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Discussions About COVID-19 Vaccination on Twitter in Turkey: Sentiment Analysis

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Abstract

Objectives: The present study aims to examine coronavirus disease 2019 (COVID-19) vaccination discussions on Twitter in Turkey and conduct sentiment analysis.

Methods: The current study performed sentiment analysis of Twitter data with the artificial intelligence (AI) Natural Language Processing (NLP) method. The tweets were retrieved retrospectively from March 10, 2020, when the first COVID-19 case was seen in Turkey, to April 18, 2022. A total of 10,308 tweets accessed. The data were filtered before analysis due to excessive noise. First, the text is tokenized. Many steps were applied in normalizing texts. Tweets about the COVID-19 vaccines were classified according to basic emotion categories using sentiment analysis. The resulting dataset was used for training and testing ML (ML) classifiers.

Results: It was determined that 7.50% of the tweeters had positive, 0.59% negative, and 91.91% neutral opinions about the COVID-19 vaccination. When the accuracy values of the ML algorithms used in this study were examined, it was seen that the XGBoost (XGB) algorithm had higher scores.

Conclusions: Three of 4 tweets consist of negative and neutral emotions. The responsibility of professional chambers and the public is essential in transforming these neutral and negative feelings into positive ones.

There have been many pandemics in history, such as Ebola, Middle East respiratory syndrome coronavirus (MERS-CoV), and SARS, which caused deaths.[1] The COVID-19 pandemic first broke out in Wuhan, China, in December 2019 and spread rapidly worldwide.[2] Due to the high rate of transmission and death rates of the prevalence of COVID-19, the COVID-19 pandemic is a significant threat that can affect various aspects of physical and mental health.[3] The World Health Organization (WHO) stated that COVID-19 is an urgent global public health problem, and all countries should take a role in detecting and preventing infection.[4] Due to high infection and death rates, countries had to take restriction measures in many areas.[5] Governments worldwide implemented masks, social distancing, and isolation measures to prevent the spread of the coronavirus; the COVID-19 vaccines were developed in some countries.[6,7]

Social media applications (Twitter, Facebook, Instagram, Reddit, and the rest) known as Web 2.0 applications that provide interaction between users have become popular in recent years for information about health and vaccines.[8] Social and statistical studies have shown that users' time on monthly, weekly, and daily social media use affects human behavior (Statista, 2019). Social media is not only a critical interface for sharing vital information but has also turned into a media where false information is spread.[9] Vaccine hesitancy and opposition negatively affect immunization services. Anti-vaccination campaigns and normalizing anti-vaccination are undermining public health confidence. The public continues to be exposed to anti-vaccine conspiracy theories on social media and other online platforms as vaccination hesitancy increase. It is stated that the reason for the hesitation is related to the increase in doubts about scientific consensus.[10]

Researchers have focused on emotions from the beginning of COVID-19 and have extensively studied the increase in negative emotion,[11–13] anxiety,[14] and their regulation[15] in the public related to the COVID-19 pandemic. Although the COVID-19 vaccines are essential in preventing the disease, vaccination has traditionally faced public fears, hesitations, and even opposition.[16,17] Identifying human emotions from social media is essential for public awareness and policy development.[18] It was stated in the study of Singh et al. that many epidemics and pandemics can be quickly brought under control if health-care professionals take into consideration social media data.[19]

According to the "Digital 2020: Global Digital Overview" report, Twitter is a free microblogging platform with approximately 340 million registered users. Turkey is one of the countries that use Twitter the most. Turkey ranks 6th in the world and 2nd in Europe with 11.8 million Twitter users.[20,21] The most followed accounts on Twitter in Turkey belong to government officials, politicians, sports clubs, government agencies, media persons, and organizations.[22] Twitter data can be used in research due to easy accessibility.[23] The popularity of Twitter and its greater adoption than other social platforms motivated the use of Twitter for the present study. The increase in the use of Twitter and other social media in the COVID-19 pandemic has brought about the effects of the pandemic with sentiment analysis and the examination of opinion mining in countries.[23] Sentiment analysis of Twitter data, which provides essential information about public health crises, is done by the Natural Language Processing (NLP) method. This method is the artificial intelligence (AI) analysis of texts in English and Turkish languages by computer programming. Sentiment analysis methods are preferred in analyzing society or groups of different scales, especially in appreciation, comment, and opinion mining.

Big data analysis of social media discussions about the COVID-19 vaccines is limited.[24,25] Research involving the latest social media data is needed to understand the public debate about the COVID-19 vaccines during the pandemic. Individuals or patients need to benefit from the opinions and advice of other individuals in making decisions about medical problems.[26] Knowing about the content of the COVID-19 vaccination discussion on Twitter will provide a possible explanation for users' attitudes and their acceptance or hesitancy of the COVID-19 vaccines. The current study is the first known study in Turkey to conduct sentiment analysis using Twitter data for the COVID-19 vaccines. Public debate and concerns about the COVID-19 vaccines need extensive monitoring. The public is at great risk for COVID-19. Therefore, risk communication techniques are used effectively in public health interventions. Notable changes in critical issues and sentiments need to be recognized; public awareness of public health education and campaigns needs to be raised. In addition, it is crucial for health professionals to understand the emotional aspect of Twitter messages and to be able to make the right interventions in reducing concerns about the COVID-19 vaccines. Nurses always maintain close contact with patients/healthy people. Therefore, in individual and social health assessments, nurses in particular need to know and understand the feelings of the public and take precautions. The current study aims to examine discussions about COVID-19 vaccination on Twitter in Turkey and conduct sentiment analysis.

