An Analysis of Shifts in Public Interests and Sentiments in Japan Using News Tweet Data during the COVID-19 Pandemic

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***Abstract*—Identifying the topics that interested and moved people during the COVID-19 pandemic can shed light on societal trends. Uncovering these topics can answer questions such as what induced positive feelings in a climate of widespread anxiety caused by COVID-19? How did COVID-19-induced anxiety change? Did other topics induce more anxiety than COVID-19? We analyzed shifts in people's interest in and sentiments about topical events that reported in Japan during the COVID-19 pandemic from February 2020 to May 2022. We did so using tweets posted by news sites on Twitter and replies to those tweets. Specifically, we performed topic analysis on news tweets to identify topics focusing on real-world events. We then counted the number of replies to each tweet on a topic and visualized how people's interests changed. We performed sentiment analysis on reply tweets to assess whether people expressed positive or negative feelings about the news and examined how each topic evolved according to the numbers of positives and negative responses. We found that the Tokyo Olympics and celebrity marriages were hot topics prompting positive sentiments, negative sentiments may be shifting from topics related to COVID-19 to the Ukraine–Russia conflict, and people's interests may be primarily in negative events that evoke negative feelings.**

***Keywords*—Sentiment Analysis, Topic Analysis, Twitter**

I. Introduction

The COVID-19 outbreak that first emerged in December 2019 was one of the most transformative events of 2020 and beyond, with the topic of new COVID-19 infections dominating the news. Between January and March 2020, when the topic of COVID-19 first captured public attention, COVID-19 aroused negative feelings [1] and a great deal of anxiety for many people. Subsequently, reports on the numbers of new positive COVID-19 cases and the promotion of mask wearing and vaccinations against the COVID-19 gained momentum, arousing public interest and sentiments relating to these topics on a daily basis. At the same time, major global events occurred beyond COVID-19, notably the Tokyo Olympics in 2021 and the Ukraine–Russia conflict in 2022. In addition to these events, various domestic events and incidents occurred that were also reported. Therefore, people's interests and sentiments may have shifted to various topics other than those related to COVID-19. We aimed to ascertain people's interests, the topics that induced positive and negative feelings during the COVID-19 pandemic. This analysis can be shed light on overall social trends during the pandemic, the topics that induced positive feelings, and the events that were viewed more negatively than COVID-19. In addition, identified events that evoked positive feelings among many people in an anxiety-inducing context such as the pandemic can be widely shared within society and may serve as a resource for reducing psychological anxiety.

We used news tweets and reply tweets to those tweets posted on Twitter as our data for to analyzing topics that rose to prominence during the COVID-19 pandemic and people's interests and feelings regarding these topics. In recent years, with the advance of the Internet and the spread of social networking services (SNS), various news sites have procured official accounts on Twitter to disseminate information more widely. It is now easy to post comments and opinions about the news topics posted on their news accounts as replies on Twitter. Topic analysis can be performed on tweets posted by news sites to clarify topics about real-world events. Moreover, the number of replies on each topic can be aggregated and visualized to examine how people's interests have changed. In addition, sentiment analysis on a set of reply tweets can be performed to examine whether positive or negative feelings were expressed on the news topic. Thus, it is possible to obtain an overview of topics that have aroused people's feelings without analyzing all tweets. Furthermore, the news articles on the events that triggered people's interest and feelings about a particular topic can be easily referenced, as each tweet posted on the news account is directly linked to the reply tweets. Here, we demonstrate the effectiveness of our analytical approach in conducting a multifaceted analysis using news tweets and reply tweets posted by Yahoo! News, one of the best-known news sites in Japan, on Twitter during an extended period from February 2020 to May 2022. Through the experiments, we found that the Tokyo Olympics and celebrity marriages were hot topics prompting positive sentiments, and people's interests and negative sentiments may be shifting from topics related to COVID-19 to the Ukraine–Russia conflict.

II. Related Work

Many studies have analyzed changes in people's feelings relating to COVID-19. Saito and Haruyama [2] analyzed sentimental shifts in residents of New York, Los Angeles, and Chicago in response to infection conditions and state government orders during the COVID-19 pandemic. The authors examined the comparison between sentimental changes and the number of new positive COVID-19 cases and related events. Hussain et al. [3] developed an approach for identifying and categorizing public concerns and sentiments toward the COVID-19 vaccine in the United States and United Kingdom, Moreover, they conducted a time-series analysis of changes in sentiments. Wang et al. [4] analyzed controversial topics related to mask-wearing and vaccination in the United States using Latent Dirichlet Allocation (LDA) [5], examined how interest in the topics analyzed changed over time using sentiment scores calculated by TextBlob [6], and considered the factors that were caused scores to fluctuate.

