



GENERAL DENTISTRY

American Twitter users revealed social determinant-related oral health disparities amid the COVID-19 pandemic

Yangxin Fan, MSc/Hanjia Lyu, MSc/Jin Xiao, DDS, PhD/Jiebo Luo, PhD

Objectives: To assess self-reported population oral health conditions amid the COVID-19 pandemic using user reports on Twitter. **Method and materials:** Oral health-related tweets during the COVID-19 pandemic were collected from 9,104 Twitter users across 26 states (with sufficient samples) in the United States between 12 November 2020 and 14 June 2021. User demographics were inferred by leveraging the visual information from the user profile images. Other characteristics including income, population density, poverty rate, health insurance coverage rate, community water fluoridation rate, and relative change in the number of daily confirmed COVID-19 cases were acquired or inferred based on retrieved information from user profiles. Logistic regression was performed to examine whether discussions vary across user characteristics. **Results:** Overall, 26.70% of the Twitter users discussed “Wisdom tooth pain/jaw hurt,”

23.86% tweeted about “Dental service/cavity,” 18.97% discussed “Chipped tooth/tooth break,” 16.23% talked about “Dental pain,” and the rest tweeted about “Tooth decay/gum bleeding.” Women and younger adults (19 to 29 years) were more likely to talk about oral health problems. Health insurance coverage rate was the most significant predictor in logistic regression for topic prediction. **Conclusion:** Tweets inform social disparities in oral health during the pandemic. For instance, people from counties at a higher risk of COVID-19 talked more about “Tooth decay/gum bleeding” and “Chipped tooth/tooth break.” Older adults, who are vulnerable to COVID-19, were more likely to discuss “Dental pain.” Topics of interest varied across user characteristics. Through the lens of social media, these findings may provide insights for oral health practitioners and policy makers. (*Quintessence Int* 2022;53:2–14; doi: 10.3290/j.qi.b3479979)

Key words: attitude, big data, data mining, dental anxiety, logistic models, social media

After the World Health Organization declared the global spread of COVID-19 a pandemic on 11 March 2020,¹ lockdowns were enforced nationwide in the US to reduce the spread of the virus. At the early outbreak of the COVID-19 pandemic, the American Dental Association (ADA) recommended that dental practices postpone elective procedures and provide emergency-only dental services.² As a result, patients’ access to dental services greatly decreased. During the week of 23 March 2020, an ADA Health Policy Survey indicated that 19% of dental offices were completely closed and 76% were partly closed but seeing emergency patients only.³ More importantly, loss of dental insurance by many people also increased the risk of oral diseases. According to a survey commissioned by the CareQuest Institute for Oral Health,⁴ an estimated 6 million American

adults have lost their dental insurance and 28 million American adults delayed getting dental care. Although most dental clinics reopened in June 2020, dental services have not rebounded to the full capacity due to office infection control regulation, lack of personal protective equipment (PPE), and reduced patient-initiated dental visits.⁵ Additionally, studies have found that there is an association between oral health and severity of COVID-19 complications that makes preventing poor oral health even more challenging.^{6,7} An indirect connection has also been suggested that due to the work from home (WFH) policy, people increased consumption of products that are likely to be detrimental to dental health (eg, alcohol, sweets) and also increased the use of products that benefit oral health.⁸



Given the emergency of dental care caused by lack of access to dental services and loss of dental insurance, it was attempted to identify the vulnerable groups of people by analyzing factors like age, sex, population density, income, poverty rate, health insurance coverage, community water fluoridation, as well as relative change in the number of daily confirmed COVID-19 cases. In addition, the kinds of oral diseases or issues to which they were more likely to be exposed during the COVID-19 pandemic was explored. To the present authors' best knowledge, this is the first large-scale social media-based study to analyze and understand oral health in America amid the COVID-19 pandemic. It is hoped that through the lens of social media, especially the findings of social disparities, the results provide insights for oral health practitioners and policy makers.

Oral health services in the US face an unprecedented challenge during the COVID-19 outbreak. On one hand, the COVID-19 pandemic increased the risk for oral diseases in those vulnerable to COVID-19, including those in rural areas, low socioeconomic groups, older adults, disadvantaged and underprivileged children, and the uninsured.⁹⁻¹¹ On the other hand, a complex effect from intensified COVID-19 therapies and multi-drug treatment could possibly further exacerbate some oral conditions.¹² COVID-19 also has direct effects on oral health through its official symptom ageusia.¹³ Despite the fact that COVID-19 testing positivity rates were low among practicing US dental practitioners,¹⁴ the fear of contacting the virus may still lead to resistance to dental treatment, which in turn will increase of the level of dental anxiety.¹⁵

Although the COVID-19 pandemic greatly impacted people's oral health, as an innovative way of disease diagnosis, telemedicine has gained public attention since it has the potential to provide the patients with the clinical care they need while retaining the distance.¹⁶ An example of telemedicine for oral health is to utilize the instant text and image messaging functions from social media platforms to diagnose and counsel for oral diseases in the COVID-19 era.¹⁷ Many large-scale social media-based studies have investigated different public health topics amid the COVID-19 pandemic, such as acquiring insights about the US mental health during the COVID-19 pandemic from Twitter data,¹⁸ studying the nature and diffusion of COVID-19 related oral health information using tweets from Chinese social media Weibo,¹⁹ monitoring depression trends on Twitter during the COVID-19 pandemic,^{20,21} tracking mental health,^{18,22} and investigating public opinions on COVID-19 vaccines.²³⁻²⁵

Twitter has been a popular social media platform for people in the US to express their views and share their lives with each

other. As of July 2021, there are about 73 million Twitter users in the US.²⁶ In the present study, the intention was to understand online discussions on oral health during the COVID-19 pandemic. A large-scale social media-based study was conducted of 9,104 Twitter users across 26 states (with sufficient samples) in the US for the period between 12 November 2020 and 14 June 2021. Data were collected using Tweepy (<https://www.tweepy.org/>) and acquired or inferred user characteristics based on the publicly available information of Twitter users. Particularly, the present study aimed to answer the following research questions (RQs):

- RQ1: What are the major topics/oral diseases discussed in oral health-related tweets among American Twitter users?
- RQ2: How does discussion of each type of topic/oral disease vary across user characteristics including age, sex, population density, income, and poverty rate?
- RQ3: How does health insurance coverage rate, relative change in the number of daily confirmed COVID-19 cases, and community water fluoridation rate influence users' probability of tweeting about different topics/oral diseases?

