ORIGINAL RESEARCH

A quantitative analysis of Twitter ("X") trends in the discussion of rhinoplasty

Shreya Mandava BS[1] [iD] | Samuel L. Oyer MD[2] | Stephen S. Park MD[2]

[1]School of Medicine, University of Virginia, Charlottesville, Virginia, USA

[2]Department of Otolaryngology-Head and Neck Surgery, University of Virginia, Charlottesville, Virginia, USA

Correspondence
Shreya Mandava, School of Medicine, University of Virginia, 415 Ray C. Hunt Drive, Suite 2200, Charlottesville, VA 22903, USA.
Email: shreya.mandava@gmail.com

Abstract

Introduction: Rhinoplasty is one of the most common cosmetic surgical procedures performed globally. Twitter, also known as "X," is used by both patients and physicians and has been studied as a useful tool for analyzing trends in healthcare. The public social media discourse of rhinoplasty has not been previously reported in the field of otolaryngology. The goal of this study was to characterize the most common user type, sentiment, and temporal trends in the discussion of rhinoplasty on Twitter to guide facial plastic surgeons in their clinical and social media practices.

Methods: A total of 1,427,015 tweets published from 2015 to 2020 containing the keywords "rhinoplasty" or "nose job" were extracted using Twitter Academic API. Tweets were standardized and filtered for spam and duplication. Natural language processing (NLP) algorithms and data visualization techniques were applied to characterize tweets.

Results: Significantly more "nose job" tweets (80.8%) were published compared with "rhinoplasty" (19.2%). Annual tweet frequency increased over the 5 years, with "rhinoplasty" tweets peaking in January and "nose job" tweets peaking in the summer and winter months. Most "rhinoplasty" tweets were linked to a surgeon or medical practice source, while most "nose job" tweets were from isolated laypersons. While discussion was positive in sentiment overall ($M = +0.08$), "nose job" tweets had lower average sentiment scores ($P < .001$) and over twice the proportion of negative tweets. The top 20 most prolific accounts contributed to 14,758 (10.6%) of total "rhinoplasty" tweets. Exactly 90% (18/20) of those accounts linked to non-academic surgeons compared with 10% (2/20) linked to academic surgeons.

Conclusions: Rhinoplasty-related posts on Twitter were cumulatively positive in sentiment and tweet volume is steadily increasing over time, especially during popular holiday months. The search term "nose job" yields significantly more results than "rhinoplasty," and is the preferred term of non-healthcare users. We found a large

1 | INTRODUCTION

According to the American Society of Plastic Surgeons (ASPS) 2020 Report, the most popular cosmetic surgery procedure in the United States was rhinoplasty, with over 350,000 procedures performed.[1] Patients seek rhinoplasty, also known as nose reshaping, for many reasons including dissatisfaction with tip asymmetry, difficulty breathing or nasal blockage, and crookedness in the middle third of the nose.[2] The increasing popularity of rhinoplasties has been influenced by various factors, such as self-perception of nasal length in front-facing camera "selfies" and the so-called Zoom Boom of aesthetic surgery during the COVID-19 pandemic.[3–6] Several tools have been used to analyze trends in rhinoplasty, including Google Trends and RealSelf.com, an online forum that allows doctors and patients to interact and discuss aesthetic treatments (source). Patients have a variety of questions regarding appearance, function, cost, and post-operative symptoms as well as varying satisfaction rates after rhinoplasty that they may discuss on social media.[7,8] There is also evidence of significant seasonal and month-to-month variance in online searches for rhinoplasty, although some of this data is conflicting.[9–11]

Twitter, recently rebranded as "X," is another popular social media platform that is a potential tool for analyzing trends in rhinoplasty. It has over 300 million active users worldwide that publish ∼500 million posts known as "tweets" each day.[12] Twitter provides an excellent source of data for research due to the real-time, accessible, and public nature of its content and has been used to understand trends in public discourse on health topics such as infectious disease, depression, and obesity.[13] There is also recent research demonstrating correlations between plastic surgery tweet volumes and procedure volumes among some Twitter search terms. The Twitter Academic Research Product Track (TARPT) tool offers free public data to researchers and has been suggested as a tool to track trends in engagement with various plastic surgery procedures online.[14] Combined with large-scale computational methods that have been applied to health data such as natural language processing (NLP) and sentiment analysis, TARPT is a powerful tool to track trends in engagement with plastic surgery procedures online, including rhinoplasty.[15,16]

