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Sentiment and emotion trends in nurses' tweets about the COVID-19 pandemic

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Abstract

Purpose: Twitter is being increasingly used by nursing professionals to share ideas, information, and opinions about the global pandemic, yet there continues to be a lack of research on how nurse sentiment is associated with major events happening on the frontline. The purpose of the study was to quantitatively identify sentiments, emotions, and trends in nurses' tweets and to explore the variations in sentiments and emotions over a period in 2020 with respect to the number of cases and deaths of COVID-19 worldwide.

Design: A cross-sectional data mining study was held from March 3, 2020 through December 3, 2020. The tweets related to COVID-19 were downloaded using the tweet IDs available from a public website. Data were processed and filtered by searching for keywords related to nursing in the profile description field using the R software and JMP Pro Version 16 and the sentiment analysis of each tweet was done using AFINN, Bing, and NRC lexicon.

Findings: A total of 13,868 tweets from the Twitter accounts of self-identified nurses were included in the final analysis. The sentiment scores of nurses' tweets fluctuated over time and some clear patterns emerged related to the number of COVID-19 cases and deaths. Joy decreased and sadness increased over time as the pandemic impacts increased.

Conclusions: Our study shows that Twitter data can be leveraged to study the emotions and sentiments of nurses, and the findings suggest that the emotional realm of nurses was affected during the COVID-19 pandemic according to the emotional trends observed in tweets.

Clinical Relevance: The study provides insight into what nurses are feeling, and findings from this study highlight the importance of developing and implementing interventions targeted at nurses at the workplace to prevent mental health consequences.

KEYWORDS
COVID-19, emotions, nurses, pandemic, sentiments, tweets

The COVID-19 pandemic has affected millions of people around the world, and the subsequent stay-at-home mandate resulted in increased use of social media platforms like Facebook, Instagram, and Twitter (Koeze & Popper, 2020). The widespread use of social media speeds up the sharing of information, views, opinions, sentiments, and experiences about the pandemic (Chukwusa et al., 2020). Twitter is distinguished from other forms of social media by its real-time features, strong distribution, popularity, casual ambiance, and individuality. Twitter has a unidirectional framework in which users simply follow and read other users, companies, organizations, and media tweets of their interest, which improves the capacity of Twitter to disseminate information (Kwak et al., 2011). The users can share their personal opinions, concerns, and experiences by posting 280-character tweets, and can retweet the messages by others indicating the content most interesting and potentially influential (Chew & Eysenbach, 2010). Twitter data contain the thoughts or feelings of a user about a subject; thus, through sentiment analysis, it is possible to analyze the user's mood about a particular topic by extracting words from sentences containing keywords of interest.

COVID-19 has become one of the trending topics on Twitter since January 2020 and continues to be discussed (Xue, Chen, Hu, Chen, Zheng, Liu, et al., 2020; Xue, Chen, Hu, Chen, Zheng, Su, et al., 2020). Currently, social media platforms like Twitter are being used in a very innovative and promising way by nurses serving on the front lines of COVID-19 to educate the community and to show the nursing profession to society, what it does, and the value of this work (De Gagne et al., 2021; O'Leary et al., 2021; Wahbeh et al., 2020; Yousuf et al., 2017). Nurses who are the frontline workers of the pandemic are experiencing pressure, fear, exhaustion, isolation, and ongoing emotional trauma (Al Thobaity & Alshammari, 2020). This ongoing stress and trauma have an impact on their mental health, safety, and ability to provide the best possible care (Li et al., 2020). Many nurses have expressed their fear, anxiety, exhaustion, and stress through various social media platforms, especially Twitter (O'Leary et al., 2021; Wahbeh et al., 2020). Nurses are also tweeting about their mental health, personal experiences of taking care of patients, dealing with the deadly virus, lack of adequate personal protective equipment and other needed medical supplies, shortage of beds and mechanical ventilators in hospitals, and requesting government and other policymakers to take necessary actions to support the healthcare professionals (Ventures, 2020). They have used this platform to raise concerns about the effects of these workplace adversities on their mental health. In addition, they have formed different social groups and communities among nurses and have conversed within their professional community on the outbreak and clinical management of infectious disease, supporting each other by sharing information on strategies for building resilience and coping skills (O'Leary et al., 2021). Researchers have found that this act of social sharing through tweets will satisfy the basic human needs of emotional expression and social connectivity and has strong effects on the emotional well-being of sharers (Choi & Toma, 2014; Lambert et al., 2013). These tweets are available through the Twitter API, which can be used as a data source for research to learn about the sentiments and concerns of its users. This offers a more efficient means of data collection as the data are voluntarily created by users, unlike data produced through surveys or interviews (Lee et al., 2019). Twitter can be used as a beneficial tool for nurse researchers and can serve as an adjunct to established research approaches (Smith et al., 2021). Using Twitter data as a research source has its own advantages and disadvantages. It provides quick and relatively easy access to a large amount of data on people's opinions on specific topics, and because the data are in the public domain, it can be utilized without seeking informed consent (Taylor & Pagliari, 2018; Van Hoof et al., 2013). However, using Twitter as a data source is restricted to individuals who have an internet connection and use this particular social media platform to express their voices and the sample may not be representative of the population. This indicates that the findings should be interpreted with caution before generalizing them to the wider population (Ainley et al., 2021).

