Dec 11th, 12:00 AM

Influence of Twitter on Hydroxychloroquine Medication Prescriptions for COVID-19 Patients

Sai Soundarya Gorthi
McGill University, sai.gorthi@mail.mcgill.ca

Kartik Ganju
University of Minnesota, kartik.ganju@mcgill.ca

Alain Pinsonneault
McGill University, alain.pinsonneault@mcgill.ca

Influence of Twitter on Hydroxychloroquine Medication Prescriptions for COVID-19 Patients

Completed Research Paper

Sai Soundarya Gorthi
Desautels Faculty of Management
McGill University
Montreal, QC, Canada
sai.gorthi@mail.mcgill.ca

Kartik K. Ganju
Carlson School of Management
University of Minnesota
Minneapolis, Minnesota, USA
ganju006@umn.edu

Alain Pinsonneault
Desautels Faculty of Management
McGill University
Montreal, QC, Canada
alain.pinsonneault@mcgill.ca

Abstract

Social media is proposed to play a crucial role in healthcare providers' care decisions. However, social media information may not always be reliable as false information is prone to virality, and emotional cues may drive information sharing. Hence, in our study, we strive to understand the influence of social media on healthcare providers' care decisions by empirically examining the influence of Twitter discourse regarding Hydroxychloroquine (HCQ) on the actual prescribing rates of the drug in the USA for treating COVID-19 patients. We assembled panel data by collecting tweets from Twitter API v2 and Hydroxychloroquine prescriptions from the Symphony Health dataset on the COVID-19 research database to achieve our research objectives. Econometric analysis of our panel data indicates that Twitter discourse positively influences the proportion of Hydroxychloroquine prescriptions prescribed to COVID-19 patients. Our study has implications for research and practice.

Keywords: Social media, Healthcare Providers, COVID-19, Twitter

Introduction

Healthcare providers' decision-making is increasingly being influenced by information on social media. For example, a recent TikTok video on weight loss information may have increased consumption of the prescription-only diabetes drug Ozempic for weight loss (Court, 2022). However, social media information may not always be accurate or reliable (Ventola, 2014). Social media tends to emphasize anecdotal reports based on individual patient stories and create "echo chambers" where users' pre-existing beliefs are reinforced and protected from opposing viewpoints (Jang & Chung, 2022; Kaylor, 2019; Kitchens et al., 2020). In addition, false and emotionally charged information is prone to virality in the social media (Ferrara & Yang, 2015; Vosoughi et al., 2018). Thus, healthcare information from social media may be biased or incomplete and can adversely impact care decisions (Riemer & Peter, 2021).

To understand social media's influence on healthcare providers' (HCPs) care decisions, we empirically examine the influence of Twitter discourse regarding Hydroxychloroquine (HCQ) on the actual prescribing rates of the drug in the USA for treating COVID-19 patients. We examine the discourse regarding COVID-19 as it is a new disease with no previously established medical protocols, providing a unique opportunity to understand the influence of social media information on HCPs' decisions. Hence, our research question is: How does the Twitter discourse regarding prescribing Hydroxychloroquine (HCQ) for treating COVID-19 patients influence the prescription decisions of providers in the USA?

We assembled a novel dataset from different sources to answer our research question. We collected the HCQ prescription data for COVID-19 patients from the Symphony Health dataset through the "COVID-19 Research Database". Using keywords, we gathered around 16 million tweets and retweets regarding the HCQ and COVID-19 from Twitter Application Programming Interface (API) v2. We then extracted about 10 million English-language tweets and retweets from the USA. Through a mixed-method approach of machine learning, human coding, and several Natural Language Processing (NLP) and text analytic techniques, we identified relevant tweets and conceptualized the users' stance on using the HCQ for treating COVID-19.

We employed a two-way fixed effects model and an autocorrelation-corrected two-way fixed effects model with state and week fixed effects to answer our empirical research question. To account for the endogeneity in our model, we employed several different control variables and supplemented our analysis with instrumental variable estimation and other robustness checks. Our results indicate that the Twitter discourse regarding prescribing HCQ for treating COVID-19 patients positively influences the prescription decisions of providers in the USA.

Our paper contributes to both academic research and practice. Our study is among the first in IS literature to explore the influence of social media on healthcare providers' decisions through panel data analysis of Twitter data and pharmaceutical insurance claims. The practical contributions of our study are twofold. First, our study empirically demonstrates the growing influence of social media, like Twitter, in healthcare. We demonstrate how care providers are likely to utilize information from social media under high uncertainty. Second, in contrast to most of the studies employing Twitter data, we infer and use the stance of the tweets as a proxy of user opinion regarding a topic in place of the tone of tweets in our analysis. To infer the stance of the users in the topical discussion, we utilized a mixed methods approach of machine learning and human coding.

Prior Research

Social media in healthcare literature reports that social media has become an invaluable informational resource of medical information. Research has shown that patients are willingly sharing detailed information about their experiences on social media, making it a key resource for examining patients' attitudes and behaviors (Kallinikos & Tempini, 2014; Schumacher et al., 2014; Xie et al., 2022). In these social media platforms, Twitter has emerged as one of the most prominent platforms (Pershad et al., 2018; Yeung et al., 2021). As such, Twitter has been extensively used in health IT research, particularly to study patients' behavior and their medication use and abuse (Eichstaedt et al., 2015; Golder et al., 2019; Jiang et al., 2020; Jouanjus et al., 2017; Phan et al., 2017; Sarker et al., 2016).

Research also reports that healthcare providers are using social media to share information for patient education, seek advice from peers about new treatments and clinical problems, and access medical research (Pershad et al., 2018; Ventola, 2014). This has been the case, especially during the COVID-19 pandemic, where social media has become the leading medium of communication for patients and HCPs to share and seek information due to limited mobility (Asli et al., 2020; Md. Monirul et al., 2021; Tuğberk, 2020).

Healthcare professionals are often faced with making decisions in situations of high uncertainty, particularly when dealing with diseases like cancer or new diseases like COVID-19, where established medical protocols may be limited. Since social media can provide HCPs access to the latest information shared by their peers and insights into patient experiences, HCPs may turn to social media to seek relevant information in uncertain situations (Abbasi et al., 2019; Chau et al., 2020; Kallinikos & Tempini, 2014; Pershad et al., 2018; Ventola, 2014; Xie et al., 2022). However, whether the information from social media influenced HCPs' decisions during the pandemic is yet unclear.

Scope of Study

Literature indicates that social media discourse can influence HCPs' decisions through two pathways - directly through provider engagement with the topical discourse on social media and indirectly through patient engagement.

Social media can directly influence engaging HCPs through peer influence or informational persuasion. For instance, Goh et al. (2013) found that consumer engagement with social media influences their purchasing behavior through embedded information and persuasion. Similarly, Li & Yan (2020) found that user engagement with social media discourse brought a positive behavioral change regarding the dietary and exercise behavior of the users due to peer influence. Since prior research identifies social media can influence behavior change, it is reasonable to ask if healthcare providers would have also witnessed a similar change due to the social media's content– especially in times of high uncertainty. A recent survey of more than 200 physicians in November 2022 conducted by Sermo, one of the leading physician online communities, jointly with Liveworld, reports that the content on social media changes 57% of US-based physicians' perceptions regarding a medication or a treatment (Phillips, 2023). Research also demonstrates that social media can stimulate herding behaviors, whereby peer influence influences other users as well (Borst et al., 2018). We suggest that healthcare providers could be influenced similarly to the layperson by their peers on social media or due to the information they consume, thus influencing their subsequent care decisions.