In recent years, Twitter has also been notable for the rising number of physicians who publish content related to health information, marketing and self-promotion, endorsement of products/services, and medical education.[17] The field of plastic surgery in particular has been noted to have a dominant presence on Twitter, with studies showing that ∼30.1% pertinent tweets are published by plastic surgeons compared with 40.7% by the general public and 15.3% by companies.[18]
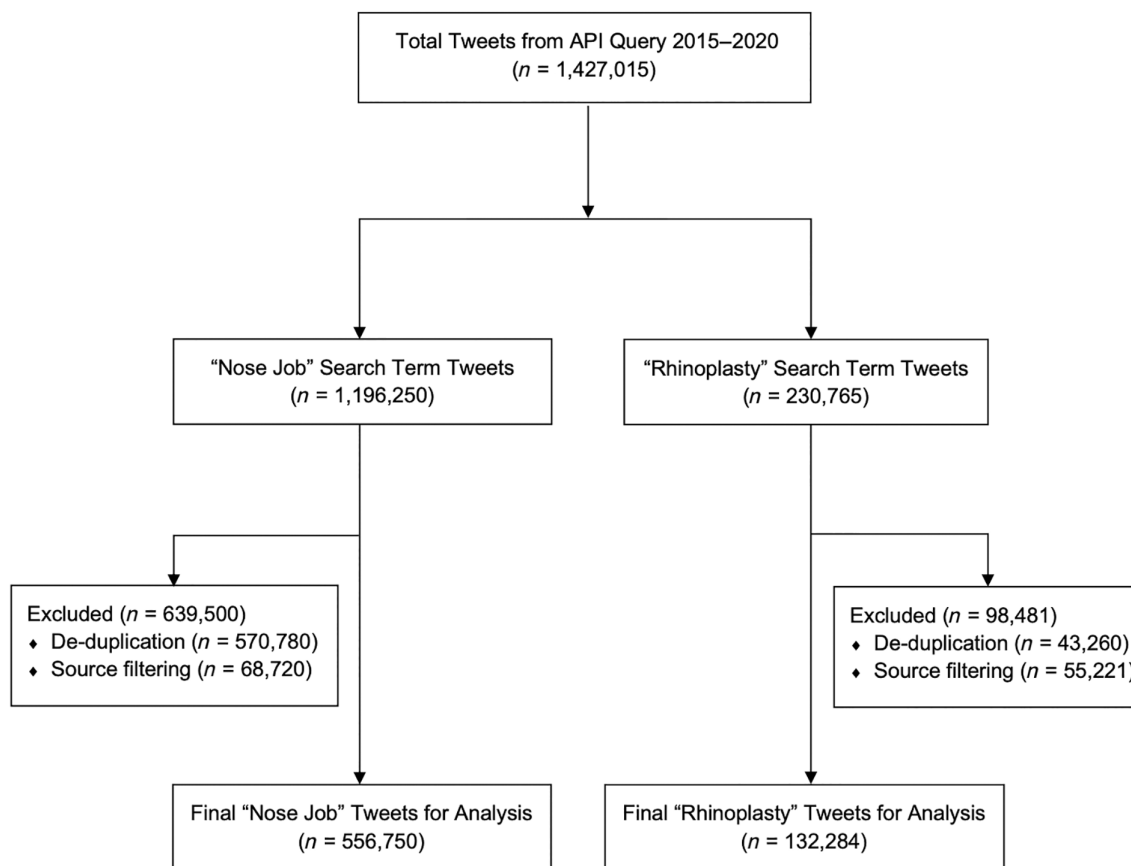
Our goal in this study was to apply large-scale computational techniques to public Twitter data sets from TARPT to: (1) Characterize the common terms, sentiment patterns, and temporal trends in the discussion of rhinoplasty; (2) Assess the digital impact of plastic surgeon users contributing to the online discussion of rhinoplasty. These online trends may ultimately guide surgeons in managing their own social media presence and discussions with patients about undergoing rhinoplasty.