The COVID-19 pandemic has propelled an increase in the number of research studies using social media data to explore public perceptions, opinions, concerns, and fears about the pandemic (Chandrasekaran et al., 2020; Sengupta et al., 2020; Xue, Chen, Hu, Chen, Zheng, Liu, et al., 2020; Xue, Chen, Hu, Chen, Zheng, Su, et al., 2020). Most of these studies have analyzed tweets from early periods of the pandemic and the number of tweets used in these studies varies from a few hundred to a few million as the majority of them extracted the tweets from a previous 10-day period. Despite the increasing usage of Twitter by nurses, studies of nurses' social media use are minimal and there is a paucity of research on its use by nurses as a form of communication to voice their concerns and stress especially during the pandemic. There is a lack of research on the sentiments of nurses who are the frontline workers of this pandemic. Most of the studies focused on the experiences of nurses during the pandemic are cross-sectional and are conducted in a smaller setting with limited sample sizes. Further, there is limited understanding of the changes in sentiments and discourse about COVID-19 over time. Therefore, our study aims to quantitatively identify sentiments and trends in a large number of nurses' tweets as COVID-19 continue to spread across the world and to explore the variations in the associated sentiments over the period of time with respect to the number of cases and deaths worldwide. Our central hypothesis is that the sentiments of the tweets will be associated with the number of COVID-19 cases and confirmed deaths across the world.

METHODS

A cross-sectional, Twitter data mining method was used to capture the sentiments in nurses' tweets. We used a publicly available Twitter dataset in the George Washington University library's dataverse (Kerchner & Wrubel, 2020). This dataset contains tweet IDs of 354,903,485 tweets related to Coronavirus, Corona outbreak, or COVID-19. The tweet IDs were collected between March 3, 2020 and December 3, 2020, from the Twitter API using Social

Feed Manager by the researchers at George Washington University (Kerchner & Wrubel, 2020). This dataset was the only one that was publicly available for research purpose uses and also had access to a large number of tweets related to Coronavirus, Corona outbreak, or COVID-19 during a period of 8 months. The tweet IDs obtained were used to download the tweets along with other details like the source of the tweet, followers' count, and user description using the Twitter API by the research team. We used global data on COVID-19 cases and confirmed deaths even though our analysis included only English language tweets. Our initial analysis with the available geolocation data showed that there were tweets from non-English speaking countries like India, Philippines, Nigeria, Switzerland, Spain, etc. So, the researchers determined that it would be best to use global data instead of regional data. The global data on COVID-19 cases and deaths were downloaded from an open-source website of Our World in Data (Ritchie et al., 2020). The number of confirmed cases and deaths on this website is updated from the COVID-19 Data Repository by the Center for Systems Science and Engineering at Johns Hopkins University (Dong et al., 2020).

The analysis dataset was created by downloading the tweet information for all the tweet IDs that we had access to. The Twitter API provided tweet specific features like user-defined location, user description, retweet counts, favorite count, quote count, and tweet full text. Tweets that included common nurse identifying keywords in their user description were selected for inclusion in the analysis dataset. Keywords included Nurs, RN, NP, BSN, MSN, DNP, CNS, CRNA, CNE, CNL, CNO, CNA CNM, LPN, LVN, NA, ASN, and ADN. Full-text tweets were then cleaned by removing retweets, hashtag symbols, characters, punctuations, @users, URLs, and stop words that do not have a specific semantic meaning (i.e., “the,” and “are”). The tweets were then further filtered by identifying users who self-identified as nurses (i.e., if the profile description had any phrase which is related to the nursing field such as registered nurse, nurse practitioner, mental health nurse, ICU nurse, school health nurse, staff nurse, clinical nurse specialist, RN BSN, Oncology nurse, DNP, etc.) in the profile description. This process was done using the text explorer feature in JMP pro 16.1 which was used to extract phrases from the description field of users, and the research team manually investigated each of the phrases to assess for suitability. Any conflicts and uncertain labels were resolved by checking the description field of users manually to assess for eligibility after an open discussion within the team. The data extraction process is described in detail in Figure 1.