Social media has the potential to influence healthcare providers' care decisions indirectly through patients. McKinlay et al. (2014), through their experimental study, observed that patient social media engagement can influence physicians' care decisions, there is yet a limited understanding regarding the effect of social media on providers' care decisions. Research indicates that patient engagement with topical discussion on social media is making them better informed by providing access to information from various sources, empowering them to be more active and assertive in the shared decision-making with their healthcare providers (Benetoli et al., 2018). In addition, prior research and theories of the prescribing report that patient requests tend to influence physicians' decisions (Hajjaj et al., 2010; Murshid & Mohaidin, 2017). The theories and models explain that, influenced by social norms and to maintain their relationship with the patients, HCPs (Murshid & Mohaidin, 2017; Raisch, 1990) tend to prescribe the drugs requested by patients. Healthcare professionals may also prescribe medications, assuming patients will follow the recommended treatment plans if they are satisfied (Hajjaj et al., 2010). Hence, social media can inform patients about their options for healthcare, potentially enabling them to advocate and persuade their providers for suitable treatments.

To summarize, in our context, Twitter could have influenced the HCPs' prescribing decisions directly through peer influence or information persuasion or indirectly through patients. However, disentangling the effects empirically is beyond the scope of the present study.

Empirical Context

Twitter serves as an appropriate social media platform to empirically examine our research objectives for four reasons. First, Twitter is one of the most prominent social media platforms, with 166 million monetizable daily active users as of 2020 (Jay, 2022). This indicates that any topical discourse on Twitter will likely engage a broad range of users, increasing the velocity of information dissemination. Second, Twitter is considered one of the most popular social media platforms and is used extensively by physicians and patients to share information. Nakagawa et al. (2022), based on their longitudinal study, report almost a 112% increase in active physicians using Twitter from 2016-2020, and Antheunis et al. (2013), through their survey of 139 patients and 153 healthcare professionals (obstetrics and gynecologists), report that around 60% of the patients use Twitter to share health information and increase their knowledge. Third, unlike other social media platforms like WhatsApp and Facebook, Twitter is an open platform for all users from different professions, such as healthcare professionals, public health officials, patients, and politicians. Twitter's accessibility for all users ensures that any topical discourse on Twitter will involve different viewpoints and perspectives. Fourth, research indicates that the Twitter algorithm allows comparatively less diversity of information sources than other platforms, providing a higher possibility of observing any influence of algorithmic filtering and social network homophily (Kitchens et al., 2020).

The Twitter discourse regarding employing HCQ for treating COVID-19 patients was chosen as the empirical context of interest for three reasons. First, during the initial period of the pandemic, COVID-19 was a rare disease with no established medical protocols of treatment for the providers to follow. Even after establishing initial protocols, there were highly opposing and polarized perspectives about using HCQ for treating COVID-19 from various reputable sources. While some published articles and professionals touted HCQ effectiveness (Zelenko protocol[1]), other sources debated its ineffectiveness and possible harm (Mehra et al., 2020) (retracted). The retraction of articles such as Mehra et al. (2020) published by reputed journals such as Lancet due to data inconsistencies increased the uncertainty around the medication efficacy. The ambiguity led to an environment where the prescription of HCQ for COVID-19 became dependent not only on the clinical guidelines and guidance of medical organizations but also on the individual providers' opinions and perspectives. It provided a unique opportunity to observe and measure the providers' care decisions in case of uncertainty. Second, discourse on HCQ was voluminous as it has been one of the most popular and controversial topics of discussion during the recent pandemic (Frenkel et al., 2020). As time passed, the discussion changed, with various viewpoints becoming popular at various times. This offered a chance to observe the impact of social media on healthcare professionals' decisions regarding HCQ, both when the popular stance was in favor and against it. Third, social media platforms like Twitter have become an important resource for monitoring, understanding, and observing patients in real-time as they have become the platform of communication for patients to share their experiences and opinions, especially in case of diseases with no established medical protocol (Huang et al., 2019; Phan et al., 2017; Yan & Tan, 2014). So, analyzing the discourse may provide insights regarding the patient's perspectives in that geolocation.

The US was chosen as the geographical context of interest to study the impact of Twitter discourse on medication usage for two reasons. First, unlike most initial countries that supported using the HCQ for COVID-19, HCQ is unavailable over the counter. It requires a provider's prescription to access the drug. This provides an opportunity to observe and measure social media's role in providers' drug-prescribing behavior. Second, the discourse regarding the drug's effectiveness in the USA continued long past the World Health Organization's (WHO) advisory to avoid using the drug to treat COVID. Thus, we examine the influence of Twitter discourse on using HCQ for treating COVID-19 patients on the proportion of HCQ prescriptions in different states of the USA.

Methodology

Our objective was to understand the effect of Twitter discourse regarding prescribing HCQ for treating COVID-19 patients on the drug prescribing decisions of HCPs in the USA in 2020. To achieve our objectives, we employed a multi-method approach to create and analyze our panel data. To create our panel data, we initially collected the prescriptions of HCQ to COVID-19 patients' data from the "*Symphony Health dataset*" available through the "COVID-19 Research Database". We then collected tweets regarding HCQ and COVID-19 from Twitter API V2. which contains the complete archive of the tweets. We employed several natural language processing techniques to clean and preprocess the collected tweets. We utilized a mixed-method approach of manual coding and machine learning to determine the relevance of the tweets to the analysis and the stance of the tweets regarding using HCQ for treating COVID-19 patients. We also utilized a mixed-method approach of manual coding and natural language processing iteratively to determine the geolocation of tweets at the state level. We then created our panel data by integrating the prescription and tweet data at the state and week level. We employed econometric modeling to analyze our panel to achieve our research objective. We provide a detailed description of the different approaches employed in data creation, preprocessing, and analysis in this section.

Data

Symphony Health Dataset

Symphony Health is a leading provider of high-value data for biopharmaceutical manufacturers, healthcare providers, and payers. The company helps clients understand disease incidence, prevalence, progression, treatment, and influences along with the patient and prescriber journeys by connecting and integrating a broad set of primary and secondary data. Symphony Health derived data improves health management

[1] https://nacn-usa.org/wp-content/uploads/Zelenko-Covid-19-Prophylaxis-Protocol.pdf

decisions and helps clients drive revenue growth while providing critical insights on how to adapt to the changing healthcare ecosystem effectively. The data has extensive coverage of markets, including 92% of retail pharmacy claims, 71% of mail-order pharmacy claims, and 65% of specialty pharmacy activity of more than 280 million patients, 1.8 million prescribers, and 16,000 health plans.

We initially collected all the patients diagnosed (ICD10 diagnosis code: U07.1- Code for COVID-19 diagnosis) from the Symphony database. Next, we collected all the patient's prescribed Hydroxychloroquine (HCQ) and chloroquine (CQ) using the Drug National Drug Code (NDC) from January 2020 to September 2021. We then integrated the COVID-19 patient data with the patients prescribed the medication to determine the COVID-19 patients prescribed HCQ. We excluded COVID-19 patients who had been prescribed the drug more than four weeks after their diagnosis or test or before their diagnosis or test. Finally, we excluded patients refilling their prescriptions after the initial refill (refill code-00) based on the prescription refill code. Due to missing data, we considered the initial prescription fill date as the date the prescription was ordered by the physician.

