Changes in Interests and Emotional Responses to News Coverage of Coronavirus Disease 2019 Case Numbers Over Time

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***Abstract*—Understanding how people's interest and emotional state change in response to news coverage of a particular topic and elucidating the characteristics of these changes can reveal the shifting nature of attention and emotion. We analyzed people's interest and emotional responses expressed via Twitter in response to news coverage of announcements of new cases of coronavirus disease 2019 (COVID-19) as a case study. As a measure of interest, we examined replies to tweets of news items posted by media outlets on Twitter, and classified the emotional content of each reply tweet using Plutchik's wheel of emotion. The analysis suggested that people were most interested in COVID-19 case numbers in April 2020, when the first wave of cases occurred and the first emergency declaration was issued, and in July 2020, when the second wave of cases emerged. The results revealed that fear was the most commonly expressed emotion. The ratio of fear-related tweets was highest in February and March 2020, a time at which new COVID-19 cases were confirmed in various locations and there was substantial public discussion regarding whether Japan would declare a state of emergency for the first time.**

Keywords—Twitter, Sentiment Analysis, COVID-19

I. INTRODUCTION

For unknown events that are of interest to a larger people, media may report every time there is some progress and event to be covered. For example, the coronavirus disease 2019 (COVID-19) outbreak that emerged in December 2019 was a novel event with global consequences, and various media outlets reported a range of related news items on a daily basis. In addition to television and newspapers, in recent years, news has been increasingly distributed through news websites and social networking services. Unfamiliar negative events often cause widespread anxiety. Ongoing news coverage can lead people to develop a deeper understanding and awareness of an event. As understanding and awareness of an event increases, some people may feel relieved. However, awareness of new problems related to the event or ongoing problems that persist may cause more interest, and some individuals may continue to feel anxious. We have an interest for understanding how people' interest and emotional responses change over time in response to news reports of specific events, and elucidating the characteristics of these changes. This information might be useful for supporting people who feel anxious, leading them to develop a sense of emotional security.

To investigate this issue, we examined the reporting of new positive cases of COVID-19 as a case study to analyze changes in people's interest and emotional responses to news coverage. In Japan, since January 2020, the Ministry of Health, Labour and Welfare has announced the number of new COVID-19 cases in each prefecture daily. Following the announcement, the Japanese media has reported the number of new positive cases as a news item, through television, newspapers, news sites and social networking services. Fig. 1 shows an example of a tweet posted on Twitter by the Yahoo!News account (username: @YahooNewsTopics). Some tweets of news headlines report the number of cases in Tokyo, and some provide additional information, such as the increase or decrease in the number of new cases compared with the previous case number. Additionally, users may tweet comments and opinions about the news in the form of replies to news tweets. In the current study, we examined news tweets posted by Yahoo!News on Twitter and users' reply tweets to analyze changes in people's interest and emotional responses regarding announcements of the number of new cases of COVID-19.

II. RELATED WORK

Over the course of the COVID-19 pandemic, a range of events have occurred, including the confirmation of COVID-19 in various locations, the discovery of COVID-19 variants, and the implementation of government policies such as vaccination, promotion of mask use, and lockdowns. Furthermore, COVID-19 has had a significant impact on education and the economy, and has been a common topic of conversation in daily life and in the media. In response, in recent years, many studies have identified various topics addressed during the COVID-19 pandemic, and have analyzed how people and media feel about each topic, and how their feelings have changed over time.

De et al. [1] conducted sentiment analysis on news articles and tweets to identify changes in sentiment and topics addressed over time in their analysis of the impact of COVID-19 in Brazil. Ghasiya et al. [2] analyzed news articles on COVID-19 in four countries (United Kingdom, India, Japan, and South Korea) using top2vec [3] and RoBERTa [4] to determine which topics were covered and how sentiment on each topic differed across countries. Additionally, a number of sentiment analysis studies have focused on specific themes and topics during the COVID-19 pandemic. Bhagat et al. [5] applied sentiment analysis to blog and newspaper articles using TextBlob [6] with the goal of identifying public opinion toward online learning during the COVID-19 pandemic. Wang et al. [7] analyzed controversial topics related to mask wearing and vaccination using latent Dirichlet allocation [8] in the United States. Specifically, the researchers analyzed how interest in the topic changed using the sentiment score calculated by TextBlob and inferred the factors that caused the sentiment score to fluctuate by comparing the changes to the actual events related to COVID-19. Hu et al. [9] analyzed how