A total of 13,868 tweets were included in the final analysis based on the inclusion and exclusion criteria. The average sentiment score was calculated for the tweets tweeted on each day using the AFINN, Bing, and NRC software in R software v 4.0.3.

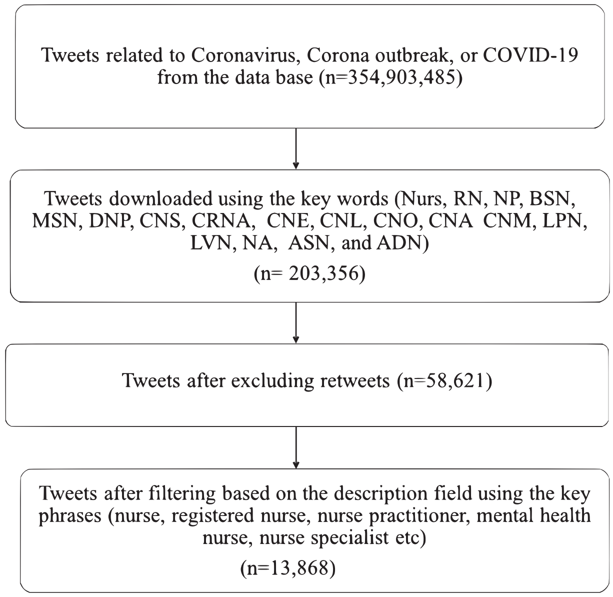

FIGURE 1 Flow chart of data extraction process

Analysis

All data preprocessing, analysis, and visualization were performed in the JMP Pro Version 16.1 and R software version 4.0.3. Sentiment analysis, a process of determining whether the polarity of a textual corpus (document, sentence, paragraph, etc.) trends toward positive, negative, or neutral, was done in the R software. The absence or presence of positivity or negativity in the tweets of nurses can be utilized to identify the mental health status of a larger sample of nurses (waning vs. healthy). As a result, while sentiments and emotions are not a foolproof indication of mental health, it is often an important indicator of how a person's mental state is progressing (Diehl et al., 2011). Sentiment analysis was done using AFINN, Bing, and NRC to get a comprehensive idea of the sentiment scores. All three lexicons are built around unigrams or single words, and the words are given ratings for positive and negative sentiment, as well as possible emotions in NRC. The NRC emotion lexicon consists of a list of English words and their association with eight primary emotions (anger, anticipation, fear, surprise, sadness, joy, disgust, and trust) and two sentiments (negative and positive; Mohammad & Turney, 2013). This software will count the number of words within the tweet that are associated with each emotion and will also identify the polarity (negative or positive) of the tweets. Tweets that are considered positive have a sentiment score of >0, neutral tweets have a sentiment score equal to 0, and negative tweets have a sentiment score of <0. The Bing lexicon categorizes words into positive and negative categories. It contains a total of 6786 words—2005 of which are positive and 4781 are negative words (Liu et al., 2005). The AFINN lexicon assigns words with a score that ranges between −5 and 5, with negative scores indicating negative sentiment and positive scores indicating positive sentiment (Nielsen, 2011). The trends and changes in emotions over time are reported via figures which were created in R (v.4.0) software. The tweets were organized based on the date and the sentiment of each tweet was calculated using all three software. The average score of the sentiment and emotions were calculated for a day and used for the final analysis. A word cloud of sentiments was prepared in JMP (Pro 16.1; JMP®, 2021; Figure 2).

FIGURE 2 Word cloud of sentiments

RESULTS

Our reports are based on data from 13,868 tweets from 5476 unique Twitter user Ids of self-identified nurses of which the source of 41.5% of the tweets was Twitter for iPhone, 23.09% from Twitter for Android, 21.6% from the Twitter for Web App, and 13.81% from others. The mean favorite count of the tweets was 16.44 ± 930.41 and the mean retweet count was 6.62 ± 480.43 (Table 1). The mean sentiment scores and range of each score were calculated using NRC, AFINN, and BING lexicon analysis, and the mean emotions scores are included in Table 1. A positive score indicates a positive sentiment, and a negative score indicates negative sentiment. The geolocation of the users was available in the dataset, but our initial analysis showed a lot of missing data, and most of the locations were marked as NA ($n = 7998$). The available location data were ambiguous and were inconsistent to conduct a subgroup analysis clustering tweet authors by geographic location and correlating sentiment scores with local cases. For example, Austin was labeled as aus, AUS, Austin, Aus, and TX, and AUS was also used as an abbreviation for Australia.