Next, based on the prescription fill date, we estimated the distinct number of COVID-19 patients prescribed HCQ in a zip code in a day and aggregated the data to the state and week level (based on the initial fill date of the prescription). We had access only to the 2-digit zip codes of the patients in the data to protect patient's privacy. Hence, while aggregating the data at the state level, we made minor assumptions while assigning the states to zip codes. For example, we considered patients from zip codes 37 & 38 to belong to Tennessee and 39 to Mississippi. Finally, we estimated the proportion of the COVID-19 patients prescribed the drugs HCQ/CQ to the total number of COVID-19 patients in a state in the week in the symphony dataset. We made similar adjustments in the Twitter data when required.

Twitter Data

We initially collected 14,802,517 million tweets from January 2020 to December 2020 using the academictwitteR package in R (Barrie & Ho, 2021). The tweets were collected from Twitter API v2, which had access to the full archive of tweets using keywords such as – *"Hydroxychloroquine", "chloroquine," "HCQ," "Plaquenil,"* and *"hydroxy"*. Next, we identified English language tweets (all tweets, including replies, quotes, and retweets) based on the language attribute of the Twitter Data. There are around 10,596,276 million English-language tweets. We then segmented the English-language tweets as retweets and tweets. Retweets are tweets starting with the letter "RT". There are 8,427,051 retweets in our sample and 2,169,253 tweets. All other tweets, such as replies and quoted tweets, were included in the tweets data.

Using manual coding and machine learning classification models, we identified 2,093,375 relevant tweets (detailed procedure in Appendix A). We then applied a similar procedure to determine tweets' stance regarding using HCQ for treating COVID-19 patients (detailed procedure in Appendix A). In both these approaches, we manually annotated the tweet data and then employed machine learning to convert text to vectors and train, test, validate, and predict labels. The manual coding approach enables us to capture subtle nuances in tweets and assign context-specific labels to create high-quality training data for machine learning models. Further, the machine learning approach assists in building a scalable approach that is consistent in determining class labels for large volumes of data. By employing a multi-method approach in our study, we were able to develop an accurate and consistent approach that is scalable and capable of understanding the context-specific nuances in determining the relevance of tweets to our study and their stance regarding using HCQ for treating COVID-19.

Next, we determined the geographic location of the tweets at the state level by employing several natural-language preprocessing techniques iteratively. For instance, we used packages such as "Spacy" in Python for named entity recognition in the text to identify geographical entities such as countries and cities (GPE and LOC) and then determined the location of the tweets at the state level. In several iterations, we manually coded the geolocation of some of the tweets as required. We could identify the geolocation of only 960,251 tweets at the USA state level. We aggregated the tweet data to the state-week levels in the final step.

We created our panel data by integrating the medication prescription data from the Symphony health dataset and the Twitter data by merging the datasets on their state and week attributes. In our panel data, we excluded the states with more than 10% missing values in the tweet or medication datasets from our final data. Our final panel data has a balanced structure with less than 10% missing values, 34 groups(states), and 42 time periods(weeks) and includes 886,493 tweets.

Variables

Dependent Variable

Our objective in this paper is to explore if the provider's decisions are influenced by social media discourse on Twitter. Hence, the dependent variable is the ratio of COVID-19 patients getting HCQ to the number of COVID-19 patients in state i in week t.[2]

Independent Variables

The topical discourse on Twitter has two characteristics that can influence providers' decisions—the volume of the discourse and the users' stance. The first characteristic is the volume of the discourse. Previous literature indicates that the volume of social media discourse could be a proxy for the popularity of the topic (Ren et al., 2022). On Twitter, the increase in the volume of discourse could increase the number of users engaging with the discourse and likely to be influenced by it. However, a competing argument could be that excessive discourse with differing opinions could overwhelm the engaging patients or providers and negatively affect their decisions. We operationalize the volume of tweets as the total number of tweets in a state i in week t to test the effect of the influence of volume on the proportion of prescriptions. We applied a logarithmic transformation to the tweets' volume to accommodate the variable skewness (as shown in Table 1) and mitigate the effect of any outliers (Xia, 2011).

The second characteristic is the tweet's stance regarding HCQ use for treating COVID-19 patients. For example, the stance of the following tweet is positive: "*You political doctors have not been saving lives but murdering by blocking cures #ivermectin & **#HydroxyChloroquine**, by giving no or wrong early treatments, by promoting the toxic jabs, and by knowingly not reporting those killed or injured by the toxic jabs.*"[3]. Users are more likely to share information that confirms their stance, viewpoints, and beliefs due to confirmation bias, influencing the number of users likely to engage with the information. We operationalize tweets' stance towards using HCQ using machine learning and manual techniques. Our variable measuring stance ranges from 1 to 3, where 1 is negative, and 3 is the positive stance toward using HCQ for treating COVID-19.

Control Variables

On Twitter, the visibility of tweets determines the number of people likely to engage with the discourse and be influenced by it. The visibility of a tweet depends on the number of followers of the user and the people mentioned in the tweet. When a user tweets, it is visible in the timeline of the followers of the user and the users mentioned in the tweet. Hence, to control the visibility of tweets, we use "$(average\ number\ of\ user\ followers)_{it}$", "$(average\ number\ of\ user\ mentions\ in\ a\ tweet)_{it}$" as control variables in our model. We log-transformed the variables to account for the skewness of variables. Due to the Twitter algorithm, the tweet's popularity determines its rank in the user timeline and visibility. Hence to control the popularity of tweets, we included the mean ratio of the number of retweets to the number of likes at the state-week level as another control variable. We control for the density of the words in the tweets by including "$(average\ word\ density\ of\ tweets)_{it}$" as a control variable similar to Wang et al. (2022) and Kumar et al. (2022)[4].

Summary Statistics of the Variables

In Table 1, we present the summary statistics of our dependent, independent, and control variables.

[2] Please note that the total number of COVID-19 patients is based on the database, similar to the number of COVID-19 patients prescribed HCQ.
[3] https://twitter.com/xbillwu/status/1587761421793771522
[4] We also control for the interest of people in the topic by using the average trend of searches on Google by the users in a state in a week based on Google trends data. Since the interest of the user in the topic can determine the likelihood of their engagement with the discourse. However, the variable was excluded due to multicollinearity.

Variable	*Number of Obs*	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*
$Proportion\ of\ Prescriptions$	1360	0.011	0.017	0	0.181
$Volume\ of\ tweets*$	1428	620.793	1322.591	4	15297
$Stance\ of\ tweets$	1428	0.122	0.235	-0.667	0.8
$Average\ number\ of\ user\ followers*$	1428	18571.63	44345.38	285.143	762115.9
$Average\ number\ of\ user\ mentions\ in\ a\ tweet*$	1428	1.682	0.884	0.485	10.861
$Average\ word\ density\ of\ tweets*$	1428	6.945	0.345	5.45	11.013
$Average\ popularity\ of\ tweet*$	1428	0.232	0.103	0	1.155
Note: Variables indicated with * are log-transformed in the econometric model					

Table 1 - Summary Statistics of the Variables

Econometric Model

To examine the influence of Twitter discourse on HCQ medication prescriptions, we estimate the following econometric model:

$$Proportion\ of\ prescriptions_{it} = \beta_0 + \beta_1 Logarithmic\ transformation\ (Volume\ of\ Tweets * Average\ Stance\ of\ tweeets)_{it-2} + \beta_2 Logarithmic\ transformation\ of\ Volume\ of\ Tweets_{it-2} + \beta_3 Average\ Stance\ of\ the\ Tweets_{it-2} + \beta Z_{it-2} + \alpha_i + \mu_t + \epsilon_{it} - \quad [1]$$

To summarize, our main dependent variable is the proportion of HCQ prescriptions for COVID-19 patients in time (t) in a state (i). We regress this measure on (1) the volume of tweets (total number of tweets) in a state (i) (2) the average stance of tweets in a state (i), and (3) the interaction of volume and stance of tweets in the state (i) at time period $t-2$. The variable Z_{it-2} measures the effect of control variables mentioned in the variables subsection of the methodology section. The variable α_i represents state-fixed effects that control time-invariant unobserved heterogeneity. The variable μ_t represents week-fixed effects controlling for week idiosyncratic differences. In our econometric model, we lag all our independent variables to account for reverse causality and simultaneity bias, similar to Peng & Dey (2013) and Parameswaran & Kishore (2020). We lagged our independent variable by two time periods as tweets require time to propagate, manifest, and influence the behavior (Venkatesan et al., 2021).

