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SENTIMENT ANALYSIS IN SOCIAL NETWORKS OF HEALTH INSTITUTIONS

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ABSTRACT

Twitter, a communication platform that creates a social impact; it conveys the messages of non-profit organizations to the masses and the emotions of the masses to non-profit organizations. This research; It aims to examine Twitter posts about health-related non-profit organizations, to determine the emotional states about these institutions on social media and to measure these feelings.

Sentiment analysis about WHO, ILO, IOM, UNICEF, FAO, Red Cross, UNDP and UNHCR were carried out using the R program. The tweets used in sentiment analysis were collected by approval of Twitter API. During the study, a total of 310,341 tweets were collected in three periods, November 2019, May 2020 and October 2020. Tweets are classified according to 10 different emotions. One of the main findings of the study is that "positive", "trust" and "anticipation" feelings are at the top of the tweets shared about these institutions under normal conditions and crisis conditions. Sentiment consistency was tested with Friedman test for each institution after emotional analysis was performed in all institutions ($p<0.05$). In all institutions except FAO, a significant relationship was found between the emotion medians of the feeling of "fear" according to the periods. However; according to the results of the sentiment analysis, an increase was observed in the "fear" feeling of the institutions during the pandemic period.

This research; non-profit international organizations that make environment, health and sustainable development a principle; provides a conceptual framework for understanding when and why follower behaviour originates. Thus, it can enable organizations to realize their missions, create meaningful support in times of crisis, increase benefit and awareness, facilitate decision-making, and increase communication and interaction.

1 INTRODUCTION

Public health; It combines various measures to promote health, prevent disease and extend the lifespan of the population. It targets all populations, particularly through the formulation of public policies regarding the determinants and priorities of health, by monitoring their health status and improving the health conditions of the population. Needs are determined by priorities and preferences [1]. Priorities and choices result in different ways to guarantee appropriate access to health care, promote health, and prevent disease. The main purpose of non-profit organizations (NPO), which aims to provide this and is established to meet the needs of the society in various issues in general, is to realize their vision and mission. In this context; institutions need to maximize their impact on society. The success of NPO's efforts is increased by providing social information to raise awareness of its aims and interacting with its followers and receiving support and feedback from potential donors and volunteers for its planned programs. This to ensure that; It needs interaction with its target audiences and awareness of the society [2]. The fastest and most effective way to increase social impact and community awareness is to use social networks correctly [3]. This research; The aim of this study is to analyse the Twitter shares of non-profit institutions that work on health and to determine the emotional states of these institutions on social media, and to measure these feelings, with sentiment analysis, which is a text mining method. Research; It was conducted to evaluate the use of social media under normal conditions and in periods of international crisis related to non-profit international organizations whose main and / or secondary goals are health. In this context; It includes the evaluation of the emotional response of social media to social events at different times and in different situations, on the basis of non-profit organizations that aim to improve health. The influence of social media in health promotion is an important tool to determine people's tendencies. A comprehensive process evaluation was made for the social media of the institutions within the scope of the research during the COVID-19 pandemic period.

2 METHODS

In the scope of the research; From a social marketing point of view, using technology and social media, and applying it on Twitter, tweets collected by Sentiment analysis method were classified as positive, negative or neutral. Sentiment analysis is the process of determining whether a text is positive, negative, or neutral. Here, for the purpose of this analysis, the “syuzhet” package has been studied. This library uses the NRC sentiment dictionary to classify tweets after text preprocessing. NRC emotion dictionary; is a list of words and their associations with eight emotions (anger, fear, anticipation, confidence, surprise, sadness, joy, and disgust) and two emotions (negative and positive). Sentiment Analysis of Institutions; Process evaluation was carried out as a comprehensive evaluation strategy for social media during the COVID-19 pandemic period. In this context; Within the scope of the study, tweets were taken three times to see how the reflections of the COVID-19 pandemic, which especially affected the world, affected the sentiment analysis of these eight institutions. “What is the sentiment score of Twitter posts about institutions?”, “What are the most frequently mentioned topics in these posts?” and “What is the change in mood scores and most frequently mentioned topics after the COVID-19 pandemic?” questions were addressed in the research. 8 non-profit organizations in the research; Sentiment analysis was conducted before and after the COVID-19 pandemic. In addition to sentiment analysis, comparisons of the most frequently used words by Twitter users who mentioned these institutions during the research periods were also included, and these words with high frequency were visualized with a word cloud.

2.1 Selecting Research Dataset

The data provider universe of the research consists of Twitter searches of some non-profit international organizations whose main or secondary field of study is health and accepted as a centre in their fields. These international organizations are the World Health Organization (WHO), United Nations Food and Agriculture Organization (FAO), United Nations Development Program (UNDP), United Nations International Children's Emergency Fund (UNICEF), International Labor Organization (ILO), International Organization for Migration (IOM), the International Committee of

the Red Cross (ICRC), the United Nations High Commissioner for Refugees (UNHCR). International organizations in the research were included in the research according to the number of Twitter followers.

Sentiment analysis of WHO, ILO, IOM, UNICEF, FAO, Red Cross, UNDP and UNHCR was performed using version 4.0.2 of R Studio program (R statistical software, www.R-project.org). In this research, a "dictionary-based" approach was used. Dictionary-based approaches are used to measure the overall emotions around the text in question [4]. Tweets to be used in sentiment analysis; It was collected by communicating with the Twitter API linked to the Twitter account. During the study, 310,341 tweets were collected. Within the scope of the study, three tweets were taken to see how the reflections of the COVID-19 pandemic, which affected the world, affected the sentiment analysis of these eight institutions. The first tweeting process; In November 2019, the second was shot in April-May 2020, a period when the impact of the COVID-19 pandemic on social media was intense, and the third was shot in October 2020, a period when the number of cases was increasing. In November 2019, 70,932 tweets were collected. From the Twitter API 6339 tweets about WHO, 5931 tweets about IOM, 8662 tweets about ILO, 10,000 tweets about FAO, 10,000 tweets about Red Cross, 10,000 about UNDP, 10,000 tweets about UNHCR, 10,000 about UNICEF tweeted. A total of 114,756 tweets were collected in May 2020. One of the important dates for the COVID-19 pandemic is January 2020, when the virus began to spread across the continents. The data extraction process carried out in April-May was repeated, limiting it to include tweets from 1 January 2020. From the Twitter API 14,816 tweets about WHO, 5483 tweets about IOM, 16,454 tweets about ILO, 10,898 tweets about FAO, 17,000 tweets about Red Cross, 16,105 tweets about UNDP, 17,000 tweets about UNHCR, about UNICEF 17,000 tweets were shot. In total in October 2020; 115,909 tweets were collected. According to WHO data, a new peak has occurred in the COVID-19 pandemic, with more than 300,000 new cases in 190 days (WHO 2020). In this context, the third group of data extraction is limited to the tweets from August 2020. The number of tweets requested from the Twitter API for each institution has been determined as 17,000. From the Twitter API 17,000 tweets about WHO, 6111 tweets about IOM, 13,887 tweets about ILO, 15,140 tweets about FAO, 14,959 tweets about Red Cross, 17,000 tweets about UNDP, 14,812 tweets about UNHCR, about UNICEF 17,000 tweets were shot.