Trends in sentiment scores with time and average number of COVID-19 deaths per 100k

We looked at the change in average weekly sentiment scores for Bing, AFINN, and NRC with time and the average number of COVID cases and deaths per 100k worldwide. A total of eight graphs corresponding to sentiment scores and the average number of COVID cases and deaths per 100k worldwide over time were examined. Figure 3 and Figure 4 illustrate descriptive meaning and the authors thought would be interesting to the readers and scientific community. The red line represent the average weekly sentiment score during that time period and the black line represents the average number of cases/deaths per 100k.

The changes in AFINN sentiment score with time and the average number of deaths per 100k are plotted in Figure 3. The AFINN sentiment scores increased initially when the COVID-19 pandemic was declared by the WHO and the scores tend to peak when the average number of deaths per 100k worldwide peaked. But as the US COVID-19 deaths passed 100,000, the sentiment scores started declining sharply. The sentiment scores further declined, and the scores tend to be more negative during the mid of July when a new record of daily US cases was reported. Once the vaccine distribution plan was announced by mid of September, the sentiment scores started increasing gradually even with an upward trend in the average number of deaths per 100k. The sentiment scores continued to increase and became more positive after the Pfizer vaccine was reported to be 95% effective. A similar pattern was observed with the average BING sentiment scores over time and the average number of COVID deaths per 100k.

TABLE 1 Description of tweets and user profiles

Variable	Mean	Standard deviation	Median	Range
Favorite count	16.44	930.42	1	0–87,195
Retweet count	6.62	480.43	0	0–55,624
Friend count	2248.85	4399.49	916	0–46,006
Follower count	3793.14	12385.15	845	0–138,462
Bing sentiment score	0.037	1.56	0	−11 to 8
AFINN sentiment score	0.38	3.32	0	−24 to 22
NRC negative score	0.76	1.19	0	0–11
NRC positive score	1.04	1.33	1	0–11
NRC anger score	0.27	0.62	0	0–7
NRC anticipation score	0.49	0.80	0	0–7
NRC disgust score	0.23	0.58	0	0–8
NRC fear score	0.49	0.87	0	0–7
NRC joy score	0.37	0.71	0	0–9
NRC sadness score	0.40	0.78	0	0–8
NRC surprise score	0.23	0.53	0	0–4
NRC trust score	0.68	0.99	0	0–7

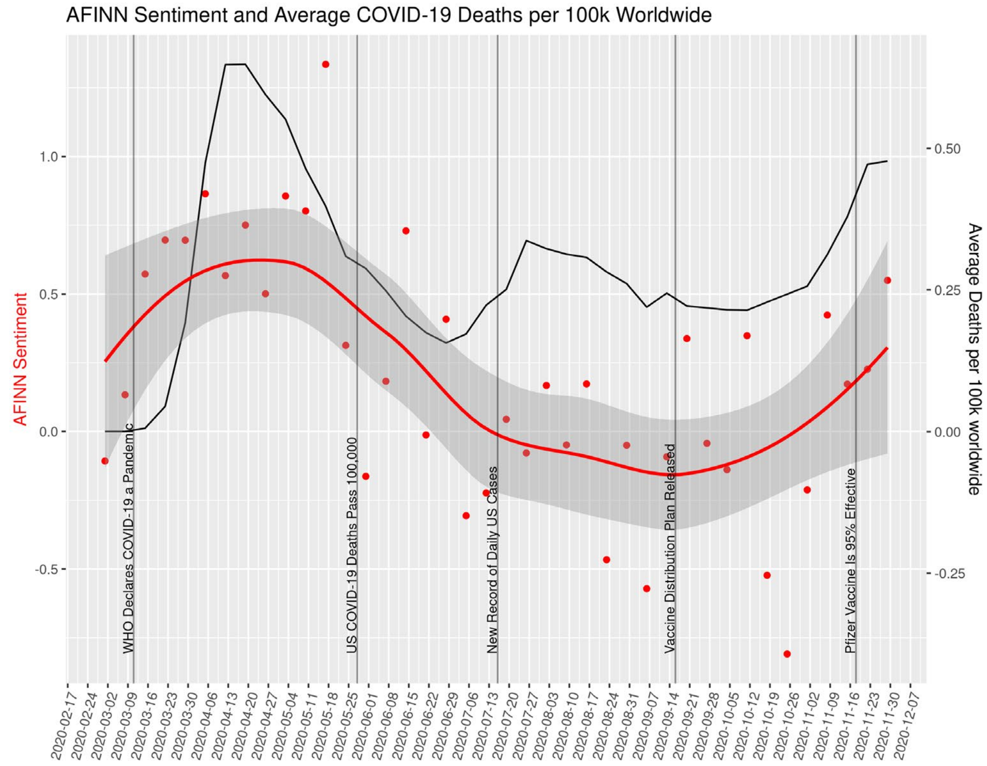

FIGURE 3 AFINN sentiment scores with time and average number of COVID-19 deaths per 100k

