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Twitter analysis of the orthodontic patient experience with braces versus Invisalign

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Twitter analysis of the orthodontic patient experience with braces versus Invisalign®

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Dentistry at Virginia Commonwealth University

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ABSTRACT

TWITTER ANALYSIS OF THE ORTHODONTIC PATIENT EXPERIENCE WITH BRACES VERSUS INVISALIGN®

By Daniel Noll, D.M.D.

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The purpose of this study was to examine the orthodontic patient experience with braces compared to Invisalign® by means of a large-scale Twitter sentiment analysis. A custom data collection program was created to collect tweets containing the words "braces" or "Invisalign." A hierarchal Naïve Bayes sentiment classifier was developed to sort the tweets into one of five categories: positive, negative, neutral, advertisement, or not applicable. Among the 419,363 tweets applicable to orthodontics collected, users posted significantly more positive tweets (61%) than negative tweets (39%) (p-value = <0.0001). There was no significant difference in the distribution of positive and negative sentiment between braces and Invisalign® tweets (p-value=0.4189). In conclusion, Twitter users express more positive than negative sentiment about orthodontic treatment with no significant difference in sentiment between braces and Invisalign® tweets.

INTRODUCTION

Communication plays a critical role in health care. Providers seek to improve patient care by connecting with patients and understanding their experiences. Traditionally, health care providers gathered this information through surveys, reviews, and word of mouth. In the past decade, communication methods have rapidly changed with the explosion of social media. Publicly available information from social media networks can be collected and analyzed on a large scale to better understand the patient experience.

Social media is a group of internet-based applications that allow the creation and exchange of interactive user-generated content. People traditionally use social media for information gathering, social interactions, and entertainment. Facebook is the most popular social media platform, followed by Twitter, LinkedIn, and Pinterest.[1] Facebook is a platform designed to connect friends and share pictures. Twitter is fast-paced, featuring concise and instant public messages.[2] LinkedIn is business-orientated, and Pinterest specializes in the sharing of common interests.

Social media has impacted industries worldwide, as companies attempt to connect with consumers and collect their feedback. The healthcare industry is adapting to these new communication methods.[3] Providers utilize social media for marketing and to broadcast information. Internet-based applications are changing how some doctors interact with patients, as virtual clinics conveniently provide patients with medical advice and even concierge services.[4] Social media is also being utilized to supplement medical education. Online medical education communities disseminate information and engage students through blogs, YouTube videos, podcasts, Twitter feeds, and Facebook posts.[2] Blogs are website-based written posts on a certain topic, while podcasts are audio-based. The American Medical Association has acknowledged the growing role of social media in health care and has issued guidelines on the appropriate use of social media for practitioners.[5] Patients use social networks to gather health information and to connect with others through social media based community support groups.[6]

Dental practices utilize social media to increase their online presence by engaging patients and soliciting patient reviews. Many practices will directly market with targeted advertisements on social networks.[7] The social media revolution has permeated the field of orthodontics, as the majority of orthodontists and orthodontic patients participate in social media.[8]

Founded in 2006, Twitter is an online, fast-paced micro-blog where users share posts in 140 characters or less. Traditional blogs allow for longer, more static content, while micro-blogs like Twitter focus on shorter, more frequent posts. With 320 million active monthly users, Twitter has grown exponentially and become a primary method of multipurpose communication throughout the world.[9]

The health care industry has embraced Twitter. Physicians use Twitter for peer education and team communication. Hospitals utilize Twitter for marketing, dispersing news, and patient interaction.[10] Medical residents share information from educational conferences through Twitter accounts.[11] The dental profession has followed this trend, exploring the potential of Twitter. Dental practices often advertise on Twitter, although the marketing effectiveness of Twitter is still unknown.[12]

While health care providers are expanding ways to utilize Twitter constructively, the majority of tweets come from patients. Similar to other social media sites, people use Twitter every day to communicate, to gather information, and for entertainment. However, people primarily utilize Twitter to express their current thoughts and feelings. Kelly categorized the content of Twitter posts and found that 41% of Twitter posts are "pointless babble" and another 38% of tweets are conversations between users. News, information, spam, and self-promotion made up the remaining 21% of the posts.[13] Thus, many Twitter posts are users' written thoughts and perceptions. Eighty percent of users now access Twitter through their mobile device, allowing people to tweet in the moment.[9]

These written thoughts and feelings posted as tweets are unsolicited, self-reported, and publicly available. As a result, Twitter is a unique source of data. Traditional surveys often introduce recall bias and are difficult to conduct on a large scale. Twitter data are collected in real-time, free from recall bias.[14] With millions of tweets per day, the potential data source is vast.

Twitter data are best analyzed on a large scale with sentiment analysis.[15, 16] Sentiment analysis, often referred to as opinion mining, is a method to extract and characterize subjective information. Twitter sentiment analysis has been employed to study many fields, from stock market indicators to political election predictions.[17-19] Companies seek ways to mine Twitter for consumer feedback and to predict future consumer behavior.[20] This immense information source is beginning to be explored in the medical and dental fields; yet, it is largely untapped in orthodontics.

Health care discussions on Twitter provide dental professionals the opportunity to better understand the patient experience.[21] Heaivilin *et al.*[22] found that the public uses Twitter to broadcast experiences and thoughts about dental pain in real time. Their Twitter results were similar to traditional surveys about dental pain, potentially validating Twitter as a data source in the dental field. Henzell *et al.*[23] analyzed 131 orthodontic-related tweets and found that orthodontic patients use social media sites such as Twitter to convey positive and negative feelings about orthodontic treatment.