To summarize, the following three major contributions were found:

- By applying Latent Dirichlet Allocation (LDA) topic modeling,²⁷ the present study discovered five major topics/oral diseases, including Dental pain, Dental service/cavity, Tooth decay/gum bleeding, Wisdom tooth pain/jaw hurt, and Chipped tooth/tooth break.
- By conducting multiple logistic regression analyses, it was found that discussions of topics/diseases varied across user demographics.
- The analyses showed social disparities in oral health, in that people from the counties with higher health insurance coverage rate tended to tweet less about oral diseases in general, and people from counties at a higher risk of COVID-19 tended to tweet less about Dental service/cavity but more about oral diseases like Tooth decay/gum bleeding and Chipped tooth/tooth break. Older people mentioned Dental pain more frequently.

Method and materials

To address RQ1, topics were extracted using Topic Modeling. To investigate RQ2 and RQ3, the user characteristics were inferred, and logistic regressions conducted.



Data collection and preprocessing

Oral health-related tweets were collected through Tweepy using a list of keywords including “tooth decay,” “cavity,” “black hole,” “food stuck on teeth,” “gums bleeding,” “gums red,” “gums inflammation,” “face swelling,” “cheek swelling,” “drain in my mouth,” “tongue swelling,” “cannot swallow,” “tooth chipped,” “tooth break,” “pain,” “throbbing,” “radiate to the ear,” “jaw hurts,” “can’t open the mouth,” and “wisdom tooth hurts” However, simply using keyword search may collect many false positive tweets. In particular, the tweets with only “pain,” “black hole,” “cavity,” or “throbbing” may not be related to dental health. Therefore, this kind of tweet was removed by adding one constraint. If the tweet only contained one of the keywords “pain,” “black hole,” “cavity,” or “throbbing” but did not contain any other keywords from the aforementioned keyword list, this tweet was excluded from the dataset. To validate this method, 1,000 tweets were randomly sampled from the tweet pool after excluding irrelevant tweets (read to examine if they were indeed related to the study). Using this method, 1.7% were labeled as relevant and 94.1% were related to dental health discussions. Of the 98.3% tweets that were labeled as irrelevant, none of them were related to dental health discussions. To verify whether this method could filter out oral health advertisements, 500 tweets were randomly sampled. Among these sampled tweets, only 1.8% were oral health advertisements and were mostly from dental practitioners. These validations indicated the high performance of the exclusion criteria for both irrelevant tweets and oral advertisements. In addition, since the study focused on understanding the online discussions of US Twitter users, the tweets that were not posted by the users whose profile indicated a US location were excluded. After removing the irrelevant tweets, the dataset was composed of 21,677 tweets for the period between 12 November 2020 to 14 June 2021 tweeted by 15,133 unique users.

Feature inference

Age and sex

Following the methods used in Lyu et al,²⁸ Face++ API (Megvii, <https://www.faceplusplus.com/>) was used to infer the age and sex information of Twitter users based on the visual information from their profile images. Face++ detected faces in images and leveraged deep-learning-based recognition algorithms to analyze face attributes including age and sex. Users may upload pictures for their profile images. There may be multiple faces in one profile image. To achieve the most robust inference of the

demographic information of the Twitter users, users with one intelligible face only were included. In addition, the invalid image URLs were removed. Face++ is one of the most robust image-based inference methods with respect to age and sex inference.²⁹ Jung et al²⁹ evaluated the performance of Face++ on sex and age inference by comparing the machine-inferred labels with the human-annotated labels. They found that Face++ achieved a good performance and matched the human annotations well. There might potentially be users who did not identify themselves as either male or female. Following the designs of most previous studies in the field of dental health,^{30,31} the present study only focused on the male and female users and framed the sex as a binary variable.

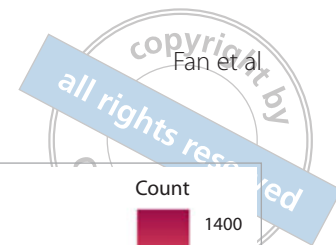
Age was divided into five groups: ≤ 18 , 19 to 29, 30 to 49, 50 to 64, and ≥ 65 years. Users who were younger than 18, between 19 and 29, between 30 and 49, and between 50 and 64 years old accounted for 1.6%, 48.6%, 37.3%, and 9.3%, respectively. The rest were at least 65 years old. According to a report from the Pew Research Center,³² among the US adult Twitter users, 29% are between 18 and 29 years old, 44% are between 30 and 49 years old, 19% are between 50 and 64 years old, and 8% are at least 65 years old. Compared to the age distribution of general Twitter users, there were proportionally more adults between 19 and 29 years old in the present dataset. This was consistent with the finding of a household survey,³³ that younger adults are most likely to report problems regarding the condition of their mouth and teeth. With respect to sex, as of January 2021, the sex distribution of Twitter users in the US is biased towards men, who account for 61.6% of total users.³⁴ However, in the present dataset, 57.4% users were women. Women tended to tweet about dental health more actively, which echoes the previous study that women are more dentally anxious.³⁵

