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Original Article

Sentiment Analysis of COVID-19 Crisis Information on Twitter During Major Outbreak Phases

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Abstract

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Introduction: The COVID-19 pandemic profoundly transformed global communication practices, with Twitter emerging as a key platform for sharing crisis-related information. This study aims to investigate public emotional dynamics across four critical phases of the pandemic: Emergence, Lockdowns, Vaccine Rollout, and Variant Surges, to capture how sentiment evolved and to highlight implications for crisis communication strategies.

Methods: This study employed a quantitative content analysis method, incorporating sentiment analysis techniques, to assess COVID-19 crisis-related tweets across key phases of the outbreak. A dataset of 2 million COVID-19-related tweets, spanning January 2020 to December 2022, was analyzed using a hybrid sentiment analysis framework. VADER was applied for lexicon-based polarity scoring, while a fine-tuned BiLSTM model enhanced contextual classification. Emotion detection, guided by the NRC Emotion Lexicon, identified eight dominant emotions, including fear, trust, anger, and joy. Comparative analyses were conducted between official sources (such as verified health agencies, government institutions, and news outlets) and citizen-generated content to assess differences in sentiment and emotional tone across the phases.

Results: Two million tweets were analyzed across four key phases of the pandemic. The majority of tweets were citizen-generated (81%). Tweet volume peaked during Phase 1 (the initial outbreak) and Phase 3 (the vaccine rollout). Polarity trends indicated heightened negative sentiment during the initial outbreak and lockdowns, followed by a substantial rise in positivity during the vaccine rollout, and renewed negativity during variant surges. Fear dominated Phase 1 (36.2%), trust rose in Phase 3 (34.7%), and anger was most pronounced during Phase 4 (28.9%). Official sources were significantly more positive in tone compared to citizens across all phases ($p < 0.05$).

Conclusion: FThe findings demonstrate the importance of phase-specific, emotion-aware communication strategies. By aligning messaging with prevailing emotional climates, health agencies can reduce public trust vulnerability to misinformation and improve the effectiveness of crisis communication during future global health emergencies.

Introduction

The COVID-19 pandemic, declared a universal health emergency by the World Health Organization in March 2020, made unprecedented upheaval across health systems, economies, and social life worldwide (1).

During such crises, suitable and accurate information becomes critical for risk awareness, public compliance, and adaptation. Early in the pandemic, social media platforms, primarily Twitter, emerged as central channels for real-time crisis communication, enabling governments, health agencies, media organizations, and citizens to exchange information, express emotions, and react to unfolding events (2, 3). Leveraging features such as real-time posting, hashtags, retweets, and mentions, the platform facilitated the rapid diffusion of official health guidance, news updates, outbreak statistics, and personal experiences, enabling it to serve as an essential channel for crisis surveillance and public awareness. Early COVID-19 studies identified sharp increases in tweet volume following official announcements, reflecting the platform's responsiveness to real-world events (4).

Besides, the COVID-19 pandemic triggered an "infodemic," an overabundance of information, including misinformation and unverifiable claims about health efforts (5, 6). While Twitter facilitated rapid information sharing, it also accelerated the spread of misinformation, rumors, and emotionally charged narratives, contributing to what has been described as a global "infodemic" (7, 8). Misinformation, often spread by verified accounts and through coordinated sharing, included rumors, stigma, and conspiracy theories, and most of them were false (8). Emotionally charged and sensational content tended to achieve higher engagement, complicating public health agencies' efforts to deliver accurate information. This widespread circulation of false information reduced adherence to public health measures and fueled vaccine hesitancy (5).

A growing body of research has applied pragmatic sentiment analysis to COVID-19, related tweets to understand public reactions. Early analyses consistently found fear, anxiety, and uncertainty dominating public discourse during the initial outbreak and lockdown phases (4, 9). As the pandemic progressed, subsequent studies observed shifts toward optimism and trust during vaccine development and rollout, followed by renewed negativity associated with emerging variants and prolonged restrictions (3, 10). Sentiment analysis consistently showed that fear was the predominant emotion expressed, with nearly half of tweets conveying negative sentiment, underscoring widespread anxiety and uncertainty (4, 2). These findings highlight the dynamic nature of public sentiment during continued crises.

