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Decoding the Tweetosphere: Analyzing Public Perceptions on the Repeal of Indian Farmer Bills 2020/2021

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Abstract
This study analyses sentiments expressed on Twitter following the repeal of the Farmer Bills 2020/2021 in India, aiming to understand the role of social media during crises and its capacity to promote or endorse specific views. Using content analysis of 14,444 tweets collected from verified and non-verified accounts across nine relevant hashtags, the data were pre-processed through transformation, tokenisation, filtering, and normalisation, and analysed with the VADER Sentiment Module of Orange Software. The findings reveal trends in tweet counts and sentiment over 12 days, showing an initial surge followed by a gradual decline in activity, with most tweets conveying positive sentiments supportive of the farmer protests and the repeal of the laws. The study underscores Twitter's role in shaping public opinion and disseminating information, while acknowledging limitations related to reliance on Twitter data and the defined timeframe. Its originality lies in providing insights into public perceptions and reactions to legislative changes following the repeal.
Keywords: *Twitter, Sentiment Analysis, Farmer Bill, Orange Software, Agriculture, Indian Farmers.*

Introduction

The Indian economy depends heavily on agriculture. About 17% of India's GDP comes from agriculture, which also employs more than half of the country's workforce, making it a significant economic sector. The last few decades have seen an astonishing expansion in Indian agriculture. Indian agricultural production is ranked second **(*India at a Glance*, 2024).** From 1950–51 to 2011–12, food grain output grew from 51 million tonnes (MT) to the greatest level since independence **(Arjun, 2013).** Three hotly debated farm bills were approved by the Union government on September 27, 2020, in Parliament: The Essential Commodities (Amendment) Bill 2020, the Farmers' Produce Trade and Commerce (Promotion and Facilitation) Bill 2020, and the Farmers (Empowerment and Protection) Agreement on Price Assurance and Farm Services Bill 2020. The new legislation was meant to allow large corporations to become more involved in the farming industry, allowing them to buy, store, and even choose what crops to grow through contract farming. The bills aimed to substantially alter and refocus the pre-existing regulatory framework of Indian agriculture. Farmers, especially those from the northwestern region (Punjab, Haryana, and western UP), perceive these rules as a direct attack on farming cultures and livelihoods. They have demanded that the new restrictions be repealed, and that price stability be extended to all agricultural commodities. These demonstrations have been ongoing for almost a year, the largest in India's recent history and possibly one of the largest in the world **(Almeida, 2020).** Farmers were reportedly demonstrating to seek the explicit inclusion of the "minimum support price" (MSP) in the act. However, the MSP option was already included in the new law, as farmers may sell goods at MSP to mandis. However, demonstrators demand that the MSP system be extended to open markets, which is unusual given that it contradicts the way free markets operate **(Sathye, 2020).** The unprecedented protests by Indian farmers against the three farm laws, which explicitly favour the profits of major enterprises in agriculture, earned sympathy and unity across the lengths and breadths of the country. World leaders, such as the Canadian Prime Minister, showed sympathy to the farmers in India.

Social media's role in information dissemination

Social media is described as "a group of internet-based applications that build on the ideological and technological foundations of Web 2.0 that allow the creation and exchange of user-generated content" **(Kaplan & Haenlein, 2010).** It is the means by which we communicate with our social networks, which encompasses all social media platforms including Facebook, LinkedIn, YouTube, and Twitter. The number of users on social media has increased dramatically in recent years, and it has been the focus of scientific research **(Wigand et al., 2010; McAfee 2006).** Facebook has about 2.5 billion members worldwide, while Twitter has 396.5 million users at the moment **(Dean, 2022).** The mechanics of information diffusion has altered due to the widespread use of social media applications. Up until a few years ago, the primary obstacle to the dissemination of knowledge within a community was the high expense of the technical infrastructure needed to reach a significant number of people. Since the Internet has become widely available, this bottleneck has been largely removed, and personal publishing modalities like social network sites (SNS), microblogging, and weblogs have become commonplace **(Kaplan & Haenlein, 2010).** The emergence of social media has drastically changed the number and type of information and news sources available, the process by which people find, organize, and coordinate groups of people with similar interests, and the capacity to solicit and share opinions and ideas across a wide range of topics **(Agrawal et al., 2011).** Twitter can provide rich insights into public opinion and "mirror the types of news that individuals are exposed to and also serve as a key source of debate about farmer protests, opposition, and disinformation"**(Tomeny et al., 2017).**

Statement of the problem

The Indian Parliament's enactment of farmer laws on 27 September 2020 attracted great interest and was widely discussed on social media. Social media sites, including Twitter, were used to discuss the Farmers Bills 2020.

