Research Article

International Journal of Advanced Technology and Engineering Exploration, Vol 10(109)
ISSN (Print): 2394-5443 ISSN (Online): 2394-7454
http://dx.doi.org/10.19101/IJATEE.2023.10101413

Quantifying and leveraging emotions to fight a pandemic

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Received: 18-April-2023; Revised: 20-December-2023; Accepted: 21-December-2023

Abstract
COVID-19 has profoundly impacted people's physical, emotional, and financial well-being. Vaccinations were developed to combat the physical health threats of the virus. However, studies suggest that the vaccinations themselves have contributed to anxiety, stress, and worry, leading to a lower rate of inoculation. Understanding and managing a pandemic requires a deep dive into how people are emotionally affected during such times and how they respond to public health initiatives like vaccines. To this end, a framework was proposed that analyzes behavioral responses from the general public's uninhibited discourses over one and a half years across five countries. The framework is built on the principle of knowledge differentiation, recognizing the mined emotional responses as basic knowledge nuggets (level zero of abstraction). Higher levels of abstraction are achieved by differentiating these basic knowledge nuggets. Simple, intuitive, and novel metrics for knowledge modelling was proposed, which consolidate and model the discovered knowledge, making it ready for practical use. From this framework, useful and insightful inferences have been drawn. The study analyzed 16 vaccines introduced in five countries over three different periods. Covaxin, initially available in Brazil and India, emerged as the most successful positive emotional influencer. AstraZeneca, first available in Brazil and the USA, was second, followed by Covishield in India and CoronaVac in Brazil. The framework also identified vaccines with the highest emotional intensities and top emotional ranks during the study periods. The insights from this proposed framework can guide government organizations in making informed decisions about the success of immunization drives and effectively curbing a pandemic. This approach highlights the importance of understanding emotional responses to enhance public health initiatives and pandemic management.

Keywords
COVID-19 Vaccination, Multi perspective emotion analysis and quantification, Emotional reach, Emotional intensity, Emotional rank.

1.Introduction
Coronavirus infectious disease 2019 also known as COVID-19 was declared a pandemic by World Health Organization (WHO) in March 2020 [1]. The outbreak significantly impacted the nations worldwide and brought the social and economic lives to a standstill. A world that hummed with the buzz of everyday activities suddenly fell quiet. Around sixty percent of the world populace was put under a total or a partial lockdown. Resultantly, economic activity across countries significantly decelerated, taking away millions of livelihoods. This, coupled with the inadequate medical facilities, and no known cure for the novel coronavirus fuelled anxiety, leading to despair and mental depression [2–4].

Vaccination was naturally the most sought of public health initiative during these challenging times. History stands witness that the development of vaccines in times of pandemics, such as the flu in 1918, not just saved the humanity from extinction but also eventually helped eradication of the underlying cause [5]. Naturally therefore, as the number of COVID-19 cases worldwide continued to skyrocket, the countries world over started preparing for the largest vaccination program in history. However, the immunization drives received a mixed response from the people. Scepticism and vaccine hesitancy negatively affected the inoculation rate and also offset the immunization drives launched by countries to curb the pandemic [6–8]. It was reported that a roughly thirty percent drop in vaccination coverage may be attributed to a one percent rise in vaccine scepticism [9]. And a major contributing factor for the public scepticism was the lack of assurance about the safety

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of the COVID-19 vaccine. Conventional vaccine development has been a laborious and intricate procedure that usually takes ten to fifteen years. However, the COVID-19 vaccine was developed in a 12-to 24-month period [10] which had a negative impact on immunisation rates. Furthermore, the immunizations were impacted by poverty caused on by lost livelihoods.

Emotional responses of people can therefore be used as a direct indicator of the difference between the expected and the actual outcomes [11–15]. It is therefore both important and interesting to study the emotional responses of people to the vaccines, over time, in order to draw conclusions regarding what held them back, so that resolutions could be reflected upon. A more important accomplishment would be to document these conclusions and possible resolutions to guide the course of action in case of any future calamity.

Social media platforms are very popular amongst citizens across the world to express their opinions regarding issues that affect their lives. As opposed to other media, where the discourses are sometimes controlled or regulated, microblogging platforms facilitate uninhibited, real-time, low-cost communication, and therefore serve as important resources to recognize, observe and assess public health issues [6–9]. Twitter is one such micro blogging platform that has showcased the potential of affecting people's lives by aiding in turning around organizational and even national policies. In times of natural calamities such as an earthquake and pandemic etc., tweets instantly flood the microblogging site [11, 12, 13, 16]. Technologies such as data mining, and machine learning etc. have the competence of swiftly combing through this gigantic data in real time and extract knowledge that can facilitate real time decision making, especially during the time of crisis.

This work presented a framework that can assess the human emotions from social media platforms, evaluate them and draw novel, actionable inferences from them in real time, that can aid the policymakers, physical health professionals, mental health professionals and researchers alike to understand the determinants of emotional health and work out action plans accordingly. More importantly, once established, such a framework can also serve as a ready template for the frameworks that can be used in case of a calamity, in future. It is noteworthy here, that assessment and evaluation of emotional responses, in any such framework, must include their quantification, as purely subjective assessments inherently bring in human bias and are not directly actionable. In contrast, quantitative metrics can not only provide objective, ready to be leveraged knowledge, they can also help consolidate the behavioural responses, studied over a period of time.

Though COVID-19 has been the centre of many a focused research endeavours, to the best of our knowledge, study, quantification of human behavioural responses for battling with the pandemic has not yet been undertaken, specially by the data mining and machine learning communities. Some studies, in human psychology, have focused on studying and quantification of emotions. An automatic music emotion system is presented in [17]. A novel dataset of music with dynamically tagged emotional content was used for the investigation. The field of affective analysis in music and other art forms may benefit from this study. The impact of emotions in decision making process is explored [18]. The study describes emotional intelligence as the ability to identify one's emotions and evaluate role of emotions for a wise decision. The emotional-gain model [19] is introduced, and the findings show that decision-making is correlated with a positive mood. In other words, accepting an offer is associated with a happier emotional change, whereas rejecting an offer is associated with a less happy emotional change. None of these, however, present any metrics that can be directly leveraged, and are not relevant for the cause or the framework envisaged in this paper.

In this paper, a temporal and spatial framework based on the concept of knowledge differentiation is presented to accomplish the following tasks:

1) Leverage the concept of knowledge differentiation to mine, restructure and study emotional responses of the people towards vaccines introduced in their respective countries over three time periods, spanning approximately one and a half years. Five countries were chosen for study, namely, India, United States of America, United Kingdom, Brazil, and France. The concept of knowledge differentiation, the proposed framework and its implementation are elucidated in Section 3.1.
2) Perform a comparative exploratory data analysis to statistically examine the response of vaccines in the five countries chosen for study. This purely objective study presented in Section 3.2 was performed to complement and set the context for the purely subjective (emotional) perspectives studied in Sections 3.3 and 3.4. The exploratory data analysis involved evaluation of facets such as the

percentage of new cases vs. vaccinations, percentage of deaths vs. number of vaccinations and the percentage of people vaccinated in the respective COVID-19 waves of the five countries.
3) Perform a comparative study of the emotional responses of people towards the respective vaccines of the five countries, chosen for study (Section 3.3). The study presented in this section serves as a pre-requisite for the restructuring and modelling work done in Section 3.4.
4) Propose novel, simple and intuitive metrics to quantity, restructure and model the emotional reach and emotional valence of a vaccine, the intensity of emotions evoked by it and its emotional rank amongst the sixteen vaccines studied in this paper (Section 3.4).
5) Study the evolution of the emotional responses temporally and spatially.

The paper is organized as follows. Section 2 reviews the research studies related to the work presented in this paper. Section 3 presents the methodology. Section 3.1 explicates the research framework, data collection and pre-processing details, and implementation details. Section 3.2 presents the exploratory data analytic study. Section 3.3 presents the emotional responses at abstraction level zero and inferences drawn from them. Section 3.4 presents the modelling of emotional responses. Section 4 presents result of all the studies outlined in section 3. Section 5 discusses the inferences drawn from the conducted studies and limitations of the current study. Section 6 concludes the paper and lays down directions for future work.

2.Literature review

The COVID-19 pandemic has raised the prevalence of psychological problems and symptoms associated with mental health. During the outbreak, public sentiment analysis gave valuable information to help with appropriate public health responses. The effects of the pandemic were assessed by utilising the opinions posted on Twitter worldwide [20]. Tweets were extracted from the platform with two significant hashtags: #COVID-19 and #Coronavirus. Applying the sentiment analysis to these tweets, the results show that public perception was primarily favourable or neutral. One reason for the positive perception was attributed to a special opportunity to socialise with their families despite being confined to their homes or being placed under quarantine. A mobile app-based questionnaire was utilised to assess psychological stress caused on by the COVID-19 pandemic [21], in the general population as well as in members and non-members of medical teams supporting the pandemic. The findings revealed that front-line nurses' vicarious traumatization scores, which included psychological reactions, were considerably lower than those of non-front-line nurses.

Large volumes of text data published by Twitter users during the outbreak were used to analyse the sentiment dynamics of people living in different nations. Sentiment polarity of the residents in the Australian state of New South Wales (NSW) [22] was examined and the results indicated that the general sentimental polarity of NSW residents was positive, and that during the epidemic, this polarity dropped. Although the majority of the study period's days had dominantly favourable sentiments, the fine-grained analysis showed that there were notable shifts in emotion from positive to negative. Additionally, this study looked at how people's sentiments were affected by lockdowns, social isolation, and government programmes like Australia's JobKeeper programme. The findings demonstrated that although events and policies did have an overall impact on people's sentiment, those effects varied depending on the stage at which they occurred. The outbreak's effects on community depression were studied [23] using multimodal features from tweets in NSW in Australia and term frequency-inverse document frequency (TF-IDF). Emotional, topical, and domain-specific cues related to depression were captured using multimodal features. The study's findings demonstrated that, in the midst of the pandemic, the depression categorization model could effectively identify community depression dynamics at the state level of NSW. It was found that people became more depressed after the outbreak in NSW. People's depression was highly sensitive to variations in the number of confirmed cases, and people became more depressed when the number of confirmed cases increased sharply. Depression levels rose as a result of government actions like the state lockdown. However, the relaxation of restrictions even resulted in increased depression.

Posts on the well-known Chinese social media platform Sina Weibo [24] were chosen at random between January 1, 2020, and February 18, 2020. Positive, neutral, and negative sentiment categories were classified using the unsupervised bidirectional encoder representations from transformers (BERT) model, while post topics were summarised using the TF-IDF model. According to the study, people were worried about four parts of COVID-19: the virus's origin, symptoms, production activity (such as starting work or school), and public health control measures such as taking temperature, shutdown.

A study was undertaken across several Spanish-speaking nations [25] to examine how the pandemic outbreak has impacted people's emotions from March 2020 to March 2021 using a total of 3 million tweets. The tweets were categorised according to popular topics including government-imposed measures and corrective activities, the psychological effects of the epidemic, the economy, employment, etc. The topics were chosen with the intention of addressing the public's main worries regarding the outbreak and the likelihood that the pandemic will be overcome in the near future. The dynamic variation in the emotional value of the phrases defining various topics connected to pandemics was captured using text analysis in conjunction with Unsupervised learning algorithm. The findings show the extent to which the pandemic has impacted and affected the populations of the chosen nations in various ways. The Stress at Work for Saudi Arabian Nurses During the pandemic was assessed and quantified [26]. To gather information for this study, the expanded nursing stress scale (ENSS) for online questionnaire survey was utilised. It was found that nurses' levels of anxiety and tension at work rose when the pandemic emerged as a novel infectious illness. Stress among healthcare professionals had a significant impact on patient safety and satisfaction as well as an organization's survival.

An emotion care strategy to assess multimodal textual data from real-time COVID-19 tweets in India was proposed [27]. Additionally, the study examined eight scale emotions—disgust, fear, joy, sadness, surprise, anger, and trust—across a number of domains, including lockdown, politics, education, the environment, and health. Since people's lives were at risk, the health sector observed fear and despair. The constant efforts of the teachers' fraternity created a more trustworthy educational system. All researched domains had experienced less "pleasure," with the exception of nature, where low pollution levels during the epidemic made people happy.