Moreover, topic modelling identified key themes including the pandemic's economic and political repercussions, outbreak transmission patterns, and prevention measures such as mask usage and social distancing (4, 5). Furthermore, the evolution of public discourse was observed through distinct stages: awareness, initial recognition of the outbreak, heightened concern over transmission, and eventual focus on symptoms and protective behaviors (2).

Sentiment analysis of COVID-19 tweets has employed a range of methods, from lexicon-based approaches to advanced machine learning techniques. Studies have used large datasets, such as COVIDSenti, to improve generalizability (11). Deep learning methods such as Convolutional Neural Networks CNN and Gated Recurrent Units have also been successfully applied (11, 12). Comparative studies report that advanced ML and deep learning models typically outperform traditional methods, achieving accuracies up to 96.66% on COVID-tweet datasets (13). Methodologically, earlier studies have used a wide range of methods, including lexicon-based tools such as VADER, traditional machine learning classifiers, and deep learning models like CNNs, GRUs, and BiLSTMs. Besides, emotion detection frameworks, such as the NRC Emotion Lexicon, have further assisted researchers in capturing discrete emotional states, including fear, anger, trust, and joy.

In this regard, another significant stream of research distinguishes between official sources (health agencies, government institutions, and news organizations) and citizen-generated content. Studies consistently show that official accounts tend to adopt more informational and reassurance-oriented tones, while citizen discourse is more emotionally volatile and reactive (2, 7). These differences have important implications for message credibility, engagement, and vulnerability to misinformation.

Despite extensive research on COVID-19 sentiment on Twitter, significant gaps remain: First, many studies have focused on short time frames or single outbreak stages of long-term emotional evolution. Therefore, a limited understanding exists of how public sentiment evolved throughout different phases of the pandemic. Second, relatively few studies have systematically aligned sentiment and emotion analysis with clearly defined phases. Third, fewer studies have conducted longitudinal comparisons between official and citizen discourse across all major phases. Addressing these gaps is essential for developing emotion-aware, phase-specific crisis message strategies.

In response to these gaps, the present study aims to examine COVID-19 crisis-related tweets from January 2020 to December 2022, analyzing sentiment polarity and emotional dynamics across four major pandemic phases: emergence, lockdowns, vaccine rollout, and variant surges, while explicitly comparing official and citizen-generated content. Specifically, the study aims to:

1. Analyze the polarity (positive, negative, neutral) of tweets containing COVID-19 crisis information across distinct outbreak phases.
2. Identify dominant emotional tones (e.g., fear, trust, anger, optimism) expressed during each phase.
3. Compare sentiment trends between official sources (e.g., health agencies) and citizen-generated content.
4. Evaluate the implications of sentiment shifts for crisis communication strategies in future pandemics.

By achieving these objectives, the study aims to provide practical insights into how public health agencies and communication specialists can tailor their messaging to respond to public emotions and improve the effectiveness of crisis communication. By integrating large-scale data, hybrid sentiment analysis methods, and phase-based segmentation, this study aims to contribute to a more comprehensive understanding of public emotional responses during prolonged global health crises.

Methods

Research Design

This study employed a quantitative content analysis method, incorporating sentiment analysis techniques, to assess COVID-19 crisis-related tweets across key phases of the outbreak. A mixed-method sentiment framework was adopted, combining lexicon-based scoring for broad coverage and machine learning (ML) classification for nuanced polarity and emotion detection.

Data Collection

In this study, tweets were retrieved from the Twitter API using the Academic Research track, which allows access to historical data. Search queries included COVID-19-related keywords such as “COVID-19,” “coronavirus,” “pandemic,” “lockdown,” “vaccine,” and hashtags like #COVID19, #StayHome, #WearAMask, and #FlattenTheCurve. The dataset covered the period from January 2020 to December 2022, encompassing various phases of the pandemic. Only English-language tweets were included to ensure consistent sentiment analysis, with no geographic restrictions applied to capture global sentiment trends. Tweets were categorized into two groups: 1) Official Sources – verified accounts of health agencies (e.g., WHO, CDC, NHS), government health departments, and major news outlets, and 2) Citizen Sources – all other non-institutional accounts. After filtering for duplicates, retweets without comments, and spam, 2 million tweets were retained for analysis.

