Analysis of International Public Emotional Responses Toward the COVID-19 Vaccine

Satoshi Fukuda
Faculty of Science and Engineering
Chuo University
Tokyo, Japan
fukuda.satoshi.3238@kc.chuo-u.ac.jp

Hidetsugu Nanba
Faculty of Science and Engineering
Chuo University
Tokyo, Japan
nanba@kc.chuo-u.ac.jp

Hiroko Shoji
Faculty of Science and Engineering
Chuo University
Tokyo, Japan
hiroko@kc.chuo-u.ac.jp

***Abstract*— The pharmaceutical companies developing the COVID-19 vaccine and national governments continuously disseminate information regarding the vaccine's effectiveness and vaccination status to reassure the public about vaccination. However, because interest in vaccines and vaccination status vary between the populations of different countries, it is likely that emotional responses toward vaccines also vary between countries. The current study analyzed and compared the emotions expressed by people in Japan, the United States, Great Britain, Canada, Australia, and India regarding the vaccine by analyzing tweets, on the basis of the Plutchik's wheel of emotions. In addition, a textual analysis was conducted using dependency analysis and burst detection to obtain information regarding positive changes in people's feelings toward vaccines. Our approach was useful for clarifying the emotional responses of people in various countries regarding the vaccine, and informing approaches for positively changing people's feelings about vaccines.**

Keywords—Twitter, Sentiment Analysis, COVID-19 Vaccine

I. INTRODUCTION

As of 2022, the outbreak of novel coronavirus disease 2019 (COVID-19) is still spreading around the world, and continues to have a significant impact on people's lives. To date, various policies have been implemented to control the spread of COVID-19, including mask-wearing recommendations and lockdowns. Among these policies, vaccination has received a large amount of public interest internationally, and vaccine development by pharmaceutical companies and promotion of vaccination by governments are underway. Pharmaceutical companies and national governments are constantly disseminating information such as the effect of the vaccine and vaccination status to reassure people. However, public impressions and emotional responses toward vaccines vary. While some people feel comfortable with vaccination, others are apprehensive or hesitant because the COVID-19 vaccine is a relatively new technology and factors such as effectiveness and future risk are not yet known. Some regions and municipalities are behind in their preparations for vaccination, causing frustration or concern for some individuals. Whereas others may not be concerned by some delays because of government announcements of vaccination status, including the number of people vaccinated per day. In addition, vaccination rates vary from country to country, possibly because of differences in the interest and perception of vaccination among different national populations. To increase a social acceptability of vaccination internationally, it is important to understand the emotional responses of people in various countries toward the vaccine and the factors that cause these emotions.

We therefore analyzed the emotional responses expressed regarding the COVID-19 vaccine over time in Japan, United States, Great Britain, Canada, Australia, and India, and investigated the differences and commonalities in the emotional responses in these countries. The emotions followed Plutchik's wheel of emotions [1] which includes eight primary emotions (Joy, Sadness, Anticipation, Surprise, Anger, Fear, Disgust, and Trust) and secondary emotions combined with specific primary emotions. As a data source, we used data from tweets posted on Twitter, which is one of the most popular tools for posting text regarding individual situations and feelings in real time internationally. For an analysis of the emotions expressed in tweets, we used the binary classifiers trained on the labeled dataset. From the classification results, we found that "Fear" was commonly expressed in Japan, "Anger" and "Disgust" were commonly expressed in the United States, Great Britain, Canada, and Australia, and "Joy" was commonly expressed in India. We then measured the correlation between changes in the daily ratio of tweets between two emotions and the similarity between two emotions based on the classification results of the tweets to reveal the relationship between emotions expressed by people regarding the vaccine. As a result, we confirmed that "Anger" and "Disgust" were intrinsically correlated, and that "Joy" and "Anticipation" tended to be independent of each other in all countries. Moreover, "Joy" and "Sadness," which are located as opposite emotions in Plutchik's wheel of emotions, exhibited a positive correlation in terms of the transitions of the daily ratio of tweets in Japan and Great Britain. These analyses are helpful for recognizing the commonly expressed emotions toward vaccines internationally, and identifying the unique patterns of emotions expressed in different countries.

