What Are People Tweeting About Mail-Order Aligner Options?

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THESIS

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LIST OF ABBREVIATIONS

AJODO	American Journal of Orthodontics and Dentofacial Orthopedics
API	Application Programming Interface
FOA	Fixed Orthodontic Appliances
LIWC	Linguistic Inquiry and Word Count
MOAO	Mail-Order Aligner Options
NLP	Natural Language Processing
SDC™	SmileDirectClub™
UIC	The University of Illinois at Chicago

SUMMARY

This study investigated the language that Twitter™ (San Francisco, CA) users used in 2018 when talking about braces, orthodontists, or orthodontics and compared it to the language they used when talking about mail-order aligner options (MOAO). The content of 50,000 tweets containing one or more of eight keywords were collected on randomly selected days in 2018 to create a body of tweets pertaining to braces/orthodontics and a body of tweets pertaining to MOAO. These tweets were analyzed using two computerized natural language processing (NLP) methods. The results of these analyses showed that, in 2018, significantly more positive or neutral language was used in tweets about MOAO than tweets about braces/orthodontics. Significantly more negative language was used in tweets about braces/orthodontics compared to tweets about MOAO. This suggests that MOAOs are gaining a positive public perception online. The orthodontic profession should be aware of how they are perceived online and be proactive in managing their reputation and the patient experience.

1. INTRODUCTION

1.1 **Background**

The ability for consumers to purchase clear tooth-aligning trays through the mail is a relatively new development. The more traditional route to straightening one's teeth has been through in-person visits with a dentist or orthodontist and the use of bonded orthodontic braces or doctor-designed clear aligners. Patients now have the option to order aligners from their computer, pay less money (on average) and never leave their home while attempting to straighten their own teeth.

There is minimal to no research available on the public perception of these two options. This is a void that the present study will begin to fill.

1.2 **Purpose of the Study**

The purpose of this study is to analyze and interpret the language people are using on Twitter™ (San Francisco, CA) to describe their perception of braces, orthodontists, or orthodontics and compare it to the language people are using when describing their perception of mail-order aligner options.

1.3 **Significance of the Study**

This study is significant because:

(1) There is minimal to no research available in this area.

(2) The increased prevalence of mail-order aligner options is a recent development.

(3) The results may inform orthodontists and mail-order aligner options how they are perceived online. This study will expand these groups' understanding of the public perception of their businesses.

1.4 **Null Hypothesis**

The null hypothesis is that the language used in tweets about braces, orthodontists, and orthodontics is no different than the language used in tweets about mail-order aligner options.

2. REVIEW OF THE LITERATURE

2.1 History of Mail-Order Aligner Options

In 1997 the use of clear aligners for orthodontic tooth movement began to gain popularity. Invisalign® (Align Technology, Inc, San Jose, CA) was introduced into the market that year.[1] Over the next two decades the use of clear aligners became routine in orthodontic practice with approximately 8% of the 3 million new orthodontic cases in North America being treated with Invisalign® products. By 2018, Align Technology was reporting $1.6 billion in annual sales.[2]

The availability of mail-order aligners is a relatively new phenomenon.[3,4] In 2014, SmileDirectClub™ (SDC™) (Nashville, TN) became the first option available in the United States.[4] Their model is to send at-home impression kits directly to prospective patients. Those impressions are sent back to SDC™ where they claim a licensed dentist or orthodontist reviews the case before aligners are sent to a patient. Treatment lasted, on average, six months and, in 2018, cost $1,850 (or $2,170 if financed over 24 months).[5] By 2018, SDC™ had established approximately 150 physical stores where prospective patients could begin the process with a digital scan rather than mailing in their impressions. They were estimated to have over 300,000 customers as of October, 2018.[6]

In the United States, the closest competitor to SmileDirectClub™ is Candid Co™ (New York, NY) which launched in September, 2017.[4] Candid Co™ began by offering at-home impression kits, then opened their first two physical locations in New York City. They plan on having 75 locations by the end of 2019.[7] Their model is to have orthodontists only (not general dentists) review cases.[8] Additionally, they employ orthodontists and dental assistants to work in their stores. Their treatment prices are very similar to SDC™. They advertise their treatment cost at $1,900 (or $2,112 if financed over 24 months).

