passenger screening at the airport
11th March	COVID-19 declared as pandemic by WHO
12th March	First reported death
13th March	Suspension of non-essential traveler visas
15th March	100 reported cases Maharashtra overtook Kerala
16th March	Land border crossing suspended
22nd March	Nation-wide Janta Curfew, suspended air travel
25th March	Nation-wide lockdown imposed till 14th April
28th March	1000 reported cases
30th March	100 reported recoveries
31st March	Tablighi Jamaat cluster identified in Delhi
5th April	100 reported deaths
14th April	Lockdown extended till 3rd May
19th April	500 reported deaths and Goa became Corona free
20th April	Manipur becomes Corona free
22nd April	20,000 reported cases
25th April	5000 reported recoveries
29th April	1000 reported deaths
1st May	Lockdown extended till 17th May
2nd May	10,000 reported recoveries
7th May	50,000 reported cases
10th May	2000 reported deaths
11th May	20,000 reported recoveries
17th May	Lockdown extended till 31st May
19th May	100,000 reported cases
23rd May	50,000 reported recoveries
27th May	150,000 reported cases

(continued)

Table 1 (continued)

Timeline	Major events
31st May	5000 reported deaths
8th June	Phased reopening begins after 75 lockdown days Around 250,000 reported cases and 7200 deaths
12th June	10,000 new cases reported
17th June	Delhi and Maharashtra report backlog fatalities India registered the highest ever spike
27th June	India reports 390,459 cases, 681 deaths, and 22,664 recoveries

allows to select the state as well as particular lockdown for which the emotional spread is to be visualized. The analysis conducted considers textual information contained in the tweets while exploiting the linguistic features. Subsequently, emotion lexicon (NRC Word-Emotion Association Lexicon[2] [15]) has been utilized to understand state-wise and lockdown-wise emotion. This emotion analysis has been conducted on the tweets posted by people during different lockdown stages. In this analysis, information has been extracted from Twitter using Twitter API.[3] The tweets associated with hashtags #CoronaVirus, #LockdownDiaries, #Lockdown, #Covid-19 that were posted on Twitter in different states of India in the duration March 2020–June 2020, have been analyzed and categorized into one of the eight emotion categories—Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise and Trust [16].

The rest of the chapter is organized in the following manner: Sect. 2 describes the related work completed in the field of emotion analysis during COVID-19 attack. Section 3 describes the proposed methodology and gives insight into the approach used to analyze the tweets of the dataset. Section 4 presents the results obtained through the analysis and a brief discussion. Section 5 concludes the chapter and throws light on the future scope of the project.

2 Related Works

Understanding the emotional state of people in such difficult times of crisis, not just pushes the public authorities to survey old guidelines, yet in addition, helps in forming new rules and undertake measures that can propel the masses and re-establish their physical and emotional wellbeing. Consequently, to examine the public feelings on different occasions during this pandemic, a few investigations have been led.

[2] http://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm.

[3] https://developer.twitter.com/en.

There are a few models proposed for dissecting the public feeling during COVID-19 pandemic.

In [17], the proposed approach examines the emotions of Weibo users in China—gender wise and age-wise. The outcomes additionally showed that the expressions of concern like "Wellbeing", "Family" and "Demise" expanded fundamentally demonstrating that with sitting back, individuals were getting more worried about their family and wellbeing. Another work [18] examines the mental health of individuals during lockdown stage 2 and lockdown stage 3 on Twitter dataset and investigated the assessment on web-based businesses (e-commerce) during this pandemic. There was a sure plunge in the level of joy, fear, and trust in lockdown stage 3 when contrasted with that of lockdown 2 while there was a sure ascent in level of disgust, anger, and anticipation. Analysts have likewise broken down the news-headline features of Coronavirus and performed sentiment and emotion association [19].

Cao et al. [20] contemplates the effect of Coronavirus on students in China. The study uncovered that approximately 25% of students have encountered tension in view of this COVID-19 episode. The outcomes inferred that the danger factor and the postponements in scholastics were the fundamental explanations behind expanding tension while factors like living with family and having consistent family earnings were defensive variables against experienced nervousness during the COVID-19 flare-up.

Landicho-Pastor [21] discussed the students' sentiment on online schooling strategy dependent on an open-ended poll. Their investigation uncovered that many students were not ready for the online method of training and were stressed over the elements like the network issues at their place.

As the pandemic began, numerous analysts were interested to gain understanding of major worries of Twiterrati on COVID-19. Abd-Alrazaq et al. [22] examined 2.8 million tweets found out twelve concepts. Heffner et al. [23] considered the public readiness to self-isolate by breaking down the conclusions on two kinds of self-isolation rules, either undermining or written in convincing language. Their outcomes showed that despite the fact that individuals evoked negative supposition for government-imposed rules, they showed readiness toward social distancing.

3 Data and Methodology

The methodology used in this chapter includes a set of major tasks performed to achieve the desired visualizations. Figure 1 shows the methodology used in the analysis.

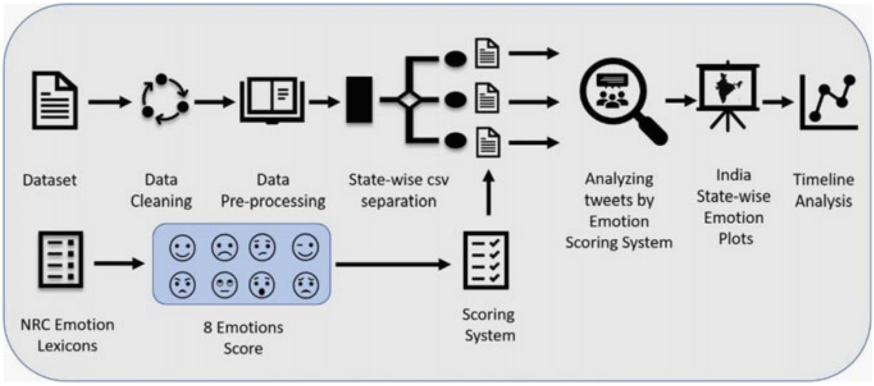


Fig. 1 Methodology

3.1 Dataset

The dataset has been curated from Twitter using public streaming API (see footnote 3) on India—specific tweets to perform analysis. The Twitter API facilitates fetching of real-time data by providing certain hashtags and specifying locations. The hashtags used for this analysis are #CoronaVirus, #LockdownDiaries, #Lockdown, and #Covid-19. The final dataset is taken into account for analysis, mainly consisted of tweets, date, time, and their locations from where the tweets were posted. The considered duration is 01-03-2020 to 09-06-2020. The word—emotion association was performed through NRC emotion lexicon (see footnote 2) which consist of scores for eight emotions: anger, fear, anticipation, trust, surprise, sadness, joy, and disgust [15]. The dataset was cleaned by removing the tuples of incorrect data and 'Not a number' values. The tweets were pre-processed using Natural Language Processing techniques [24]. Application of machine learning to explore the Impact of Air Quality on the COVID-19 Fatalities is also studied [25, 26].