Deep learning-based algorithms were used to better identify public sentiment around the pandemic in the United Kingdom [28]. A collection of tweets pertaining to the epidemic was taken from 48 distinct UK cities between February 2020 and November 2021. Results indicated that during the pandemic, optimistic and anticipatory sentiments were prevalent. Emotionally, people tended to exhibit very optimistic feelings at the start of 2020 and gradually expressed very negative feelings at the end of 2021.

Another study was conducted using English tweets concerning COVID-19 in Singapore that were taken from January 1, 2020, to August 31, 2020 [29]. Deep learning and the Lexicon-based method were used to establish correlations between real-life events and sentiment changes throughout the study period. The general sentiment polarity was found to be predominately positive. Nonetheless, emotion research showed that due to real-life circumstances, there were variations in the frequency of fear and joy emotions over time in Singapore. Twitter users responded positively to public health messages about social distancing, staying at home and being safe, and wearing masks. Conversely, negative opinions prevailed about travel and border limitations brought on by the epidemic.

The emotional and informational needs of the public during a global health emergency were investigated [30] with the use of SimSimi, a social commercially available chatbot. The authors looked at the pandemic-related topics that users talked online and analyzed the attitude expressed by users from five culturally diverse nations: United States, the United Kingdom, Canada, Malaysia, and the Philippines between 2020 and 2021. Techniques for natural language processing (NLP) were employed to determine people's emotional states. Users voiced negative sentiments while discussing masks, lockdowns, case counts, and their fears about the pandemic. Conversely, pleasant feelings predominated during casual conversations with the chatbot. The parameters influencing COVID-19 content-sharing by Twitter users were investigated through the application of NLP techniques [31]. These feature extraction techniques produced attributes that provided insight into the tweets' retweet count. The findings showed that tweets with identified entities (person, group, or place), negative emotions (anger, disgust, fear, or sadness), positive content, mental health, and named entities had a higher likelihood of being retweeted. Conversely, tweets with a higher number of hashtags and user mentions had a lower likelihood of being shared.

All the aforementioned studies indicate that the pandemic increased the mental health symptoms worldwide. Analysis of public emotion provided insightful data that aided in the development of appropriate public health programs. In the remainder of this section, related work in the areas of machine learning for analyzing emotions and quantifying them for emotion recognition and classification is reviewed, followed by a discussion of some works in human psychology that are dedicated to the characterization of emotions.

Machine learning techniques have been applied to the analysis and classification of emotions. A hybrid neural network model [32] is used to classify emotions. It consisted of a convolutional neural network (CNN) for extracting local features from text vectors and a bidirectional long short-term memory model (Bi-LSTM) for extracting global characteristics associated with text content. After fusing the two obtained features, the trained hybrid neural network was applied to categorise the emotions in new sentences with an accuracy rate of 94.2 percent. The emotional patterns of fake and real news from social media and news articles were compared using long short-term memory model (LSTM) neural network [33]. The results show that false information has different emotional patterns in each of its types, and emotions play a key role in deceiving the reader.

The literature also reports some studies in automatically recognizing emotions. Research study [34] investigated at the relationship between user-generated text on Facebook and their mental well-being and found that users who are depressed or anxious often post more negative stuff on the social media platform. A supervised learning-based method was used by Soumaya et al. to automatically identify six basic emotions from a heterogeneous emotion-annotated dataset consisting of news articles, fairy tales, and blogs [35]. According to the findings, support vector machines (SVM) outperformed the other classifiers and had good generalisation capabilities for new data. Another study on COVID-19-related tweets [36] categorised social media content as fake or real according to its sentimental value, and intensity and found that the fear and negativity propagated by false tweets was significantly greater than that of real tweets.

A dual-channel CNN was presented to detect sarcasm [37] that analyses the semantics and emotional context of the text. SenticNet is used to add common sense to the LSTM model giving the results that the proposed approach could significantly improve the performance of sarcasm detection tasks. An emotion classification model was presented [38] that uses a manually annotated deep learning model to identify positive and negative emotions related to the COVID-19 vaccines. The results show that a significant portion of the population has a positive attitude toward the vaccines. Effective predictors of publics' emotional responses to misinformation about the COVID-19 vaccine and corrective messages were identified [39]. Random forest models were used to identify the most salient predictors among over 70 predictors for both types of messages and it was found that for misinformation, political ideology of the message source was the most salient feature that predicted anxious and enthusiastic reactions, followed by message features that highlighted personal concerns and messages' network positions. Different emotion states were used to train a channel-frequency CNN (CFCNN) with recurrence quantification analysis (RQA) for measuring the electroencephalogram (EEG) signals generated in response to movie clips stimulating various emotional states [40]. Movie clips were employed as the stimuli to induce happiness, sadness, and fear emotions and simultaneously measure the corresponding EEG signals. The study mainly found that emotional features extracted from the gamma band presented a considerably higher classification accuracy of 90.51% and a Kappa value of 0.858, proving the high relation between emotional process and gamma frequency band.

There is currently relatively little published research using machine learning to assess, quantify, and utilise emotions in the fight against the epidemic. Even though emotions seem to be difficult to quantify precisely, it is nevertheless feasible to evaluate them quantitatively. A generic approach that combines emotional and rational characteristics to quantify emotions is presented [41]. To represent the varying sense of emotion, a three-axis model of human emotion was developed [42]. The valence of a future picture was predicted using EEG data in order to identify contributing neural signatures for each of the three axes. In one of the research works that most closely resembles with the work presented in this paper, Adikari et al. [43] examined the emotional transitions, intensities, and profiles of Australian netizens during the COVID-19 pandemic from January 2020 to September 2020. Their work used an artificial intelligence (AI) framework that combined word embeddings, Markov models, NLP, and the growing self-organizing map algorithm to explore social media conversations. The emotions and concerns that were expressed and recorded on social media during the study period reflected the mental health of the general public. In contrast, proposed study in this work spanned five countries, for a period of almost eighteen months. Secondly and more importantly, the emotion profiles in the work reported by Adikari et al. were all derived from the emotions mined at the lowest level of abstraction. The metrics proposed in the current study help to derive conclusions at higher abstraction levels by reorganizing and consolidating emotions, that weren't employed in the previously reported studies.

Though the aforementioned investigations have been successful in establishing a link between spoken or written language and the feelings that people experience, but quantification of public emotions to draw inferences is largely unknown. This work uses an emotional study of the numerous vaccines used by various nations to fight the epidemic. In order to quantify the results of the emotional analysis, novel metrics were proposed, and vaccinations were ranked. Next section presents the general framework to draw conclusions at higher levels of abstraction by consolidating and reorganising knowledge acquired at lower levels of abstraction. Measuring emotional reaction and intensity may help extract knowledge at higher abstraction levels that is immediately applicable for effective pandemic management.

3.Methods

Details about the framework, data and implementation are presented in section 3.1. Sections 3.2 elucidates the three purely objective exploratory studies that were conducted. This objective analysis, serves as a complement and contextual foundation for the subjective emotional perspectives examined in sections 3.3 and 3.4.

3.1General framework

In this section, details about the sourcing of data and its pre-processing is presented first in section 3.1.1. The general framework underlying the work done in this paper is elucidated next in section 3.1.2. The programming environment used for implementation of the general framework laid down in section 3.1.2 is detailed in section 3.1.3.

3.1.1Data collection and pre-processing

The country-specific data used for exploratory data analysis in this study was obtained from Kaggle.com [44], an online platform that primarily enables data science and machine learning practitioners to discover and publish data sets. This data set includes the total number of immunizations in the country as well as the number of individuals who were vaccinated between 15 December 2021 and 9 April 2021. It was integrated with data downloaded from 'Our world in Data' [45], an online publication that focuses on global issues of importance. The gathered data was in the .csv format containing the total number of COVID-19 cases and deaths from 30 January 2020 to 10 April 2021. *Figure 1* depicts how the downloaded data was managed for the exploratory data analysis.

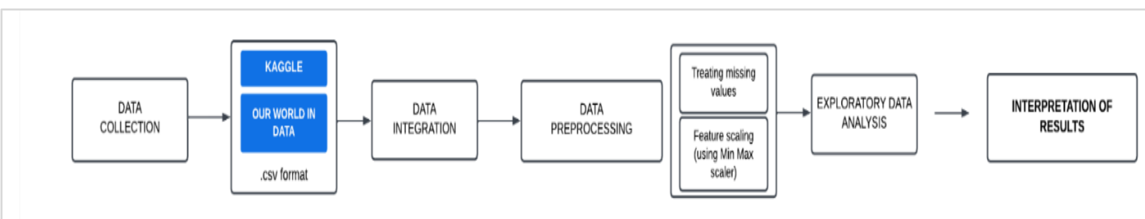


Figure 1 Data for exploratory data analysis

The downloaded data was subjected to data preprocessing. The missing values were dealt with by replacing not a number (NaN) values by zeros, by function replace (nan, 0). After eliminating NaN values, the data from Kaggle and our world in data was combined using pandas' merge function.

This was followed by feature scaling, since the dataset contained numerical features with different scales. Feature scaling involved normalizing the numeric data using the "min-max scaler", provided by the scikit-learn library in Python, which scales each input variable independently to the range 0 to 1.

For emotion analysis, a total of 55K tweets were retrieved from Twitter using twitter intelligence tool (TWINT), an advanced open-source Python library, as opposed to the Twitter API, due to TWINT's user-friendly setup and fast processing speed. TWINT facilitated the scraping of Twitter data without the constraints of rate limits and the necessity for application programming interface (API) keys. Complementary Python libraries used for implementation in this framework include pandas for working with data frames, nest_asyncio for managing runtime errors, and sys for manipulating various aspects of the runtime environment. *Figure 2* shows how the scaped tweets were managed throughout the research process.

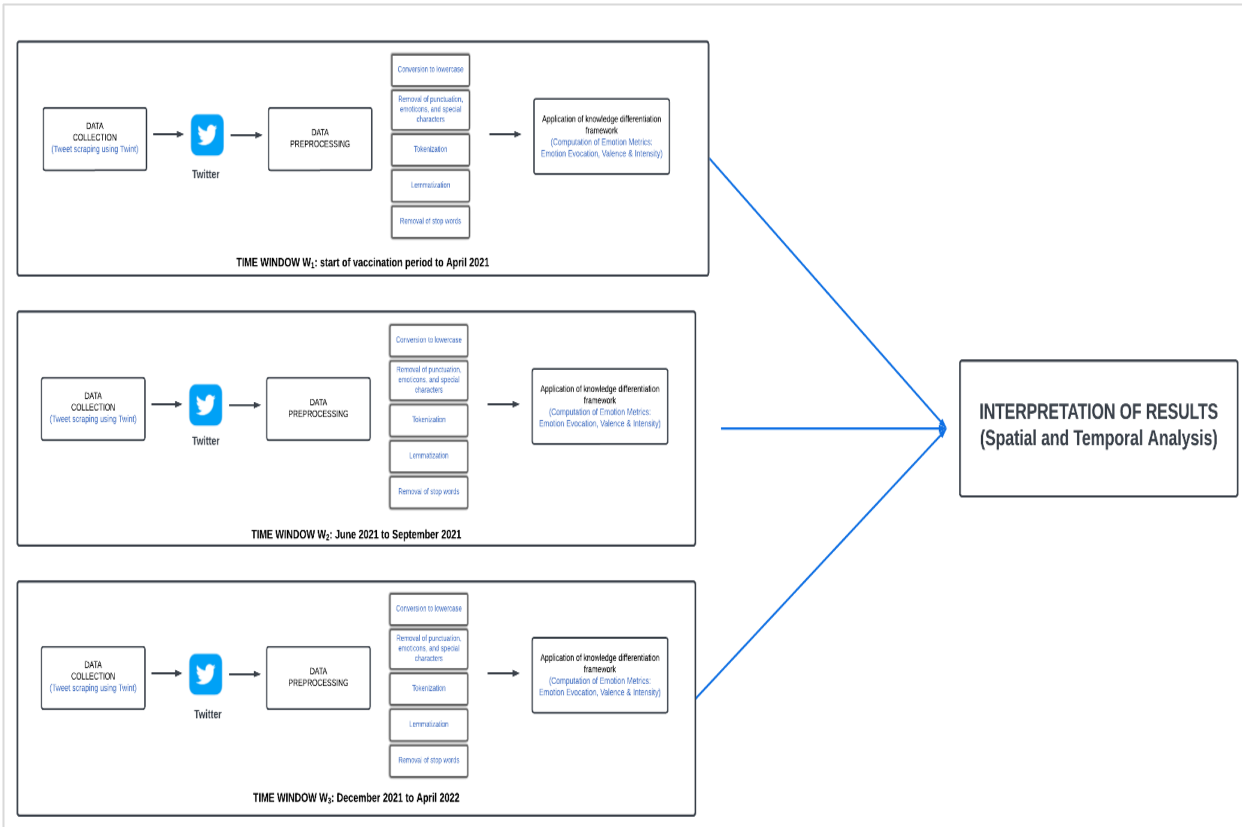


Figure 2 Tweet collection, preprocessing and usage

Pre-processing the collected tweets was essential to enhance subsequent data analysis. Initially, the tweets underwent conversion to lowercase, and the re library was employed to eliminate punctuations, emoticons, and special characters such as @, unform resource locators, and #. Subsequently, utilizing the natural langauge toolkit (NLTK) Python library, the tweets underwent tokenization, lemmatization, and removal of stop words. Tokenization involved splitting tweets into smaller units, or tokens, using the function word_tokenize () to gauge word frequencies through data mining models.