There are several other companies in the US with very similar business models to SmileDirectClub™ and Candid Co™. Two of these companies are Smilelove™ (Holladay, TN) and Orthly™ (Philadelphia, PA). Smilelove™ opened in August 2017. They operate solely via patients sending in impressions and Smilelove™ sending back aligners. There are no physical locations.[9] Smilelove™ charges $1,895 per case if paid in advance. As with other companies, it is more expensive to finance over 24 months.

Orthly™ launched in February, 2017[10]. They market themselves as superior to other mail-order aligner companies because they require at least one visit to a partnered dental office.[11] At that visit an initial scan is performed and an exam is completed by the dentist or orthodontist. Most cases will receive their aligners in the mail and complete treatment remotely. However, if a case requires interproximal reduction or a restoration prior to treatment, the patient is asked to return to the dentist. The cost of treatment is $1,900 for simple cases and $2,600 for complex cases. Again, there is a slight increase in cost if financed over 24 months.

The United States is not the only country where mail-order aligners are available. Internationally, the most prominent option is YourSmileDirect™, located in Dublin, Ireland.[3,12] They will either deliver impression kits via the mail, or prospective patients can visit one of their four physical locations in Ireland, the United Kingdom, or France. They will ship impression kits and aligners to 36 countries around the globe. They charge 99€ ($112 US dollars) for an impression kit and 1,799€ ($2,039 US dollars) per case (with monthly payment plans available).

2.2 **<u>The Use of Twitter™ in Healthcare Research</u>**

Twitter™ (San Francisco, CA) is a social media website that first launched in 2006.[13] By 2018, the Twitter™ platform was used by 326 million people each month, with a volume of 500 million tweets sent each day.[14] The Pew study, *Social Media Use in 2018*, found that Twitter™ was the seventh most-popular social media site in the United States.[15] Pew reported that 45% of adults between 18 and 24 years old routinely use Twitter™. This percentage drops with age down to 14% for adults 50 years and older.

Twitter™ is a very popular form of communication worldwide. Many people share a broad range of their life experience on Twitter™, including their experiences accessing healthcare. There is some evidence that Twitter™ is the most popular platform used for healthcare communication.[16,17]

Medical professionals have capitalized on these online trends. Physicians and dentists have utilized Twitter™ to help spread accurate health information to the public.[16,18] Medical professionals use the site to exchange pertinent information and new research with one another.[19,20] The American Dental Education Association has suggested that the use of Twitter™ and other social media platforms in dental pedagogy could lead to deeper learning and higher student engagement.[21] Twitter™ data have been used to survey public health and facilitate rapid responses to disease outbreaks.[22,23] It has been proposed that the information patients share on Twitter™ can help identify adverse drug reactions.[24]

Twitter™ is a versatile tool with multiple healthcare applications. There are numerous examples of medical professionals learning from one another, teaching the public, and mining Twitter™ data to answer questions of interest to the medical community.[25] The present study will add to the growing body of literature.

2.3 **Natural Language Processing**

The words we use have meaning. Psychologists have long believed this. Sigmund Freud postulated in 1901 that words are so important, even the words that "slip" into our speech have profound meaning.[26] Throughout the decades since Freud, researchers and psychologists have continued to affirm that the words we choose to use reflect a deeper meaning or feeling within ourselves.[27–29]

Since the advent of computers and the internet, it has become possible to digitize a large amount of text and employ a computer to analyze that text. However, it is difficult to teach a computer to understand natural human language. For example, computers cannot read into the context of a statement or a sentence; the phrase, "You're so bad!" could mean multiple things, depending on context. Computers also cannot inherently understand colloquialisms we routinely use in speech; the phrase, “I’m feeling blue,” would not be interpreted as negative by a computer because blue is a color word. These are just some of the difficulties computers have when it comes to understanding human language.