The passage of Bills in Parliament elicited reactions from the public. Prime Minister Narendra Modi's government finally repealed the bills on 19 November 2021. The study aims to examine the nature of people's views expressed through tweets on Twitter following the repeal of the Farmer Bills 2020/2021.

Review of Literature

This literature review aims to showcase existing sentiment analysis research. Sentiment analysis is a branch of Natural Language Processing (NLP) that investigates subjective opinions or feelings about a topic gathered from multiple sources **(Bushkovskyi, n.d.).** Sentiment analysis can also be used to demonstrate shock and astonishment, as well as to provoke protests. Researchers have divided sentiment analysis into two groups: general sentiment analysis research and political sentiment analysis research. General sentiment analysis is used to understand people's views regarding products and services, but political sentiment analysis is used to understand Twitter users' opinions regarding political parties and political news **(Yadav, et al., 2021). Öztürk and Ayvaz (2017)** investigated public opinions and sentiments towards the Syrian refugee crisis. They examined approximately 2,381,297 relevant tweets posted in Turkish and English. The results indicate that tweets by Turkish people show more optimistic sentiments for Syrian refugees as compared to English tweets, which contain neutral sentiments followed by negative ones. **Gul et al. (2017)** studied tweets on Twitter related to the Kashmir floods in 2014. They attempted to visualise people's online behaviour on Twitter during natural calamities and how people used social media to convey and articulate their opinions, emotions, and experiences while facing a natural calamity. Public opinions of COVID-19 vaccines were examined by **Mir et al. (2021)** in tweets (positive, neutral, and negative), as well as the influence of tweets on online social networks. **Neogi et al. (2021)** collected information about farmers' protests from the microblogging site Twitter in order to gauge the opinions of the global audience. Based on a collection of over 20,000 tweets on the protest, they employed models to classify and analyze sentiments. The study was conducted using TF-IDF and Bag of Words. By developing a sentiment analysis model and determining the direction that the protest was taking, they investigated methods for comprehending people's sentimentality. According to their findings, the majority of tweets were neutral, with negative sentiments ranking lowest and good sentiments coming in second. **Bugden (2020)** used the hashtag keyword "farmers protest" to extract 150 tweets on the protest from each day between November 4, 2020, and March 5, 2021. This study's primary goal was to ascertain how the general public felt about protests by farmers that were posted on the microblogging platform Twitter. **Feizollah et al. (2021)** investigated Twitter data to determine the subject users tweet about "halal tourism" and analyze the sentiment of the tweets based on emotions. According to the data, the term "halal" was most frequently used in tweets and was most frequently linked to the term's "food" and "hotel." Sentiment analysis was performed on the data gathered about the tweets of individuals from the top 10 infected nations, along with one additional country selected from the Gulf region, Oman, in order to comprehend the sentiments of people from COVID-19-affected countries. More than 50,000 tweets sent between June 21, 2020, and July 20, 2020, including hashtags such as #covid-19, #COVID19, #CORONAVIRUS, #CORONA, #StayHomeStaySafe, #Lockdown, #Quarantine, #COVID, etc., were taken into consideration. Their study sought to comprehend the coping mechanisms of individuals from various afflicted nations **(Kausar et al., 2021). Tariq Soomro *et al.* (2020)** examined tweets to determine whether there was a relationship among the general people's sentiment and the rise or decline of coronavirus infections. As the Internet expands globally, users post comments in several languages. Sentiment analysis in one language increases the risk of omitting crucial details from texts written in other languages. **Mir et al. (2022)** examined the opinions of the general public regarding COVID-19 vaccines**,** along with the effects of tweets on online social networks. Over time, a steady decrease in the volume of tweets was observed. Majority of the tweets expressed positive sentiments, followed by neutral and negative ones. In addition, the research demonstrates a notable distinction in the influence of tweets from verified and unverified users, with those pertaining to verified users having a greater influence on retweets and likes than tweets expressing neutral or negative sentiments. **Wankhade et al. (2022)** conducted a comprehensive literature survey to analyse the various strategies and techniques used in sentiment analysis. The study compares several sentiment analysis methodologies, highlighting their benefits and drawbacks. **Bryan-Smith et al. (2023)** analyzed social media tweets to detect and assess flood disasters using a combination of approaches. The conclusion outlines that while social media data can be useful for flood event detection, obstacles such as limited tweet sample sizes and uneven categories can impact the analysis's performance. In addition, the study highlighted that incorporating visual data and emojis into sentiment analysis models can increase their performance and provide useful insights for real-time disaster decision-making and response. **Maulida and Devi (2023)** examined tweets about sustainable agriculture over the previous 12 months, finding that 642 tweets from Brussels, Belgium, were the most active during the observation period. With 68.5% of tweets expressing a good attitude toward sustainable agriculture, neutral sentiments—with neither strong positive nor negative tendencies—followed by positive sentiments. Just 9.1% of tweets were negative, suggesting that just a small percentage of tweets had unfavorable opinions about sustainable agriculture.