Lemmatization aimed at stripping away inflectional endings and returning the base or dictionary form of a word, known as the lemma. As compared to stemming, lemmatization is considered more robust, as it leverages lexical knowledge bases to accurately identify the base form of each word. The NLTK class WordNetLemmatizer() facilitated the lemmatization process. Additionally, the NLTK stopword library aided in removing common words, known as stop words, which contribute little value to the text, from the tweets.

The cleaned tweets were then filtered to include tweets about COVID-19 vaccines for three distinct time periods: time period 1 (start of vaccination period to April 2021 – 19K tweets), time period 2 (June 2021 - September 2021- 18K tweets), and time period 3 (December 2021 - April 2022 – 18K tweets).

3.1.2Research framework

The schematic diagram of the general framework, based on the principle of knowledge differentiation [46–49] is shown in *Figure 3*. Knowledge differentiation involves studying the change in knowledge with respect to some other parameter such as time or space etc. The principle is based on the concept of abstraction that facilitates multi-perspective analysis. Mined emotional responses are treated as the knowledge nuggets at level zero of abstraction. Knowledge nuggets at higher levels of abstraction are then obtained by modelling i.e., consolidating and restructuring the knowledge nuggets obtained at the lower levels of abstraction. Knowledge modelling can be accomplished by designing suitable metrics.

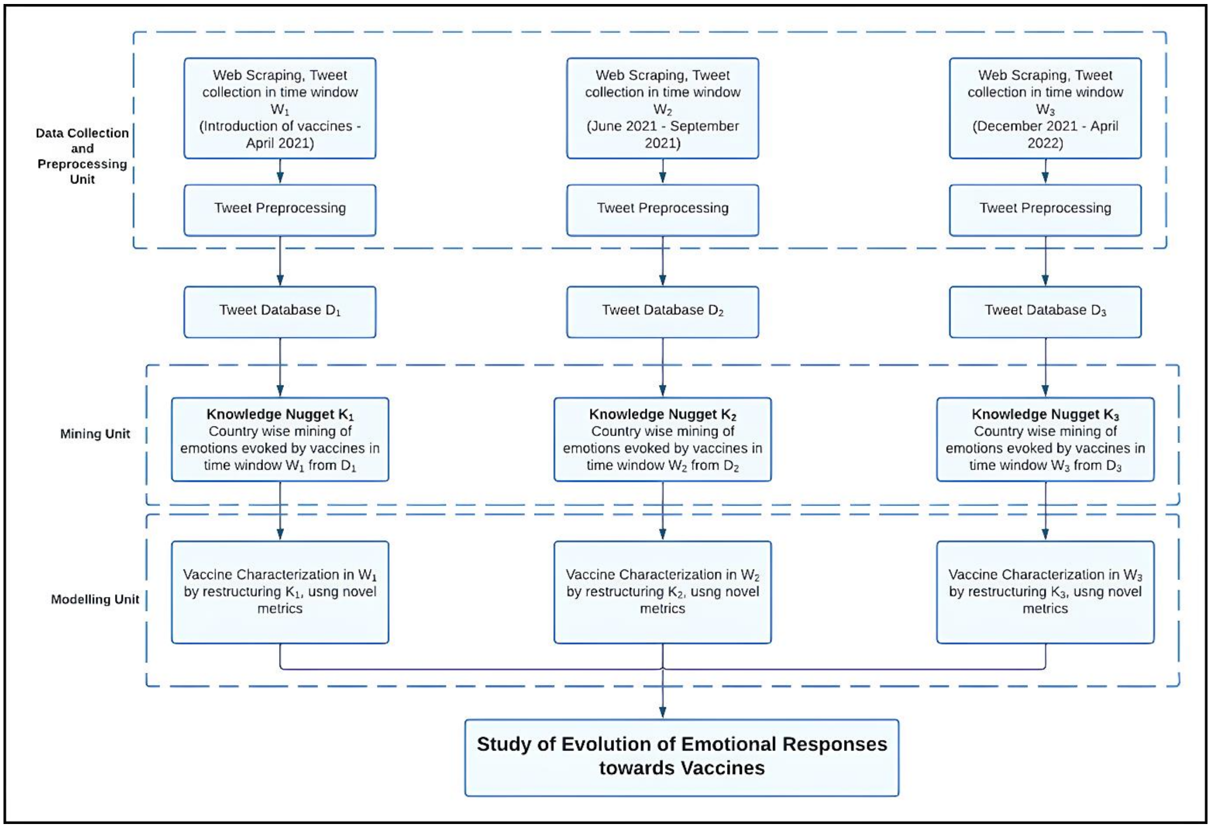


Figure 3 Research framework to classify, characterize and leverage the knowledge from COVID-19 tweets

The framework consists of a data collection and pre-processing unit, that collects data and processes it to ready it for deployment, as detailed in the previous subsection 3.1.1. The tweets, collected and pre-processed in the time window (start of vaccination period to April 2021), denoted by W1, form the tweet database D1, at a time instant t1. The tweets collected in the time window (June 2021 - September 2021), denoted by W2, form tweet database D2, at a time instant t2. The tweets collected in the time window (June 2021 - September 2021), denoted by W3, form tweet database D3, at a time instant t3 (December 2021 - April 2022).

The mining unit, mines knowledge pertaining to statistical, emotional and sentiment facets, of the tweets referring to the vaccines of the respective five countries under study. These knowledge nuggets from the tweet databases Di, are denoted by Kis. The emotional knowledge nuggets, mined by the mining unit and passed onto the modelling unit are elucidated in Section 5.

The modelling unit is responsible for restructuring the emotional and sentimental knowledge nuggets Ki, by applying on them the new metrics, proposed in this work. These metrics help to quantify the hitherto subjective responses of the people w.r.t. the COVID-19 vaccines introduced in their respective countries. Emotional and Sentimental Rank of vaccines w.r.t the other vaccine in the same country is also computed by the modelling unit. The results drawn from the modelling unit can be used to look at changes in the values of metrics thereby revealing the evolution traits of public’s responses towards the vaccines.

3.1.3Setting up the environment

The research framework was implemented using Python version 3.8.1. Data from India, the United States of America, the United Kingdom, France, Brazil, and were collected for the exploratory data analysis study presented in Section 4. Python modules and packages such as Pandas - a Python library for working with datasets - and NumPy - a library for working with arrays were utilized for managing large amounts of data. Matplotlib 3.3.4, NumPy 1.20, and Plotly 4.14.3 were employed to visualize the data. These graphical tools were used to examine the patterns of deaths and new cases, as well as the effect of vaccines on these two variables. Using these tools, the relationship between new cases and vaccinations as well as the association between deaths and vaccination were also plotted.

For emotional analysis, the re library was used to clean up the noisy tweets and the Pandas package was utilized for data merging, shaping, cleaning, and manipulation. NRCLex 3.0.0, a library, specifically designed for emotion analysis, was deployed on the cleaned tweets to assess the emotional impact of tweets. The tweet texts were converted to objects and their highest emotions were computed using the function tweet_object.top_emotions

The overall score of each emotion, namely, fear, anger, anticipation, trust, surprise, sadness, disgust and joy, was then calculated for each vaccine in each country, in each time period of study (see *Tables 1 to 3*), using the following formula:

$$\left(\frac{No.of\ tweets of\ one\ emotion}{Total\ tweets\ for\ a\ country\ in\ a\ time\ window}\right) \times 100$$

The resulting scores were then incorporated into a two-dimensional vector for further analysis. The study utilized three emotions for each positive sentiment: trust, surprise, and pleasure, as well as three emotions for each negative sentiment: anger, fear, and disgust. The accumulated scores of the emotions were employed to further quantify Emotion Evocation. Similarly, the difference between these scores was used to compute Emotional Valence. Emotional Intensity was then calculated by dividing Emotional Evocation by Emotional Valence. Based on the results of the calculations for Emotional Intensity, the Emotional Rank was determined.

3.2 Fighting the pandemic with vaccines – global statistical perspectives

Different countries across the globe deployed different vaccines to deal with the COVID-19 pandemic, and had to face a surge of virus cases, called a COVID wave, in different periods of time. This section lists three case studies conducted to compare the vaccines that were introduced in each country and how, the statistics such as the new cases, number of deaths, and the percentage of people vaccinated varied with the COVID waves in the five countries under study, namely, India, United States of America, United Kingdom, Brazil, and France. The exploratory data analytic case studies undertaken in this paper are outlined in sections 3.2.1, 3.2.2, 3.2.3.

3.2.1 A Study of the new cases vs. vaccinations

We conducted a study of the comparison of new cases that kept arising due to COVID-19, even as the vaccination rate went high. The study was conducted for five countries namely, India, the United States of America, the United Kingdom, Brazil, and France.

In India, on January 1, 2021, the Drug Controller General of India, authorized the emergency or conditional use of AstraZeneca's COVID-19 vaccine AZD1222 and marketed it as Covishield. Covishield was developed by the University of Oxford and its spin-off business, Vaccitech. It is a viral vector vaccine based on a replication-deficient Adenovirus that causes cold in Chimpanzees. On January 2, 2021, another vaccine, BBV152, which is marketed as Covaxin, was approved. The vaccine was developed by Bharat Biotech in collaboration with the Indian Council of Medical Research and the National Institute of Virology, for emergency or conditional use. An expert panel in India approved the Sputnik-V vaccine's emergency use on April 12, 2021. The vaccination drive in India began on 16 January 2021, across 3006 vaccination centers, one of the largest vaccination drives in the world.

The United States of America began its mass vaccination on December 14, 2020 following the food and drug administration (FDA's) December 10, 2020 approval of the Pfizer–BioNTech COVID-19 vaccine. Later, on December 17, 2020, the Moderna COVID-19 vaccine was approved for use, and onFebruary 27, 2021, the Johnson & Johnson COVID-19 vaccine was approved.

In the United Kingdom, the Medicines and Healthcare products Regulatory Agency (MHRA) approved the PfizerBioNTech COVID-19 vaccine (BNT162b2) on December 2, making the United Kingdom the first country in the world to approve a COVID-19 vaccination. The (ChAdOx1 nCoV-19 or AZD1222) vaccine developed by Oxford University and AstraZeneca (the British-Swedish pharmaceutical and biopharmaceutical company) became the second COVID-19 vaccine approved for use in the United Kingdom on December 30th, with deployment beginning the following week. This advancement was claimed to allow for a rapid increase in the pace of the vaccination program, due to more doses being available and the Oxford vaccine's higher storage temperature making delivery easier. The United Kingdom began the vaccination drive on 8 December 2020 with BioNTech or Pfizer (Comirnaty), AstraZeneca (AZD1222) and Moderna (MRNA-1273). The United Kingdom was the first to authorize and begin using the Pfizer–BioNTech COVID-19 vaccine in a mass immunization programme. By early

2021, the United Kingdom had one of the world's highest immunization rates.

