Using Tweets to Assess Mental Well-being of Essential Workers During the COVID-19 Pandemic

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ABSTRACT

The Covid-19 pandemic has led to large-scale lifestyle changes and increased social isolation and stress on a societal level. This has had a unique impact on US "essential workers" (EWs) – who continue working outside their homes to provide critical services, such as hospital and infrastructure employees. We examine the use of Twitter by EWs as a step toward understanding the pandemic's impact on their mental well-being, as compared to the population as a whole. We found that EWs authored a higher ratio of mental health related tweets during the pandemic than the average user, but authored fewer tweets with Covid related keywords than average users. Despite this, sentiment analysis showed that, on average, EWs' tweets yield a more positive sentiment score than average Twitter users, both before and during the pandemic. Based on these initial insights, we highlight our future aims to investigate individual differences in this impact to EWs.

CCS CONCEPTS

• Human-centered computing; **• Collaborative and social computing**; **• Collaborative and social computing theory, concepts and paradigms**; **• Social media**;

KEYWORDS

Social media, Mental health, Sentiment analysis, Essential workers, Covid-19

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1 INTRODUCTION

The recent Covid-19 pandemic has had a significant impact on mental health and well-being of the population as a whole, leading to large-scale lifestyle changes, social isolation, and increased stress. This has been especially pertinent to essential workers — from those in the medical field treating patients to those in retail supply chains meeting the needs of everyday life. This has introduced new life stressors, such as high workloads, insufficient safety supplies, and risk to their own health and the health of their families when returning home [13, 16]. This, combined with reduced in-person support, suggests a highly complex and challenging situation for essential workers.

Approximately 55 million Americans have been deemed "essential workers" (EW) since the start of the pandemic [14]. In the United States, the Economic Policy Institute specifies 12 categories of essential employment for providing services critical to the country's infrastructure. The majority of essential workers in the US are employed within the healthcare industry (30%) — including clinicians and any hospital staff, agriculture and food production (20%), and the commercial service industry (12%) — such as retail or grocery store workers [14]. Within these industries, different employee roles can then be determined EWs on a state by state level [14]. It is also important to note that the US essential workforce, especially agriculture and service industries, is disproportionately comprised of women, minorities, immigrants, people over 50 years old, and low-income employees [16], which can put these workers at a greater disadvantage and increased stress. For low-income workers or single income families, this can involve making the difficult decision between personal health and safety and earning a paycheck [13].

EWs have continued to work outside of their homes, often in highly public-facing roles. This has raised concerns for their health and safety in the workplace and increased the need for safety procedures and protective supplies, especially for those in the healthcare sector facing exposure to individuals with confirmed cases of the Covid-19 virus [13]. Not only are workers' physical health put at risk, but their mental health as well. US healthcare professionals, in particular, are now at higher risk for mental health conditions than the general public, reporting on average enough symptoms to be diagnosed with depression during the pandemic [15]. EWs have reported higher levels of stress, anxiety, and tiredness, perceive lower feelings of control over their lives, and are less likely to engage in "proactive coping" — preparing themselves for future stressful events [15]. While this initially only speaks to healthcare EWs, those in other essential industries face similar stressors that may also put them at risk for depression or other mental health conditions.

Research has highlighted how users leverage platforms like Facebook, Instagram, and Twitter to connect with others about shared experiences, from coping with mental health conditions to voicing workplace concerns. Social media can provide a supportive discussion space for those coping with diagnosed conditions like depression or seeking informational or social support for day to day well-being [2–4, 8, 10], as well as advocate for these concerns [12]. In cases of depression, anxiety, or other sensitive and stigmatizing topics, these platforms can help people connect with similar people outside of their existing social support networks — either because no one in their existing circle understands their experiences or because they do not feel comfortable sharing [3]. These shared experiences, along with the perceived anonymity available online, can prompt users to disclose their mental health concerns more openly [4, 8]. Through the same means, social media platforms like Twitter have also become tools to voice shared societal concerns, allowing individuals to organize online movements for change — such as unionization [17] and Fight for 15, a movement for a higher minimum wage sparked by retail and food service workers across the US [1]. These connections made through social media can help users feel less isolated and allow them to bond with others in similar situations that they lack access to in their offline lives.