Population density

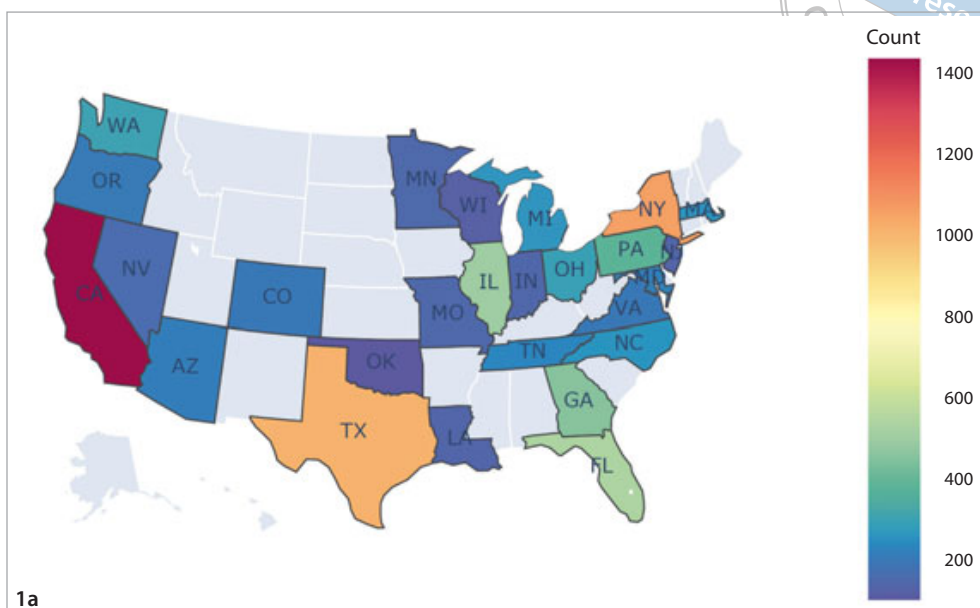
A Python package, USZipcode search engine (Sanhe Hu, <https://pypi.org/project/uszipcode/>), was applied to extract the population density of each Twitter user’s location based on their profile information reported by themselves. The population density was categorized into three levels:

- urban (greater than 3,000 people per square mile)
- suburban (1,000 to 3,000 people per square mile)
- rural (less than 1,000 people per square mile).

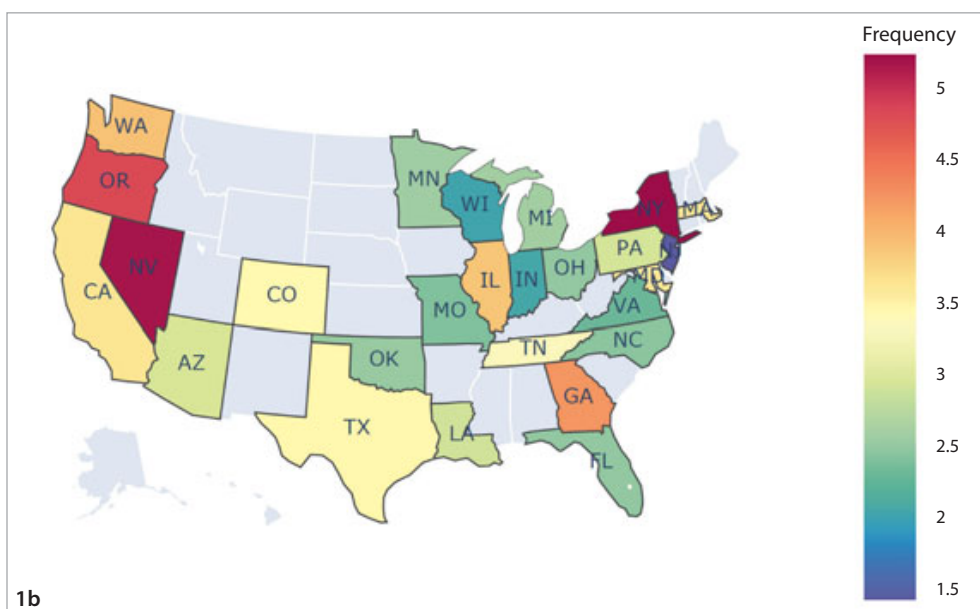
In the present study population, 72.0% were urban, 12.1% were suburban, and 15.9% were rural, which is similar to the proportions reported in a previous report of the Pew Research Center,³⁶ that most Twitter users live in urban areas.



Figs 1a and 1b State-level user distributions showing the number of users tweeting about oral health and the relative frequency (number of Twitter users per 10,000 of total population).



1a



1b

Income and poverty rate

Studies have shown that income or poverty rate is strongly associated with oral cancer, dental caries prevalence, caries experience, and traumatic dental injuries.³⁷ Therefore, the socioeconomic status of the Twitter users was incorporated into the present study. Specifically, the Census API (<https://www.census.gov/data/developers.html>) was used to retrieve median per capita income and poverty rate at the county level from the 2019 American Community Survey (ACS).

Health insurance coverage rate

To the present authors' best knowledge, there is no publicly disclosed detailed information about dental insurance coverage rate at the county or city level. However, Pérez-Núñez et al³⁸ found that having medical insurance is positively correlated with better dental care coverage. Compared with the people with private health insurance, those who are not insured are more likely to be unable to get dental care.³⁹ The positive association between the health insurance coverage and the accessibility to

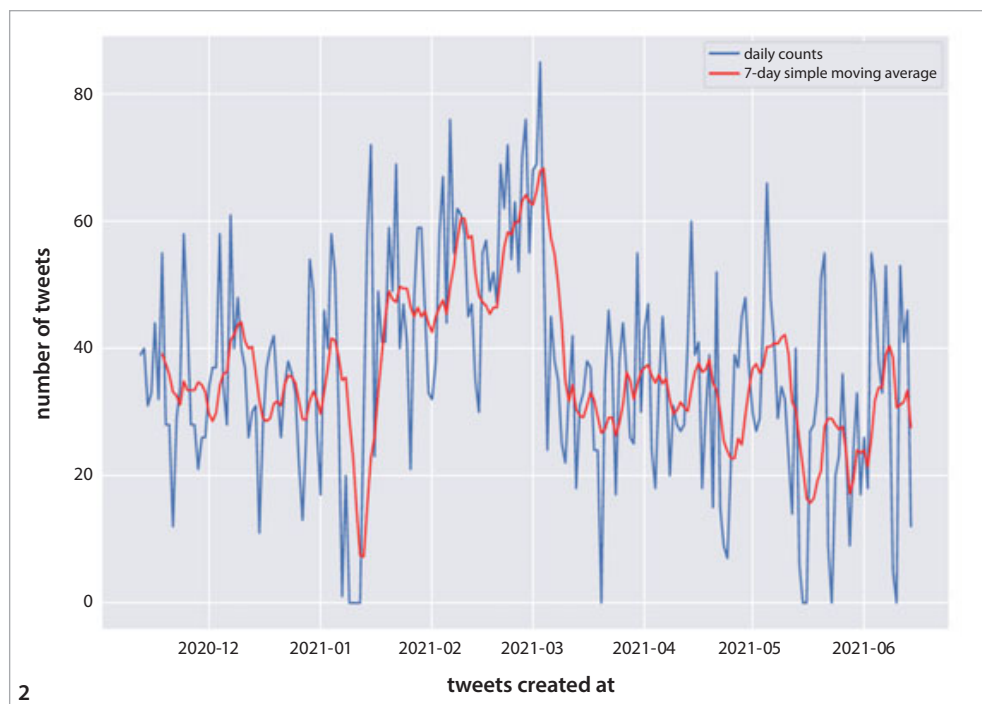


Fig 2 Trend of tweet activity (unique tweets).