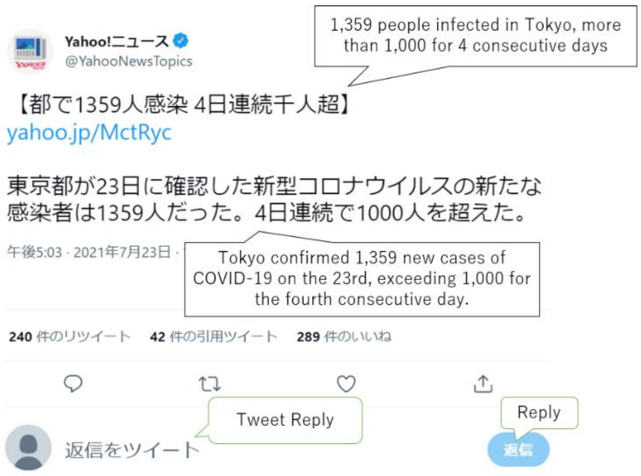

Fig. 1. Example of a tweet regarding news of new cases of COVID-19 by Yahoo!News on Twitter

sentiments and opinions about vaccines 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 the Moderna vaccine, and the administration of the first dose of the COVID-19 vaccine in the United States. Yousefinaghani et al. [10] used VADER [11] to make positive or negative classifications of a set of tweets regarding the COVID-19 vaccine in various countries, including the United States, United Kingdom, and Canada, and extracted keywords that appeared in each sentiment. They then defined the categories "anti-vaccine," "hesitant," and "pro-vaccine" and the keywords associated with each category, and analyzed the volume of tweets for each category in each country. In the current study, we focused on news coverage of announcements of the number of new cases on Twitter, which were regularly reported during the COVID-19 pandemic, to determine how interest in and feelings about the topic changed over time. By examining reply tweets to news reports, we focused directly on interest in and feelings about this topic.

III. Methodology

Our analytical approach comprised two main components: 1) collecting tweets posted by news accounts on Twitter and replies to those tweets; and 2) sentiment analysis and word extraction for each reply tweet. Each of these steps is described in detail below.

A. Tweet Data Collection

The corpus of the tweet set was constructed as follows. First, tweets posted by a particular news account were collected via the Twitter application programming interface. At the same time, tweets that were replies to the tweets posted by the account were collected. Specifically, we used the account name of a news site beginning with @ as a query and collected tweets that contained it. We named the former set of tweets the news tweet set, and the latter the reply set. Then, using the tweet ID information that shows the reply-to tweet included in each tweet in the reply set, each tweet in the reply set was linked to the corresponding tweet in the news tweet set.

We used Yahoo! News (username: @YahooNewsTopics) as the news site account under examination. The collection period was from February 1, 2020, when the number of positive COVID-19 cases began to be announced, to May 31, 2022. From this dataset, news tweets regarding the announcement of the number of new positive COVID-19 cases and tweets that were replies to those tweets were extracted, and emotional analysis and word extraction were performed on each reply tweet. As described in Section I, news tweets regarding the announcement of the number of new cases may include information regarding the increase or decrease in new cases compared with previously reported case numbers. We therefore compared how people's interest and emotional responses changed in response to such statements in news tweets. To achieve this, the following query was used to identify tweets posted by Yahoo!News. Note that not all news tweets centered on the announcement of new COVID-19 cases were covered, and other news tweets may have been included.

Query 1: コロナ AND 東京都 AND 感染 AND 新た AND [0-9]+人
(In English: corona AND Tokyo AND infected AND new AND [0-9]+ person)
Query 2: コロナ AND 東京都 AND 感染 AND 新た AND [0-9]+人 AND (下回 OR 減っ OR 減少)
(In English: corona AND Tokyo AND infected AND new AND [0-9]+persons AND (down OR decrease OR decline))
Query 3: コロナ AND 東京都 AND 感染 AND 新た AND [0-9]+人 AND (上回 OR 増え OR 増加)
(In English: corona AND Tokyo AND infected AND new AND [0-9]+person AND (up OR increase OR larger))

B. Sentiment Analysis and Lexical Extraction

As a dataset for classification, we used the Japanese emotion analysis dataset[1] compiled by Kajiwara et al. [12]. This dataset contains 43,200 texts posted on social networking services labeled with Plutchik's eight emotions [13] on four levels of emotional intensity (none, weak, medium, and strong). Additionally, the labels included five types: one applied by the writer of the text, three applied by three readers of the text, and one that was constructed 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 identified by the three readers were used, with weak, medium, and strong emotional intensity being positive, and none being negative.