Research Questions

1. What are the sentimental polarities of the statements on Twitter about COVID-19 vaccines?
2. What is the frequency of words in Turkish tweets about COVID-19?
3. What is the relationship between document segments and relative frequency?
4. What are the accuracy values of tweets about COVID-19 vaccines according to ML algorithms?

Methods

Sentiment analysis of Twitter data was performed in the present study with the Natural Language Processing (NLP) method of artificial intelligence (AI). For a flowchart of the proposed model, see Figure 1.

Data Collection

The tweets were retrieved retrospectively from March 10, 2020, when the first COVID-19 case was seen in Turkey, to April 18, 2022. Tweets collected on April 18, 2022. With the hashtags in Turkish (#covid19asi (#covid19vaccine), #covid19asisi (#covid19-vaccination), #coronaasi (#coronavaccine), #coronaasisi (#coronavaccination), #koronaaşısı (#koronavaccine), #koronaaşı (#koronavaccination), #biontech, #sinovac, #turkovac) were collected. 10308 tweets accessed. One of the methods frequently used to collect data is Twint.[27] Tweets were collected using the Twint library, which has no application programming interface (API) restrictions.

The data analysis was done in Google Colab using Python 3.0 programming language and Python 3.0 compatible Pandas, NumPy, Matplotlib, NLTK, Scikit-learn, and TextBlob libraries. In addition to using Dictionary-based methods, this research used several ML (ML) models for sentiment analysis on an annotated dataset of COVID-19 vaccine tweets. The resulting dataset was used for training and testing ML classifiers. The model was trained and tested with naive Bayes (NB), random forest (RF), XGBoost (XGB), and logistic regression (LR) algorithms. Performance was evaluated using accuracy. The accuracy values of ML algorithms were evaluated as Count vectors accuracy, Word-level TF-IDF accuracy, N-Gram TF-IDF accuracy, Charlevel accuracy.

Data Preprocessing

Figure 1 presents the data preprocessing flowchart.

Sentiment Analysis

Dictionary-based methods are used to calculate emotion score to identify a tweet's hashtag as positive, negative, or neutral using polarity score with dictionary methods. Sentiment analysis of Twitter data was made with the data that was preprocessed and prepared at this stage. AI's NLP method was used; this method includes analyzing the keywords that appear in search topics, exploring the sentiment expressed on everything related to COVID-19 vaccines, including word frequency statistics and word clouds. Polarity and subjectivity scores of tweets ranging from -1 to 1 and 0 to 1 were calculated. A subjectivity score of 0 means that the tweet is objective, and a score of 1 means that the tweet is subjective. Polarity scores between -1 and 0 were classified as negative, those equal to 0 as neutral, and between 0 and 1 as positive emotions. The polarity of positive, negative, and neutral text is found with the TextBlob library. It is seen that the accuracy is quite high in the studies in which Turkish sentiment analysis is performed.[28–33]

Ethical Approval

Written permission was obtained from the Twitter developers to use the data. Due to the type of research, ethical permission was not required. The tweets used in the current study are accessible to the public as they are published openly. Still, the privacy of the tweeters was taken into consideration. Due to the impossibility of obtaining informed consent from all tweeters, no personal and sociodemographic data were analyzed. The data were collected using an automated process. Hence, the privacy of those who tweeted was protected.[34]

Findings

Tweets about the COVID-19 vaccines were classified according to basic emotion types using sentiment analysis. It was found that 7.50% of the tweeters were positive, 0.59% negative, and 91.91% neutral about the COVID-19 vaccines. In addition, some polarity examples of tweets can be seen in Table 1.

The data were filtered before analysis due to excessive noise.

↓

First, the text is tokenized.

↓

The following steps were used to normalize the texts.

↓

- All tokens have been converted to lowercase. However, the same tokens were merged, and the dimensionality of the text was reduced.
- Vaccine-related words were filtered out. All URL links in texts were replaced with spaces.
- All usernames, URL, and hashtags were replaced with white spaces.
- All punctuation marks were removed. Stop words*, the most common words in the text were removed using the Natural Language Toolkit (NLTK).
- Tokens, lines of text, and extra spaces at the end of paragraphs were removed.
- Numerical expressions in texts have been removed.
- Tweets and retweets containing homonyms were excluded.
- Tweets and retweets from fake and bot accounts were removed.
- Additionally, lemmatization was done in the preprocessing of the text. Lemmatization reduces inflectional words to a common root or a single term.
- Term Frequency - Inverse Document Frequency (TF-IDF) weighting is done.

* The stopwords in the Turkish language are: 'acaba', 'ama', 'aslında', 'az', 'bazı', 'belki', 'biri', 'birkaç', 'birşey', 'biz', 'bu', 'çok', 'çünkü', 'da', 'daha', 'de', 'defa', 'diye', 'eğer', 'en', 'gibi', 'hem', 'hep', 'hepsi', 'her', 'hiç', 'için', 'ile', 'ise', 'kez', 'ki', 'kim', 'mı', 'mu', 'mü', 'nasıl', 'ne', 'neden', 'nerde', 'nerede', 'nereye', 'niçin', 'niye', 'o', 'sanki', 'şey', 'siz', 'şu', 'tüm', 've', 'veya', 'ya', 'yani'

Figure 1. Data preprocessing.