The text of tweets in the form of a string was first word tokenized into individual words. Then, as a step towards cleaning of tweets—slang, misspelled words, hashtags, URLs, and emoticons have been removed [27]. Additionally, the tweets have been converted to lowercase. User mentions along with re-tweets were removed, followed by elimination of punctuations, special symbol characters (except a–z, A–Z). A list of English stop words has been imported from NLTK library which is used to remove the stop words present in tweets.

3.2 Two-Way Emotion Characterization

In this chapter, a two-way emotion characterization of tweets has been presented state-wise and lockdown-wise:

(a) State-Wise Emotion Analysis—In this analysis, tweets of the people from different states of India have been collected, cleaned, and analyzed. The approach processes each tweet and categorizes it into one of the eight emotions. The results of this analysis are visualized on the map of India, with each state depicting the intensity of a particular emotion.
(b) Lockdown-Wise Emotion Analysis—In this analysis, tweets posted during four lockdown phases observed in India have been taken and dissociated according to different states. Tweets have been cleaned, analyzed, and categorized into one of the eight emotions. The results were analyzed using stacked bar charts for different states of India.

3.2.1 State-Wise Analysis

The dataset is dissociated according to different states. The tweets are POS tagged to help identify adjectives and adverbs. The state-wise emotions are given a score based on the most frequent words found in tweets and NRC emotion lexicon list. A 'state-wise-emotion-count-dictionary' dictionary is formed which contains words with their occurrence frequency. This dictionary is used to calculate the sum total of eight emotions. With these scores, the heat maps of India have been created depicting respective state-wise emotion intensity levels (ref. Sect. 4, Fig. 3). The heat maps of India for different emotions have been developed using boundary shape file "Indian states.shp". The shape file included features: state name and geometry. The merged data frame was formed by combining state emotion count with the Indian state shape file (.shp file). The plots of separate emotions were created by using Matplotlib's subplot and plot function in Seaborn style.

3.2.2 Lockdown-Wise Analysis

The lockdown-wise analysis is carried out with the help of dates extracted from tweets in the dataset. The same has been presented through stacked bar charts (ref. Sect. 4, Fig. 4). This lockdown-wise analysis has been carried out for lockdown 1, lockdown 2, lockdown 3, and lockdown 4 during COVID-19 pandemic. The lockdown phases are listed in Table 2.

Table 2 depicts the dates of lockdown issued by the Indian government. The lockdown-wise emotion analysis was conducted for separate states of India. A word

Table 2 Lockdown phases

Lockdown	Dates
Lockdown 1	25-03-2020 to 14-04-2020
Lockdown 2	15-04-2020 to 03-05-2020
Lockdown 3	04-05-2020 to 17-05-2020
Lockdown 4	18-05-2020 to 31-05-2020

count dictionary was created containing words with frequency segregated according to four lockdown phases. This was then categorized into different emotions based on the NRC emotion lexicon list. Stacked bar plots were obtained for top 12 states and are depicted in Sect. 4, Fig. 4, using Matplotlib.

3.3 Internet Portal

An internet portal has also been launched as an outcome of this analysis, as shown in Fig. 2. It depicts graphical figures that quantify public emotions during COVID-19. The portal provides the users with two menus—based on the states and the emotions.

4 Results and Discussion

The pandemic caused by coronavirus has been one of the most unexpected and grave casualties for the whole world. This section presents visual analysis depicting a tremendous downpour of public emotions expressed towards the lockdown on an eight-pointer scale of emotions: anger, fear, joy, disgust, anticipation, surprise, sadness, and trust. Figure 3 presents the state-wise emotion wise analysis.

Despite massive amounts of efforts by the government, Maharashtra, Delhi, Haryana, Uttar Pradesh, Karnataka, Madhya Pradesh, Tamil Nadu, and Rajasthan have been worst affected. Figure 3 depicts this analysis. There is an apparent relationship between the states where more cases were reported, and huge mix of emotions were also reported from those states only.

Some states like Goa and Manipur have managed the pandemic situation commendable as depicted in Table 3. People have been quite enthusiastic about the lockdown time. They have considered it a time for personal productivity and growth. Some are also happy spending time with their families. While others who have lost their jobs have been really worried and upset. Economy of the nation has been completely shattered by the situation. This has been depicted in Sect. 1, Table 1.

Being the capital of the nation, Delhi has had huge responsibilities of catering to everyone's healthcare needs. Many people have been moving to Delhi for their treatment as it is considered to have the best medical facilities. This has been a reason for chaos and worry amongst the people and has caused a shortage of hospital beds and other medical facilities like ventilators and oxygen cylinders.

Another issue that has been an area of concern throughout was public gatherings like Tablighi Jamaat and mismanaged movement of people who lost their jobs across state borders. There was a shortage of food and a lack of facilities for these laborers to go back home. These people had to walk back home covering hundreds of kilometers all by themselves. This has been the major cause of anger throughout the nation as these people were highly susceptible to catching infection. During the lockdown phases, international travel had completely stopped. This was another cause of stress for the Indian citizens stuck outside and for their families. The government played a very positive role in resolving this issue by trying to get all the people back to their country. This gave people relief.

Figure 4 and Table 4 depict lockdown-wise emotion analysis of states. In the case of Maharashtra, it can be clearly observed that there was a sharp rise in anticipation and sadness amongst the citizens. This has been the general pattern in almost all the states like Delhi, Gujarat, West Bengal, Rajasthan, Punjab, Goa, and Karnataka.