Data Pre-processing

To prepare the dataset for sentiment analysis, a series of systematic pre-processing steps was implemented to ensure text uniformity, relevance, and quality. All tweet text was converted to lowercase to maintain consistency and avoid case-sensitive mismatches during analysis. URLs, hashtag symbols, and user mentions were removed to eliminate extraneous elements, while retaining meaningful hashtag words that could contribute to sentiment interpretation. Emojis were converted to descriptive text to preserve their emotional context, and non-ASCII characters and symbols were removed from the data. Stop words, such as “the,” “is,” and “at,” were removed to reduce noise and improve analytical efficiency. The tweets were then tokenized, breaking them into individual terms, and lemmatized to reduce words to their base forms (e.g., “running” → “run”), thereby standardizing lexical variations. As a final quality control step, spam and bot-detection measures were applied, excluding accounts with abnormally high posting frequencies or repetitive content patterns, ensuring that the dataset reflected genuine human discourse.

Sentiment Analysis Methods

The sentiment analysis used multiple techniques to enhance accuracy and contextual understanding. For polarity classification, a hybrid approach was adopted. First, a lexicon-based method using VADER (Valence Aware Dictionary and Sentiment Reasoner) was applied to assign initial sentiment scores (positive, negative, or neutral) based on predefined lexical cues. Second, a machine learning method leveraging a Bidirectional Long Short-Term Memory (BiLSTM) deep learning model, fine-tuned on a COVID-19-specific tweet sentiment dataset, was employed to capture nuanced linguistic patterns and contextual dependencies. This combination enabled both broad coverage via lexicon-based scoring and deeper semantic interpretation via a neural network.

Emotion classification was performed using the NRC Emotion Lexicon, which categorized tweets into eight primary emotions: Anger, anticipation, disgust, fear, joy, sadness, surprise, and trust. This offered a more detailed view of emotional shifts during the different stages of the outbreak.

Outbreak Phase Segmentation

To track sentiment changes over time, the dataset was divided into four key pandemic phases based on major global milestones:

1. Phase 1 – Emergence and Initial Outbreak (January-March 2020)
2. Phase 2 – Lockdowns and Containment (April-September 2020)
3. Phase 3 – Vaccine Development and Early Rollout (October 2020-June 2021)
4. Phase 4 – Variant Surges and Adaptation (July 2021-December 2022)

Data Analysis

The data analysis used a multi-layered approach to examine sentiment changes throughout the entire study. Descriptive statistics were used to summarize key features of the dataset, including total tweet volume, the distribution of polarity categories (positive, negative, neutral), and the prevalence of specific emotional tones within each pandemic phase, thereby providing a baseline view of public discourse. A comparative analysis was then conducted to evaluate differences between official sources (verified health agencies, government departments, and major news outlets) and citizen sources (non-institutional accounts). Chi-square tests were applied to detect statistically significant variations in categorical sentiment distributions, while independent-samples t-tests compared mean polarity scores between the two groups. To capture temporal shifts, trend analysis was performed using moving averages, sentiment shifts over time, and the uncovering designs connected to major pandemic events, lockdowns, vaccination campaigns, and case surges. All statistical tests were conducted with a significance threshold of $p < 0.05$ to ensure that detected differences or changes were not due to random variation, thereby enabling robust identification of meaningful sentiment shifts across pandemic phases.

Results

Table 1 shows that a total of 2,000,000 tweets were analyzed across the four pandemic phases: emergence, lockdowns, vaccine rollout, and variant surges. Citizen-generated tweets made up the majority (81%), while official sources accounted for 19%. Tweet volume reached its highest during Phase 1 (580,000) and Phase 3 (430,000).

Table 2 shows that polarity trends indicated a dominance of negative sentiment during the early outbreak (52.8%) and lockdowns (48.2%), with a steady rise in positive sentiment during the vaccine rollout (35.4%). Neutral tweets stayed consistent (~30%).

Using the NRC Emotion Lexicon, eight emotions were tracked. Table 3 shows that Fear dominated Phase 1 (36.2%), trust rose in Phase 3 (34.7%), and anger was most pronounced during Phase 4 (28.9%) due to frustration over variant surges.

Table 4 shows the average polarity scores for the official and citizen sources. Findings show that official sources were significantly more positive in tone than citizens across all phases ($p < 0.05$). Furthermore, citizens expressed higher levels of anger and fear, especially during early and variant phases.