dental services might be because (1) having health insurance may affect ability to pay for dental services,⁴⁰ and (2) health insurance is consistently related to the use of preventive medical and dental care.⁴¹ Thus, it was decided to use the health insurance coverage rate to approximately measure each user’s accessibility to dental services. The Census API was used to retrieve health insurance coverage at the county level from the 2019 ACS.

Fluoridation rate

Studies have shown that drinking fluoridated water can keep teeth strong and reduce cavities by about 25% in children and

adults.⁴² To better understand how community water fluoridation rate influence the dental health topics that people usually tweet about, we used the latest state-level fluoridation statistics from the Centers of Disease Control and Prevention to approximate the fluoridation rate of water that users use and drink.⁴³

Pandemic severity

To measure the pandemic severity, the county-level 7-day average relative change in the number of daily COVID-19 confirmed cases was calculated. Each user was associated with a tweet in the dataset, and there was a timestamp for each tweet. The date the user posted the tweet was chosen to calculate this variable. The data were collected from the data repository maintained by the Center for Systems Science and Engineering (CSSE) at John Hopkins University (Fig 1).⁴⁴

After inferring or extracting sex, age, population density, income, poverty rate, health insurance coverage rate, community fluoridation rate, and relative change of the number of daily confirmed COVID-19 cases and retaining states having at least 100 unique users, the final dataset consists of 10,883 tweets posted by 9,104 Twitter users with all inferred features included. States with fewer than 100 unique users were excluded to ensure data quality, ie by removing noises from states with small sample sizes. Figure 1a shows the geographic distribution of Twitter users in the present study. California, Texas, and New

Table 1 Top 10 keywords of each topic

Topic	Keywords
Dental pain	pain, dental, work, good, oral, surgery, care, start, lot, people
Dental service/cavity	dentist, cavity, time, make, year, dentistry, ago, fill, month, call
Tooth decay/gum bleeding	tooth, gum, decay, eat, bleed, food, brush, hard, stop, floss
Wisdom tooth pain/jaw hurt	pain, wisdom, bad, tooth, hurt, day, jaw, mouth, week, back
Chipped tooth/tooth break	tooth, chip, break, feel, today, pull, give, front, fix, toothache



York were the top three states with regard to the number of users who tweet about oral health. However, this could be because that these states are most active in general.⁴⁵ Figure 1b shows that New York, Nevada, and Oregon tend to have higher relative frequency of users who tweet about oral health. It is noteworthy that Oregon has the highest dental care utilization among adults with private dental benefits.⁴⁶ Figure 2 illustrates the trend of daily frequency of unique tweets. Apart from the big “down” and “up” between early January 2021 and mid-March 2021 which roughly corresponded to the trend of daily COVID-19 confirmed cases in the US,⁴⁴ the daily tweet activity stayed relatively stable and varied mostly between 20 and 60 tweets per day.

Topic modeling

LDA²⁷ was used to extract topics from tweets. Twitter handles, hashtags, links, punctuation, numbers, special characters, and stop words were removed to clean the text of the tweets. The spaCy package was used to only keep the words whose part of speech was either “NOUN,” “ADJ,” “VERB,” or “ADV.” Grid search was applied to find the optimal hyperparameters setting for num_topics, α , and β . The optimal setting was as follows: num_topics = 5, α = 0.01, and β = 0.41, with a coherence score of 0.53.

Logistic regression

Logistic regression models were constructed for the five topics uncovered by topic modeling. The target for logistic regression model LR_i was binary, with label 1 indicating that a user had posted a tweet \in Topic_i, and label 0 indicating that a user had not posted a tweet \in Topic_i. Coefficients of features in LR_i were used to interpret the strength and direction of the associations between Twitter users’ individual features and Topic_i. In the present dataset, on average, one user posted 1.19 tweets during the entire study period. The topic of each user could easily be assigned based on the single tweet he/she posted. However, it was still possible that a user posted multiple tweets of different topics. The topic that a user posted most was assigned to be his/her topic. In the end, the study group comprised 9,104 unique Twitter users. The choices of the topics might not be independent. To verify this, 100 users were randomly sampled, and the corresponding tweets read. It was found that only five tweets were reactions to other users’ posts.

Results

To address RQ1, it was attempted to capture what topics or oral diseases are discussed when Twitter users post about oral



Fig 3 Word cloud of the five topics extracted by the LDA model. Topic 1: Dental pain, Topic 2: Dental service/cavity and dentist, Topic 3: Tooth decay/gum bleeding, Topic 4: Wisdom tooth pain/jaw hurt, Topic 5: Chipped tooth/tooth break.

health. Table 1 shows the five topics extracted by the LDA topic modeling. The title of each topic was assigned based on its top 10 keywords. One word might have appeared in multiple topics, but the rank of the word in that topic indicated the importance of it to the topic. Guided by the combinations of the keywords, the focus of each topic was inferred. For instance, “cavity” and “dentistry” are in Topic 2, “gum,” “decay,” “bleed,” and “food” are in Topic 3. By reading the keywords, it was clear that the focuses of these two topics were different. For simplicity, the topics with short labels were summarized. However, to interpret the meaning of each topic, the keywords needed to be referred to instead of the labels.

The relative frequency of keywords in each topic is visualized in Fig 3. The differences of the top keywords between topics suggest that LDA has captured the major component of each topic, and there is a good separation. LDA calculated the weights of five topics of each tweet. The topic that had the highest weight was considered as the dominant topic of the tweet. The tweets were grouped into five classes based on their dominant topic.