Conversely, the way people use social media, how often they post, and the types of content they share can be used to infer well-being or specific mental health conditions [6, 8, 9]. For instance, temporal factors, such as tweet timestamps and activity data, can be used to map out irregular sleep patterns, which is a common occurrence with depression and anxiety. The use of sentiment analysis methods on tweet content has shown that the stress, anxiety, or depression experienced by a user often reflects in more negatively associated posts online [6, 9]. This same process applied to large-scale social media posts can be used to assess shared positive and negative experiences on a societal-level, over a period of time. This work also highlights keywords most commonly associated with depression. The use of these keywords, along with sentiment and linguistic characteristics have allowed researchers to infer users with depression from non-diagnosed user populations [7, 9]. Given how much we can learn about one's mental health through what they share on social media, we ask how this same process can be applied to a niche type of user—EWs—and how their Twitter-use and general well-being may differ from average US Twitter users, before and during the pandemic.

The Covid-19 pandemic and its subsequent lifestyle changes has created a unique but important situation to better understand online mental health discourse and the role of social media in times of isolation, economic uncertainty, and additional work-life stressors. Specifically, the experiences of EWs—who face the stress of working in the public while also physically distanced from many of their offline sources of support—can provide unique insight into preexisting concerns, as well as highlight potential preventative actions for future situations. Our broader body of work aims to understand the ideal role of technology in mediating stress and social isolation, but also help call attention to larger, societal concerns at play for essential workers.

With this initial study, we make the following contributions. Based on multiple US government agencies, we develop a working definition of who is considered an EW for the purposes of this research and how these defining characteristics align with information provided on public Twitter accounts. We document our sampling and verification methodology to demonstrate how to infer this niche population from general Twitter users. We provide preliminary findings about the Twitter usage and well-being indicators of EWs across time and in comparison to the general US Twitter users. In particular, we show how EWs author fewer tweets and do so with a different temporal pattern. Despite assumptions, on average, EWs' tweets yield a more positive sentiment score, but still show a higher ratio of tweets related to mental health. In closing, we also discuss the potential implications of these findings and how future work—including a more granular analysis of different types of EWs on Twitter and in-depth qualitative interviews—can inform new design features to help support niche populations and remote socialization through online social networks.

2 METHODS

2.1 Sampling Essential Workers on Twitter

To explore these questions, we first gathered two different samples of Twitter accounts: one consisting of essential workers located in the United States and a random sample of all US geolocated accounts, to represent the average Twitter user. Overall, 4055 accounts were analyzed: 1752 EW accounts and 2303 random Twitter accounts. Only publicly visible accounts were included in this sample. Self-authored tweets (not including retweets) were gathered for each account from January 2019 through September 2020.

To gather Twitter accounts belonging specifically to EWs, we conducted a keyword search by using Snscrape [1], a Python scraper for social networking services, with the following inclusion criteria. First, the account authored a tweet containing a phrase self-identifying as an EW: "I am (I'm) an essential worker", from January to September 2020. No retweets were included; only self-authored tweets met this criteria. The "retweet_status" in Twitter object was used to identify the retweets. Quote retweets authored by these users were not excluded. To account for pandemic response and experience differences across countries, Twitter accounts were also limited to only those located in the United States.

To gather accounts for random Twitter users, we first crawled 15000 tweets/accounts by using Tweepy [2], an open source Python package for crawling Twitter data, with a set of specified COVID-related keywords: coronavirus, corona, covid-19, covid19. Narrowing the data to US users, the same criteria was applied. To further authenticate the data, we removed the accounts whose usernames and profile descriptions included keywords: news, channels, and official.