2 | MATERIALS AND METHODS

The TARPT database allows academic researchers to access a full archive of real-time and historical public data. We obtained permission to access the TARPT application programming interface (API) and then extracted tweets in R using the "academictwitteR" package. We constructed a search query that extracted tweets published between 2015 and 2020 and excluded retweets or tweets not in the English language. The search terms "nose job" and "rhinoplasty" (as well as "rinoplasty," "rhinoplaste," and "rhinoplasti" to account for spelling errors) were used and yielded 1,427,015 raw tweets. Data available from web-scraping included date of creation, source, author ID, tweet ID, and URLs. There was a high frequency of posts by spam "bots," which are automated software programs that post repetitively and typically imitate a human user. We developed code that de-duplicated and filtered the tweets based on the source of origin to only include legitimate platforms (e.g., Twitter Web Client, Facebook, Google) to filter for bots. This yielded a total of 689,034 tweets for final review, of which 132,284 were rhinoplasty-related and 556,750 were nose job related (see Figure 1).

Texts from the tweets were isolated and standardized to contain lowercase letters, remove punctuation, remove numbers, consolidate common stems, and remove "stop" words that did not contain meaning (e.g., "a," "the," "is"). We were able to isolate the most frequent terms from the samples and identify common themes by applying the R package "topicmodels." Topicmodels uses Latent Dirichlet Allocation (LDA) to rate model every topic as a word distribution and every document as a topic distribution using conditional probabilities, ultimately yielding discrete categories of words.[16,19] LDA analysis enabled us to extract topics containing 10 words from each sample which were then manually reviewed by an independent coder to label the topic.

We also analyzed the sentiment of the tweets using R package "Valence Aware Dictionary and sEntiment Reasoner (VADER)," which is a lexicon and rule-based sentiment analysis tool. Sentiment is

Total Tweets from API Query 2015–2020
(n = 1,427,015)

"Nose Job" Search Term Tweets
(n = 1,196,250)

"Rhinoplasty" Search Term Tweets
(n = 230,765)

Excluded (n = 639,500)
♦ De-duplication (n = 570,780)
♦ Source filtering (n = 68,720)

Excluded (n = 98,481)
♦ De-duplication (n = 43,260)
♦ Source filtering (n = 55,221)

Final "Nose Job" Tweets for Analysis
(n = 556,750)

Final "Rhinoplasty" Tweets for Analysis
(n = 132,284)

**FIGURE 1**   Flowchart depicting web scraping and filtering of raw tweets from API query.

defined by emotional polarity on content ranging from highly negative to positive. VADER quantifies these sentiments as scores between −1 and +1 to individual tweets based on an algorithm assigning sentiment value to their content. Cutoff values of less than or equal to −0.05 are coded as negative, between −0.05 and +0.05 coded as neutral, and greater than or equal to +0.05 coded as positive. VADER can help determine the positive, neutral, and negative emotional context of a tweet with cut-off score ranges for each category.[15]

We studied tweet frequency, user type data, and temporal trends over the course of months and years and modeled these trends using ggplot2 in R. We were able to extract user type data from the rhinoplasty-related tweets using our tweet meta-data to organize the tweets based on username and count the number of times a user published a tweet containing the term "rhinoplasty" or "nose job." We further examined these user accounts to determine linkage to healthcare or non-healthcare accounts. We manually stratified user accounts based on frequency of posts and randomly sampled 100 user IDs who tweeted at variable frequencies. The content generated by these IDs was linked to online accounts and coded manually as either healthcare or non-healthcare accounts. We found that accounts who posted at least 15 times in the period of 2015–2020 were consistently (>95%) associated with surgeon or medical practice accounts while those who only posted once were consistently (>95%) non-healthcare accounts, and so the accounts were categorized accordingly for further analysis.

Conclusions could not be drawn about accounts that posted between 2 and 15 times and they were thus labeled "Unknown." Welch's t-tests and chi-squares were used to analyze the statistical significance of quantitative findings (α = 0.05).