Objectives

The study aims to conduct a sentiment analysis of tweets on Farmer Bills 2020 posted on X (Formerly Twitter) by people worldwide after the bills were repealed. This study seeks to address the following research questions:

RQ1: What is the function of social media in times of crisis, particularly Twitter?

RQ2: What do people on social media promote or endorse during humanitarian crises?

Scope & Methodology

This study is based on a content analysis of tweets related to the repeal of the Farm Bills 2020/2021. The study was confined to 12 days, that is, from 7 December 2021 to 18 December 2021. Tweets were retrieved from both verified and non-verified X handles without geographical restrictions.

In order to identify the hashtags related to "Farm Bills 2020/2021," various software such as Awario, Brand24, Hashtagify, Keyhole, RiteTag, Talkwalker, TrackMyHashtag, Trendsmap, TweetDeck, Twubs were used. This was achieved by concentrating on hashtags and identifying a collection of pertinent ones. Out of the twelve hashtags found, the following nine had pertinent information:

#farmerprotest	*#farmersprotest*	*#farmbills2020*
#westandwithfarmers	*#kisanektazindabad*	*#istandwithfarmers*
#farmlawsrepealed	*#kisanektamorcha*	*#farmerswon*

Tweets were mined using the X API. The API key generated from the developer account was executed in the "Orange Software." With the "twitteroauth" version of the public API that runs directly on internet servers or local hosts, filtering options such as search by language and maximum tweet limit were used to execute the query. All hashtags were individually executed using Orange Software.

Accordingly, 14, 444 tweets were downloaded for the nine hangtags. The tweets were aggregated into a single Excel spreadsheet for analysis. Information such as tweet ID, text, client name, likes, retweets, and geographical location was extracted and documented for each tweet and all the tweets were migrated to the orange software.

Pre-processing:

Pre-processing techniques improve the effectiveness of tweet sentiment analysis **(Bashir et al., 2021).** The default data-cleaning and pre-processing techniques available in the "Orange Software" were applied to the dataset, which includes transformation, tokenization, filtering, and normalization

1. Transformation: This technique helps convert raw data into a machine-understandable format and clean the data to resolve irregularities and

prevent data inconsistency **(Neogi et al., 2021).**

2. Tokenisation: This is an important step in the modelling of text data. It helps understand the meaning behind the text by analysing word sequences (Neogi et al., 2021). " Tokenisation is used to identify the words or groups of words in a sentence, which is the foundation of text analysis"**(Rahman et al., 2021).**
3. Filtering: "In this process, unnecessary words, such as stop words (i.e., pronouns, articles, prepositions such as "the", "a", "about", "we", "our", etc. that do not have any significant contribution to text classification), noises (i.e., punctuation, special characters), and abusive words (i.e., slang words) are removed from the text"**(Rahman et al., 2021).**
4. Normalisation: applies stemming (to remove postfix from each word, such as "ing", "tion") and lemmatisation to words. For example, I have always loved cats. → I have always loved cats. For languages other than English, we used the Snowball Stemmer (offers languages available in its NLTK implementation). The data pre-processing step ensured that the tweet content that did not contribute to the sentiment of a tweet was ignored.