[1]Snscrape: https://github.com/JustAnotherArchivist/snscrape
[2]Tweepy: https://github.com/tweepy/tweepy

2.2 Method Validation and Primary Analysis

A sub-sample of 50 EW accounts was manually reviewed for accuracy against this criteria. A co-author reviewed the “I am an essential worker” tweets that qualified each account for sample inclusion to infer from context whether these accounts were from genuine EWs (*e.g.* about their own experiences, rather than quoting someone else).The co-author also documented if each account disclosed their specific employer, job type, or essential industry. Of this subsample of 50 EW accounts, only one was listed as outside of the US (Canada) at the time of data verification. The other 49 accounts were indeed located within the US. This subsample included users from 20 different states and three who listed their location as the USA, broadly. After manually verifying the EW status of each account, 48 of the 50 accounts were confirmed as essential workers based on the context of their self-identifying statement. Two accounts in the sample were not confirmed as EWs as they had authored tweets quoting the experience of an essential worker in contrast to their own experience working from home. Of these 48 EW accounts, many did not specifically disclose their job information or censored the name of their employer (*e.g.* “St*rbucks” to evade keyword search). This is likely because some may be incentivized to keep this information off of public-facing accounts due to social media policies put in place by their employers or to avoid workplace consequences. Conversely, other types of EWs openly disclosed this information as part of an online presence and media outreach necessary for their careers (*e.g.* physicians, medical students). Those who disclosed this information spanned multiple EW categories, including retail and food service employees, medical students, government employees, public transportation, warehouse workers, etc. Given these characteristics, it was determined that this sample of EWs on Twitter would sufficiently represent EWs in the broader US population.

2.3 Tweet Collection and Analysis

Following validation, we began collecting tweets and replies for the essential worker and randomly selected Twitter accounts, from January 2019 to September 2020. First, Snscrape was used to crawl the id of the tweets from January 2019 to September 2020. Then, Tweepy was used to collect tweets from the tweet ids. Lastly, 1,752 essential US workers and 2,303 average US Twitter accounts were collected, representing essential workers and the general population in the United States. Once these two data sets were gathered and normalized by time zone, the data were analyzed for the following: volume by month (Table 1), frequency by hour (Fig. 1, 2) and by month (Fig. 3). Each of these analyses were performed on EW tweets and average user tweets to compare between groups, as well as tweets and replies from 2019 (pre-pandemic baseline) and 2020 (during pandemic), to compare changes within each group over time.

2.4 Sentiment Analysis

We performed sentiment analysis on each collected tweet with the lexicon and rule-based sentiment analysis tool, VADER (Valence Aware Dictionary and Sentiment Reasoner) sentiment analysis [11]. Sentiment analysis identifies and extracts subjective information of a text to identify its polarity—positive, negative or neutral. VADER produces four scores: the pos, neu, neg, and the compound scores [11]. The first three scores are the ratios for proportions of text that fall in each category, which add up to one. The compound score is the result of the synthesis of these three scores

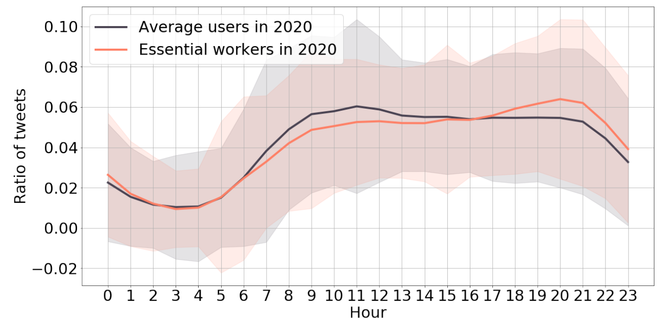

Figure 1: Ratio of tweets and replies posted for average users and essential workers in 2020 in each hour. The standard deviations of each timestamp are shown by colored regions. Average Twitter users show a higher ratio of tweets posted earlier in the morning, compared to EWs who show a higher ratio of tweets posted later in the evening, 5pm-1am.