As a classification model, we used BERT [14]. Parameters were set to 32 for batch size, 5 for epochs, 1e-5 for learning rate, and 128 for the number of tokens. Adam [15] was used for optimization. As a learning model, we used bert-based-japanese-whole-word-masking[2].

Table I shows the classification performance for each emotion. These classifiers were used to classify the reply tweets. Note that each reply tweet could be classified into multiple emotions because of the binary classification of each emotion.

Next, each news tweet was divided by month and the number of replies was counted by month. Then, the number of tweets from which the word was extracted and the number of users who posted those tweets for each emotion-category

[1] https://github.com/ids-cv/wrime

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

TABLE I. CLASSIFICATION PERFORMANCE

EMOTION	RECALL	PRECISION
JOY	0.799	0.710
SADNESS	0.409	0.702
ANTICIPATION	0.745	0.803
SURPRISE	0.519	0.577
ANGER	0.229	0.423
FEAR	0.203	0.742
DISGUST	0.042	0.923
TRUST	0.000	0.000

were counted by month. By comparing the number of tweets from which a word was extracted with the number of users who posted the corresponding tweets, it was possible to verify whether the word had generality. For example, if the number of tweets and the number of users were almost equal, the extracted word was considered to have generality, and if the number of users was very small, the word was assumed to have been generated by a specific person or group.

IV. RESULTS AND DISCUSSION

A. Distribution of News Tweets

Fig. 2 shows the transitions of the number of tweets collected by Queries 1, 2, and 3 in the news site set and the number of new COVID-19 cases in Tokyo in the open data set available on the Ministry of Health, Labour and Welfare website[3]. From Query 1 (as shown in Fig. 2), news tweets about the announcement of the number of new cases peaked in July 2020, with 49 tweets posted. In that month, the number of new COVID-19 cases increased for the second time, and this period was known as the second wave in Japan. The news tweets included news items that only announced the number of new cases, as well as news items that included the number of new cases accompanied by a call to action by the government and Tokyo Metropolitan Government for the public to limit their behavior and their views regarding COVID-19. In May 2020, September 2020, and December 2021, the number of news tweets identified using Query 1 showed a decrease. These periods roughly coincided with periods in which there were decreases in the number of new cases.

A comparison of Query 1 and Query 3 revealed that the news tweet trends were similar until February 2022, whereas the news tweet trends identified using Query 2 and Query 3 appeared to conflict. A comparison of the trends in Query 2 and 3 and the number of new cases revealed that the number of news tweets matching Query 2 increased during the period in which the number of new cases was decreasing, and the number of news tweets matching Query 3 increased during the period in which the number of new cases was increasing. However, in the period after February 2022, the results indicated that the transition between Query 1 and Query 2 was similar than the transition between Query 1 and Query 3. These results suggest that until February 2022, there were more news reports about the increase or the highest number of new cases of COVID-19 compared with the past, and after February 2022, reports about the decrease in the number of new cases became dominant.