Analysis & Results

Given the longitudinal nature of our data, we employ panel data analysis. We estimate two-way fixed effects (FE) and autocorrelation-corrected fixed effects panel regression models, which account for state fixed effects (α_i) and week fixed effects variable μ_t to control time-invariant individual heterogeneities as well as time trends. We estimate with clustered standard error at the state level that allows a fully general structure with respect to heteroskedasticity and serial correlation in the model (Arellano, 1987). We checked for serial correlation using Stata's XTSERIAL command (Drukker, 2003). The results indicated a first-order correlation in our data ($p<0.05$). Hence, we estimate the autocorrelated two-way fixed effects model, as autocorrelation-corrected two-way fixed effects lead to more efficient parameter estimates (Cameron & Trivedi, 2022). The Autocorrelated two-way fixed effects model first transforms to eliminate the effect of first-order serial correlation (AR (1)) error and then transforms again, estimating mean difference to eliminate the individual effect (Cameron & Trivedi, 2022). For the normality, we log-transformed the main independent variable to accommodate their skewness (Xia, 2011). Columns 1 and 2 in Table 2 show the results of our two-way fixed effects model and Autocorrelation fixed effects model.

Dependent Variable	***Proportion of HCQ Prescriptions for COVID-19 Patients***		
Models	*Two–Way Fixed Effects*	*Autocorrelation Corrected Two–Way Fixed Effects*	*Instrumental Variable (Second Stage)*
	(1)	(2)	(3)
$Log(Volume\ of\ Tweets)_{it-2} * Average\ Stance\ of\ Tweets_{it-2}$	0.0016*	0.0017**	0.0015**
	(0.0008)	(0.0007)	(0.0007)
$Log(Volume\ of\ Tweets)_{it-2}$	-0.0064**	-0.0048**	-0.0045**
	(0.0027)	(0.0019)	(0.0020)
$Average\ Stance\ of\ Tweets_{it-2}$	-0.0073*	-0.0094*	-0.0053
	(0.0035)	(0.0036)	(0.0032)
$\mathrm{Log}(Average\ popularity\ of\ tweets)_{it-2}$	0.0024	0.0012	0.0001
	(0.0037)	(0.0031)	(0.0033)
$\mathrm{Log}(Average\ number\ of\ user\ followers)_{it-2}$	0.0003	-0.0001	0.0001
	(0.0003)	(0.0003)	(0.0002)
$Log(Average\ number\ of\ user\ mentions\ in\ tweets)_{it-2}$	0.0008	0.0004	0.0003
	(0.0010)	(0.0011)	(0.0008)
$Log(Average\ word\ density\ of\ tweets)_{it-2}$	0.0016	-0.0118	-0.0041
	(0.0063)	(0.0073)	(0.0045)
Observations	1323	1289	1255
R-squared	0.76	0.57	0.01
Number of states	34	34	34
State FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
Cragg-Donald Wald F statistic			1.0e+11
Kleibergen-Paap rk Wald F statistic			1.1e+11
Note: 1. Clustered standard errors in parentheses	2. *** p<0.01, ** p<0.05, * p<0.1		

Table – 2 – Results of Influence of Tweets Volume and Stance on Proportion of HCQ Prescriptions

In Table 2, we present the results of our FE and autocorrelation-corrected FE panel regression models. The result of the fixed effects model (1) indicates that volume has a significant negative influence on the proportion of HCQ prescriptions. A 100 % increase in the number of tweets leads to a decrease in the proportion of prescriptions by 0.0064. Model 1 also indicates that the interaction of volume and stance has a slightly significant positive influence on the proportion of HCQ prescriptions for COVID-19 patients. A 100% increase in the number of tweets with a positive stance leads to an increase in the proportion of prescriptions by 0.0016. The result of the autocorrelation-corrected two-way fixed effects model (2) is similar to the fixed effects model with a slight variation in the coefficient of the variables. In Model 2 also, the volume has a significant negative influence on the proportion of HCQ prescriptions. A 100 % increase in the number of tweets leads to a decrease in the proportion of prescriptions by 0.0048. The interaction of volume and stance has a slightly significant positive influence on the proportion of HCQ prescriptions for COVID-19 patients, with a 100% increase in the number of tweets with a positive stance causing an increase of 0.0017 in the proportion of prescriptions. The results in models 1 & 2 also indicate that the stance of the tweets has a slight negative influence on the proportion of HCQ prescriptions.

The FE and Autocorrelated FE models are potentially subject to endogeneity issues due to omitted variables. Addressing this issue is crucial to ascertain the validity of our results. To account for the endogeneity issues, we constructed instrument variables for our main independent variables named $PeersVolume\_it - 2, Peersstance\_it - 2, and\ PeersVoluemstance\_it - 2$. Following Bramoullé et al. (2009) & Saifee et al. (2019), we constructed our instrumental variables by estimating the average volume (stance) of tweets across states of the USA. Here, peer states refer to states other than the state under analysis, and the focal state is the state under analysis. The rationale behind these IVs is that the tweets and stances of users in another state could affect the tweets and stances of users in the focal state. However, it is unlikely to affect prescriptions directly. Two assumptions must hold for this instrument to be valid. First, the social media discourse (volume, stance, volume, and stance) between the peer and focal states should be correlated. The first assumption holds because the discourse from one state is influenced by the discourse from other states in a global social media platform like Twitter. The statistical relationship between the instrumental variable and the endogenous variables is found to be significant (Vol - $p<0.00$; stance - $p<0.00$; Vol*stance - $p<0.00$), and a high first-stage F-statistic (8.3e+11, 1.6e+12, 3.5e+12) suggests that the instruments are not weak. Second, the proportion of prescriptions in the focal state should be influenced by the peer states only through the focal state's discourse. We argue that the second assumption is reasonable in our context. Since there was limited mobility during COVID-19, the patients received prescriptions from providers within the state (excluding telemedicine channels across states). Therefore, ideally, patients from within the state can only make requests from the providers to prescribe the medication. Hence, tweets from other states can influence the provider's decisions only by influencing the users' stance in that state and not directly.