Despite the inherent challenges, researchers have made huge strides teaching computers to analyze language. Employing a computer for this purpose allows people to evaluate large bodies of text. This field of computer science is called Natural Language Processing (NLP). NLP has been applied to a wide range of applications. It has been used in molecular biology,[30,31] weather forecasting[32,33] and city navigation.[34]

Over the last few decades, computers have been trained to perform helpful NLP analyses.[35] They are able to assist humans with assigning huge volumes of language (written or spoken) into categories (such as positive or negative categories for sentiment analysis).[36] If one wishes to disassemble a text (or even images)[37] into component parts and look at the structure of language differently (a process called parsing), this can be done on a large scale with NLP.[38] Computer models can also be employed to generate a summary of multiple texts that compares well with human-generated summaries.[39]

People have been very successful teaching computers/machines to read, interpret and understand human language. This study utilized two NLP tools to analyze a large volume of tweets related to the research question.

The first tool is known as Linguistic Inquiry and Word Count (LIWC). LIWC was developed by a group from the Department of Psychology at the University of Austin.[40,41] The purpose of LIWC is to provide a means to study the various emotional, cognitive, and structural components present in a large body of text. LIWC reviews all words in a text, compares each word to recognized dictionaries, and counts matching words that fall under different categories. The dictionaries have been vetted and verified through an extensive development and review process described by Pennebaker et al.[40] Other authors have found LIWC analysis to be a valid form of measuring verbal expression of emotion,[42] of analyzing human dream content[43] and of quantifying narcissism displayed in social media profiles.[44] The fourth and most recent version of the software, LIWC2015,[45] was employed for the analysis of the data by means described in the methods section.

The second tool was the utilization of a sentiment lexicon called AFINN. The AFINN lexicon was built specifically for use in Twitter™ sentiment analysis.[46] AFINN contains 2,477 words and phrases with different rankings of positive and negative sentiment. Words are ranked as integers between +5 and -5. +5 indicates a word with the greatest possible positive sentiment and -5 indicates a very negative word. The sum of the words in a set of text is used to determine the overall sentiment of the text. A sum greater than zero indicates positive sentiment, less than zero indicates negative sentiment, and exactly zero indicates neutral sentiment. AFINN was chosen from among four sentiment lexicons, as described in the methods.

2.4 **Review of Similar Studies**

There are few studies currently available in the orthodontic literature that evaluate the public perception of MOAO. There are primarily opinion-based and editorial articles to be found on the subject.[47–50] However, there are a number of studies that utilize language analysis of social media posts to answer an orthodontic-related question. Below is a review of studies of this type.

The authors of this first study, Livas et al., evaluated the information shared on YouTube™ (San Bruno, CA) concerning Invisalign® (Align Technology, Inc, San Jose, CA) treatment.[51] They aimed to (1) evaluate the completeness of information shared in the most-viewed YouTube™ patient testimonials, (2) determine the emotional content of viewer comments and (3) evaluate the patterns between video metrics (views, likes, dislikes, etc.), information completeness and the sentiment of viewer comments.