Trends in sentiment scores with time and average number of COVID-19 cases per 100k

Even though the average number of COVID-19 cases per 100k increased initially, the sentiment scores were more positive, but as the number of cases plateaued, the average sentiment scores started declining and it further dropped and was more negative during the mid of July when the new record of daily US cases was reported (Figure 4). The increase in sentiment scores during the mid of September was observed even with a steep increase in the average number of COVID-19 cases per 100k. A similar pattern was observed with the average BING sentiment scores over time and the average number of COVID cases per 100k.

Trends in emotions of tweets with time and average number of COVID-19 cases per 100k

We looked at the average weekly NRC emotions of tweets and how they changed over the period of time along with the average number of COVID-19 cases and deaths per 100k population worldwide. We will be only reporting significant trends observed in emotions over time with the average number of cases per 100k because the patterns observed in both cases and deaths were similar. The NRC emotion joy increased initially even though the COVID-19 was declared as a pandemic, and the average number of cases continued to increase, but joy gradually decreased as the deaths in the US crossed 100,000. The joy in nurses' tweets increased slightly once the vaccine distribution plan was announced and further increased when the Pfizer vaccine was reported to be 95% effective. This increase is notable even with the sharp increase in the average number of COVID-19 cases (Figure 5). A similar pattern was observed with the emotion joy over time and the average number of COVID-19 deaths per 100k.

The NRC emotion sadness increased gradually during the early months of the pandemic, and it peaked when a new record of daily US cases was reported in mid-July (Figure 6). The sadness then decreased slightly when the number of COVID-19 cases started declining during late July and August. But as the number of cases started increasing in the early fall, the sadness started increasing gradually and this increase is noticed even after announcing the vaccine distribution plan and the Pfizer vaccine was reported to be 95% effective.

The NRC emotion fear increased during the initial period when COVID-19 was declared as a pandemic by WHO and the fear peaked when a new record of daily US cases was reported in mid-July. The fear emotion remained stable and did not change even when the average number of cases per 100k increased sharply during the fall and even after the vaccine distribution plan was announced. The NRC emotion anger remained stable during the initial period when the pandemic was announced but it increased gradually over a period of time and did not decrease even after the vaccine distribution plan was announced and Pfizer was reported to be 95% effective. The NRC surprise score increased gradually over the months, peaked after the vaccine distribution plan was announced, and began to decline by mid of October when the COVID-19 cases peaked.