Our model is just identified; as a result, we are incapable of assessing any overidentifying restrictions. We assess the relevance criterion (i.e., instrument strength) by considering the Cragg-Donald Wald F statistic (1.0e+11), which is well above the most stringent Stock-Yogo critical value (Stock & Yogo, 2005). We present the results of the second stage of our instrumental variable analysis in column 3 of Table 2. The results in column 3 are similar to the fixed effects and autocorrelation-corrected models in columns 1 and 2 of Table 2. The results indicate that volume has a significant negative influence on the proportion of HCQ prescriptions. Specifically, the results indicate that a 100 % increase in the volume (number of tweets) tweets leads to a decrease in the proportion of prescriptions by 0.0045. The results also indicate that the interaction of volume and stance has a significant positive influence on the proportion of HCQ prescriptions for COVID-19 patients. A 100% increase in the number of tweets with a positive stance leads to an increase in the proportion of prescriptions by 0.0015.

Based on the results of the models in Table 2, we can infer the following. First, the volume has a robust significant negative effect on the proportion of HCQ prescriptions. The results also indicate that the overall discourse has a positive influence on the proportion of prescriptions. That is the increase in the volume of tweets with a positive stance regarding the medication is causing an increase in the proportion of prescriptions, indicating the increasing influence of Twitter discourse on medication prescription decisions during COVID-19. Though not robust, the results in columns 1 and 2 indicate stance has a slightly significant negative influence on the proportion of HCQ prescriptions prescribed to COVID-19 patients.

Discussion

With the increase in the adoption of social media by HCPs, it is critical to understand its influence on their care decisions. While prior research has focused on social media's influence on patients' care behavior and decisions, our study focuses on the influence of social media on HCPs' decisions. To understand the influence, we empirically examined the influence of Twitter discourse regarding HCQ for treating COVID-19 patients on the actual proportion of prescriptions in the USA through econometric analysis. To control for the influence of the complex interplay of factors that could have influenced the providers' decisions, we employed several control variables in our econometric models and performed several robustness checks.

Our results indicate that the volume has a robust and significant negative influence on the proportion of prescriptions. Though not robust across the models, the results also indicate that stance has a significant negative influence on the proportion of HCQ prescriptions. There could be several possible reasons why the volume and stance of the discourse could have a significant negative effect on the prescription. First, the proportion of tweets with a negative stance could be high, leading to a negative influence on the proportion of prescriptions. However, our analysis indicates that the proportion of positive and negative tweets is very similar (46.01% - positive, 41.05% - negative, and 12.94% - neutral). Hence, the proportion of tweets could not be the cause of the negative influence observed in the results. Another reason could be that despite the similar proportion of tweets with a positive and negative stance in data, the negative stance tweets were more influential than positive stance tweets. The other possible reason could be that the increase in the volume may have increased the ambiguity of the users engaged with the discourse. Under such uncertain situations, HCPs may have been more cautious in prescribing the discussed medication as its efficacy and impacts are unclear.

Our results also indicate that the interaction of volume and stance representing the overall discourse of social media has a significant and robust positive influence on the proportion of prescriptions. The higher the number of tweets with a positive stance, the higher the likelihood of influencing provider decisions. This might be because when there are more tweets, users are more likely to see and trust the content. Hence, the higher the number of tweets with a positive stance, the higher the likelihood of users trusting in the efficacy of the drug.

There are two potential pathways through which Twitter discourse could have influenced HCPs' behavior. First, Twitter may have influenced provider behavior directly through provider engagement. Literature indicates that social media platforms such as Twitter can influence engaging users through information persuasion (Goh et al., 2013) or peer influence (Borst et al., 2018). In our context, one pathway through which HCP's could have been persuaded to prescribe the drug HCQ for treating their COVID-19 patients is either by the tweets suggesting the efficacy of HCQ in treating COVID-19 or by their peers supporting the efficacy of the drug.

Second, Twitter could have indirectly influenced provider behavior through patient engagement with Twitter. Research suggests that platforms like Twitter, through their informational support, encourage patients to be active and assertive in shared decision-making with healthcare providers (Benetoli et al., 2018). The extant theories and models of prescribing medications based on elaboration likelihood models explain that due to social norms and to maintain their relationship with patients, physicians tend to be influenced by patients' requests for specific drugs (Murshid & Mohaidin, 2017; Raisch, 1990). Hence, in our context, another pathway through which Twitter could have indirectly influenced the HCPs prescribing decisions is through patients. Twitter by influencing the engaging patients about the efficacy of HCQ in treating COVID-19 through its tweets and conversations, could have encouraged the patients to actively request the drug from their HCPs. To summarize, in our context, the Twitter discourse could have influenced the provider's prescription decisions either through information persuasion or patients' social influence (Murshid & Mohaidin, 2017), or peer influence (Borst et al., 2018). Therefore, the more users support a stance and publicly show their support through their tweets, the higher the likelihood of the tweets influencing other users, leading to an increase in the proportion of HCQ prescriptions prescribed to treat COVID-19 patients in the USA in 2020.

Contributions

Research Contributions

Our study contributes to two distinct research streams. It contributes to the physician-centric research stream of social media in healthcare literature because it is among the first to examine the influence of social media discourse on providers' care decisions. We combine machine learning and statistical and econometric methods to evaluate the impact of Twitter discourse on providers' care decisions. Our approach goes beyond an empirical analysis. Based on the literature, we also discuss the different pathways of influence on providers' decisions and explain why and how they are more likely to be influenced, contributing to the literature. Our study also contributes to the patient-centric research stream of social media in healthcare literature by explaining the implications for healthcare providers due to patients' social media engagement.

We also contribute to the literature on applying machine learning methods to assess and extract information from user-generated unstructured data. We synthesized a framework of mixed methods that permits the automation of information extraction in the future. We employ different approaches to extract information from the text regarding the user's stance (tweets) and the possible geolocation of the user in the USA at the state level (tweets, user profile description, user profile location). Utilizing a mixed method approach combining manual and machine learning methods has shown great promise in the required information extraction and contributed to superior performance than the conventional machine learning approach and contributed to the robustness of our research. Also, through our study, we showcased how the actual stance of the user regarding the topic of interest is an important factor to consider while analyzing textual information.

Practical Contributions

With the growing importance of social media in healthcare, our study offers several contributions to practice. First, from prescribing Hydroxychloroquine, Remdesivir, and Ivermectin for COVID-19 patients to prescribing Ozempic, a diabetic drug for non-diabetic patients for weight loss, there has been a plethora of anecdotal evidence of social media like Twitter and TikTok influencing the medication prescription decisions of providers. We are the first study to examine and demonstrate this phenomenon through rigorous analysis. Understanding the possible impact of social media engagement on providers offers several policy implications for generating and utilizing healthcare resources. Healthcare organizations or users generating health information should provide accurate information and proof to disprove any perpetuating misinformation. Providing preapproved, trusted online sources for information may mitigate the effects of any misinformation. However, care must be taken to avoid overwhelming patients or providers with information, as it could generate counterproductive results.

Second, social media platforms like Twitter and Facebook have recently been trying to flag and remove misinformation. Considering the growing influence of social media in healthcare, health policymakers, and public health officials could consider working with platform officials to mitigate misinformation, especially during public health emergencies and pandemics such as the recent COVID-19.

Third, prior research for assessing the textual information primarily relies on the sentiment derived from the automatic natural language processing logarithms such as VADER. However, we operationalized a scalable approach based on a mixed method of human annotation and machine learning approaches to determine the topical stance of the user, thereby overcoming any unacknowledged bias in the algorithms.