2.2 Sentiment Analysis with R

Analysis of Twitter data with R program; It starts with extracting text from Twitter. The extracted text is then transformed to create a document term matrix. After this conversion process, the most frequently spoken words on Twitter are obtained in the matrix structure. Word cloud is used to present important words in documents [5]. Before probing a data on Twitter using the API, Twitter authentication needs to be done using an application created by Twitter. twitteR, ROAuth, tm, wordcloud, ggplot2, RColorBrewer, stringr, plyr, SnowballC, syuzhet packages are the main packages used in sentiment analysis. The "searchTwitter ( )" function is used to access and search the data [5]-[16]. This function belongs to the twitteR package and enables searching Twitter based on a given search string [17]. In the research; keywords "World Health Organization" for WHO, "unicef" for UNICEF, "undp" for UNDP, "unhcr" for UNHCR, "fao" for FAO, "ilo" for ILO, "iom" for IOM, and Red Cross It is designated as "red cross". Search words were chosen based on their international abbreviations, except WHO and Red Cross. Since the abbreviation of WHO is frequently used both as a relative and interrogative pronoun, the full name of the institution was preferred instead of the abbreviation. The open version of Red Cross was preferred because it is generally more known than the international abbreviation of red cross. The R program used; It is widely used in text mining studies. When working with R, the related packages must be downloaded first and then the downloaded packages must be called. First, the tweets are analysed using the text dictionary and the sentiment values of the sentence (positive, negative and neutral) are calculated. Due to the noisy nature of tweet data, tweets about COVID-19 often included similar words. Each dataset contains its own identifying information about users, the content of their tweets, including hashtags and hyperlinks, and the relationships between users (retweets, mentions, and replies).

2.3 Text Preprocessing

The text must be preprocessed before the tweet data can be analysed. In the preprocessing (ontology-based normalization process) step, first, a cleaning process; spell checking, changing abbreviations, removing duplicated characters, and grammar rules [18]. Text data can be white spaces, punctuation, stop words, etc. contains. These characters do not carry much information and are difficult to

process. To ensure that the handled data is clean; convert text to lowercase (words such as “write” and “write” are considered the same word for analysis), remove numbers, remove English stop words (for example, “the”, “is”, “of”, etc.), remove punctuation (eg “,”, “?” etc.), removing excess spaces, root finding operations are carried out [16]. The "Tm" package in R is used to perform this operation. The main structure used to manage documents in TM is called Corpus, which represents a collection of text documents. The modification of the words in the tweets is done by the mentioned cleaning process. The purpose of using the “tm” library includes rooting words, removing stop words, and other methods as noted. Basically, all conversions work on single-text documents. Preprocessing was done by removing noisy data from tweets, irrelevant comments, Twitter usernames starting with @, URLs starting with http:// to the next field, Twitter common words like “available”, “via”, hashtag topics, Punctuation Marks [19].

2.4 Analysis of Tweets

Different Symbolic and Machine Learning techniques are used to identify the emotions from the text. Machine learning techniques are simpler and more efficient than symbolic techniques. These techniques can be applied for sentiment analysis. There are some issues with identifying sentimental keywords from tweets with multiple keywords. It is also difficult to use misspellings and slang words. To deal with these problems, an effective feature vector is created by performing two-step feature extraction after appropriate preprocessing. In the first step, Twitter-specific features are extracted and added to the feature vector. After that, these features are extracted from the tweets and feature extraction is done again as if it were done on normal text. These features are also added to the feature vector [20].

3 RESULTS

Analyzes are made on the data sets created within the scope of the research, in which the dictionary-based approach is adopted. Aim; classifying tweets as one of the categories of “positive”, “negative”, “anger”, “hate”, “sadness”, “fear”, “expectation”, “joy”, “confidence” and “surprise”. Due to the use of international abbreviations, the majority of tweets are in English. Tweets to be used in sentiment analysis; It was collected by communicating with the Twitter API linked to the

Twitter account. After obtaining authorization from the API, tweets were taken in three separate periods, November 2019, May 2020, and October 2020, for eight institutions determined. 301,586 tweets collected during the study are in raw form. The raw dataset; contains several syntactic features that are not necessary for evaluating the dataset. Such undesirable features need to be pre-processed. For pre-processing, the spaces, URLs, various symbols, and stop words in the tweets have been removed, and capital letters have been converted to lowercase. In this process, which is done to ensure data quality and to make algorithms progress faster and more accurately, the before and after tweets change. As seen in Table 1-3 in the periodical sentiment analysis study of institutions, according to the sentiment analysis results of the datasets taken in November 2019; When institutions are evaluated according to the number of tweets containing positive emotions; IOM, UNDP and FAO are at the top, while UNHCR, UNICEF are at the bottom.

***Table 1**. Distribution of sentiment analysis results of tweets taken btw. November 2019*

	November 2020		
	Positive	**Negative**	**Neutral**
WHO	798	261	5280
UNICEF	285	29	9686
FAO	737	183	9080
ILO	807	307	7548
IOM	937	379	4615
UNDP	812	183	9005
UNHCR	280	196	9524
RC	655	351	8994

According to the results of the sentiment analysis of the datasets taken in May 2020; When institutions are evaluated according to the number of tweets containing positive emotions; UNDP, WHO and RC are at the top, while UNHCR, UNICEF are at the bottom. According to the results of the sentiment analysis of the datasets taken in October 2020; When institutions are evaluated according to the number of tweets containing positive emotions; UNDP, RC and FAO are at the top, while UNHCR, WHO are at the bottom (Table 1,2,3).