Table 1. Example tweets and polarities

Polarity	Sentiment	Text
-0.5	Negative	Az önce ellerim dolu telefonda random playlist çalıyo aklımdan geçirdiğim şarkı çalmaya başladı birden. Benim biontech'te yerleştirilen çipler çalışmaya başladı galiba
-0.1	Negative	Bono aşıkarşıtı olsa, yarın 2 doz Çin + 4 doz Biontech yaptırırım.
0.0	Neutral	Ben de Biontech aşılı olmama rağmen 2 yıldır diğer insanlar için mücadele ettim benim aşıdan zarar görüp görmemem çocukların geleceğinden daha önemli değil diyerek, eminim sizden de Ahmet beyden de daha büyük mücadeleler verdim. Siz de kendinizi kurtarmışsınız tebrikler.
0.0	Neutral	Abi birileri hala telefonun bluetoothuyla biontech asililari buldugunu falan iddia ederken, beklentin fazla yuksek geldi bana
0.5	Positive	Bir ara Turkovak diye bir aşı çıktı 3 ay sonra hiç satılmadan yok oldu. Oysa Turkovac ticari firması bakana çok güvenmişti.
0,15	Positive	Biontech doz aşıdan sonra uzun süre yorgunluk halsizlik hissetmek normal midir bunu yaşayan kaç kişi var acaba ay oldu neredeyse

For Wordcloud, https://voyant-tools.org/,[34] an online, open source, known, Turkish character supported software was used and it is shown in Wordcloud Figure 2. In the WordCloud, the most used and prominent words in Turkish tweets are seen. The size of the words in the word cloud map depends mainly on the word frequency, which is essentially a view of the statistics of high-frequency words. The word that occupies the largest area in the figure is the most frequently repeated. Also, repetitive tweets, stop words, punctuation, and hashtags were removed. This word-cloud has document with 15.754 total words and 6.040 unique word forms. Vocabulary Density is 0.383. Readability Index is 18.668. Average Words Per Sentence is 16.2. Most frequent words in the wordcloud is biontech (415); aşı (237); sinovac (221); doz (185); 2 (146). There are 105 words in this wordcloud shown in Figure 2.

The links of the frequently used words in the analysis are shown in Figure 3. The relationship between document segments and relative frequency is shown in Figure 4. Count vectors accuracy, Word-level TF-IDF accuracy, N-Gram TF-IDF accuracy, and Charlevel accuracy values of ML algorithms are shown in Table 2. When the accuracy values of the ML algorithms used in this study were examined, it was seen that the XGB algorithm had higher scores.

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Figure 2. Wordcloud of sentiment tweets in Turkish.

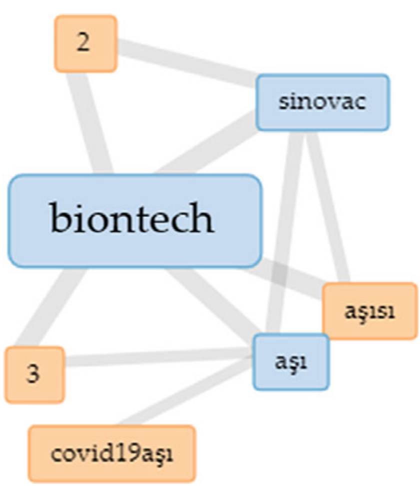

Figure 3. Links of the frequently used words.

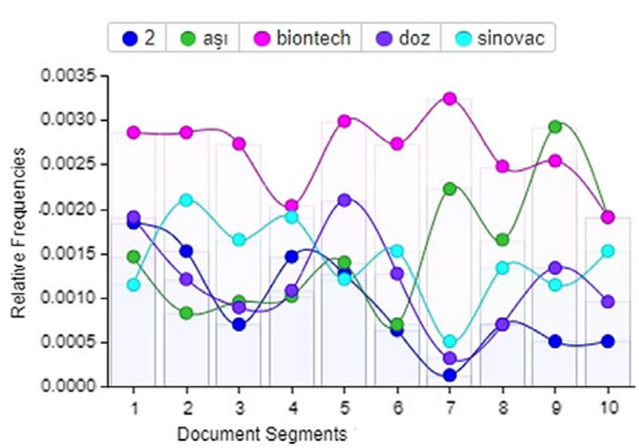

Figure 4. The relationship between document segments and relative frequency.

Table 2. Accuracy values according to ML algorithms

	NB	RF	XGB	LR
Count vectors accuracy	0.225	0.381	0.411	0.231
Word-level TF-IDF accuracy	0.155	0.182	0.210	0.205
N-Gram TF-IDF accuracy	0.215	0.281	0.310	0.291
Charlevel accuracy	0.321	0.388	0.418	0.201

Discussion

Defined as “the cornerstone of public health safety” by the WHO, surveillance aims to detect high morbidity and mortality rates, take control measures, and report any event to WHO.[35] Historically, public health workers have used data from multiple sources to measure disease burden and other health outcomes, prevent and control disease, and guide health-care activities. With the spread of the Internet and the advent of modern technology, potential new sources of data are emerging. In recent years, researchers have accepted that social media platforms such as Twitter and Facebook can also provide data on health and behavior at the national level.[36]

Social media applications are characterized as a valuable source of information for health research.[37] Internet users follow health-related issues on social media and share personal health information. They cited social media data and studies on communicable diseases such as influenza, as well as noncommunicable diseases such as mental health. It is stated that Twitter data are used to assist public health efforts related to surveillance, event detection, pharmacovigilance, prediction, disease tracking, and geographic identification and has yielded positive results.[38] According to Tavoschi et al. used 693 Twitter data on vaccines in Italy and automatically classified them as pro-vaccine, anti-vaccine, and abstaining.[39]

It has been found in the current study that 7.50% of tweeters in Turkey have a positive opinion, 0.59% a negative opinion, and 91.91% a neutral opinion about the COVID-19 vaccines. Similarly, in the study in which sentiment analysis of the COVID-19 vaccine was conducted from Japanese Twitter users between August 1, 2020, and June 30, 2021, it is stated that emotions are generally neutral.[40] After the first COVID-19 vaccine was given to Minister of Health Fahrettin Koca on January 13, 2021, vaccination was started in Turkey.[41] The vaccination scheme of the Ministry of Health of the Republic of Turkey against COVID-19 is shown in Figure 5.