Livas et al. evaluated the most popular YouTube™ videos on Invisalign® and found that the completeness of information, video duration and time since upload had no effect on the number of views, likes, dislikes, subscriptions or comments. One of their conclusions was that the behavior of the YouTube™ audience is unpredictable. However, there is a large amount of activity on YouTube™ surrounding Invisalign® treatment. This study found significantly more positive comments about Invisalign®'s aligners in the viewer comments. Overall, these authors recommend caution when assessing orthodontic trends on YouTube™.[51]

In 2011, Knösel and Jung were also interested in YouTube™ video sharing.[52] They submitted an analysis of YouTube™ videos that pertained to orthodontics. Knösel and Jung found that there was a large audience on YouTube™ seeking orthodontic information. They noted that a lot of orthodontic patients posted YouTube™ videos and those seemed to get more views than videos posted by dental professionals. They deemed the informational content of videos to be low and reported that there was a poor-to-inadequate representation of orthodontics.[52]

Also in 2011, Heaivilin et al. published a study of Twitter™ users' experience with dental pain.[53] This group found that most tweets (83%) only offered a statement about how much their tooth hurt or how distressing the pain was. The next most common category of tweets (22%) described specific actions taken to address pain. The most common actions mentioned included seeing a dentist or taking some type of medication. The authors concluded that Twitter™ may be an interesting tool for evaluating public health. They speculated that there was the potential to identify need and determine appropriate action using – in part – data obtained from Twitter™.[53]

In a very interesting study, researchers out of Norway (Johnsen et al.) aimed to compare tweets about dentists to tweets about medical doctors.[54] They speculated that tweets about dentists would contain more negative emotion-related words and pain-related words than tweets about medical doctors. After collecting pertain tweets using a keyword search, the authors employed a tool known as Linguistic Inquire and Word Count (LIWC) to obtain proportions of negative emotion-indicating and pain-indicating words.

Johnsen et al. determined that more negative emotion words were used about dentists than doctors. Additionally, more pain-related words were associated with dentists than doctors. They also found higher proportions of anger, anxiety and sadness words in tweets about dentists compared to doctors. They concluded that their initial speculation was correct. They suggested that more could be done to reduce the negative associations and stereotypes that dentists had on Twitter™.[54]

A recent study published in the American Journal of Orthodontics and Dentofacial Orthopedics (AJODO) asked what people were tweeting about orthodontic retention.[55] The authors collected 660 tweets that they deemed pertinent to their study question. After reviewing and categorizing all tweets, they found that the negative social effects of wearing retainers, their impact on daily activities and the required maintenance composed a large portion of the content shared about orthodontic retainers on Twitter™. Overall, wearing one's retainers was portrayed in a negative light.[55]

A research group out of New Zealand (Henzell et al.) asked about patient experience with orthodontic treatment as reflected on Twitter™.[56] This group performed a qualitative analysis of orthodontic patients' experience using tweet content. They asked what New Zealanders were tweeting about their experiences as orthodontic patients and what that could tell us about the patient perception of having braces.

To accomplish this, they collected every tweet mentioning “braces”, “orthodontics” or “orthodontist” sent within 1,000 miles of Wellington (New Zealand’s capital). Since this was a qualitative study, the authors shared some examples of the tweets that fit in general categories and did not perform any quantitative analysis. They concluded that orthodontic patients in New Zealand tweeted both positive and negative things about their experience with braces. They reported that some negative views during treatment were counterbalanced by more positive thoughts near the end of treatment.[56]

Noll et al. utilized Twitter™ data to compare patient experience with braces to their experience with Invisalign®.[57] This group, which included a Boston-based computer engineer, created two custom software programs to analyze the approximately 500,000 tweets they collected.

These authors found that most tweets that expressed an emotion were positive whether the user was discussing braces or Invisalign®. In fact, there was no significant difference in the distribution of positive and negative tweets between the braces and the Invisalign® group. Most negative comments focused around painful teeth or discomfort while chewing. Most positive comments expressed gratitude for the patient’s new/improved smile. Overall, Noll et al. found no difference in the sentiments expressed in tweets about braces compared to tweets about Invisalign®.[57]

3. MATERIALS AND METHODS

3.1 **Data Collection**

All tweets were collected from the Twitter^{TM} Application Programming Interface (API). To collect tweets that pertained to public perception of braces or orthodontics, the keywords "braces", "orthodontist" and "orthodontics" were selected. To collect tweets that pertained to public perception of MOAO, the keywords "smiledirectclub", "candid co", "orthly", "yoursmiledirect" and "smilelove" were selected.

