Nursing Perspectives on The Impacts of COVID-19: A Social Media Analytics Approach

Ainat Koren, Mohammad Arif Ul Alam, Sravani Koneru, Alexa DeVito, Lisa Abdallah, Benyuan Liu

Submitted to: JMIR Formative Research
on: June 22, 2021

Table of Contents

Nursing Perspectives on The Impacts of COVID-19: A Social Media Analytics Approach

Ainat Koren[1*] PhD, DNP; Mohammad Arif Ul Alam[2*] PhD; Sravani Koneru[2] MSc; Alexa DeVito[1]; Lisa Abdallah[1] PhD; Benyuan Liu[2] PhD

[1]Solomont School of Nursing, University of Massachusetts Lowell Lowell US
[2]Department of Computer Science University of Massachusetts Lowell Lowell US
[*]these authors contributed equally

Abstract

Background: Nurses are at the forefront of the COVID 19 pandemic. During the pandemic nurses faced an elevated risk of exposure and experienced hazards related to a novel virus. While being heralded as lifesaving heroes on the front lines of the pandemic, nurses experienced more physical, mental and psychosocial problems as a consequence of the COVID-19 outbreak. Social media discussions by nursing professionals participating in publicly formed Facebook groups is a valuable resource that offers longitudinal insights.

Objective: This study aimed to explore how COVID-19 impacted nurses through capturing public sentiments expressed by nurses on social media discussion platforms and how the sentiments changed over time.

Methods: We collected over 110,993 Facebook discussion posts and comments in an open COVID 19 group for nurses from March 2020 until the end of November 2020. A deidentified offline HTML scraping on social media posts and comments was performed. Using subject-matter expert opinions and social media analytics (topic modeling, information retrieval and sentiment analysis), we performed a human-in-a-loop nursing key perspectives analysis to understand the trends of the COVID-19 impact among at risk nursing communities. We further investigated the key insights of the nursing perspectives trends by reporting the temporal changes of emotional effects, frustration reasoning, impacts of isolation, shortage of safety equipment and the frequency of safety equipment uses. Anonymous quotes were highlighted to add context to the data.

Results: We identified that COVID-19 impacted nurses' physical, mental and psychosocial health expressed in the form of emotional distress, anger, anxiety, frustration, loneliness and isolation. Major topics discussed were related to work during a pandemic, misinformation from media, improper PPE, PPE side effects, testing positive and loss days of work related to illness.

Conclusions: Public Facebook nursing groups are venues for nurses to express their experience, opinions and concerns and can offer researchers an important insight to understand the COVID-19 impact on health care workers.

(JMIR Preprints 22/06/2021:31358)
DOI: https://doi.org/10.2196/preprints.31358

Preprint Settings

1) Would you like to publish your submitted manuscript as preprint?

✓ **Please make my preprint PDF available to anyone at any time (recommended).**
Please make my preprint PDF available only to logged-in users; I understand that my title and abstract will remain visible to all users.
Only make the preprint title and abstract visible.
No, I do not wish to publish my submitted manuscript as a preprint.

2) If accepted for publication in a JMIR journal, would you like the PDF to be visible to the public?

✓ **Yes, please make my accepted manuscript PDF available to anyone at any time (Recommended).**
Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain v
Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in <a href="http

Original Manuscript

Nursing Perspectives on The Impacts of COVID-19: A Social Media Analytics Approach

Ainat Koren[2], PhD, DNP, Mohammad Arif Ul Alam[1], PhD; Sravani Koneru[1], M.S; Alexa DeVito[2] ; Lisa Abdallah[2], PhD, RN, CNE; Benyuan Liu[1], Ph.D;

[1]Department of Computer Science, University of Massachusetts Lowell, MA, USA
[2]Solomont School of Nursing, University of Massachusetts Lowell, MA, USA

Corresponding Author:
Ainat Koren, PhD, DNP, PMHNP
Solomont School of Nursing
University of Massachusetts Lowell
113 Wilder Street, Suite 200 Lowell, MA 01854
Email: Ainat_Koren@uml.edu

Abstract

Background: Nurses are at the forefront of the COVID 19 pandemic. During the pandemic, nurses have faced an elevated risk of exposure and have experienced the hazards related to a novel virus. While being heralded as lifesaving heroes on the front lines of the pandemic, nurses have experienced more physical, mental and psychosocial problems as a consequence of the COVID-19 outbreak. Social media discussions by nursing professionals participating in publicly formed Facebook groups constitute a valuable resource that offers longitudinal insights.

Objective: This study aimed to explore how COVID-19 impacted nurses through capturing public sentiments expressed by nurses on social media discussion platforms and how these sentiments changed over time.

Methods: We collected over 110,993 Facebook discussion posts and comments in an open COVID-19 group for nurses from March 2020 until the end of November 2020. A de-identified offline HTML scraping on social media posts and comments was performed. Using subject-matter expert opinions and social media analytics (topic modeling, information retrieval and sentiment analysis), we performed a human-in-a-loop nursing key perspectives analysis to identify trends of the COVID-19 impact among at-risk nursing communities. We further investigated the key insights of the nursing perspectives trends by detecting temporal changes of comments related to emotional effects, feeling of frustration, impacts of isolation, shortage of safety equipment and the frequency of safety equipment uses. Anonymous quotes were highlighted to add context to the data.

Results: We determined that COVID-19 impacted nurses' physical, mental and psychosocial health as expressed in the form of emotional distress, anger, anxiety, frustration, loneliness and isolation.

Major topics discussed by nurses were related to work during a pandemic, misinformation spread by the media, improper Personal Protective Equipment (PPE), PPE side effects, the effects of testing positive and lost days of work related to illness.

Conclusions: Public Facebook nursing groups are venues for nurses to express their experience, opinions and concerns and can offer researchers an important insight to understand the COVID-19 impact on health care workers.

Keywords: mental health; information retrieval; corona virus; COVID-19; nursing; nurses; healthcare workers; pandemic; impact; social media analytic;

Introduction

Nursing is an occupation with unique potential for exposure to environmental and occupational hazards in the work setting. Nurses confront potential exposure to infectious diseases, toxic substances, stress, back injuries, and radiation [1]. The COVID-19 epidemic poses a unique health, risk situation that is rapidly evolving [2]. The American Nurses Association Code of Ethics (2015) states that the nursing profession's nonnegotiable ethical practice standard, according to Provision 2 of the Code, is that “the nurse’s primary commitment is to the patient.” Provision 5 of the Code states that “the nurse owes the same duty to protect themselves” [3]. These two equal obligations can be in conflict during pandemics, when nurses must continually care for critically ill infectious patients, under extreme circumstances including insufficient or inadequate resources and uncontained contagious diseases.

Professional nurses historically bring compassionate competent care to disaster responses but are faced with challenges to provide care when the nature of their work puts them at increased risk. Nurses struggle with feeling physically unsafe in the disaster response situation, such as in times of scarce resources where supplies of PPE may be inadequate [4]. Nurses are concerned about professional, ethical, and legal protection when asked to provide care in such high-risk situations, such as the COVID-19 pandemic. According to DeWolfe (2000), disasters, such as the Covid-19 pandemic impact those who experience them psychologically and socially [5]. Whether one considers the Covid-19 pandemic a human-caused or natural disaster, the human effects of living through such an experience are significant, especially when exposure to such a disaster is felt personally. For example, nurses working on the front lines throughout the Covid-19 pandemic have felt a direct effect of this disaster and therefore could experience an unusually large number of psychological and social reactions to this experience [5]. DeWolfe (2000) explains that high exposure survivors, such as nurses and other health care workers, could experience a range of effects

such as anxiety, depression, sadness, post-trauma symptoms, somatic symptoms and substance abuse [5].

Researchers around the world who have been examining the psychological impact on nurses and other healthcare workers as a result of the Covid-19 pandemic, have shown that nurses and other health care workers are experiencing high anxiety and fear, especially as these relate to concerns of infecting family members, being unable to socialize, and transmission of COVID-19 in their work settings [6]. A cross-sectional descriptive analysis of 204 COVID-19 infected healthcare workers showed that not only does the lack of PPE put nurses at risk of contracting COVID-19 from patients, but the lack of compliance from fellow employees to wear masks and practice social distancing, especially during breaks, puts nurses at risk [6]. An et al (2020) found that depressive symptoms among Emergency Department nurses in China were common and those reporting higher depressive symptoms also reported lower quality of life [7].

Hu et al (2020) examined frontline nurses in Wuhan, China; their findings demonstrated that nurses experienced moderate to high levels of anxiety, depression, burnout and fear, along with reporting having one or more skin lesions [8,9]. Nurses are also facing ethical dilemmas, such as which patients to prioritize and who should receive ventilation because of lack of sufficient number of ventilators [10] as well as moral distress related to uncertainty about their skills to tackle the virus [10]. Qualitative studies have demonstrated that nurses in China who were providing direct care to Covid-19 patients experienced a range of both positive and negative emotions [11]. Liu et al (2020) identified key themes that stress the emotional toll being experienced by nurses, specifically related to feelings of facing challenges and danger, fear of being infected, exhaustion and stress [12]. Along with these feelings, nurses also expressed their strong sense of duty and responsibility for being a health care provider during this pandemic, along with the hope that the epidemic would be overcome [12].

Sun et al (2020) found that in the early weeks of dealing with the pandemic, nurses primarily experienced negative emotions such as fatigue, discomfort, helplessness, fear and anxiety [11]; however, with time working in the setting and with knowledge growth of the care they provided, nurses expressed many positive emotions such as those focusing on coping and self-care, confidence in their self-prevention, and happiness gained from their patients' respect and from their family and team support. The stress of working with COVID -19 patients carries over into the daily life of nurses, as they feel isolated from family and friends as well as having child caregivers quit because of fear of infection and being unable to attend funerals of loved ones [6]. Some nurses became frustrated as they became out of work for the first time and wished they could do more to help [10].

Gap in Knowledge

The media have played a major role in the COVID-19 pandemic, being major sources of information for the public. However, the media have presented contradictory opinions and viewpoints about the virus, causing some to take the virus less seriously than others, leading to more distress for nurses [10]. The science of understanding health-related information that is distributed via a social medium to inform public health and public policy, known as infodemiology, has been particularly useful for identifying disease outbreak patterns and studying public perceptions of various diseases. Analysis of health event data posted on social media platforms not only provides firsthand evidence of health event occurrences but also enables faster access to real-time information that can help health professionals and policy makers frame appropriate responses to health-related events. Nurses have begun to use social media as a voice for health care workers on the frontlines. Online videos have surfaced, showing the chaos of hospital wings, and firsthand accounts of the traumas and struggles nurses have face have appeared on sites such as Facebook [10, 13].

Nurses are using social media in order to communicate with the public and advocate for more supplies and support [13]. For example, the "#GetMePPE" on Twitter was generated in order to spread awareness of the PPE shortages; this led to creation of a petition with over 62,000 signatories and combined with a website, GetUsPPE.org, allowed health care workers to obtain hundreds of thousands of articles of PPE [14]. The COVID-19 outbreak has resulted in a set of studies that have examined public perceptions, thoughts, and concerns about this pandemic through the use of social media data. All of these studies relied on data from public digital media such as Twitter or Weibo platforms and analyzed data from early periods of the pandemic, using different sentiment analysis techniques on the general population, irrespective of users' profession or evolution of sentiments over time on temporal events. In this study, we specifically analyzed social media discussions by nursing professionals participating in publicly formed Facebook groups to develop longitudinal insights related to the pandemic's impacts in terms of what health care providers experienced over time.

Study Aims

The primary aim of this study was to explore nurses' work experiences in dealing with the coronavirus pandemic and how it affected their emotional state. To achieve this, we specifically employed sentiment analysis, topic modeling and information retrieval techniques to estimate the influence of physical, mental and psychosocial factors of nurses related to the COVID-19 pandemic. The analysis captured major themes presented by the nurses who participated in publicly available social media groups from March to the end of November 2020. The analysis examined comments made to the posts as well. Specifically, we analyzed the major topics of concern that were posted by

nurses (e.g., lack of masks/PPEs/ventilators, fear of being infected, family difficulty, worrying about employment, etc.) The major topics were identified, guided by findings presented in recent publications. The analysis also focused on how these topics changed over time (e.g., from medical equipment shortages in the beginning of the pandemic to treatment in later stages). In addition, using a sentiment analysis technique, we analyzed the feelings and emotions (positive and negative) expressed in the posts and comments.

This study was reviewed by the University of Massachusetts Lowell Institutional Review Board and determined to be exempt from review.

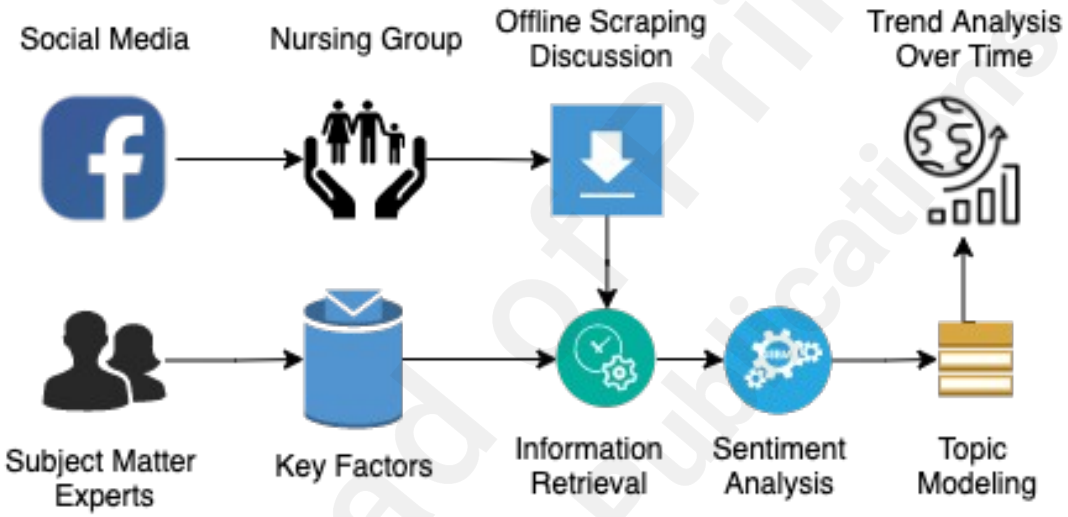
Social Media Analytics State-of-Art

Various approaches were used for text sentiment extraction by researchers which can be divided into four categories: ‘Keyword’, ‘Lexicon’, ‘Machine-learning’-based and ‘Hybrid’. Some researchers also used linguistic rule-based methods [15], keyword-based [16], emotion-based models [17, 18], natural language processing [19] and case-based reasoning [20]. Keyword-based methods detect sentiment by looking for a match between words in a piece of text and emotion keywords, providing a matching index, which is also called information retrieval [16]. Lexicon-based methods use a sentiment lexicon or dictionary to detect the correct emotion from a piece of text [21]. Machine-learning methods use both supervised [22,23] and unsupervised [24,25] learning for emotion detection, using various existing classification and clustering methods. Hybrid methods merge more than one of the above techniques and apply the results to recognize text emotion [16,26, 27, 28]. Emotion is generally defined and described by various emotion models. All existing emotion models can be divided into ‘Categorical’ and ‘Dimensional’ models [29]. Categorical emotion models such as Ekman’s model [31], Shaver’s model [32] and Oatley’s model [33] categorize all human emotions into a few major classes (i.e., Anger, Disgust, Fear, Joy, Love, Positive, Negative etc.). In contrast, dimensional sentiment models such as Plutchik’s model [34], Circumplex model [35], Cognitive Structure of Emotions Model [36] and Loveim’s model [35] classify sentiment in detail, using multiple dimensions (i.e., valence, arousal, dominance, etc.) and intensities (i.e., basic, mild, intense, etc.) in a form of question-answer form. We used the most popular methods from the existing literature: Information Retrieval Technique (keyword), pre-defined dictionary-based Linguistic Inquiry and Word Count (Lexicon) and Pre-Trained Bidirectional Encoder Representations from Transformers or BERT (Machine learning) [37] methods to identify sentiments in various use cases.