3 | RESULTS

After data filtration, there were 689,034 total unique tweets with a higher proportion of "nose job" tweets (556,750, 81%) compared with "rhinoplasty" tweets (132,284, 19%). There were significant differences in the annual tweet frequency from 2016 to 2020 (P < .001) and average monthly tweet frequency (P < .001) for "rhinoplasty" and "nose job" tweets according to Chi square analysis. Duplicate tweets and tweets posted by bots were not included in this analysis. Overall, there was a positive percentage increase in the frequency of tweets published each year, with the exception of the 2016–2017 interval. The most significant increase occurred between 2017 and 2018 with a 52% increase in number of tweets, due in large part to the 69% increase in "nose job" tweets that year. Overall, there were 81,842 tweets posted in 2016 compared with the 190,531 tweets posted in 2020, which is a 133% increase over the 5-year period (Figure 2). There was also monthly and seasonal variation in the frequency of tweets. "Rhinoplasty" tweets demonstrated an average peak in tweet
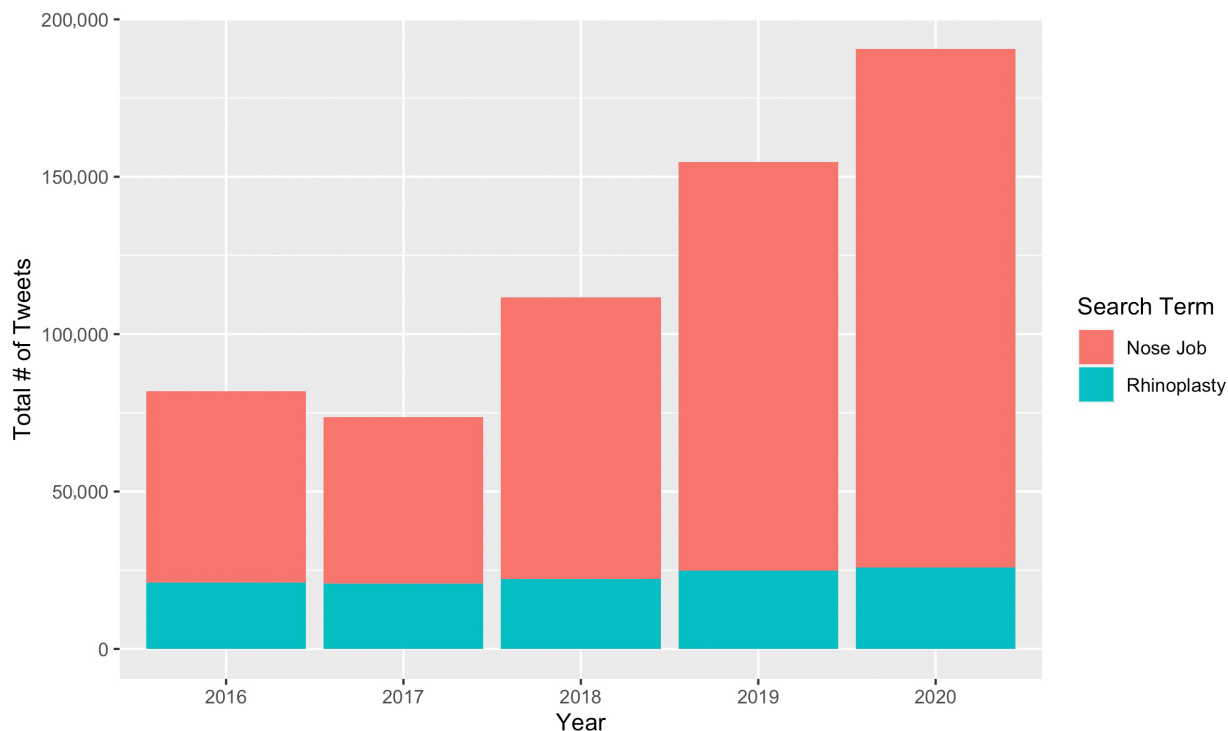
FIGURE 2   Annual frequency of "rhinoplasty" and "nose job" tweets from 2016 to 2020.

frequency in January, while "nose job" tweets appeared to be increased in the winter and summer months, particularly December, January, June, July, and August (Figure 3).

According to LDA analysis, topics that appeared in rhinoplasty-related tweets were expressed desire/interest in rhinoplasty, rhinoplasty-related improvements, payment, surgical techniques, advertising/consultations, post-operative results, associated plastic surgery procedures, and YouTube videos.