Clear aligner therapy is becoming more popular in the field of orthodontics. Providers should have a thorough understanding of the benefits and drawbacks of the two most common modalities of orthodontic treatment: full fixed appliances (braces) and Invisalign®. The current literature regarding the patient experience with braces compared to Invisalign® is sparse and conflicting. Miller *et al*.[24] compared the two treatment methods and found that Invisalign® patients experienced less discomfort, pain, and analgesic use during their first week of orthodontic treatment than patients with traditional appliances. However, Shalish *et al*.[25] found that Invisalign® patients reported more pain and increased analgesic use the first days after insertion and a similar level of speech and swallowing dysfunctions compared to traditional appliances. Traditional braces patients reported more oral sores and food accumulation but similar levels of sleep and daily life disturbances. Given the increasing popularity of clear aligners, further research is needed to investigate other aspects of the patient experience such as esthetics and treatment satisfaction. Twitter provides a new and exciting medium to examine the impact of orthodontic treatment on everyday life.

The aim of this study was to examine the orthodontic patient experience with braces compared to the patient experience with Invisalign® by means of a large-scale Twitter analysis. The null hypothesis was that there is no difference in sentiment between tweets about braces and tweets about Invisalign®

MATERIALS AND METHODS

The Virginia Commonwealth University Institutional Review Board granted an exemption for this project. Tweets were collected over a five-month period from April 29th through September 29th, 2015. All tweets were publicly accessible from Twitter's database. Inclusion criteria consisted of any tweet that contained the words "braces" or "Invisalign." Each tweet was classified into one of five categories: Positive, Negative, Neutral, Advertisement, or Not Applicable. Applicable tweets were defined as pertaining to orthodontics and written in the English language.

The software programs for this project consisted of two sections: data collection and data interpretation. The data collection program was written to interact with Twitter's servers and continuously collect all tweets that met the inclusion criteria. Twitter has a search feature that allows a user to search through its massive repository of tweets. However, this search feature does not return a complete list. Rather, it automatically filters the results based on popularity. While this is useful to the average user, a complete list of all search results was desired for the study. Therefore, an alternative data collection program was created using Twitter's Application Programming Interface (API), which allowed unfiltered access to the information on Twitter's servers.[10]

A second program was written for the interpretation of the entire collected database. Each tweet was classified into one of the five previously listed categories by machine-learning sentiment analysis. The program was constructed using a Hierarchical Naive Bayes classifier, the preferred method for Twitter sentiment analysis.[15] Naive Bayes Classifiers are probabilistic classifiers that break down a block of text into a group of independent words and classify the text into a category based on the text's similarity to pre-categorized texts.[26] Thus, the program, or "machine", "learns" from the pre-categorized texts. Traditional sentiment classifiers do not take context into account when classifying. For example, the tweet, "Pepsi is so much better than Coke," would be classified as a positive tweet for both the Pepsi category and the Coke category.[27] Eke [28] raised concern about the use of Twitter for research, worrying that since context is not taken into account when extracting specific words, such a method could result in low predictive values. To reduce this issue, the Naïve Bayes classifying technique employs "context-aware" machine learning.

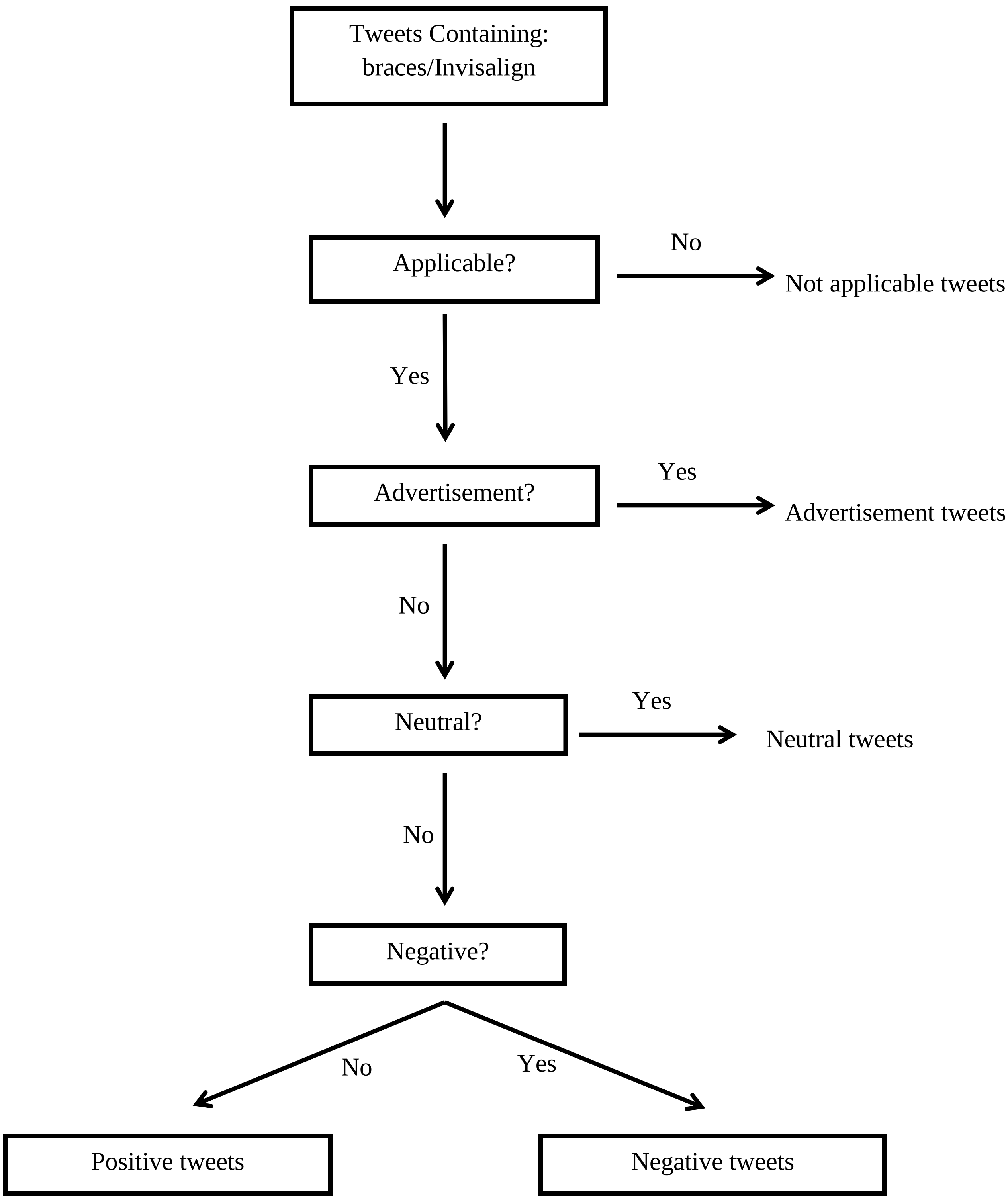
Another advantage of Naïve Bayes classifiers is the ability to sort every tweet in the database. Other classifiers predominately rely on emoticons like ":)" to classify tweets. This method must omit the many tweets that do not contain cannot emoticons. Naïve Bayes classifiers are able to sort every tweet by analyzing context of the entire post.