Methods

Social media refers to a digital platform where people can express their ideas, providing easy access to a diverse population all over the world. In particular, Facebook, with 2.7 billion monthly active users (till Nov 2020), being the largest platform, and plays a dominant role in social networks. In this study, we applied data mining techniques with added quotes to understand nursing professionals' perspectives regarding the COVID-19 pandemic as discussed in trusted open Facebook groups of nurses. Fig 1 illustrates the flow chart of our methodology.

Figure 1: Methodology Flow Chart



Data Preparation

Our data preparation phase consisted of group selection, data collection and preprocessing. First, we selected a public nursing professionals' group (which consisted of 108,354 members) formed by nursing professionals with the sole purpose of COVID-19 related discussion and collected nurses' posts. Facebook group posts data collection is more challenging than use of any other similar social media such as Twitter. Since, Facebook group Application Programming Interface (API) lacks the capability to extract comments and other necessary information (reactions, photos), we utilized the Facebook HTML page offline downloader and parsed the HTML tags (using Beautiful SOAP) to extract various Post id, Hash value of Usernames (deidentified), Post text, Number of likes, Date, and the comments for the posts. To represent the emotion pattern during the pandemic situation we collected posts from the beginning of the pandemic until November (March 01 to November 30, 2020) and saved them in a relational database of two tables: main posts and related comments, with appropriate private-public keys definition. The collected raw data contained background noises such as URLs, hashtags, emoji, stop words and empty posts, which were removed from the data by the use

of python-based data cleaning tools in order to provide increased precision scores.

Data Analysis Tools

We used two different analytical tools to analyze collected data:

(i) Sentiment analysis tool: Sentiment analysis is used as a process to determine the character of a text (positive, negative or neutral) assisting one to understand overall perceptions regarding a topic of conversation. Bi-directional Encoder representations from transformers (BERT) is a transformer-based machine learning technique for natural language processing (NLP) pre-training developed by Google to extract sentiments. We initially trained and validated our BERT-based supervised model on an existing 1.6 million Twitter dataset [38] That has *four labels: joy, sad, anger, and fear*. For this research study, we utilized the BERT [37] framework to extract sentiments from the selected data texts.

(ii) Information retrieval tool: Informational retrieval (IR) is a process of getting information or phrases out of the document repository. More specifically, the IR tool returns texts from the database that consist of the information queried by users in the form of texts, sentences or phrases, in order to represent top ranking or similarity scores. For this research study, we used the python-based IR tool Whoosh (Anserini), which can take either phrases/words/documents of text or a set of conditional phrases (connected with AND/OR relation) and return related posts with confidence of existence of queried phrases. (See Appendix 1) [39].

Validity of Choosing Analytic Tools

To analyze the nursing perspectives of the COVID-19 outbreak (i.e. nurses' psychology [40, 41], decision making [42, 43], emotions [44], concerns [45] etc), we applied current social media text analytic techniques [45-46]. In this section, we explain the validity of selecting BERT for sentiment analysis and Whoosh for information retrieval tools.

(i) Bidirectional Encoder Representations from Transformers (BERT): Natural language processing (NLP) is one of the most cumbersome types of machine learning in the area of data preprocessing. Apart from the preprocessing and tokenizing text datasets, it takes a great deal of time to train successful NLP models. In 2018, a team of Google scientists proposed and open-sourced BERT, a major breakthrough which took the Deep Learning community by storm because of its incredible performance. BERT is a transformer-based machine learning technique for natural language processing (NLP) pre-training method [47, 48]. As per a Google scholarly citation, BERT has been considered the most popular sentiment analysis tool for use with social media posts (cited 21,000+ times). There are two pre-trained general BERT variations: (i) BERT-Base: a 12-layer, 768-hidden, 12-heads, 110M parameter neural network architecture, and (ii) BERT-Large: a 24-layer, 1024-

hidden, 16-heads, 340M parameter neural network architecture. Both of the BERT models have been trained on English Wikipedia (2,500M words) and BooksCorpus (800M words) and achieved the best accuracies for some of the NLP tasks, such as sentiment analysis [49, 50]. In this paper, we used a pre-trained BERT model proposed by Dai et. al. for extracting sentiments from social media posts [51]. This particular model used the original vocabulary of BERT-Base as their underlying word piece vocabulary and used the pretrained weights from the original BERT-Base as the initialization weights. Then, the model used English tweets from September 1 to October 30, 2018 to pretrain BERT-Base model on total 60 million English tweets, consisting of 0.9B tokens. This particular BERT model achieved remarkable accuracies on sentiment analysis (> 91% accuracy on Twitter posts and fake news detection (> 98% accuracy on Twitter posts), which inspired us to choose this pre-trained model for our study [51].

Table 1: Our pre-trained BERT Model performance compared with other models.

Target Text Type	BERT-Base	Pre-trained BERT on Target
Tweets	Precision 89.9%, Recall: 89.4%, F1: 88.0%	Precision 91.7%, Recall: 91.1%, F1: 89.5%
Forum Posts	Precision 92.6%, Recall: 92.4%, F1: 92.2%	Precision 93.8%, Recall: 93.4%, F1: 93.0%

(ii) Anserini Tool: Anserini is an open-source software toolkit for the Lucene-based search engine via information retrieval towards building real-world search applications [39]. The Lucene-based search engine (Apache Lucene), first proposed in a Lucene4IR paper [52] and later improved by Grand et. al. [53] and Kamphuis [54], is widely used and is a standard foundation for search applications. The central purpose of the Anserini engine is to provide ranking (indexes) of documents/ sentences based on searched expression. The core components of the Anserini architecture are a multi-threaded indexing engine or wrapper, a streamlined information retrieval evaluator and a relevance feedback engine. The wrapper provides abstractions for document collections as well as the implementing an efficient, high-throughput, a multi-threaded indexer that takes advantage of these abstractions. The evaluator develops a multi-stage ranking architecture by extracting document features from the abstraction. The feedback component develops a relevance feedback index based on a vocabulary mismatch method between searched expressions and document collections. The final output index represents the ranking of similarity index, where a higher value means greater similarity. We used Anserini for identifying the existence of COVID-19 related key information from the social media

posts [39].

Data Analysis

We used state-of-art Natural Language Processing (NLP) for cleaning, topic modeling, sentiment analysis and information retrieval. During the data cleaning step, we removed background noise such as URLs, hashtags, emoji's, stop words and empty posts from the entire data to increase the precision score. Then, we used BERT for detecting sentiments. In this process, we used hugging face's transformer library written in tensorflow to label our collected data with sentiments, along with the frequency [55]. 'Hugging face' is a python-based transformer library that can support our pre-trained BERT model and can be used to label any collected data with sentiments. This library particularly shows the potential sentiments from a text, and one needs to confirm the sentiments from an interface. One graduate student was engaged to confirm the sentiments from the 'Hugging face' interface. It should be mentioned that one or more sentiments can be associated with a single post; thus, a single post can be associated with multiple sentiments. In that case, the single post can be considered multiple times for multiple sentiments. These detected sentiments were used and subdivided into subtopics later. After getting the emotions measure, we explored additional topics (e.g., lack of masks/PPEs/ventilators, fear of being infected, family difficulty, worrying about employment, etc.) which are specific and cannot be detected/retrieved by use of sentiment analysis or topic modeling methods. Therefore, we used an informational retrieval technique (Anserini) to further label posts. Anserini is a Python-based search engine similar to Lucene search indexing. This will result in the posts on these topics, along with the score which is term frequency–inverse document frequency (TF-IDF) for the topic [39]. Based on the emotional themes identified, specific anonymized posts and comments were included in this paper to highlight qualitatively examples of nurses' own words.

Results

The following results illuminate the negative and positive emotions expressed by nurses over time. The emotions are related to a variety of identified nurses' experiences during a nine-month period (March 1 through November 30, 2020) of the COVID-19 pandemic. Sample data (comments and posts) are displayed in Table 1.

Table 2: Distribution of posts and comments over months

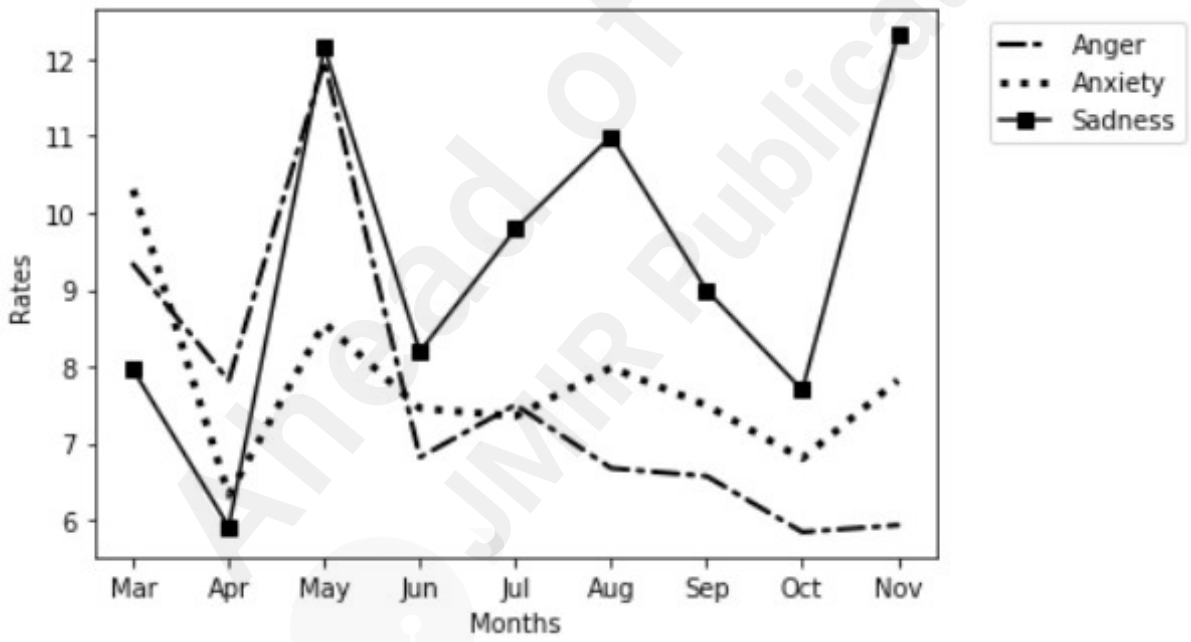
Months	Number of Posts	Number of Comments
March	8	1739
April	7	1939

May	64	11432
June	111	11777
July	144	16627
August	457	16553
September	218	24274
October	178	8313
November	361	16791
Total	1548	109,445
Total posts and comments	110,993	

Detection of Negative Emotions Expressed by Nurses Over Time
Anger, Anxiety and Sadness

This graph shows the rate variation among the emotions of sadness, anger, and anxiety. The rate was calculated by dividing the number of specific posts and comments of the expressed emotion by the overall emotional posts and comments for the month.

Figure 2: Rates of posts and comments related to the emotions of anger, anxiety and sadness over time.



The trend displayed demonstrates that rates of all emotions (posts and comments) rates peaked in May, July and August. Sadness and anxiety showed an added peak in November, while anger was trending down.

Sample posts/comments that exemplify these emotions are as follows:

One nurse posted the following comment that displays anxiety with her role during the pandemic:

"*I am terrified we will end up hospitalized or dead. My chest feels tight, but I think it's anxiety and not a COVID symptom.*"

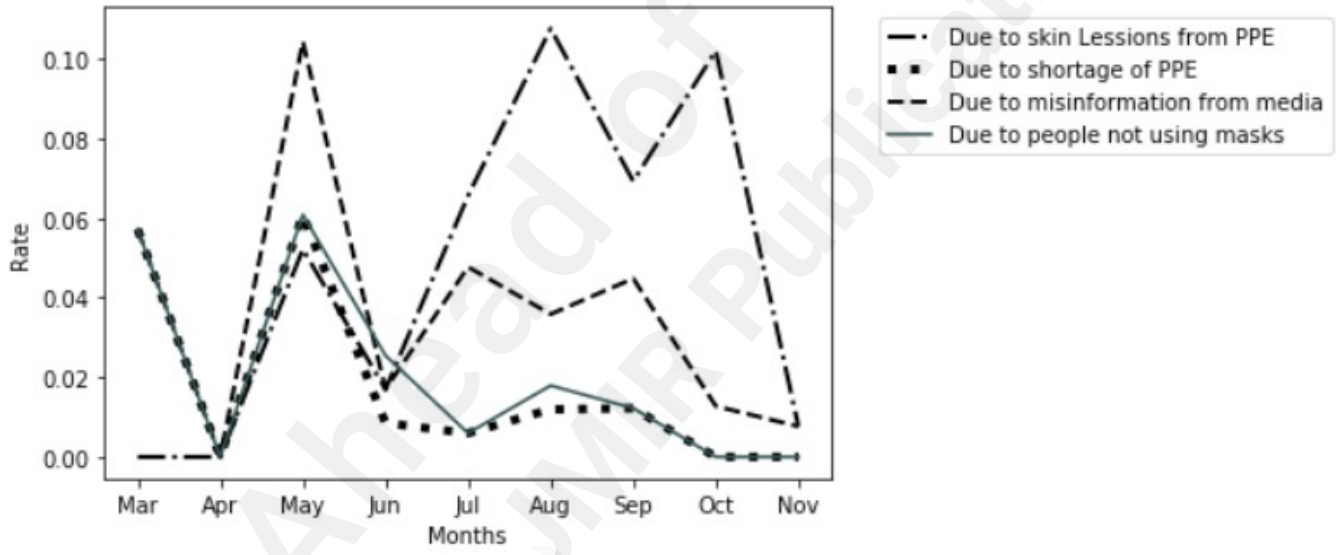
One nurse posted a comment that demonstrates anger related to non-defined policies on returning to work after exposure to COVID-19:

"I am so mad they let a nurse who is covid positive back to work with no rescreening done. He gets two hours into shift and has to go home sick. Thanks for the exposure people"
One nurse shared her feelings about depression and unhappiness which led to reconsidering her profession as a result.

"...This pandemic is absolutely draining and has even made me reconsider nursing. I am currently making a slight change and jumping into resource nursing. I've worked the covid ICU now for months and have noticed myself progressively becoming more depressed and unhappy. I'm making this change for mine and my family's sanity..."

Frustration due to Mask Side Effects, Shortage of PPE, Media Misinformation, and Lack of Compliance with Masks

Figure 3: Rates of posts and comments related to PPE and misinformation from media over time



Frustration with misinformation from the media was ongoing, with the highest peaks from April through June. Frustration caused by shortage of PPE peaked from April through June. Frustration from Skin Lesions was ongoing, with highest peaks in August and October. Frustration due to people not complying with mask recommendations peaked from April through July and again from July through September.

The following Post/comments illuminated the emotion expressed as it relates to frustration related to skin lesions, shortage of PPE, misinformation from media, and people not complying with mask recommendations.