Other studies have analyzed both news and tweets. De Melo and Figueiredo [7] performed a sentiment analysis of the impact of COVID-19 in Brazil using news articles and tweets to identify changes in sentiment and topics over time. Evans et al. [8] compiled news tweets about COVID-19 posted on the Twitter accounts of several news media outlets in the United Kingdom and reply tweets in response to them. They analyzed topics relating to COVID-19 using LDA model and performed sentiment analysis using RoBERTa model [9] for each tweet set to identify emotions in the news and users. Our study differs from these other studies in that it does not only analyze changing sentiments among people interested in topics related to COVID-19. Instead, it focuses on a variety of topics reported by news sites about real-world events to determine how societal interests and emotions as a whole have shifted.

III. METHODOLOGY

Our analytical approach entailed four components: (1) collecting news tweets posted on Twitter news accounts and reply tweets; (2) topic analysis performed on the set of news tweets; (3) sentiment analysis conducted on the set of reply tweets; and (4) visualization and analysis of changes in people's interests and sentiments using the results of the topic and sentiment analysis. Each of these steps is described in detail below.

A. Tweet Compilation

News tweets posted on a Twitter news account and reply tweets in response to them were collected via the program interface of the Twitter application. We selected Yahoo! News (username: @YahooNewsTopics) as the news site account for our study. Yahoo! News provides information disseminated by various newspapers and news agencies in Japan and is a popular news service in Japan. By analyzing news tweets posted on the Yahoo! News Twitter account and tweets in response to them, we obtained an overview of topics that occurred in Japan and people's sentimental responses to them. The collection period was from February 1, 2020, to May 31, 2022.

After compiling the news tweets, we removed the URL and hashtag from each news tweet, and the URL from each reply tweet. News tweets in which the content sentences were deleted as a result of this operation were excluded. The number of reply tweets for each news tweet was counted, and news tweets with less than 20 reply tweets were considered as less newsworthy as a viewpoint of the people's interest and therefore excluded. The numbers of news tweets and reply tweets compiled were 31,530 and 2,780,110, respectively.

B. Topic Modeling for News Tweets

To perform a topic analysis on the news tweet set, we used BERTopic [1] [10], which can handle short sentences represented by an embedding model using Sentence-BERT [11]. For the clustering model in BERTopic, we used HDBSCAN [12]. The minimum topic size was set at 16, which was 0.05% of the total number of news tweets. As a preprocessing, we conducted the morphological analysis for each news tweet. The Japanese morphological analyzer, MeCab, was used to divide news tweet sentences into morphemes. News tweets considered as outliers using BERTopic were excluded from the subsequent analysis. Ultimately, 229 topics were generated for the news tweet set. After conducting the topic analysis, we extracted the compound nouns for each topic using c-tfidf to represent the generated topics.

C. Sentiment Analysis on Reply Tweets

For the sentiment classification of the reply tweets, we used the WRIME dataset (version 2)[2] [13][14]. This dataset contains 35,000 texts posted on SNS labeled with Plutchik's eight emotions [15] on four levels of emotional intensity (none, weak, medium, and strong), and sentimental polarity on five levels (strong negative, negative, neutral, positive, strong positive). They also covered five types of labels: one applied to the writer of the text, three applied to three readers of the text, and one that was the average of the emotional intensities assigned by the three readers. According to the Train/Dev/Test distribution on the WRIME dataset, we used 30,000 pieces of data for training, 2,500 pieces of data for validation, and 2,500 pieces of data for evaluation. We applied labels representing the average emotional intensity identified by three readers. Emotional polarity labels were used to examine shifts in people's positive and negative feelings during the COVID-19 pandemic. To construct the positive classifier, we used strongly positive and positive labels to illustrate positive examples, and to construct the negative classifier, we used strongly negative and negative labels to illustrate positive examples.

BERT [16] was used as the classification model with the following parameters: 32 for batch size, 10 for max epochs, 1e-5 for learning rate, and 128 for the number of tokens. The Adam method [17] was used for optimization. We used the BERT-based-Japanese-whole-word-masking model as a learning model[3]. Table I shows the precision and recall values for the positive and negative classification, respectively. These classifiers were used to determine whether each reply tweet was positive/negative.

D. Visualization and Analysis of Shifts in People's Interests and Sentiments

Figure 1 depicts the workflow in the process of visualizing changes in people's interests and sentiments about topics relating to real-world events. The steps in the process are described below.