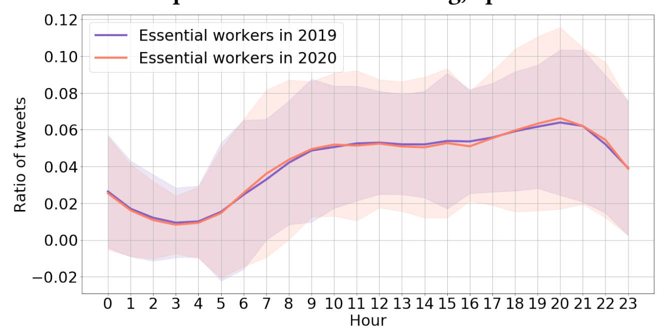

Figure 2: Ratio of tweets and replies posted for essential workers in 2019 and 2020 in each hour. The standard deviations of each group are shown by colored regions. The pattern of EWs posting tweets later in the evening remains consistent before and during the pandemic.

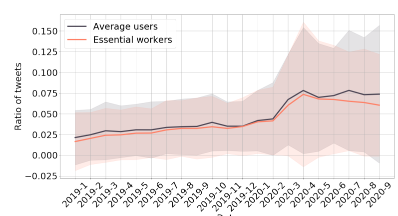

Figure 3: Ratio of tweets and replies posted for average users and essential workers in each month from January 2019 to September 2020. The standard deviations of each group are shown by colored regions. While the ratio of tweets increased for both groups during the pandemic, EWs produced a lower ratio of tweets than average Twitter users, overall.

	Essential US Worker		Average US User	
Date	(2019) 1/1 ∼ 12/31	(2020) 1/1 ∼ 9/30	(2019) 1/1 ∼ 12/31	(2020) 1/1 ∼ 9/30
average tweets per user	1622.994	1895.009	2646.777	3165.952
average tweets per user per month	135.249	211.140	220.466	350.273

Table 1: Essential workers average tweets posted comparison between 2019 and 2020.

and its value range between -1 (most extreme negative) and +1 (most extreme positive), which provides the most comprehensive sentiment analysis.

The temporal comparison of tweets' sentiment between average users and essential workers indicated by the compound score is shown in Figure 4. Averaging all tweets' sentiment score for each day regardless of the Twitter account could result show bias toward Twitter accounts that tweet much more than the other ones, making a larger impact to the average score. To exclude this bias, we first calculated each Twitter account's average sentiment score for each day and then took the average of these values as the final average sentiment score for each day.

2.5 Keyword Analysis

For this preliminary analysis, we compiled a list of keywords commonly used on Twitter for both Covid-19 pandemic related topics and mental health related topics, based on previous research [5, 9]. The following Covid-19 keywords were used: Covid, Covid 19, Coronavirus, mask(s), safe, pandemic, sick, and risk. We used the following mental health keywords and partial word matching, two words are matched if a keyword appeared in a part of the word, to identify tweets related to mental health: sad, struggle, stress, stressed, anxiety, anxious, depression, depressed, coping, and mental health. The volume and frequency of the keywords were calculated for each user and the average among users.

3 PRELIMINARY FINDINGS

3.1 Twitter Usage

First, there is a significant difference for the amount of tweets and replies posted between essential US workers and average US users, demonstrated in Table 1. Second, in Fig. 1, the essential workers present relatively higher numbers of tweets from 5pm to 1am, showing late active hours on Twitter. This difference in active hours could be associated with stress or other mental health indicators. Previous work [7] showed that users who display depression signs tend to be more active during the evening and nights due to sleep disruption. While late night active hours could indicate signs of their mental status, we cannot claim this definitively. Additionally, the active hours were not prompted by the pandemic, as shown in Fig. 2, where the active hours in 2019 overlap the hours in 2020. To study behavioral changes between pre-pandemic and during the pandemic, we calculated the volume and ratio of tweets and replies posted in each month. From Table 1 and Fig. 3, for essential workers and average US users, both of them demonstrate significant differences in the numbers of tweets and replies posted between 2019 to 2020. In addition to an increase in number, Fig. 3 also shows the variance increase in 2020, indicating polarized tweeting behaviors among users during the pandemic.

3.2 Sentiment Analysis

Based on sentiment analysis from frequency normalized tweets, we see essential workers' sentiment is relatively higher than that of average Twitter users, both before and during the pandemic, as shown in Fig. 4. Both groups show similar patterns, such as a sentiment peak at the start of each new year consistent with the holidays and a drop off in June 2020, likely due to protests and political unrest that began in the US at that time. However, EW tweets remain consistently higher in sentiment, overall. When looking at only Covid-related tweets, tweet sentiment scores drop significantly for both groups, showing a more negative attitude as compared to that of all tweets. However, we do not see a clear distinction between EWs and average users regarding COVID-related tweets, which is likely due to sample size.