Naive Bayes classifiers require manual classification of a number of tweets to act as reference material to train the program. In this study, an independent reviewer manually sorted 3,784 tweets into one of the five categories. These pre-classified tweets, referred to as a corpus, were used to achieve two objectives: to train the program and to test the program. From the corpus, 71% (2,706 tweets) were used to "train" the classifier on what words and features were most representative of each category. The other 1,078 tweets in the corpus were used to test agreement between the human-sorting and the program-sorting. To test for inter-rater agreement, a second independent reviewer sorted a random sample of 1,098 from the 3,784 tweets corpus sorted by the first independent reviewer.

Text classifiers are most effective when classifying text into one of two categories. The program sorted tweets into the five categories in a specific sequence (Figure 1). This method is known as hierarchical classification.[29] The first classifier determined whether the text was applicable to orthodontics. Examples of not applicable tweets included posts such “Britain braces for election gridlock” or tweets about knee braces. If the tweet was classified as applicable, the text advanced to the second classifier, which determined whether the tweet was an advertisement. If it was not an advertisement, the text was sent to the third classifier, which determined whether the tweet was neutral or expressed a strong sentiment. If the tweet was not neutral, it advanced to the fourth and final classifier, which determined whether the tweet expressed a positive sentiment or a negative sentiment.

Next, the corpus of 3,784 tweets was analyzed and evaluated for specific content. Frequently used words were incorporated into tables of indicator words and ratios. These indicator ratios showed how likely a specific word was to cause a tweet to be sorted into a certain category.[26] Frequently used words within each category offer insight into the content of the Twitter posts.

Figure 1. Classifying sequence



Statistical methods

Chi-squared tests were employed to identify significant differences in the proportion of advertisements and the distribution of positive and negative tweets between braces and Invisalign® tweets. All analyses were performed in Statistical Analysis System (SAS) EG v6.1.[30, 31] The Kappa statistic was used to determine agreement between the two sets of human-sorted tweets and the agreement between the human-sorted tweets and the program-sorted tweets. Suggested interpretation of Kappa statistics classifies κ from 0.80-0.90 to be strong and $\kappa>0.90$ to be almost perfect.[32]

RESULTS

Over a five-month period a total of 477,054 tweets were collected, of which 419,363 were applicable to orthodontics. Many more tweets contained the word “braces” (96%) than “Invisalign” (4%).

Figure *2* is a flow chart of all collected tweets and their classification. Tweets not applicable to orthodontics made up 12% (57,691) of all collected tweets and were excluded. Among the applicable tweets, advertisements made up 8% (34,819). The remaining 92% of the tweets applicable to orthodontics were assumed to be from orthodontic patients or people interested in orthodontics. Next, 53,677 tweets were classified as neutral and filtered out. The remaining subset contained 330,867 positive and negative tweets about the orthodontic experience.

In order to compare and contrast the two treatment modalities, the flow chart was separated into the two categories: braces (Figure *3*) and Invisalign® (Figure *4*).