There were a total of 50,544 accounts that tweeted about "rhinoplasty" between 2015 and 2020. Based on our algorithm for determining account type, a minority of accounts posting "rhinoplasty" are healthcare accounts (1.74%), but their tweets made up the largest subset of our total 2015–2020 tweet sample (45.3%) of 132,283 tweets. On the other hand, general public users who published a single "rhinoplasty" tweet in this period made up a majority of total users (79.2%) but only accounted for only 30.2% of the total tweets (see Figure 4). The "nose job" sample was composed of a diverse range of user types, as both a majority of users (81.5%) and total tweets (58.6%) came from individual layperson posters.

A manual review was conducted to characterize the top 20 accounts, which published a combined 14,758 (10.6%) of total "rhinoplasty" tweets from 2015 to 2020. Exactly 18/20 (90%) accounts were associated with non-academic surgeons/practices while 2/20 (20%) of accounts were linked to surgeons with academic affiliations. Exactly 14/20 (70%) of the surgeons/practices were based in the United States, while the other 6/20 (30%) were based in other countries (India, Pakistan, Iran, Turkey, and Korea). The user metadata for each of these accounts was reviewed and it was found that they

frequently reposted content from RealSelf (60%, 12/20) and Instagram (15%, 3/20).

The final analysis involved the VADER sentiment score tool which assigns a positive, neutral, or negative value to tweets based on their content. Overall, the average sentiment score of rhinoplasty-related tweets was slightly positive ($M = 0.084$). A Welch's two sample t-test that the mean compound sentiment score of the "rhinoplasty" sample ($M = 0.143$; CI 0.072–0.2133) was significantly higher ($P < .001$) than "nose job" sample ($M = 0.070$; CI -0.005 to 0.145), although both values are mildly positive (<.05). The breakdown of positive, neutral, and negative tweets also differed between the "rhinoplasty" and "nose job" samples. "Rhinoplasty" tweets were 37.9% positive, 49.2% neutral, and 12.9% negative, while "nose job" tweets were 41.4% positive, 31.4% neutral, and 27.3% negative. Chi square analysis with Bonferroni correction demonstrated the two samples had significantly different sentiment compositions ($P < .001$) (see Table 1). Furthermore, we calculated the mean scores within the "rhinoplasty" tweets for healthcare versus non-healthcare tweets in the 2015–2020 period using the previously discussed criteria. A Welch's two sample t-test showed that the mean healthcare score ($M = 0.150$; CI 0.109–0.190) was significantly higher ($P < .001$) than the mean non-healthcare score ($M = 0.104$; CI 0.055–0.154). The average sentiment scores for healthcare user tweets increased each year from 2015 to 2020.

4 | DISCUSSION

Our results demonstrated a significant increase in the number of "rhinoplasty" and "nose job" tweets posted over the 5-year analysis

(A)