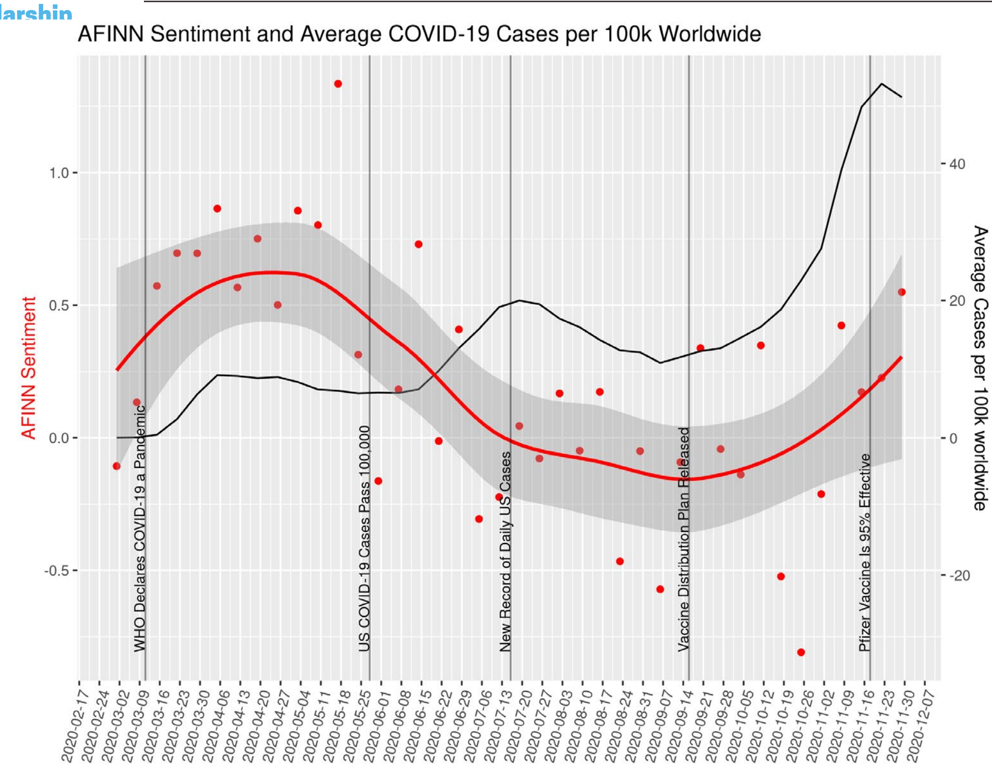

FIGURE 4 AFINN sentiment scores with time and average number of COVID-19 cases per 100k

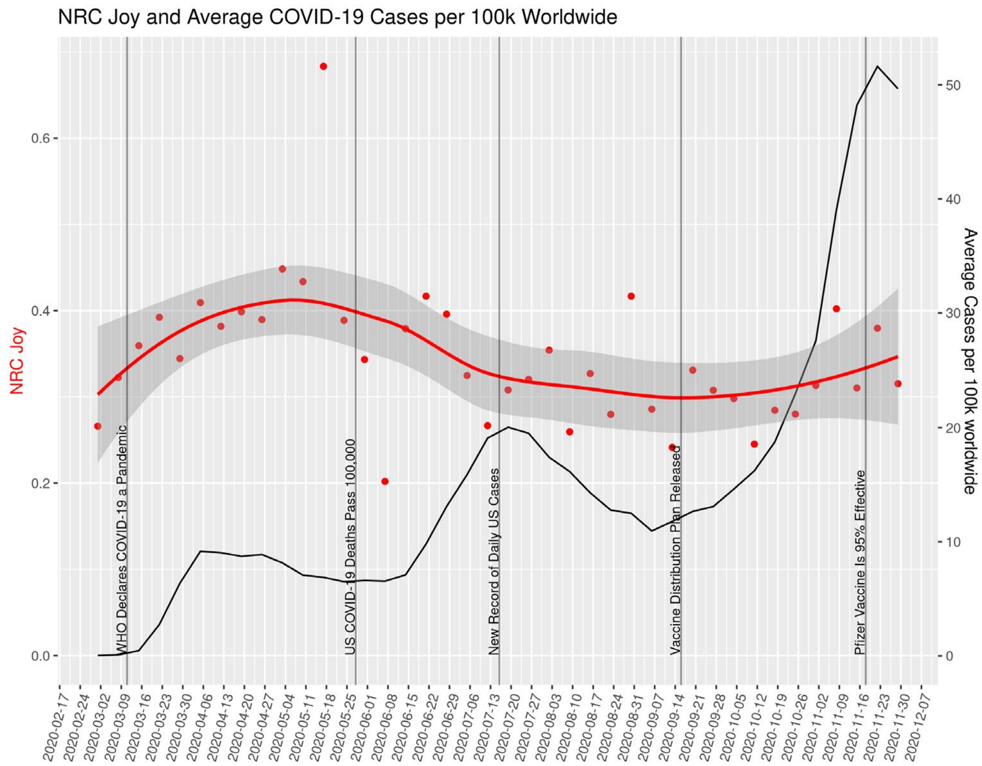

FIGURE 5 Trends in joy with time and average number of COVID-19 cases per 100k

DISCUSSION

The investigation of the sentiments and emotions expressed through tweets by the nurses revealed that the COVID-19 pandemic has influenced the thoughts and emotions of nurses in several ways, during the time frame studied and likely still doing so today. On the one hand, it compelled nurses to reflect deeply and communicate their thoughts and opinions through social media, while on the other,