Sentiment analysis was performed using Orange Software's lexicon-based valence-aware dictionary for sentiment reasoning (VADER) Sentiment Module. Sentiment analysis predicts each tweet's sentiment score in a corpus, that is, positive, negative, or neutral. The difference between the sum of positive, negative, and neutral words, normalised by the document length and multiplied by 100, is the final sentiment score represented by the Compound Score. The final score indicates the sentiment difference of the tweet as a percentage.

Data Analysis and Interpretation

Trends in Tweet Count

Fig. 1 represents the everyday trend of tweets and sentiment expression for 12 days (07 December to 18 December). There are 14,444 tweets with 2,258,142 likes (mean 752,714) and 6,513,270 retweets (mean 2,171,090). The highest number of tweets was posted on 15 December, and a tweet frequency exhibited a gradual downward trend over the observed period.

Trends in Positive Tweet Count

Fig. 2 depicts the positive tweet count regarding the repeal of the Farmer Bills of 2021. The most positive tweets were recorded on 10 December and there was a sharp decline in positive tweets from the 11th to the 14th of December. Again, there was a sharp rise in positive tweets on 15 December.

Fig. 1: Trends in Tweet Count

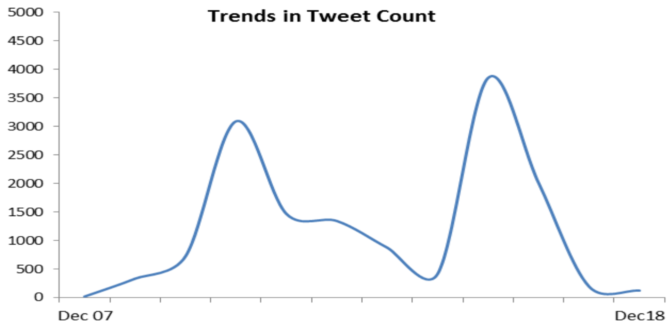
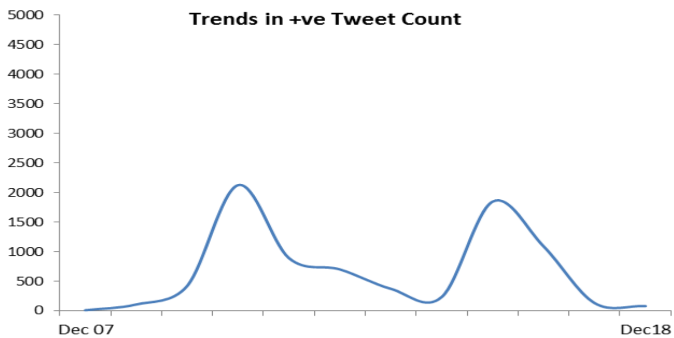


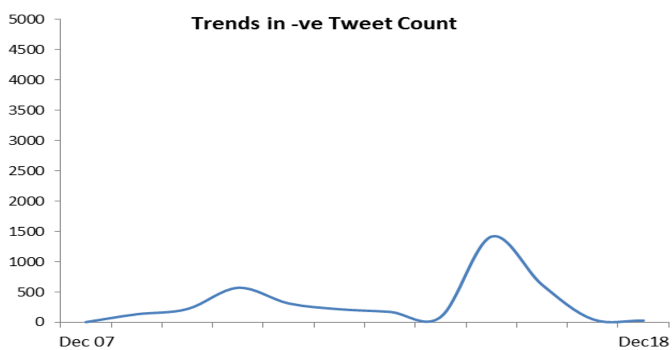
Fig. 2: Trends in Positive Tweet Count



Trends in Negative Tweet Count

Fig. 3 depicts the negative tweet count regarding the repeal of the Farmer Bills of 2021. The most negative tweets were recorded on 15 December and there was a sharp decline in negative tweets during the rest of the period, except for 8 December.

