Influence of Twitter Discourse on Providers' Decisions

Abstract

Social media is transforming the healthcare industry. By empowering patients and professionals with informational and infrastructural support to improve the holistic care of patients, social media is improving patient quality of care outcomes. However, while the research has well-documented social media's influence on patients' decisions, there is limited understanding regarding the impact on the provider's clinical decisions. We examine the influence of social media discourse on providers' decisions since they influence patients' health care decisions and, thus, their well-being. Using econometric modeling, we empirically examine the influence of Twitter discourse regarding HCQ on its prescription patterns for treating Covid patients in the USA. Our preliminary results indicate that social media discourse has a positive influence on the provider's decisions and the higher the volume of the positive discourse the higher the influence on the decisions of the provider. We aim to contribute to both academics and practice through our study.

Introduction

Social media has been transforming the healthcare industry by empowering patients and providers with the necessary platform (e.g., Q. Q. B. Liu et al., 2020) and support (e.g., X. Liu et al., 2020). By providing a platform for open dialogue between patients and providers (Q. Q. B. Liu et al., 2020) social media has expanded the boundaries of clinical care and bridged the knowledge gap between patients and providers, enabling shared decision-making between them (X. Liu et al., 2020). By evolving into an invaluable information repository for patients (X. Liu et al., 2020) and healthcare providers (Antheunis et al., 2013), and acquired the potential to influence their behaviors.

However, social media features such as the algorithmic filtering (Kitchens et al., 2020) and algorithmic audiencing (Riemer & Peter, 2021) tend to create tremendous heterogeneity in the information consumed by a user. Also, false information is prone to virality in the social media (Vosoughi et al., 2018). The heterogeneity in the information received could create a filter bubble of misinformation around the provider. This can adversely influence providers' decisions making and, ultimately, the patient's well-being as the physician is an integral element of patient care decisions. Additionally, there is yet a limited understanding regarding the influence of social media discourse (e.g., Q. Q. B. Liu et al., 2020; Wang et al., 2020; Zhu et al., 2019) on the clinical decisions of providers. This is a timely phenomenon to examine due to two reasons. First, social media has become invaluable for understanding patient perspectives and behaviors (Xie et al., 2022). Second, social media has become a valuable resource for monitoring, detecting, and preventing adverse events (Abbasi et al., 2019; Chau et al., 2020). Thus, in this short paper, we examine the influence of social media discourse on the provider's decisions.

Specifically, we empirically examine the influence of volume and valence of Twitter discourse regarding Hydroxychloroquine (HCQ) on the actual prescribing rates of the drug for the treatment of Covid patients. We examine the discourse regarding HCQ for two reasons. First, HCQ is a prescription drug in the US and requires a healthcare provider's prescription for access. Second, it was one of the most viral topics under discussion during the recent pandemic. The topic has generated a multitude of discourse across social media platforms (Frenkel & Alba, 2020) from different perspectives by providers and patients. Thus, it provides a unique opportunity to examine the influence of ambiguity in the discourse on the provider's decisions and the type of discourse (positive/negative) that is likely to influence them.

We utilize Twitter to study our research question because Twitter is one of the most prominent social media platforms, with 166 million monetizable daily active users as of 2020 (Jay, 2022). Further, Twitter is the most popular social media platform for sharing healthcare communication (Pershad et al., 2018), and most of its users consider it a trusted source of health information &,(Hitlin & Olmstead, 2018; Mitchell et al., 2021) and hence are likely to be influenced by its discourse. All healthcare personnel, such as nurse practitioners, physicians, physician assistants, and pharmacists who can dispense a prescription, are considered healthcare providers in our study. We examine the influence of volume and valence of Twitter discourse on the prescribing rate of health care professionals at an aggregate level. We consider aggregate level analysis to understand the effect of discourse and the social contagion of discourse on the provider's decisions. To summarize our research question.

1) Can the social media discourse influence providers' clinical decisions?
2) If so, what characteristics of the discourse influence the provider's decisions?

We aim to contribute to both academic research and practice. We aim to contribute to the literature stream on social media in healthcare by highlighting its critical role in shaping healthcare decisions. We also aim to provide initial insights to the social media managers and public health professionals seeking to integrate the social media discourse as part of their clinical decision support systems.