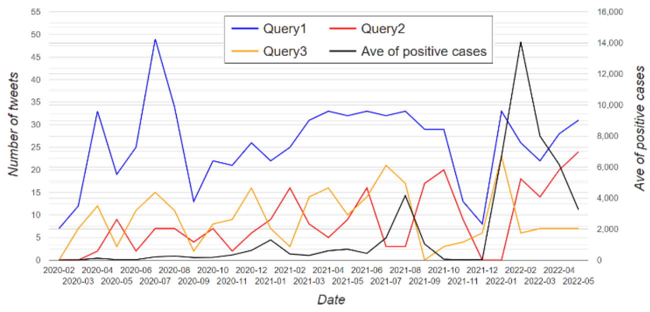

Fig. 2. Number of tweets collected by Queries 1–3 in the news site set

B. Distribution of Reply Tweets

Fig. 3 shows the number of tweets replying to news tweets in each month collected by each query, and the number of new COVID-19 cases in Tokyo. The transition of Query 1 in Fig. 3 shows that the number of replies peaked in April 2020 and July 2020. Japan had its first and second waves of COVID-19 infections in April and July 2020, respectively. Table II shows some of the nouns (phrases) extracted from reply tweets in April and July 2020 collected by Query 1. The numbers to the left and right in parentheses indicate the number of tweets and users from which the word or phrase was extracted, respectively. In Table II, the term "emergency declaration" appeared in April 2020. In Japan, the government issued emergency declarations in the period from April to May 2020. This suggests that the increase in reply tweets in April 2020 was caused by a lack of information about COVID-19 and the fact that the public had not experienced a declaration of a state of emergency before, and, therefore, were highly interested in the event. Additionally, the term “emergency declaration” also appeared in July 2020. In that month, no emergency declarations were issued in Japan, but the number of new cases had begun to increase. These results suggest that the increase in reply tweets in July 2020 may have been primarily caused by discussions among the public about declaring a state of emergency in response to the increase in the number of new cases. Incidentally, the word "Phone" in April 2020 in Table II appeared in tweets that replied to a tweet containing the news item entitled "Of the 118 people newly confirmed infected by the Tokyo Metropolitan Government on April 4, nearly 70% have no known route of infection. It is particularly difficult to identify the route of infection in the younger age groups, and the public health center said that they do not answer our phone calls for interviews." ("東京都が 4 日新たに感染確認した 118 人のうち、7 割近くが感染経路不明。特に感染経路の特定が難しいのが若年層で、保健所からは「聞き取り調査のための電話に出てくれない」との声。) Many of the reply tweets expressed opinions and impressions of the interview methods for younger people. Although this news title contained information about new cases, the main topic was the identification of the route of infection among young people. In future, additional approaches should be considered for selecting only news tweets that primarily announced the number of new cases.

3 https://www.mhlw.go.jp/stf/covid-19/open-data.html

TABLE II. EXAMPLE OF WORDS EXTRACTED FROM REPLY TWEETS COLLECTED USING QUERY 1

2020-04			2020-07		
Word	Num of Tweets	Num of Users	Word	Num of Tweets	Num of Users
infect	341	312	infect	280	251
phone	299	297	goverment	209	179
emergency declaration	245	223	emergency declaration	202	170
self-restraint	197	188	counter-measure	174	158

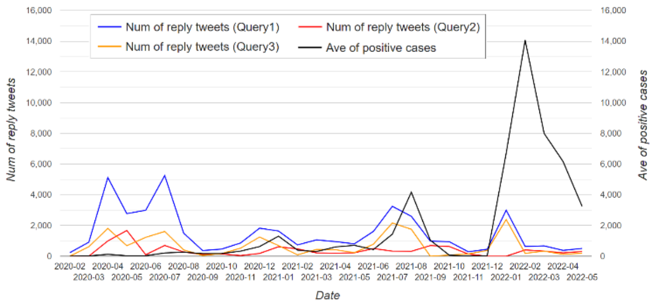

Fig. 3. Number of tweets replying to the tweets in the reply set

Subsequently, increases in the number of replies were found in December 2020, July 2021, and January 2022. These periods correspond to the months before peak in third, fifth, and sixth wave for number of new positive cases, respectively (i.e., the timing of the increase in the number of new cases). Additionally, as in Fig. 2, the transitions for Query 1 and Query 3 were similar, while those for Query 1 and Query 3 appeared to conflict. These results indicate that the media and public interest in the announcement of the number of new COVID-19 cases was related to the increase in the number of new positive cases.

C. Sentiment Analysis Results for Reply Tweets

Fig. 4, Fig. 5, and Fig. 6 show the ratio of tweets with each emotional label relative to the number of tweets in each month for each reply tweet in Queries 1, 2, and 3. In Fig. 4 through to Fig. 6, "Fear," "Surprise," and "Anticipation" were the main emotions expressed. In particular, the comparison of classification results shown in Table I revealed that "Fear" was the main emotion expressed, despite its lower classification accuracy compared with "Anticipation" and "Surprise". These results indicate that "Fear" was a commonly expressed emotional response to reports of the number of new positives.

Specifically examining the transition of "Fear," Query 1 indicated that the ratio of "Fear" tweets was very high in February and March 2020. In addition, in November 2020 and January 2022, the ratio of "Fear" tweets increased compared with the previous 2 months, indicating a peak in the ratio of tweets. The same tendency was observed for "Fear" in Figure 6 (Query 3). Table III shows some of the words extracted from the "Fear" reply tweets in February 2020, March 2020, November 2020, and January 2022 in Query 1, and Table IV shows some of the words extracted from the "Fear" reply tweets in March 2020, November 2020, and January 2022 in Query 3. Table III shows that in February 2020, the words "facility," "elderly," and "nursing home" appeared. In March 2020, the terms "hospital," "hospital infection," and