Limitations

Our study has several areas for future improvement. First, we could only perform state and week-level analysis due to data availability constraints. We could not include the characteristics of patients or providers in our models. Future research could examine the influence of various patient and HCP characteristics, such as demographics, socio-economic factors, experience, and training of providers, to develop an in-depth understanding of who are more likely to be influenced by social media discourse. Second, due to privacy constraints, we only had access to the two-digit zip codes of the patients prescribed the medications. Hence, we had to make minor assumptions while aggregating the data at the state level. The assumptions could have led to a small margin of error in our results.

Third, despite a sizeable Spanish-speaking population in the USA, we included only English-language tweets (71.5% of total tweets in our data) in our analysis. Future research could expand the models to include tweets from all languages. Fourth, in our study, we only consider the influence of Twitter and not other social media platforms like WhatsApp, Reddit, and TikTok that did essay a key role in spreading information during the pandemic due to data limitations. Our results, hence, represent only the lower bound values of the influence of social media platforms on providers' decisions. Future research can compare and contrast the magnitude of the influence of different social media platforms on healthcare decisions and behaviors to empirically develop a comprehensive understanding of the phenomenon.

Fifth, in our study, we were unable to study if the prescription decisions persist even in the absence of Twitter. Future research can compare the effect on the prescriptions in the presence and absence of social media platforms like Twitter to better understand if they are amplifying or mitigating the influence of word-of-mouth or social influence on the prescribing decisions of HCPs. Sixth, Twitter data, which has been used in recent studies to better understand and predict user behavior and decisions in healthcare and other contexts, cannot be verified in a similar manner to that of qualitative data (Gao et al., 2021; Venkatesan et al., 2021; Xie et al., 2022).

Seventh, our study uses a mixed-method approach to predict the relevance and stance of tweets and the user's geolocation. Though we have strived to ensure the accuracy of our predictions, there is a scope for improvement. A more accurate and sophisticated text analytic framework for analyzing social media data can automate the utilization of social media data in future research and enable researchers to gain deeper and more accurate insights into the behavior and attitudes of patients and providers. Future work could refine the integrated framework to create an even more accurate machine learning framework by further tuning the algorithms and NLP processing models by utilizing the newer methods in text mining.

Finally, in our study, we explain the possible mechanisms of how social media discourse can influence the provider's decisions. However, since we considered the overall discourse and did not distinguish HCPs and patients, we were unable to empirically tease out the direct and indirect effects in our study. Future research could probably disentangle the mechanisms to determine the most prominent path of influence.

Conclusion

In this study, we synthesize machine learning and econometric methods to empirically examine the influence of Twitter discourse on providers' decisions to prescribe HCQ to COVID-19 patients since our objective was to develop an in-depth understanding of social media influence on providers' care decisions. To achieve our objectives, we collected the prescription medication data from insurance claims data and discourse from Twitter API. We extracted the relevant tweets, their stances, and the users' geolocation through machine learning and manual annotation. Then, through econometric analysis of the influence of the characteristics of Twitter discourse on the proportion of prescriptions. Our findings have implications for healthcare professionals, policymakers, and IS researchers. Our study mainly contributes to social media in healthcare literature by explaining the possible impact of patient social media engagement on providers' care decisions and empirically demonstrating the positive influence on providers' care decisions.

References

Abbasi, A., Li, J. J., Adjeroh, D., Abate, M., & Zheng, W. H. (2019). Don’t Mention It? Analyzing User-Generated Content Signals for Early Adverse Event Warnings. *Information Systems Research*, *30*(3), 1007–1028. **https://doi.org/10.1287/isre.2019.0847**

Antheunis, M. L., Tates, K., & Nieboer, T. E. (2013). Patients’ and health professionals’ use of social media in health care: Motives, barriers and expectations. *Patient Education and Counseling*, *92*(3), 426–431. **https://doi.org/10.1016/j.pec.2013.06.020**

Arellano, M. (1987). Computing robust standard errors for within-groups estimators. *Oxford Bulletin of Economics and Statistics*, *49*(4), 431–434.

Asli, V., Ertugrul, G., Aziz, Ö., Filiz, K., & Oguz, K. (2020). Knowledge and Attitudes Towards COVID-19 Among Emergency Medical Service Workers. *Revista Da Associação Médica Brasileira*. **https://doi.org/10.1590/1806-9282.66.11.1553**

Barrie, C., & Ho, J. C. (2021). AcademictwitteR: an R package to access the Twitter Academic Research Product Track v2 API endpoint. *Journal of Open Source Software*, *6*(62), 3272.

Benetoli, A., Chen, T. F., & Aslani, P. (2018). How patients’ use of social media impacts their interactions with healthcare professionals. *Patient Education and Counseling*, *101*(3), 439–444. **https://doi.org/10.1016/j.pec.2017.08.015**

Borst, I., Moser, C., & Ferguson, J. (2018). From friendfunding to crowdfunding: Relevance of relationships, social media, and platform activities to crowdfunding performance. *New Media & Society*, *20*(4), 1396–1414. **https://doi.org/10.1177/1461444817694599**

Bramoullé, Y., Djebbari, H., & Fortin, B. (2009). Identification of peer effects through social networks. *Journal of Econometrics*, *150*(1), 41–55.

Cameron, A. C., & Trivedi, P. K. (2022). *Microeconometrics using Stata* (Second edition., 1–1 online resource (2 volumes) : illustrations). Stata Press.

Chau, M., Li, T. M. H., Wong, P. W. C., Xu, J. J., Yip, P. S. F., & Chen, H. (2020). Finding People With Emotional Distress In Online Social Media: A Design Combining Machine Learning And Rule-Based Classification. *MIS Quarterly*, *44*(2), 933–955. **https://doi.org/10.25300/misq/2020/14110**

Court, E. (2022, December 22). *A TikTok Trend Sold Out Ozempic, Leaving People With Diabetes Dizzy, Scared*. Bloomberg Prognosis.

Drukker, D. M. (2003). Testing for Serial Correlation in Linear Panel-data Models. *The Stata Journal*, *3*(2), 168–177. **https://doi.org/10.1177/1536867x0300300206**

Eichstaedt, J. C., Schwartz, H. A., Kern, M. L., Park, G., Labarthe, D. R., & Merchant, R. M. (2015). Psychological language on Twitter predicts county-level heart disease mortality. *Psychol Sci*, *26*, 159–169. **https://doi.org/10.1177/09567976145**

Ferrara, E., & Yang, Z. (2015). Measuring emotional contagion in social media. *Plos One*, *10*(11), e0142390.

Frenkel, S., Alba, D., & Zhong, R. (2020). Surge of virus misinformation stumps Facebook and Twitter. *The New York Times*, *8*.

Gao, Y., Duan, W., & Rui, H. (2021). *Does Social Media Accelerate Product Recalls? Evidence from the Pharmaceutical Industry*.

Goh, K. Y., Heng, C. S., & Lin, Z. J. (2013). Social Media Brand Community and Consumer Behavior: Quantifying the Relative Impact of User- and Marketer-Generated Content. *Information Systems Research*, *24*(1), 88–107. **https://doi.org/10.1287/isre.1120.0469**

Golder, S., Chiuve, S., Weissenbacher, D., Klein, A., O'Connor, K., Bland, M., Malin, M., Bhattacharya, M., Scarazzini, L. J., & Gonzalez-Hernandez, G. (2019). Pharmacoepidemiologic Evaluation of Birth Defects from Health-Related Postings in Social Media During Pregnancy. *Drug Safety*, *42*(3), 389–400. **https://doi.org/10.1007/s40264-018-0731-6**

Hajjaj, F. M., Salek, M. S., Basra, M. K., & Finlay, A. Y. (2010). Non-clinical influences on clinical decision-making: A major challenge to evidence-based practice. *Journal of the Royal Society of Medicine*, *103*(5), 178–187.