Nurses posted comments about their struggle with mask rash and lesions caused by wearing masks

all day:

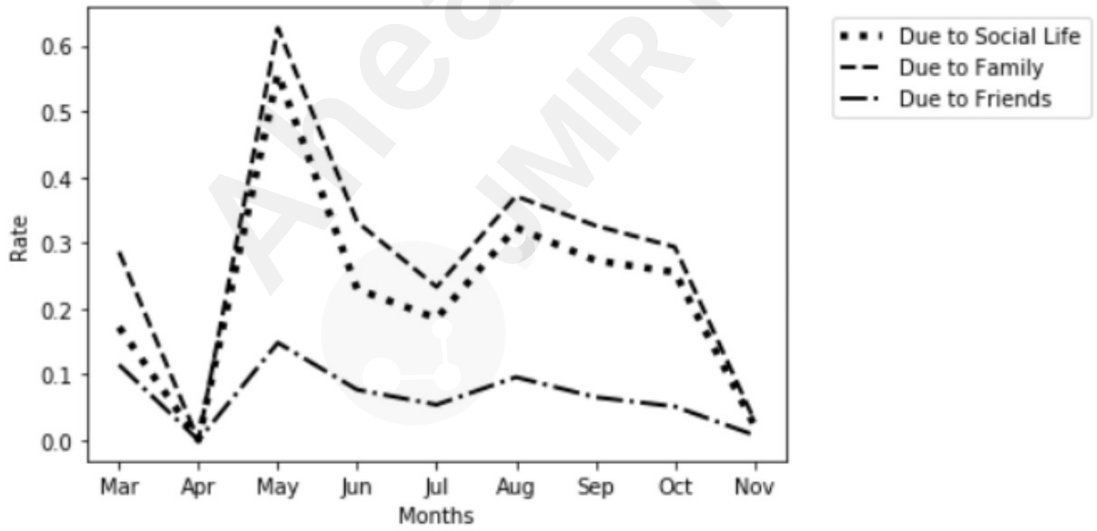
“I’m starting to get pressure ulcer on the tip of my nose from 12 hr shifts w surgical masks on...”
Nurses also reported receiving improper PPE for example:

“They gave us surgical masks and then when Covid probable, they didn't give us N95s until cases were exponentially increasing. FYI (I had my own N95 and brought it). Then they gave us these N95s that were not fitted - that broke when I was using it (I had to staple the straps)”
Another nurse shared that her facility controlled access to PPE:
"Heck, our acute care hospital locks up the PPE. We have to sign it out and are only allowed 1 mask a shift”

Some nurses posted comments about frustration with those who refuse to wear masks at work:
“Anyone else returning from work after being sick with covid annoyed/anxious over staff removing their mask at the nurses' station all day long? Worried for my staff getting sick and tired of people just not caring. I get it we are all sooo tired of this but covid is still here."
A few nurses expressed their concerns about the spread of misinformation about the virus:
“... I’m so sick and tired of people with ZERO credentials and experience in the medical field telling others the virus is a hoax and wearing a mask is pointless and literally trying to convince others this virus isn’t a problem. People are so shortsighted on their little soapbox that they don’t realize PEOPLE are DYING and their constant ramming of conspiracy theories down people’s throats could be enough to convince someone this virus isn’t deadly and can get someone killed. I’m so irritated right now.“

Isolation as it Relates to Social Life, Family and Friends:

Figure 4: Rates of posts and comments related to Isolation over time



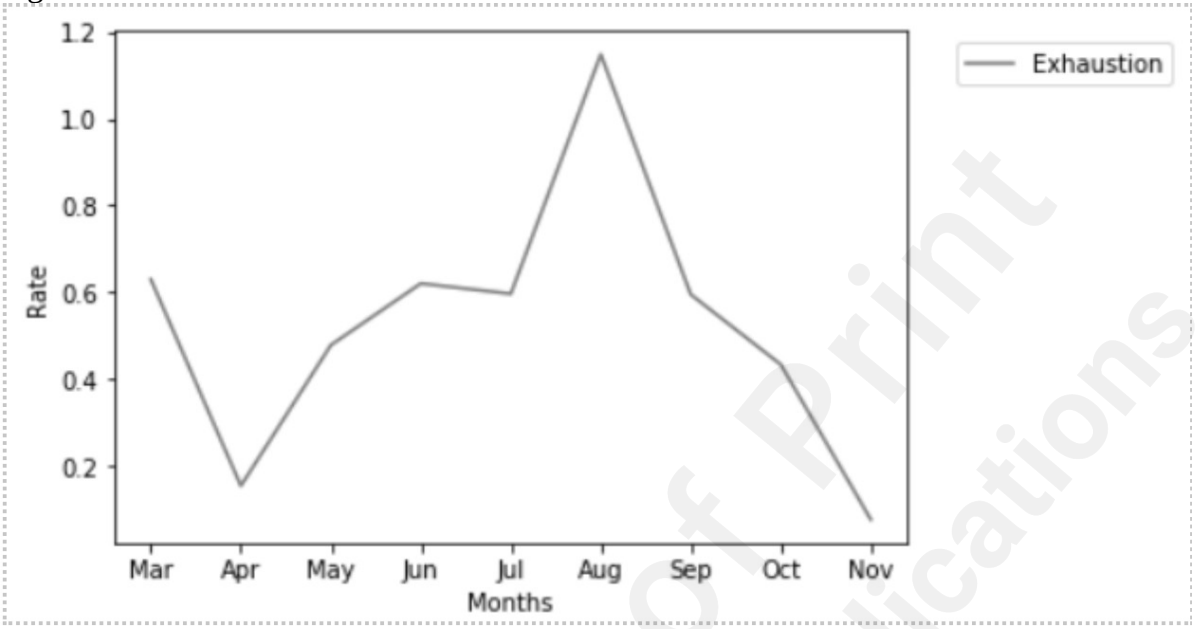
The rate of Isolation posts/comments across all categories peaked across all months, with the highest rates from April through June, followed by another rate increase in July to October.

Nurses expressed concerns about isolation from family due to fear of infecting them.
"I don't personally care about the risk to myself, it's more the fact that I'd like to be able to see my parents again and possibly hug my mom at least once this year. She has 3 autoimmune diseases. Me being in the same room as her is a major risk.”

""I miss my kids. I won't go near them. haven't in 3 weeks. I talk to them from 10-12 feet away with a mask. It sucks."

Exhaustion and Loneliness

Figure 5: Rates of Posts and Comments related to Exhaustion Over Time

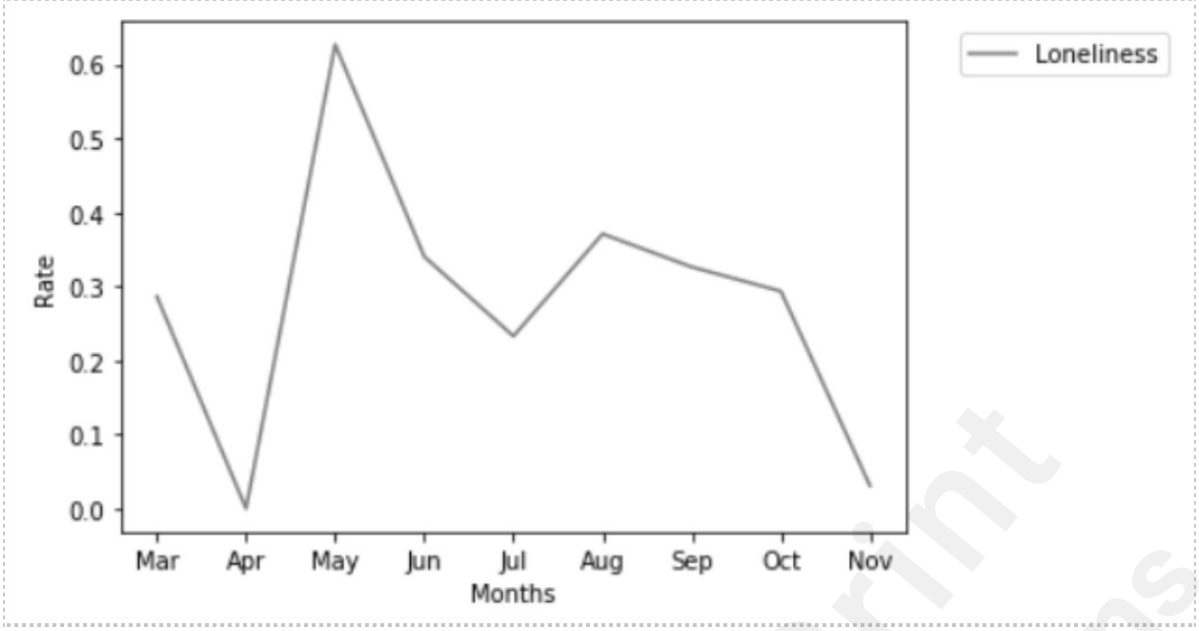


The trend displayed demonstrates that exhaustion peaked over time, with a significant peak from July through September.

Nurses describes the mental and emotional exhaustion of watching patients decline from COVID-19:

"Seeing these people suddenly tank and say goodbye before they get put on the vent. Face timing their loved ones, one last time, it don't get any easier. How do you fit a lifetime of love and relationships into a 2-minute phone call? I am struggling with asking to take a break from my unit. I am exhausted mentally and emotionally".

Figure 6: Rates of Posts and Comments related to Loneliness Over Time



The trend displayed demonstrates that loneliness peaked from April to the end of May, with another peak from July through October.

One nurse commented on how the isolation and longing to hug their family has led them to question their career choice:

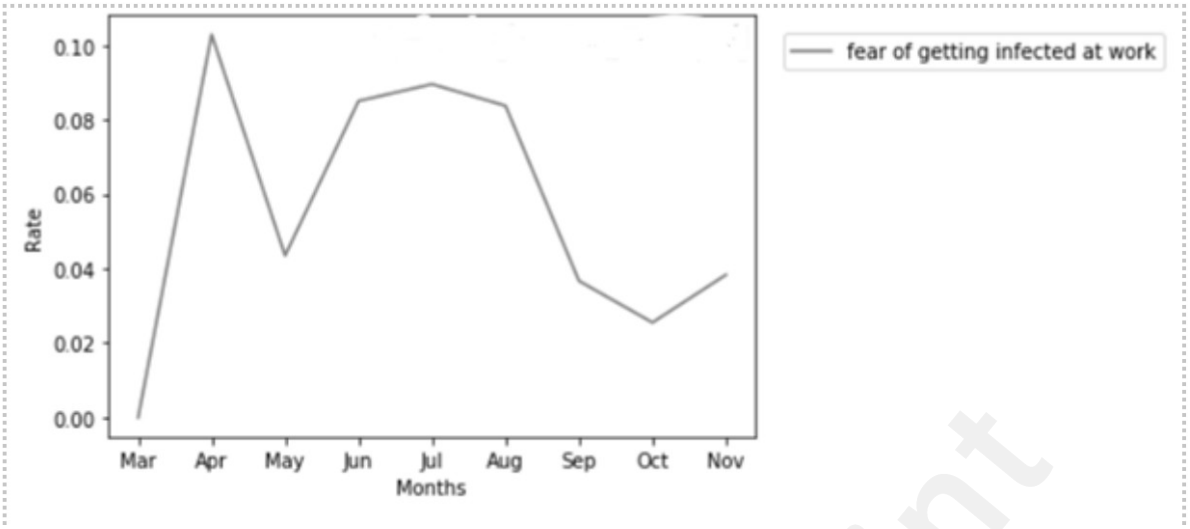
“I love being a nurse and I love taking care of people; however, this pandemic has made me question my career. I’ve had a lot of time in isolation to think about it. As I long to hug my family but will only FaceTime them to keep them safe. I even had to watch my daughter's graduation online. Is it worth it to risk my life and my families for this career?”

Another nurse commented on feeling alone because of family not understanding what they are going through:

“For those working third shift (like myself) how are you handling all this with your families??? Mine doesn’t understand at all.. and I feel so utterly alone right now. They tell me that I “signed up for this job” so I’m not allowed to be saddened by it. I just don’t know what to do, but I’m extremely depressed”.

Infected at work

Figure 7: Rates of posts and comments related to fear of getting infected at work over time



The posts/comments related to fear of getting infected peaked in April, followed by a decrease in the rate of posts/comments and another increase during June and July, after which they gradually decreased across the remaining months.

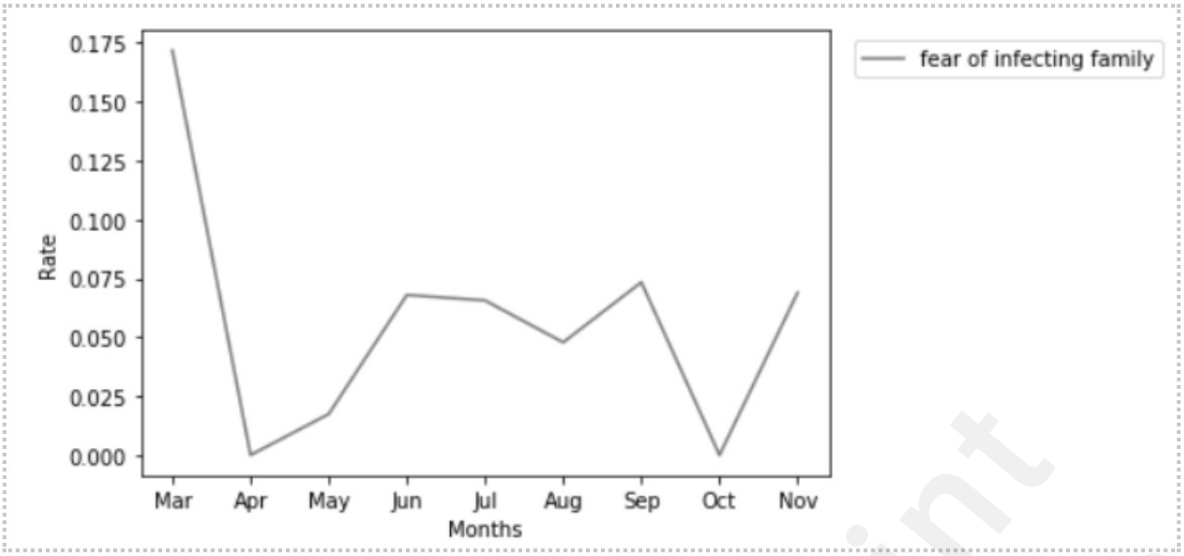
We have had nearly 50 positive cases between staff and residents in our facility. No one is intentionally spreading it and we are all doing the best we can... Today was my absolute worst day ever in healthcare. I know everyone is under a lot of stress right now, but we all need to be a team. And when a teammate returns after an illness that landed them in the ER to go back at it and put themselves right back in the line of fire, have some compassion and show some respect!

A nurse explains how she believes she got infected from the improper PPE they were given at work:
“I believe I got infected with an ill-fitting KN95 back when we had to tape them to our faces. It makes me so damn angry that the US is the "richest" country in the world and yet PPE is still a problem nine months into this crud.”

Another nurse discusses how mask wearing and social distancing are not followed in breakrooms:
“We have a very low number of positives. We have been doing masks and social distancing where required. At work we have to wear masks in the lab but when we hit the breakroom, masks come off and no social distancing. “

Fear of infecting family

Figure 8: Rates of posts and comments related to fear of infecting family over time



Nurses described the fear of infecting their family members who live in their home:

"... I think the ultimate challenge is protecting our families. I don't think the public totally gets the stress of how that burdens us."