1) Visualization of shifts in people's interests

We regarded the number of reply tweets as the degree of interest in the news (topic), and measured people's interest in each topic as follows. First, for each topic identified in the topic analysis, news tweets were arranged chronologically by month. Next, the tweets in response to the news tweets were counted, and the total value was calculated for each month.

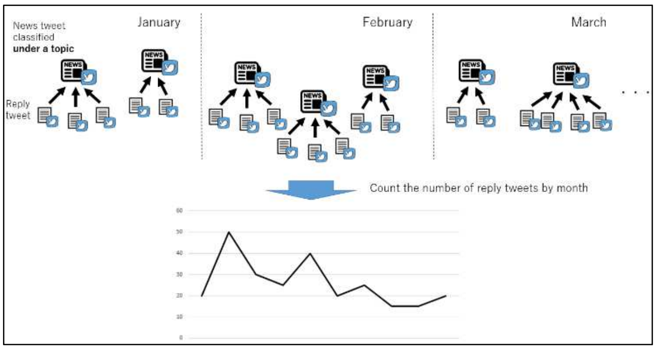
2) Visualization of shifts in people's sentiments

In our study, by identifying whether each news was positive or negative for people, we judged what people had positive/negative feelings about the topic to which the news belonged. First, we identified whether the news was received as positive or negative. Specifically, for each news tweet, the

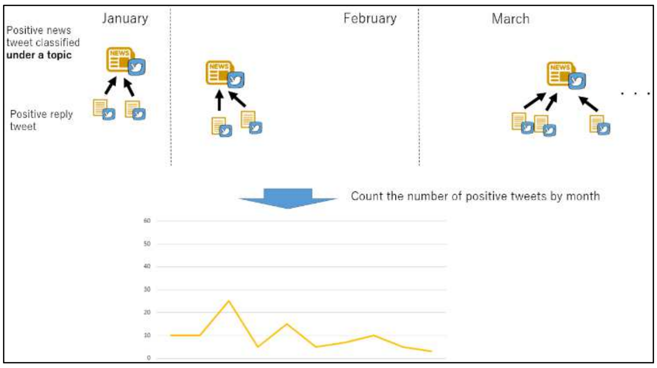
[1] https://maartengr.github.io/BERTopic/index.html
[2] https://github.com/ids-cv/wrime
[3] https://huggingface.co/cl-tohoku/bert-base-japanese-whole-word-masking

TABLE I. CLASSIFICATION PERFORMANCE

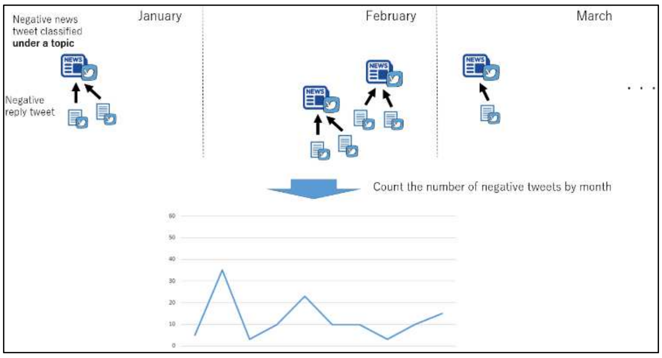
	Precision	Recall
Positive	0.780	0.799
Negative	0.727	0.756



(a) Visualizing shifting public interest in a topic



(b) Visualizing shifting positive sentiments toward a topic



(c) Visualizing shifting negative sentiments toward a topic

Fig. 1. Shifts in people's interest, and their positive and negative sentiments toward a topic. Note: news tweets for which the ratio of the number of positive (negative) tweets to the number of reply tweets was ≥0.3 were regarded as positive (negative).

ratio of the number of tweets with positive or negative responses to the number of reply tweets was measured, and those with a ratio of or above 0.3 were considered positive or negative news tweets. Next, for each topic, we sorted positive or negative news for each month. Last, we counted the positive or negative reply tweets and calculated the total value for each month.

IV. RESULTS

We present the results obtained using our analytical approach and analyze changes in people's interests and sentiments during the COVID-19 pandemic in Japan. The analysis was performed from three perspectives: (1) shifts in people's interests and sentiments during the period from February 2020 to May 2022; (2) the relationship between the number of news tweets and the number of reply tweets; and (3) correlations between interest and positive and negative sentiments. Note that topic numbers labeled using BERTopic were used for identified topics.