The first vaccination studies in Turkey started with Sinovac. Biontech, which was produced later, was put on the market. The Sinovac vaccine was announced to be less protective against some variants, according to Biontech. Therefore, Biontech was seen as a reliable vaccine by the Turkish society. In February 2022, Minister of Health Dr. Koca announced that the Turkovac vaccine, which was produced in Turkey and received Emergency Use Approval, will be made as a reminder dose. However, the Phase 3 study of the vaccine has not yet been published. On the other hand, statements that the number of cases in Turkey were explained incorrectly took place in the media. The number of COVID-19 cases has been corrected by the Ministry and started to be published. These statements undermined public confidence. In the study, in which the self-orientalist discourses regarding the Turkovac vaccine are determined with the data obtained from Twitter, it is seen that the East does not or will not have the capacity to follow modern scientific developments as much as the West.[42] There are also discourses about the reality of Turkovac. In this context, policy makers need to act quickly, follow the pulse of the public on

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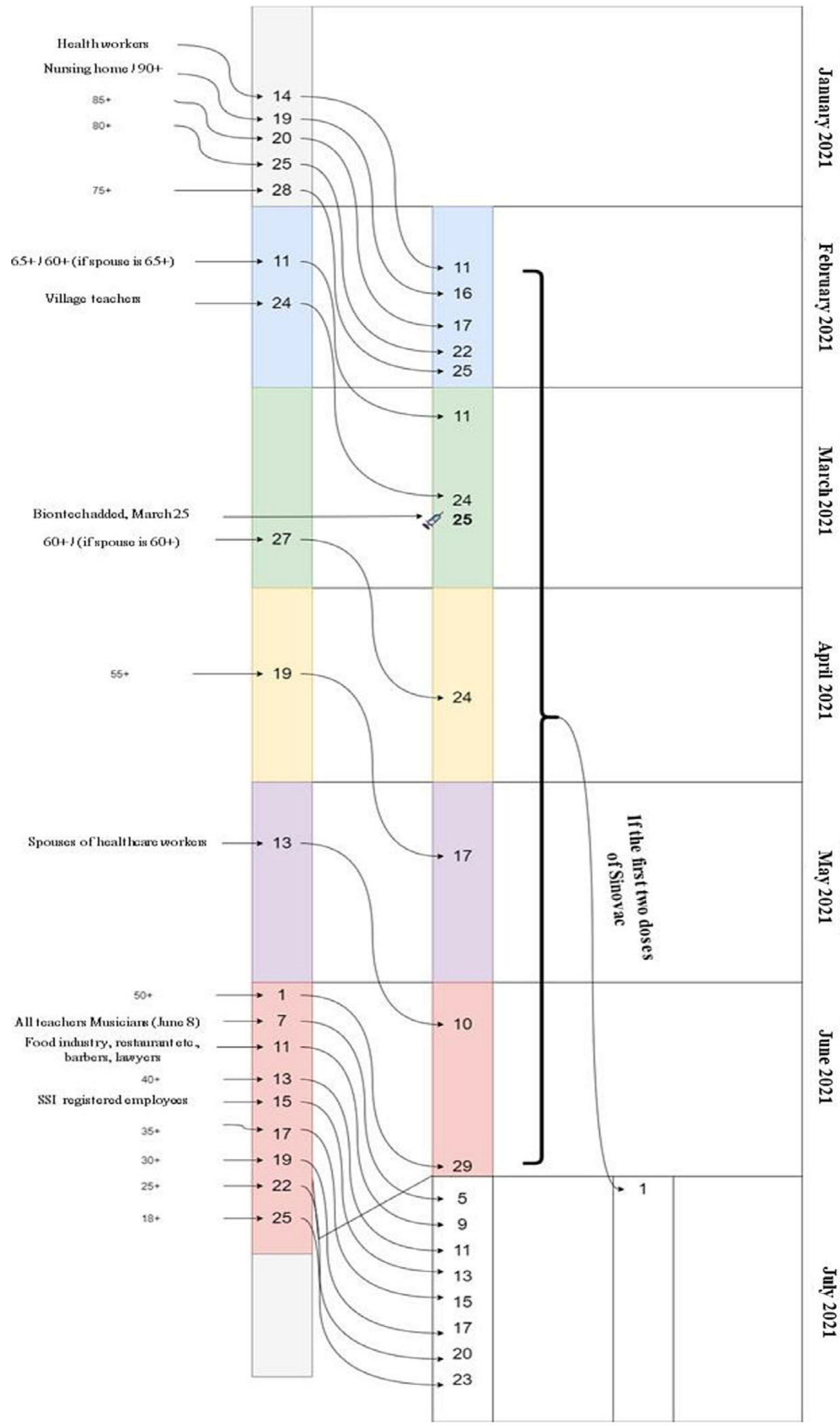

Figure 5. Republic of Turkey Ministry of Health vaccination scheme against COVID-19.

social media, and make reliable statements. People's perceptions of vaccines, the widespread disruptions caused by the COVID-19 pandemic on Turkish soil, society seem to be neutral toward the benefit of the vaccine. The success of the COVID-19 vaccine in achieving herd immunity depends on widespread adoption of the vaccine. The expansion of the anti-vaccine community, which is largely spread on social media, is likely to discourage such adoption, giving the virus an edge.