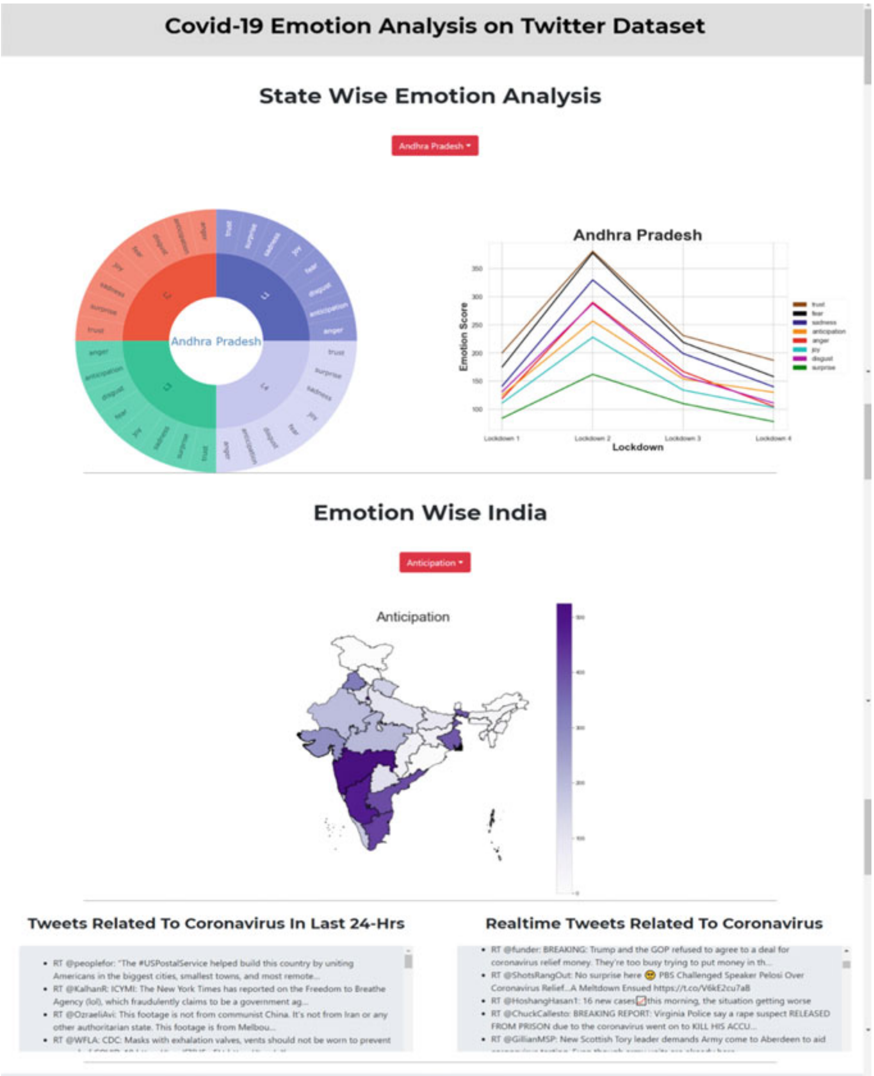
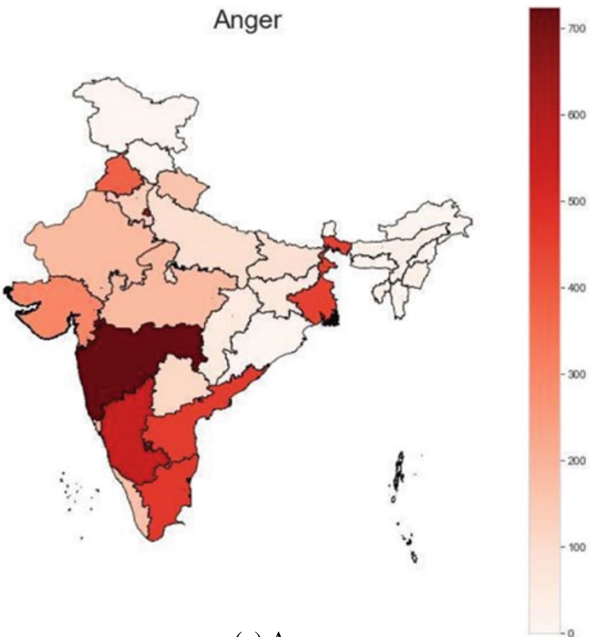
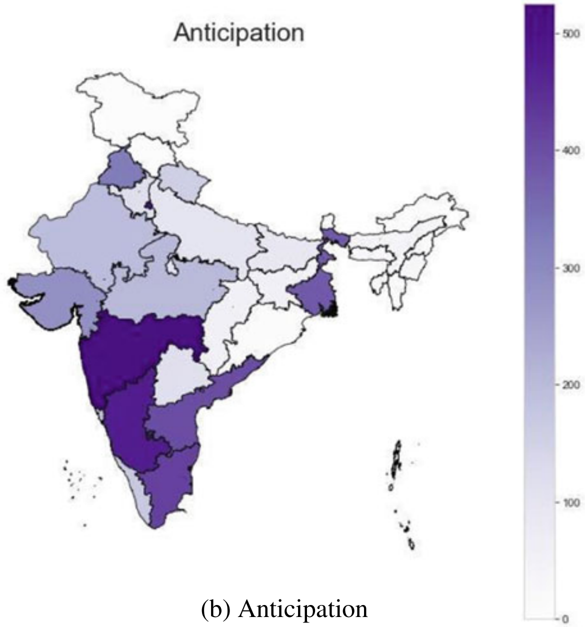