***Table 2**. Distribution of sentiment analysis results of tweets taken btw. May 2020.*

	May 2020		
	Positive	**Negative**	**Neutral**
WHO	1533	784	12,499
UNICEF	308	173	16,519
FAO	695	252	9951
ILO	1312	873	14,269
IOM	747	362	4374
UNDP	1563	352	14,190
UNHCR	571	402	16,027
RC	1517	613	14,870

Table 3*. Distribution of sentiment analysis results of tweets taken btw. October 2020.*

	October 2020		
	Positive	**Negative**	**Neutral**
WHO	520	208	16,272
UNICEF	691	307	16,002
FAO	1095	321	13,724
ILO	699	364	12,824
IOM	753	362	4996
UNDP	2764	3761	10,475
UNHCR	860	397	13,555
RC	1850	904	12,205

In the descriptive statistics of the dataset; Institutions with the highest median in November 2019; UNICEF, UNDP and FAO. Institutions with the highest median in May 2020; They are FAO, UNDP and WHO. In October 2020; institutions with the highest medians; UNICEF and FAO (Table 4). During this period, UNICEF's median and average values were remarkably high, while the median of many institutions was quite low.

***Table 4**. Descriptive statistics of tweets taken by institutions btw. November 2019-May 2020 and October 2020*

	November 2019		May 2020		October 2020	
	Median	**Mean**	**Median**	**Mean**	**Median**	**Mean**
WHO	0.40	0.492	0.40	0.325	0.0	0.304
UNICEF	0.75	0.968	0.00	0.518	1.25	1.171
FAO	0.50	0.533	0.500	0.573	0.50	0.377
ILO	0.25	0.435	0.25	0.324	0.00	0.193
IOM	0.40	0.419	0.25	0.356	0.25	0.233
UNDP	0.50	0.646	0.50	0.555	0.00	0.139
UNHCR	0.00	0.255	0.25	0.048	0.00	0.255
RC	0.40	0.249	0.30	0.309	0.05	0.195

The word clouds containing the most frequently used words of the institutions in tweets on a period basis are presented in Figure 1-8. The most frequently used visualization in tweets analysed in these word clouds.

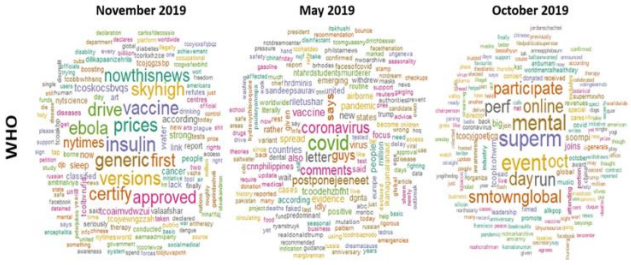


***Figure 1**. Word Clouds of Periodic Datasets of WHO*

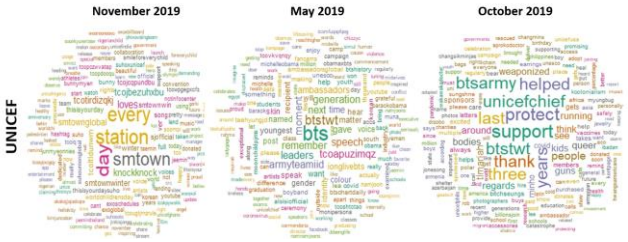


***Figure 2**. Word Clouds of Periodic Datasets of UNICEF*

***Figure 3**. Word Clouds of Periodic Datasets of FAO*

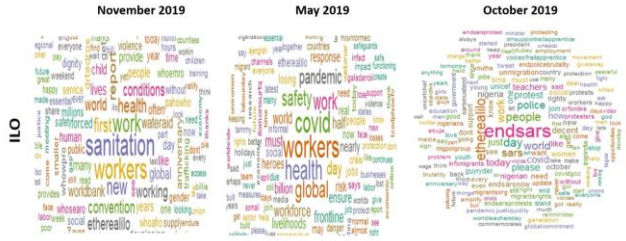


***Figure 4**. Word Clouds of Periodic Datasets of ILO*

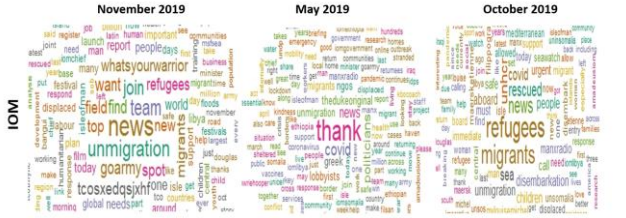


***Figure 5**. Word Clouds of Periodic Datasets of IOM*

***Figure 6**. Word Clouds of Periodic Datasets of UNDP*

***Figure 7**. Word Clouds of Periodic Datasets of UNHCR*

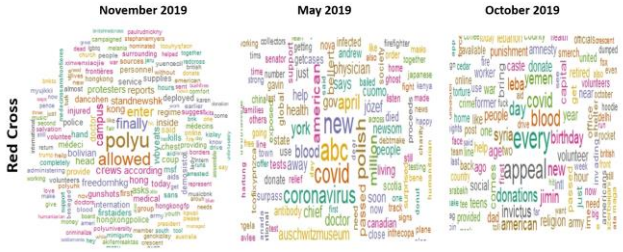


***Figure 8**. Word Clouds of Periodic Datasets of Red Cross*

In the sentiment analysis of the tweets taken about the institutions within the scope of the research, "positive", "negative", "trust", "expectation", "joy", "surprise", "hate", "fear", "sadness", "anger" words were used periodically. The averages of their emotions were calculated. In this context; The distributions of the medians of all institutions for a certain emotion for the November 2019, May 2020 and October 2020 periods were tested with the Friedman Test. There was only a significant difference between the emotional medians of the institutions according to the periods of fear (x2=6.75; p=0.034). When the emotional medians of the three periods of WHO are compared, especially in the beginning of the pandemic, positive emotions (“Expectation”, “Confused”, “Confidence”, “Joy”, “Positive”) decreased, Negative emotions (“Anger”, “Fear”, “Hate”, “Sadness”, “Negative”) increase. In the period of October 2020; emotion medians decrease in all emotions compared to other periods. When the emotional medians of UNICEF's three periods are compared, especially in the beginning of the pandemic, there is a decrease in positive emotions (“expectation”, “surprise”, “trust”, “joy”, “positive”), negative emotions (“anger”, “fear”, “hate”, “sadness”, “negative”). In the period of October 2020; In the emotional medians, there is an increase in all emotions compared to other periods. Comparing the emotional medians of FAO's three periods, especially in the initial period of the pandemic, positive emotions (“expectation”, “surprise”, “trust”, “joy”, “positive”) and negative emotions (“anger”, “fear”, “hate”, “sadness”, “negative”) slight changes are observed. When the emotional averages of the three periods of the ILO are compared, it is observed that all emotions except “positive”, “confidence”, “joy” and “sadness” increase in May 2020 and decrease in October 2020. When the emotional averages of IOM's three periods are compared, a slight increase is observed in the emotions of "negative" and "fear", especially in the initial