Although COVID-19 vaccines were available at the time of the research, it can be argued that the reason for the high number of neutral thoughts in this study is due to the prevailing feeling of insecurity. Because it is known that the effect value of Sinovac is low and Turkovac has not been used yet. In addition, the fact that Biontech is an mRNA vaccine, a technology used for the first time in vaccines, has created disinformation among the public. Vaccination dates are also effective in neutral thinking (Figure 5). Big data analysis shows that positive attitudes of people on twitter toward the COVID-19 vaccine in 10 countries show a decline in positive attitude over the time period.[43] This situation may be directly proportional to the decrease in trust.

In the wordcloud given in this research (Figure 2), it was seen that the most popular vaccine among people living in Turkey is Biontech. In a study conducted in the United States, the most popular vaccine among people was Pfizer.[44] This is thought to be due to the difference in vaccines produced and imported in different countries.

Unlike the present study results, there are studies in which the public has a negative opinion. In the study in which the sentiment analysis of the COVID-19 vaccines discussions using Twitter data in Indonesia, it was reported that 39% of the individuals had a positive opinion, 56% a negative opinion, and 1% a neutral opinion.[45] In the study of Bonnevie et al. to measure the rise of anti-vaccination during the COVID-19 pandemic in the United States, it was stated that anti-vaccine users on Twitter increased by 80% over the period.[24] It was stated that the most negative emotion was fear.[46] A sentiment analysis study conducted in Canada indicated that most of those tweeting were hesitant about vaccination.[47] A study containing sentiment analysis of the COVID-19 vaccines with tweets in the United Kingdom and United States expressed that approximately 40% of the population of both countries had negative emotions. People living in the United States were more concerned about the side effects and safety of the vaccine due to the few deaths that occurred after the vaccination.[44] In a sentiment analysis conducted in Korea between February 23 and March 22, 2021, it was observed that tweets with negative views were relatively high.[48] A study examining tweets in the United States and India shows that negative feelings dominate the COVID-19 vaccines in both countries.[49] In the sentiment analysis of a COVID-19 vaccine made in Iran, it was stated that negative attitudes toward domestic and imported vaccines increased in some periods.[50] It is reported that the reason for the negative feelings of the public toward the COVID-19 vaccine is due to the dominance of anti-vaccine and vaccine hesitancy groups that appear on social media.

When the accuracy values of the ML algorithms used in this study were examined, it was seen that the XGB algorithm had higher scores. In the COVID-19 vaccine sentiment analysis study, which uses a worldwide dataset, it is stated that the LSTM-GRNN algorithm outperforms TextBlob and deep learning models.[51] ML models were used in the study, in which the dialogues about the COVID-19 vaccine opposition were analyzed. These models are RF, Support Vector Machines (SVM), Multilayer Perceptron (MLP), Gradient Boost (GB), Long Short Term Memory (LSTM). Among these models, it was observed that the ones with the best performance were RF, SVM, and GB, respectively.[52] In the study, which deals with the perspective of Sinovac and Pfizer with Twitter data in Indonesia, it is stated that the SVM algorithm performs well.[53] In the study of Ritonga et al., it is stated that the performance of the NB algorithm is high in sentiment analysis of Twitter data related to the COVID-19 vaccine. Likewise, in another study using NB, the results were highly accurate.[54] In a study where Twitter data were trained with Bi-LSTM, SVM, and NB models, it was stated that the Bi-LSTM model performed better than the others.[55] As can be seen, accuracy values differ in studies conducted with different datasets and using different algorithms. Therefore, in this study, the best performing XGB algorithm is proposed.

Studies with positive feelings toward the COVID-19 vaccines are seen in the literature. A study in which sentiment analysis of vaccine discussions on Twitter was conducted using ML methods between January and October 2020 in Australia showed that approximately two-thirds of Australian people had a positive opinion about the COVID-19 vaccines. Approximately one-third had a negative opinion. In a sentiment analysis study conducted with tweets collected from the United States, United Kingdom, Canada, India, Australia, Ireland, and Nigeria over 4 mo from December 1, 2020, to March 31, 2021, the positive opinion of AstraZeneca/Oxford, Pfizer/BioNTech and Moderna vaccines continued to be stable.[56] In a study conducted in the United States between November 1 and December 16, it was noted that 48.3% of the tweets were positive, 36.1% of the tweets were neutral, and 15.6% of the tweets were negative.[57] In another study conducted in the United States, it was emphasized that the majority of COVID-19 vaccines Twitter posts have pro-vaccine sentiment (45.7%), neutral sentiment (28.6%), and anti-vaccine sentiment (25.7%).[58] Lyu et al. carried out a sentiment analysis of the COVID-19 vaccine-related tweets posted from March 11, 2020, to January 31, 2021.[14] The most dominant emotion shown in the pre-April COVID-19 vaccine tweets was fear in the study. However, it was declared that as of the week of April 1, 2020, the fear changed to trust and continued. It was determined that the feeling of confidence reached its peak on November 9, 2020, when it was announced that the Pfizer vaccine was 90% effective. The public has positive opinions about the vaccine since it is thought that trust has increased and will continue to increase over time.

Public health professionals and those who use Twitter as a dissemination tool can benefit from the presence of trust evident in a subset of tweets. Public health professionals can use language that allows for confidence building when composing tweets. Trusting public health officials and their actions during a crisis is critical and a common theme in public health literature. Public health professionals can build trust on issues of public health importance by creating tweets that engage the public through social media, education, regular and timely communication, and evidence-based information.[59]

Conclusions

Few of the tweets reviewed were pro-vaccine and positive sentiment; however, anti-vaccination takes precedence. Most tweets consist of neutral emotions. According to research question 1; it was found that 7.50% of the tweeters were positive, 0.59% negative, and 91.91% neutral about the COVID-19 vaccines. According to research question 2, most frequent words are biontech (415); aşı (237); sinovac (221); doz (185); 2 (146). According to research question 3, in the relationship between document sections and relative frequency, the most correlated word is biontech (Figure 4). According to research question 4, when the accuracy values of tweets about Covid-19 vaccines are examined according to ML algorithms, it is seen that the XGB algorithm has the most accurate value (Table 2).