To obtain information regarding positive changes in people's feelings toward vaccine, we analyzed tweets in two cases: when the tweets with "Joy" increased in India, and when the tweets with "Joy" and "Sadness" simultaneously increased in Japan, using dependency analysis and burst detection. In the former case, we found that the dissemination of information about vaccines through an app developed by the Indian government may be linked to "Joy." In the latter case, we found the case that people expressed opposite emotions at the same time, even in relation to the same event, depending on each person's situation. These findings will be useful for informing approaches to promote vaccination worldwide.

II. Related Work

In recent years, many studies have analyzed changes in emotional responses toward COVID-19 and vaccination over time. Hussain et al. [2] developed a classification approach for identifying public concerns and sentiments toward the COVID-19 vaccine in United States and United Kingdom, and conducted a time-series analysis of sentiment change. Their approach used BERT [3] and two lexical-based methods (VADER [4] and TextBlob [5]) to classify texts posted on Twitter and Facebook along three axes: Positive, Neutral, and Negative. They then analyzed the relationship between world events and the increase or decrease in the prevalence of text classified into each emotional category over time, as well as the intensity of emotions at the state or regional level. Yousefinaghani et al. [6] used VADER to make Positive or Negative decisions regarding tweets about the COVID-19 vaccine in the United States and United Kingdom, and extracted keywords that appeared in each sentiment. They then defined the categories "anti-vaccine," "hesitant," and "pro-vaccine," and the keywords associated with the categories for opinions about the vaccine, and analyzed the volume of tweets for each category in each country. Hu et al. [7] analyzed how sentiments and opinions about vaccines have changed in the United States by splitting the time-frame by two events regarding the vaccine that occurred between March 1, 2020 and February 28, 2021; clinical trials of Moderna and the first dose of the COVID-19 vaccine administered. They used three sentiments (Positive, Neutral, Negative) in VADER and eight emotions in Plutchik's wheel of emotions from NRCLex [8], which is an emotion association dictionary for emotion analysis, as well as using latent Dirichlet allocation [9] and word cloud mapping for opinion analysis. Wang et al. [10] analyzed controversial topics against opinions on mask wearing and vaccination using latent Dirichlet allocation in the United States. In this approach, they analyzed how interest in the topic changed using the sentiment score calculated by TextBlob, and to infer the factors that caused the sentiment score to fluctuate by comparing it to the actual events related to COVID-19. Our study analyzes the differences and common elements in the emotions expressed by people in various countries. We also obtained useful information for developing approaches to encourage the development of positive feelings toward the COVID-19 vaccine by analyzing tweets from people expressing positive feelings toward the vaccine.

III. Analysis Approach

A. Collection of Tweet Data

To collect Japanese tweet data, we used the Twitter Search API. The data were collected from June 13, 2021 to November 30, 2021, using "ワクチン(vaccine)" as the query. English tweet data were obtained from the dataset[1] constructed by DeVerna et al. [11]. This dataset contains IDs of tweets collected using 76 vaccine-related English keywords, divided by date until October 11, 2021. We analyzed the set of tweets from June 13, 2021 to October 11, 2021. We then classified tweets on the basis of the country code assigned to each tweet and included countries with a total of 30,000 or more tweets in our analysis. Table I shows the number of tweets in each country. Note that retweets were excluded.

TABLE I. Total Number of Tweets by Countries

Country	***Total Number of Tweets***
Japan	24,292,412
United States	325,743
Great Britain	58,462
Canada	47,097
Australia	35,274
India	32,337

B. Classification Model

As a classification method for tweets, we used machine learning by binary classification. We describe the dataset and parameter settings used to construct the classifiers, as well as the classification performance for each emotion, below.

- Dataset

For the classification of Japanese tweets, we used the Japanese emotion analysis dataset compiled by Kajiwara et al. [12]. This dataset contains 43,200 texts posted on social networking services labeled with Plutchik's eight emotions on four levels of emotional intensity (none, weak, medium, and strong). In addition, the labels included five types: one applied by the writer of the text, three applied by three readers of the text, and one by averaging the emotional intensities assigned by the three readers. We used 40,000 data for training, 1,200 data for validation, and 2,000 data for evaluation. Labels representing the average emotional intensity by the three readers were used, with weak, medium, and strong emotional intensity being positive, and none being negative.