A. *Analysis of the People's Interests and Sentiments*

Tables II, III, and IV respectively show the top 10 topics with the highest numbers of reply tweets, positive tweets, and negative tweets, respectively, during the period from February 2020 to May 2022. Figures 2, 3, and 4 respectively show changes in the numbers of reply tweets, positive tweets, and negative tweets for the top 10 topics per month. Using the results shown in Table II and Figure 2, we first examined people's interests. Table II shows that people's main interests were broadly divided among the following categories: topics related to COVID-19 (Topics 1, 2, 5, 8, 3, 6, 23); the Ukraine–Russia conflict (Topic 0); and marriage and dating (Topic 4). Figure 2 also indicates that topics related to COVID-19 attracted interest from time to time until January 2022. Specifically, from February to May 2020, key topics covered the mask (Topic 5), closure of the school due to the spread of COVID-19 (Topic 2), and requests for closure of restaurants due to the emergency declaration (Topic 6) and benefit of the 100,000 yen (Topic 23). In July, November, and December 2020, discussions and trends relating to GoTo Travel, a government-led campaign to revitalize the travel industry and domestic travel after economic losses, were reported (Topic 8). Beside this, since the beginning of 2020, the media also covered the number of new positive cases of COVID-19 reported on an almost daily basis along with increases and decreases in the number of people who tested positive for the virus. Topic 3 is likely that people's interest in this topic increased because COVID-19 was an unknown virus, and the state of emergency and self-restraint and confinement of activities in 2020 were new experiences for many Japanese from April to July 2020. Subsequently, from May to September 2021, there was considerable discussion about the COVID-19 vaccine (Topic 1). We checked the news tweets categorized under Topic 1 during this period, and revealed that the focus was mainly on trends related the government' vaccination and environmental improvement initiatives and news about vaccination status. In October 2020, Topic 4, which is not related to COVID-19, emerged as a hot topic. We checked the news tweets categorized under Topic 4 during this month, and revealed active coverage of several issues related to the marriages of members of the royal family. In November 2021, Topic 23, which attracted attention in April 2020, once again emerged as a hot topic. A comparison of news tweets categorized under Topic 23 in April 2020 and November 2021 showed that the government's restrictions on who could or could not receive the benefits and the 100,000-yen handout were hot topics of discussion in the news during both periods.

Then from February 2022, people's interests focused on the Russia-Ukraine conflict. Apart from this topic, mask (Topic 5) and school (Topic 2), which were prominent topics in February 2020, were also slightly prominent in May 2022. An examination of the news tweets categorized into topics revealed that a lot of news tweets posted in and around February 2020 focused on Topic 5 covering mask shortages and resale issues. However, in May 2022, the most newsworthy topic had shifted to daily mask wearing. In February 2020, Topic 2 covering temporary school closures

TABLE II. TOPICS OF INTEREST, WORDS, AND THE TOTAL NUMBER OF REPLY TWEETS

Topic	Examples of words	No. of replies
0	Russia, Ukraine, Russian military, Ukraine invasion, President Putin, invasion, attack, President Zelensky, Russia, blame	85,887
1	vaccine, vaccination, new coronavirus vaccine, third dose, adverse reaction, elderly, local government	85,784
2	school, faculty, closed, student, temporary closed, primary school, guardian, university, high school	77,982
5	mask, cloth mask, wearing, distributing, wearing masks, Abenomask, outdoor, all households, recommended	73,613
4	marriage, divorce, actress, relationship, husband, affair, public woman	45,750
8	GoTo Travel, tourism support program, travel, suspension, GoTo Campaign, campaign, business, government, exclusion	37,132
3	Tokyo, new, infected, confirmed, new type of coronavirus, severely ill	34,801
6	restaurant, store, closure request, closing, closed, liquor, business hours, department store	34,719
7	layoffs, companies, stop, employees, bonuses, voluntary retirement, recruitment, jobs, state employees, telecommuting	30,745
23	benefit, 18 years old, 100,000 yen equivalent, income limit, economic stimulus, cash benefit, payment, 100,000 yen, children	29,991

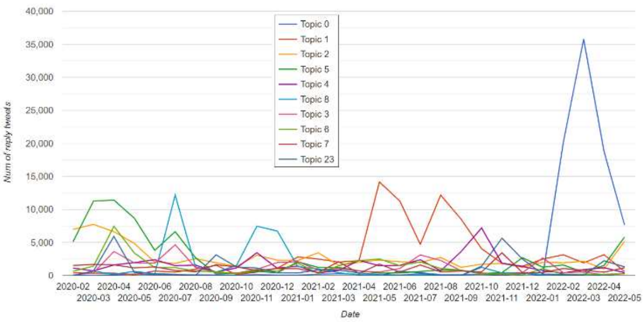


Fig. 2. Shifts in people's interests indicated by the number of reply tweets

and cancellation of graduation ceremonies as a countermeasure against COVID-19 featured prominently in the news. However, in May 2022, public interest focused on a variety of news stories that were not related to COVID-19, such as news about the banning nicknames in schools, the problem of the gym sitting, and bullying issues.