One hundred days in 2018 were selected at random (Supplemental Table I, Appendix B). Any tweet containing one or multiple of the eight keywords was extracted from the Twitter^{TM} API. Only the text of the tweet was collected. No Twitter^{TM} handles, profile pictures, location information, or other potentially-identifying information was collected.

For this first search, it was immediately evident that the phrase "braces for" would not generate an orthodontically-related tweet. Weather-related or news-related tweets often used this phrase (for example, "The east coast *braces for* storms" or "Theresa May *braces for* another no-confidence vote"). Therefore, the first search of Twitter^{TM} used the desired eight keywords while excluding instances of the phrase "braces for". This search resulted in the collection of 49,989 tweets.

These 49,989 tweets were examined manually. Three problems were identified:

(1) Several duplicate tweets and re-tweets were collected. All re-tweets and duplicates were removed from the data set.

(2) Removing the search term "braces for" was insufficient to eliminate a large number of unrelated tweets from the collected data set. Utilizing the methods of Noll et al., Heaivilin et al., and a provisional read of the data set, thirty-one additional problematic words/phrases were identified.[53,57] Tweets containing the 31 problematic words/phrases were removed from the data set (Table I).

(3) There were 18 instances in which a tweet contained a search term from both desired subject groups; tweets about public perception of braces/orthodontics and tweets about public perception of MOAO. Since this situation occurred only 18 times in the 49,989 tweets initially collected, the decision was made to remove those instances.

TABLE I

CLEANING THE TWEET DATA SET

31 keywords/phrases utilized to clean the initial set of collected tweets. A general reason/justification for the removal of all tweets containing these words/phrases is given.

Words/phrases tagged for exclusion	**Reason/justification for exclusion**
1. "offer"	High probability of being advertisements
2. "advertisement"	
3. "call us"	
4. "visit us"	
5. "contact us"	
6. "promotion"	
7. "alternative"	
8. "ankle braces"	Indicated different types of braces
9. "knee braces"	
10. "body braces"	
11. "arm braces"	
12. "leg braces"	
13. "thumb braces"	
14. "finger braces"	
15. "toe braces"	
16. "neck braces"	
17. "back braces"	
18. "braces himself"	Phrases routinely used in weather-related or news-related tweets
19. "braces herself"	
20. "braces themselves"	
21. "braces itself"	
22. "braces against"	
23. "braces up for"	
24. "curly braces"	Terms commonly used to discuss computer programming
25. "redundant braces"	
26. "semicolon"	
27. "java"	
28. "python"	
29. "suspenders"	Miscellaneous unrelated subjects
30. "beach braces"	
31. "porn"	

The result of the removal of duplicates/re-tweets, the striking of tweets containing the 31 words/phrases listed in Table I, and the deletion of the 18 tweets with keywords from multiple groups was the loss of 9,915 tweets. The cleaned data set consisted of 40,075 tweets. Of these, 39,400 were then assumed to be tweets about public perception of braces/orthodontics and 675 were assumed to be tweets about public perception of mail-order aligner options.

This data set was analyzed using two forms of computerized natural language analysis: (1) word count analysis and (2) sentiment analysis.

3.2 **Natural Language Analysis**

3.2.1 **Word Count Analysis**

For this analysis, it was first decided to analyze all tweets about braces/orthodontics as one corpus of language and analyze all tweets about mail-order aligner options as a different corpus of language. All the words from the tweets were compiled and divided into two files: tweets about braces/orthodontics and tweets about MOAO. The natural language processing software known as Linguistic Inquiry and Word Count (LIWC; pronounced "Luke") was employed.

3.2.2 **Sentiment Analysis**

For this analysis, an attempt was first made to train a custom program to categorize the 40,075 tweets into one of five categories: (1) positive, (2) negative, (3) neutral, (4) unrelated and (5) advertisement. A random sample of 1,400 tweets was manually sorted into these categories.