period of the pandemic. Apart from these increases, there is a periodic decrease in emotional averages in general. When the emotion averages of the three periods of UNDP are compared, it is seen that there is an increase in the average of emotions in general. Especially in the period of October 2020, there is a great increase in Positive emotions and Negative emotions (“Anger”, “Fear”, “Hate”, “Sadness”, “Negative”). When the emotional medians of UNHCR's three periods are compared, an increase is seen in eight other emotions, except for "hate" and "negative" emotions. However; In "hate" and "negative" feelings; The decrease in the period of May 2020 and the increase in the period of October 2020 attract attention. When we look at the emotional medians of the three periods of RC, negative emotions (“Anger”, “Fear”, “Sadness”, “Negative”) correspond to positive emotions (“Expectation”, “Confusion”, “Confidence”, “Joy”, “Positive”) appears to be ahead of it. A large increase is observed in the medians of negative emotions in the period of October 2020 (Figure 9-16).

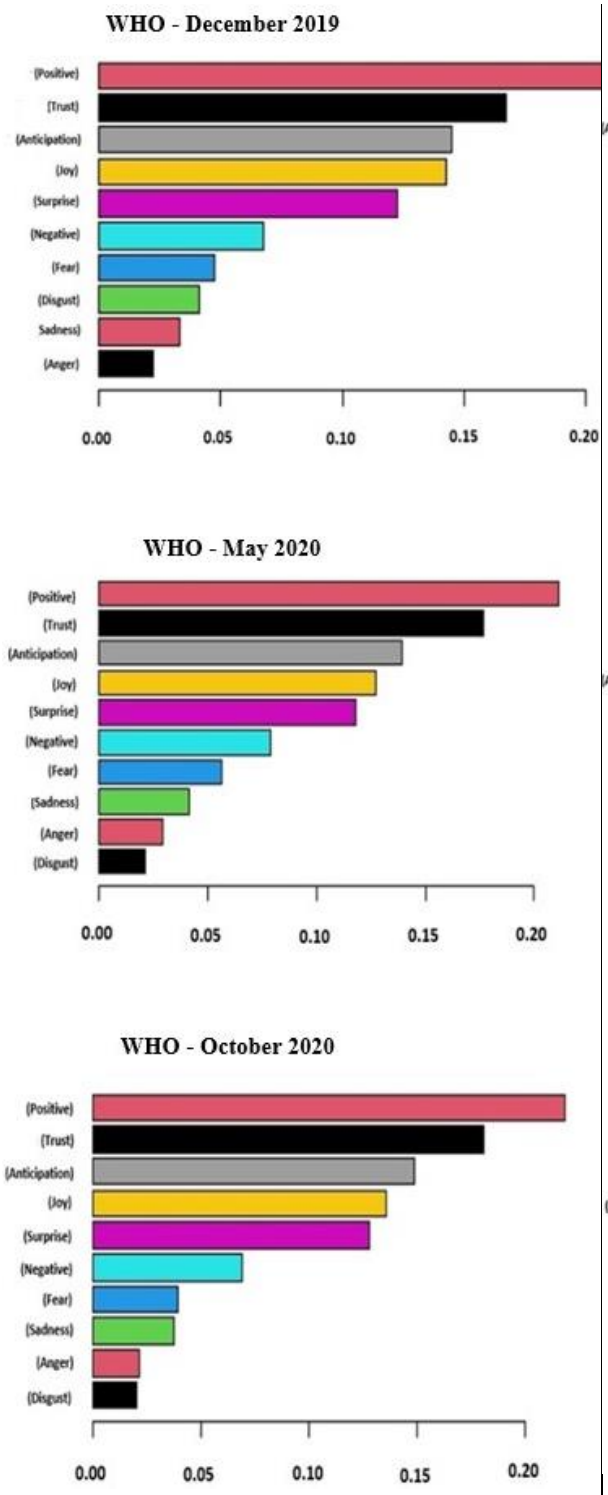


***Figure 9**. Mood Distribution of Institution's Periodic Datasets of WHO*

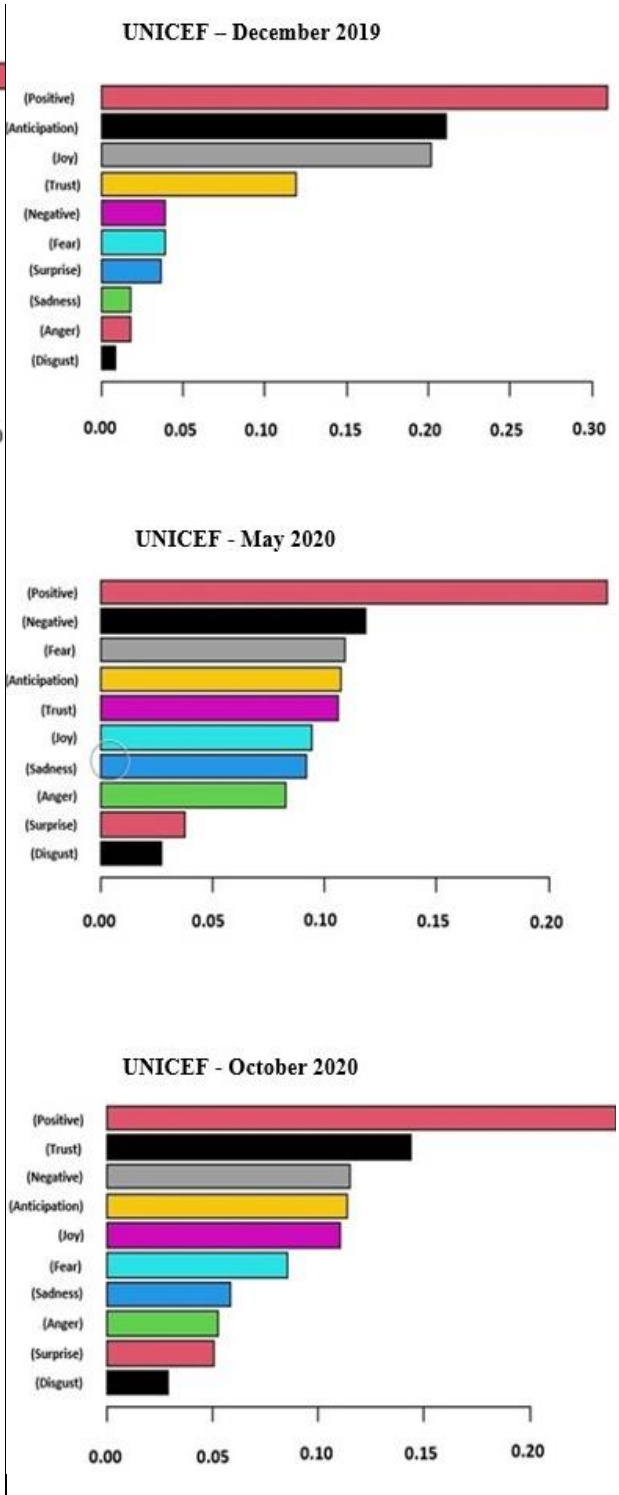
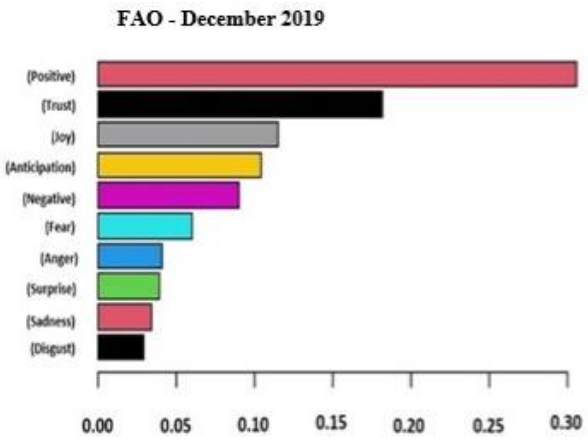
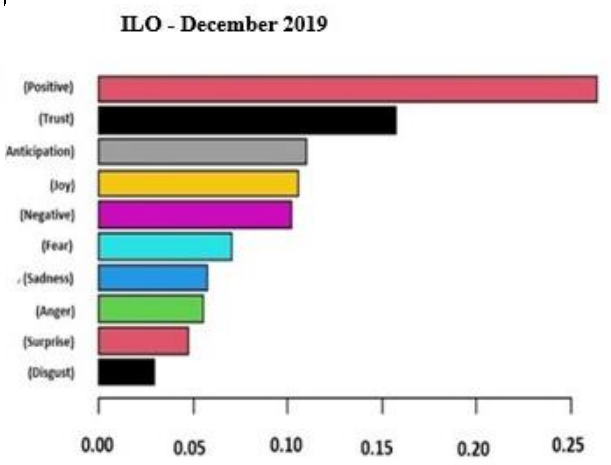
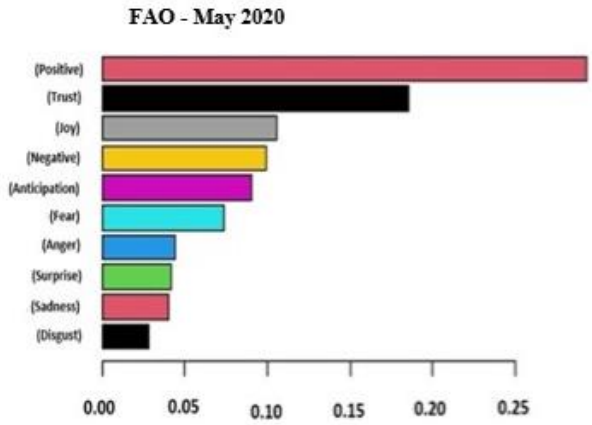
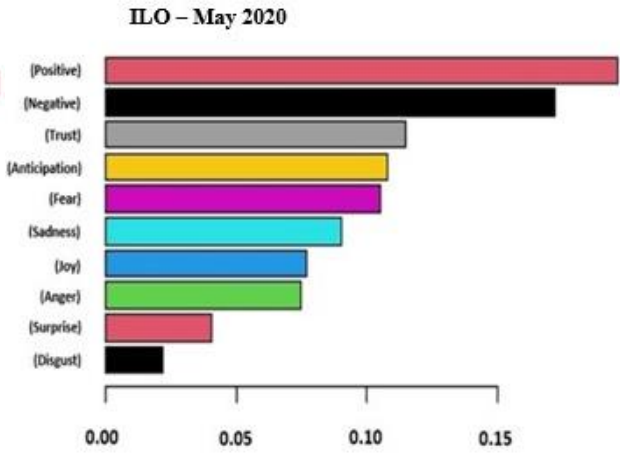


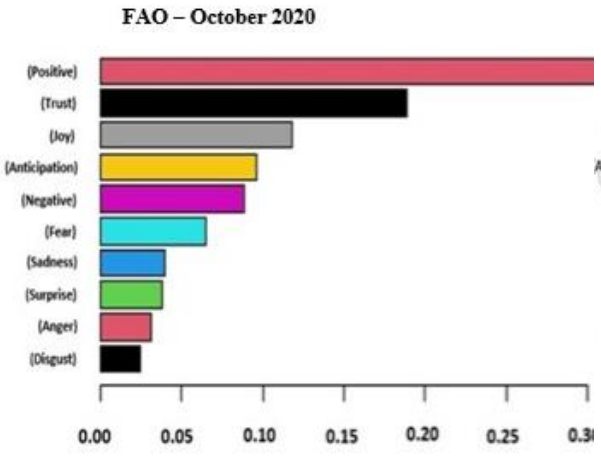
Figure 10. Mood Distribution of Institution's Periodic Datasets of UNICEF