As indicated by the previous studies, people increased consumption of products that are detrimental to oral health⁸ during work from home. To investigate such effects, a list of keywords was constructed of snacks and alcohol (“drunk,” “liquor,” “beer,” “champagne,” “wine,” “gin,” “vodka,” “rum,” “whisky,”



Table 2 Topic distribution by user characteristics

Variable	Dental pain	Dental service/cavity	Tooth decay/ gum bleeding	Wisdom tooth pain/ jaw hurt	Chipped tooth/ tooth break
Total	16.23%	23.86%	14.24%	26.70%	18.97%
Urban	16.01%	24.68%	13.77%	26.66%	18.88%
Suburban	17.00%	24.23%	16.37%	24.50%	17.90%
Rural	16.67%	19.85%	14.73%	28.56%	20.19%
Age ≤ 18 y	10.74%	24.16%	14.09%	34.90%	16.11%
Age 19–29 y	12.83%	26.99%	11.38%	28.12%	20.67%
Age 30–49 y	18.12%	21.30%	15.09%	27.21%	18.27%
Age 50–64 y	23.38%	19.27%	22.68%	19.74%	14.92%
Age ≥ 65 y	28.42%	19.06%	23.38%	14.75%	14.39%
Male	16.34%	20.13%	16.73%	27.42%	19.38%
Female	16.16%	26.63%	12.39%	26.17%	18.66%

“brandy,” “tequila,” “bourbon,” “sweet food,” “sugar,” “candy,” “spaghetti sauce,” “sports drinks,” “chocolate milk,” “granola,” “honey,” “glucose,” “corn sugar,” “milkshakes,” “juice,” “cream soda,” “cake,” “cereal,” “chocolate,” “honey,” “milk,” “yogurt,” “ice cream,” “cookie,” “dried sweetened mango,” “candied tamarind”) and performed a keyword search in all the tweets to examine whether or not the tweets mentioned sweet snacks/drinks or alcohol. Overall, 1.7% tweets mentioned sweets or alcohol. In particular, the tweets mentioning sweets or alcohol accounted for 1.0%, 0.4%, 4.2%, 0.7%, and 1.8% for the topics of Dental pain, Dental service/cavity, Tooth decay/gum bleeding, Wisdom tooth pain/jaw hurt and Chipped tooth/tooth break, respectively. A higher proportion of tweets mentioning sweets or alcohol was observed in Tooth decay/gum bleeding and Chipped tooth/tooth break. For each user, the topic that the user tweeted most frequently was assigned as the dominant topic. The proportions of the topics of users were as follows (Table 2):

- Topic 1 (Dental pain) accounted for 16.23% of all Twitter users. In these tweets, people often mentioned pains caused by dental diseases or infections. An example tweet is: “I’ve been dealing with severe dental pain for the past like 10 years. I can handle it but it suuuucks. Compounded that I just had another molar yanked out on Monday morning.”
- Topic 2 (Dental service/cavity) represented 23.86% of all Twitter users in the study, where people mainly shared their experience with dental practitioners to fix their dental problems and/or talk about specific oral disease like cavity.

An example tweet is: “Shout out to Smile Studio in Zachary. I hate going to the dentist, and I am super-sensitive to pain. 44 years without a cavity and I had to have an extraction today. They made it almost painless.”

- Topic 3 (Tooth decay/gum bleeding) constituted 14.24% of all users, including the keywords “tooth,” “gum,” “decay,” “eat,” and “bleed.” In this topic, Twitter users mainly talked about two of the most common oral diseases: tooth decay and gum bleeding. An example tweet is: “My fake tooth chipped off on Xmas one month after losing dental so I’m ugly now 29. 62% of people who brush their teeth rinse their mouth out with water, which actually makes tooth decay more likely.”
- Topic 4 (Wisdom tooth pain/jaw hurt) was the most tweeted topic in the present study, and accounted for 26.70% of all users. People mostly posted about pains from wisdom tooth or jaw hurt, containing keywords “chip,” “front,” “dog,” “miss,” and “walk.” An example tweet is: “Yooo I don’t wish the wisdom tooth pain not even on my worse enemy. Shit is wild Painful tooth Can’t get straight to your dentist <hashtag> <hashtag>.”
- Topic 5 (Chipped tooth/tooth break) represented 18.97% of all users, where people mostly talked about chipped tooth/teeth or break their own tooth/teeth. The keywords included “tooth,” “chip,” “break,” “feel,” and “today.” An example tweet is: “I’m gonna get my chipped front tooth fixed tomorrow. It was broken when my dad smacked me as a kid. His wedding ring. He regretted it. I probably deserved it. I’ve been getting it fixed for 30 years. God, I miss him.”



Table 3 Logistic regression outputs for all topics against variables of interest (N = 9,104)

Variable	Dental pain	Dental service/ cavity	Tooth decay/ gum bleeding	Wisdom pain/ jaw hurt	Chipped tooth/ tooth break
Urban (0 = No, 1 = Yes)	-0.0045 (0.081)	0.1550* (0.074)	0.0334 (0.086)	-0.1278 (0.067)	-0.0588 (0.075)
Suburban (0 = No, 1 = Yes)	-0.0001 (0.108)	0.2044* (0.097)	0.1419 (0.111)	-0.2290* (0.092)	-0.1435 (0.102)
Income	0.0316 (0.027)	0.0979*** (0.022)	-0.0078 (0.030)	-0.0326 (0.024)	-0.0664* (0.028)
Poverty rate	-0.0222** (0.007)	0.0202*** (0.005)	-0.0138* (0.007)	-0.0139** (0.005)	-0.0048 (0.006)
Age ≤18 y (0 = No, 1 = Yes)	-1.2473*** (0.296)	0.0010 (0.240)	-0.4958 (0.275)	1.0641*** (0.235)	0.0609 (0.275)
Age 19–29 y (0 = No, 1 = Yes)	-1.0320*** (0.139)	0.1600 (0.149)	-0.7450*** (0.149)	0.7446*** (0.163)	0.3788* (0.165)
Age 30–49 y (0 = No, 1 = Yes)	-0.6085*** (0.138)	-0.0605 (0.150)	-0.4925** (0.148)	0.6735*** (0.164)	0.2028 (0.166)
Age 50–64 y (0 = No, 1 = Yes)	-0.3000 (0.154)	-0.1474 (0.168)	-0.0189 (0.162)	0.2632 (0.181)	-0.0519 (0.187)
Male (0 = No, 1 = Yes)	-0.1291* (0.060)	-0.3082*** (0.053)	0.2700*** (0.062)	0.1077* (0.050)	0.1083 (0.056)
Fluoridation rate	-0.0010 (0.002)	-0.0005 (0.001)	-0.0008 (0.002)	-0.0014 (0.001)	0.0005 (0.002)
Health insurance coverage rate	-0.0071** (0.003)	-0.0184*** (0.002)	-0.0147*** (0.003)	-0.0119*** (0.002)	-0.0169*** (0.003)
Pandemic severity	0.0465 (0.049)	-0.1730*** (0.048)	0.2824*** (0.048)	-0.2760*** (0.047)	0.1718*** (0.045)