75% of those tweets were utilized to train various computer models and the remaining 25% were used to test the models. This is a method very similar to that used by Noll et al.[57] The best accuracy achieved with any of these trained computer models was less than 30%. Due to this low accuracy, it was decided to utilize an accepted sentiment lexicon for tweet categorization.

Four sentiment lexicons were utilized to classify the body of 40,075 tweets as either positive, negative, or neutral. These lexicons were AFINN,[46] Bing,[58] Harvard IV,[59] and Quantitative Discourse Analysis Package (QDAP).[60] All are commonly used lexicons[61–63] and have been previously validated.[64,65] The resulting analysis delivered from each lexicon after processing of the full body of 40,075 tweets varied minimally (Supplemental Figure 1, Appendix B).

To select a lexicon, all four were utilized to analyze the 1,400 manually-sorted tweets. The lexicon that most agreed with the manual sorting of tweets was AFINN. This lexicon matched 57.2% of the tweets to the manually-sorted categories. Bing showed a 56.8% match rate, the QDAP match rate was 46.5% and the Harvard IV match rate was 44.5%. AFINN was thereby chosen for the final analysis.

3.3 **Statistical Analysis**

For the word count analysis, proportions of positive emotion and negative emotion words were obtained. Proportions of words that deal with anxiety, anger and sadness were also obtained.

For the sentiment analysis, distributions of positive, negative, and neutral tweets in the set of 39,400 tweets about braces/orthodontics were obtained. The same was obtained for the set of 675 tweets about mail-order aligner options.

Descriptive statistics, Chi-squared tests and bar graphs were used to analyze the proportions. Statistical significance was set at 5%. For the data analysis, R Software[66] (R-Core team (2013). R: A language and environment for statistical computing. Jul 16, 2013) and SPSS Software[67] (IBM Corp. Released 2017. IBM SPSS Statistics for Windows, Version 25.0. Armonk, NY: IBM Corp) were used.