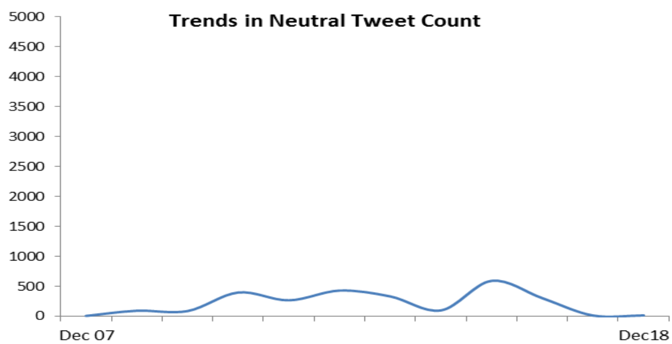
Fig. 3: Trends in Negative Tweet Count



Trends in Neutral Tweet Count

Fig. 4 shows a graphical representation of neutral tweets about the Farmer Bills 2021. The maximum number of neutral tweets was recorded on 15 December, and the minimum number was recorded on 8 December. The neutral tweet count remained constant for the rest of the period at approximately 500 tweets per day.

Fig. 4: Trends in Neutral Tweet Count



Nature of Tweet Expression

Sentiment analysis of the tweet's using VADER was performed on the entire dataset of tweets, which classified tweets into positive, neutral, and negative. The study revealed that the highest number of tweets (7995; 55.35%) expressed positive sentiments, implying that the public remained positive and hopeful about the repeal of farmers' bills. The word cloud of positive tweets showcases topmost words related to positive sentiments are "farmers victory" "farmers protests" and "Govt" (Table 5).

"Negative" sentiments about bills are expressed by one-fourth (3828; 26.5%) of the tweets. In this category, people mainly express different opinions in favor of bills and against their repeal. However, many tweets also show neutral sentiments (2620; 18.14%).

Table 1: Tweet Expressions

Tweet category	Tweet count	%age
Positive	7995	55.35
Neutral	2620	18.14
Negative	3828	26.5

Tweet expression and impact

Retweets and likes are essential features of Twitter. Tweets marked as favourites indicate the user's liking for a particular tweet. Retweet denotes re-posting someone else's tweet to share it with their followers. On a positive note, both features suggest a reward or acknowledgement of the work (tweets). Thus, retweets and likes were used to measure the impact of tweets.

It is evident from Table 2 that “neutral” tweets have the highest impact in terms of the number of retweets, with an average retweet count of 1510.93, followed by “positive” tweets, with an average retweet count of 275.83. The “negative” tweets have the most negligible impact, with an average retweet count of 91.26. Therefore, it is significant that tweets expressing neutral sentiments have the highest impact compared to “positive” and “negative” ones.

Table 2: Tweet Expressions and Impact

Tweet Category	Tweet count	Retweet count	Avg. Retweet count
Positive	7995	2205308	275.83
Neutral	2620	3958627	1510.93
Negative	3828	349335	91.26

Tweet expression and Favourites

It is evident from Table 3 that “positive” tweets have the most impact in terms of the number of likes, with an average like count of 275.83, followed by “negative” tweets with an average like count of 12.35. The “neutral” tweets had the most negligible impact, with an average like count of 2.12. Therefore, it is significant that tweets expressing positive sentiments have the highest impact compared to “negative” and neutral ones.

Table 3: Tweet Expressions and Favourites

Tweet Category	Tweet count	Likes count	Avg. Likes count
Positive	7995	2205308	275.83
Neutral	2620	5548	2.12
Negative	3828	47286	12.35

Top 10 most Influential users during Farmer Protests

To identify the key mainstream media players who are more active on Twitter, a dataset of 48 tweets confined to 12 days—from 7 December 2021 to 18 December 2021 have been collected. These forty-eight tweets were retrieved using the keyword “Farmers protest” on Twitter. Once these tweets were collected, they were categorised and filtered to determine the top ten most influential users during the Farmer Protests. Several tweets from the ten most influential users during the Farmers’ Protest were categorised and filtered using NVivo. The study identified 11 tweets by TIMES Now and Zee News English, DNA- 8, India Today – 5, Economic Times- 4, Hindustan Times- 3, Ashutosh and NDTV- 2, Rahul Kanwal and Economic Times- 1.