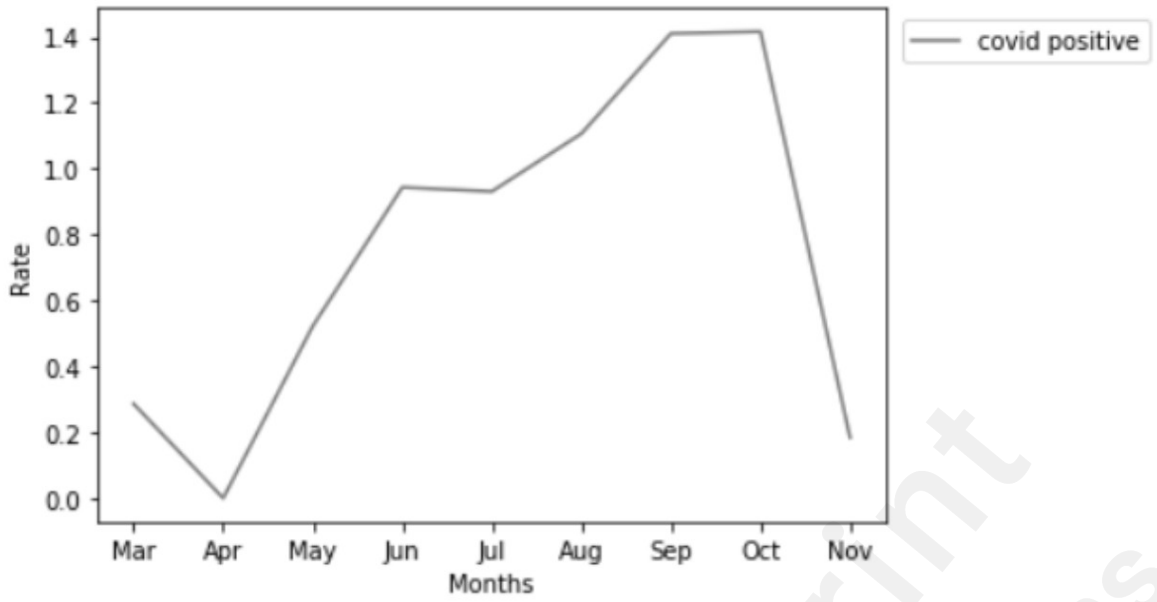
Another nurse describes the fear of infecting their family and others as well as having to isolate from their children:

"….The increasing fear every day that I walk into the hospital that today is the day that someone who refuses to keep their mask on and coughs on me will give me the virus. I am afraid that I will be forced to self isolate and will have to explain to my small children why I can't give them hugs and kisses, or even come upstairs. I am afraid that I will unknowingly bring it home to my family, or my next patient that I come into contact with. I am afraid that if I do just one tiny thing wrong during the donning and doffing process, that I will be the reason someone gets sick...."

Another nurse explains how constantly changing protocols make her fearful of bringing COVID home:
"...I definitely don't want to bring it home and infect my family. I just don't understand why the protocols seem to differ from day to day, and even hour by hour."

COVID-19 Positive Tests

Figure 9: Rates of posts and comments related to Testing Positive for COVID-19 over time



The rate of posts regarding testing positive for COVID 19 peaked from April through October.

Nurses infected with COVID described symptoms they experienced.

One nurse posted: *"Is there light at the end of the tunnel? On day 8 and day 6-7 I thought I was dying. Currently wondering if I should medicate for 100.5-degree temp or if it's better to let immune system fight it. Shortness of breath is better but cough is still there along with chills, body aches, diarrhea, stress incontinence from coughing so much. I was dizzy, had numbness and pins and needles in hands and feet and did nothing but sleep for 48 hours"*

Symptoms from the virus lasted after recovery from the infection, compromising the ability to work.

"...19 days post symptom onset, went back to work ...on Sunday to work three 12s in a row after being off for almost three weeks. I am EXHAUSTED, my brain is straight fog and I move so slow. My body kills and my feet are swollen. And I'm tachy with palpitations for 90% of the night unless I'm sitting for a long period of time which does not ever happen. I don't know how I will survive another night shift tonight. I can't breathe in my surgical mask, let alone my n95. My chest hurts from struggling to breathe through these shifts. I know it takes time to get completely back to normal but I am so frustrated and tired ..."

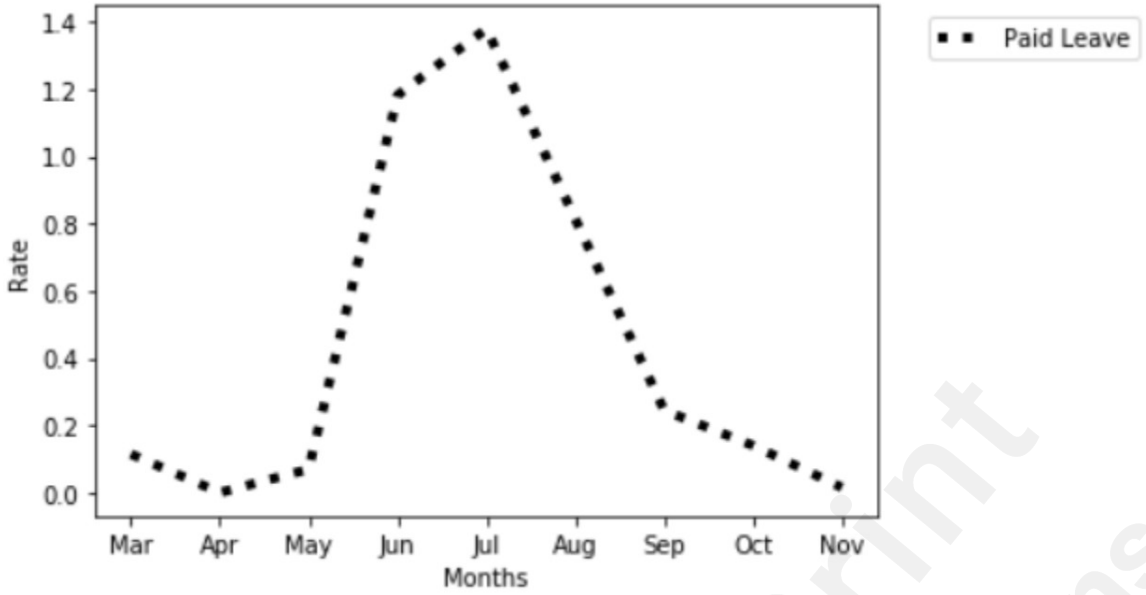
In addition, some of the nurses had long lasting symptoms.

One nurse posted in October: *"I had Covid in July and my sense of smell is not anywhere back to normal. When there is an odor, I smell the most rancid smell I could ever imagine. Anyone else experiencing this?! Will I ever go back to normal?!*

Exposure to the virus resulted in contracting COVID and isolation from family *" ...have been isolated from my family for a week. I was diagnosed last Sunday. Breaks my heart that I can't see my children and I have to blow kisses to them from a screen. I tried my best to keep me and them safe. Praying for your health. This is no joke. I don't wish this upon anyone."*

Paid Leave

Figure 10: Rates of posts and comments related to paid leave due to COVID over time



The rate of posts related to paid leave peaked from the beginning of May until mid-July and then declined through November.

Nurses posted comments about their high-risk occupation that is not reflected in hazard pay. One of the nurses posted:

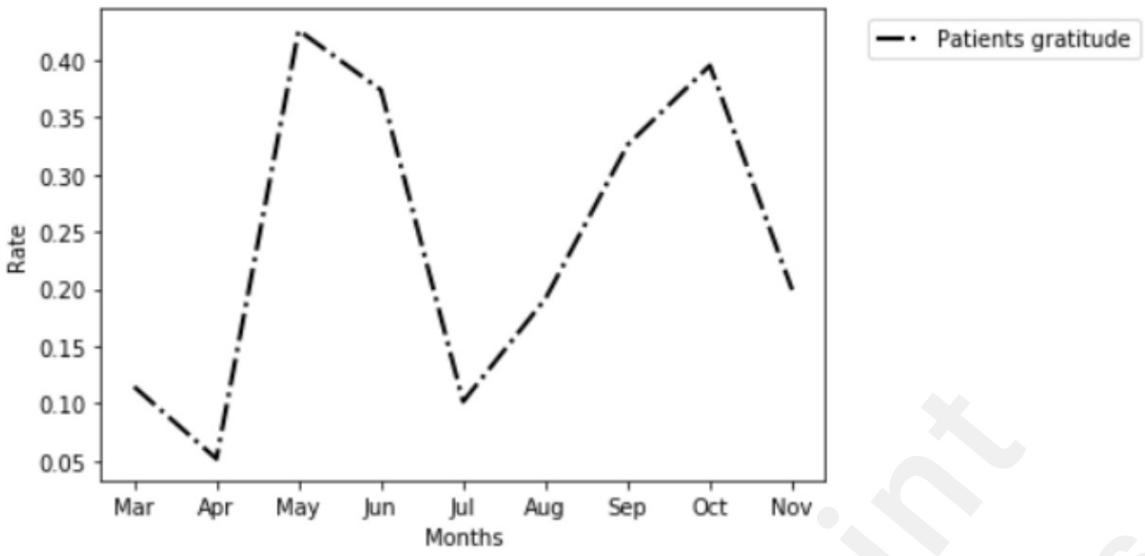
“have been a nurse for 23 years and I agree with you. It’s a shame that we are at such high risk, and the pay truly doesn’t match the risk, not to mention the lack of pay when you finally test positive and have to stay home for 2-3 weeks (where I am now).”

Many nurses were struggling with unpaid leave that added an economic burden. Variability was seen among states regarding the policy of paid or non-paid leave for nurses who tested positive for COVID-19.

“Just tested positive. Contracted it at work... I’m now home for 2 weeks, unpaid. Can someone help me understand how this is okay.... My company doesn’t have to compensate me despite contracting the virus while working. Tips? Ideas?

Detection of Positive Emotions Expressed by Nurses Over Time
Patient Gratitude

Figure 11: Rates of positive posts and comments related to patient gratitude over time



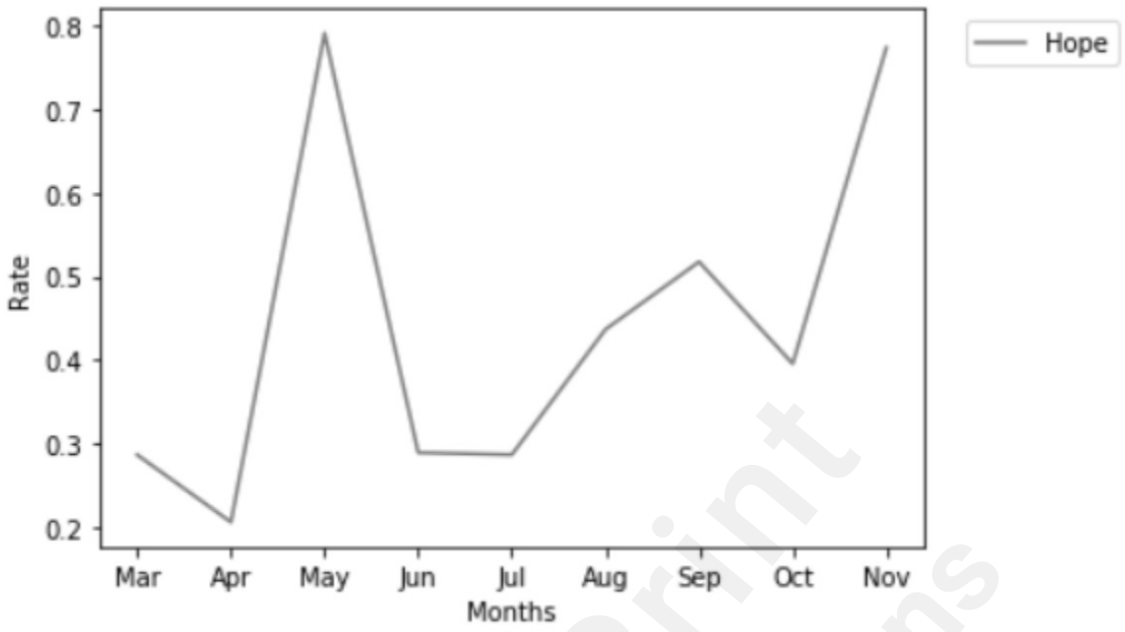
Posts/comments related to patient gratitude peaked from April through June and August through October.

One of the nurses shared an example of appreciation expressions:

“We had one of our nurses have her gas paid for by another patron. I have a friend who was given a gift card to Walmart when she was shopping. And I know someone who is giving the local hospital staff certificates for a free massage as they leave work …"
Comment:...this makes me so happy! I’m glad some people are appreciative.”

Hope

Figure 12: Rates of “hope” and comments over time



.

Expressions of hope and positivity varied across the time periods, with highest hope and positivity in May, followed by a smaller peak in September and then a continued increase from October through November.

One comment represents the positivity and hope expressed as it relates to the strength gained from teamwork and not going through this pandemic alone:
“You are not alone. In your fear Frustration and Anger We see the tears wishing for better days You are not alone We see the strength Teamwork Desire to wrap your arms around a tired coworker Your loved ones The patient With no family near Pride in profession You are not alone We see you We are you.”

Many comments reflected hope that the peak effects of the pandemic will subside and a return to some normalcy is on the horizon:

“Hopefully someday it will be less overwhelming.”
“Our peak/wave is over here and hopefully never comes back.”
Other comments reflected positivity as nurses encouraged each other to keep hopeful:
“You will come out of it soon! ……. Protect yourself at all cost. Most of all keep the faith. God bless you”

Discussion

This social media study combined sentiment-detecting technology and major discussion themes to explore nurses' emotional expressions from the beginning of the pandemic through November 2020. The analyses were supported by direct quotes illuminating the experience of being a nurse during the COVID-19 pandemic. Our data methodologies follow the standard social media text analytic literature, which has been proven effective and trustworthy and has been applied in

significant social media text analytics for nursing and COVID-19 trend studies in the past [39-47]. Apart from that, because of the lack of ability of the Facebook API to extract the necessary group posts, we developed our own offline textual information extraction techniques, with appropriate de-identification to preserve users' privacy, as per IRB exemption conditions. Combining BERT-based sentiment analytic and Anserini-based information retrieval techniques facilitated development of full-fledged generalized social media analytics framework that can be utilized in any study domain that includes, but is not limited to perspectives of students, media personalities, social workers and minority groups with regards to adverse social events.

Sentiments described in the posts and comments reflected a variety of negative and positive emotions to the pandemic experience. The negative sentiments expressed by nurses were anger, specifically as it relates to non-defined policies such as returning to work after being infected; anxiety because of being a frontline worker during the pandemic, and sadness caused by witnessing patients decline and die as well as being isolated. Nurses expressed mental and emotional exhaustion. The recent literature has expressed similar sentiments. In a cross-sectional descriptive correlative study on burnout of 2014 frontline nurses in Wuhan, China 835 nurses reported high levels of emotional exhaustion, and 556 nurses experienced high level of depersonalization [8]. Sentiments related to anger and anxiety, specifically as they relate to non-defined policies during nurses' service as frontline workers during the pandemic, were also expressed in recent studies. A commentary published by Nelson and Lee-Winn 2020 highlighted the anxiety nurses experienced as they dealt with very frequent changes in policies and protocols as the pandemic evolved [39]. Hu et.al., 2020 showed that 40% to 45% of frontline nurses experienced anxiety or depression, with 11% to 14% having moderate to severe anxiety or depression [8]. Results from a cross-sectional online survey of 1103 frontline ED nurses demonstrated that engaging in clinical services for COVID-19 patients was significantly associated with a higher risk of depression (43.6%) [7].