Figure 1 is a flow diagram summarizing the data acquisition and analysis methods

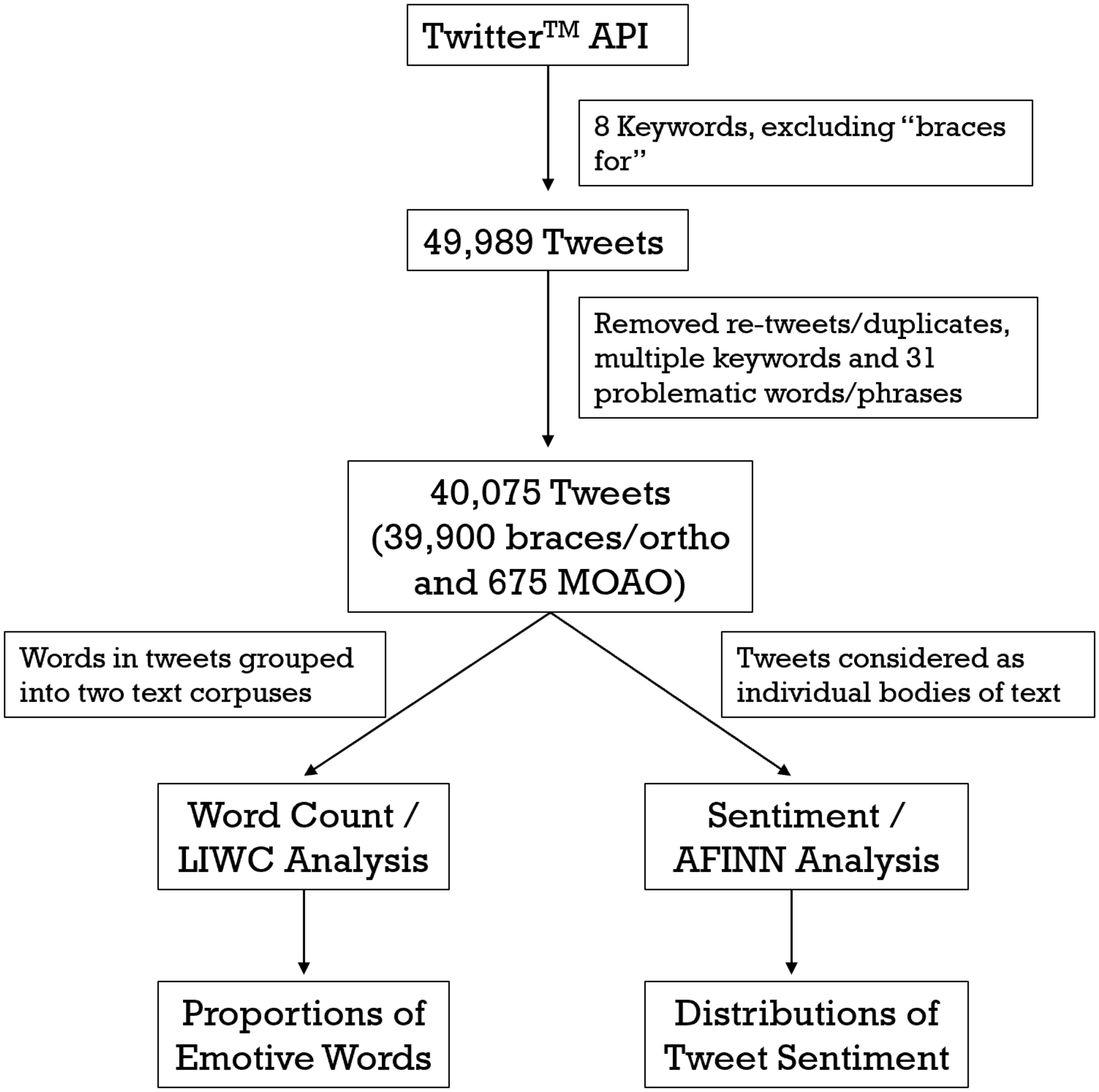

Figure 1: Flow Diagram of Data Acquisition and Analysis

4. RESULTS

4.1 Word Count Analysis

When all tweets about braces/orthodontics were combined into a single text file, they created a corpus of 542,787 words. When all tweets about MOAO were combined, they created a corpus of 8,695 words. After running the corpuses through the LIWC2015 software, 77.7% of words in the braces/ortho corpus and 70.6% of words in the MOAO corpus were matched to the LIWC internal dictionaries. The proportions of emotive words are presented in Table II and Figure 2.

TABLE II

PROPORTIONS OF EMOTIVE WORDS

Proportions (percentages) of emotive words identified in the LIWC analysis. All numbers are percentages of the total word count in the text corpus (542,787 words for Braces/Ortho and 8695 words for MOAO). Note that the proportions of anxiety, anger and sadness words are subcategories of negative emotion words. Positive emotion words have no subcategories in LIWC.

Sample	% Positive Emotion (PE)	% Negative Emotion (NE)	% Anxiety	% Anger	% Sad
Braces/Ortho Word Corpus	3.45	2.83	0.21	1.21	0.59
MOAO Word Corpus	12.69	0.99	0.06	0.23	0.21