(B)
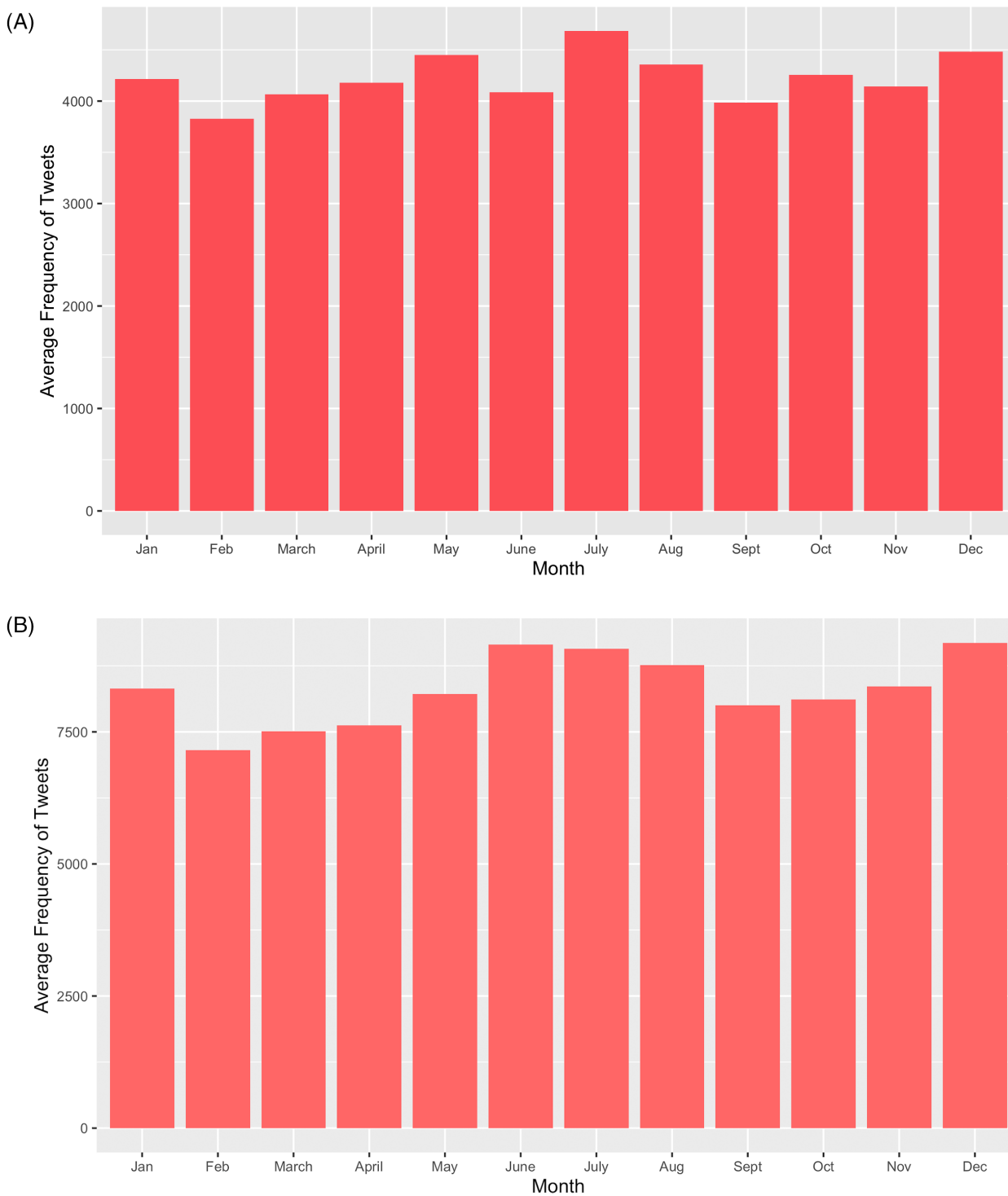
FIGURE 3   (A) Average monthly "rhinoplasty" tweet frequency from 2016 to 2020; (B) Average monthly "nose job" tweet frequency from 2016 to 2020.

period. This trend seems to support the rising popularity of rhinoplasty procedures in the United States as well as the rising use of social media among the general population and physicians. There were 786,852 rhinoplasties performed in 2016 compared with the 852,554 performed in 2020.[1,20] This is especially interesting considering that 2020 was largely dominated by the COVID-19 pandemic.

Some studies have shown that the demand for plastic surgery procedures, including rhinoplasty, increased once the full lockdown stage of the pandemic ended.[5,21] Our tweet frequency data appears to support this phenomenon.