Nurses shared factors that contributed to increased stress and anxiety. One example from this analysis was related to conspiracy theories and "fake news". Recent research has supported these findings [10]. Other contributing factors to the nurses' stress and anxiety were the shortage of PPE and noncompliance with rules on mask wearing. Nurses also reported development of skin lesions as a consequence of wearing PPE daily for long shifts. Similarly, Hu found that 1910 out of 2014 nurses had one or more skin lesion(s) caused by PPE [8,9]. Because of the shortage of PPE, the fear of becoming infected with COVID-19 as well as infecting their family members presented another factor in elevated anxiety and depression among the nurses. In addition, nurses expressed feelings of loneliness caused by isolation from their social life, family, and friends. Nelson and Lee-Win 2020

reported similar concerns. Similarly, a 20202 survey by the ANA of 10,997 nurses found that 28% felt depressed and 29% felt isolated and lonely [39-46].

Positive sentiments expressed by nurses were related to patient gratitude and hope as it related to teamwork and support of one another throughout the pandemic as well as hope for better days. Recent studies reported that nurses simultaneously with reporting negative emotions experienced positive emotions as well. There was a sense of responsibility and professional identity while they supported each other. The nurses also felt patient's gratitude [47]. These results agreed with our findings.

The emotions described also changed over time from the beginning of the pandemic until late November 2020. The findings resemble the psychosocial and emotional responses associated with the phases of disaster as described by DeWolfe (2000) [5]. Nurses spoke about their fears and anxiety, especially as it related to their sense of loss of ability to protect themselves and others, particularly their family members. These sentiments were noted throughout the timeframe of posts and comments analyzed but were heightened in the early phase of the COVID-19 pandemic. This resembles the Phase 1 or pre-disaster phase and Phase 2 impact phase of a disaster as described by DeWolfe (2000) [5]. As the COVID-19 pandemic timeframe continued (Appendix 2), emotions experienced followed the Phase 2 impact and Phase 3 heroic phase of disaster but quickly moved to the Phase 5 disillusionment phase, as in this phase the realization of limited assistance and noncompliance of the public leads to emotions of stress and burnout, with many reactions such as exhaustion, frustration, anger, and depression being exhibited in the sentiments that were expressed. As vaccines were developed and the number of cases declined, positive emotions of gratitude and hope were displayed in the sentiments of posts and comments. This resembles the Phase 4 honeymoon phase. Specifically, optimistic comments were related to patient gratitude, teamwork and support, as well as keeping the faith that all will return to normal.

Limitations

Although this study was designed to be a unique representation of the perspective of nurses during the COVID-19 pandemic, there is a potential error in that some posts in this group could have been made by non-nurse individuals because of open group posting allowance. Because of the specificity of comments and group rules that were monitored by administrators, the chances of this are low and presumably would not have affected the analysis. An additional limitation to this study is that the data originated from one specific open group on Facebook and might not represent all nurses' perspectives; however, this one group the membership included 106K nurses. In addition, findings from this study were in agreement with findings in the current published literature about this topic.

Although the authors based the analysis on the definitions described in Appendix 3 they might not capture all the emotions experienced by the nurses. We considered the pre-trained BERT model, with four sentiment labels: joy, sadness, anger, and fear, which may slightly limit our analytic results. On the other hand, a single post can be counted multiple times which regards to different sentiments, carries the risk of introducing error into our analytic results. However, recent studies have found that considering only the above four sentiment labels and making multiple counts of the same posts for the different sentiments sustain the analytic results for COVID-19-related posts as per different machine learning techniques, which affirm the consistency of our results [57]

Conclusions

The significance of this study is that it adds to the importance of documentation about a historical pandemic from the nurses' experience. The COVID-19 pandemic is a unique experience that the world was not prepared for and for which we were not preparing student nurses in the nursing curriculum. Themes and information gathered from this analysis will constitute evidence of what transpired in the United States in the time of the pandemic outbreak. It will provide a voice of the nurses who served on the front line. It will also serve as a basis for articulating lessons learned and a basis for ethical discussions of other topics in health care. In addition, it will be particularly useful to various government agencies, hospitals, organizations, and communities that wish to better understand the major concerns related to crises of public health and make policies to address them.

Acknowledgements

The project has been supported by UMass Lowell Internal Grant for COVID-19 Impact analysis

Conflicts of Interest

"None declared"

Appendix 1
Table 3: Topics and the Associated Phrases /Methods Used in this Analysis

Theme/ Sentiment	Definition	Phrases	Method
Anger	a strong feeling of displeasure and usually of antagonism [57]	Used BERT for sentiment analysis	BERT
Anxiety	apprehensive uneasiness or nervousness usually over an impending or anticipated ill : a state of being anxious [57]	Used BERT for sentiment analysis	BERT
Sadness	affected with or expressive of grief or unhappiness [57]	Used BERT for sentiment analysis	BERT
Mask Side Effects	The unfavorable response and adverse effect to wearing a mask	skin problem from wearing masks, Maskacne, Acne from wearing masks, Face breakouts, cyst, pimples, pimples around my chin	Whoosh
Shortage of PPE	Shortage - Lack, deficit [57] PPE- personal protective equipment	Ranout off PPE, Limited quantity of PPE, PPE shortage, lack of affordable healthcare, without proper availability of PPE	Whoosh
Media Misinformation	misinformation - incorrect or misleading information[57] related to COVID -19 originated from media	Media's half-truth, Wrong about knowledge on pandemic, false reported, misinformation by all sides of media, inaccurate news, fake news,	Whoosh

		fact check should be done by journalist	
Lack of Compliance with masks	the act or process of complying to a desire, demand, proposal, or regimen or to coercion [57] of wearing a mask	without mask, not wear mask, workers not, wearing masks, noses hanging out	Whoosh and BERT
Isolation	Isolate- to set apart from others [57]	It's hard to see family and friends, miss my work, isolation feeling, missing family, not able to go out, going in and out of isolation, crying alone, keeping away from family and friends	Whoosh
Exhaustion	Exhausted- depleted of energy : extremely tired [57]	I was Exhausted, Burnout, I am tired, drained	Whoosh
Loneliness	Lonely- a. being without company b. cut off from others [57]	I am alone, in agony alone, isolation, family abandoned, loneliness, helplessness	Whoosh
Fear of infection/ infecting family	Fear - an unpleasant often strong emotion caused by anticipation or awareness of danger [57] Infection- the state produced by the establishment of one or more pathogenic agents (such as a bacteria, protozoans, or viruses) in or on the body of a suitable host [57] Infect- : to contaminate with a disease-producing substance or agent (such as bacteria) [57]	Catching infection from patients, symptoms from patients, contacting patients	Whoosh and BERT
Covid positive	Testing positive to COVID-19 virus [57]	tested covid positive, positive and quarantined, being tested positive	Whoosh
Paid leave	Time away from work by an employee for which the employee received	paid leave, paid administrative leave, 2 weeks, paid leaves if tested	Whoosh

	compensation [57]	positive, paid sick leave	
Patients gratitude	Gratitude- the state of being grateful [57]	gratitude to express how much nurses care, thank you, patient express gratitude, thankful and grateful for work, you are super hero	Whoosh
Hope and positivity	to cherish a desire with anticipation : to want something to happen or be true [57] the quality or state of being positive [57]	keep the faith, hang in there, hope helps, optimism, stay strong, believe in yourself, team work	Whoosh
Loss of Pay	Losing pay due to being out of work with COVID-19	no sick leave, loss of pay, no pay if sick, no pay during apr/may	Whoosh
Family Support	Assist, help [57] from family members of nurses on the frontlines	Family or friends that help, happy because of family support, grateful, care and love from family	Whoosh

Appendix 2
Table 4: COVID 19 Timeline

Political/ Governmental Actions	March 13 — Trump Declares COVID-19 a National Emergency September 16 — Trump Administration Releases Vaccine Distribution Plan November 9 — President-Elect Biden Announces COVID-19 Transition Team
Care	July 23 — Antibody Cocktail May Treat, Prevent COVID-19 August 4 — Rural Hotspots Face Lack of Intensive Care Unit Beds August 23 — Convalescent Plasma Is Cleared for Use by FDA September 3 — Steroids Reduce Mortality in Severe Cases October 22 — FDA Approves Remdesivir as First COVID-19 Drug
Vaccines	May 21 — United States and AstraZeneca Form Vaccine Deal July 14 — Early Moderna Data Point to Vaccine Candidate's Efficacy July 27 — Moderna Vaccine Begins Phase 3 Trial September 16 — Trump Administration Releases Vaccine Distribution Plan September 21 — Johnson & Johnson Begins Phase 3 Vaccine Trial October 9 — US Signs Deal with AstraZeneca

	Mid November — High efficacy results for Moderna and Pfizer are reported.
COVID 19 Spread	March 11 — WHO Declares COVID-19 a Pandemic June 10 — US COVID-19 Cases Reach 2 Million July 7 — US Surpasses 3 Million Infections, Begins WHO Withdrawal July 9 — WHO Announces COVID-19 Can Be Airborne August 17 — COVID-19 Now the Third-Leading Cause of Death in the US August 28 — First Known Case of COVID-19 Reinfection Reported in the US September 23 — A New, More Contagious Strain of COVID-19 Is Discovered September 28 — Global COVID-19 Deaths Surpass 1 Million October 15 — US Cases Spike Again

Appendix 3

Table 5: Number of posts by sentiments and themes over time

Month	March	April	May	June	July	August	September	October	November
Total number of posts	8	6	63	103	129	438	211	177	355
Total number of comments	1739	1939	11432	11661	16627	16282	24322	7661	12691
Figure 2									
Sad	97	51	733	532	1158	1478	113	366	1159
Anger	367	89	668	380	716	714	784	274	390
Anxiety	315	164	1077	1186	1803	2005	2338	690	1510
Figure 3									
Not wearing a mask	1		7	3	1	3	3		
Frustration due to skin lesion	6			2	11	18	17	8	1
Frustration due to PPE shortage	1		7	3	1	3	3		
Frustration due to misinformation	1		12	2	8	6	11	1	1
Figure 4									
Isolation due to social life	3		64	27	31	54	67	20	3
Isolation due to Family	5		72	39	39	62	80	23	4
Isolation due to Friends	2		17	9	9	16	16	4	1

Figure 5									
Exhaustion	11	3	55	73	100	192	146	34	10
Figure 6									
Loneliness	5	0	72	40	39	62	80	23	4
Figure 7									
Fear of getting infected by patients		2	5	10	15	14	9	2	5
Figure 8									
Fear of infecting family	3		2	8	11	8	18		9
Figure 9									
Tested positive for COVID	5		60	111	156	185	346	111	24
Figure 10									
Paid leave			8	139	231	136	60	11	2
Figure 11									
Patients' gratitude	2	1	49	44	17	32	80	31	26
Figure 12									
Hope	5	4	91	34	48	73	127	31	101

References

1. Pope, AM, Meta AS, Mood LH. Nursing, health, & the environment: strengthening the relationship to improve the public's health. Washington, DC: Institute of Medicine, National Academy Press. 1996; PMID: 25121198
2. Haddad, LM, Geiger RA. Nursing Ethical Considerations. StatPearls [Internet]. U.S. National Library of Medicine, 2020. https://www.ncbi.nlm.nih.gov/books/NBK526054/ [Accessed Jan. 2020].
3. Morley, G, Grady, C, McCarthy, J, Ulrich, C. Covid-19: Ethical challenges for nurses. Hastings Center Report. 2020; 50(3):35-39. doi:10.1002/hast.1110
4. Cabarkapa, S, Nadjidai, SE, Murgier, J, Ng, CH. The psychological impact of COVID-19 and other viral epidemics on frontline healthcare workers and ways to address it: A rapid systematic review. Brain, Behavior, & Immunity - Health. 2020; 8. doi:10.1016/j.bbih.2020.100144.
5. DeWolfe, DJ. U.S. Department of Health and Human Services, Substance Abuse and Mental Health Services Administration, Center for Mental Health Services. Training manual for mental health and human service workers in major disasters Second Edition. 2000
6. Aksoy, YE, V, Koçak. Psychological effects of nurses and midwives due to COVID-19 outbreak: the case of turkey. Archives of Psychiatric Nursing. 2020; 34 (5): 427–433. doi:10.1016/j.apnu.2020.07.011.
7. An Y, Yang Y, Wang A, Li Y, Zhang Q, Cheung T,Ungvari GS, Qin M, An F, Xiang Y. Prevalence of depression and its iImpact on quality of life among frontline nurses in emergency departments during the COVID-19 outbreak. Journal of Affective Disorders. 2020; 276: 312. doi:10.1016/j.jad.2020.06.047.
8. Hu D, Kong Y, Li W, Han Q, Zhang X, Zhu LX, Wan SW, Liu Z, Shen Q, Yang J, He HG,

Zhu J. Frontline nurses' burnout, anxiety, depression, and fear statuses and their associated factors during the COVID-19 outbreak in Wuhan, China: a large-scale cross-sectional study. EClinicalMedicine. 2020;24. doi:10.1016/j.eclinm.2020.100424.

9. Shaukat N, Ali MD, Razzak J. Physical and mental health impacts of COVID-19 on healthcare workers: a scoping review. International Journal of Emergency Medicine. 2020; 13 (1). doi:10.1186/s12245-020-00299-
10. Turale S, Meechamnan C, Kunaviktikul W. Challenging times: Ethics, nursing and the COVID-19 pandemic. International Nursing Review. 2020; 67 (2): 164. doi:10.1111/inr.12598
11. Sun N, Wei L, Shi S, Jiao D, Song R, Ma Lili, Wang H, Yanli Y, Liu S, Wang H. A qualitative study on the psychological experience of caregivers of COVID-19 patients. AJIC: American Journal of Infection Control. 2020. 48 (6): 592. doi:10.1016/j.ajic.2020.03.018
12. Liu Y-E, Zhai Z-C, Han Y-H, Liu F-P, Hu D-Y. Experiences of front-line nurses combating coronavirus disease-2019 in China: A qualitative analysis. Public Health Nursing. 2020; 37 (5):757. doi:10.1111/phn.12768
13. Abu-El-Noor NI, Abu-El-Noor MK. Ethical issues in caring for COVID-patients: A view from Gaza. Nursing Ethics. 2020; 27 (8): 1605–1606. doi:10.1177/0969733020956733
14. He S, Ojo A, Beckman A, Gondi S, Betz M, Faust JS, Choo E, Kass D, Raja AS. The story of #GetMePPE and GetUsPPE.Org to mobilize health care response to COVID-19: rapidly deploying digital tools for better health care. Journal of Medical Internet Research. 2020; 22 (7). doi:10.2196/20469
15. Lee SYM, Chen Y, Huang C. A text-driven rule-based system for emotion cause detection. Proceedings of the NAACL HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text, June 2010. Los Angeles, California. Association for Computational Linguistics.2010. https://www.aclweb.org/anthology/W10-0206
16. Benali H, Wu C, Potdar V. Computational approaches for emotion detection in text. Proceedings of the 4th IEEE International Conference on Digital Ecosystems and Technologies (DEST). 2010 May; Perth, Australia. 2010. https://www.researchgate.net/publication/224185404_Computational_approaches_for_emotion_detection_in_text
17. Maryam Hasan, Elke A. Rundensteiner, Emmanuel Agu: Automatic emotion detection in text streams by analyzing Twitter data. Int. J. Data Sci. Anal. 7(1): 35-51 (2019)
18. Shivhare SN, Khethawat S. Emotion detection from text. Computer Science & Information Technology. 2012. 5: 371-377. doi:10.5121/csit.2012.2237
19. Kao EC, Liu C, Yang T, Hsieh C, Soo V. Towards text-based emotion detection a survey and possible improvements. Proceedings from the 2009 International Conference on Information Management and Engineering, April 2009. doi:10.1109/ICIME.2009.113.
20. Jain V, Kumar S, Fernandes SL. Extraction of emotions from multilingual text using intelligent text processing and computational linguistics. Journal of Computational Science. 2017; 21: 316–326. doi:10.1016/j.jocs.2017.01.010
21. Desmet B, Hoste V. Emotion detection in suicide notes. Expert Systems with Applications. 2019; 40 (16): 6351–6358. doi:10.1016/j.eswa.2013.05.050
22. Joshi A, Tripathi A, Soni R, Bhattacharyya P, Carman MJ. EmoGram: an open-source time sequence-based emotion tracker and its innovative applications. AAAI Workshop: Knowledge Extraction from Text. 2016.
23. Mohammad SM, Kiritchenko S.Using hashtags to capture fine emotion categories from