Next, we examined expressions of positive feelings. As shown in Table III, topics that tend to convey positive feelings, for example, those related to marriage and romance (Topic 4, Topic 38) and childbirth (Topic 41) were ranked highest. As Figure 3 shows, various topics were prominent at each month. In addition, the Tokyo Olympic was held from July 23 to August 8, 2021, and Topic 64, which is a sports-related topic, aroused excitement. This topic also sparked excitement in February 2022 by the Beijing Olympics. These results suggest that even when anxiety was widespread within society, as was the case during the COVID-19 pandemic, people tended to respond honestly to any positive event. Sharing these results with a larger number of people could lead to a slight abatement of the prevailing sense of anxiety.

TABLE III. TOPICS AROUSING POSITIVE FEELINGS, WORDS, AND THE TOTAL NUMBER OF POSITIVE REPLY TWEETS

Topic	Examples of words	No. of replies
4	marriage, divorce, actress, relationship, husband, affair, public woman	5,302
41	first child, birth, pregnancy, report, second child, first child pregnancy, talent, actress, mother and child	2,646
16	death, cartoonist, actor, voice actor, pneumonia, hospital, active, obituary, 81	2,483
30	starring, drama, movie, broadcast, cast, actor, actress, protagonist	2,129
38	this week, featured, topic, marriage, W announcement, 3400 comments	2,060
64	women's curling, defeated 400m individual medley, gold medal, silver medal, falls, protection	1,786
2	school, faculty, closed, student, temporary closed, primary school, guardian, university, high school	1,555
25	sales, pork, lunch, cooking, popular, launch, cup noodles, luxury bread, shopkeepers, eggs	1,476
0	Russia, Ukraine, Russian military, Ukraine invasion, President Putin, invasion, attack, President Zelensky, Russia, blame	1,091
19	broadcast, end, NTV, TBS, curtain, MC, start, history, Fuji TV, information program	1,088

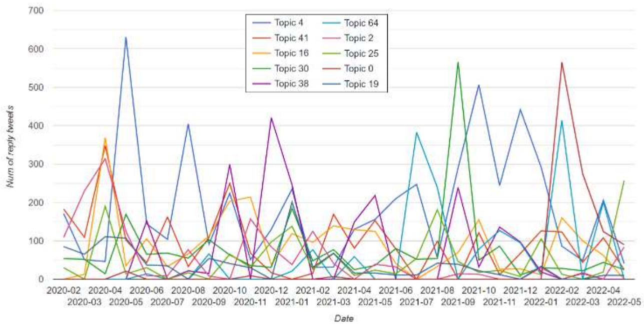


Fig. 3. Shifts in people's positive feelings indicated by the number of positive reply tweets in response to positive news tweets

However, it is striking that Topic 16 concerning the death of celebrities appeared at the top of the list of positive events. To explore this finding further, we examined news tweets that were categorized under this topic and found that when, for example, a film director or a cartoonist died, Twitter users tweeted their memories about this individual's work, while at the same time praying for the repose of their soul. Also, when an athlete or celebrity died, they recalled past scenes when the celebrity was at their peak. It is also noteworthy that Topic 0, which appears in Table II, and IV, also appears at the top of Table III. An examination of the news tweets categorized under Topic 0 confirmed relatively positive responses to some news in the enlistment of volunteers in the Ukrainian army, statement by President Zelensky and donations/support for Ukraine whereas there was a negative reaction to most of the news. In addition, Topic 2, which appears in Table II, is reflected in both the positive and negative responses in Tables III and IV, respectively. Our analysis of news tweets related to the COVID-19 categorized under Topic 2, which were posted in February to April 2020, revealed that news about temporary school closings and cancellation of graduation ceremonies were deemed negative, whereas some news about