Table 4: Top 10 most Influential users during Farmer Protests

Screen Name	Influencers	Follower Count	No. of Tweets
NDTV	@ndtv	16452465	2
TIMES NOW	@TimesNow	10141064	11
Hindustan Times	@htTweets	8325073	3
India Today	@IndiaToday	5886441	5
Zee News English	@ZeeNewsEnglish	5519795	11
News18	@CNNnews18	4644653	1
Rahul Kanwal	@rahulkanwal	4534791	1
Economic Times	@EconomicTimes	4085664	4
Ashutosh	@ashutosh83B	2342150	2
DNA	@dna	2251692	8

Top 10 frequently occurring terms in tweets

Table 5 shows the ten most frequently occurring terms people used to share their thoughts regarding the farmers' bills. "Farmer protest" is the leading term used more than 1400 times, followed by "Farmer Victory" used more than 900 times and "rt satishacharya" used 887 times in the tweets. However, "Govt" and "Arrest ajaymishrteni" were used more than 400 times. The rest of the words, such as "Tweet", "World", "Polouse", "Someone", and "Connection", have been used more than 300 times.

Table 5: Top 10 frequently occurring terms in Tweets

Rank	Term	Occurrences	Relevance Score
1	Farmer protest	1455	0.4415
2	farmers victory	904	0.5306
3	rt satishacharya	887	0.5311
4	Govt	468	0.4532
5	Arrest ajaymishrteni	405	1.2324
6	Tweet	397	0.8945
7	World	342	0.5127
8	Polouse	304	0.628
9	Someone	303	0.9284
10	Connection	302	0.6291

Word clouds

The collective analysis of the three-word clouds—representing positive, negative, and neutral tweets—offers a comprehensive view of the digital discourse surrounding the farmers' protest. Common across all sentiments are central terms like *"farmersprotest," "farmers," "farmerswon,"* and *"kisanektamorcha,"* reflecting the widespread engagement and recognition of the protest as a significant socio-political movement. The positive tweets emphasize themes of triumph, unity, and justice, with words such as *"victory," "support,"* and *"farmlawsrepealed"* celebrating the repeal of the contentious legislation. In contrast, the negative tweets are marked by calls for accountability, with frequent mentions of *"mishra," "murderer," "arrest,"* and *"lakhimpur,"* indicating public outrage over specific incidents of violence and perceived political impunity. Neutral tweets, while devoid of overt sentiment, contribute to the broader narrative through informational content, updates, and references to media figures and campaigns. Together, these visualizations highlight the multifaceted public response to the farmers' movement, blending emotional solidarity, critical activism, and factual documentation across the Twitter landscape.