Fig. 2 Internet portal. https://emotiontrackerindia.herokuapp.com/

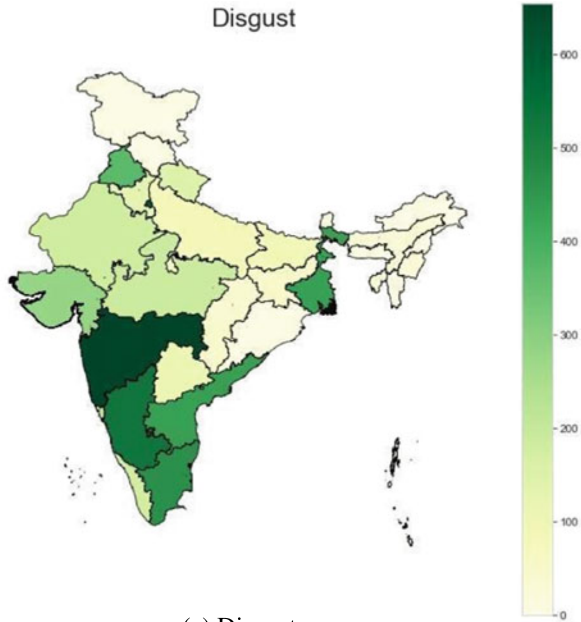


(a) Anger

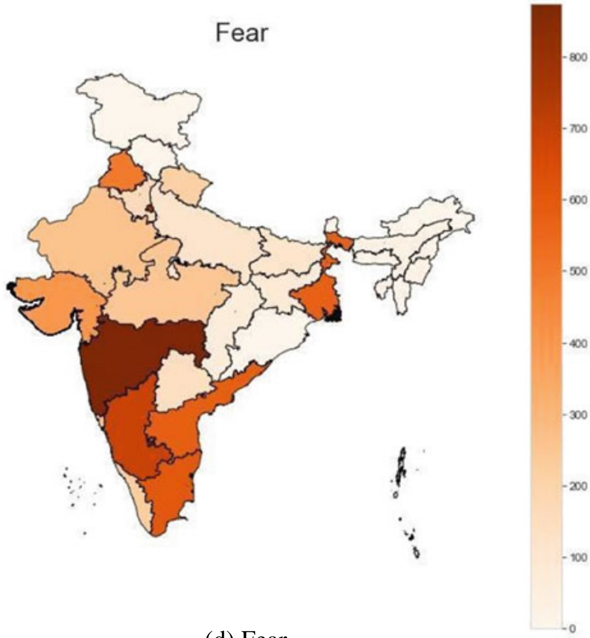


(b) Anticipation

Fig. 3 **a**–**h** Country-wide heat map of all emotions

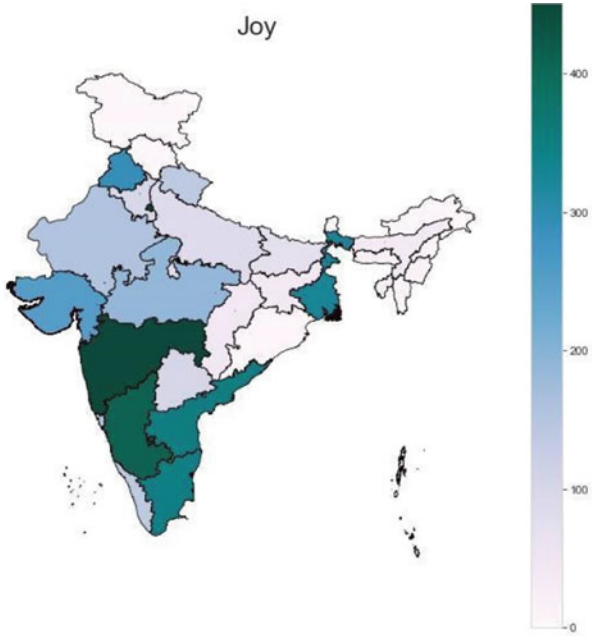


(c) Disgust

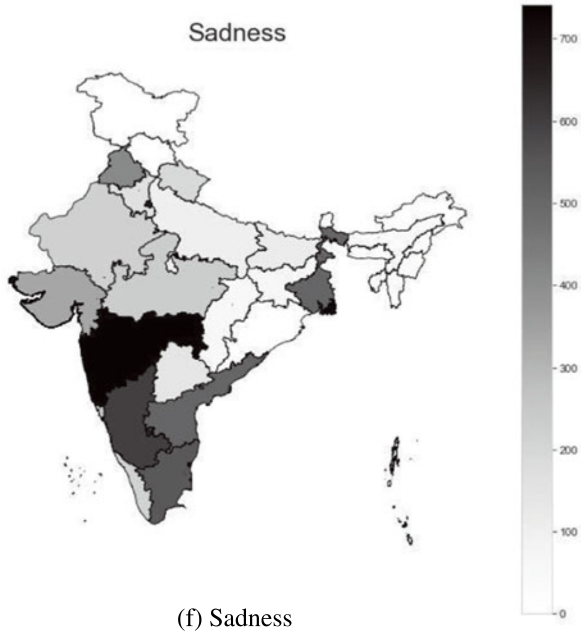


(d) Fear

Fig. 3 (continued)

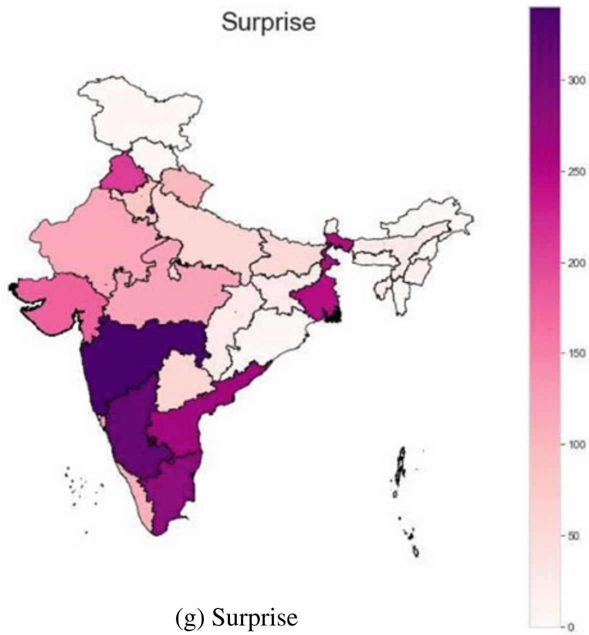


(e) Joy

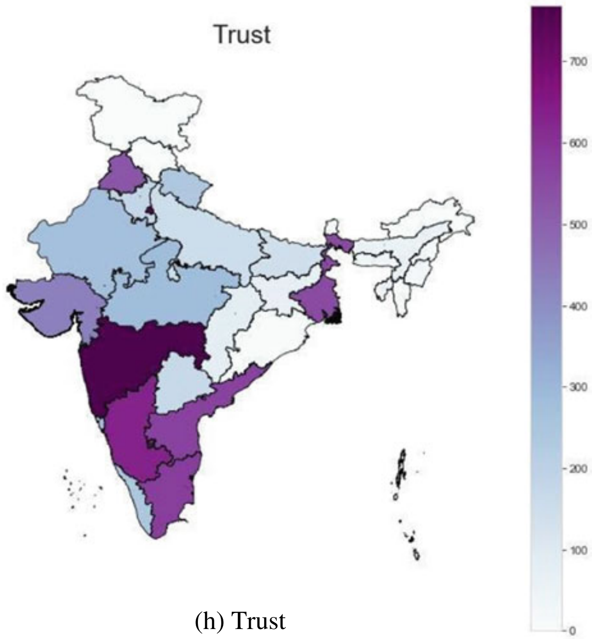


(f) Sadness

Fig. 3 (continued)



(g) Surprise



(h) Trust

Fig. 3 (continued)

Table 3 Reported, recovered, and deceased cases of worst hit Indian states

States/lockdown	Cases	Lockdown 1 (25th March to 14th April)	Lockdown 2 (15th April to 3rd May)	Lockdown 3 (4th May to 17th May)	Lockdown 4 (18th May to 31st May)
Maharashtra	Reported	2558	10,294	20,079	34,602
	Recovered	259	1856	5573	21,641
	Deceased	178	370	650	1088
Tamil Nadu	Reported	1178	1819	8201	11,109
	Recovered	81	1298	2793	8585
	Deceased	12	18	49	97
Delhi	Reported	1526	2988	5206	10,089
	Recovered	31	1331	2840	4276
	Deceased	30	34	84	325
Karnataka	Reported	209	353	533	2074
	Recovered	68	222	216	709
	Deceased	9	15	12	12
Andhra Pradesh	Reported	474	1099	797	1191
	Recovered	16	472	968	884
	Deceased	11	22	17	12
Uttar Pradesh	Reported	622	1985	1819	3611
	Recovered	50	704	1882	2207
	Deceased	8	35	69	105
Gujarat	Reported	612	4778	5952	5414
	Recovered	59	983	3457	5420
	Deceased	28	262	369	379
West Bengal	Reported	181	1008	1479	2824
	Recovered	36	96	827	1198
	Deceased	7	115	116	79
Rajasthan	Reported	967	1881	2316	3629
	Recovered	147	1209	1699	2977
	Deceased	11	60	60	63
Madhya Pradesh	Reported	726	2126	2110	3112
	Recovered	64	734	1605	2439
	Deceased	53	103	92	102
Punjab	Reported	153	918	862	299
	Recovered	27	90	1249	621
	Deceased	13	8	14	10
Goa	Reported	4	0	22	42
	Recovered	5	2	0	37