It is also notable that the growth rate of rhinoplasty discussion on Twitter outpaces the increase in overall activity on Twitter.
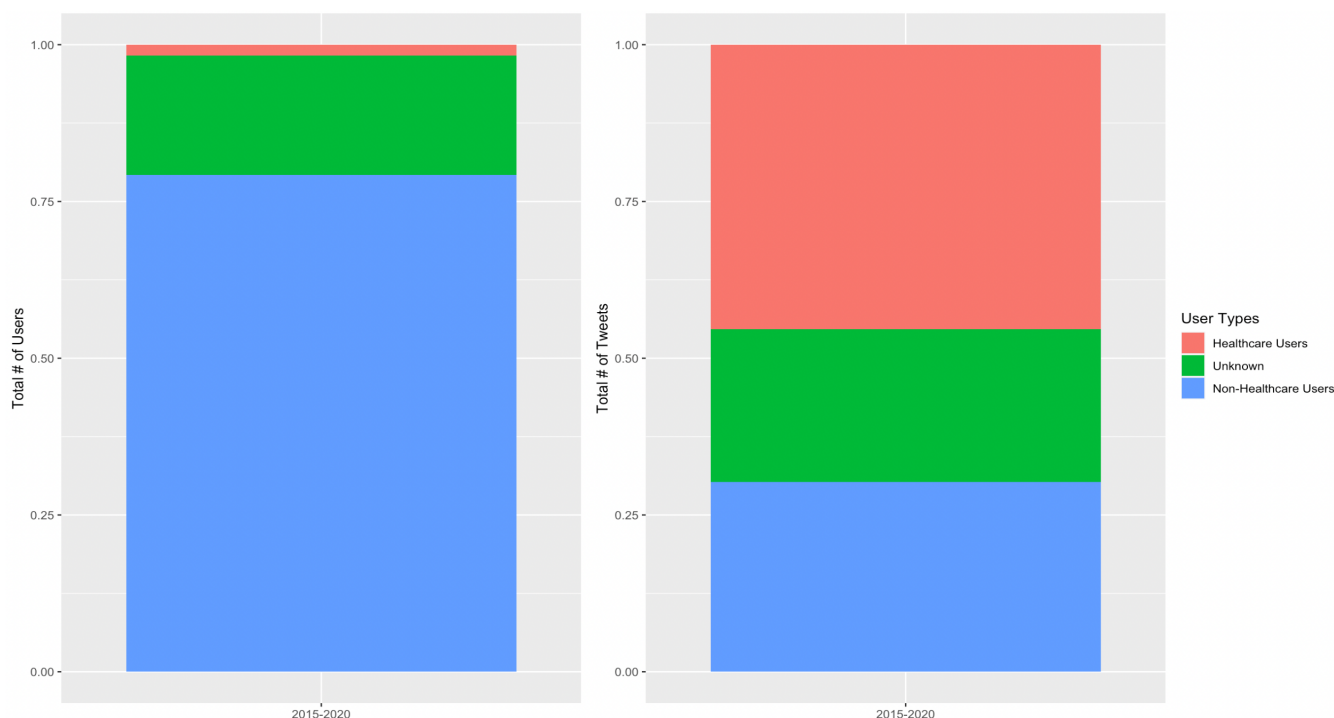
FIGURE 4 Proportion of non-healthcare versus healthcare users who published tweets with the term "rhinoplasty" between 2015 and 2020 (Left) versus Proportion of tweets with the term "rhinoplasty" published by healthcare versus non-healthcare users between 2015 and 2020 (Right). Unknown users were unable to be classified.

TABLE 1 Average VADER sentiment scores (range from −1 to +1) and composition of "rhinoplasty" and "nose job" tweets.

	Search term		
	Rhinoplasty	**Nose job**	**P-value**
Sentiment scores			
Average total score	0.143	0.070	<.01
Average positive score	0.523	0.486	<.01
Average negative score	−0.433	−0.480	<.01
Sentiment composition			
# of positive tweets	50,181 (37.8%)	230,342 (41.4%)	
# of neutral tweets	65,095 (49.2%)	174,615 (31.4%)	
# of negative tweets	17,020 (12.9%)	151,929 (27.3%)	
P-value	<.01	<.01	

While the annual totals for tweets published are not publicly available, Twitter began publishing its monetizable active users (dMAUs) in financial reports from recent years. Twitter had a 69% increase in monetizable active users (dMAUs) from 110 million in 2017 to 186 million in 2020 compared with the 159% increase in rhinoplasty-related tweets over the same period.[22] This suggests that the increasing discussion of rhinoplasty on Twitter is attributable to factors beyond the rising number of general public and healthcare users.

Another finding was that monthly tweet frequency appeared to peak in January of each year for "rhinoplasty" and during popular holiday months for "nose job." There are a variety of reasons that may explain this temporal variation. Since a large number of "rhinoplasty" tweets are published by surgeons, this data may indicate a marketing surge at the start of each new year. In addition, previous literature analyzing Google Trends has found December/January and June/July to be popular times for "rhinoplasty" searches, potentially due to these being common vacation or student break months.[11] Our "nose job" data reflects the findings from Google Trends. However, more data is needed to fully understand the reasons for seasonal variation in rhinoplasty discussion and whether it correlates with monthly procedure volumes.