3.3 Keyword Use

When looking at the frequency of of Covid-19 and mental health related keywords, significant differences were shown between EW Twitter users and average Twitter users. In tweets from 2020, average Twitter users showed a higher frequency of the Covid-related keywords, with a usage rate of 0.086 per tweet, as compared to EW Twitter users (0.055 per tweet). However, EW accounts used mental health related keywords more than average Twitter users. Mental health keywords were used at a frequency of 0.008 per tweet. Average Twitter accounts used these keywords at the frequency of only 0.006 per tweet. The occurrence numbers for average US users are generally higher, which is caused by a higher average number of tweets posted per month compared to essential workers. The results for essential US workers and average US users are shown in Table 2.

4 DISCUSSION

Looking at EWs across these characteristics, our findings suggest that, although EWs post a lower volume of tweets, often late at night, they yield a more positive average sentiment score and are more likely to post about mental health related topics. Based on patterns established from general Twitter users [6, 9], the temporal use of Twitter and common keywords could indicate potential mental health concerns and help support previous assertions of essential medical professionals [15]. However, there are likely additional factors related to this pattern as well. Other findings are more surprising, such as the higher positive sentiment scores of EW tweets, compared to average Twitter users. Despite the stressful lifestyle and workplace changes for EWs, this positivity remained consistent during the pandemic and sits in contrast to EWs' higher ratio of mental health related tweets, as compared to average Twitter users. Although we cannot yet confirm why EW tweets show these unique characteristics nor speak definitively about their current

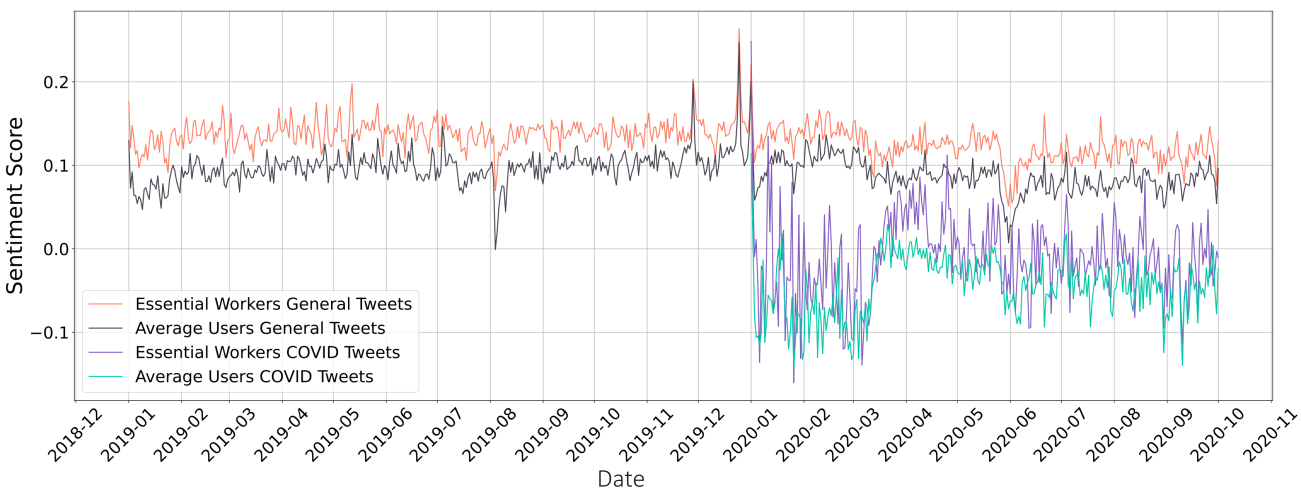

Figure 4: Sentiment Score (compound score) of tweets and replies posted for average users and essential workers in each month from January 2019 through September 2020. The COVID-19 related tweets are extracted starting from January 2020 through September 2020. Overall, EWs show higher tweet sentiment scores than average Twitter users, before and during the pandemic. Tweets related to Covid-19 show a lower sentiment score for both groups.