TABLE IV. TOPICS AROUSING NEGATIVE FEELINGS, WORDS, AND THE TOTAL NUMBER OF NEGATIVE REPLY TWEETS

Topic	Examples of words	No. of replies
1	vaccine, vaccination, new coronavirus vaccine, third dose, adverse reaction, elderly, local government	43,132
2	school, faculty, closed, student, temporary closed, primary school, guardian, university, high school	40,949
0	Russia, Ukraine, Russian military, Ukraine invasion, President Putin, invasion, attack, President Zelensky, Russia, blame	40,309
5	mask, cloth mask, wearing, distributing, wearing masks, Abenomask, outdoor, all households, recommended	37,534
8	GoTo Travel, tourism support program, travel, suspension, GoTo Campaign, campaign, business, government, exclusion	19,871
6	restaurant, store, closure request, closing, closed, liquor, business hours, department store	17,625
3	Tokyo, new, infected, confirmed, new type of coronavirus, severely ill	17,314
4	marriage, divorce, actress, relationship, husband, affair, public woman	15,399
7	layoffs, companies, stop, employees, bonuses, voluntary retirement, recruitment, jobs, state employees, telecommuting	15,360
23	benefit, 18 years old, 100,000 yen equivalent, income limit, economic stimulus, cash benefit, payment, 100,000 yen, children	14,498

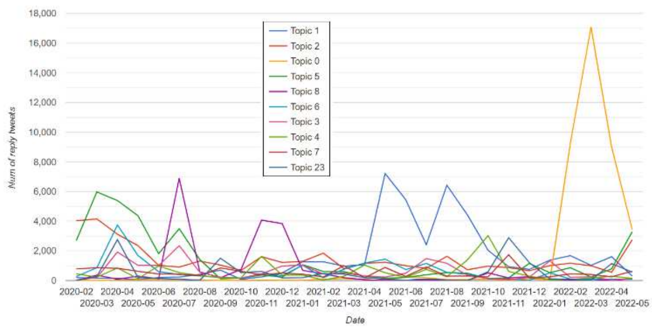


Fig. 4. Shifts in people's negative feelings indicated by the number of negative reply tweets in response to negative news tweets

supports to students to prevent COVID-19 transmission were deemed positive. Thus, and as seen in the large difference in the number of positive and negative tweets in Topics 0 and 2 shown in Tables 3 and 4, we found that people mainly showed negative feelings to these topics, however positive feelings to some news.

An analysis of the negative feelings conveyed in Table IV and Figure 4 showed that the distribution of topics and transitions in topics were similar to those of people's interests depicted in Table II and Figure 2. Interestingly, Topic 4, covering marriage and dating reports, appeared in both Tables III (positive) and IV (negative). However, unlike the shift for positive feelings, Topic 4 rose in prominence in only October 2021. Our examination of the negative news tweets in October 2021 revealed negative feelings of several issues related to the marriages of members of the royal family. From these results, it can be posited that public anxiety during the pandemic shifted from events related to COVID-19 to marriage issues concerning the royal family, subsequently focusing on the Ukraine–Russia conflict.

B. *The Relationship between the News Tweets and the Reply Tweets*

It is natural that a lot of news related to a topic that attracts people's interest or makes them feel sentimental is taken up. That is, it can be said that the number of replies increases as the number of news classified into topics increases. To investigate whether the number of reply tweets on a specific topic depended on the posting of news tweets, we investigated the relationship between the number of news tweets on a specific topic. We here examined the topics shown in Tables II, III, and IV and measured correlation between news and replies in the topic using Pearson's product-moment correlation based the number of news tweets and reply tweets on each month. The results are shown in Table V.

Table V reveals that the overall correlation value was high, and the numbers of news tweets and reply tweets were proportional. In particular, the value of the correlation coefficient for almost all topic in interest and negative exceeded 0.8. These results suggest that there is a correlation between the amount of media coverage on COVID-19-related topics and the Ukrainian-Russian conflict, and public interest and negative sentiment. In positive, unlike interest and negative, it tends to be low. In particular, Topic 30 covering movies had correlation coefficients below 0.25. This is likely due to the high positive sentiment toward certain events in the movie and drama topic. On the other hand, Topic 64 related to sports had a very high value of 0.951. It is thought that this was because the Olympics-related news was actively covered, and in conjunction with that, many people showed positive feelings about the athletes' results and their progress.

C. *Correlation between Interest and Positive and Negative Feelings about Topics*

As mentioned above, from Figures 2, 3, 4 and Tables 2, 3, 4, it appears that people's interests are more similar in the negative than in the positive. We investigated the relationship between people's interest in a topic and their positive and negative feelings about it. To do so, we counted the number of reply tweets for each topic under three categories: interest, positive, and negative. We then measured the correlation coefficient using Spearman's rank correlation between two of them. As a result, we obtained correlation values of 0.285 for interest and positive feelings, 0.943 for interest and negative feelings, and 0.090 for positive and negative feelings. These results suggest that people's interest during the COVID-19 pandemic may be associated with the negative feeling more than positive feeling.