For the classification of English tweets, we used the English emotion analysis dataset from the Emotion Classification (E-c) task, which is included in the dataset distributed in SemEval 2018 Task 1: Affect in Tweets [13]. This dataset contains 6,838, 886, and 3,259 data sets for training, validation, and evaluation, respectively, and each text posted on a social networking service is labeled with 11 different emotions (Anger, Anticipation, Disgust, Fear, Joy, Love, Optimism, Pessimism, Sadness, Surprise, Trust). We used eight of the eleven emotions (Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, and Trust) to unify our classification with the emotion labels used in the dataset of Kajiwara et al.

- Parameter Settings

We used BERT [3] as a classification model. Parameters were set to 32 for batch size, 5 for epochs, 1e-5 for learning rate, and 128 for the number of tokens, and Adam [14] was used for optimization. For the learning model in the construction of the Japanese classifiers, we used a language model additionally trained on the Japanese BERT. Specifically, we trained bert-based-japanese-whole-word-masking [2] using 3,000,000 Japanese tweets as training data and 300,000 Japanese tweets as verification data that were randomly selected from the tweets from June 13, 2021 to November 30, 2021. For the learning model in the construction of the English classifiers, we used a language model additionally trained on the English BERT.

[1] https://zenodo.org/record/5563154

[2] https://huggingface.co/cl-tohoku/bert-base-japanese-whole-word-masking

Specifically, we trained bert-base-uncased [3] using 3,000,000 tweets as training data and 300,000 tweets as verification data that were randomly selected from the tweets from June 13, 2021 to October 11, 2021 collected using tweet IDs in [11]

C. Classification Performance

Table II shows the classification performance for each emotion in Japanese and English. These classifiers were used to classify the tweets collected in Section III-A. Note that URL and username beginning with @ were removed from the tweets, and each tweet could be classified into multiple emotions because of the binary classification of each emotion.

D. Our Approach for Comparing and Analyzing Emotions

Our analysis comprised two approaches: comparison of relationships between emotions based on the classification results from the emotion classifier described in Section III-B, and text analysis using a set of tweets classified as reflecting a specific emotion. Each approach is described in detail below.

- Comparison of Relationships Between Emotions

We measured the relationships between emotions on the basis of the classification results of tweets in each country using two calculation methods. One measured the correlation rate between emotions by Pearson’s correlation coefficient. This method was measured based on ratios of tweets expressing an emotion to the daily set of tweets. The other method measured the similarity between emotions using the Dice coefficient based on two sets of tweets with emotion labels. Plutchik's wheel of emotions defines secondary emotions by combining eight different emotions. The higher the correlation between the two emotions based on the transitions of the ratio of tweets and the results of the tweet classification, the clearer people’s inherent coexisting emotions toward COVID-19 vaccines. Combining those emotions could then reveal more complex emotions. Furthermore, comparison of the results of the analyses in different countries can elucidate the common emotions that people in various countries share toward vaccines as well as the unique emotions expressed by people in each country.

- Text Analysis Approach

Our text analysis method used the dependency relation and burst detection, and comprised two steps. First, dependency analysis was performed for the tweets, and dependency relationships were extracted from each tweet. Then, for each emotion, burst detection for each dependency relation was performed on the basis of the number of tweets that the dependency relationship extracted from the tweet set with the emotion and the number of tweets with the emotion label for each day. Compared with word-based methods, this method was able to more easily capture the factors that led to an increase in tweets with a certain emotion. We used spaCy [4] as the dependency parsing tool, ja_ginza[5] for the Japanese model, and en_core_web_sm[6] for the English model. For burst detection, we used Kleinberg’s method [15]. The parameters of Kleinberg’s burst detection for Japanese and foreign tweets were manually set to $\gamma = 20$, $s = 2$ and $\gamma = 2$, $s = 2$, respectively.