Methodology

Econometric Model Specification

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

$$Proportion\ of\ prescriptions_{it} = \beta_0 +$$

$$\beta_1(Inverse\ hyperbolic\ transformation\ of\ Number\ of\ Tweets\ *$$

$Average\ Stance\ of\ the\ tweets)_{it-1} +$

$\beta_2 Inverse\ hyperbolic\ transformation\ of\ Number\ of\ Tweets_{it-1} +$

$\beta_3 Average\ Stance\ of\ the\ tweets_{it} + \beta_4 \log\,(Interest\ on\ Web)_{it} + \beta_5 Popularity\ of\ Tweet_{it} +$

$\beta_6 \log\,(Popularity\ of\ user)_{it} + \beta_7 \log\,(Number\ of\ usermentions\ in\ tweet)_{it} +$

$\beta_8 \log\,(Word\ density\ of\ tweet)_{it} + \alpha_i + \delta_t + \varepsilon_{it}$

Where, $Proportion\ of\ prescriptions_{it} = \frac{Number\ of\ distinct\ Covid\ Patients\ prescribed\ HCQ\ in\ a\ state\ in\ a\ week}{Number\ of\ total\ Covid\ Patients\ in\ the\ database\ in\ a\ state\ in\ a\ week}$

The volume of discourse – The number of tweets; the valence of discourse – the stance of the tweet regarding HCQ usage for treating COVID patients; $Popularity\ of\ tweet_{it} = \frac{Number\ of\ retweets\ of\ tweet}{Number\ of\ likes\ of\ tweet}$;

$Popularity\ of\ user_{it} = Number\ of\ followers\ of\ the\ user$

To summarize, we consider our main dependent variable proportion of prescriptions of HCQ for Covid patients in time (t) in a state divided by the total number of COVID patients. We regress this measure on (1) the 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). We control for the visibility of the tweets by including the popularity of tweets and, the popularity of users, average user mentions in the tweets in the model. We control the users' interest in the topic in a state by including the average search interest in the web in the state (i). We control for the influence of characteristics of the tweets by including the word density of the tweet, the average polarity of the tweet, and the average subjectivity of the tweet as control variables in the model. Here, the polarity of tweets indicates the combination of the positive and negative emotions in a sentence based on the words used, and the subjectivity of a tweet quantifies the amount of opinion and factual information contained in the text. The word density of the tweets is a proportion of the number of characters in a tweet to the number of words in the tweet. The variable αi represents state fixed effects that control time-invariant unobserved heterogeneity, and the variable δt represents week fixed effects controlling for week idiosyncratic differences.

Data

To achieve our objectives, we collected data regarding the proportion of HCQ prescriptions to COVID patients from the Symphony health dataset through the "COVID-19 Research Database". Using keywords, we collected around 15 million tweets and retweets from Twitter regarding the HCQ and COVID in the US from Twitter API v2. Utilizing a mixed-method approach of machine learning and human coding, we performed topic modeling of the tweets and conceptualized the users' stance about using HCQ to treat COVID of around 4 million tweets and retweets. Using various natural language processing techniques, we identified the geographic location of around 1.6 million tweets and retweets at the state level. We cleaned, aggregated, and integrated the HCQ prescription and Twitter data to the state and weekly levels. We transformed the variables as required to account for the skewness and outliers in the variables. For example, we transformed the count of the number of tweets through inverse hyperbolic transformation to mitigate the skewness of the variable. Since our valence has a scale from 0 to 1, we chose inverse hyperbolic transformation as it allows for the presence of positive, zero, and negative values. Our panel data is balanced data with 34 states and 43 periods. There are less than 10% missing values in our data. Since in our panel data, our groups are less than the time period (T>N), we employ the fixed effects models to estimate the influence. Also, to mitigate the issue of autocorrelation of the first order, we employ the autocorrelation corrected fixed effects model in which the autocorrelation is treated as a disturbance. Also, we use clustered robust standard errors at the state level to account for heteroskedasticity. We present the preliminary results of the OLS, fixed effects, and autocorrelation corrected fixed effects model in table 1 below.

Table -1 – Results of the OLS, Fixed effects, Autocorrelation corrected FE

Variables	(1) OLS	(2) Two-Way FE	(3) Autocorrelation corrected FE
ihs(Number of tweets)$_{it}$	*-0.00168***	*-0.00130*	*-0.00004*
	(0.00074)	*(0.00123)*	*(0.00124)*
Average stance of tweets$_{it}$	*-0.01311***	*-0.01309**	*-0.01020***
	(0.00624)	*(0.00689)*	*(0.00431)*
ihs(Number of tweets)$_{it}$ # Average stance of tweets$_{it}$	*0.00366****	*0.00231**	*0.00157***
	(0.00125)	*(0.00128)*	*(0.00072)*
Log (Number of user followers)$_{it}$	*0.00000*	*0.00117****	*0.00093****
	(0.00028)	*(0.00040)*	*(0.00034)*