Table 1. Tweet volume by phase and source

Phase	Dates	Citizen tweets		Official tweets		Total tweets	
		Number	Percent	Number	Percent	Number	Percent
P1 – Emergence	Jan-Mar 2020	480,000	82.8%	100,000	17.2%	580,000	100%
P2 – Lockdowns	Apr-Sep 2020	340,000	81.4%	80,000	18.6%	420,000	100%
P3 – Vaccines	Oct 2020-Jun 2021	460,000	81.4%	110,000	18.6%	570,000	100%
P4 – Variants	Jul 2021-Dec 2022	340,000	79.1%	90,000	20.9%	430,000	100%
Total		1,620,000	81.0%	380,000	19.0%	2,000,000	100%

Table 2. Polarity distribution (%) by phase

Phase	Positive	Neutral	Negative	Total
P1 – Emergence	18.5%	28.7%	52.8%	100%
P2 – Lockdowns	21.3%	30.5%	48.2%	100%
P3 – Vaccines	35.4%	32.1%	32.5%	100%
P4 – Variants	28.9%	31.0%	40.1%	100%

Table 3. Dominant emotion per phase (top 3 by frequency)

Phase	#1 Emotion	#2 Emotion	#3 Emotion	Other emotions	Total
P1	Fear (36.2%)	Sadness (22.8%)	Trust (15.6%)	25.4%	100%
P2	Fear (31.5%)	Anger (19.4%)	Trust (18.2%)	30.9%	100%
P3	Trust (34.7%)	Joy (26.5%)	Anticipation (21.8%)	17%	100%
P4	Anger (28.9%)	Fear (25.3%)	Sadness (20.5%)	25.9%	100%

Table 4. Average polarity scores (–1 = Most Negative, +1 = Most Positive)

Phase	Official sources	Citizen sources
Phase 1	–0.12	–0.32
Phase 2	–0.08	–0.25
Phase 3	+0.18	+0.05
Phase 4	+0.05	–0.15

This study revealed public sentiment and emotional dynamics associated with COVID-19 crisis information on Twitter. By a hybrid sentiment analysis method and distinguishing between official and citizen-generated content, the study provides a longitudinal and comparative perspective on how public emotions evolved throughout the pandemic.

A total of 2,000,000 tweets were analyzed across four key pandemic phases: emergence, lockdowns, vaccine rollout, and variant surges. The majority of tweets were citizen-generated (81%). Tweet volume peaked during Phase 1 (initial outbreak) and Phase 3 (vaccine rollout). Polarity trends indicated a dominance of negative sentiment during the early stages of the epidemic and lockdowns, with a steady rise in positive sentiment during the vaccine rollout. Fear dominated Phase 1 (36.2%), trust rose in Phase 3 (34.7%), and anger was most pronounced during Phase 4 (28.9%). Official sources were significantly more positive in tone compared to citizens across all phases ($p < 0.05$).

Discussion

The majority of negative sentiment during the emergence and lockdown phases perceived in this study is consistent with earlier COVID-19 Twitter analyses. Medford et al. Stated that fear, uncertainty, and anxiety dominated early pandemic discourse as users reacted to rising case numbers, limited medical knowledge, and rapidly changing public health measures (4). Likewise, Lwin et al. found that negative sentiment peaked during stages of increasing infections and policy uncertainty (3). The high proportion of negative tweets recognised in this study during Phases 1 and 2 reinforces these findings and confirms that Twitter functioned as a space for emotional coping during the initial crisis.

The vaccine rollout phase marked a substantial shift toward positive sentiment and expressions. This outline aligns with findings by Boon-Itt and Skunkan et al., who suggested increasing optimism and positivity as vaccines became available and public health messaging emphasized protection (2). Furthermore, Medford et al. reported improvements in vaccine-related discussions, particularly in tweets referencing hope, safety, and a return to normal life (4). The consistency across studies indicates that vaccination efforts played a crucial psychological role in improving public morale.

Nevertheless, the recovery of negative sentiment during the variant surge phase indicates that public optimism was not sustained. Increased anger and frustration during this period correspond with observations by Cinelli et al., who related renewed negativity to prolonged restrictions, policy fatigue, and the emergence of new virus variants (7). Additionally, Jalil et al. reported that public sentiment became increasingly polarized as pandemic fatigue intensified (13). These parallels show that sentiment during prolonged crises follows cyclical patterns rather than a linear recovery trajectory.