It is crucial for the Turkish government to actively encourage its citizens to get vaccinated and to help them understand the importance of vaccination. The best way to educate citizens about the positive side of vaccination is to address the fears they have expressed in social media posts about COVID-19 vaccines. The effective use of social media by the Ministry of Health and professional organizations to reach the broader masses in providing accurate information about vaccines, presenting explanations, and scientific studies in plain language can effectively eliminate the confusion in society. Trusting public health officials and their actions during a crisis is critically important. Establishing and monitoring risk communication is indispensable in managing and controlling an extraordinary public health emergency such as COVID-19. Risk communication specialists can create tweets. Public health specialists engage the public through education. In addition, public health professionals experienced in risk communication should engage in health education and health promotion interventions. Public health professionals can create tweets that engage the public through education, regular and timely communication, and evidence-based information on social media. In addition, public health authorities can analyze tweets using hashtags. They can measure the feelings of the people and try to understand them. The use of ML algorithms in sentiment analysis provides fast and high accuracy values. Therefore, the accuracy value of the XGB algorithm was found to be high for this study. Health policies can be formed according to the health status of the people. It can increase confidence in matters of public health importance. It may be recommended to conduct other ML algorithms and analyze population subgroups' feelings about the COVID-19 vaccines. In addition, it can be thought that it would be helpful to conduct studies that evaluate tweets since the introduction of the COVID-19 vaccines.

Limitations

The research limitations are that Twitter represents community engagement, the demographics of user profiles are low, the group with low media literacy and not using Twitter is mostly elderly, and the sample tweets used do not fully represent COVID-19 vaccines. The high representation of minorities among Twitter users makes it difficult to assess health services inequalities. Also, the accuracy of the Twint library is limited. Accuracy is limited as Sentiment analysis is performed in Turkish language. The strengths of the current study are instant captures as tweets are sent in real-time, using AI to evaluate tweets, and analyzing big data faster than humans can. The rapid change of tweet content is the weakness of the present study. The results of the study show the insights that tweets can provide for a health-related event.

References

1. **McMullan LK.** Clinical trials in an Ebola outbreak seek to find an evidence-based cure. *EBioMedicine*.2020;52:102614. doi: 10.1016/j.ebiom.2019.102614
2. **Zhang Y, Ma ZF.** Impact of the COVID-19 pandemic on mental health and quality of life among local residents in Liaoning Province, China: a cross-sectional study. *Int J Environ Res Public Health.* 2020;17(7):2381. doi: 10.3390/ijerph17072381
3. **Rothan HA, Byrareddy SN.** The epidemiology and pathogenesis of coronavirus disease (COVID-19) outbreak. *J Autoimmun.* 2020;109:102433. doi: 10.1016/j.jaut.2020.102433
4. **WHO**. Director-General's remarks at the media briefing on 2019-nCoV on 11 February 2020. Published February 11, 2020. Accessed July 16, 2021. https://www.who.int/director-general/speeches/detail/who-director-general-s-remarks-at-the-media-briefing-on-2019-ncov-on-11-february-2020
5. **Dutta S, Smita MK.** The impact of COVID-19 pandemic on tertiary education in Bangladesh: students' perspectives. *Open J Soc Sci.* 2020;8(9):53. doi: 10.4236/jss.2020.89004
6. **Le TT, Cramer JP, Chen R, *et al.*** Evolution of the COVID-19 vaccine development landscape. *Nat Rev Drug Discov.* 2020;19(10):667-668. doi: 10.1038/d41573-020-00151-8