Average Polarity of tweet $_{it}$	*0.01789***	*-0.00114*	*0.00006*
	(0.00703)	*(0.00826)*	*(0.00718)*
Average Subjectivity of tweet $_{it}$	*-0.01385*	*0.00021*	*-0.00058*
	(0.00845)	*(0.00839)*	*(0.00614)*
Log (Average word density of tweet) $_{it}$	*-0.02084***	*-0.01002*	*-0.00280*
	(0.00811)	*(0.00790)*	*(0.00453)*
Log (Average web search) $_{it}$	*-0.00532**	*-0.00109*	*-0.00091*
	(0.00274)	*(0.00212)*	*(0.00137)*
Average Popularity of tweet $_{it}$	*0.00392*	*-0.00094*	*0.00129*
	(0.00309)	*(0.00323)*	*(0.00415)*
Log (Average user mentions in tweet) $_{it}$	*-0.00053*	*0.00169*	*0.00144*
	(0.00160)	*(0.00117)*	*(0.00162)*
Constant	*0.12965****	*0.07393****	*0.00355*
	(0.02472)	*(0.02511)*	*(0.00571)*
Observations	*1,360*	*1,360*	*1,326*
R-squared	*0.70297*	*0.73369*	*0.6851*
State FE	*No*	*Yes*	*Yes*
Week FE	*Yes*	*Yes*	*Yes*
Number of s	*34*	*34*	*34*

*Robust standard errors in parentheses - *** p<0.01, ** p<0.05, * p<0.1*

Our preliminary results indicate that the social media discourse significantly influences providers' decisions. The results indicate that the volume of discourse has no significant robust effect, while the valence of discourse has a robust significant negative effect on the provider's decisions. Also, the interaction of the volume and valence of the tweets positively affect the providers' decisions. Based on the above results, we can infer that the higher the number of tweets with a positive stance towards the usage of HCQ, the higher the proportion of HCQ prescriptions. The results also indicate that the popularity of the user also has a robust significant positive effect on the provider's decisions.

Discussion and Future Work

We aim to examine the influence of social media discourse and its characteristics on providers' clinical decisions in a context where was severe ambiguity in the discourse. Our preliminary results indicate that social media discourse has a positive influence on the decision of providers. The higher the volume of discourse and the more positive the discourse is, the more positive the discourse's influence on the providers' decisions. In the next step, we aim to ensure the robustness of our results using Timeseries models and instrumental variable regression. We also aim to test the boundary of influence under heterogeneous conditions such as the role of geographical proximity, the political lineation of states, and the moderating effect of authority (Food and Drug Administration) and experts(medrxiv) on the influence. We also aim to explore the underlying mechanism of influence.

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 [Article]. *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.

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 [Article]. *Mis Quarterly*, *44*(2), 933-955. https://doi.org/10.25300/misq/2020/14110

Frenkel, S., & Alba, D. (2020). Misleading virus video, pushed by the Trumps, Spreads Online. *The New York Times*, *28*.

Hitlin, P., & Olmstead, K. (2018). The science people see on social media. Washington, DC: Pew Research Center. In.

Jay, A. (2022). *Number of Twitter Users 2022/2023: Demographics, Breakdowns & Predictions*. FinancesOnline. https://financesonline.com/number-of-twitter-users/

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 [Article]. *Mis Quarterly*, *44*(4), 1619-1649. https://doi.org/10.25300/misq/2020/16371

Liu, Q. Q. B., Liu, X. X., & Guo, X. T. (2020). The effects of participating in a physician-driven online health community in managing chronic disease: evidence from two natural experiments [Article]. *Mis Quarterly*, *44*(1), 391-419. https://doi.org/10.25300/misq/2020/15102

Liu, X., Zhang, B., Susarla, A., & Padman, R. (2020). Go to youtube and call me in the morning: use of social media for chronic conditions [Article]. *Mis Quarterly*, *44*(1), 257-283. https://doi.org/10.25300/misq/2020/15107

Mitchell, A., Shearer, E., & Stocking, G. (2021). News on Twitter: Consumed by Most Users and Trusted by Many.

Pershad, Y., Hangge, P., Albadawi, H., & Oklu, R. (2018). Social Medicine: Twitter in Healthcare [Review]. *Journal of Clinical Medicine*, *7*(6), Article ARTN 121. https://doi.org/10.3390/jcm7060121

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

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

Wang, L. A., Yan, L., Zhou, T. X., Guo, X. T., & Heim, G. R. (2020). Understanding Physicians' Online-Offline Behavior Dynamics: An Empirical Study [Article]. *Information Systems Research*, *31*(2), 537-555. https://doi.org/10.1287/isre.2019.0901

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).

Zhu, X., Wu, J., & Zhao, J. L. (2019). *Physicians' Social Media Use and In-hospital Service Quality: An Empirical Investigation*.