	Essential US Worker		Average US User	
	Volume	Frequency	Volume	Frequency
Covid-19 related	107.004	0.055	257.178	0.086
Mental health related	13.381	0.008	29.088	0.006

Table 2: Occurrence and ratio of keywords mentioned in the tweets among Twitter users in 2020

mental health status, this has prompted new hypotheses to explore in future qualitative work.

For instance, more positive tweets from EWs, regardless of the pandemic, could suggest that characteristics of essential jobs and the people who hold those jobs could prompt EWs to have a more positive online presence. For example, some essential jobs—such as healthcare workers—can provide increased job security, higher pay, higher perceived sense of purpose, as compared to those in other job roles, which could affect how they present on Twitter. However, this is not the case for all essential jobs, such as retail and service jobs, which generally provide lower pay and less stability [16]. Those included in the EW sample are more likely to be personal individual user accounts, whereas average Twitter accounts can be more variable—such as meme accounts or secondary accounts used more anonymously. Similar to why some users keep employment information private, EWs may also avoid negative or polarizing topics due to perceived work-related consequences, potentially skewing the average sentiment of their tweets. Conversely, the average Twitter users randomly sampled in this study could possess characteristics that lead them to post more negatively-associated content, as compared to EW users. Additionally, EWs may also turn to Twitter for different purposes than the average user. Considering that EWs use Twitter later in evening, they might be motivated to seek out more positive connections with others following long, stressful work days. While this initial study helps address how EWs are using Twitter, additional research is needed to understand what underlying factors drive these characteristics.

5 FUTURE WORK

We acknowledge that this initial look into the lives and experiences of essential workers based on their use of Twitter does not yet tell the whole story of what has been a very complex and challenging period of time. It does, however, provide us with key insights to guide future work. We intend to take on a more nuanced approach to understand the differences within different EWs and their unique individual experiences, through both online and offline means. Through the future use of Twitter's full tweet archive, we can broaden our sample to include a larger sample of essential workers and a more accurate sampling of average Twitter users. To examine differences within EW Twitter users, we mean to refine how we infer not only whether users are essential workers, but the specific type of essential job they hold, from profiles and post content. We also plan to incorporate topic modeling and deploy a more sophisticated sentiment classifier to increase accuracy. Through these steps, we can hone in on the leading issues that drive Twitter discourse for essential workers, help explain the uniquely positive sentiment patterns shown in this work, and better understand how EW Twitter use may differ from the platform at-large.

Additionally, we plan to further ground this work by conducting in-depth, qualitative interviews with essential workers across a wide range of job roles to shed light on their individual experiences. By talking directly to EWs about the changes and challenges they have faced during the pandemic—like balancing their home and work lives, caring for others, and dealing with the public—we can provide the context behind what they choose to share online. Although this initial work focuses on Twitter use, a discussion on social media and technology use more broadly could help show the impact the pandemic has had on their daily lives, well-being, and relationships with others. By better understanding the role that social technologies has had for EWs in mediating the effects of decreased in-person socialization, stressful workplace environments, and large scale lifestyle change during this critical period can help inform future design. Through this work we aim to support better mental health and provide more positive means of online social connections during periods of high stress and crisis situations.

6 CONCLUSION

This work provides us with an initial look into how essential workers use Twitter as compared to average users. We see differences in when they tweet, how often they tweet, and the sentiment behind their tweets. While EWs may author fewer tweets than the average user, their tweets are more likely to include mental health topics and include more positively associated content, both before and during the pandemic. While this sheds light on some unique characteristics of essential workers by way of their Twitter accounts, we cannot yet answer why these differences persist despite the challenges the Covid-19 pandemic has presented for EWs. Our future research aims to explore the on and offline experiences of different types of essential workers through in-depth interviews and a more nuanced analysis of the topics they share on social media. Through this, we can better understand the role that technology can play in mediating these challenges and help support users in future high-stress, crisis situations.

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