7. **Li Y, Tenchov R, Smoot J, *et al.*** A comprehensive review of the global efforts on COVID-19 vaccine development. *ACS Cent Sci.* 2021;7(4):512-533. doi: 10.1021/acscentsci.1c00120
8. **Appel G, Grewal L, Hadi R, *et al.*** The future of social media in marketing. *J Acad Mark Sci.* 2020;48(1):79-95. doi: 10.1007/s11747-019-00695-1
9. **Gölbaşı SD, Metintas S.** Covid-19 pandemic and infodemia. *ESTÜDAM Halk Sağlığı Dergisi, 5(COVID-19 Özel Sayısı).* 2020;5:126-137. doi: 10.35232/estudamhsd.797508
10. **Bernard R, Bowsher G, Sullivan R, *et al.*** Disinformation and epidemics: anticipating the next phase of biowarfare. *Health Secur.* 2021;19(1):3-12. doi: 10.1089/hs.2020.0038
11. **Berkovic D, Ackerman IN, Briggs AM, *et al.*** Tweets by people with arthritis during the COVID-19 pandemic: content and sentiment analysis. *J Med Internet Res.* 2020;22(12):e24550. doi: 10.2196/24550
12. **Cerbara L, Ciancimino G, Crescimbene M, *et al.*** A nation-wide survey on emotional and psychological impacts of COVID-19 social distancing. *Eur Rev Med Pharmacol Sci.* 2020;24(12):7155-7163. doi: 10.26355/eurrev_202006_21711
13. **Chen Q, Min C, Zhang W, *et al.*** Unpacking the black box: how to promote citizen engagement through government social media during the COVID-19 crisis. *Comput Human Behav.* 2020;110:106380. doi: 10.1016/j.chb.2020.106380
14. **Lyu JC, Han EL, Luli GK.** COVID-19 vaccine-related discussion on Twitter: topic modeling and sentiment analysis. *J Med Internet Res.* 2021;23(6):e24435. doi: 10.2196/24435
15. **Restubog SLD, Ocampo ACG, Wang L.** Taking control amidst the chaos: emotion regulation during the COVID-19 pandemic. *J Vocat Behav.* 2020;119:103440. doi: 10.1016/j.jvb.2020.103440
16. **Ball P.** Anti-vaccine movement could undermine efforts to end coronavirus pandemic, researchers warn. *Nature.* 2020;13:581(7808):251-251.
17. **Abbasi J.** COVID-19 conspiracies and beyond: how physicians can deal with patients' misinformation. *JAMA.* 2021;325(3):208-210. doi: 10.1001/jama.2020.22018
18. **Alamoodi AH, Zaidan BB, Zaidan AA, *et al.*** Sentiment analysis and its applications in fighting COVID-19 and infectious diseases: a systematic review. *Expert Syst Appl.* 2021;167:114155. doi: 10.1016/j.eswa.2020.114155
19. **Singh R, Singh R, Bhatia A.** Sentiment analysis using ML technique to predict outbreaks and epidemics. *Int J Adv Sci Res.* 2018;3(2):19-24. http://www.allsciencejournal.com/archives/2018/vol3/issue2/3-2-15
20. **Twitter**. Global impact report. Accessed June 15, 2021. https://about.twitter.com/content/dam/about-twitter/en/company/global-impact-2020.pdf
21. **DATAREPORTAL**. Digital 2020: global digital overview. Accessed February 17, 2022. https://datareportal.com/reports/digital-2020-global-digital-overview
22. **Wikipedia**. List of Twitter accounts with the most followers (Turkey). Accessed February 17, 2022. https://tr.wikipedia.org/wiki/En_çok_takipçisi_olan_Twitter_hesapları_listesi_(Türkiye)
23. **Mathur A, Kubde P, Vaidya S.** Emotional analysis using Twitter data during pandemic situation: COVID-19. In 2020 5th International Conference on Communication and Electronics Systems (ICCES) IEEE. 2020;845-848. doi: 10.1109/ICCES48766.2020.9138079
24. **Bonnevie E, Gallegos-Jeffrey A, Goldbarg J, *et al.*** Quantifying the rise of vaccine opposition on Twitter during the COVID-19 pandemic. *J Commun Healthc.* 2021;14(1):12-19. doi: 10.1080/17538068.2020.1858222
25. **Hussain A, Tahir A, Hussain Z, *et al.*** Artificial intelligence-enabled analysis of public attitudes on Facebook and Twitter toward Covid-19 vaccines in the United Kingdom and the United States: observational study. *J Med Internet Res.* 2021;23(4):e26627. doi: 10.2196/26627
26. **Abualigah L, Alfar HE, Shehab M, *et al.*** Sentiment analysis in healthcare: a brief review. In: *Recent Advances in NLP: The Case of Arabic Language.* Springer: 2020;29-141. doi: 10.1007/978-3-030-34614-0_7
27. **Agustiningsih KK, Utami E, Al Fatta H.** Sentiment analysis of COVID-19 vaccine on Twitter social media: systematic literature review. In: 2021 IEEE 5th International Conference on Information Technology, Information