The vaccination in Brazil started in late January 2021. Two vaccines were being given, Coronavac (Sinovac, China) and AZD1222 (Oxford-AstraZeneca, United Kingdom). Initially, vaccination phase started for four priority groups, health workers, the elderly - starting with those aged 85 years or more, and gradually vaccinating younger age groups, indigenous populations, and institutionalized individuals. By April 22, 17.4% of Brazil population had received first dose of either vaccine, and 7.1% had received second dose, CoronaVac accounted so far for 77.3% and AstraZeneca for 15.9% for all doses delivered in Brazil. COVID-19 vaccination began in France on December 27, 2020, following the European Union commission's approval of the Pfizer/BioNTech vaccine.

The results of this study are presented in section 4.1 and interpretations are detailed in section 5.1 respectively.

3.2.2A Study of the deaths vs. vaccinations

In this study, the percentage of deaths due to COVID-19 with respect to the number of days the vaccination drive began during the period of study i.e., January 2021 – May 2021, in the countries selected for study viz. India, United States of America, United Kingdom, Brazil, and France was analyzed. The results of this study are detailed in section 4.1.2 and inferences are presented in section 5.1.2.

3.2.3A study of the percentage of population vaccinated

In this study, the percentage of the population vaccinated with respect to the number of days the vaccination drive began during the period of study i.e., January 2021 – May 2021, in the countries selected for study viz. India, United States of America, United Kingdom, Brazil, and France was analyzed. The results of this study are detailed in section 4.1.3 and inferences are presented in section 5.1.3.

3.3Emotional responses towards immunization drives: global perspectives

This section elucidates the findings the emotional study of five countries, namely India, United States of America, United Kingdom, Brazil and France, chosen for study. The tweets collected and preprocessed, as detailed in Section 3.1, using the NRC Emotion Lexicon is presented in this section. The mined emotional reactions presented in this section forms the knowledge nuggets that form basis of aggregation and restructuring in the next section. Using the NRC Emotion Lexicon [8, 9], the emotions linked with the collected tweets of different vaccines from different nations were examined.

3.4Studying the emotional impressions of vaccines

In this section we propose some simple, intuitive, novel metrics as a step towards developing capabilities to be able to quantify how the people responded emotionally to the vaccines introduced in their country. These metrics quantity the behavioural reach of a vaccine, the intensity of sentiments and emotions evoked by it and rank it accordingly. These four proposed metrics, presented below, restructure the emotion nuggets, K1, mined in section 5 (Tables 1 to 3), and yield the knowledge nuggets K2.

3.4.1Emotion evocation of vaccine

Emotion evocation of a vaccine signifies its behavioural outreach i.e., the number emotions it could evoke in people, irrespective of whether the emotions were positive or negative. It conveys the reach of a vaccine in terms of the feelings it evoked among general public. Represented by the symbol Ee (Evocation of Emotions), the proposed metric is defined as the sum of positive and negative emotions as shown in Equation 1.

$$E_e = P_e + N_e \tag{1}$$

Where,

Pe: positive emotional score i.e., tweets talking about the vaccine with positive emotions, namely, trust, surprise, and joy, and Ne: Negative emotional score i.e., tweets talking about the vaccine with negative emotions, namely, fear, anger, and sadness. Equation 1 shows that low values of emotion evocation suggest minimal public response to the vaccine, while high values indicate that the vaccine has generated notable and polarized reactions from people, whether positive or negative.

3.4.2Emotional valence of vaccine

The Emotional Valence of a vaccine signifies its effective positive behavioural outreach i.e., the amount of positive emotions it could evoke in people excluding the negative ones. It conveys the reach of the vaccine in terms of the positive feelings it evoked among general public. It is represented by the symbol Ve (Positive valence based on Emotions), and defined as the difference of positive and negative emotions as shown in Equation 2.

$$V_e = P_e - N_e \tag{2}$$

Where,

Pe: positive emotional score i.e., tweets talking about the vaccine with positive emotions, namely, trust, surprise, and joy, and

Ne: Negative emotional score i.e., tweets talking about the vaccine with negative emotions, namely, fear, anger, and sadness.

Equation 2 shows that low values of emotional valence suggest a predominant negative public response towards the vaccine while high values indicate a higher positive response towards the vaccine.

3.4.3 Emotional intensity of vaccine

Emotional Intensity of Vaccine signify the strength of positive emotions invoked by it with respect to all the emotions invoked by it. The emotional intensity is represented by the symbol Ie and defined as its emotional valence as a fraction of its emotion evocation.

$$I_e = \frac{V_e}{E_e} \qquad (3)$$

where,
Ve: emotional valence of a vaccine and
Ee: emotion evocation.

Equation (3) shows that low values and high values of emotional intensity signify a smaller fraction and larger fraction of positive public response towards a vaccine w.r.t. all emotions evoked respectively.

3.4.4 Emotional rank of vaccine

The emotional rank of a vaccine, represented by the symbol Re, orders the vaccines in a country, according to their emotional intensities. The significance of ranking the vaccines is to be able to identify the vaccines with maximum and minimum emotional intensities in a country. A lower emotional rank implies that when all the vaccines in a country are ordered with respect to their emotional intensities, the rank of the particular vaccine is low. A higher emotional rank on the other hand indicates a higher emotional intensity than other vaccines.

3.4.5 Algorithm

The intuitive algorithm for computing the rank of vaccines offered in various countries is presented below.

Algorithm1: Compute_Emotion_Metrics
Input: Name of the Country, Name of the Vaccine, Number of vaccines
Output: EmoTrix, the matrix of emotions
Begin

1. Initialize n = no. of vaccines, c = Name of Country, v = Name of the Vaccine
2. $P_e = P_1 + P_2 + P_3$

   // PositiveEmotionalScore: the sum of emotion score of 3 positive sentiments i.e., trust, surprise, and joy denoted by P_1, P_2 and P_3 respectively.
3. $N_e = N_1 + N_2 + N_3$

   //NegativeEmotionalScore is the sum of emotion score of 3 negative sentiments i.e. anger, fear, and disgust denoted by N_1, N_2 and N_3 respectively.
4. E_e = Pe + Ne // set value of Emotion Evocation in EmoTrix
5. V_e = Pe – Ne // set value of Emotional Valence in EmoTrix
6. I_e = Pe / Ne // set value of Emotional Intensity in EmoTrix
7. Rank [] = Sort n vaccines of country c in descending order of Emotional Intensity
8. R_e = index i of vaccine v in matrix Rank []
   // EmotionalRank of a vaccine v
9. Return the matrix EmoTrix []

End

4. Results

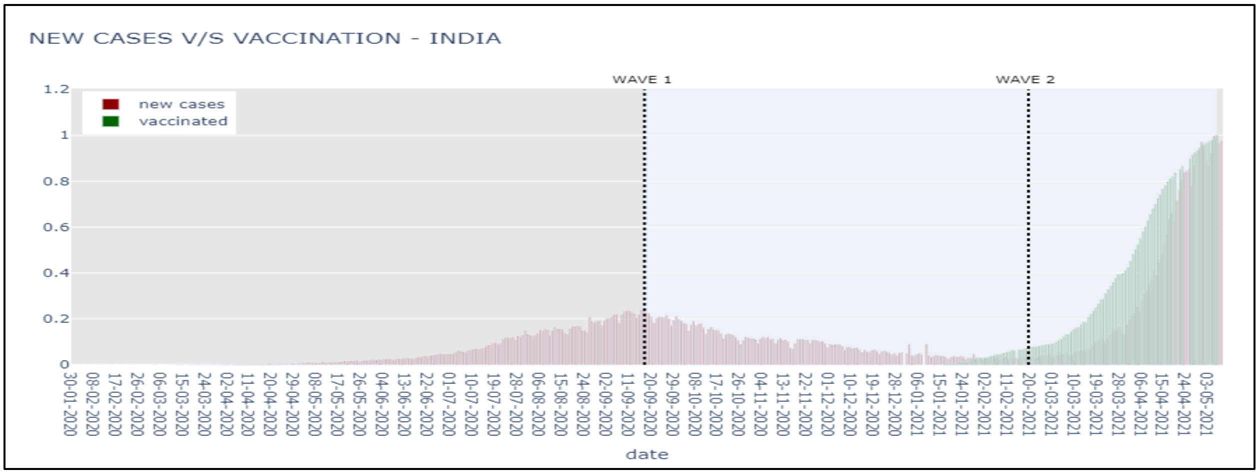
In this section, results for the exploratory and emotional studies conducted in section 3 are presented. Section 4.1 presents the results for the three exploratory studies outlined in section 3.2, namely, 'Fighting the pandemic with Vaccines – Global Statistical Perspectives', 'Emotional Responses towards Immunization Drives: Global Perspectives', and 'Studying the Emotional and sentimental impressions of vaccines. The results of emotional studies conducted in sections 3.3 and 3.4 are presented in the subsections 4.2 and 4.3 respectively.

4.1 Results for Study on Fighting the pandemic with Vaccines – Global Statistical Perspectives

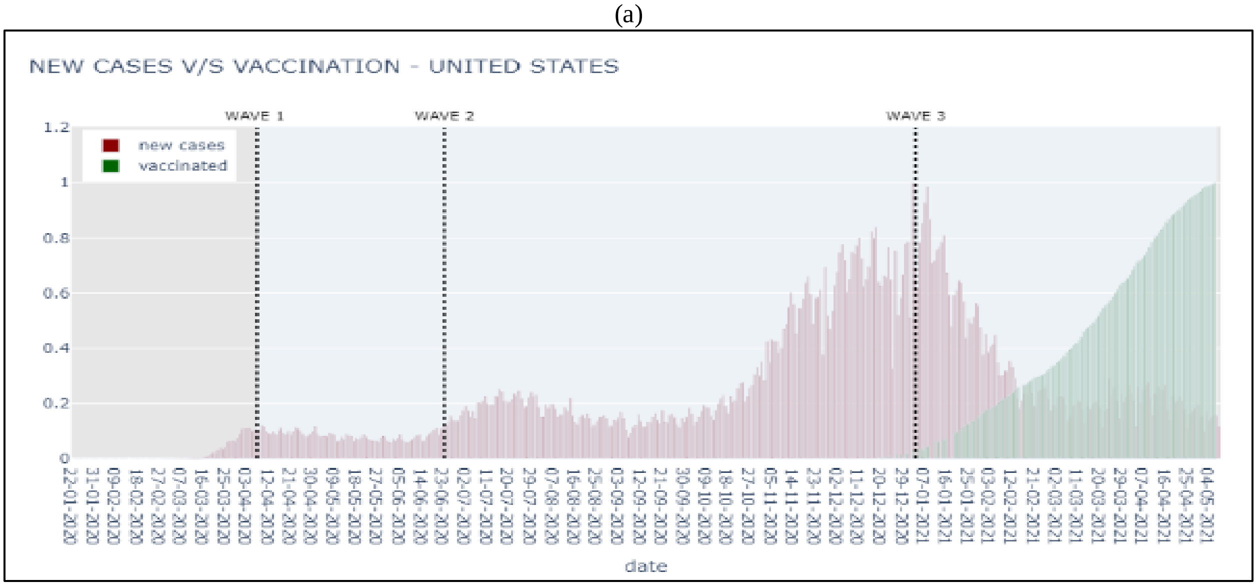
4.1.1 A study of the new cases vs. vaccinations

The influence of COVID-19 w.r.t the new cases in comparison to the vaccinations in the five countries during two different COVID waves (including the vaccination period) is shown in *Figure 4* and *Figure 5*. The figures use red bars to show the number of new cases across all COVID waves and green bars to show the number of vaccinations. The length of the COVID waves is represented by the sky-blue colour.

Figure 4 (a) shows the number of new COVID-19 cases in India during the first and second waves using the red bars and the number of vaccinations using the green bars. *Figure 4 (b)* shows the number of new COVID cases in United States of America.



(a)



(b)

Figure 4 (a) New cases vs. vaccinations in India (b) New COVID-19 Cases vs vaccinations in united states of America during the different COVID waves

Figure 5 (a) shows the number of new COVID-19 cases in United Kingdom, during the first and second waves using the red bars and the number of vaccinations using the green bars. *Figures 5 (b)* and *5 (c)* show the number of new COVID-19 cases in Brazil and France respectively. The inferences drawn from this study are presented in section 5.1.1.