(continued)

Table 3 (continued)

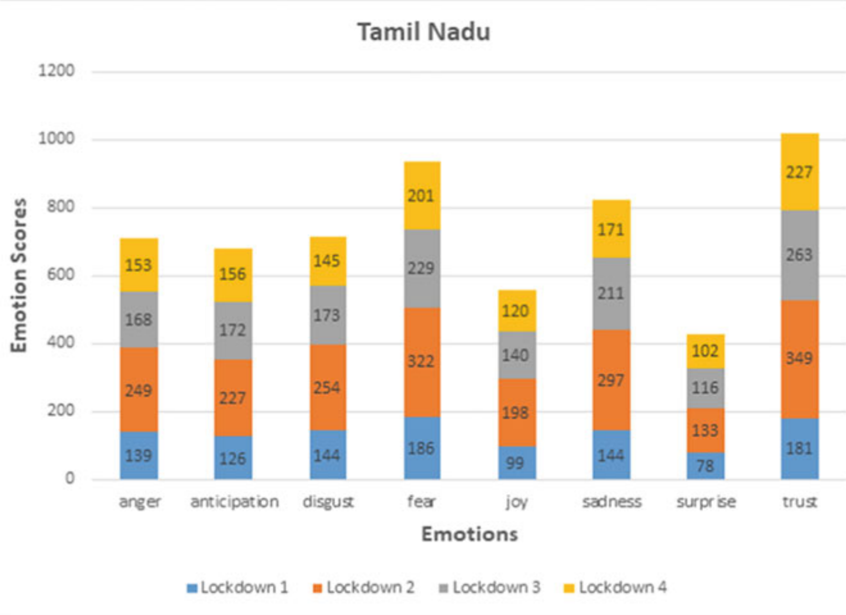
States/lockdown	Cases	Lockdown 1 (25th March to 14th April)	Lockdown 2 (15th April to 3rd May)	Lockdown 3 (4th May to 17th May)	Lockdown 4 (18th May to 31st May)
	Deceased	0	0	0	0

These states have seen massive growth in Coronavirus cases even after following the strict rules of the first lockdown. These emotions tend to lower down during lockdowns 3 and 4 which may be due to the increase in recovery rates. On the other hand, cases in Uttar Pradesh reduced in the second lockdown, and hence the counts somewhat decreased there. The same decreasing pattern was observed for the 3rd and 4th lockdowns. The number of Corona cases in Madhya Pradesh was not very high during lockdowns 1 and 2 but the people there were shocked by the growth during lockdowns 3 and 4. This led to an emotional upheaval amongst the people. Observing the general trend, it can be quoted that lockdown 2 had shown the maximum rise in the number of COVID-19 cases which decreased down during lockdown phases 3 and 4. The emotional pattern of the people was widely linked to the number of reported cases, recovered cases, and deceased cases during different lockdown stages.

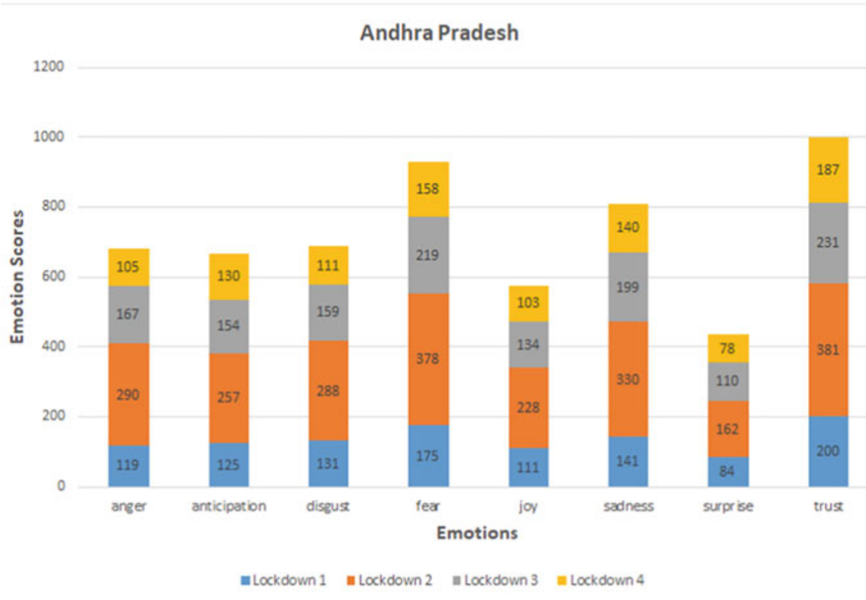
Overall, pandemic time has been stressful as expected. But at the same time it has brought the people of India together, fighting for one mission—to keep the nation safe and healthy. India has again proved that there is unity in diversity. People of India, under all circumstances, stand strong together.

5 Reflections

This chapter studies the social consequences of COVID-19. The pandemic posed unusual challenges to human behavior and mental health [27]. In this study, tweets posted across India during different lockdown phases have been analyzed to gain an understanding of the psychological health of the people. Heat maps have been plotted on the map of India, denoting the intensity of emotion in different states. This kind of analysis can help policy makers to conduct psychosomatic assessments of people in order to provide support in times of crisis. The notion of sustainability somewhere lies in settling the recent concerns and also parallelly focusing on long haul answers for battling with comparative issues in future. With everything taken into account, lockdown would not have been forced in the event that we would have been ready for such pandemic circumstances physically, intellectually, emotionally, and financially. Undertaking right sustainability measures at the perfect time fortifies the system alltogether. These proactive measures likewise search for long haul help habitats for individuals worldwide. We should recognize the issues deeply and afterward work on them. A nation leads by its residents, and it is similarly imperative to keep up sanity and psychological wellbeing of individuals. This chapter also puts forward an