Systems and Electrical Engineering (ICITISEE) IEEE. 2021;121-126. doi: 10.1109/ICITISEE53823.2021.9655960
28. **Demircan M, Seller A, Abut F, *et al.*** Developing Turkish sentiment analysis models using ML and e-commerce data. *Int J Cogn Comput Eng.* 2021;2:202-207. doi: 10.1016/j.ijcce.2021.11.003
29. **Kemaloğlu N, Küçüksille E, Özgünsür M.** Turkish sentiment analysis on social media. *Sakarya Univ J Sci.* 2021;25(3):629-638. doi: 10.16984/saufenbilder.872227
30. **Shehu HA, Tokat S, Sharif MH, *et al.*** Sentiment analysis of Turkish Twitter data. In: AIP Conference Proceedings. 2019;2183(1):080004. doi: 10.1063/1.5136197
31. **Rumelli M, Akkuş D, Kart Ö, *et al.*** Sentiment analysis in Turkish text with ML algorithms. In 2019 Innovations in Intelligent Systems and Applications Conference (ASYU) IEEE. 2019;1-5. doi: 10.1109/ASYU48272.2019.8946436
32. **Gezici G, Yanıkoğlu B.** Sentiment analysis in Turkish. In: *Turkish Natural Language Processing*. Springer, Cham. 2018;255-271. doi: 10.1007/978-3-319-90165-7_12
33. **Balli C, Guzel MS, Bostanci E, *et al.*** Sentimental analysis of Twitter users from Turkish content with natural language processing. *Comput Intell Neurosci.* 2022. doi: 10.1155/2022/2455160
34. **Voyant Tools.** Accessed April 20, 2022. https://voyant-tools.org
35. **World Health Organization**. The world health report 2007 - a safer future: global public health security in the 21st century. Accessed February 17, 2022. https://www.who.int/whr/2007/en/
36. **Neiger BL, Thackeray R, Burton SH, *et al.*** Evaluating social media's capacity to develop engaged audiences in health promotion settings: use of Twitter metrics as a case study. *Health Promot Pract.* 2013;14(2):157-162. doi: 10.1177/1524839912469378
37. **Conway M, Hu M, Chapman WW.** Recent advances in using natural language processing to address public health research questions using social media and consumergenerated data. *Yearb Med Inform.* 2019;28(1):208. doi: 10.1055/s-0039-1677918
38. **Edo-Osagie O, De La Iglesia B, Lake I, *et al.*** A scoping review of the use of Twitter for public health research. *Comput Biol Med.* 2020;122:103770. doi: 10.1016/j.compbiomed.2020.103770
39. **Tavoschi L, Quattrone F, D'Andrea E, *et al.*** Twitter as a sentinel tool to monitor public opinion on vaccination: an opinion mining analysis from September 2016 to August 2017 in Italy. *Hum Vaccin Immunother.* 2020;16(5):1062-1069. doi: 10.1080/21645515.2020.1714311
40. **Niu Q, Liu J, Nagai-Tanima M, *et al.*** Public opinion and sentiment before and at the beginning of COVID-19 vaccinations in Japan: Twitter analysis. *medRxiv.* 2021. doi: 10.1101/2021.07.19.21260735
41. **Republic of Turkey Ministry of Health**. Accessed June 15, 2021. https://www.saglik.gov.tr/TR,78148/ilk-koronavirus-asisi-saglik-bakani-fahrettin-kocaya-yapildi.html#:~:text=Sağlık%20Bakanı%20Dr.,Sağlık%20Bakanı%20Koca%27ya%20yapıldı.
42. **Çankal G.** Self-Orientalist discussions about Turkovac Vaccine in social media. *J Media Relig Stud.* 2021;4(2):223-235. doi: 10.47951/mediad.1021243
43. **Greyling T, Rossouw S.** Positive attitudes towards COVID-19 vaccines: a cross-country analysis. *PLoS One.* 2022;17(3):e0264994. doi: 10.1371/journal.pone.0264994
44. **Na T, Cheng W, Li D, *et al.*** Insight from NLP analysis: COVID-19 vaccines sentiments on social media. *arXiv.* 2021;2106.04081. doi: 10.48550/arXiv.2106.04081
45. **Pristiyono, Ritonga M, Al Ihsan MA, *et al.*** Sentiment analysis of COVID-19 vaccine in Indonesia using Naïve Bayes Algorithm. In: *IOP Conference Series: Materials Science and Engineering.* 2021;1088(1):012045. doi: 10.1088/1757-899X/1088/1/012045
46. **Kwok SWH, Vadde SK, Wang G.** Tweet topics and sentiments relating to COVID-19 vaccination among Australian Twitter users: ML analysis. *J Med Internet Res.* 2021;23(5):e26953. doi: 10.2196/26953
47. **Griffith J, Marani H, Monkman H.** COVID-19 vaccine hesitancy in Canada: content analysis of Tweets using the theoretical domains framework. *J Med Internet Res.* 2021;23(4):e26874. doi: 10.2196/26874
48. **Shim JG, Ryu KH, Lee SH, *et al.*** Text mining approaches to analyze public sentiment changes regarding COVID-19 vaccines on social media in Korea. *Int J Environ Res Public Health.* 2021;18(12):6549. doi: 10.3390/ijerph18126549
49. **Sharma S, Sharma A.** Twitter sentiment analysis during unlock period of COVID-19. In: 2020 Sixth International Conference on Parallel, Distributed and Grid Computing (PDGC). IEEE. 2020;221-224. doi: 10.1109/PDGC50313.2020.9315773
50. **Nezhad ZB, Deihimi MA.** Twitter sentiment analysis from Iran about COVID 19 vaccine. *Diabetes Metab Syndr.* 2022;16(1):102367. doi: 10.1016/j.dsx.2021.102367
51. **Reshi AA, Rustam F, Aljedaani W, *et al.*** COVID-19 vaccination-related sentiments analysis: a case study using worldwide Twitter dataset. *Healthcare.* 2022;10(3):411. doi: 10.3390/healthcare10030411
52. **Paul N, Gokhale SS.** Analysis and Classification of vaccine dialogue in the Coronavirus era. In: 2020 IEEE International Conference on Big Data (Big Data) IEEE. 2020;3220-3227. doi: 10.1109/BigData50022.2020.9377888
53. **Nurdeni DA, Budi I, Santoso AB.** Sentiment analysis on Covid19 vaccines in Indonesia: from the perspective of Sinovac and Pfizer. In: 2021 3rd East Indonesia Conference on Computer and Information Technology (EIConCIT) IEEE. 2021;122-127. doi: 10.1109/EIConCIT50028.2021.9431852
54. **Villavicencio C, Macrohon JJ, Inbaraj XA, *et al.*** Twitter sentiment analysis towards Covid-19 vaccines in the Philippines using naïve bayes. *Information.* 2021;12(5):204. doi: 10.3390/info12050204
55. **To QG, To KG, Huynh VAN, *et al.*** Applying ML to identify anti-vaccination tweets during the COVID-19 pandemic. *Int J Environ Res Public Health.* 2021;18(8):4069. doi: 10.3390/ijerph18084069
56. **Marcec R, Likic R.** Using Twitter for sentiment analysis towards AstraZeneca/Oxford, Pfizer/BioNTech and Moderna COVID-19 vaccines. *Postgrad Med J.* 2022;98(1161):544-550. doi: 10.1136/postgradmedj-2021-140685
57. **Rahul K, Jindal BR, Singh K, *et al.*** Analysing public sentiments regarding COVID-19 vaccine on Twitter. In: 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS) IEEE. 2021;488-493. doi: 10.1109/ICACCS51430.2021.9441693
58. **Scannell D, Desens L, Guadagno M, *et al.*** COVID-19 vaccine discourse on Twitter: a content analysis of persuasion techniques, sentiment and mis/disinformation. *J Health Commun.* 2021;26(7)443-459. doi: 10.1080/10810730.2021.1955050
59. **Papadopoulos A, Sargeant JM, Majowicz SE, *et al.*** Enhancing public trust in the food safety regulatory system. *Health Policy.* 2012;107(1):98-103. doi: 10.1016/j.healthpol.2012.05.010