Beyond polarity classification, this study's emotion analysis offers more profound insight into public emotional responses. Fear emerged as the dominant emotion during the emergence and lockdown phases, corroborating earlier findings by Medford et al. and Obagbuwa and Chibaya, who recognised fear as the most prevalent emotional response during the early outbreak (4, 12). This emotion was primarily driven by uncertainty regarding transmission, mortality, and economic consequences.

During the vaccine rollout phase, trust and joy became more prominent, reflecting increased confidence in public health interventions. Lwin et al. observed a similar rise in trust-based language in tweets from both citizens and official accounts during periods of policy stabilization and vaccine announcements (3). Conversely, the variant surge phase saw anger replace fear as the dominant emotion, echoing findings by Cinelli et al. (7) and Islam et al. (8), who associated anger with the discovery of misinformation, inconsistent policies, and perceived institutional shortcomings. These results highlight how emotional drivers shift in response to both epidemiological and communication factors.

A key focus of this study is its systematic assessment of sentiment between official sources and citizen-generated tweets across all phases. The increasingly positive tone observed in official accounts supports prior research indicating that health agencies and government institutions intentionally employ reassurance-focused, trust-building communication strategies (2, 3). This strategic positivity is intended to promote compliance and maintain public confidence. In contrast, citizen-generated content exhibited greater emotional volatility, with stronger expressions of fear during early phases and anger during variant surges (7). Similarly, it was reported that citizen discourse was more reactive and emotionally charged, often amplifying negative narratives (8). Noted that emotionally intense citizen content is more susceptible to spreading. The divergence between official optimism and citizen frustration observed in this study recommends a potential communication gap that may demoralise message credibility during prolonged crises.

By comparing sentiment patterns across clearly defined pandemic phases, this study examined the past research that often focused on short-term or single-phase analyses. Consistent with recommendations from infodemic research (5, 7), monitoring emotional shifts, particularly increases in anger or fear, can help public health agencies anticipate misinformation risks and adapt messaging accordingly.

While many studies have examined COVID-19 sentiment on Twitter, most have focused either on sentiment polarity or topic modelling, without systematically linking emotional changes to defined outbreak phases. This study contributes to the literature by integrating phase-based segmentation, emotion detection, and source-level comparison within a unified analytical framework. By doing so, it provides a more nuanced understanding of how public emotions evolve during prolonged global crises and offers practical insights for improving future crisis communication strategies.

Conclusion

This study revealed public sentiment and emotional dynamics associated with COVID-19 crisis information on Twitter. Findings indicate heightened negative sentiment during the initial outbreak and lockdowns, followed by a substantial rise in positivity during the vaccine rollout, and renewed negativity during variant surges. Fear and sadness dominated early phases, and joy peaked during vaccination, and anger escalated during variant-driven disruptions. Official accounts consistently maintained a more positive, trust-building tone, whereas citizen discourse showed greater emotional volatility and sharper swings across phases.

The findings underscore the importance of phase-specific and emotion-aware communication strategies. Early-stage communication should prioritize reducing fear and uncertainty, while later phases must address fatigue, anger, and declining trust. Aligning official communication tone with public emotional states, rather than maintaining uniformly positive messaging, may enhance credibility and engagement.

Declaration

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Conflict of Interest

The authors declare no conflict of interest.

Ethical Statement

This study analysed publicly available Twitter data in accordance with Twitter's Developer Policy and Terms of Service. No private, protected, or personally identifiable information was collected or reported. Usernames and any potential identifiers were removed during data processing to ensure anonymity. As the study relied exclusively on publicly accessible data and did not involve direct interaction with human participants, formal ethical approval was not required. Nevertheless, ethical principles related to responsible data handling, confidentiality, and the sensitive nature of crisis communication data were strictly observed throughout the research process.

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Authors' Contribution

M.A. conceptualized the study, conducted data analysis, and drafted the manuscript. M.T. contributed to study design, interpretation of findings, and critical revision of the manuscript. Both authors approved the final version.

Use of Artificial Intelligence

AI-based tools were used solely for language refinement. All interpretations, conclusions, and final decisions remain the responsibility of the authors.

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