4.1.2A study of the deaths vs. vaccinations

The death vs vaccinations for 5 countries that is India, United States of America, United Kingdom, Brazil and France is are presented *Figures 6* and *7*. Both these figures use blue bars to represent the number of deaths throughout the COVID waves and the vaccination time. The blue background color represents the length of the COVID waves, and the green color represents the vaccination period.

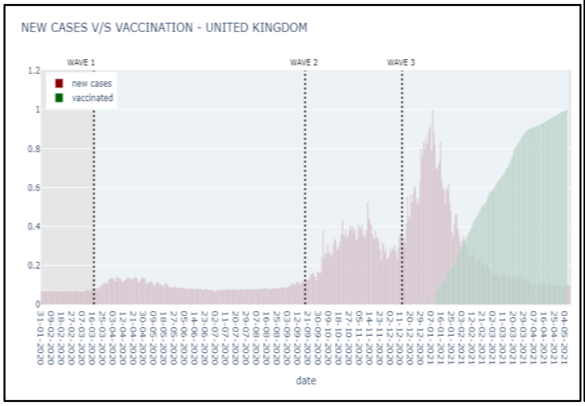
The inferences drawn from this study are presented in section 5.1.2.

4.1.3A study of the percentage of population vaccinated

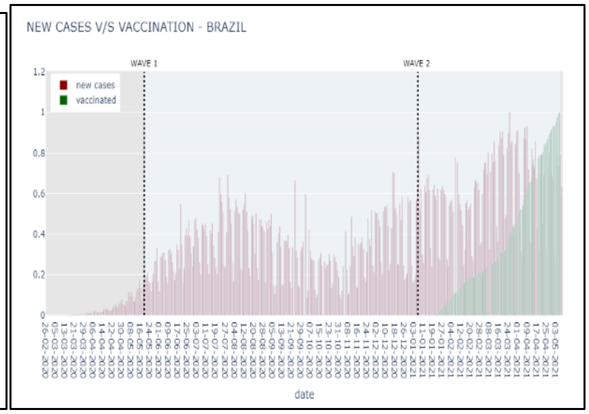
In this subsection, the results of the population vaccinated with respect to the number of days the vaccination drive began during the period of study i.e., January 2021 – May 2021, in the countries selected for study viz. India, United States of America, United Kingdom, Brazil, and France are presented. *Figures 8* and *9* employ a colour meter to display the percentage of people vaccinated according to the legend included in the *Figures 8* and *9*. The inference of this study is presented in Section 5.1.3.

4.2 Results for study on emotional responses towards immunization drives: global perspectives

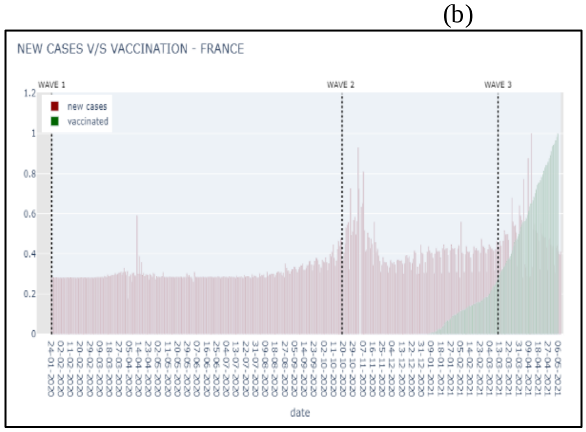
Tables 1 to *3* display the scores obtained by the use of emotion lexicon on tweets about vaccines introduced in India, United States of America, United Kingdom, Brazil and France in the three time periods of study. The inferences of this study are presented in Section 5.2.



(a)

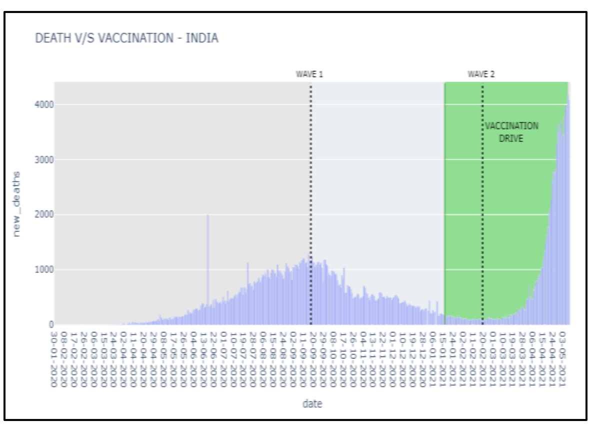


(b)

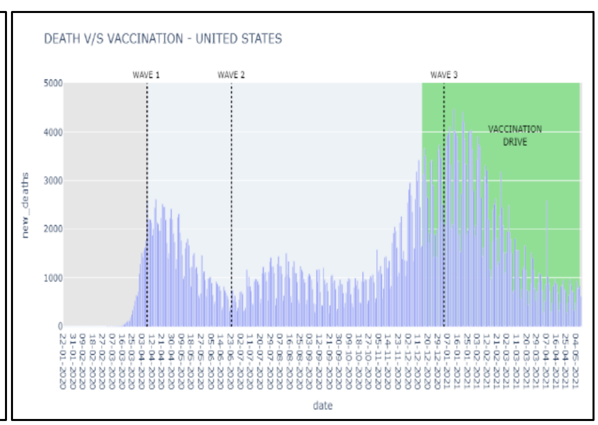


(c)

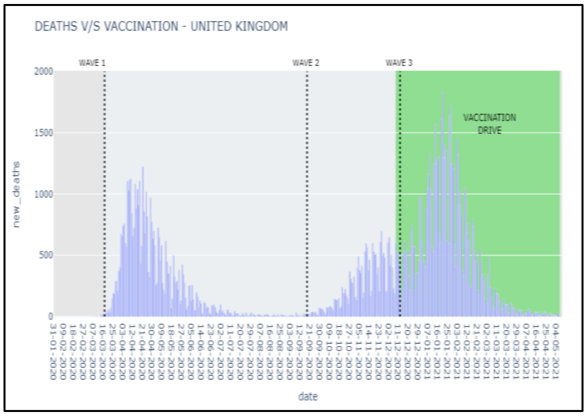
Figure 5 New Cases vs. Vaccinations in (a) United Kingdom, (b) Brazil, (c) France during the different COVID waves



(a)

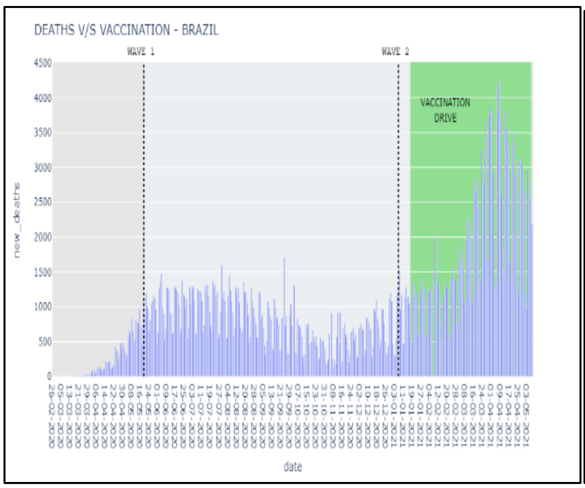


(b)

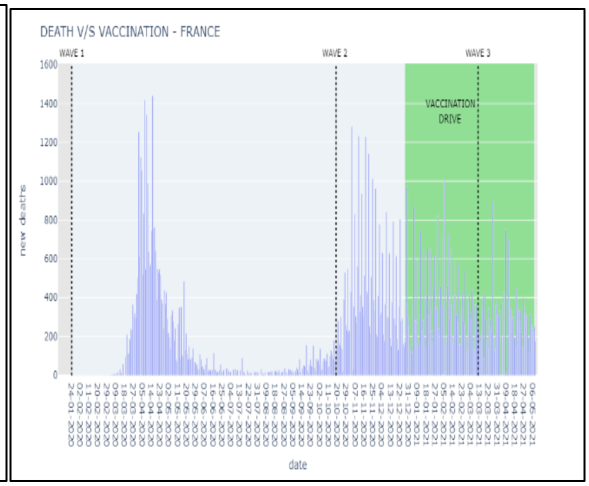


(c)

Figure 6 Deaths vs. Vaccinations in (a) India, (b) United States of America, (c) United Kingdom during the different COVID waves

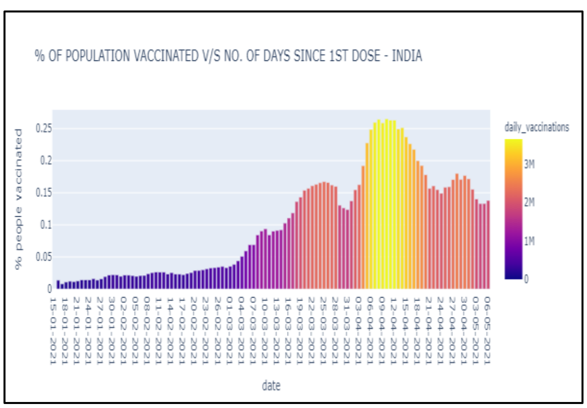


(a)

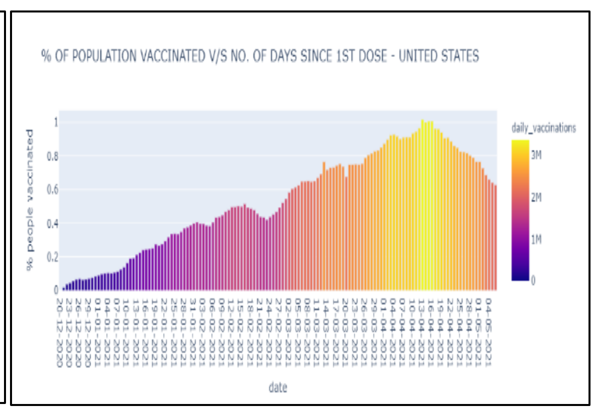


(b)

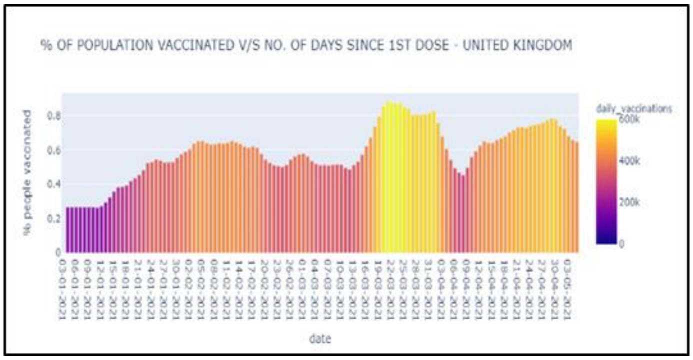
Figure 7 Deaths vs. Vaccinations in (a) Brazil, (b) France during the different COVID waves



(a)

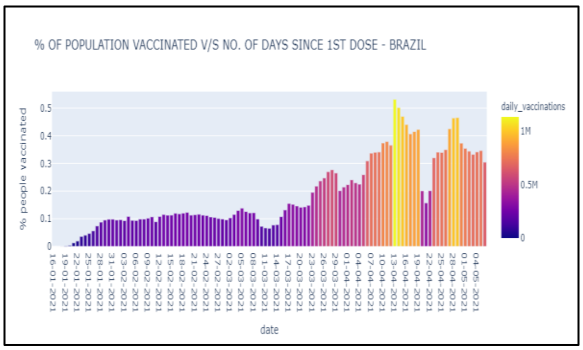


(b)

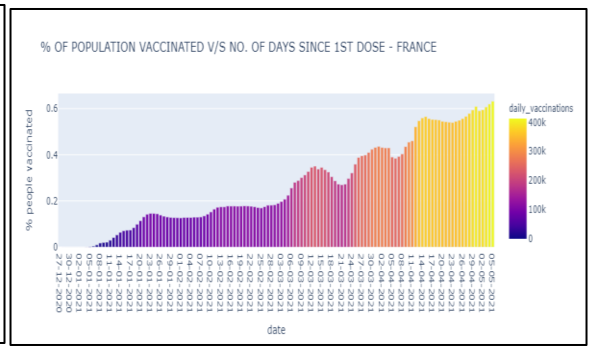


(c)