tweets. Computational Intelligence. 2015 31 (2): 301-326. doi:10.1111/coin.12024.
24. Hasan M, Rundensteiner E, Agu E. “EMOTEX: detecting emotions in twitter messages. Proceedings of the 2014 ASE BIGDATA/SOCIALCOM/CYBERSECURITY Conference. 2014 May 27-31; Stanford University. 2014. https://web.cs.wpi.edu/~emmanuel/publications/PDFs/C30.pdf.
25. Agrawal A, An A. Unsupervised emotion detection from text using semantic and syntactic relations. Proceedings of the 2012 IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology, 2012 December. doi10.1109/wi-iat.2012.170.
26. Douiji Y, Hajar M, Hassan AM. Using YouTube comments for text-based emotion recognition. Procedia Computer Science.2016; 83: 292. doi:10.1016/j.procs.2016.04.128.
27. Tiwari SP, Vijaya Raju M, Phonsa G, Deepu DK. A novel approach for detecting emotion in text. Indian Journal of Science and Technology. 2016; 9(29). doi:10.17485/ijst/2016/v9i29/88211
28. Diman G, Inkpen D, Szpakowicz S. Prior and contextual emotion of words in sentential context. Computer Speech & Language. 2014; 28 (1): 76-92. doi:10.1016/j.csl.2013.04.009
29. Grover S, Verma A. Design for emotion detection of Punjabi text using hybrid approach. Proceedings of the International Conference on Inventive Computation Technologies (ICICT). 2016 August 26-27; Coimbatore, India doi:10.1109/INVENTIVE.2016.7824823
30. Calvo RA, Mac Kim S. 2013. Emotions in text: dimensional and categorical model. Computational Intelligence. 2013; 29 (3): 527–543. doi: 10.1037/t11194-000
31. Ekman P. An argument for basic emotions. Cogn Emot. 1992; 6:(3-4): 169–200. doi:10.1080/02699939208411068
32. Shaver P, Schwartz J, Kirson D, and O'Connor C. Emotion knowledge: further exploration of a prototype approach.Journal of Personality and Social Psychology. 1987; 52 (6): 1061–1086.10.1037//0022-3514.52.6.1061
33. Oatley K, Johnson-laird PN. Towards a cognitive theory of emotions. Cognition & Emotion. 1987; 1(1): 29–50. doi:10.1080/02699938708408362
34. Plutchik R. Emotion: A Psychoevolutionary Synthesis. New York: Harper & Row; 1980
35. Russell JA. A circumplex model of affect. Journal of Personality and Social Psychology. 1890; 39(6): 1161–1178. doi:10.1037/h0077714
36. Ortony A, Clore GL, Collins A. The Cognitive Structure of Emotions. 1988. Cambridge University Press;198le8. ISBN:0521386640
37. Devlin J, Chang M, Lee K, Toutanova K. 2019. BERT: pre-training of deep bidirectional transformers for language understanding. NAACL: North American Chapter of the Association for Computational Linguistics. 2019:4171–4186.
38. Go A, Bhayani R, Huang L. Twitter sentiment classification using distant supervision. CS224N Project Report. 2009; 1:12
39. Yang P, Fang H, Lin J. Anserini: reproducible ranking baselines using Lucene. Journal of Data and Information Quality.2018; 10(4): 1-20. doi:10.1145/3239571
40. Nelson SM, Lee-Winn AE. The mental turmoil of hospital nurses in the COVID-19 pandemic. Psychological Trauma: Theory, Research, Practice, and Policy, COVID-19: Insights on the Pandemic’s Traumatic Effects and Global Implications. 2020;12 (S1): S126-S127. PMID:32584109
41. Al Maskari Z, Al Blushi A, Khamis F, Al Tai A, Al Salmi I, Al Harthi H, Al Saadi M, Al Mughairy A, Gutierrez R, Al Blushi Z. Characteristics of healthcare workers infected with COVID-19: a cross-sectional observational study. International Journal of Infectious

Diseases. 2021; 102: 32. doi:10.1016/j.ijid.2020.10.009
42. Blei DM, Ng AY, Jordan MI. Latent dirichlet allocation. Journal of Machine Learning Research. 2003; 3 (4–5): 993–1022. doi:10.1162/jmlr.2003.3.4-5.993
43. Slavik CE, Buttle C, Sturrock SL, Darlington JC, Yiannakoulias N. Examining Tweet content and engagement of Canadian public health agencies and decision makers during COVID-19: mixed methods analysis. J Med Internet Res.2021; 23(3):e24883 doi: 10.2196/24883
44. Xue J, Chen J, Hu R, Chen C, Zheng C, Su Y, Zhu T. Twitter discussions and emotions about the COVID-19 pandemic: machine learning approach. J Med Internet Res. 2020 ;22(11):e20550 doi: 10.2196/20550
45. Abd-Alrazaq A, Alhuwail D, Househ M, Hamdi M, Shah Z. Top concerns of Tweeters during the COVID-19 pandemic: infoveillance study. J Med Internet Res. 2020; 22(4):e19016 doi: 10.2196/19016
46. Lyu JC, Luli GK. Understanding the public discussion about the centers for disease control and prevention during the COVID-19 pandemic using Twitter data: text mining analysis study. J Med Internet Res. 2021; 23(2):e25108 doi: 10.2196/25108
47. Devlin, Jacob; Chang, Ming-Wei; Lee, Kenton; Toutanova, Kristina (11 October 2018). "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding". arXiv:1810.04805v2
48. "Open Sourcing BERT: State-of-the-Art Pre-training for Natural Language Processing". Google AI Blog. Retrieved 2019-11-27.
49. Singh M, Jakhar AK, Pandey S. Sentiment analysis on the impact of coronavirus in social life using the BERT model. Soc Netw Anal Min. 2021;11(1):33. doi: 10.1007/s13278-021-00737-z. Epub 2021 Mar 19. PMID: 33758630; PMCID: PMC7976692.
50. Kaliyar RK, Goswami A, Narang P. FakeBERT: Fake news detection in social media with a BERT-based deep learning approach. Multimed Tools Appl. 2021 Jan 7:1-24. doi: 10.1007/s11042-020-10183-2. Epub ahead of print. PMID: 33432264; PMCID: PMC7788551.
51. Xiang Dai, Sarvnaz Karimi, Ben Hachey, Cécile Paris: Cost-effective Selection of Pretraining Data: A Case Study of Pretraining BERT on Social Media. EMNLP (Findings) 2020: 1675-1681
52. Azzopardi, Leif; Moshfeghi, Yashar; Halvey, Martin; Alkhawaldeh, Rami S.; Balog, Krisztian; Di Buccio, Emanuele; Ceccarelli, Diego; Fernández-Luna, Juan M.; Hull, Charlie; Mannix, Jake; Palchowdhury, Sauparna (2017-02-14). "Lucene4IR: Developing Information Retrieval Evaluation Resources using Lucene". ACM SIGIR Forum. 50 (2): 58–75. doi:10.1145/3053408.3053421. ISSN 0163-5840.
53. Grand, Adrien; Muir, Robert; Ferenczi, Jim; Lin, Jimmy (2020), Jose, Joemon M.; Yilmaz, Emine; Magalhães, João; Castells, Pablo (eds.), "From MAXSCORE to Block-Max Wand: The Story of How Lucene Significantly Improved Query Evaluation Performance", Advances in Information Retrieval, Cham: Springer International Publishing, 12036: 20–27, doi:10.1007/978-3-030-45442-5_3
54. Kamphuis, Chris; de Vries, Arjen P.; Boytsov, Leonid; Lin, Jimmy (2020), Jose, Joemon M.; Yilmaz, Emine; Magalhães, João; Castells, Pablo (eds.), "Which BM25 Do You Mean? A Large-Scale Reproducibility Study of Scoring Variants", Advances in Information Retrieval, Cham: Springer International Publishing, 12036: 28–34, doi:10.1007/978-3-030-45442-5_4
55. https://huggingface.co/transformers/
56. Rustam F, Khalid M, Aslam W, Rupapara V, Mehmood A, et al. (2021) A performance

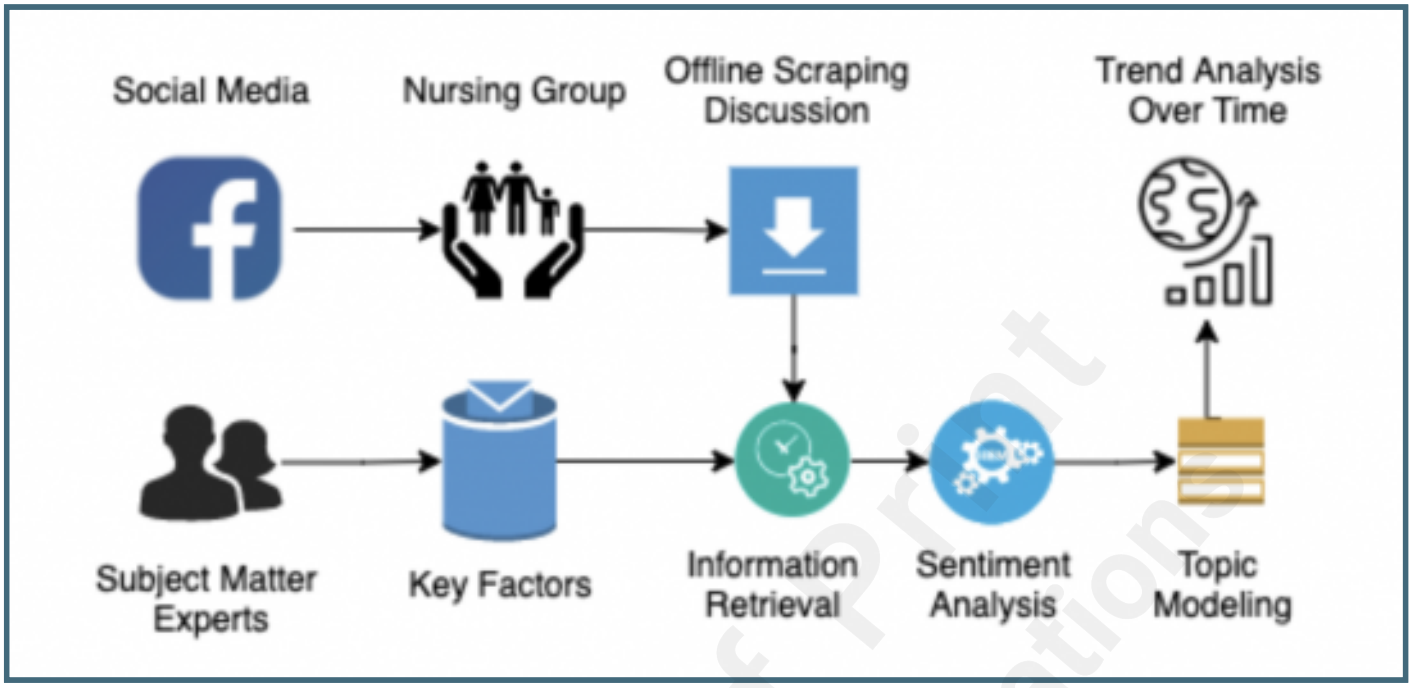
comparison of supervised machine learning models for Covid-19 tweets sentiment analysis. PLOS ONE 16(2): e0245909. https://doi.org/10.1371/journal.pone.0245909

57. Merriam-Webster. https://www.merriam-webster.com/ [Accessed Aug. 16, 2021].
58. ANA Enterprise. Pulse on the Nation's Nurses COVID-19 Survey Series: Mental Health and Wellness. Nursing World. https://www.nursingworld.org/practice-policy/work-environment/health-safety/disaster-preparedness/coronavirus/what-you-need-to-know/mental-health-and-wellbeing-survey/. [Accesed June 8, 2021]
59. Abuhammad S, AlAzzam M, Mukattash T. The perception of nurses towards their roles during the COVID-19 pandemic. International Journal of Clinical Practice. 2003; 75(4): e131919. doi:10.1111/ijcp.13919