Huang, K. Y., Chengalur-Smith, I., & Pinsonneault, A. (2019). Sharing Is Caring: Social Support Provision And Companionship Activities In Healthcare Virtual Support Communities. *MIS Quarterly*, *43*(2), 395-+. **https://doi.org/10.25300/misq/2019/13225**

Jang, S. M., & Chung, M. (2022). Can We Blame Social Media for Polarization? Counter-Evidence Against Filter Bubble Claims During the COVID-19 Pandemic. *New Media & Society*. **https://doi.org/10.1177/14614448221099591**

Jay, A. (2022). *Number of Twitter Users 2022/2023: Demographics, Breakdowns & Predictions*.

Jiang, K. Y., Huang, L. Y., Chen, T. Y., Karbaschi, G., Zhang, D. K., & Bernard, G. R. (2020). Mining Potentially Unreported Effects from Twitter Posts through Relational Similarity: A Case for Opioids. *IEEE International Conference on Bioinformatics and Biomedicine-BIBM*, 2603–2609. **https://doi.org/10.1109/bibm49941.2020.9313468**

Jouanjus, E., Mallaret, M., Micallef, J., Ponte, C., Roussin, A., & Lapeyre-Mestre, M. (2017). Social Media Mining for Toxicovigilance: Automatic Monitoring of Prescription Medication Abuse from Twitter. *Drug Safety*, *40*(2), 183–185. **https://doi.org/10.1007/s40264-016-0497-7**

Kallinikos, J., & Tempini, N. (2014). Patient Data as Medical Facts: Social Media Practices as a Foundation for Medical Knowledge Creation. *Information Systems Research*, *25*(4), 817–833. **https://doi.org/10.1287/isre.2014.0544**

Kaylor, B. (2019). Likes, retweets, and polarization. *Review & Expositor*, *116*(2), 183–192. **https://doi.org/10.1177/0034637319851508**

Kitchens, B., Johnson, S. L., & Gray, P. (2020). Understanding Echo Chambers And Filter Bubbles: The Impact Of Social Media On Diversification And Partisan Shifts In News Consumption. *MIS Quarterly*, *44*(4), 1619–1649. **https://doi.org/10.25300/misq/2020/16371**

Kumar, N., Qiu, L. F., & Kumar, S. (2022). A Hashtag Is Worth a Thousand Words: An Empirical Investigation of Social Media Strategies in Trademarking Hashtags. *Information Systems Research*.

Li, Y., & Yan, X. (2020). How Could Peers in Online Health Community Help Improve Health Behavior. *International Journal of Environmental Research and Public Health*, *17*(9), 2995.

McKinlay, J. B., Trachtenberg, F., Marceau, L. D., Katz, J. N., & Fischer, M. A. (2014). Effects of patient medication requests on physician prescribing behavior: Results of a factorial experiment. *Medical Care*, *52*(4), 294–299. **https://doi.org/10.1097/MLR.0000000000000096**

Md. Monirul, I., M. Mazharul Islam, Faroque, A., & Afrin Sadia, R. (2021). Creative Social Media Use for Covid-19 Prevention in Bangladesh: A Structural Equation Modeling Approach. *Social Network Analysis and Mining*. **https://doi.org/10.1007/s13278-021-00744-0**

Mehra, M. R., Desai, S. S., Ruschitzka, F., & Patel, A. N. (2020). *RETRACTED: Hydroxychloroquine or chloroquine with or without a macrolide for treatment of COVID-19: A multinational registry analysis*. Elsevier. **https://doi.org/10.1016/S0140-6736(20)31180-6**

Murshid, M. A., & Mohaidin, Z. (2017). Models and theories of prescribing decisions: A review and suggested a new model. *Pharmacy Practice (Granada)*, *15*(2).

Mutlu, E. C., Oghaz, T., Jasser, J., Tutunculer, E., Rajabi, A., Tayebi, A., Ozmen, O., & Garibay, I. (2020). A stance data set on polarized conversations on Twitter about the efficacy of hydroxychloroquine as a treatment for COVID-19. *Data in Brief*, *33*, 10. **https://doi.org/10.1016/j.dib.2020.106401**

Nakagawa, K., Yang, N. T., Wilson, M., & Yellowlees, P. (2022). Twitter Usage Among Physicians From 2016 to 2020: Algorithm Development and Longitudinal Analysis Study. *J Med Internet Res*, *24*(9), e37752. **https://doi.org/10.2196/37752**

Parameswaran, S., & Kishore, R. (2020). Network Positions and Engagement in Social Media: An Empirical Examination in the Context of Online Health Communities. *AMCIS 2020 Proceedings*. *17*. **https://aisel.aisnet.org/amcis2020/virtual_communities/virtual_communities/17**

Peng, G., & Dey, D. (2013). A Dynamic View of the Impact of Network Structure on Technology Adoption: The Case of OSS Development. *Information Systems Research*, *24*(4), 1087–1099. **https://doi.org/10.1287/isre.2013.0494**

Pershad, Y., Hangge, P. T., Albadawi, H., & Oklu, R. (2018). Social Medicine: Twitter in Healthcare. *Journal of Clinical Medicine*, *7*(6). **https://doi.org/10.3390/jcm7060121**

Phan, N., Chun, S. A., Bhole, M., Geller, J., & Ieee. (2017). Enabling Real-Time Drug Abuse Detection in Tweets. *IEEE 33rd International Conference on Data Engineering (ICDE)*, 1510–1514. **https://doi.org/10.1109/icde.2017.221**

Phillips, L. (2023). *Social media is changing choices for patients, providers, and pharma marketers*. Emarketer.

Raisch, D. W. (1990). A model of methods for influencing prescribing: Part II. A review of educational methods, theories of human inference, and delineation of the model. *DICP*, *24*(5), 537–542.

Ren, J., Dong, H., Popovic, A., Sabnis, G., & Nickerson, J. (2022). Digital platforms in the news industry: How social media platforms impact traditional media news viewership. *European Journal of Information Systems*, 18. **https://doi.org/10.1080/0960085x.2022.2103046**

Riemer, K., & Peter, S. (2021). Algorithmic audiencing: Why we need to rethink free speech on social media. *Journal of Information Technology*, *36*(4), 409–426. **https://doi.org/10.1177/02683962211013358**

Saifee, D. H., Bardhan, I. R., Lahiri, A., & Zheng, Z. Q. (2019). Adherence to Clinical Guidelines, Electronic Health Record Use, and Online Reviews. *Journal of Management Information Systems*, *36*(4), 1071–1104. **https://doi.org/10.1080/07421222.2019.1661093**

Sarker, A., O'Connor, K., Ginn, R., Scotch, M., Smith, K., Malone, D., & Gonzalez, G. (2016). Social Media Mining for Toxicovigilance: Automatic Monitoring of Prescription Medication Abuse from Twitter. *Drug Safety*, *39*(3), 231–240. **https://doi.org/10.1007/s40264-015-0379-4**

Schumacher, K. R., Stringer, K. A., Donohue, J. E., Yu, S., Shaver, A., Caruthers, R. L., Zikmund-Fisher, B. J., Fifer, C., Goldberg, C., & Russell, M. W. (2014). Social Media Methods for Studying Rare Diseases. *Pediatrics*, *133*(5), e1345–e1353. **https://doi.org/10.1542/peds.2013-2966**

Stock, J., & Yogo, M. (2005). Testing for Weak Instruments in Linear IV Regression. In D. W. K. Andrews (Ed.), *Identification and Inference for Econometric Models* (pp. 80–108). Cambridge University Press. **http://www.economics.harvard.edu/faculty/stock/files/TestingWeakInstr_Stock\%2BYogo.pdf**

Tuğberk, K. (2020). The Changes in the Effects of Social Media Use of Cypriots Due to COVID-19 Pandemic. *Technology in Society*. **https://doi.org/10.1016/j.techsoc.2020.101380**

Venkatesan, S., Valecha, R., Yaraghi, N., Oh, O., & Rao, H. R. (2021). Influence In Social Media: An Investigation Of Tweets Spanning The 2011 Egyptian Revolution. *MIS Quarterly*, *45*(4), 1679–1714. **https://doi.org/10.25300/misq/2021/15297**

Ventola, C. L. (2014). Social media and health care professionals: Benefits, risks, and best practices. *P T*, *39*(7), 491–520.