Figure 2. Overall Flow Diagram Results

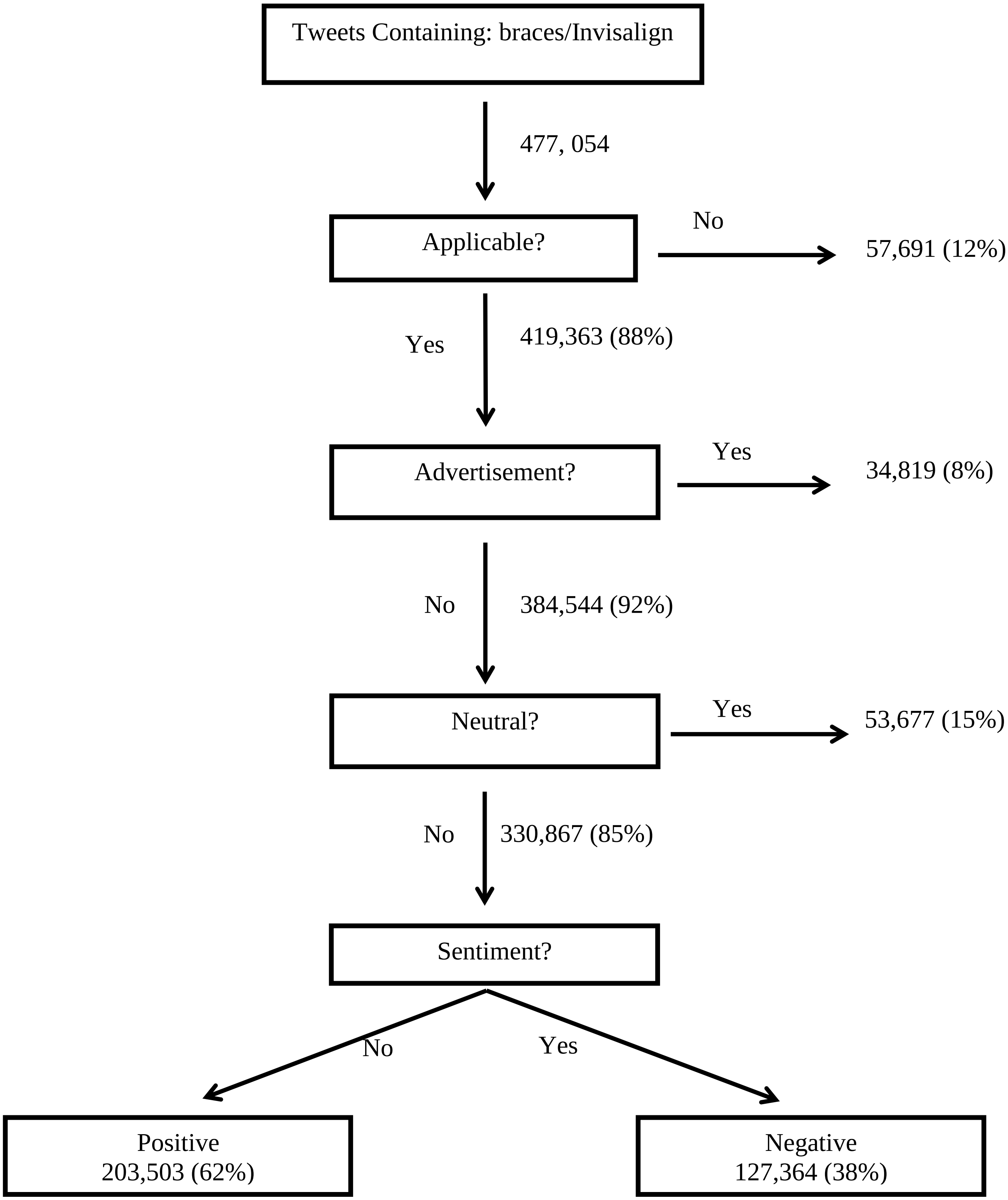


Figure 3. Braces Flow Diagram Results

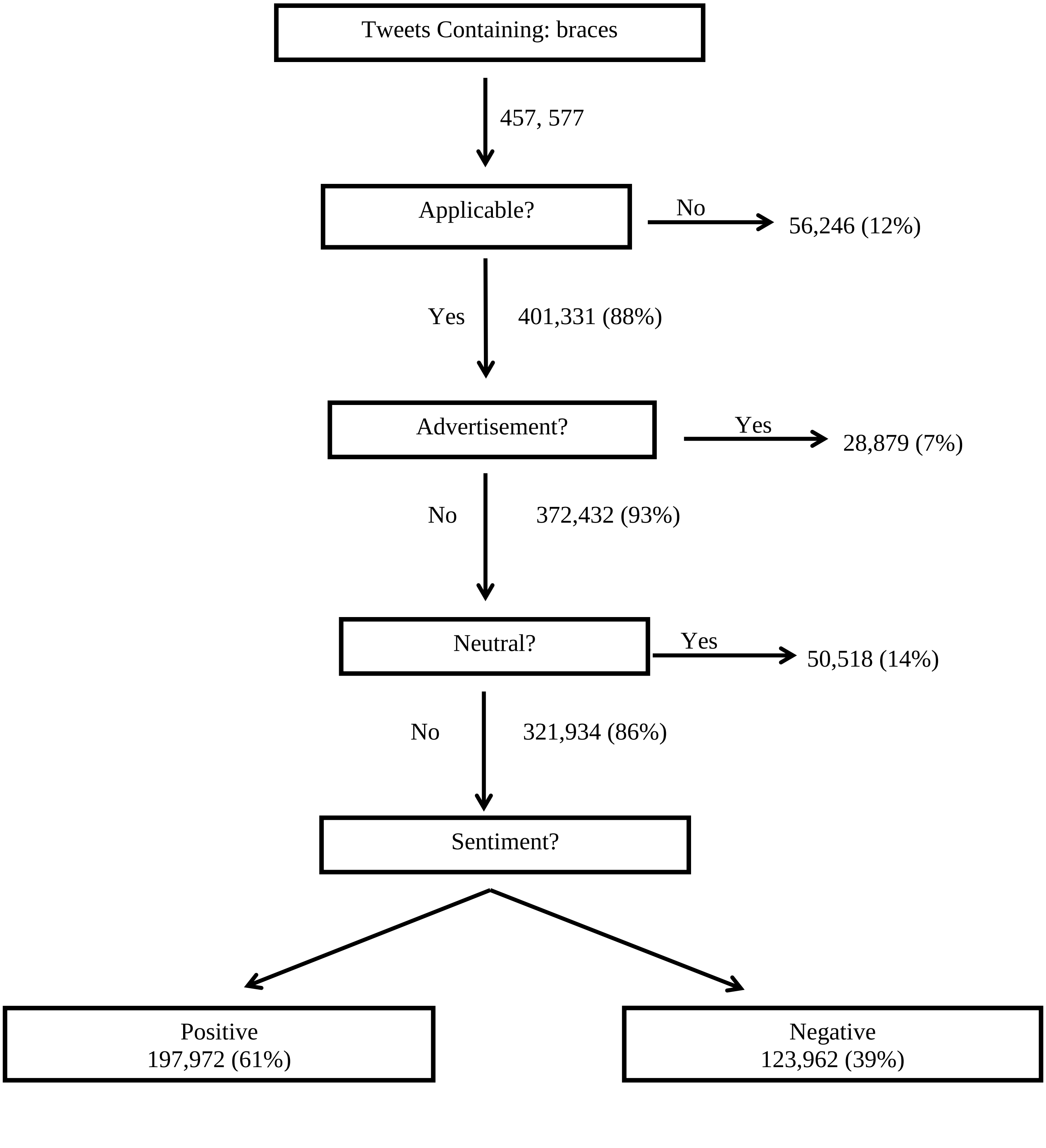


Figure 4. Invisalign® Flow Diagram Results

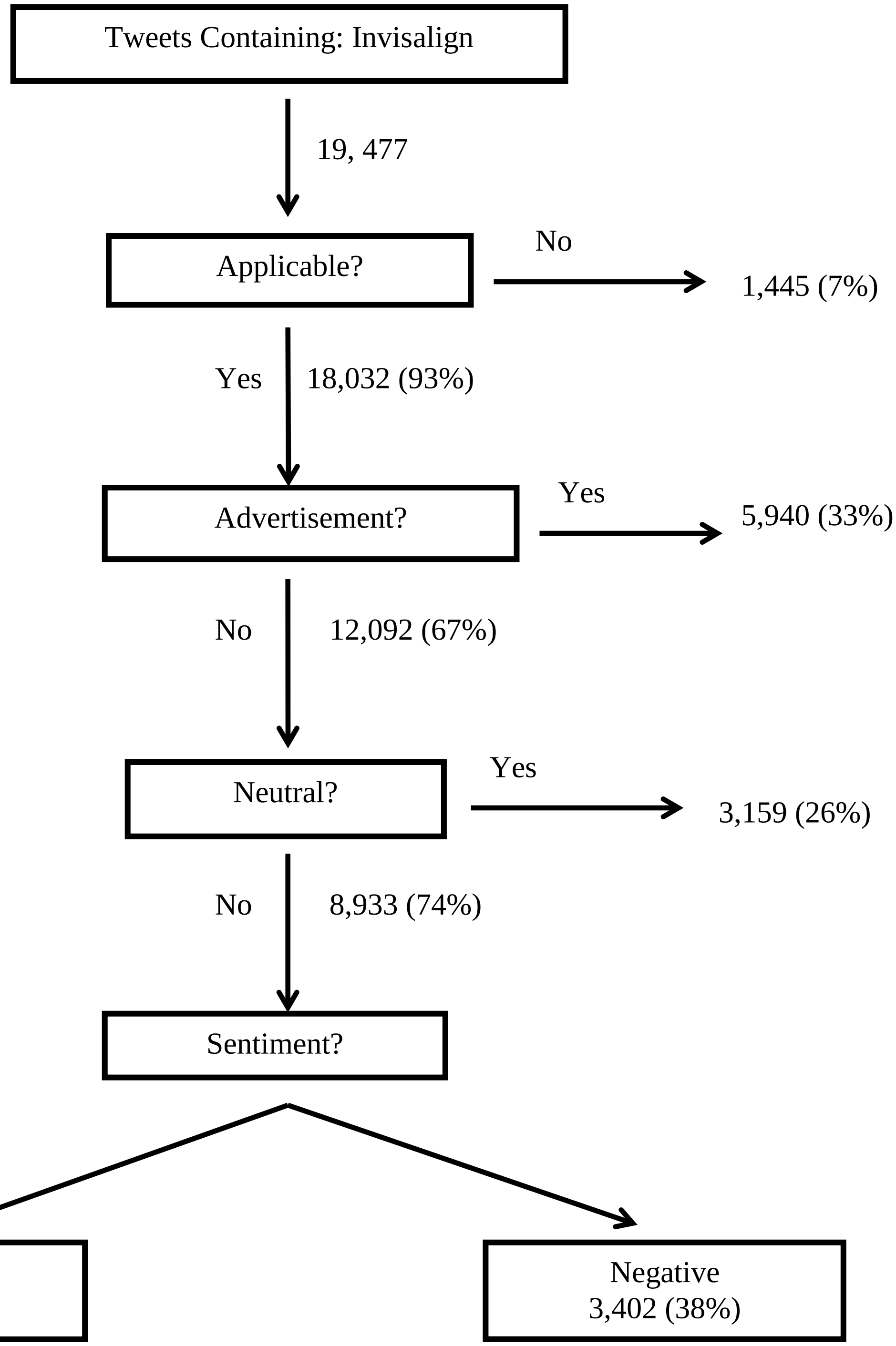


Table *1* shows a breakdown of the "not applicable" and "applicable" indicator words among the 3,784 braces and Invisalign® tweets that were analyzed for specific content. For example, "weather" commonly showed up in tweets that were classified as not applicable. If the word "weather" appeared in a tweet from this subset, it was 76.2 times more likely to be classified as "not applicable" than "applicable." In contrast, the word "teeth" was 47.4 times more likely to be classified as "applicable" to orthodontics.

Table 1. Not Applicable/Applicable Indicator Words

Not Applicable	
Indicator Words	**Not Applicable : Applicable**
weather	76.2 : 1.0
severe	34.9 : 1.0
#suspenders	28.7 : 1.0
#menswear	27.1 : 1.0
#fashion	11.6 : 1.0
Applicable	
Indicator Words	**Applicable : Not Applicable**
teeth	47.4 : 1.0
off	46.4 : 1.0
want	13.9 : 1.0

Advertisements