* $P < .05$; ** $P < .01$; *** $P < .001$.

Table entries are coefficients (SEs). Income is scaled down by 10,000 while poverty rate, fluoridation rate, pandemic severity, and health insurance coverage rate are scaled up by 100.

Logistic regression results

To answer RQ2 and RQ3, multiple logistic regression analyses were conducted to examine how each variable including age, sex, population density, income, and poverty rate influence whether or not a user will tweet about a specific topic. Table 3 lists the logistic regression results for different topics against variables of interest. Each column represents a logistic regression model. Figure 4 illustrates the correlations between the variables for logistic regression analyses.

Older adults tended to tweet more about Dental pain but less about Wisdom tooth pain/jaw hurt. In the logistic regression analysis, age was divided into five groups: ≤ 18 , 19 to 29, 30 to 49, 50 to 64, and ≥ 65 years. For the topic Tooth pain/dental services, logistic regression coefficients for the first three age groups were all negative, which means adults in their 50s or above were more likely to talk about Dental pain in general ($P < .001$). For the topic Wisdom tooth pain/jaw hurt, logistic regression coefficients for the first three groups were positive, which means adults in their 50s or above are less likely to talk about Wisdom tooth pain/jaw hurt ($P < .001$).

Women tended to talk more about Dental pain and Dental service/cavity while men tweeted more Tooth decay/gum bleeding and Wisdom tooth pain/jaw hurt. Men were less likely to talk about Dental pain ($B = -0.1291$, standard error [SE] = 0.060, $P < .05$, odds ratio [OR] = 0.8789, 95% confidence interval [CI] = 0.7819, 0.9881) and Dental service/cavity ($B = -0.3082$, SE = 0.053, $P < .001$, OR = 0.7402, 95% CI = 0.6630, 0.8146). Men

were more likely to talk about Tooth decay/gum bleeding ($B = 0.2700$, SE = 0.062, $P < .001$, OR = 1.3100, 95% CI = 1.1595, 1.4800) and Wisdom tooth pain/jaw hurt ($B = 0.1077$, SE = 0.050, $P < .05$, OR = 1.1137, 95% CI = 1.0101, 1.2275).

People from rural areas were less likely to discuss Dental service/cavity and people from suburban areas were less likely to talk about Wisdom tooth pain/jaw hurt. By conducting logistic regression, it was found that the Twitter users who live in rural areas tweeted less about Dental service/cavity ($P < .05$) since the coefficients for urban and suburban were both positive in logistic regression analysis of the topic Dental service/cavity. Suburban people tweeted less about Wisdom tooth pain/jaw hurt ($B = -0.2290$, SE = 0.092, $P < .05$, OR = 0.7953, 95% CI = 0.6643, 0.9522).

People on higher incomes tended to talk more about Dental service/cavity but less about Chipped tooth/tooth break. As the income increased by \$10,000/year, the odds of tweeting about Dental service/cavity was 1.1029 times ($B = 0.0979$, SE = 0.022, $P < .001$, OR = 1.1029, 95% CI = 1.0555, 1.1526) and the odds of tweeting about Chipped tooth/tooth break was 0.9358 times ($B = -0.0664$, SE = 0.028, $P < .05$, OR = 0.9358, 95% CI = 0.8869, 0.9881).

People from counties with higher poverty rate talked less about Dental pain, Tooth decay/gum bleeding, and Wisdom tooth pain/jaw hurt, and more about Dental service/cavity. As the poverty rate increased by 1%, the odds of talking about Dental pain was 0.9780 times ($B = -0.0222$, SE = 0.007, $P < .01$, OR = 0.9780, 95% CI = 0.9656, 0.9910), the odds of talking about Tooth decay/gum bleeding was 0.9863 times ($B = -0.0138$, SE = 0.007, $P < .05$, OR = 0.9863, 95%