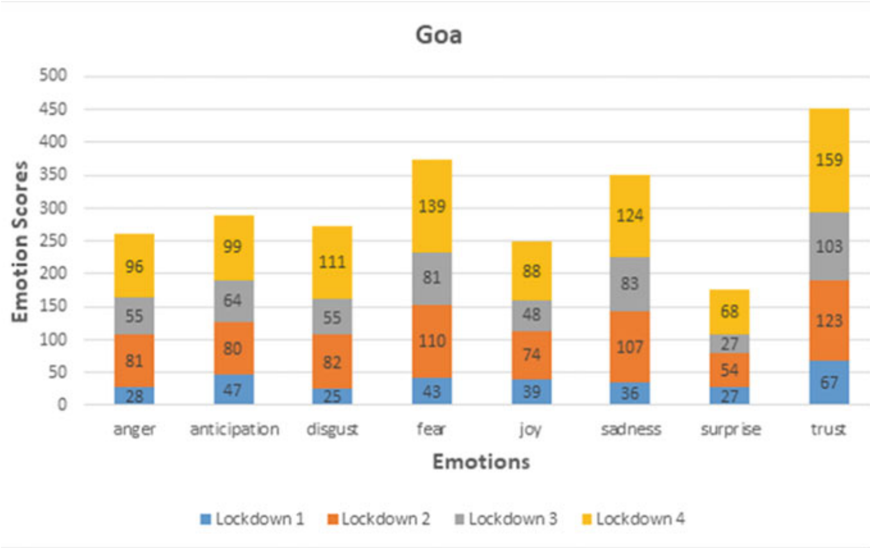


(a) Tamil Nadu

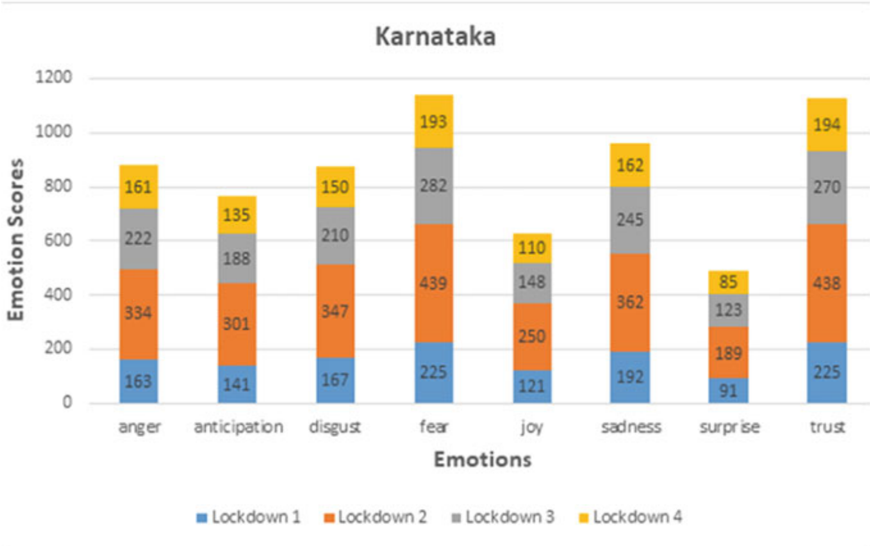


(b) Andhra Pradesh

Fig. 4 **a–l** Lockdown-wise analysis of emotions in 12 states

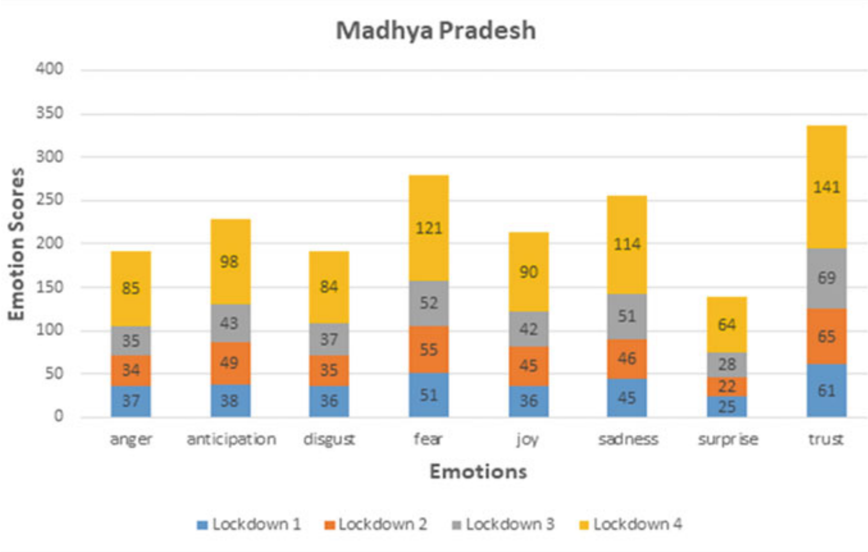


(c) Goa

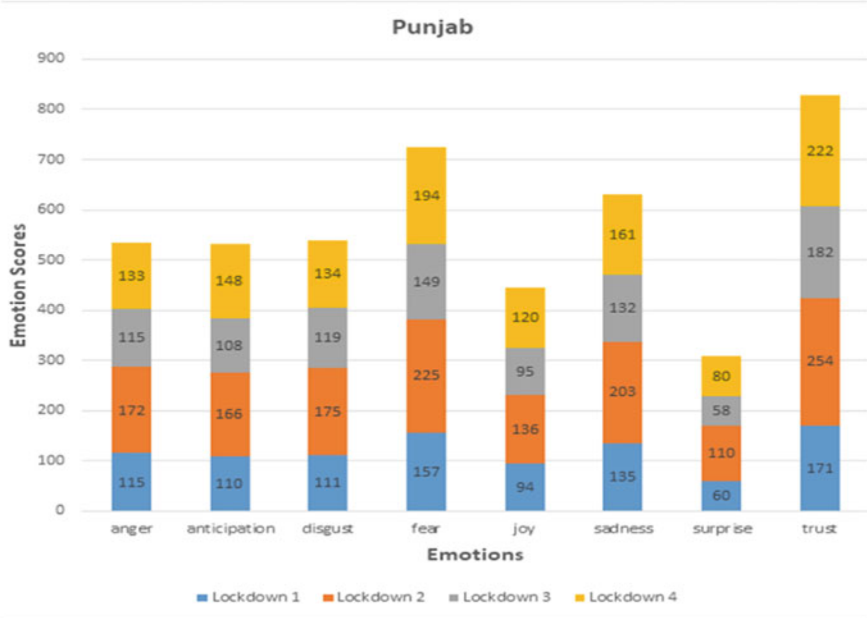


(d) Karnataka

Fig. 4 (continued)