Figure 8 Percentage of population vaccinated in (a) India, (b) United States of America, (c) United Kingdom since the vaccination drive began



(a)



(b)

Figure 9 Percentage of population vaccinated in (a) Brazil, (b) France since the vaccination drive

Table 1 Emotion analysis of the tweets from the countries with its vaccines during time period 1 (Start of the vaccination period in a country till April 2021)

Countries	Vaccines	Fear (%)	Anger (%)	Anticipation (%)	Trust (%)	Surprise (%)	Sadness (%)	Disgust (%)	Joy (%)	Positive (%)	Negative (%)
India	Covaxin	9.65	9.15	9.94	10.22	8.83	9.08	8.44	8.80	15.46	10.43
	Covishield	9.52	9.00	9.89	9.96	8.20	8.86	7.69	8.13	18.16	10.61
	SputnikV	9.03	8.26	8.79	7.45	9.75	9.92	7.93	8.01	16.92	11.09
United States of America	Johnson & Johnson	8.04	5.04	6.75	6.97	5.31	7.45	4.50	4.18	40.25	11.52
	Astra-Zeneca	8.42	5.94	6.44	9.90	5.94	7.43	4.95	2.97	37.13	10.89
	Pfizer	10.45	6.87	6.73	7.87	6.30	10.09	5.94	5.58	27.34	12.81
	Moderna	11.60	5.46	5.81	8.19	6.48	9.22	4.95	4.61	30.89	12.80
United Kingdom	Astra-Zeneca	10.21	8.64	8.64	7.52	6.73	9.43	6.85	6.85	22.56	12.57
	Pfizer	9.59	7.35	8.07	8.47	7.27	9.27	6.55	7.19	25.42	10.79
	Moderna	8.53	4.65	5.43	6.20	5.43	8.53	4.65	6.20	37.21	13.18
France	Astra-Zeneca	10.41	9.59	9.18	9.57	8.74	9.66	8.69	8.41	14.08	11.67
	Pfizer	9.83	10.56	10.76	10.01	8.49	9.04	8.63	8.65	11.95	12.07
	Moderna	9.89	9.31	11.05	11.00	9.08	9.32	9.10	9.38	11.77	11.00
Brazil	CoronaVac	9.90	8.62	8.98	9.18	8.88	9.34	8.31	8.11	17.65	11.03
	Astra-Zeneca	9.92	9.68	9.86	9.81	9.64	9.74	9.60	9.60	12.04	10.01
	Covaxin	8.24	7.68	9.30	9.37	7.39	7.39	6.97	7.89	25.14	10.63

Table 2 Emotion Analysis of the tweets from the countries with its vaccines in time period 2 (June - September2021)

Countries	Vaccines	Fear (%)	Anger (%)	Anticipation (%)	Trust (%)	Surprise (%)	Sadness (%)	Disgust (%)	Joy (%)	Positive (%)	Negative (%)
India	Covaxin	9.42	8.67	9.88	11.04	8.48	9.04	8.11	8.60	16.19	10.56
	Covishield	9.73	8.82	9.38	10.97	8.58	9.00	8.06	8.66	15.97	10.83
	Sputnik V	10.11	9.61	9.40	9.91	9.10	9.71	8.90	8.90	14.26	10.11
United States of America	Johnson & Johnson	9.72	8.99	9.18	8.99	8.07	9.72	7.89	8.44	17.98	11.01
	Astra Zeneca	10.03	9.52	9.26	9.26	9.01	9.77	9.26	9.14	13.71	11.04
	Pfizer	9.86	9.36	8.77	9.42	8.45	9.79	7.75	7.72	15.97	12.89
	Moderna	9.97	9.20	8.97	9.64	8.48	9.76	7.67	8.02	14.58	13.72
United Kingdom	Astra Zeneca	8.54	10.19	9.13	10.72	7.08	8.35	6.99	7.86	19.60	11.55
	Pfizer	8.88	9.89	9.65	10.29	7.79	8.83	7.53	8.09	17.18	11.87
	Moderna	9.09	9.99	9.63	9.64	8.05	8.94	7.80	8.79	16.00	12.07
France	Astra Zeneca	10.41	9.76	9.68	9.76	9.60	9.85	9.52	9.52	11.15	10.74
	Pfizer	10.71	9.77	9.50	9.68	9.57	9.83	9.35	9.18	11.31	11.11
	Moderna	10.56	9.57	9.35	9.52	9.45	9.95	9.47	8.99	11.15	11.99
Brazil	CoronaVac	10.07	10.02	9.88	10.09	9.87	9.93	9.86	9.85	10.18	10.24
	Astra Zeneca	10.06	10.01	9.85	10.11	9.81	10.00	9.92	9.80	10.21	10.24
	Covaxin	10.00	10.11	9.80	10.16	9.75	9.90	9.76	9.78	10.19	10.55

Table 3 Emotion analysis of the tweets from the countries with its vaccines time period 3 (December - April 2022)

Countries	Vaccines	Fear (%)	Anger (%)	Sadness (%)	Trust (%)	Surprise (%)	Joy (%)	Disgust (%)	Anticipation (%)	Positive (%)	Negative (%)
India	Covaxin	9.46	8.63	8.78	10.5	8.32	8.68	8.11	9.57	17.26	10.71
	Covishield	9.66	9.12	9.12	9.96	8.35	8.66	8.35	9.65	16.09	11.03
	SputnikV	9.8	9.8	9.8	9.8	9.8	7.84	7.84	9.80	15.69	9.8
United States of America	Johnson & Johnson	11.82	10.0	10.45	8.18	7.27	6.82	8.64	6.82	16.82	13.18
	Astra Zeneca	10.12	8.93	8.93	10.12	8.63	9.52	8.93	8.63	15.48	10.42
	Pfizer	9.9	9.27	9.43	9.9	8.44	8.21	7.93	9.59	15.24	12.09
	Moderna	9.84	9.17	9.25	9.58	8.75	8.46	7.99	9.49	14.97	12.5
United Kingdom	Astra Zeneca	8.7	9.74	8.52	10.96	7.13	7.65	6.61	8.87	19.83	12.0
	Pfizer	9.53	9.89	8.89	10.25	7.83	8.05	7.56%	9.58	15.43	12.98

Countries	Vaccines	Fear (%)	Anger (%)	Sadness (%)	Trust (%)	Surprise (%)	Joy (%)	Disgust (%)	Anticipation (%)	Positive (%)	Negative (%)
	Moderna	9.05	10.24	9.22	10.07	8.43	8.29	8.07	9.80	14.06	12.77
France	Astra Zeneca	10.31	9.42	10.54	10.54	8.74	8.74	9.64	8.96	11.66	11.66
	Pfizer	9.99	9.77	9.75	9.98	9.51	9.26	9.5%	9.77	11.43	11.05
	Moderna	10.06	9.94	9.92	9.82	9.75	9.28	9.61	9.64	11.02	10.95
Brazil	CoronaVac	10.01	10.01	9.95	10.06	9.88	9.85	9.88	9.86	10.16	10.34
	Astra Zeneca	10.04	10.0	10.12	10.02	9.83	9.78	9.92	9.81	10.13	10.35
	Covaxin	9.73	10.56	9.66	10.08	9.66	9.87	9.66	9.66	10.08	11.03

4.3 Results for study on studying the emotional and sentimental impressions of vaccines

The computed values of the metrics, namely emotional evocation, emotional valence, emotional intensity and the emotional rank of a vaccine in its country constitute a matrix of emotional inferences, called EmoTrix. *Tables 4 to 6* depict the EmoTrix for the three time periods of study i.e., Time period 1 (Start of vaccination in the respective country – April 2021), Time period 2 (June - September2021), and Time period 3 (December - April 2022). *Table 7* shows the vaccines with top 5 emotional ranks in the three periods of study. The inferences drawn from this study are presented in section 5.3.

Table 4 EmoTrix – the matrix of Emotional inferences during Time period 1 (Start of the vaccination period in respective countries - April 2021)

Country	Vaccine	Positive emotions score (P) (%) $P_1+P_2+P_3=P^*$	Negative emotions score (N) (%) $N_1+N_2+N_3=N^*$	Emotion evocation P+N (%)	Emotional Valence P-N (%)	Emotional intensity (P-N)/(P+N) (%)	Emotional rank
India	Covaxin	27.85	27.88	55.73	-0.03	-0.00054	3
	Covishield	26.29	27.35	53.64	-1.06	-0.01976	5
	Sputnik	25.21	27.21	52.42	-2.00	-0.03815	7
United States of America	Johnson & Johnson	16.46	20.53	36.99	-4.07	-0.11003	13
	AstraZeneca	18.81	21.79	40.60	-2.98	-0.07340	11
	Pfizer	19.75	27.61	47.36	-7.86	-0.16596	16
	Moderna	19.28	26.28	45.56	-7.00	-0.15364	15
United Kingdom	AstraZeneca	21.10	28.28	49.38	-7.18	-0.14540	14
	Pfizer	22.93	26.21	49.14	-3.28	-0.06675	10
	Moderna	17.83	21.71	39.54	-3.88	-0.09812	12
France	AstraZeneca	26.72	29.66	56.38	-2.94	-0.05214	9
	Pfizer	27.15	29.43	56.58	-2.28	-0.04029	8
	Moderna	29.46	28.52	57.98	0.94	0.01621	2
Brazil	CoronaVac	26.17	27.86	54.03	-0.69	-0.02476	6
	AstraZeneca	29.05	29.34	58.39	-0.29	-0.00496	4
	Covaxin	24.65	23.31	47.96	1.34	0.02794	1

Table 5 EmoTrix – the matrix of Emotional inferences during Time period 2 (June - September2021)

Country	Vaccine	Positive Emotions Score (P) (%) $P_1+P_2+P_3=P$*	Negative Emotions Score (N) (%) $N_1+N_2+N_3=N$*	Emotion Evocation P+N (%)	Emotional Valence P-N (%)	Emotional Intensity (P-N)/(P+N) (%)	Emotional rank
India	Covaxin	28.12	27.13	54.37	0.63	0.01158	1
	Covishield	28.21	27.55	54.87	-0.93	-0.01694	7
	Sputnik	27.91	29.43	56.84	-1.96	-0.03448	12
United States of America	Johnson & Johnson	25.50	28.43	54.54	-10.00	-0.18335	16
	AstraZeneca	27.41	29.32	56.25	0.29	0.00515	2
	Pfizer	25.59	29.01	55.15	-2.05	-0.03717	13
	Moderna	26.14	28.93	55.05	-1.47	-0.02670	10
United Kingdom	AstraZeneca	25.66	27.08	52.70	-1.22	-0.02314	9
	Pfizer	26.17	27.60	54.44	-2.18	-0.04004	15
	Moderna	26.48	28.02	55.30	-1.72	-0.03110	11
France	AstraZeneca	28.88	30.02	58.29	-2.25	-0.03860	14
	Pfizer	28.43	30.31	58.26	-0.76	-0.01304	6
	Moderna	27.96	30.08	58.77	-1.07	-0.01820	8
Brazil	CoronaVac	29.81	30.02	59.76	-0.18	-0.00301	3
	AstraZeneca	29.72	30.07	59.79	-0.53	-0.00886	5
	Covaxin	29.69	30.01	59.56	-0.34	-0.00570	4

* Where Positive emotions score is the sum of emotion score of 3 positive sentiments i.e. trust, surprise, and pleasure denoted by P_1, P_2 and P_3
* Where Negative emotions score is the sum of emotion score of 3 negative sentiments i.e. anger, fear, and disgust denoted by N_1, $N_2$and N_3

Table 6 EmoTrix – the matrix of emotional inferences during time period 3 (December - April 2022)