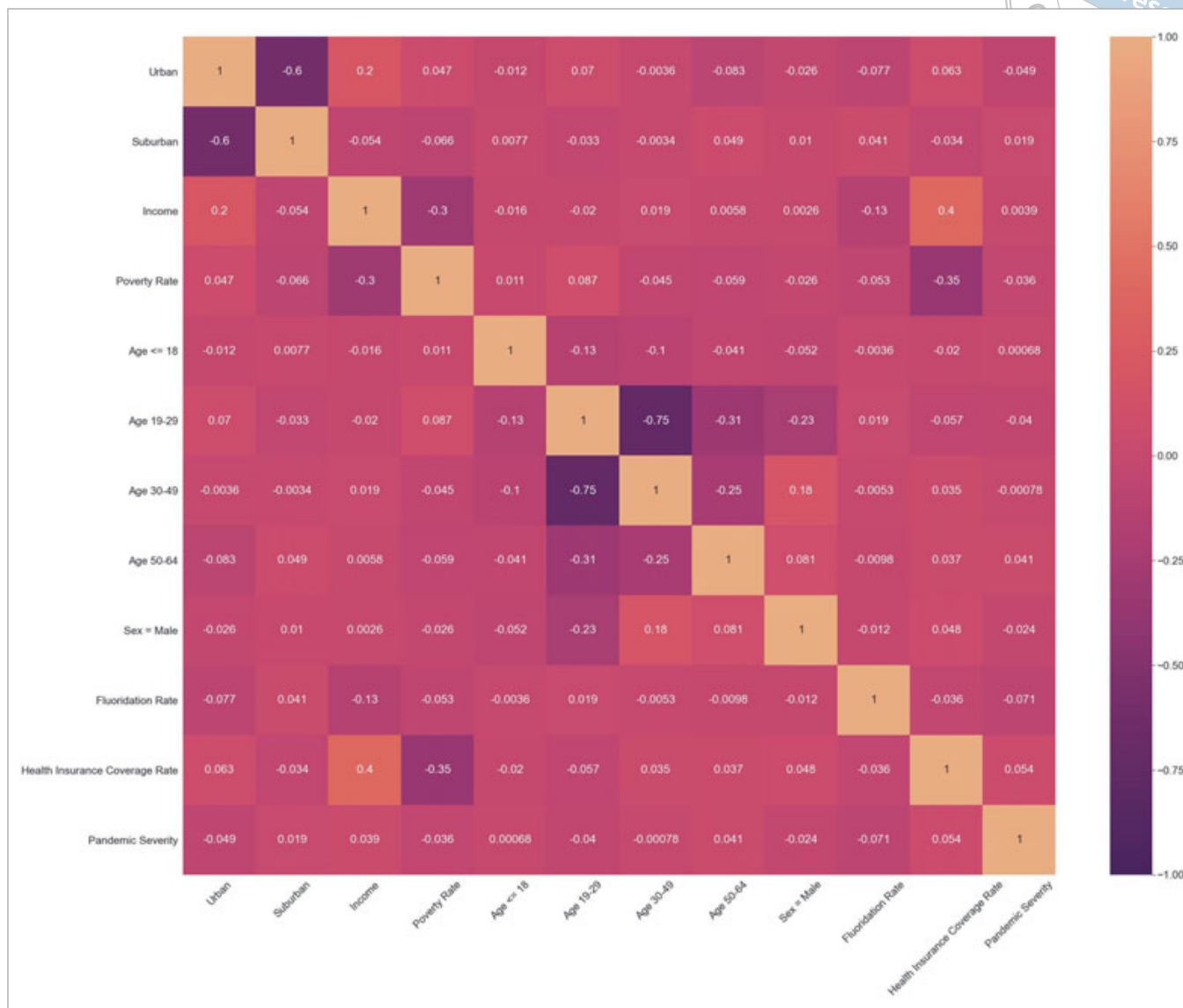
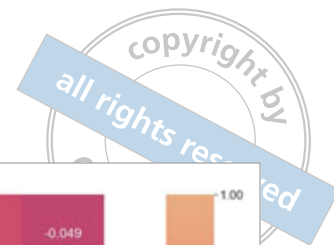


Fig 4 Correlation heat map of the variables for logistic regression.

CI = 0.9734, 0.9995), the odds of talking about Wisdom tooth pain/jaw hurt was 0.9862 times ($B = -0.0139$, $SE = 0.005$, $P < .01$, $OR = 0.9862$, 95% CI = 0.9763, 0.9960), and the odds of talking about Dental service/cavity was 1.0204 times ($B = 0.0202$, $SE = 0.005$, $P < .001$, $OR = 1.0204$, 95% CI = 1.0101, 1.0315).

People from counties with higher health insurance coverage rate tended to tweet less about all oral health-related topics. As the health insurance coverage rate increased by 1%, the odds of tweeting about Dental pain was 0.9929 times ($B = -0.0071$, $SE = 0.003$, $P < .01$, $OR = 0.9929$, 95% CI = 0.9881, 0.9980), Dental service/cavity was 0.9817 times ($B = -0.0184$,

$SE = 0.002$, $P < .001$, $OR = 0.9817$, 95% CI = 0.9773, 0.9861), Tooth decay/gum bleeding was 0.9854 times ($B = -0.0147$, $SE = 0.003$, $P < .001$, $OR = 0.9854$, 95% CI = 0.9802, 0.9910), Wisdom tooth pain/jaw hurt was 0.9882 times ($B = -0.0119$, $SE = 0.002$, $P < .001$, $OR = 0.9882$, 95% CI = 0.9831, 0.9930), and chipped tooth/tooth break was 0.9832 times ($B = -0.0169$, $SE = 0.003$, $P < .001$, $OR = 0.9832$, 95% CI = 0.9782, 0.9881).

People from counties at a higher risk of COVID-19 talked less about Dental service/cavity and Wisdom tooth pain/jaw hurt, and more about Tooth decay/gum bleeding and Chipped tooth/tooth break. If the seven-day average relative change of the

number of daily COVID-19 confirmed cases grew by 1%, the odds of tweeting about Dental service/cavity was 0.8411 times ($B = -0.1730, SE = 0.048, P < .001, OR = 0.8411, 95\% CI = 0.7657, 0.9240$), Wisdom tooth pain/jaw hurt was 0.7588 times ($B = -0.2760, SE = 0.047, P < .001, OR = 0.7588, 95\% CI = 0.6921, 0.8319$), Tooth decay/gum bleeding was 1.3263 times ($B = 0.2824, SE = 0.048, P < .001, OR = 1.3263, 95\% CI = 1.2080, 1.4564$), and Chipped tooth/tooth break was 1.1874 times ($B = 0.1718, SE = 0.045, P < .001, OR = 1.1874, 95\% CI = 1.0876, 1.2969$).