(e) Madhya Pradesh



(f) Punjab

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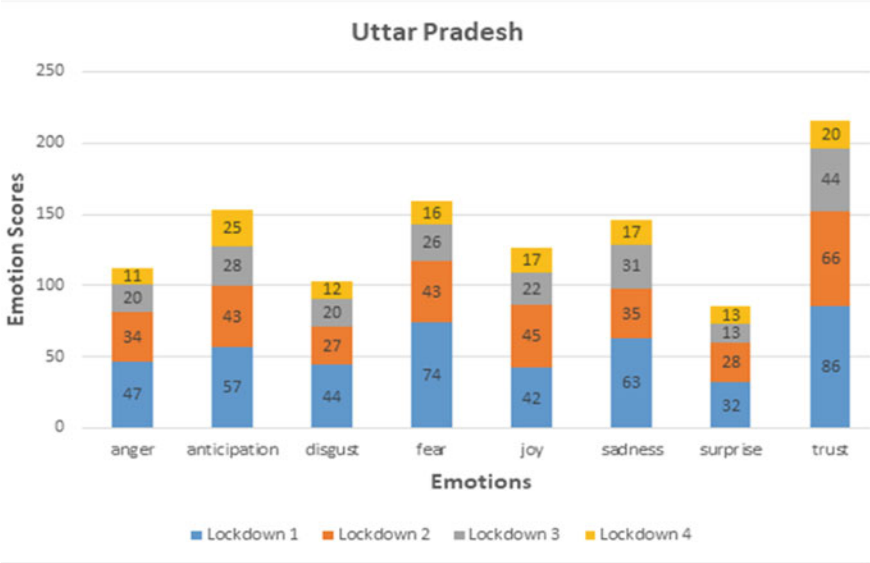
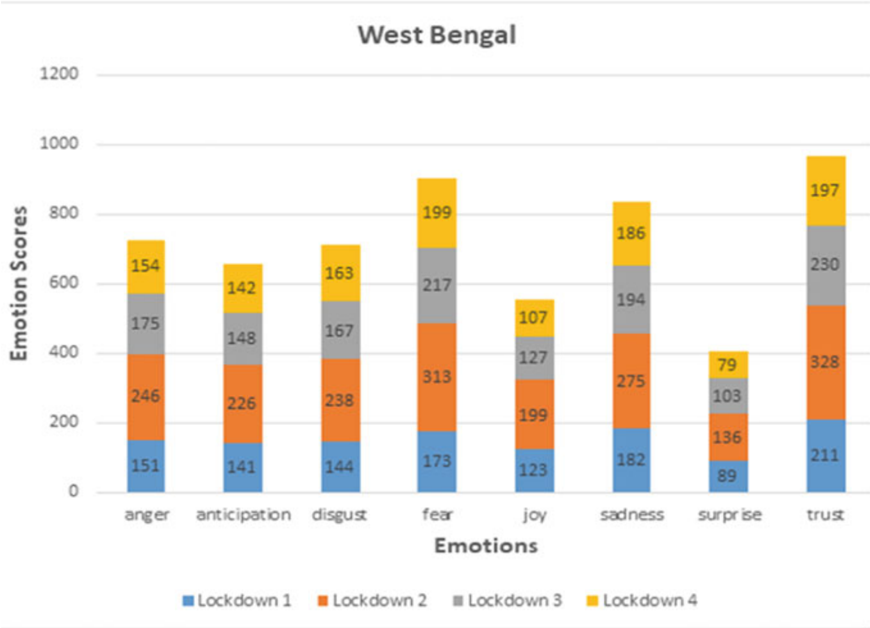
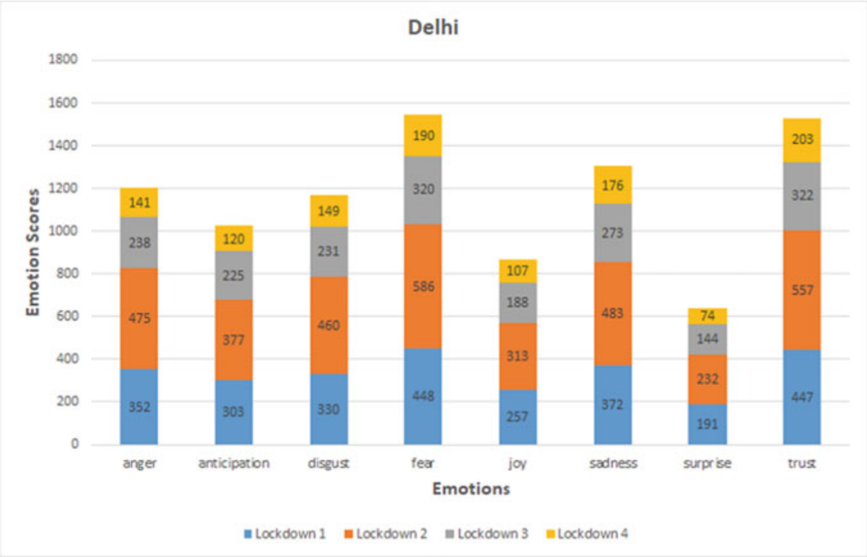


(g) Uttar Pradesh

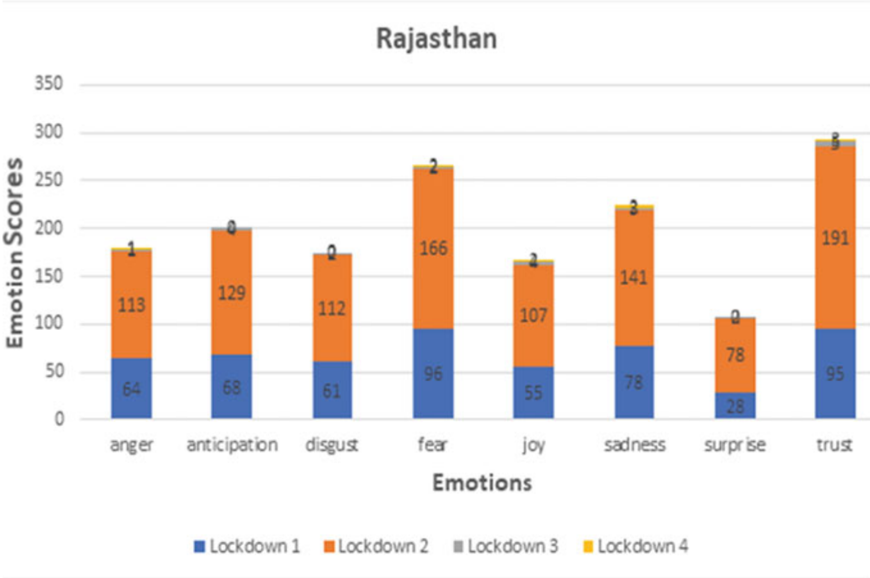


(h) West Bengal

Fig. 4 (continued)