There was a significant difference in the proportion of advertisements between Invisalign® and braces tweets (p-value<0.0001), with 33% of Invisalign® tweets being classified as advertisements and only 7% of braces tweets classified as such (Figure *5*). Despite this difference in proportion, a greater number of braces advertisements (28,879) were collected than Invisalign® advertisements (5,940). Table *2* displays the total counts and percentages for each category.

Table 2. Distribution of Advertisements for Braces and Invisalign® Tweets

	Advertisement	**Not Advertisement**
Invisalign	5,940 (33%)	12,092 (67%)
Braces	28,879 (7%)	372,452 (93%)

Figure 5. Distribution of Advertisements for Braces and Invisalign®

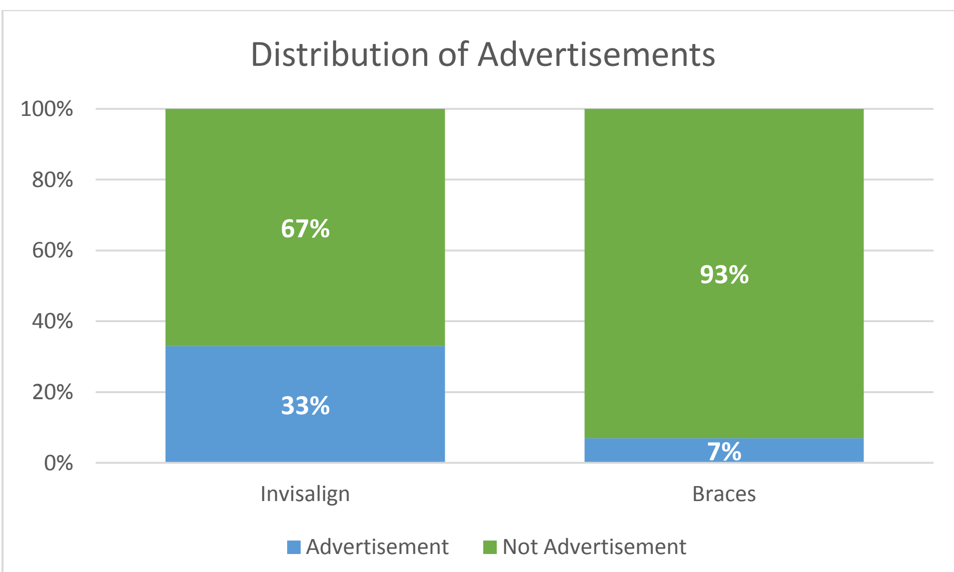


Table *3* presents the indicator words for the advertisement tweets broken down between braces and Invisalign® tweets. The indicator words listed in the table were much more frequently found in tweets that were classified as advertisements than non-advertisements. In contrast to Table *1*, the indicator words in Table *3* has a braces column and an Invisalign® column to compare and contrast the advertising differences between the two groups. Among braces tweets, a post containing "smile!" was 31.1 times more likely to be classified as an advertisement than not an advertisement. Among Invisalign® posts, a tweet containing the word "offer" was 8.3 times more likely to be classified as an advertisement than not an advertisement. Orthodontic advertisements often contained words like smile, offer, whitening, clear, alternative, open, and website links.

Table 3. Advertisement Indicator Words

Advertisements			
Braces		**Invisalign®**	
Indicator Words	**Ad : Not Ad**	**Indicator Words**	**Ad : Not Ad**
smile!	31.1 : 1.0	offer	8.3 : 1.0
straight	26.5 : 1.0	whitening	7.2 : 1.0
traditional	21.9 : 1.0	alternative	7.2 : 1.0
offer	19.6 : 1.0	#smile	6.2 : 1.0
#beauty	17.3 : 1.0	open	6.1 : 1.0
free	14.5 : 1.0	http:…	5.0 : 1.0
clear	14.3 : 1.0	start	3.9 : 1.0
		today!	3.9 : 1.0

Sentiment

Sentiment was then analyzed after separating tweets into the two main categories of braces and Invisalign®. The distribution of positive and negative sentiment within each category is presented in Figure 6. There was no significant difference in the distribution of positive and negative tweets for braces compared to Invisalign® (p-value=0.4189), as 38% of Invisalign® tweets were classified as negative and 39% of braces tweets were classified as negative. Therefore, the null hypothesis that there is no difference in sentiment between tweets about braces and tweets about Invisalign® was not rejected.