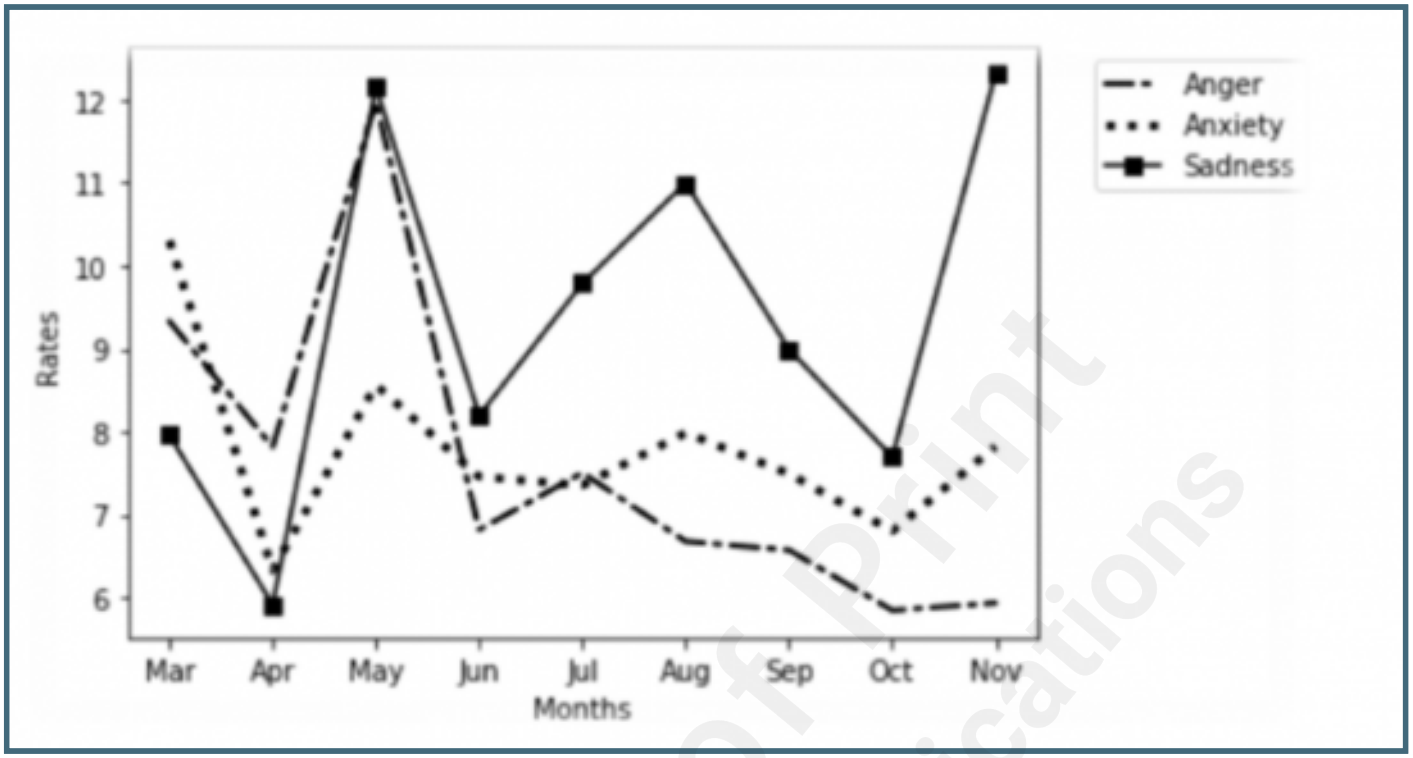
Supplementary Files

Figures

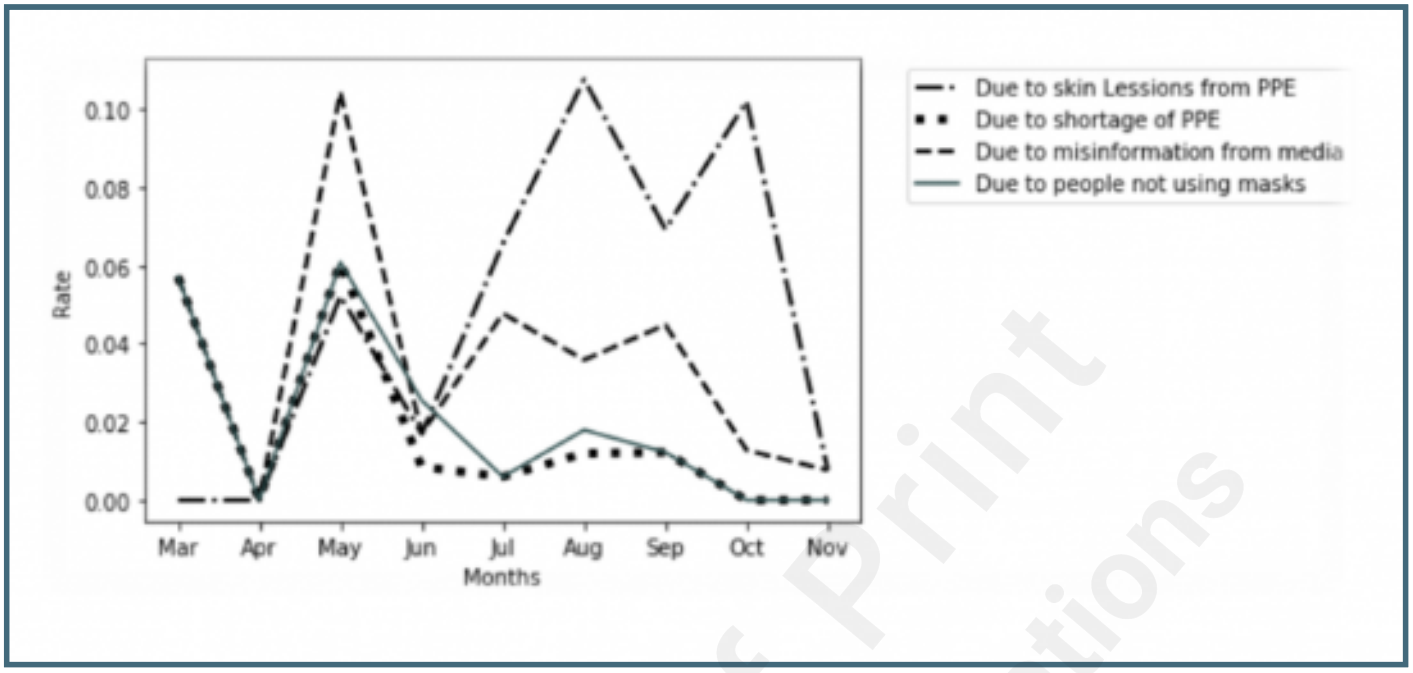
Methodology Flow Chart.



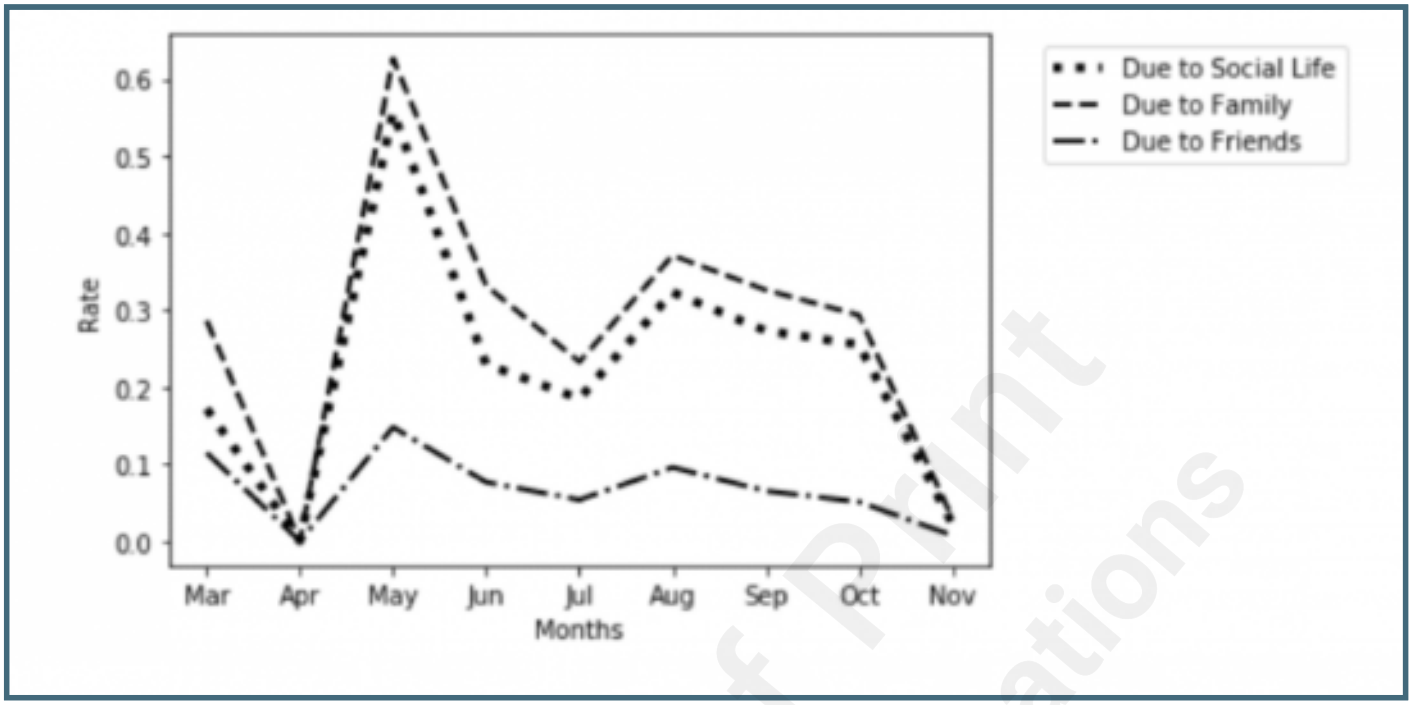
Rates of posts and comments related to the emotions of anger, anxiety and sadness over time.



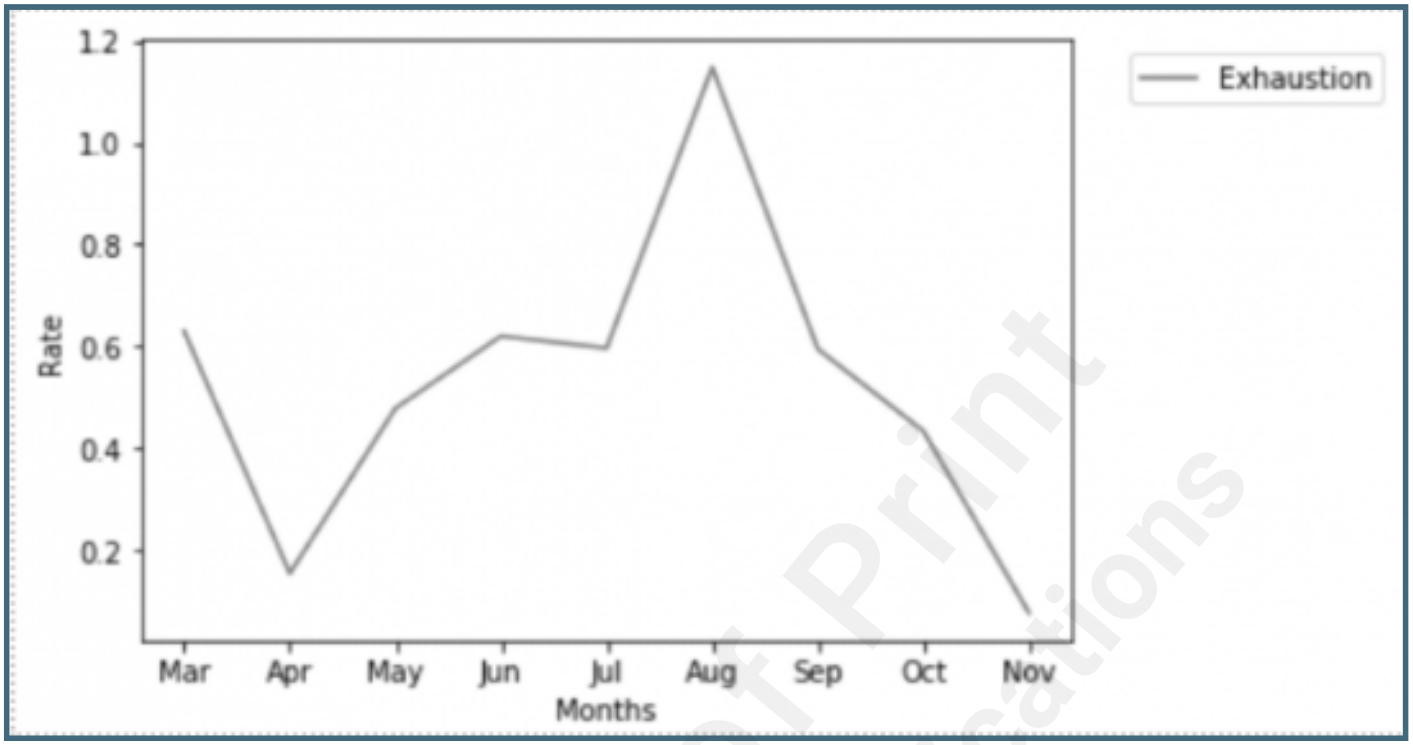
Rates of posts and comments related to PPE and misinformation from media over time.



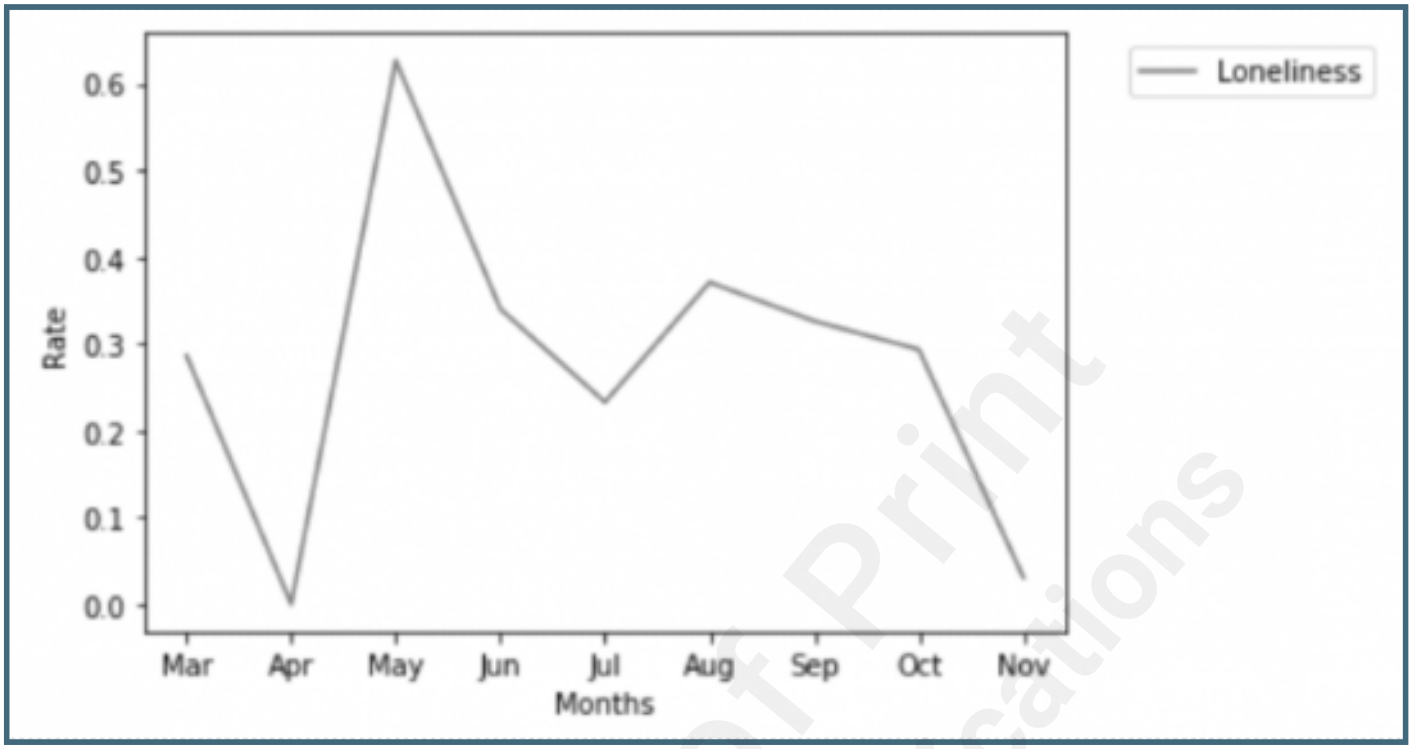
Rates of posts and comments related to Isolation over time.