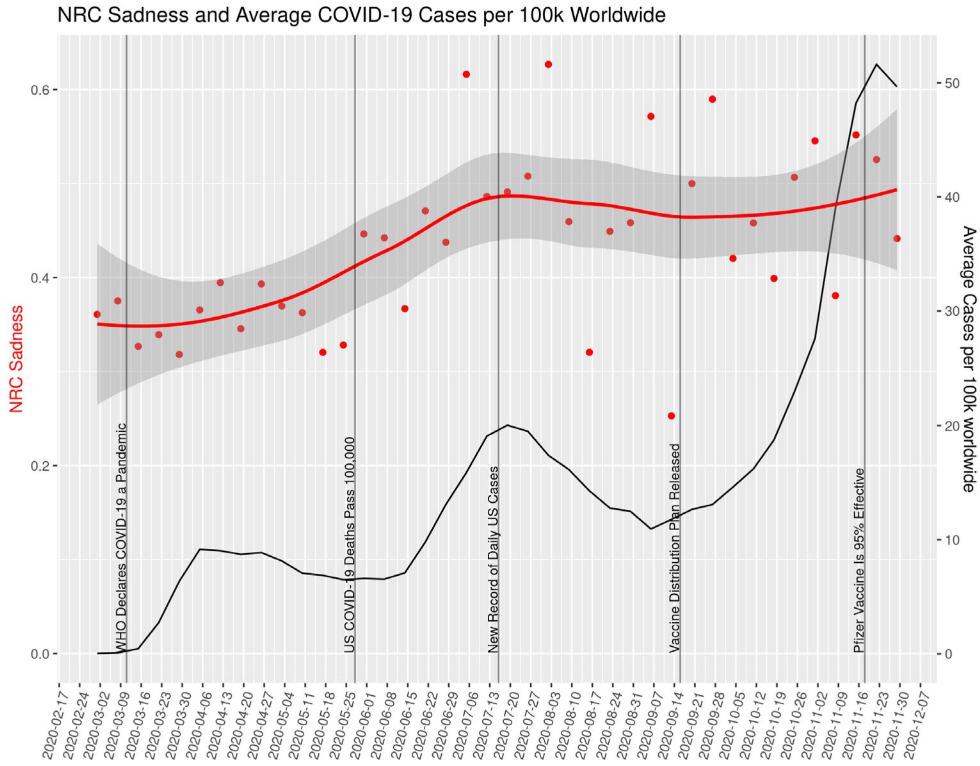

FIGURE 6 Trends in sadness with time and average number of COVID-19 cases per 100k

it evoked negative emotions (Wicke & Bolognesi, 2021). Our findings suggest that the overall sentiment polarity and emotions of tweets by nurses changed over time. The average sentiment score of nurses' tweets was increasingly positive during the first few months of the pandemic until April 2020, while it drops dramatically and became more negative from May till the end of September. Within the first few months of the pandemic when cases were starting to be reported across different countries in the world and when many countries were in lockdown, despite the fear of unknown situation, the nurses expressed positivity in their tweets as a form of mutual encouragement and education to the public to stay home in order to prevent the spread and to embrace the difficult situation. During the later dates, that is from May to September, even with a decrease in the average number of deaths per 100k, the sentiments in nurses' tweets dropped and became more negative. The negativity in nurses' tweets could be attributed to the increasing community spread with the gradual reopening of the economy, shortage of personal protective equipment and other needed medical supplies, shortage of beds and mechanical ventilators in hospitals experienced across the world during the time frame as well as general fatigue of the whole situation These findings are consistent with the study findings by Wicke and Bolognesi (2021) and Kaur et al. (2020), who reported that the general attitude of the public tended to be slightly optimistic and increasingly positive during the first few months of the pandemic (February to April) and during the later days (May, June, and July) the attitude dropped substantially toward a much more negative end. The drop-in sentiment score was also reported by Hu et al. (2021) and was attributed to the misinformation and conspiracy theories related to the COVID-19 pandemic and vaccines. Our investigation also showed a gradual increase in the sentiments score by the mid of September when the vaccine distribution plan was released and when the Pfizer vaccine was reported to be 95% effective. This increase was noted even with a significant increase in the average number of cases per 100k and the average number of deaths per 100k. Nurses play a significant role in the vaccination uptake process. They spend a lot of time talking to patients and educating patients, parents, families, and the general public about the benefits, side effects, and safety of vaccines, as well as administering them (Deem, 2018). Therefore, the observed positive trend could be attributed to the confidence and hopefulness of the nurses and also as a measure to create awareness among the public. A similar upward trend in sentiment score was also reported by Wicke and Bolognesi (2021) and Yousefinaghani et al. (2021) during the same period of time and they found that 34% of the tweets were positive with the majority of them relating to scientific breakthroughs, medical advice, promoting optimism, and spreading hope. In contrast, Niu et al. (2021) reported a surge in both positive and negative sentiments as in November 2020, when the Pfizer vaccine was reported to be 95% effective. The negative tweets were mainly related to the public expressing concerns about the safety of the vaccines and were also caused by the accumulation of negative news from several vaccines' clinical trials.