Country	Vaccine	Positive emotions score (P) (%) $P_1+P_2+P_3=P$*	Negative emotions score (N) (%) $N_1+N_2+N_3=N$*	Emotion evocation P+N (%)	Emotional valence P-N (%)	Emotional intensity (P-N)/(P+N) (%)	Emotional rank
India	Covaxin	27.50	26.87	55.25	0.99	0.01791	1
	Covishield	26.97	27.90	55.76	0.66	0.01183	2
	Sputnik	27.44	29.40	57.34	-1.52	-0.02650	7
United States of America	Johnson & Johnson	22.27	32.27	53.93	-2.93	-0.05432	15
	AstraZeneca	28.27	27.98	56.73	-1.91	-0.03366	12
	Pfizer	26.55	28.60	54.60	-3.42	-0.06263	16
	Moderna	26.79	28.26	55.07	-2.79	-0.05066	14
United Kingdom	AstraZeneca	25.74	26.96	52.74	-1.42	-0.02692	9
	Pfizer	26.13	28.31	53.77	-1.43	-0.02659	8
	Moderna	26.79	28.51	54.50	-1.54	-0.02825	10
France	AstraZeneca	28.02	30.27	58.90	-1.14	-0.01935	6
	Pfizer	28.75	29.51	58.74	-1.88	-0.03200	11
	Moderna	28.85	29.92	58.04	-2.12	-0.03652	13
Brazil	CoronaVac	29.79	29.97	59.83	-0.21	-0.00350	3
	AstraZeneca	29.63	30.16	59.79	-0.35	-0.00585	5
	Covaxin	29.61	29.55	59.70	-0.32	-0.00536	4

* Where Positive emotions score is the sum of emotion score of 3 positive sentiments i.e. trust, surprise, and pleasure denoted by P_1, P_2 and P_3
* Where Negative emotions score is the sum of emotion score of 3 negative sentiments i.e. anger, fear, and disgust denoted by N_1, $N_2$and N_3

Table 7 Vaccines with Top 5 Emotional Ranks in the three periods of study

Emotional rank	Time period T1	Time period T2	Time period T3
Emotional Rank 1	Brazil, Covaxin	India, Covaxin	India, Covaxin
Emotional Rank 2	France, Moderna	United States of America, AstraZeneca	India, Covishield
Emotional Rank 3	India, Covaxin	Brazil, CoronaVac	Brazil, CoronaVac
Emotional Rank 4	Brazil, AstraZeneca	Brazil, Covaxin	Brazil, Covaxin
Emotional Rank 5	India, Covishield	Brazil, AstraZeneca	Brazil, AstraZeneca

5.Discussion

In this section, we discuss the inferences that could be drawn from the results of the three exploratory and two subjective emotion-based studies, laid down in section 4 (section 5.1-5.3) and limitations of this study in section 5.4.

5.1 Inferences for the study on fighting the pandemic with vaccines – global statistical perspectives

The following interpretations can be derived from results presented in figures of section 4.1 about the five countries under study.

5.1.1 A Study of the new cases vs. vaccinations

It can be inferred from the *Figure 4 (a)* that after the vaccination drive in India started on 16th January 2021, the number of cases per day dropped considerably for approximately a month. By February 2021, daily cases had fallen to 9,000 per-day showing the positive outcome of vaccination drive. The numbers however soon started rising leading to the second wave, in March 2021 due to the factors such as new virus mutants, shortage of resources such as vaccinations, hospital beds, oxygen cylinders, and medicines in most parts of the country.

As per *Figure 4 (b),* United States of America reported more than 32,000 cases in April of last year, then the curve flattened, but new infections increased again in July. At its peak, the United States of America reported more than 70,000 cases in July 2020, nearly double the number of cases reported in the first wave. Following this, America's numbers continued to rise throughout the third wave. By January of this year, the United States of America was reporting about 300,000 cases each day as new infections soared nine-fold. However, the epidemic seems receding in the United States of America, due to a vigorous vaccination programme, and by the end of last month, new cases in the country had dropped by as much as 26%.

Figure 5 (a) shows the rate of daily cases in United Kingdom after the start of immunization program. It can be clearly seen that the curve of the cases declines significantly with the rise in the number of vaccinated people. *Figure 5 (b)* shows that the vaccinations in Brazil started amongst almost an epidemic rise in the COVID-19 cases. The rise in the cases could not be brought down as the number of vaccinations barely struggled to keep up with the number of new infections. However, in the last fortnight from 17th April – 03 May 2021 with the vaccination drive catching up, the number of cases can be seen declining. *Figure 5 (c)* shows that vaccinations in France were introduced during the second wave of COVID and during the third wave of COVID, around four months after the vaccinations were introduced, the number of new cases started falling.

5.1.2 A study of the deaths vs. vaccinations

Figure 6 (a) shows that India reported a maximum of 2000 deaths even before the first wave was officially declared. Though the deaths can be seen declining towards the end of the wave 1, after the introduction of vaccines the number of deaths was observed to have significantly decreased. The number of fatalities however skyrocketed in the initial phases of the second wave of the COVID-19 infection in India.

Figure 6 (b) shows the rate of daily deaths in US. The country recorded more than 2,000 deaths during the first wave in April 2020, and by January 2021, towards the peak of the third wave, the country was reporting about 4,000 deaths each day. It is noteworthy that despite introduction of vaccines in December 2020, the fatalities only started subsiding by April 2021.

Figure 6 (c) shows the dramatic increase in mortality during the first and third waves of the COVID-19 outbreak in the United Kingdom. However, there is a time between the middle of wave 1 and the beginning of wave 2 when the death toll becomes negligible. Mirroring the US, inspite of introduction of vaccines in December 2020, the number of deaths took around three months to drop. *Figure 7 (a)* shows a peculiar case where the rate of mortality in Brazil kept sharply increasing even after introduction of vaccines in January 2021. *Figure 7 (b)* shows the number of deaths per day during wave 1 in France as it progressed to its peak in mid-April 2020. However, soon after the dramatic lockdown throughout the nation, the daily death count had significantly decreased and had almost become insignificant. The number of fatalities began to increase when wave 2 slammed the nation. The vaccination campaign began on December 27, 2020, taking the number of peaks down. Wave 3, beginning March 2021 shows a much lower rate of fatalities.

5.1.3A study of the percentage of population vaccinated

Figure 8 (a) depicts the percentage of people vaccinated vs the number of days since the vaccination drive began in India. The figure reports low overall vaccination percentages, and significant drops in between, during the first three months, due to significant shortage of vaccinations. After picking up for a short period in April 2021, COVID-19 shots again dropped from an, due to reduced imports and low supply of the vaccination from the domestic firms. Till the completion of the study period, India was only able to immunize 9.5 percent of its 1.35 billion citizens.

Each state in the US was responsible for managing the launch of the vaccines, with vaccines being distributed to states based on population. The newly elected US administration signed an executive order that included expanded immunization supply and set an initial goal of 100 million doses during their first 100 days in office. This objective was accomplished on March 19, 2021. The US government established a new COVID-19 immunization goal on March 25, 2021, calling for 200 million injections to be given within the first 100 days of their administration. April 21, 2021, marked the final achievement of this goal, as shown by the consistently increasing vaccination rate shown in *Figure 8 (b)*.

With BioNTech or Pfizer's Comirnaty, AstraZeneca's AZD1222 and Moderna, the United Kingdom launched its immunization campaign on December 8, 2020. (MRNA-1273). The Pfizer-BioNTech COVID-19 vaccine was approved and used in a mass vaccination programme for the first time in the United Kingdom. One of the highest immunization rates in the globe by the beginning of 2021 was reported by the United Kingdom. Like United States of America, the percentage of vaccinated United Kingdom population shown in *Figure 8 (c)* shows an always increasing vaccination rate despite a small number of highs and lows.

CoronaVac and AstraZeneca were responsible for 77.3% and 15.9%, respectively, of all doses administered in Brazil during the period of study. By April 22, 202, 117.4% of Brazil's population had received either vaccine's first dose, or 7.1% had received its second. *Figure 9 (a)* demonstrates how the vaccination rate struggled for the first three months, finally picking up in mid-April 2021. The daily distribution of the vaccine to the populace of France is shown in *Figure 9 (b)*. After a low vaccination rate for two months, the vaccination rate continued to increase for the entire period of study.

5.2Inferences for emotional responses towards immunization drives: global perspectives

In time period 1 (start of the vaccination period in a country till April 2021) (*Table 1*), it can be seen that fear factor associated with the COVID-19 vaccines is highest for Moderna (11.60%), and Pfizer (10.45%), both in United States of America, followed by AstraZeneca (10.41%) in France. French citizens were most outraged against Pfizer (10.56%) and AstraZeneca (9.59%), with Brazilians joining them in their outrage against AstraZeneca (9.68 percent). The anticipation tally was also led by French for vaccines Moderna (11.05%), Pfizer (10.76%), followed by Covaxin (9.94%) in India. The most trusted vaccines were Moderna (11.00%) in France, Covaxin (10.22%) in India and Pfizer (10.01%) in France. Indians seemed most surprised by introduction of Sputnik V (9.75%) followed by Brazilians by AstraZeneca (9.64%) and French by Moderna (9.08%). Pfizer (10.9%) in United States of America, Sputnik (9.92%) in India and AstraZeneca (9.64%) in Brazil invoked sad responses in people. Interestingly, AstraZeneca (9.60%) invoked almost equal joy in Brazilians as the sadness, as noted above. Moderna (9.38%) in France and Covaxin in India (8.80%) also led the joyful responses of people around the world.

Three months later, in the time window June-Sept 2021 (*Table 2*), the fear factor tally was totally led by France: Pfizer (10.71%), Moderna (10.56%), and AstraZeneca (10.41%). The United Kingdom expressed anger against AstraZeneca (10.19%), while Brazilians joined them against Covaxin (10.11%) and AstraZeneca (10.02%). India and Brazil lead the anticipated tally for vaccinations Covaxin (9.88%) and CoronaVac (9.88%), followed by AstraZeneca (9.85%) in Brazil. Covaxin (11.04%), Covishield (10.97%) in India and AstraZeneca (10.72%) in United Kingdom were the most trusted vaccines. CoronaVac (9.87%) surprised the most Brazilians, followed by AstraZeneca (9.81%) and Covaxin (9.75%). People in Brazil were saddened by AstraZeneca (10.00%), Moderna (9.95%), and CoronaVac (9.93%) while CoronaVac (9.85%), AstraZeneca (9.80%), and Covaxin (9.78%) brought joy and AstraZeneca (9.92%), CoronaVac(9.86 %), Covaxin (9.76 %) caused distrust in Brazil.

In the third time period of study i.e., December-July 2022 (*Table 3*), the fear associated with COVID-19 vaccinations was greatest for Johnson & Johnson in the United States of America (11.82 %), followed by AstraZeneca in France (10.31 %) and the United States of America (10.12 %). Covaxin caused anger among Brazilians the most (10.56 %), followed by Moderna in the United Kingdom (10.24 %) and CoronaVac in Brazil (10.01 %). Anticipations ran high for CoronaVac (9.86 %) and AstraZeneca (9.81%) in Brazil, and Moderna (9.8) in United Kingdom. AstraZeneca was the most trusted vaccine in United Kingdom (10.96%) and France (10.54%), while Indians trusted Covaxin (10.50 %). CoronaVac (9.88 %) and AstraZeneca (9.83 %) appeared to surprise Brazilians the most, while SputnikV (9.80 %) surprised Indians the most. The French were most saddened with AstraZeneca (10.54 %), followed by Americans with Johnson & Johnson (10.45 %) and Brazilians with AstraZeneca (10.12 %). Covaxin (9.87 %), CoronaVac (9.85 %), and AstraZeneca (9.78 %) have made Brazilians the happiest people in the world.

The above inferences are both useful and interesting. However, the task of drawing such inferences from so many statistics is time consuming, subjective, and leads to low comprehension. It will be more useful to restructure this information, and derive aggregated information that may provide some alternate, aggregated and abstracted view of this knowledge. This is the subject matter of discussion in Section 6.

5.3 Inferences for the study on studying the emotional and sentimental impressions of vaccines

Figure 10 shows a study of the number of vaccines eliciting any kind of emotions, quantified in the range 0- 100%, divided in class intervals of size 5. The quantification of emotions is achieved by the metric Emotion Evocation. The study is performed over three time periods of study i.e., time period 1(Start of vaccination in the respective country – April 2021), time period 2 (June - September2021), and time period 3 (December - April 2022). Only in the first time period less than 50% emotion evocation response is seen for eight out of the sixteen vaccinations studied across five nations.