V. CONCLUSION

We analyzed shifting topics of interest and sentiments as conveyed by the Japanese public during the period of the COVID-19 pandemic. We did so by applying topic analysis and sentiment analysis to news tweets posted by Yahoo! News on their Twitter account and replies to them. We examined trends in people's interests in and sentiments toward each topic according to the number of replies. This study was conducted over an extended period from February 2020 to May 2022. During this period, positive feelings were expressed about the Tokyo Olympics, celebrity marriages, and love-related topics. Beside this, COVID-19-related topics dominated the news in terms of public interest and negative feelings until January 2022. However, beginning in February 2022, the Ukraine–Russia conflict was the main focus of

TABLE V. PEARSON'S PRODUCT-MOMENT CORRELATION COEFFICIENT CALCULATED FOR THE NUMBER OF NEWS TWEETS AND REPLY TWEETS FOR EACH TOPIC

Interest		Positive		Negative	
Topic	Value	Topic	Value	Topic	Value
0	0.985	4	0.618	1	0.958
1	0.956	41	0.621	2	0.857
2	0.859	16	0.838	0	0.983
5	0.960	30	0.224	5	0.956
4	0.843	38	0.812	8	0.942
8	0.943	64	0.951	6	0.967
3	0.813	2	0.767	3	0.799
6	0.969	25	0.644	4	0.883
7	0.628	0	0.892	7	0.586
23	0.818	19	0.799	23	0.826

attention. Our analysis of the correlation between public interest, positive feelings, and negative feelings indicates that there may be strong correlation between people's interest and their negative feelings. In the future, we plan to undertake a analysis in which we compare shifts in topics of interest and sentiments in other countries with those found in Japan.

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REFERENCES

[1] U. Naseem, I. Razzak, M. Khushi, P. W. Eklund, and J. Kim, "COVIDSenti: A large-scale benchmark Twitter data set for COVID-19 sentiment analysis", IEEE Trans. Comput. Social Syst., vol. 8, no. 4, pp. 1003–1015, 2021.

[2] R. Saito and H. Haruyama, "Estimating time-series changes in social sentiment @ Twitter in US metropolises during the COVID-19 pandemic", Computational Social Science, 2022.

[3] A. Hussain, A. Tahir, Z. Hussain, Z. Sheikh, M. Gogate, K. Dashtipour, A. Ali, and A. Sheikh, "Artificial intelligence-enabled analysis of UK and US public attitudes on Facebook and Twitter towards COVID-19 vaccinations", Internet Res, 2021.

[4] Y. Wang, M. Shi, and J. Zhang, "What public health campaigns can learn from people's Twitter reactions on mask-wearing and COVID-19 vaccines: A topic modeling approach", Cogent Social Sciences, vol.7, no.1, 2021.

[5] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent dirichlet allocation", Machine Learning Research, vol. 3, pp. 993–1022, 2003.

[6] S. Lorla, TextBlob Documentation, 2020: https://buildmedia.readthedocs.org/media/pdf/textblob/latest/textblob.pdf [accessed May. 31, 2023]

[7] T. de Melo and C. M. Figueiredo, "Comparing news articles and tweets about COVID-19 in Brazil: Sentiment analysis and topic modeling approach", JMIR Public Health and Surveillance, vol. 7, no. 2, 2021.

[8] S.L. Evans, R. Jones, E. Alkan, J.S. Sichman, A. Haque, F.B.S. de Oliveira, and D. Mougouei, "The emotional impact of COVID-19 news reporting: A longitudinal study using natural language processing", Human Behavior and Emerging Technologies, 2023.

[9] Y. Liu, M. Ott, N. Goyal, J. Du, M. Joshi, D. Chen, O. Levy, M. Lewis, L. Zettlemoyer, and V. Stoyanov, "RoBERTa: A robustly optimized BERT pretraining approach", arXiv preprint arXiv:1907.11692, 2019.

[10] M. Grootendorst, "BERTopic: Neural topic modeling with a class-based TF-IDF procedure", arXiv preprint arXiv:2203.05794, 2022.

[11] N. Reimers and I. Gurevych, "Sentence-BERT: Sentence embeddings using Siamese BERT-networks", Proc. of EMNLP-IJCNLP, 2019.