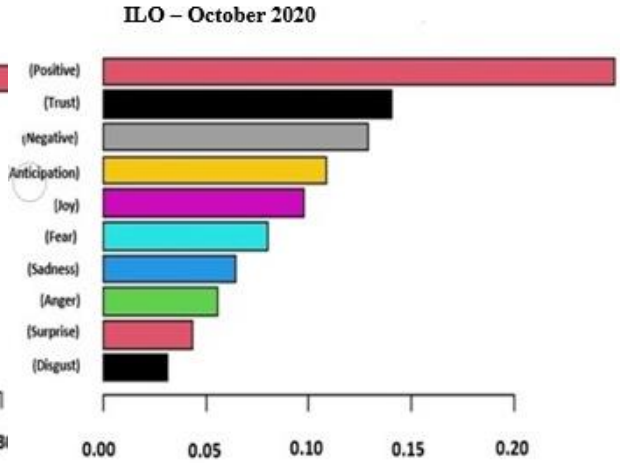


Figure 11*. Mood Distribution of Institution's Periodic Datasets of FAO*

Figure 12. Mood Distribution of Institution's Periodic Datasets of ILO

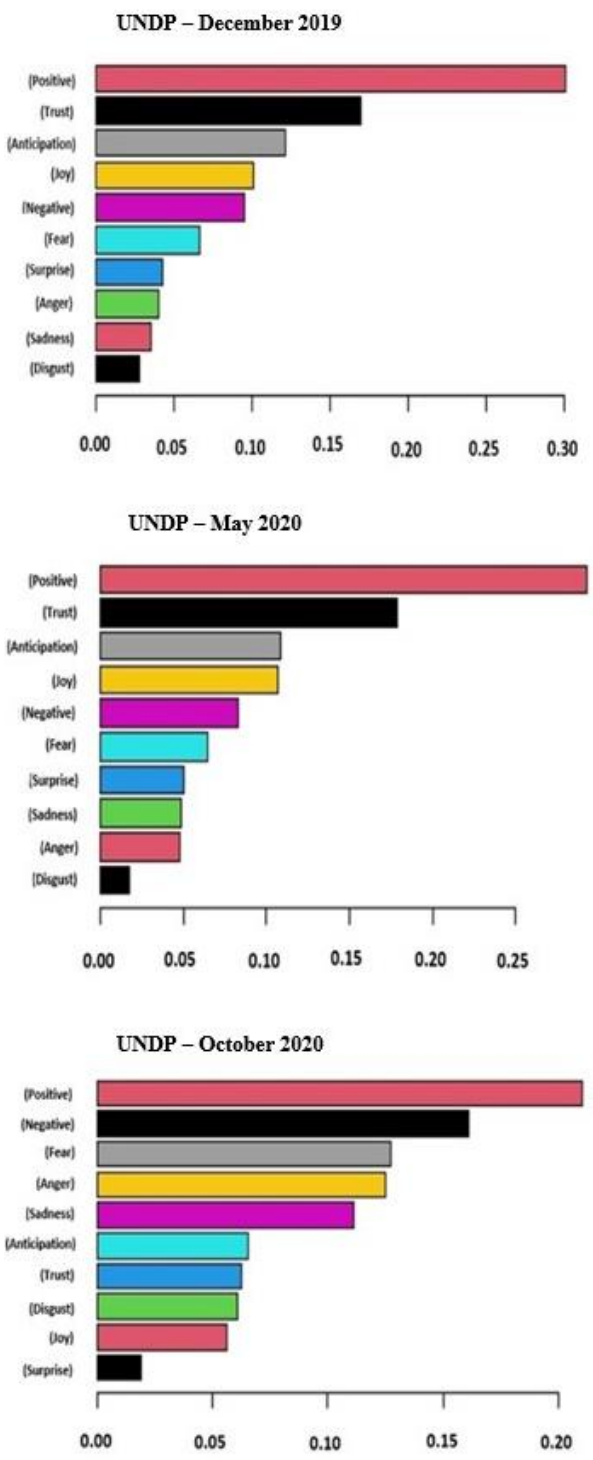


Figure 13. *Mood Distribution of Institution's Periodic Datasets of UNDP*

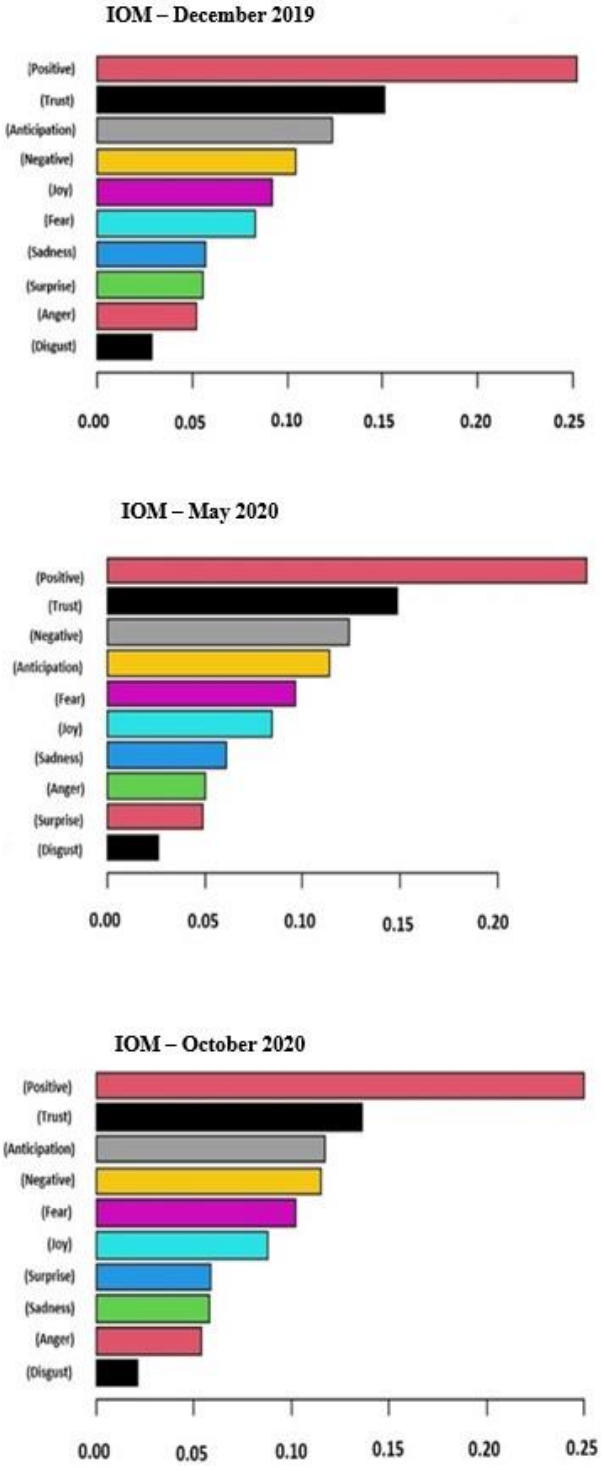


Figure 14. Mood Distribution of Institution's Periodic Datasets of IOM

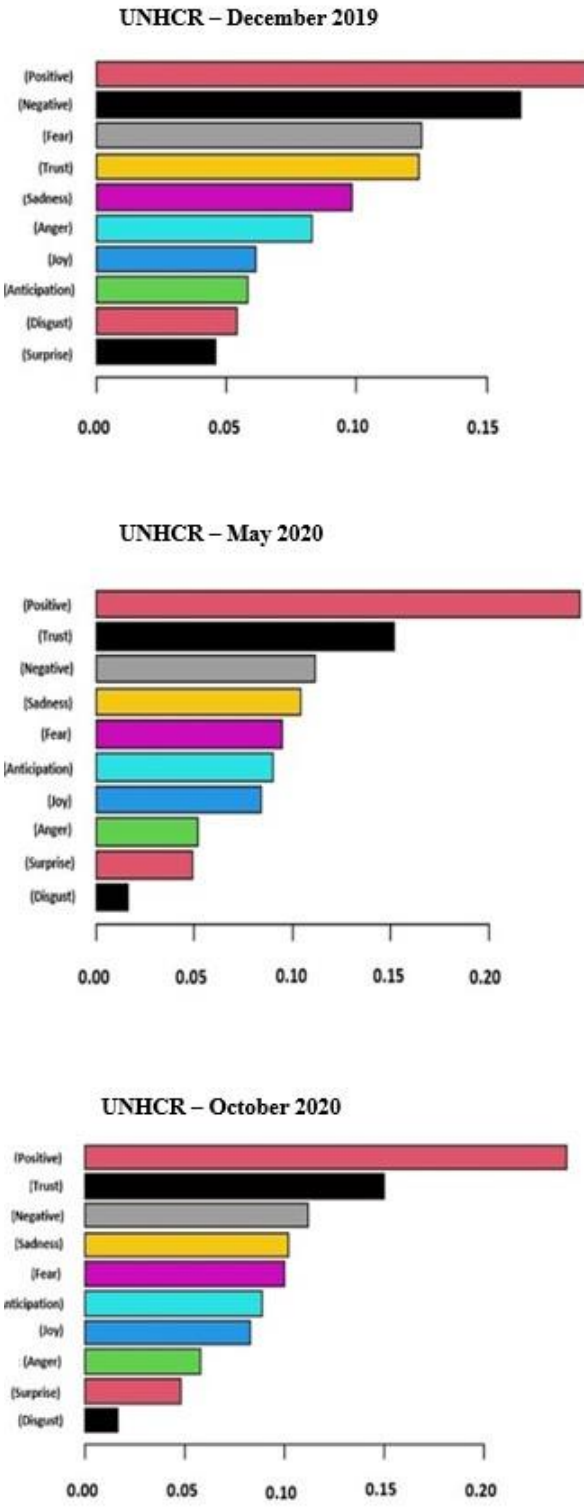


***Figure 15**. Mood Distribution of Institution's Periodic Datasets of UNHCR*

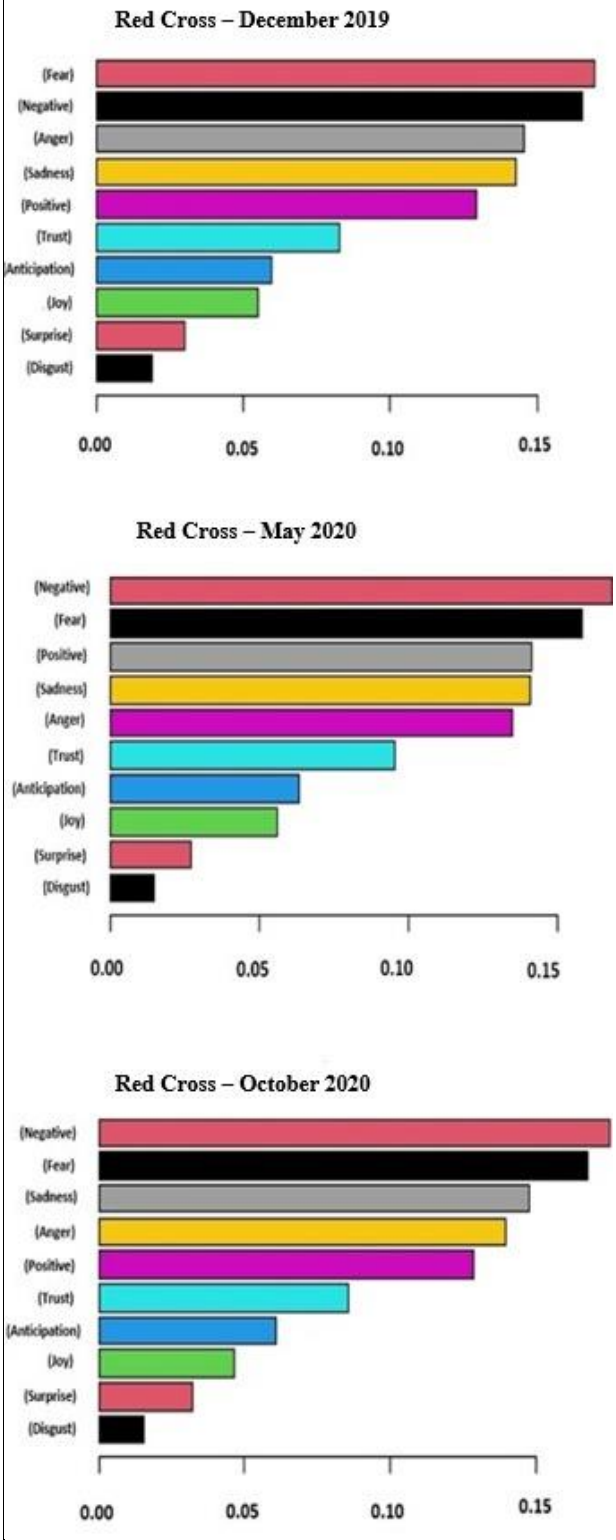


Figure 16. Mood Distribution of Institution's Periodic Datasets of Red Cross

There are differences between the emotional medians of the institutions according to the periods related to Expectation, Trust, Anger, Hated, Surprise, Joy, Sadness, Positive and Negative emotion. The distributions of the emotional medians of the three periods of the institutions in all institutions were tested with the Friedman Test.

***Table 5**. Distribution of the emotional medians of the institutions for the three periods in all institutions (Friedman Test)*

	x^2	P $(\leq 0,05)$	Kendall's W
Surprised	17,821	0,013	0,849
Expectation	15,333	0,032	0,730
Anger	15,111	0,035	0,720
Sadness	14,556	0,042	0,693
Joy	14,444	0,044	0,688
Negative	14,333	0,046	0,683
Fear	14,222	0,047	0,677
Positive	13,222	0,067	0,630
Trust	13,556	0,060	0,646
Disgust	10,111	0,182	0,481

The distributions of the emotional medians of all institutions for the three periods were tested with the Friedman Test. There is a significant difference between the periodic distributions of Expectation, Anger, Fear, Surprise, Joy, Sadness, Negative emotions and the emotional medians of the relevant institutions. There is no significant difference between the periodic distributions of the three-period medians of Trust, Hate, and Positive emotion across all institutions.