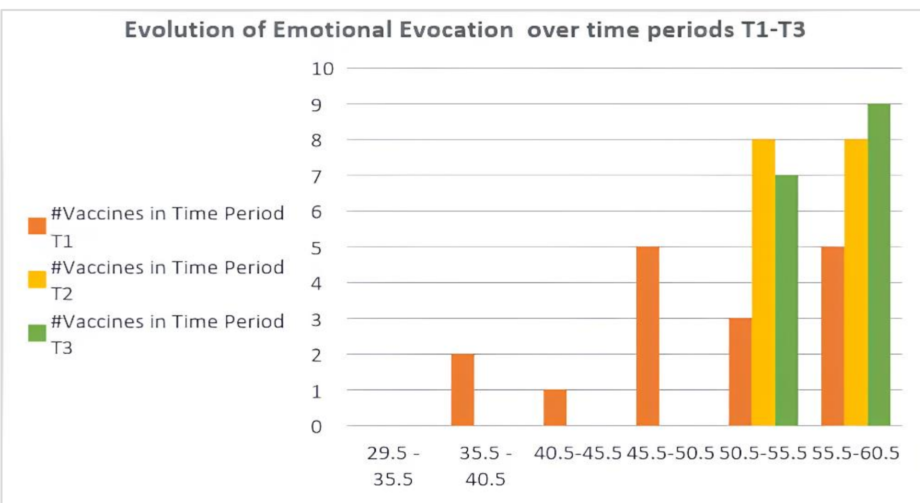


Figure 10 Evolution of emotional evocation of sixteen vaccines in five countries over one and a half years

In the second and third time period the vaccines elicited 50% - 60% emotional responses. No vaccine could however evoke responses less than 30% or more than 60%.

Figure 11 shows most of the vaccines, in all the three time periods of study depicted a negative valence. In particular only two out of sixteen vaccines studied showed positive valence in each time period. In the time period the two vaccines were Covaxin in Brazil and Moderna in France. In the second time period the vaccines with positive valence again included Covaxin, but this time in India and AstraZeneca in United States of America. In the third time period again India's Covaxin and Covishield got a positive response. From *Figure 11*, it can be also be inferred that most of the vaccines elicited lot of negative emotional response from the people. Only two vaccines per time period show a positive response and stand an exception to the former finding. Another interesting inference was that many vaccines, however, showed an improvement in their positive valence the three time periods of study.

Figure 12 shows a comparison of the emotional intensities of the vaccines over the three periods of study. As concluded from the previous figure, Figure 10, vaccines introduced in India and United Kingdom can be seen to have got improved emotional responses from time period T1 to T3. While in United States of America, France and Brazil the emotional intensities of the vaccines keep on varying. Covaxin, both in India and Brazil depicts highest emotional intensities, followed by Moderna in France and AstraZeneca in United States of America. Vaccines in the United States of America show least positive emotional intensities. Johnson and Johnson (United States of America) shows the least emotional intensity in T2, followed by Pfizer, Moderna and AstraZeneca in T1. *Table 7* shows the names of the vaccines with highest five emotional ranks in three time periods of study. Covaxin leads the emotional rank in all time periods. While Brazil leads the charts in time period T1, in Time periods T2 and T3 in India's Covaxin takes over as the number one positive emotion bagger. Moderna in France, AstraZeneca in United States of America and Covishield in India hold the second rank in Time periods T1, T2 and T3 respectively. The third rank in the time periods T1 is held by India's Covaxin but taken over by Brazil's CoronaVac in T2, and T3.

Brazil can be seen all over the rank 4 with its vaccine AstraZeneca in Time period T1, followed by Covaxin in T2 and T3. Fifth emotional rank is held by India's Covishield in T1 followed by Brazil's AstraZeneca in time periods T2 and T3. It is easy to conclude from the *Table 7* that out of all the vaccines studied Covaxin (introduced in India, Brazil) has been the highest influencer of people's emotions, followed by AstraZeneca (Brazil, United States of America), Covishield (India) and CoronaVac (Brazil). France's Moderna also finds a place in the top five tally of emotional rankers once.

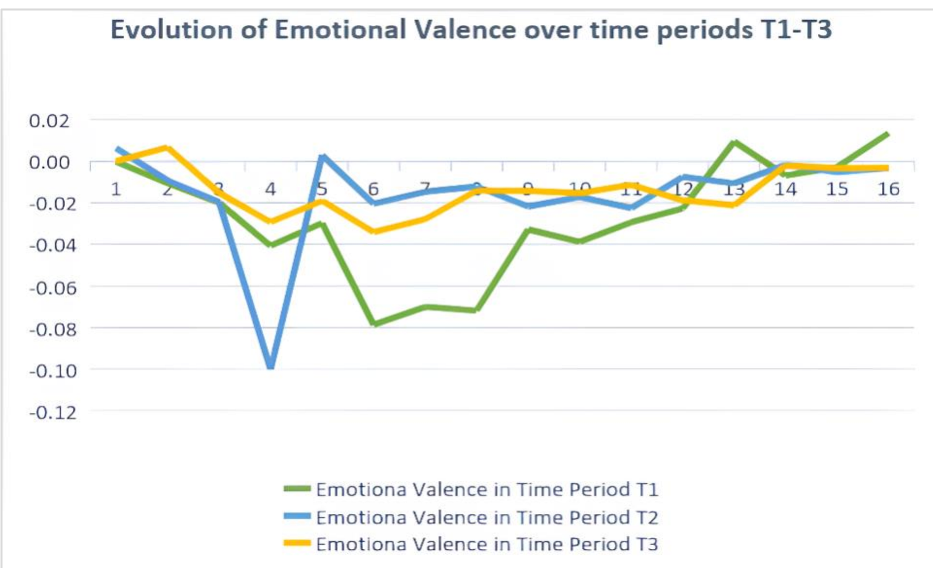


Figure 11 Evolution of emotional valence of sixteen vaccines in five countries over one and a half years

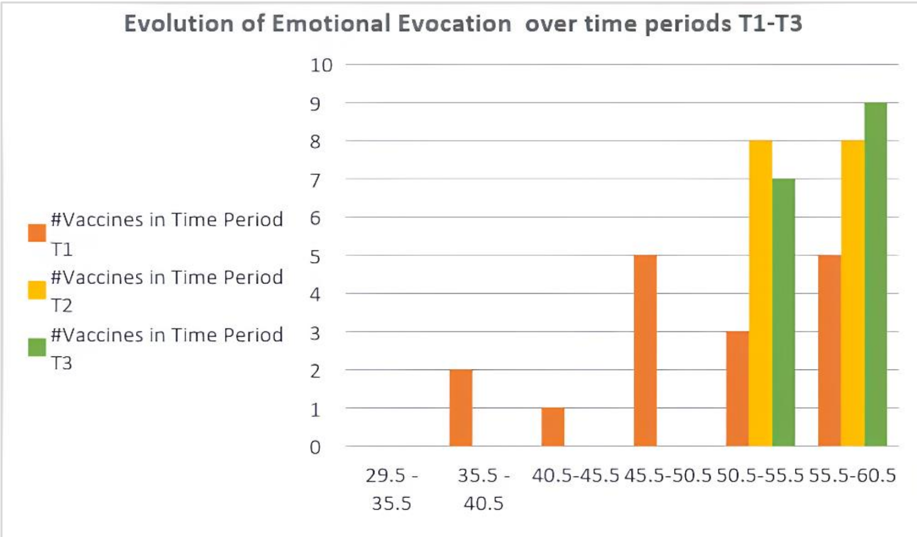


Figure 12 Evolution of emotional intensity of sixteen vaccines in five countries over one and a half year

5.4Limitations of the current study

The current study is based on data collected for three specific time windows and from five selected countries. The scope of the study can be expanded to cover longer durations and a greater number of countries to enhance its comprehensiveness. In this research, the focus was solely on the study of emotions, and emoticons were removed during the preprocessing phase. Future studies could explore how the inclusion of emoticons might enrich the understanding of emotional perspectives. Additionally, for a more holistic subjective analysis, investigating sentimental perspectives alongside emotional ones could provide deeper insights into public sentiment and reactions. A complete list of abbreviations is shown in *Appendix I*.

6.Conclusion and future work

The research presented in this paper aims to highlight the importance of understanding, quantifying, and leveraging human emotions to address issues like anxiety, fear, and inherent skepticism about government action plans designed to combat emergent situations. This work represents a novel step in a relatively unexplored area of research, particularly within the machine learning community, focusing on using quantified emotions to support decision-making during critical times, such as a pandemic. The proposed framework is designed to extract and analyze the emotional responses of the general public from five countries concerning the vaccines introduced in their regions to combat the novel coronavirus. This approach seeks to provide valuable insights that can enhance the effectiveness and acceptance of crucial public health initiatives.

These responses are aggregated, modelled over three time-windows, covering almost a year and a half, in accordance with the principle of knowledge differentiation. Novel metrics are proposed for this task that quantify the valence, reach and intensity of emotional responses of people to aid objective decision making, in a quick glance. Noticeable, beneficial results were drawn from the framework at both the lower and higher abstraction levels. Inferences at lower levels unearthed the vaccines and countries that lead the emotions such as the fear, anger, anticipation, surprise, sadness and joy. Knowledge nuggets at the higher level of abstraction yielded consolidated, restructured results. For instance, one glance conclusions about the vaccines that could evoke most emotions amongst the sixteen vaccines studied across five countries and their emotional valence could be readily drawn, quantified in numerical ranges and compared over the time of one and a half years. Some other interesting inferences could also be readily drawn. The magnitude of emotions aroused by any vaccine lied in the range of 30%-60%. In the first time period i.e., time of the vaccination introduction in a particular country to April,2021, around eight out of the sixteen vaccinations showed less than 50% emotional response. Whilst, in the second time period (June 2021- September2021) and the third time period (December 2021 - April 2022), the vaccines elicited 50% - 60% emotional responses. Similarly, it could be concluded that most of the vaccines, in all the three time periods of study depicted a negative valence. In fact, only two out of sixteen vaccines studied showed positive valence in each time period. Positivity of vaccines introduced in India and United Kingdom got improved from time period T1 to T3, while in United States of America, France and Brazil the emotional intensities of the vaccines kept on varying. It is easy to see that conclusion drawn such as these, can enable objective, quick glance aid to decision making, as claimed at the outset of this paper.

A purely statistical, data exploratory study has also presented in the paper to help understand the effect of vaccines in terms of other important facets such as the new cases, number of deaths, and the percentage of people vaccinated in the five countries under study, namely, India, United States of America, United Kingdom, Brazil, and France. Such a study completes and sets the context for the study of emotions.

In future, the work can be extended to include other novel metrics that may allow comparison of individual emotions amongst themselves. It will be also interesting to characterize and quantify the sentiments and see the interplay of emotions and sentiments together, i.e., their corroboration and contradiction to each other.

Acknowledgment
None.

Conflicts of interest
The authors have no conflicts of interest to declare.

Author's contribution statement
Sarabjeet Kaur Kochhar: Conceptualization, writing – original draft, review and editing, analysis and interpretation of results. **Shruti Jain, Megha Karki, Gunjan Rani:** Data collection, Investigation, Data curation, implementation. **Vibha Gaur:** Study conception, design, supervision, investigation on challenges and draft manuscript preparation.

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Appendix I

S. No.	Abbreviation	Description
1	AI	Artificial Intelligence
2	API	Application Programming Interface
3	BERT	Bidirectional Encoder Representations from Transformers
4	BLSTM	Bidirectional Long Short-Term Memory
5	CFCNN	Channel-Frequency Convolutional Neural Network
6	CNN	Convolutional Neural Network
7	COVID	Coronavirus Infectious Disease
8	EEG	Electroencephalogram
9	ENSS	Expanded Nursing Stress Scale
10	FDA	Food and Drug Administration
11	LSTM	Long Short-Term Memory
12	MHRA	Medicines and Healthcare products Regulatory Agency
13	NaN	Not a Number
14	NLTK	Natural Langauge Toolkit
15	NLP	Natural Language Processing
16	NSW	New South Wales
17	RQA	Recurrence Quantification Analysis
18	SVM	Support Vector Machine
19	TF-IDF	Term Frequency-InverseDocument Frequency
20	TWINT	Twitter Intelligence Tool
21	WHO	World Health Organization