TABLE II. CLASSIFICATION PERFORMANCE OF EACH EMOTION

	Japanese		***English***	
	Recall	***Precision***	***Recall***	***Precision***
Joy	0.773	0.784	0.751	0.903
Sadness	0.652	0.661	0.531	0.802
Anticipation	0.758	0.843	0.169	0.447
Surprise	0.623	0.508	0.159	0.403
Anger	0.417	0.435	0.787	0.781
Fear	0.400	0.688	0.709	0.793
Disgust	0.457	0.608	0.737	0.766
Trust	0.147	0.579	0.007	0.200

IV. ANALYSIS RESULTS

A. Classification Results and Comparison of Relationships Between Emotions

Figs. 1 to 6 show the weekly average of the ratio of tweets with an emotion to the daily number of tweets for the six countries, respectively. The data shown in these figures suggest that the main emotions toward vaccines in each country fall into three types. Overall, “Fear” was commonly expressed in Japan. In contrast, “Anger” and “Disgust” were commonly expressed in the United States, Great Britain, Canada, and Australia. “Joy” was commonly expressed in India.

The Pearson’s correlation coefficient and Dice coefficient values between emotions in each country are shown in Tables III through VIII. The values in the cells above the shaded line are the Pearson’s correlation coefficients, and the values in the cells below the shaded line are the Dice coefficients. The data in the tables suggest that all countries shared a strong correlation between “Anger” and “Disgust” in the transition of the tweet ratio, and a high rate of simultaneous labeling of tweets. Here, examining the combination of emotions in Plutchik's wheel of emotions, the secondary emotion from the combination of “Anger” and “Disgust” is defined “Contempt.” Therefore, if people expressed “Anger” or “Disgust” regarding a vaccine event, they may simultaneously express the other emotion or “Contempt.” In countries other than India, in which the correlation between the transition of the ratio of tweets in “Joy” and “Anticipation” was relatively high, the rate of simultaneous labeling of tweets was not so high. In Plutchik's wheel of emotions, the secondary emotion resulting from the combination of “Joy” and “Anticipation” was “Optimism.” We infer that people may not necessarily have optimistic feelings regarding the vaccine. In Japan and Great Britain, the values of Pearson’s correlation coefficients between “Joy” and “Sadness” were relatively high (0.722 and 0.315, respectively), whereas Dice coefficients were low (0.027 and 0.010, respectively) as shown in Tables III and V. From these results, it can be inferred that “Joy” and “Sadness” events regarding vaccines were independent, and that these events occurred simultaneously.

B. Text Analysis to Obtain Useful Information for Encouraging Positive Feelings Toward Vaccines

In this section, we describe case studies of text analysis using dependency analysis and burst detection to obtain useful information regarding approaches for positively changing

[3] https://huggingface.co/bert-base-uncased
[4] https://spacy.io/
[5] https://megagonlabs.github.io/ginza/
[6] https://spacy.io/models/en

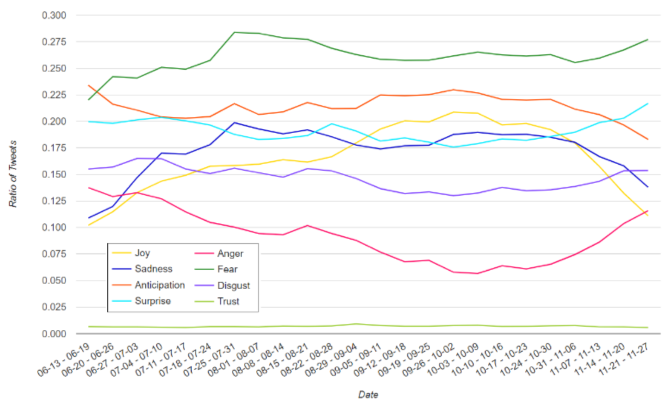

Fig. 1. Ratio of tweets with each emotion label in Japan.

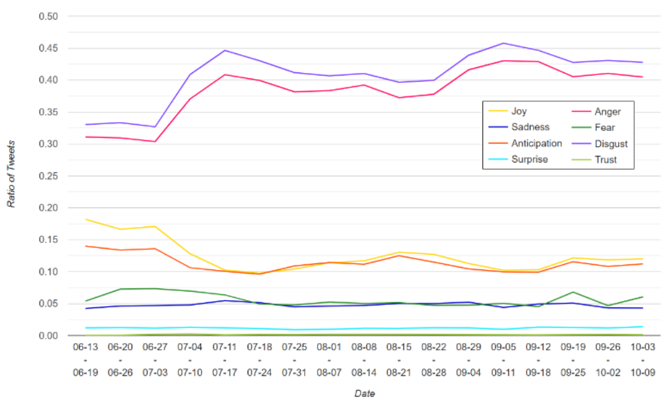

Fig. 2. Ratio of tweets with each emotion label in United States.