4 DISCUSSION

Researching the direction of the sharing of ideas on Twitter is important in terms of determining the tendencies of people and the emotions contained in the shares. In this context; Sentiment analysis method was used to evaluate tweet texts where WHO, FAO, ILO, IOM, UNICEF, UNDP, UNHCR or RC were tagged or used in sentences. With the NRC emotion dictionary, words are classified according to 10

emotions. Except for the October 2020 period of UNDP, the number of positively tagged tweets was overestimated by negative tweets in all periods of all institutions. In this context, this difference in UNDP can be interpreted as the reflection of poverty and deprivation in developing countries on Twitter. As a result of tagging with the NRC dictionary, the number of neutral tweets was found to be considerably higher than the number of positive and negative tweets. In order to maximize the effectiveness of using Twitter; It is important to understand the factors that will increase the dissemination of information shared by such institutions. There are many studies investigating factors that facilitate the retransmission of tweets, including adding hashtags, URLs, photos, and videos [3], [21]. However; Sentiment analysis of non-profit organizations and their followers' communication on Twitter has not been mentioned much in the literature. The efforts of these organizations to convey their messages to the masses are of high importance for institutions. With these efforts, institutions; He also uses Twitter as his main communication channel, where he publishes mission and various updates and communicates with his followers by adding different content features to his tweets [22].

In the research; As a result of sentiment analysis, the number of retweets containing various factors such as hashtags, URLs, photos and videos in tweets taken in the periods of November 2019, May 2020 and October 2020 was found to be considerably higher than the number of positive and negative tweets in all institutions within the scope of the research. It shows that they are able to realize the dissemination of information, which is one of the main purposes of using social media.

In the study of Park et al.; They examined how major health organizations, such as the sampled American Heart Association, American Cancer Society, and American Diabetes Association, use Twitter to spread health information, build relationships, and promote actions they take to improve health. Content analysis of tweets was conducted to examine these organizations' use of Twitter's interactive features and to understand the message functions and topics of their tweets. As a result, it has been found that all organizations share original tweets most frequently, and the use of retweet and reply functions differs according to organizations. Your followers; It has been revealed that people tend to retweet and like messages [23]. Chung et al., who conducted a sentiment analysis for the Women Who Code, a non-

profit organization that supports women's advancement in technology against sexist norms; He noted the use of URLs, adding photos, adding videos, and number of emojis by encoding the content categories for each tweet. In the research findings; It has been shown that using an emoji or URL in a tweet has a positive effect on the retweet. This research of Chung et al.; helping to understand nonprofits' use of Twitter; offers practical implications for tech-savvy female audiences so they can strategically spread their message [22]. In their study, which Thackeray et al. described as the first study to evaluate the public health situation among state health units; He randomly sampled tweets and coded them under the headings of "dissemination of information", "participation" and "action". In the research; It is stated that the units mostly establish one-way communication and focus on personal health. Researchers; states that institutions need to establish more two-way communication and interaction in order to realize their connection and relationship development potential [3]. In this context; Within the scope of the work of non-profit organizations, the research provides followers and supporters with meaningful insights on how mutual exchanges, including periods of great crisis, contain positive emotion and are associated with the retweetability of organizations or factors related to these organizations. However, as the spread of the pandemic increased, this situation caused a change in the feelings and emotions in tweets about institutions. Aydemir and Akyol in their study; they state that hashtag activism against immigrant and anti-immigrant rhetoric resulting from the Covid-19 pandemic has generally received positive reactions and emotions, therefore it has been successful in raising awareness and delivering information to large masses [24]. This work; is in line with the findings of the study. In addition, some researchers; argues that online activists participating in campaigns via social media are less likely to go beyond tweeting [25]. In addition to the findings of sentiment analysis; Statistical analysis of the emotional medians included in the tweets taken periodically on the basis of institutions was made and a significant relationship was found in all institutions except FAO. When the statistical analysis of emotion medians is evaluated; A significant relationship was found between the medians of "fear" feeling of all institutions during the period. With this; in sentiment analysis results; Especially during the pandemic period, there was an increase in the feeling of "fear" in the posts about institutions. In the research of Hubert et al., who investigated

state presence and public participation in social media; visual analysis and emotion analysis were used together. Researchers; They stated that they found the effectiveness of Twitter valuable in the fields of health, social development, education, environment and business [26]. Menendez et al.; Sentiment analysis was applied to group the sample of tweets using the #WorldEnvironmentDay hashtag according to the emotions expressed. The tweets, which determine the main factors related to the environment and public health that are most relevant to Twitter users, are grouped according to the Sustainable Development Goals (SDG). Researchers; predicts that research results can facilitate environmental decision making for companies, institutions and non-profit organizations [27].

5 CONCLUSIONS

As a result; health with the Covid-19 pandemic process, which has its own social and political conditions; It has become a global concern for almost all industries. In this context; There is a necessity to evaluate health promotion with a holistic perspective together with technology. This research, in which tweets are classified according to 10 different emotions; non-profit international organizations that make environment, health and sustainable development a principle; It provides a conceptual framework for understanding when and why follower behaviour occurs. This; It is very important for institutions to realize their missions, to create the necessary meaningful support in times of crisis, to increase benefit and awareness, to facilitate decision-making, and to increase communication and interaction. In the research, negation, irony and sarcasm were not included due to the large number of institutions and data collection for 3 periods. This subject, which is the main limitation of the research and which is difficult to analyse in the field of natural language processing and includes different algorithms, is planned to be applied in the future study.

Conflict of Interest

There is no conflict of interest between the authors.

Authors Contributions

The authors' contribution rates in the study are equal. Conceptualization, Ö.Ç. and E.Ö.; methodology, Ö.Ç. and E.Ö.; software, Ö.Ç.; formal analysis, Ö.Ç.; investigation, E.Ö.; resources, Ö.Ç.; data curation, Ö.Ç. and E.Ö.; writing—original draft preparation, Ö.Ç. writing—review and editing, Ö.Ç. and E.Ö.; visualization, Ö.Ç.; supervision, E.Ö.; project administration, Ö.Ç. and E.Ö.

Research and Publication Ethics

The study is complied with research and publication ethics

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