Another finding was that surgeons and medical practice accounts have a large digital impact on the quantity of "rhinoplasty" tweets published. While healthcare accounts make up a minority of users who posted about rhinoplasty in our time period of interest, they posted the most "rhinoplasty" tweets. This is primarily due to the prolific nature of the healthcare accounts, many of whom posted hundreds or thousands of "rhinoplasty" tweets in this period. In fact, the top 20 accounts published over 10% of total "rhinoplasty" tweets, with most of these accounts linked to private practice surgeons based in the United States. User metadata showed that many "rhinoplasty" tweets are posted for marketing or educational purposes, with reposts from sites such as RealSelf.com and Instagram comprising up many healthcare accounted-generated tweets.

These results are in line with research which has demonstrated an increase in usage of Twitter by plastic surgeons, especially non-academic surgeons.[23] Since social medial followers and presence are becoming more significant factors in practice-building and optimal Google placement, both academic and non-academic surgeons who perform rhinoplasty should consider how this impacts their practice.[24,25]

Additionally, comparing the "rhinoplasty" and "nose job" tweet samples provided insight into the differences between healthcare-focused and public-focused discussions of rhinoplasty. Research has previously found that search term selection is important for analyzing for plastic surgery procedure trends on Twitter.[13] Our results showed that general public discourse centers around the term "nose job" while the preferred term among healthcare users appears to be "rhinoplasty." The overall sentiment for rhinoplasty-related search term tweets was positive, however "nose job" tweets were less positive than "rhinoplasty" tweets. These differences may be explained by healthcare users tweeting more promotional material with highly positive terms using the term "rhinoplasty." Plastic surgeons interested in using Twitter for marketing and business purposes can extend their reach and better assess trends in rhinoplasty among the general public by using the search term "nose job" and posting more frequently, like the most prolific accounts.

The ability to mine large amounts of electronic data has allowed us to broadly examine the global conversation of rhinoplasty as relevant to both patients and surgeons. Future studies may apply similar data science techniques to TARPT data with search terms from other plastic surgery procedures to compare trends in discussion. While this study benefits from its large sample size enabled by computational methods, it has several limitations. The models used for NLP are rules-based and subject to error based on program capacity limitations. For example, the VADER program has not been shown to account for sarcasm when calculating sentiment scores. We also made assumptions in the interpretation of our user type data since our metadata did not automatically characterize healthcare versus non-healthcare users. We used an initial sample of 100 accounts to guide classification and were unable to assign user type to accounts tweeting "rhinoplasty" between 2 and 14 times. There is inherent error associated with this approach and we could not draw conclusions from a subset of the data. We also reviewed the top 20 accounts which contributed to over 10% of rhinoplasty tweets, but they only represent the most prolific healthcare accounts and not all healthcare accounts. Also, while tweets were extracted from around the world, we filtered for English language due to limitations of NLP, which likely biased the sample toward Western countries.

5 | CONCLUSION

This study utilized Twitter data and computational analysis to identify trends in the public discourse of rhinoplasty on social media. The overall discussion of rhinoplasty has been increasing over time, especially during peak summer and winter months. Plastic surgeon affiliated accounts, especially those that are non-academic and US-based, have a large digital impact on the discussion of rhinoplasty. They make up the minority of accounts yet post content that is more prolific and positive in sentiment than general public users. Additionally, there is a difference in search term preference among users with more surgeons using the term "rhinoplasty" and more laypersons using the term "nose job."

Given the rising discussion of rhinoplasty on social media, it is imperative for both academic and non-academic surgeons specializing in this procedure to consider how online promotion and engagement with patients may benefit their practices. Surgeons utilizing Twitter for the purpose of marketing or monitoring patient trends in rhinoplasty should adjust their social media presence based on the described search term preferences, seasonal tweet volume, and sentiment patterns.

CONFLICT OF INTEREST STATEMENT
The authors declare that they have no conflicts of interest to disclose.

INFORMED CONSENT
For this type of study informed consent is not required.

ORCID
Shreya Mandava https://orcid.org/0000-0003-2443-3583

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