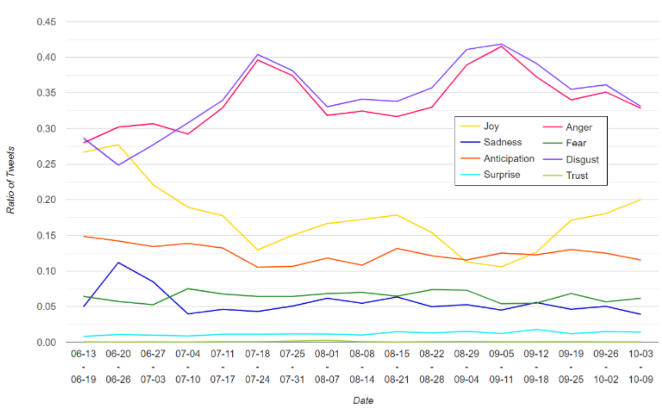

Fig. 3. Ratio of tweets with each emotion label in Great Britain.

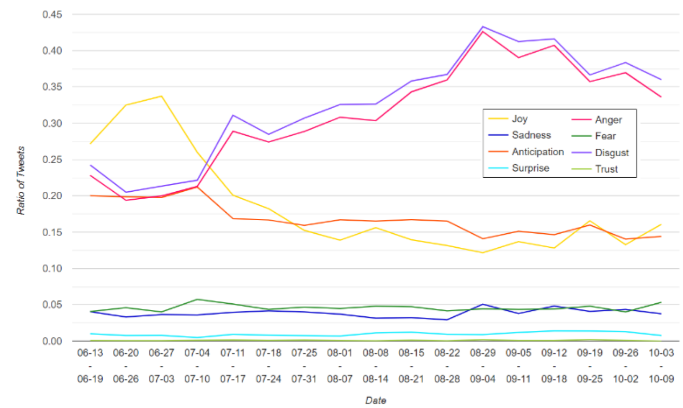

Fig. 4. Ratio of tweets with each emotion label in Canada.

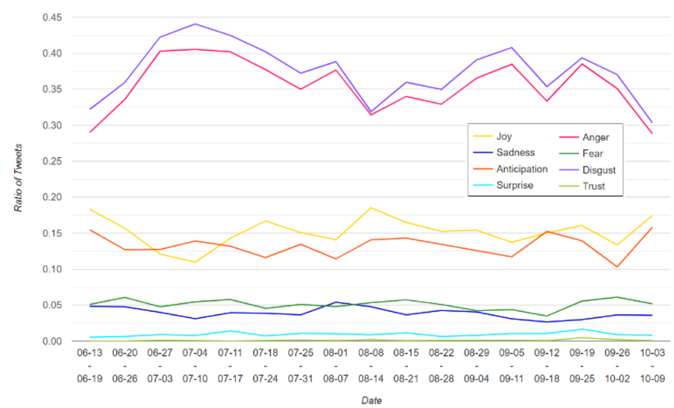

Fig. 5. Ratio of tweets with each emotion label in Australia.

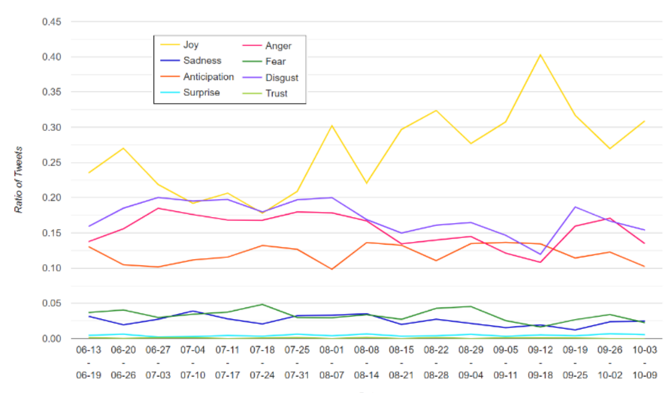

Fig. 6. Ratio of tweets with each emotion label in India.

emotional responses toward the COVID-19 vaccine. Here we show the results of our analysis of "Joy" tweets in India, and in Japan, indicating that the ratio of "Joy" and "Sadness" tweets increased simultaneously.