Vosoughi, S., Roy, D., & Aral, S. (2018). The spread of true and false news online. *Science*, *359*(6380), 1146–1151.

Wang, S. T., Pang, M. S., & Pavlou, P. A. (2022). Seeing Is Believing? How Including A Video In Fake News Influences Users? Reporting Of Fake News To Social Media Platforms. *MIS Quarterly*, *46*(3), 1323–1354.

Xia, J. (2011). Mutual dependence, partner substitutability, and repeated partnership: The survival of cross-border alliances. *Strategic Management Journal*, *32*(3), 229–253. **https://doi.org/10.1002/smj.873**

Xie, J., Liu, X., Dajun Zeng, D., & Fang, X. (2022). Understanding Medication Nonadherence From Social Media: A Sentiment-Enriched Deep Learning Approach. *MIS Quarterly*, *46*(1).

Yan, L., & Tan, Y. (2014). Feeling Blue? Go Online: An Empirical Study of Social Support Among Patients. *Information Systems Research*, *25*(4), 690–709. **https://doi.org/10.1287/isre.2014.0538**

Yeung, A. W. K., Kletecka-Pulker, M., Eibensteiner, F., Plunger, P., Völkl-Kernstock, S., Willschke, H., & Atanasov, A. G. (2021). Implications of Twitter in Health-Related Research: A Landscape Analysis of the Scientific Literature. *Frontiers in Public Health*, *9*. **https://doi.org/10.3389/fpubh.2021.654481**

Appendix

Data Modeling

To determine the tweets' relevance, one of the authors initially manually coded a random sample of 8,067 tweets dichotomously as relevant and non-relevant. For example, tweets such as “A fresh batch of our FE Goat Milk Facial cream is on the shelf! ……” are irrelevant to examining our research question and are therefore excluded. We also excluded tweets that only quote the hashtag of Hydroxychloroquine but have different content other than the current topic of interest and tweets that discuss only the medication's supply-related or financial issues. For example, we deemed the following tweet: “How much stock does Trump have in hydroxychloroquine?” non-relevant to the current analysis, as they do not directly or indirectly convey the user's stance regarding HCQ usage. In our manual coding, 1,057 tweets were coded as non-relevant tweets (Around 13% of the tweets). An independent coder also coded the sample of data along with the author, and the interrater reliability was 0.94 for this initial coding. Since the data was collected during 2020, most of the tweets we collected from Twitter regarding HCQ were discussing COVID-19 either directly or indirectly. Our annotated data reflects this real-world scenario. Despite that, we applied several techniques to address the issue of class imbalance, such as assigning a higher weight to the nonrelevant (minority class) category, choosing the model based on F-score and accuracy and stratified random sampling. We developed a logistic regression CV text classification model with 91.8% validation accuracy based on the manually coded sample. The classification model was employed to classify the tweets as relevant and non-relevant to our analysis. After excluding the non-relevant tweets, we had a total of 2,093,375 tweets.

Next, to determine the stance of the tweets regarding the use of HCQ for treating COVID-19 patients, we applied a similar procedure. Initially, we excluded non-relevant tweets from the random sample collected in the previous step. One of the authors and the independent coder manually coded the remaining 6010 tweets as positive, negative, and neutral regarding the tweet's stance concerning using HCQ for treating COVID-19 patients. A tweet was coded as positive if it directly or indirectly supported using HCQ for treating COVID-19 patients. A tweet was coded as negative if it directly or indirectly cautioned/opposed the use of medication HCQ for treating COVID-19 patients. A tweet is considered neutral if it asks for information regarding the medication or statements in a neutral tone or only shares information without any claim, comment, or emoji. The independent coder also coded the tweets along with the author independently. The inter-rater reliability of the author and the independent coder was 0.897.

Stance	*Tweet Example*
Positive	"Huh, go figure. #HCQ works."
Negative	"POTUS again recommends Hydroxychloroquine - a drug that has not been yet proven to be an effective treatment for #COVID-19: "What do you have to lose?..I'm not a doctor but I have common sense."
Neutral	"Scientists Identify 69 Drugs to Test Against the Coronavirus"

Table 1 - Stance and Tweet Examples

We utilized a publicly available tweet dataset published by Mutlu et al. (2020) that manually annotated the stance of tweets regarding HCQ use for treating COVID-19 patients through a rigorous process. The dataset had the tweet id and their stance about using HCQ towards COVID-19 patients for 14,374 tweets. The definitions of their stance codes employed in the coding process were highly similar to our definitions. Hence, we rehydrated[5] tweets using the hydrator app based on tweet ids. However, we were only able to rehydrate 9,381 tweets. We then compared the codes of the overlapping tweets in both of our manually coded data and found high agreement between the data sets (0.956). We supplemented our manually coded data with the annotated data to form training and testing data of 15,391 manually coded tweets. We preprocessed the tweets employing several techniques such as parts of speech tagging, conversion of emojis and emoticons to words, removed user mentions, links, stop words, and punctuations and lemmatized the text using several different Python packages such as demoji, textfeatures, and NLTK. We then performed feature engineering on the extracted features to determine the best features for modeling. In the fifth step, we split and vectorized the data using the NLTK package. We created a random split of 60% for training, 20% test and 20% for validation of the coded data and transformed the tweets using the term frequency-inverse document frequency (Tf-idf) vectorizer. We applied the Tf-idf approach for transforming the tweets to generate the weights of the terms to evaluate their importance in determining the stance of the tweets.

Using the Lazy-text Python package, we developed and tested several ML classification models on training datasets. We chose the top 3 models, fine-tuned their parameters, and tested their accuracy and efficiency. We chose the top model with high testing and validation accuracy. Our final text classification model was the Extra Trees Classifier, an extension of the Random Forest Classifier with a test accuracy of 76.5% and validation accuracy of 75.57%. We preprocessed and transformed the remaining tweets whose stance regarding HCQ has yet to be determined and applied the developed Extra Trees classification model to predict their stance. We employed the ensemble tree model– selected based on both F-score and accuracy as they can learn signals from different classes due to their hierarchical structure[6]. Thus, we determined the stance of the relevant tweets in our sample.

[5] Due to Twitter's terms and conditions by not providing only tweet Ids and stances were published in the dataset. Hence, we used the tweet Ids to retrieve full details of the tweets by querying the Twitter API through a process known as rehydration.
[6] https://elitedatascience.com/imbalanced-classes