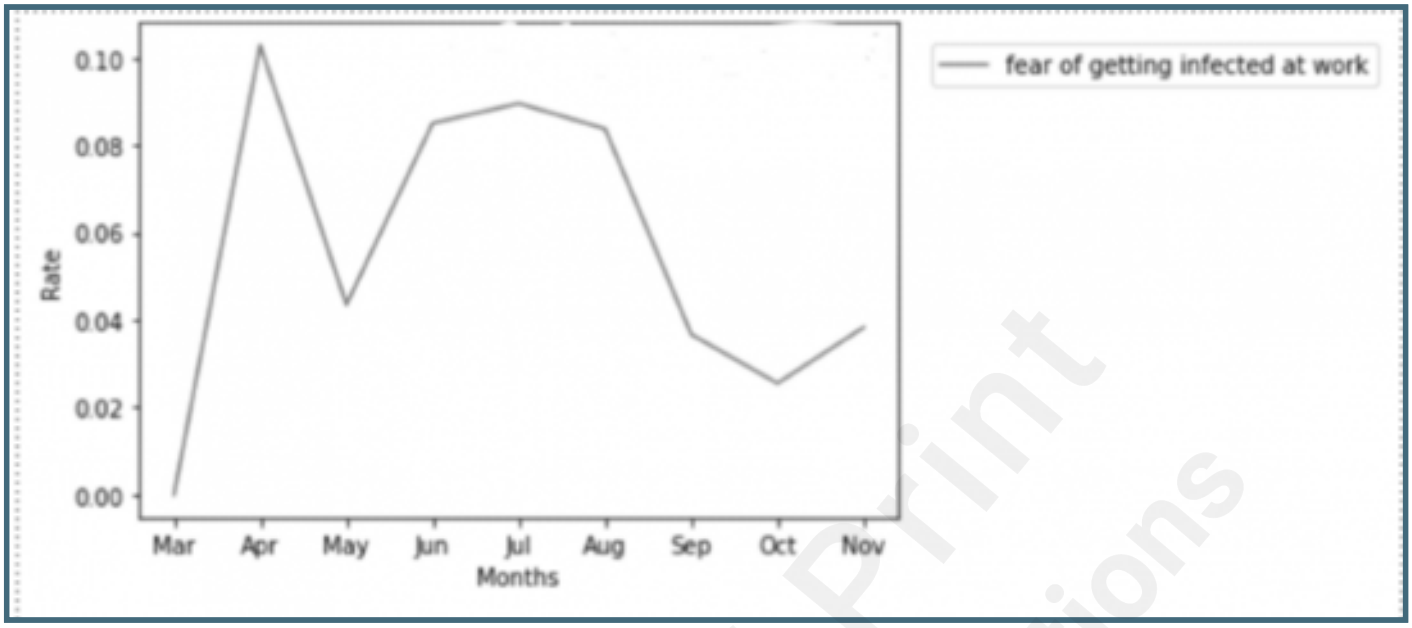
Rates of Posts and Comments related to Exhaustion Over Time.



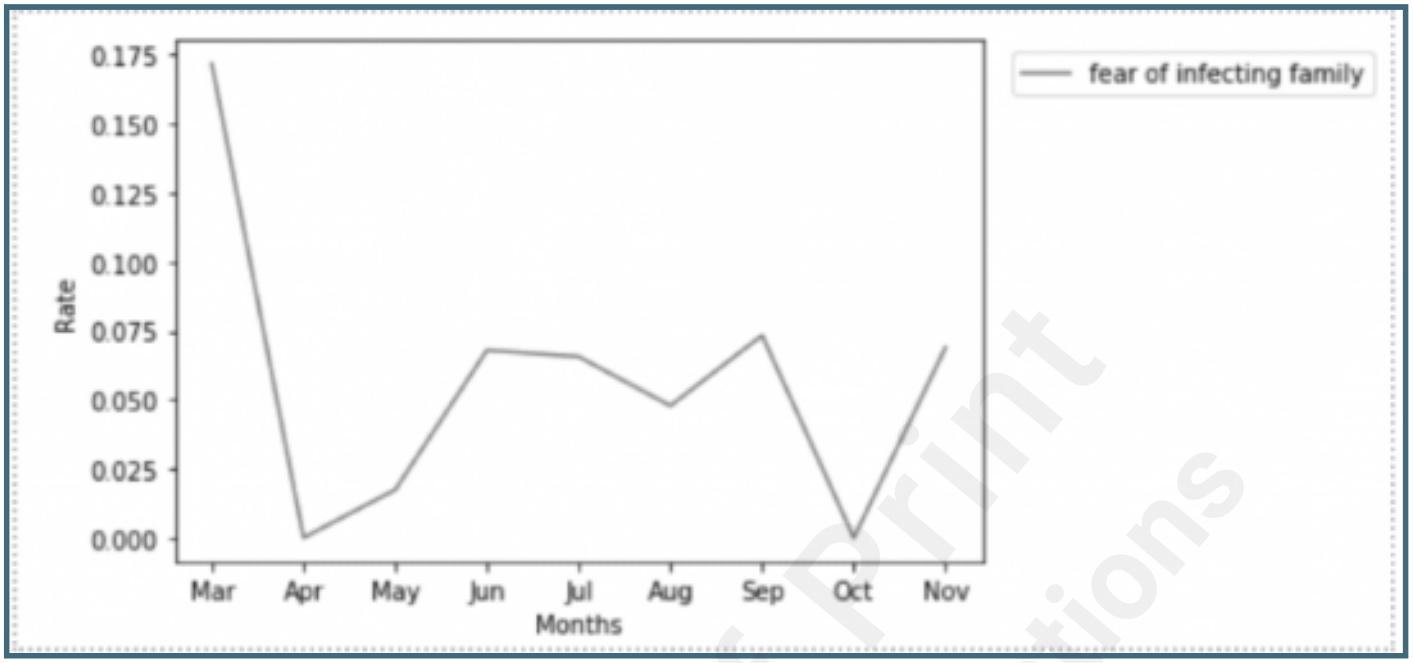
Rates of Posts and Comments related to Loneliness Over Time.



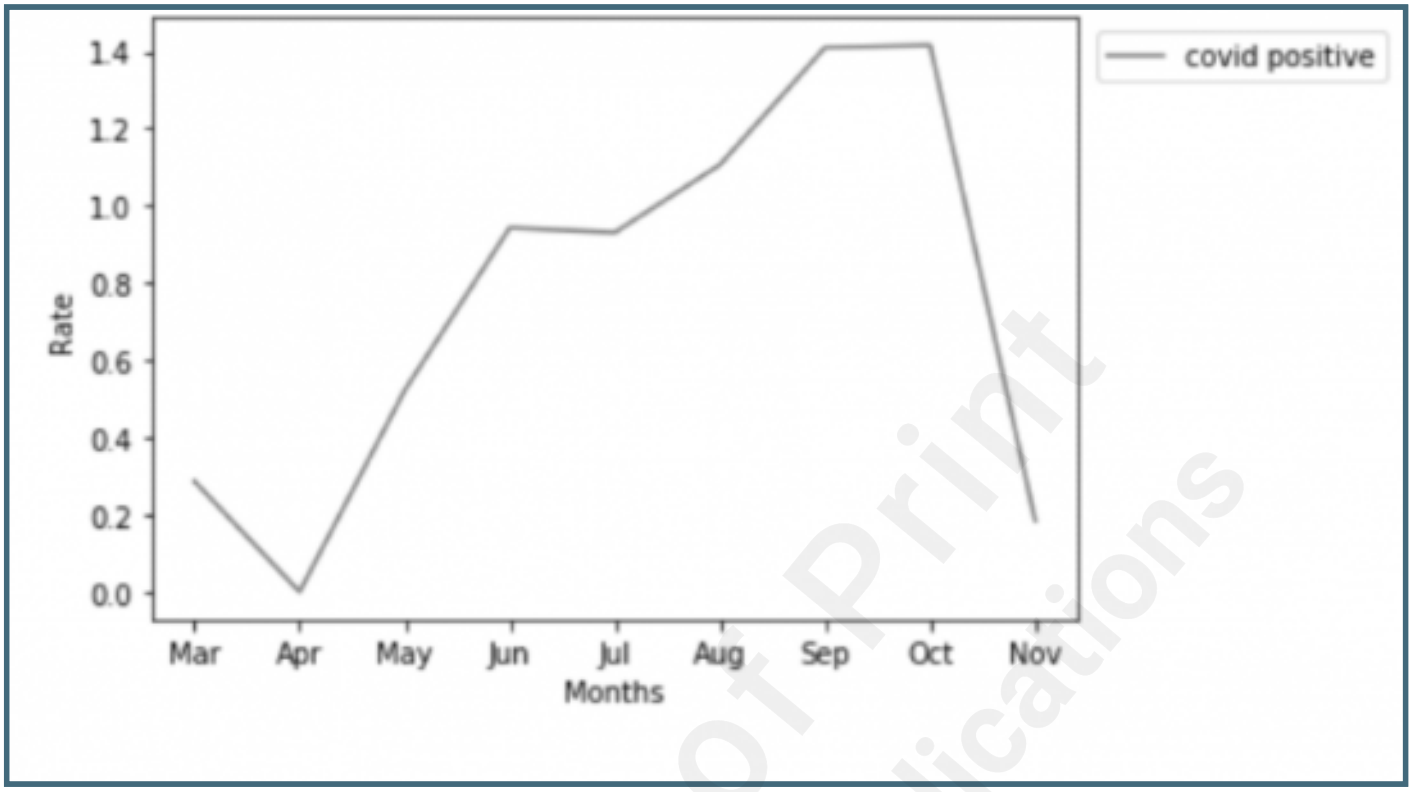
Rates of posts and comments related to fear of getting infected at work over time.



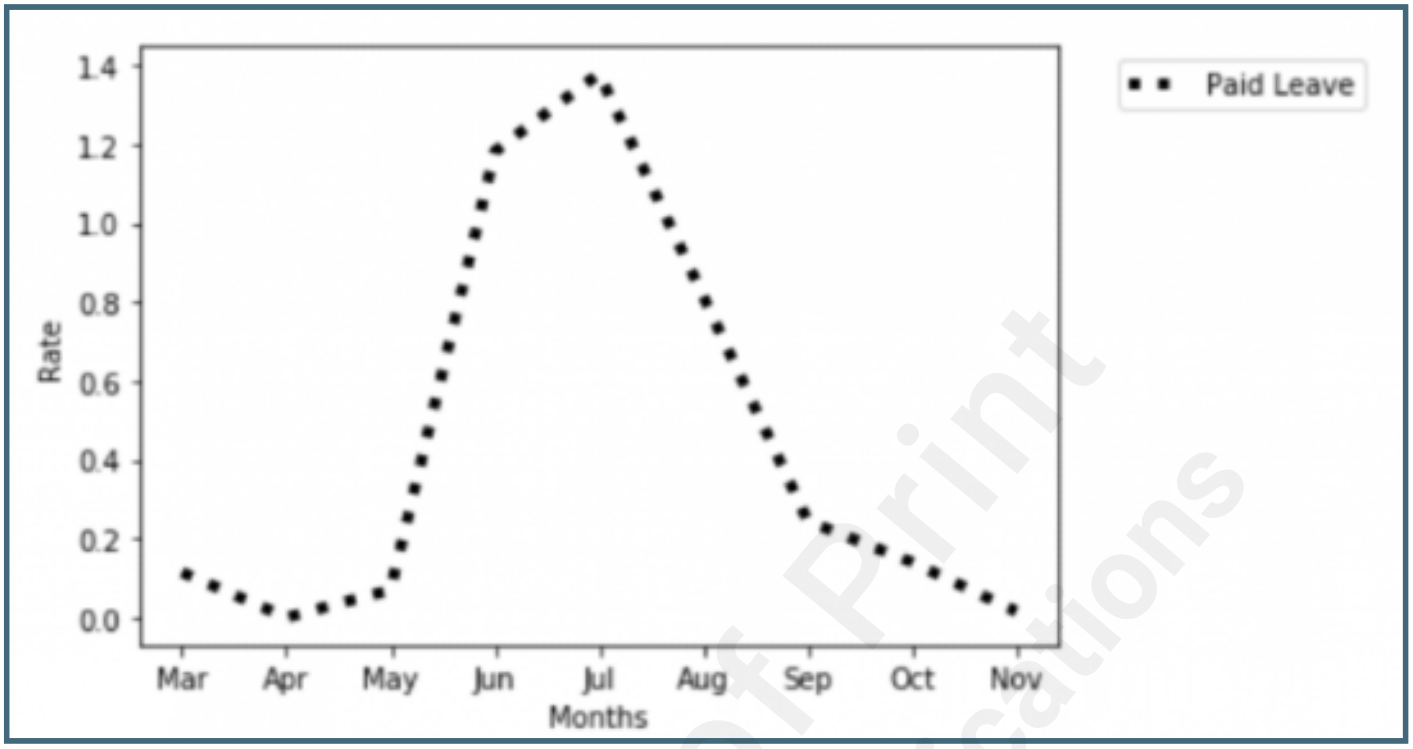
Rates of posts and comments related to fear of infecting family over time.



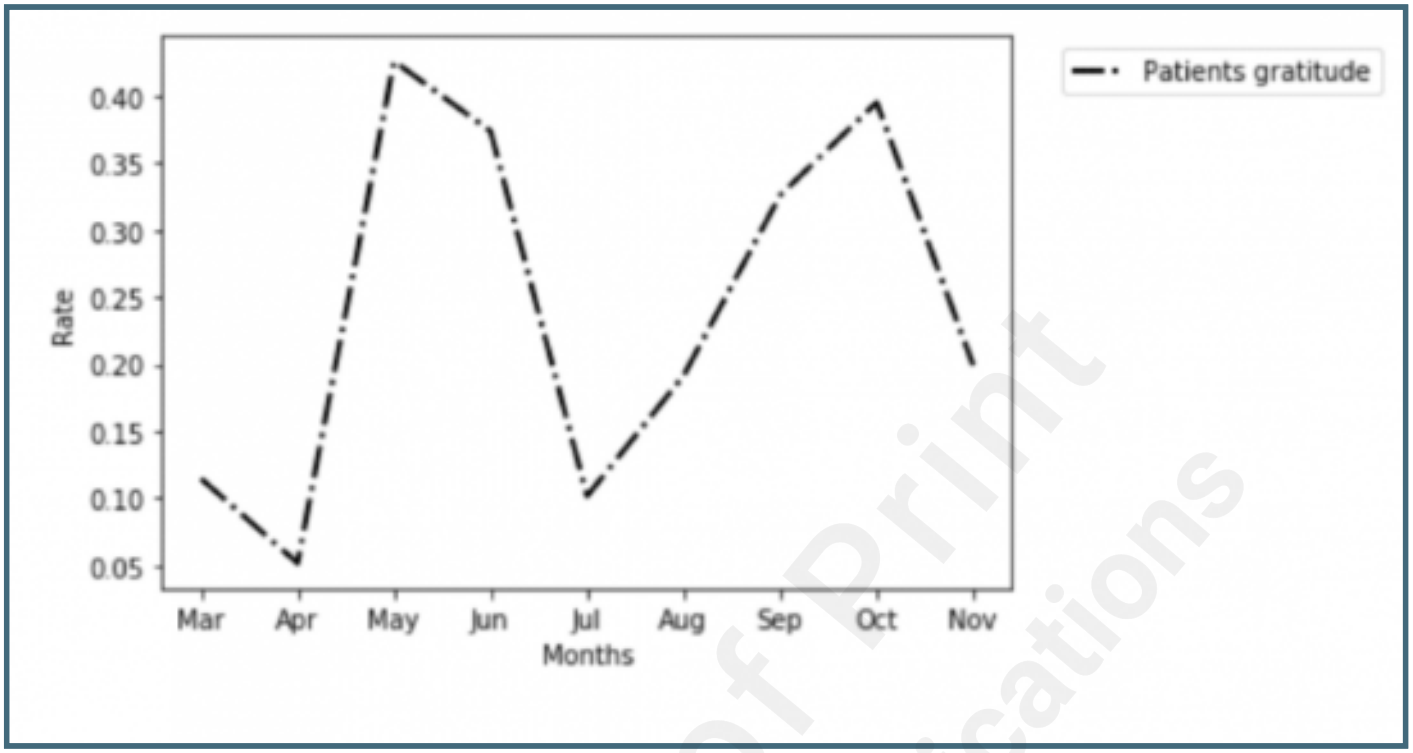
Rates of posts and comments related to Testing Positive for COVID-19 over time.



Rates of posts and comments related to paid leave due to COVID over time.



Rates of positive posts and comments related to patient gratitude over time.



Rates of “hope” comments over time.