First, Table IX shows examples of the dependency relations in which bursts were detected during the periods of August 1 to August 6, August 22 to August 28, and September 12 to September 18, 2021, when the ratio of "Joy" tweets peaked in India. From Table IX, we infer that tweets regarding vaccination status are often posted. More detailed examination revealed that the dependency relations; (India, crossed), (vaccine doses, of), (the total number, crossed), and (the second highest country, becomes), detected in the period from August 1 to August 6 in Table IX, were obtained from the vaccine-related news title, "India crossed the total number of vaccine doses administered in the country. With the 47 crore doses administered, India becomes the second highest country in the world to vaccinate the masses." The dependency relations; (at least one dose, got), (50%, got), and (Vaccine milestone, reached), detected in the period from August 22 to August 28, were obtained from the news title, "Vaccine milestone reached: 50% have got at least

TABLE III. THE VALUES BY PEARSON'S CORRELATION COEFFICIENT (UPPER RIGHT) AND BY DICE COEFFICIENT (LOWER LEFT) BETWEEN EMOTIONS IN JAPAN.

	Joy	Sad ness	Antici pation	Surp rise	Anger	Fear	Dis gust	Trust
Joy		0.722	0.477	-0.723	-0.902	0.092	-0.707	0.396
Sadness	0.027		0.095	-0.522	-0.640	0.536	-0.271	0.193
Anticipation	0.384	0.084		-0.582	-0.381	-0.324	-0.447	0.275
Surprise	0.146	0.206	0.065		0.687	-0.068	0.597	-0.405
Anger	0.005	0.130	0.062	0.193		-0.213	0.862	-0.342
Fear	0.049	0.478	0.120	0.310	0.191		0.032	-0.057
Disgust	0.006	0.429	0.040	0.228	0.528	0.396		-0.309
Trust	0.069	0.003	0.021	0.017	0.002	0.002	0.001	

TABLE IV. THE VALUES BY PEARSON'S CORRELATION COEFFICIENT (UPPER RIGHT) AND BY DICE COEFFICIENT (LOWER LEFT) BETWEEN EMOTIONS IN UNITED STATES.

	Joy	Sad ness	Antici pation	Surp rise	Anger	Fear	Dis gust	Trust
Joy		-0.275	0.746	0.089	-0.795	0.297	-0.825	-0.136
Sadness	0.006		-0.304	0.013	0.066	0.075	0.116	-0.030
Anticipation	0.212	0.004		0.110	-0.641	0.158	-0.702	-0.062
Surprise	0.034	0.005	0.026		0.030	0.097	0.008	0.081
Anger	0.025	0.088	0.037	0.016		-0.280	0.973	0.020
Fear	0.010	0.099	0.034	0.026	0.098		-0.222	0.151
Disgust	0.016	0.089	0.040	0.014	0.884	0.103		0.037
Trust	0.005	0.000	0.001	0.000	0.000	0.001	0.000	

TABLE V. THE VALUES BY PEARSON'S CORRELATION COEFFICIENT (UPPER RIGHT) AND BY DICE COEFFICIENT (LOWER LEFT) BETWEEN EMOTIONS IN GREAT BRITAIN.

	Joy	Sad ness	Antici pation	Surp rise	Anger	Fear	Dis gust	Trust
Joy		0.315	0.330	-0.197	-0.731	-0.150	-0.825	-0.214
Sadness	0.010		-0.055	-0.101	-0.071	-0.234	-0.401	0.003
Anticipation	0.230	0.006		-0.027	-0.384	-0.113	-0.365	-0.248
Surprise	0.025	0.006	0.027		0.144	0.060	0.143	-0.073
Anger	0.013	0.122	0.036	0.021		-0.107	0.861	0.101
Fear	0.012	0.124	0.036	0.024	0.114		0.065	0.088
Disgust	0.008	0.087	0.039	0.019	0.867	0.126		0.122
Trust	0.002	0.000	0.000	0.000	0.000	0.000	0.000	

one dose." The dependency relations; (India, sets), (PM's birthday, on), and (Covid-19 vaccines, for), detected in the period September 12 to September 18, were obtained from "With 2.5 crore jabs on PM's birthday, India sets new record for Covid-19 vaccines." In addition, some of the tweets including these news titles included the text "via NaMo App," which also appeared in Table IX. NaMo App is the official distribution system of Prime Minister Narendra Modi and provides the latest information regarding the Prime Minister and his government. The app also sends out news about vaccinations, and such information can be tweeted on Twitter by users of the NaMo App. In addition, examination of tweets extracted the relation (a single day, in), detected from August 22 to August 26 and September 12 to September 18, revealing that many tweets praising the 100 and 200 million people vaccinated in a single day were posted, respectively.