Discussion

Among the Twitter users in the present study, 26.70% talked about Wisdom tooth pain/jaw hurt, 23.86% tweeted about Dental service/cavity, 18.97% discussed Chipped tooth/tooth break, 16.23% talked about Dental pain, and 14.24% talked about Tooth decay/gum bleeding. Overall, women were more likely to discuss oral health amid the COVID-19 pandemic. On one hand, this might be because men are more likely to ignore their dental health and visit dental practitioners less frequently for disease prevention.⁴⁷ On the other hand, studies^{30,35} showed that women are more dentally anxious, which might lead to physiologic, cognitive, behavioral, health, and social issues.³¹ COVID-19 has also changed people's work patterns as many companies encourage or require employees to work from home to prevent the spread of virus,⁴⁸ which was found to influence people's oral health by increasing the consumption of products that are detrimental to oral health such as snacks and alcohol and increasing the consumption of oral health products.⁸ Another potential reason that women tended to talk about oral health amid the COVID-19 pandemic is that they were more likely to reduce work hours and spend more time on oral health since they could stay home longer.^{49,50} With respect to age, younger adults (19 to 29 years) tended to tweet more often about oral health problems. This echoes the finding that younger adults experience a higher prevalence of dental fear and anxiety (DFA), high DFA, and severe DFA.⁵¹

The topics of interest varied across user characteristics including age, sex, population density, income, poverty rate, and health insurance coverage rate. Older adults, who are identified as the highest risk group for fatal COVID-19 clinical outcomes^{10,52} were more likely to talk about Dental pain ($P < .001$). Due to the pandemic, older adults are facing lack of access to the oral health care.⁵³ In the present study, the older adults were less likely to tweet about Wisdom tooth pain/jaw hurt, as expected as the age at which the third molars erupt is generally early twenties.⁵⁴

It is noteworthy that the focus was intended to be discovering the age pattern instead of any specific age group. According

to the logistic regression results shown in Table 3, the coefficients of the age groups that passed the statistical tests showed a consistent pattern with the ages. That is, the changes in the coefficients were consistent with the changes in the ages. Women tended to focus more on Dental pain ($P < .05$) and Dental service/cavity ($P < .001$) whereas men were more interested in discussing Tooth decay/gum bleeding ($P < .001$) and Wisdom tooth pain/jaw hurt ($P < .05$). Studies have shown that women are almost twice as likely to have received a regular dental check-up and are more likely to report general fear of dental pain compared to men.^{55,56} People from rural areas were less likely to discuss Dental service/cavity ($P < .05$), which is possibly due to the lack of access to dental care. People living in rural America had about 8% (children) to 10% (adults aged 18 to 64 years) less access to dental services compared with their urban counterparts in 2017.⁵⁷ Suburban people talked less about Wisdom tooth pain/jaw hurt ($P < .05$). People on higher incomes talked more about Dental service/cavity ($P < .001$) but less about Chipped tooth/tooth break ($P < .05$). High cost is the most significant reason for people not visiting dentists in the US.³³ Those on higher incomes may care less about the high cost and have more frequent dental services, which suggests disparities in oral health. People from counties with a higher poverty rate talked less about Dental pain ($P < .01$), Tooth decay/gum bleeding ($P < .05$), and Wisdom tooth pain/jaw hurt ($P < .01$). Although Kim et al⁵⁸ suggested that community water fluoridation is associated with lowering the risks of having certain oral diseases like dental caries, the present study has shown that state-level fluoridation rate is not associated with the prediction of any oral health-related topics. This may be due to the limitation of not having publicly available more granular fluoridation rate data. Health insurance coverage rate was the most important predictor for the logistic regression for topic prediction. People from counties with a higher insurance coverage rate tended to tweet less about all topics of oral health ($P < .01$), which is consistent with the findings of Zivkovic et al⁵⁹ that health, or more specifically dental insurance, plays an important role in improving people's oral health conditions. Combined with the findings with respect to the income and poverty rate, the present authors consider these variables to be related with oral health because they impact the ability to pay for dental services and preventive medical and dental care. With respect to the pandemic severity, people from counties at a higher risk of COVID-19 talked less about Dental service/cavity ($P < .001$) and Wisdom tooth pain/jaw hurt ($P < .001$) but more about Tooth decay/gum bleeding ($P < .001$) and Chipped tooth/tooth break ($P < .001$). On one hand, it was likely that people delayed or avoided dental visits because of closure and reduced hours of dental care and



the fear of being infected with the virus during their dental appointments.^{11,60} On the other hand, COVID-19 has a negative effect on oral health possibly resulting from xerostomia, loss of taste or smell sensation, and mental health breakdown.⁶¹

There might be potential biases in the study samples. It was chosen to conduct the study at a large scale with almost 10,000 participants to address the bias issue. More importantly, as discussed above, most of the findings are consistent with previous studies and polls, which validates the robustness of the study. Another merit of the study regarding addressing the sample biases is that collection of social media data, ie observing the social media users in a passive way, could potentially alleviate the social desirability biases⁶² introduced in the survey data of a traditional design.⁶³

The findings of the present study have implications for the community of general dental practitioners. Public social media can be an important source of information for the community to have a more comprehensive understanding of dental need, especially during a pandemic when accessibility to dental services is limited and the communication between the patients and clinicians is less frequent. Policies can be designed to provide more dental care to the people in need based on the finding that the topics of interest vary across user characteristics.

Limitations

There are some limitations of the present study. Some states with a smaller sample size were not included in the study pop-

ulation. Temporal changes have not been investigated. Future work can be directed to analyzing oral health-related discussions across multiple social media platforms and combining the insights of the survey data to achieve broader and more comprehensive perspectives.

Conclusion

This is the first large-scale social media-based study to understand the public discussions on oral health during the COVID-19 pandemic in the US. In total, 10,883 tweets were analyzed from 9,104 Twitter users across 26 states (with sufficient samples) during the period of 12 November 2020 to 14 June 2021. The topics of interest varied across user characteristics. Tweets inform social disparities in oral health during the pandemic. It is hoped that this work can promote research on public health issues through the lens of social media, provide insights for oral health practitioners and policy makers, enhance the public awareness of the importance of oral health, and ultimately improve oral health in America in future pandemics. ■■

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Yangxin Fan

Yangxin Fan PhD Student, University of Rochester, Goergen Institute for Data Science, Rochester, NY, USA

Hanjia Lyu PhD Student, University of Rochester, Department of Computer Science, Rochester, NY, USA

Jin Xiao Associate Professor, University of Rochester, Eastman Institute for Oral Health, Rochester, NY, USA

Jiebo Luo Albert Arendt Hopeman Professor, University of Rochester, Department of Computer Science, Rochester, NY, USA

Correspondence: Dr Jiebo Luo, 3101 Wegmans Hall, University of Rochester, Rochester, NY 14627, USA. Email: jluo@cs.rochester.edu