Our study investigated the nurses' emotions over time and shows that joy, sadness, fear, anger, and surprise fluctuated corresponding to the events that happened during the period of time. Joy in the tweets decreased in May 2020, when the COVID-19 deaths crossed

100,000. Sadness increased by the end of May 2020, when COVID-19 deaths in the United States crossed 100,000. The increase in sadness and decrease in joy were also reported by Kaur et al. (2020) and Elyashar et al. (2021). This was noted even with a decrease in average deaths per 100k and the average number of cases per 100k remained stable. Kaur et al. (2020) attributed the abovementioned trend to the killing of George Floyd on May 25, 2020. Further retrieval of tweets found that people from all around the world sympathized with him and the ones affected by COVID-19 (Kaur et al., 2020). The fear and anger increased over time and did not change much once they peaked. The observed trend could be a mixed response because of the increasing number of cases and deaths and the announcement of vaccine rolling out plans starting with health-care workers. This contrasts with the findings by Elyashar et al. (2021) who reported that the health-care workers' fear had a decreasing trend over time, although the pandemic impact increased.

With the value of big data in nursing scholarship gaining momentum and becoming more widely recognized (Brennan & Bakken, 2015), Twitter and other social media sites are huge data sources with thousands of users that will allow for robust analyses (Smith et al., 2021). Our findings add further insights into the use of social media as a platform for communicating the stress and emotions experienced during the pandemic, and nurses are increasingly embracing digital media to communicate and promote health in real time. This has significant implications for nursing's future as a digitally engaged health profession with the potential of informing the stakeholders of their problems and concerns. Additionally, there is a need to develop theories that are grounded specifically in nursing or revisit and extend the existing nursing theories on communication through the lens of digital technologies in a virtual environment as the existing theories and conceptual models focus on face-to-face interactions or written forms of communication documented in health records (O'Leary et al., 2021).

Recommendations

Future research could explore the changes and trends in sentiments scores and emotions across various geographic locations and the reported number of cases and deaths. Future studies should be conducted to gain access to sentiment from nurses in a more streamlined fashion and could be extended into the later phases of the pandemic (the year 2021). Researchers can also incorporate emotional intelligence on the tweets so that the sentiments and emotions of nurses who are the frontline workers can be explored in a fruitful approach and these findings could be utilized to develop interventions targeted at addressing their concerns and stress. This approach can be also used on a real-time basis so that the concerns of the nurses can be heard and addressed to prepare them for any future outbreaks. Further research is needed to determine how nurses could use social media effectively, as well as what kind of communicative techniques they should employ to completely connect with and impact stakeholders and policyholders digitally.

Limitations

Our study only analyzed the sentiments and emotions expressed through tweets by nurses and did not confirm them with interviews or questionnaires. Twitter users are not representative of all nurses and topics and trends in tweets indicate an online user's opinion, beliefs, and sentiments about the COVID-19 pandemic. Our analysis used the lexical approaches to sentiments and may not distinguish genuine positive sentiments from sarcastic ones. This is a major limitation in sentiment analysis. We also filtered the tweets of nurses using the description field in the profile and this process might have resulted in missing tweets of nurses who did not explicitly tag themselves as a nurse. In addition, we only sampled the tweets which used the hashtag Coronavirus, Corona outbreak, or COVID-19, as a result tweets that used other hashtags related to COVID-19 were not included in our analysis. We used a rigorous systematic process to screen the tweets to be included in the study and to make sure that these tweets were from users who self-identified as nurses but there is no clear guarantee that tweets are authentic and not coming from a chatbot or an artificially intelligent agent. But this is a major limitation of any study using data from Twitter. The geolocation data captured in the dataset were ambiguous and mostly missing and thus limited our ability to conduct geographic-specific correlations between sentiment scores, COVID-19 cases, and death rates. This limits our ability to look at how nurses' sentiments were negatively affected by surges or other setbacks that occurred in different regions at various times. Our findings demonstrate that there appears to be a pattern at a macro level and directionality/causality should not be inferred from these twitter data or our findings.

CONCLUSION

As the COVID-19 pandemic continues to affect people around the world and with an increasing threat of the emergence of new variants, our research sheds light on changing trends in sentiments and emotions regarding this pandemic among nurses. The study shows that Twitter data can be leveraged to study the emotions and sentiments of nurses, and the findings suggest that the sentiments can be used as a marker or proxy of stress levels experienced by nurses and their emotional realm was affected during the COVID-19 pandemic according to the emotional trend expressed in tweets. This also highlights the need to examine and address the psychological impact of COVID-19 on nurses.

CLINICAL RESOURCES

Twitter Developer Platform. How to analyze the sentiment of your own Tweets. https://developer.twitter.com/en/docs/tutorials/how-to-analyze-the-sentiment-of-your-own-tweets.

Monkey Learn. Twitter sentiment analysis in real-time. https://monkeylearn.com/blog/sentiment-analysis-of-twitter/

Duke Artificial Intelligence Society. Twitter API meets text sentiment analysis: [part I]. https://medium.com/duke-ai-society-blog/twitter-api-meets-text-sentiment-analysis-part-i-d7e150f12df5

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