TABLE VI. THE VALUES BY PEARSON'S CORRELATION COEFFICIENT (UPPER RIGHT) AND BY DICE COEFFICIENT (LOWER LEFT) BETWEEN EMOTIONS IN CANADA.

	Joy	Sad ness	Antici pation	Surp rise	Anger	Fear	Dis gust	Trust
Joy		-0.163	0.583	-0.189	-0.842	0.009	-0.855	-0.027
Sadness	0.005		-0.226	-0.086	0.181	0.087	0.164	0.250
Anticipation	0.250	0.004		-0.164	-0.673	-0.008	-0.667	0.014
Surprise	0.022	0.003	0.018		-0.035	-0.123	0.287	-0.004
Anger	0.018	0.097	0.045	0.014		-0.043	0.978	0.039
Fear	0.007	0.097	0.029	0.023	0.094		-0.019	0.151
Disgust	0.012	0.096	0.050	0.014	0.876	0.100		0.037
Trust	0.002	0.000	0.001	0.000	0.000	0.000	0.000	

TABLE VII. THE VALUES BY PEARSON'S CORRELATION COEFFICIENT (UPPER RIGHT) AND BY DICE COEFFICIENT (LOWER LEFT) BETWEEN EMOTIONS IN AUSTRALIA.

	Joy	Sad ness	Antici pation	Surp rise	Anger	Fear	Dis gust	Trust
Joy		-0.090	0.419	0.125	-0.654	-0.011	-0.662	0.022
Sadness	0.010		-0.154	-0.172	0.001	0.228	-0.036	-0.251
Anticipation	0.172	0.004		0.005	-0.513	-0.100	-0.475	0.052
Surprise	0.026	0.005	0.020		0.068	-0.043	0.045	0.204
Anger	0.015	0.096	0.046	0.015		-0.053	0.952	-0.077
Fear	0.009	0.093	0.036	0.020	0.094		-0.047	-0.088
Disgust	0.009	0.098	0.051	0.013	0.890	0.098		-0.054
Trust	0.003	0.000	0.001	0.000	0.000	0.002	0.000	

TABLE VIII. THE VALUES BY PEARSON'S CORRELATION COEFFICIENT (UPPER RIGHT) AND BY DICE COEFFICIENT (LOWER LEFT) BETWEEN EMOTIONS IN INDIA.

	Joy	Sad ness	Antici pation	Surp rise	Anger	Fear	Dis gust	Trust
Joy		-0.281	-0.208	0.011	-0.573	-0.330	-0.559	-0.042
Sadness	0.002		-0.001	0.060	0.134	0.120	0.073	0.099
Anticipation	0.116	0.002		0.078	-0.043	0.020	-0.115	0.047
Surprise	0.007	0.006	0.010		-0.035	-0.123	0.287	-0.118
Anger	0.004	0.102	0.015	0.013		0.144	0.890	0.020
Fear	0.003	0.077	0.022	0.011	0.104		0.172	-0.160
Disgust	0.003	0.097	0.021	0.011	0.808	0.114		-0.018
Trust	0.002	0.000	0.001	0.000	0.000	0.000	0.000	

TABLE IX. DEPENDENCY RELATIONS WHERE BURSTS WERE DETECTED IN THE SET OF TWEETS CLASSIFIED AS "JOY" IN INDIA.