Among all braces and Invisalign® tweets that expressed polarity, there were significantly more positive tweets than negative tweets (p-value<0.0001), as 62% of polarized tweets were positive and 38% were negative.

Table *4* displays the total counts and percentages for each category. Table *5* displays a breakdown of indicator words for the positive and negative tweets. "Thank," "#smile," "#selfie," and "😁" were commonly found in the positive tweets. Negative tweets contained the words like hate, pain, food, rubber, lisp, ugly, retainers, and broke. The word "thank" was 6.4 times more likely to be classified as positive than negative. In contrast, the word "hate" was 26.5 times more likely to be classified as negative than positive.

Figure 6. Distribution of Sentiment for Braces and Invisalign®

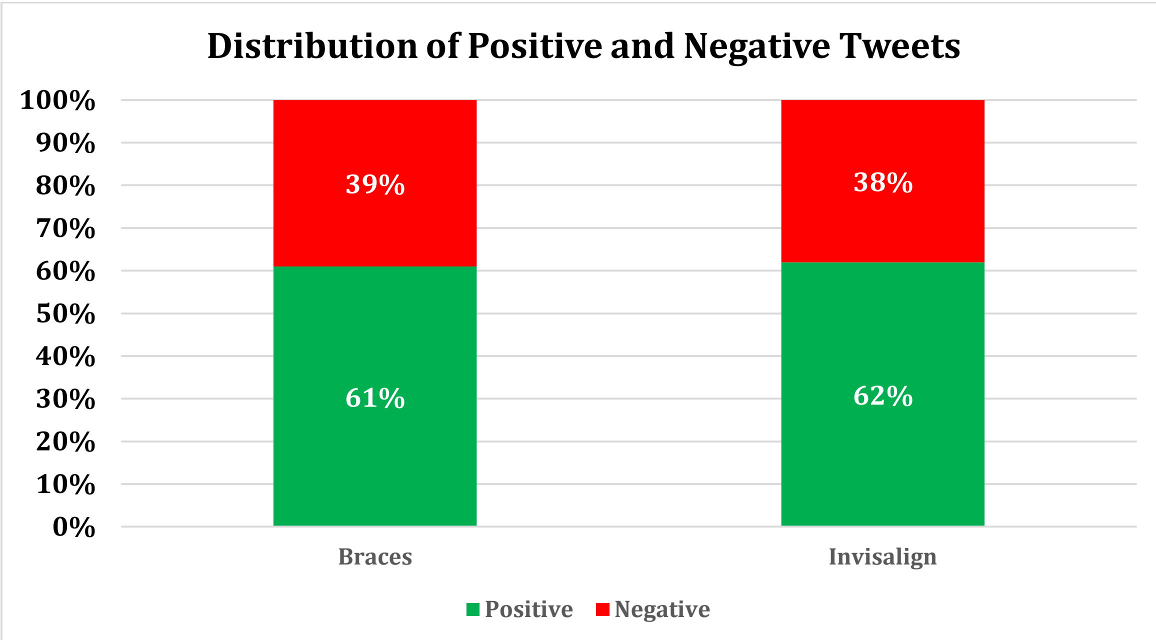


Table 4. Distribution of Sentiment for Braces and Invisalign® Tweets

	Positive	**Negative**
Invisalign	5,531 (62%)	3,402 (38%)
Braces	197,792 (61%)	123,962 (39%)

Table 5. Sentiment Indicator Words

Positive	
Indicator Words	**Pos : Neg**
thank	6.4 : 1.0
#smile	6.0 : 1.0
#selfie	4.7 : 1.0
😬	3.7 : 1.0
Negative	
Indicator Words	**Neg : Pos**
hate	26.5 : 1.0
pain	17.5 : 1.0
hurts	13.5 : 1.0
food	8.5 : 1.0
rubber	7.5 : 1.0
lisp	6.5 : 1:0
ugly	6.5 : 1.0
school	5.7 :1.0
retainers	5.5 :1.0
broke	5.5: 1.0
bands	5.5 :1.0
sick	4.5 :1.0

Agreement

In order to test the agreement between human sorters, a total of 1,098 common tweets was sorted by two independent individuals. The inter-rater agreement between the two human sorters was strong (κ=0.81). Table *6* contains the breakdown of their classifications. The first column of Table *6* shows the 340 of the tweets from the subset that Human 1 classified as advertisements. Among these 340 tweets, Human 2 classified 324 of them as advertisements, six as not applicable, seven as neutral, and three as positive.

The agreement between the human sorting and the program sorting was found to be almost perfect (κ=0.97). The human-program sorting agreement is presented in Table *7*.