Fig. 5: Word cloud of positive Tweets

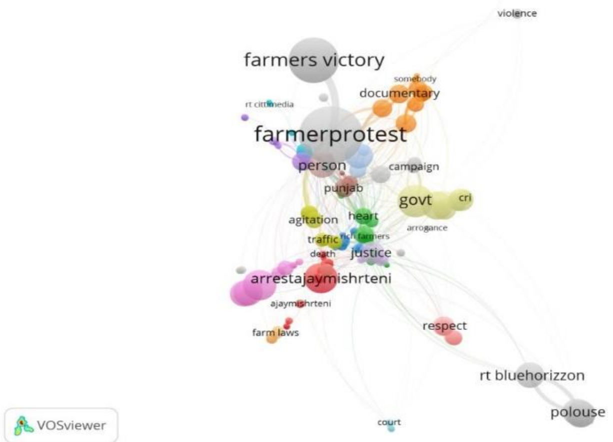
Fig. 6: Word cloud of negative Tweets

Fig. 7: Word cloud of neutral Tweets

Keyword Network Visualization of Tweets

VOS viewer was used to visualise the word frequency from the dataset. The dataset was exported to the VOS viewer, which extracted 8011 keywords from 14,444 tweets. A visualisation network of keywords was generated. A visual representation of the words appearing in the tweets is presented in Fig. 5. The keyword network visualization of tweets surrounding the repeal of the 2020 farm laws reveals the centrality of the "farmerprotest" as the dominant theme in public discourse. Closely linked terms like "farmers victory," "govt," and "arrestajaymishtreni" highlight how the conversation evolved from protest to political critique and demands for justice, particularly in relation to high-profile incidents like the Lakhimpur Kheri case. Distinct clusters show that users engaged with multiple dimensions of the protest — from grassroots agitation and emotional appeals to broader political narratives and media coverage. While keywords like "justice," "campaign," and "farm laws" reflected the core concerns of protestors, peripheral terms such as "violence" and "respect" hint at the wider socio-political undercurrents shaping the debate. Overall, the network reflects a rich tapestry of resistance, solidarity, and civic engagement that defined the farmers' movement online.

Fig. 8: Keyword network visualization of Tweets



Discussion

In this study, we investigated the use of Twitter during and after the "Repeal of Farmers Bills 2020/2021" by examining tweets related to the Bills. A gradual drop in the number of tweets was observed over time. The highest number of tweets was posted in the starting days, while the score declined with the passing days. This suggests that individuals are lively in expressing their viewpoints when an event occurs, but its importance diminishes over time. Even **Gul et al. (2018)** reveal that "time heals everything, and an event, no matter how people are connected to it, begins to fade from their memory. "They also witnessed heavy traffic of tweets related to the Kashmir floods on Twitter in the initial days, but a decline is observed in the number of tweets with every passing day". Another study on tweets related to the "Syria

Chemical Attack" confirms that with the passing days, the discussion traffic over Twitter decreases **(Bashir et al., 2021).** Examining the intricacies of social media platforms can provide insights into society and the environment. Consequently, there was an enormous increase in the number of tweets from users expressing their opinions during the Indian farmers' protest. Every group expressed their agitation over the issue due to the Indian farmers' protests. Most tweets express positive sentiments, implying that the Twitter population supports the protestors and considers the retaliation by farmers to be an essential reaction to the laws. The positive tweets that were liked and retweeted by users indicate that most users favour farmers' protests, as evidenced by the fact that people worldwide were doing so. Similarly, it is also revealed that, compared to the others, NDTV is the essential key actor in expressing more farmer actions and reactions. TIMES NOW presents Twitter narratives from various people and their points of view in a balanced way. The reactions of celebrities and government activities are given more hype by ZEE NEWS ENGLISH than the other types of Twitter narratives. Although all media organisations develop their Twitter narratives around the farmers' protest, the content and intent of those narratives vary depending on their agenda-setting agendas.

People increasingly use the Internet and social media platforms to monitor public opinions on controversial issues such as the Farmer's Bill **(Brunson, 2013).** Twitter expresses farmers' interests and criticises government policies **(Yousefinaghani et al., 2021).** Twitter data were extracted and sentimentally analysed in agriculture using labelled corpora. Moreover, the study shows the capability of Twitter to act as a ''citizen journalist' as users disseminate real-time information with timely updates.

Conclusion

Twitter, one of the most popular microblogging services, allows users to create and share ideas and information without barriers. It changes public opinion and produces social change; therefore, it assumes importance due to the privilege of changing the narrative and the way some audiences view the crisis **(Brogan, 2015)**. Twitter plays an essential role in breaking news and acts as a social network and news source, creating awareness of the situation **(Kwak et al., 2010).** Twitter is used to connect with the masses during disasters, but it can sometimes create confusion due to incorrect information being posted **(Brogan, 2015).** Twitter is increasingly used for sentiment analysis, which provides a way to understand public emotions about events, products, brands, or other related phenomena. Sentiment analysis is a reliable and promising method for extracting new information from large amounts of unstructured data **(Philander & Zhong, 2016).** The study demonstrates Twitter's capability to share information on farmer protests.

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