Period	Dependency Relation
August 1 - 6	(NaMo App, via), (India, crossed), (vaccine doses, of), (the total number, crossed), (the second highest country, becomes)
August 22 - 28	(NaMo App, via), (at least one dose, got), (50%, got), (Vaccine milestone, reached), (a single day, in)
September 12 - 18	(NaMo App, via), (a single day in), (India, sets), (PM's birthday, on), (Covid-19 vaccines, for)

In Japan, our analysis revealed that the ratios of "Joy" and "Sadness" tweets were increased in the period between July 25 and July 31, 2021. For the tweet sets classified as "Joy" and "Sadness" during this period, the dependency relation (ワクチン接種券，届い) ((vaccination ticket, delivered)) was included in common in the dependencies extracted by the burst detection.

Here, when examining the tweets from which (vaccination ticket, delivered) was extracted, we found that in “Joy” tweets, many users reported that they had received a vaccination ticket. Conversely, in “Sadness” tweets, there were many tweets about not having received the vaccination ticket, or having received it but not being able to make an appointment, which was different from “Joy.” We also examined the time-series trends of the occurrence of tweets with (vaccination ticket, delivered) in the “Joy” and “Sadness” tweets. The daily ratios of tweets expressing “Joy” and “Sadness” are shown in Fig. 7. It can be seen that the ratios of tweets in both emotions peaked in late June and early July, and that the transitions of both emotions were almost identical. These results suggest that the opposite emotions may be simultaneously increased, even in response to the same event, depending on people’s physical or psychological situation, and that this is one of the reasons for the high correlation coefficient between “Joy” and “Sadness” shown in Table III. Moreover, in the event of the dispatch of vaccination ticket, the improvement in the distribution of vaccination ticket and reservation system could lead to an increase in the number of people who express secure and positive feelings about vaccines from the two types of tweet sets that expressed the opposite emotions of “Joy” and “Sadness.”

V. Conclusion

We analyzed the differences and commonalities in emotional responses toward COVID-19 vaccination among people in Japan, the United States, Great Britain, Canada, Australia, and India by classifying tweets and using Pearson’s correlation coefficients and Dice coefficients. Our analysis results revealed that “Fear” was commonly expressed in Japan, “Anger” and “Disgust” were commonly expressed in the United States, Great Britain, Canada, and Australia, and “Joy” was commonly expressed in India. The results also suggested an intrinsic correlation between “Anger” and “Disgust,” whereas “Joy” and “Anticipation” tended to be independent of each other. In addition, “Joy” and “Sadness,” which are represented as opposite emotions in Plutchik's wheel of emotions, were confirmed to be positively correlated in terms of the transitions of the ratios of tweets in Japan and Great Britain.

We additionally analyzed the “Joy” tweet set in India and the “Joy” and “Sadness” tweet sets in Japan using dependency analysis and burst detection. In India, we found that the dissemination of information about vaccines through an Indian government application could be linked to “Joy.” In Japan, we found that (vaccination ticket, delivered) was detected for both emotions. We analyzed the tweets from which we extracted each dependency relation in more detail, and found that many “Joy” tweets reported that “I had received the vaccination ticket” in response to the event of the delivery of the vaccination ticket,” and many “Sadness” tweets reported that “I have not received my vaccination ticket” and “I received my vaccination ticket, but I can’t make an appointment.” These results suggest that the same event can simultaneously arouse opposite emotions, depending on each person’s situation. In addition, our findings indicated that solving the problems described in “Sadness” tweets could lead a person to express “Joy” instead. This approach is useful for obtaining useful data to inform approaches for encouraging positive feelings toward vaccination.

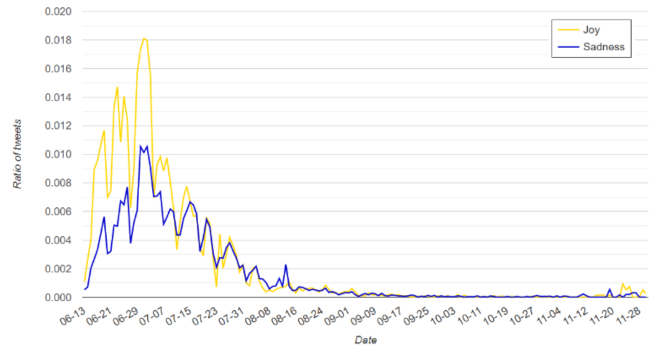

Fig. 7. Transitions in the ratio of tweets expressing “Joy” and “Sadness” from which (vaccination ticket, delivered) were extracted.

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