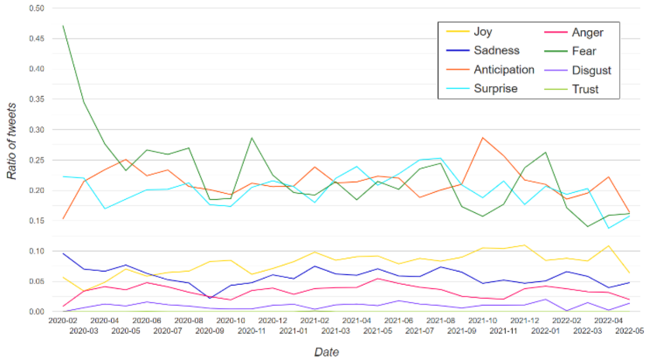

Fig. 4. Ratios of tweets with each emotion label replying to the tweets in Query 1

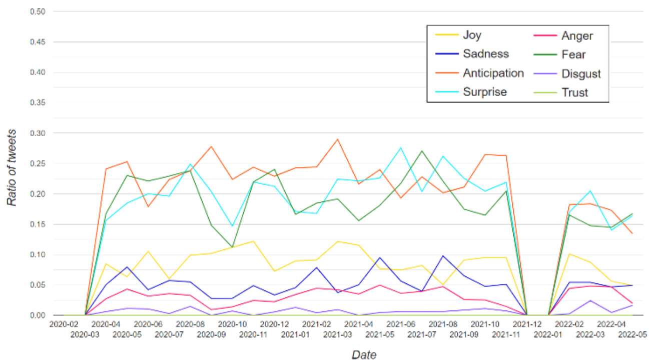

Fig. 5. Ratios of tweets with each emotion label replying to the tweets in Query 2

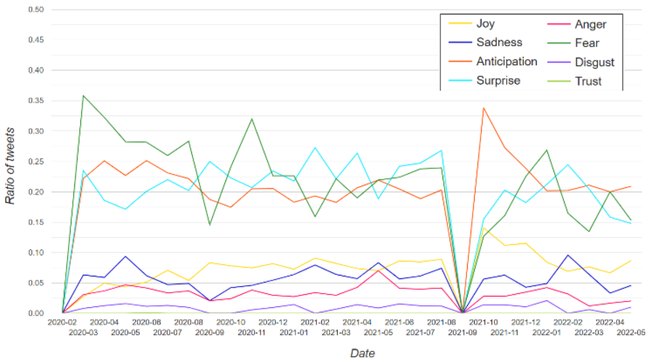

Fig. 6. Ratios of tweets with each emotion label replying to the tweets in Query 3

"medical collapse" were identified, as shown in Tables III and IV. In February and March, COVID-19 cases were identified in nursing homes and hospitals, respectively, and these cases made headlines in Japan. Furthermore, in March 2020, as shown in Table 4, the term "emergency declaration" appeared. In Japan, the first emergency declaration was issued by the government in April 2020. However, the results indicate that the topic had been talked about since the previous month, when the number of new cases increased. These findings indicate that the reason for the appearance of expressions of "Fear" among the people was related to the increase in the number of new COVID-19 cases and their discovery in various locations, as well as the emergency declaration, which was an event that had not previously been experienced in Japan. The results shown in Tables III and IV also indicated that the term "emergency declaration" appeared in both

TABLE III. EXAMPLES OF WORDS EXTRACTED FROM REPLY TWEETS EXPRESSING "FEAR" COLLECTED USING QUERY 1

2020-02			2020-03		
Word	Num of Tweets	Num of Users	Word	Num of Tweets	Num of Users
infect	25	24	infect	55	54
facility	13	13	hospital	20	20
elderly	12	12	medical collapse	16	14
nursing home	8	8	hospital infection	15	15
2020-11			**2022-01**		
Word	Num of Tweets	Num of Users	Word	Num of Tweets	Num of Users
infect	40	35	infect	103	96
seriously illness	18	16	cold (illness)	79	73
emergency declaration	15	15	emergency declaration	56	49
government	11	11	omicron	45	38

TABLE IV. EXAMPLES OF WORDS EXTRACTED FROM REPLY TWEETS EXPRESSING "FEAR" COLLECTED USING QUERY 3

2020-03		
Word	Num of Tweets	Num of Users
infect	30	29
self-restraint	12	12
emergency declaration	11	11
hospital	10	10

2020-11			2022-01		
Word	Num of Tweets	Num of Users	Word	Num of Tweets	Num of Users
infect	30	26	cold (illness)	66	62
emergency declaration	11	11	seriously illness	54	46
counter-measure	9	9	emergency declaration	40	36
mask	8	6	omicron	33	31

November 2020 and January 2022. In these months, the number of new positive cases began to increase, but no emergency declarations were issued in Japan at the time. This finding suggests that each time the number of new cases increased, emergency declarations became a topic of conversation, possibly leading to expressions of "Fear".