[12] L. McInnes and J. Healy, "Accelerated hierarchical density based clustering", Proc. of ICDMW, pp. 33–42, 2017.

[13] H. Suzuki, S. Tarumoto, T. Kajiwara, T. Ninomiya, Y. Nakashima, and H. Nagahara. "Emotional intensity estimation based on writer's personality", Proc. of AACL-SRW, pp.1–7, 2022.

[14] T. Kajiwara, C. Chu, N. Takemura, Y. Nakashima, and H. Nagahara, "WRIME: A new dataset for emotional intensity estimation with subjective and objective annotations", Proc. of NAACL-HLT, pp. 2095–2104, 2021.

[15] R. Plutchik, "A general psychoevolutionary theory of emotion", Theories of Emotion, pp. 3–33, 1980.

[16] J. Devlin, M.W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding", Proc. of NAACL-HLT, pp. 4171–4186, 2019.

[17] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization", Proc. of ICLR, 2015.

[1] U. Naseem, I. Razzak, M. Khushi, P. W. Eklund, and J. Kim, ‘‘COVIDSenti: A large-scale benchmark Twitter data set for COVID-19 sentiment analysis,’’ IEEE Trans. Comput. Social Syst., vol. 8, no. 4, pp. 1003–1015, 2021.
[2] R. Saito and H. Haruyama, "Estimating Time-Series Changes in Social Sentiment @ Twitter in US Metropolises during the COVID-19 Pandemic," Computational Social Science, 2022.
[3] A. Hussain, A. Tahir, Z. Hussain, Z. Sheikh, M. Gogate, K. Dashtipour, A. Ali, and A. Sheikh, "Artificial Intelligence-Enabled Analysis of UK and US Public Attitudes on Facebook and Twitter towards COVID-19 Vaccinations," Internet Res, 2021.
[4] Y. Wang, M. Shi, and J. Zhang, "What Public Health Campaigns can Learn from People's Twitter Reactions on Mask-Wearing and COVID-19 Vaccines: a Topic Modeling Approach," J. Cogent Social Sciences, vol.7, no.1, 2021.
[5] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent Dirichlet allocation," J. Machine Learning Research, vol. 3, 2003, pp. 993–1022.
[6] S. Lorla, TextBlob Documentation, 2020: https://buildmedia.readthedocs.org/media/pdf/textblob/latest/textblob.pdf [accessed April. 23, 2023]
[7] T. de Melo and C. M. Figueiredo, "Comparing News Articles and Tweets about COVID-19 in Brazil: Sentiment Analysis and Topic Modeling Approach," JMIR Public Health and Surveillance, vol. 7, no. 2, 2021.
[8] S.L. Evans, R. Jones, E. Alkan, J.S. Sichman, A. Haque, F.B.S. de Oliveira, and D. Mougouei, "The Emotional Impact of COVID-19 News Reporting: A Longitudinal Study Using Natural Language Processing," Human Behavior and Emerging Technologies, 2023.
[9] Y. Liu, M. Ott, N. Goyal, J. Du, M. Joshi, D. Chen, O. Levy, M. Lewis, L. Zettlemoyer, and V. Stoyanov, "RoBERTa: a robustly optimized BERT Pretraining approach," 2019, http://arxiv.org/abs/1907 .11692.
[10] Grootendorst, M.: BERTopic: Neural Topic Modeling with a Class-based TF-IDF Procedure. arXiv preprint arXiv:2203.05794, 2022.
[11] N. Reimers and I. Gurevych, "Sentence-BERT: Sentence embeddings using Siamese BERT-networks," Proc. of EMNLP-IJCNLP, 2019.
[12] L. McInnes and J. Healy, "Accelerated hierarchical density based clustering," Proc. of ICDMW, 2017, pp. 33–42.
[13] H. Suzuki, S. Tarumoto, T. Kajiwara, T. Ninomiya, Y. Nakashima, and H. Nagahara. "Emotional Intensity Estimation based on Writer's Personality," Proc. of AACL-SRW, 2022, pp.1–7.
[14] T. Kajiwara, C. Chu, N. Takemura, Y. Nakashima, and H. Nagahara, "WRIME: A new dataset for emotional intensity estimation with subjective and objective annotations," Proc. of NAACL-HLT, pp. 2095–2104, 2021.
[15] R. Plutchik, "A General Psychoevolutionary Theory of Emotion," Theories of Emotion, 1980, pp. 3–33.
[16] J. Devlin, M.W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," Proc. of NAACL-HLT, pp. 4171–4186, 2019.
[17] D. P. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization," Proc. of ICLR, 2015.