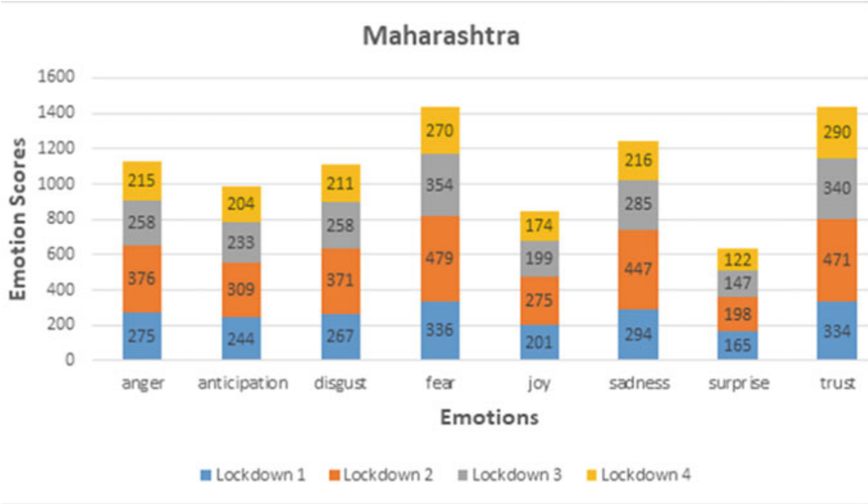


(i) Delhi

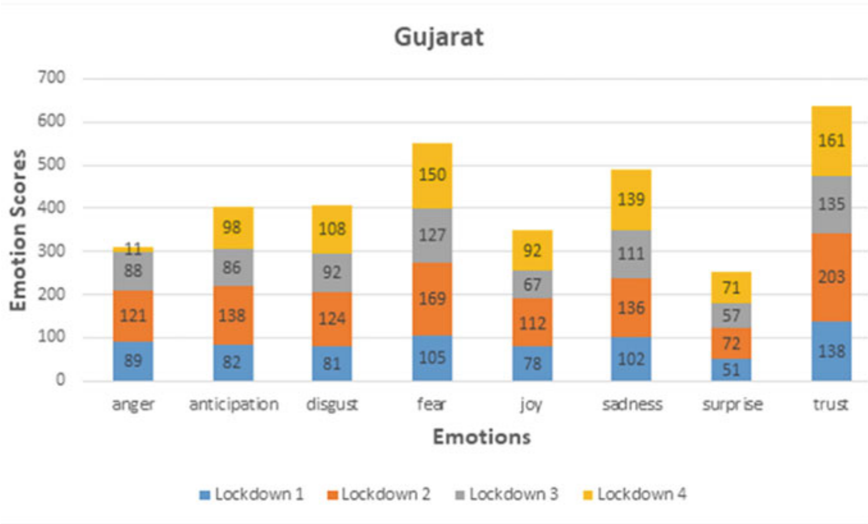


(j) Rajasthan

Fig. 4 (continued)



(k) Maharashtra



(l) Gujarat

Fig. 4 (continued)

internet portal, as a by-product that can show intensity levels of different emotions in different states of India alongwith different timelines.

Table 4 Emotion depicted by Indian states during different lockdown stages

States	Lockdown phases[a]	Emotions[b]							
		😡	😦	😫	😰	🥳	😔	😲	😌
Maharashtra	L1	275	244	267	336	201	294	165	334
	L2	376	309	371	479	275	447	198	471
	L3	258	233	258	354	199	285	147	340
	L4	215	204	211	270	174	216	122	290
Tamil Nadu	L1	139	126	144	186	99	144	78	181
	L2	249	227	254	322	198	297	133	349
	L3	168	172	173	229	140	211	116	263
	L4	153	156	145	201	120	171	102	227
Delhi	L1	352	303	330	448	257	372	191	447
	L2	475	377	460	586	313	483	232	557
	L3	238	225	231	320	188	273	144	322
	L4	141	120	149	190	107	176	74	203
Karnataka	L1	163	141	167	225	121	192	91	225
	L2	334	301	347	439	250	362	189	438
	L3	222	188	210	282	148	245	123	270
	L4	161	135	150	193	110	162	85	194
Andhra Pradesh	L1	119	125	131	175	111	141	84	200
	L2	290	257	288	378	228	330	162	381
	L3	167	154	159	219	134	199	110	231
	L4	105	130	111	158	103	140	78	187
Uttar Pradesh	L1	47	57	44	74	42	63	32	86
	L2	34	43	27	43	45	35	28	66
	L3	20	28	20	26	22	31	13	44
	L4	11	25	12	16	17	17	13	20
Gujarat	L1	89	82	81	105	78	102	51	138
	L2	121	138	124	169	112	136	72	203
	L3	88	86	92	127	67	111	57	135
	L4	11	98	108	150	92	139	71	161
West Bengal	L1	151	141	144	173	123	182	89	211
	L2	246	226	238	313	199	275	136	328
	L3	175	148	167	217	127	194	103	230
	L4	154	142	163	199	107	186	79	197
Rajasthan	L1	64	68	61	96	55	78	28	95
	L2	113	129	112	166	107	141	78	191

(continued)

Table 4 (continued)

States	Lockdown phases[a]	Emotions[b]							
		😡	😟	😫	😰	🥳	😔	😲	😌
	L3	1	4	2	2	4	3	2	5
	L4	1	0	0	2	2	2	0	3
Madhya Pradesh	L1	37	38	36	51	36	45	25	61
	L2	34	49	35	55	45	46	22	65
	L3	35	43	37	52	42	51	28	69
	L4	85	98	84	121	90	114	64	141
Punjab	L1	115	110	111	157	94	135	60	171
	L2	172	166	175	225	136	203	110	254
	L3	115	108	119	149	95	132	58	182
	L4	133	148	134	194	120	161	80	222
Goa	L1	28	47	25	43	39	36	27	67
	L2	81	80	82	110	74	107	54	123
	L3	55	64	55	81	48	83	27	103
	L4	96	99	111	139	88	124	68	159

[a]Lockdowns are represented as L1—lockdown 1, L2—lockdown 2, L3—lockdown 3, and L4—lockdown 4

[b]The emotions are represented by 😡—anger, 😟—anticipation, 😫—disgust, 😰—fear, 🥳—joy, 😔—sadness, 😲—surprise, 😌—trust

The scope of this chapter is not only limited to the tweets on Twitter. The analysis can be broadened if we move to other social media platforms such as Facebook, Mastodon, Gab, and Peeks. The work presented in this chapter can be extended to aspect-based emotion analysis on the dataset. Furthermore, this analysis can be scaled to encompass different countries with different native languages.

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