Table 6. Human-Human Sorting Agreement

		Human 1 Classifier				
		Ad	N/A	Negative	Neutral	Positive
Human 2 Classifier	Ad	324	10	0	19	12
	N/A	6	261	0	16	2
	Negative	0	2	88	10	5
	Neutral	7	6	12	161	33
	Positive	3	1	4	16	100

Table 7. Human-Program Sorting Agreement

		Human1 Classifier				
		Ad	N/A	Negative	Neutral	Positive
Program Classifier	Ad	631	1	0	2	3
	N/A	4	140	0	0	0
	Negative	0	0	81	0	0
	Neutral	0	1	0	106	7
	Positive	0	0	0	0	102

DISCUSSION

Researchers can access the publicly available insights from social media users. As social media grows in popularity, the database of information available for research increases significantly. While investigating migraines, Nascimento *et al*.[14] detailed the incredible power of social media research in the healthcare industry by collecting "headache" tweets over seven days. Their methods reduced the experimenter-induced error and memory bias inherent in large epidemiological studies by exploiting the spontaneous data gathered from Twitter. Ahlwardt *et al*.[21] and Heaivilin *et al*.[22] showed that similar techniques can be applied to the dental field. With over 2,700 orthodontic-related Twitter posts made each day, a wealth of information related to the orthodontic industry is constantly expanding.

This study expanded on the findings of Henzell *et al*.[23] who concluded that orthodontic patients tweet positive and negative feelings about their treatment. Improvements upon their study design consisted of automatic classification, quantitative analysis, more specific content breakdown, and a much larger collection of tweets. These improvements allow for a more comprehensive and informative investigation.

Interestingly, no difference in positive and negative sentiment was found between braces and Invisalign® tweets. Align technology advertises Invisalign® treatment as offering an improved patient experience over braces, emphasizing, "virtually invisible teeth-straightening" with fewer irritations.[33] Miller *et al*.[24] found that Invialign patients experienced less discomfort, while Shalish *et. al*.[25] found more mixed experiences between braces and Invisalign patients. The results of this Twitter study did not support any difference in the perception of the patient experience between the two treatment modalities.

Overall, the majority of tweets expressed positive sentiments. Many users expressed gratitude for their orthodontic treatment, using the word "thank" to express appreciation for their new smile. Many of the positive "#selfie" tweets were accompanied with photographs of patients showing their new smile shortly after removal of braces. This finding demonstrates that appliance removal defines an important day in the life of patients. Additionally, these moments are important for the orthodontic practice, as social media can be viewed as word of mouth on steroids. Practices can encourage patients to post their "selfies" on the practice's social media pages.

The negative tweets give insight into the frustrations of orthodontic treatment. Many users expressed their dislikes and complained about the pain from orthodontic treatment. Others bemoaned the challenges of eating restrictions and the challenges of wearing rubber bands. Lisps developed from Invisalign® aligners were another objection, while some patients thought their braces were "ugly." Retainers and broken appliances were other sources of irritation. Some patients said they were "sick of braces." Orthodontic providers need to have a thorough understanding of these common negative reactions to treatment in order to improve the orthodontic patient experience.

The breakdown of indicator words offers valuable insight in the content of each category of tweets. Among the non-applicable tweets, many concerned severe weather, as in "California braces for the storm." Other non-applicable tweets were from the menswear industry, which advertised braces for suspenders. Interestingly, the word "off" was found in tweets applicable to orthodontic treatment at a ratio of 46.4:1; however, it was not found in the negative or positive list of Table *1*. While some users excitedly tweeted about getting their braces off, others complained that their orthodontist won't take off their braces. Therefore, a tweet containing the word “off” was almost always applicable to orthodontics, but the sentiment of the tweets was as likely to be positive as negative.

Orthodontic advertisements on Twitter emphasized smiles. Advertisements often contained the word “offer.” Some of these tweets stated the services offered by the office, and others announced special offers to begin orthodontic treatment. Advertisements for braces sometimes detailed the advantages of “traditional” braces, while others attempted to attract new patients by showcasing “clear” braces. Among the Invisalign® tweets, the word “alternative” was often used. Some of these Invisalign® advertisements emphasized the product as an “alternative” to traditional orthodontic treatment and highlighted the advantages of Invisalign®. Some advertisers offered “whitening” along with Invisalign® treatment. Others encouraged prospective patients to “start today!” Some providers distributed practical information like hours of operation and practice website links.

The word “braces” was tweeted 24 times more than “Invisalign” over the 5-month collection period. Some of this discrepancy can be explained by the demographics of orthodontic patients and Twitter users. More orthodontic patients are treated with traditional appliances than clear aligners, particularly among teenagers who use Twitter more frequently than adults. [34] [35] Nevertheless, it was still surprising that the quantity of braces tweets was so much greater than the quantity of Invisalign® tweets.

One limitation of the study was that only the subset of 3,784 tweets was examined for specific content and not the entire database of collected tweets. Additionally, an assumption was made that any tweet that was applicable to orthodontics and not an advertisement, was about the orthodontic patient experience. Some tweets could have been from non-patients merely expressing their thoughts on braces or Invisalign®.

This study demonstrated a way to utilize the abundance of publicly available information on social media platforms like Twitter. Future studies can utilize similar methods to examine other aspects of the orthodontic patient experience.

CONCLUSIONS

- Twitter users share more positive orthodontic experiences than negative experiences
- There is no significant difference in positive and negative sentiment between tweets about braces and tweets about Invisalign®
- Negative orthodontic-related tweets feature complaints about pain, rubber bands, lisps, and poor esthetics.
- Positive orthodontic-related tweets often highlight gratitude for a great smile accompanied with “selfie” photographs.

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