The ratio of tweets for each emotion in October and November 2021 in Query 1 (as shown in Fig. 4) revealed that "Anticipation" exhibited the highest value. The results revealed similar patterns for Query 2 (as shown in Fig. 5) and Query 3 (as shown in Fig. 6). Examples of words extracted from "Anticipation" reply tweets collected by Queries 1, 2, and 3 in October and November 2021 are shown in Tables V–VII, respectively. The words “vaccine” and “vaccination” appear in each of these tables. The Japanese government has promoted vaccination of its citizens since April 2021, and implemented policies such as distribution of vaccination coupons and development of a COVID-19 vaccination appointment system. Vaccination is one of the policies of great interest to Japanese people in the fight against COVID-19, and the total number of vaccinations exceeded 100 million by August 2021[4]. In addition, in October and November 2021, the number of new cases decreased. The results described above suggest that the increase in expressions of anticipation during this period could potentially be attributed to the greater number of people becoming hopeful about the effectiveness of the vaccine for decreasing the number of new cases.

TABLE V. EXAMPLES OF WORDS EXTRACTED FROM REPLY TWEETS EXPRESSING "ANTICIPATION" COLLECTED USING QUERY 1

2021-10			2021-11		
Word	Num of Tweets	Num of Users	Word	Num of Tweets	Num of Users
vaccine	15	15	vaccine	9	7
vaccination	15	8	spread of infection	5	5
infection	13	11	6 wave	5	5
6 wave	12	9	mask	5	5

TABLE VI. EXAMPLES OF WORDS EXTRACTED FROM REPLY TWEETS EXPRESSING "ANTICIPATION" COLLECTED USING QUERY 2

2021-10			2021-11		
Word	Num of Tweets	Num of Users	Word	Num of Tweets	Num of Users
vaccination	11	6	vaccine	6	5
election	9	9	spread of infection	5	5
Infect	9	8	mask	3	3
vaccine	8	8	6 wave	2	2

TABLE VII. EXAMPLES OF WORDS EXTRACTED FROM REPLY TWEETS EXPRESSING "ANTICIPATION" COLLECTED USING QUERY 3

2021-10			2021-11		
Word	Num of Tweets	Num of Users	Word	Num of Tweets	Num of Users
emergency decralation	2	2	6 wave	4	4
death	2	2	vaccine	3	3
treat	2	2	stay home	2	2
infect	2	2	increase	2	2

V. CONCLUSION

We analyzed changes in interest in and feelings about news items on Twitter using the topic of new cases of COVID-19 as a case study. Replies to news tweets were used to investigate this topic. The results revealed that people in Japan exhibited the highest level of interest in April 2020, when the first wave of new cases occurred in the country and the first emergency declaration was issued, and in July 2020, when the second wave of new cases emerged. We also conducted emotion classification of the tweets on the basis of Plutchik’s wheel of emotion and found that "Fear" was the most commonly expressed emotion. In particular, the ratio of tweets expressing fear was very high in February and March 2020, possibly because of the occurrence of the first increase in the number of COVID-19 cases in various locations, and interest in the first emergency declaration. Additionally, the highest ratios of tweets expressing a feeling of anticipation occurred in October and November 2021, likely because of interest in the effectiveness of vaccination and the decrease in the number of new positive cases.

[4] https://www.kantei.go.jp/jp/content/vaccination_data5.pdf

In future, we plan to analyze changes in interest in and feelings about news topics other than COVID-19, such as climate change and automated driving technology. News regarding the number of new COVID-19 cases is often described in factual terms, and the sentiment of the news media is less likely to be expressed. In contrast, for topics such as emergency declarations and vaccinations, the media often express their opinions and arguments through editorials. Thus, we also plan to analyze and compare changes in interest and sentiment between the media and the public.

ACKNOWLEDGMENTS

This work was supported by the Chuo University Research Cluster Formation Support Program in FY2021 and JSPS KAKENHI Grant Number JP22K18152.

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