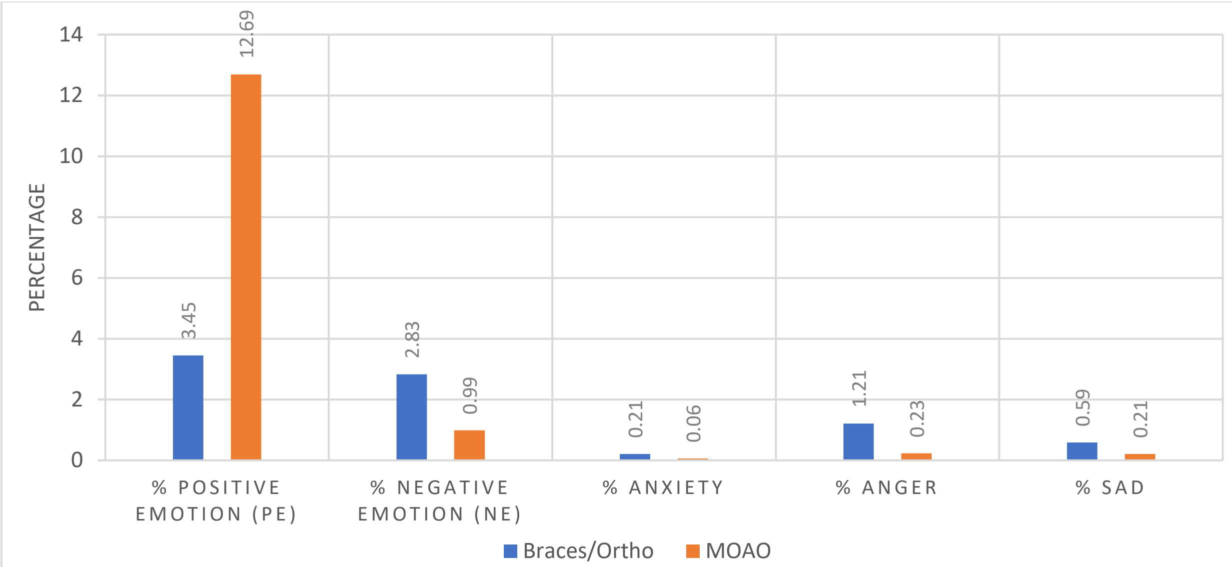

Figure 2: Proportions of Emotive Words. Obtained via LIWC analysis.

The proportions in Table II were analyzed and the results are presented in Table III. As can be seen in Table III, every comparison of proportions of emotive words was statistically-significant. A significantly greater proportion of positive words than negative words were used in tweets about either braces/ortho or about MOAO. When comparing those two groups, a significantly greater proportion of positive words were tweeted about MOAO and a significantly smaller proportion of negative words, anxiety-indicating words, anger-indicating, and sadness-indicating words were tweeted about MOAO.

TABLE III

TESTS OF STATISTICAL SIGNIFICANCE FOR LIWC WORD ANALYSIS

Proportions Compared	**X-Squared Value**	**p-value**
% PE Braces/Ortho vs % PE MOAO	2105.2	<0.001*
% NE Braces/Ortho vs % NE MOAO	105.75	<0.001*
% Anxiety Braces/Ortho vs % Anxiety MOAO	8.5789	0.003*
% Anger Braces/Ortho vs % Anger MOAO	68.806	<0.001*
% Sad Braces/Ortho vs % Sad MOAO	20.634	<0.001*
% PE Braces/Ortho vs %NE Braces/Ortho	455.32	<0.001*
% PE MOAO vs %NE MOAO	931.89	<0.001*

Significant values are marked with an asterisk (*).

4.2 **Sentiment Analysis**

The results of the sentiment analysis expressed as proportions of positive, negative, and neutral tweets as identified by the AFINN lexicon are presented in Table IV and Figure 3.

TABLE IV

AFINN ANALYSIS OF TWEET SENTIMENT

Proportions of positive, negative, and neutral tweets as identified by the AFINN lexicon.

Sample	**AFINN Sentiment**		
	% Positive	**% Negative**	**% Neutral**
Braces/Ortho Tweets	32.2	27.9	39.9
MOAO Tweets	40.1	10.1	49.8
% Difference	-7.9	17.8	-9.9

As described in the methods, the distributions of positive negative and neutral tweets were compared and the result is presented in Figure 3.

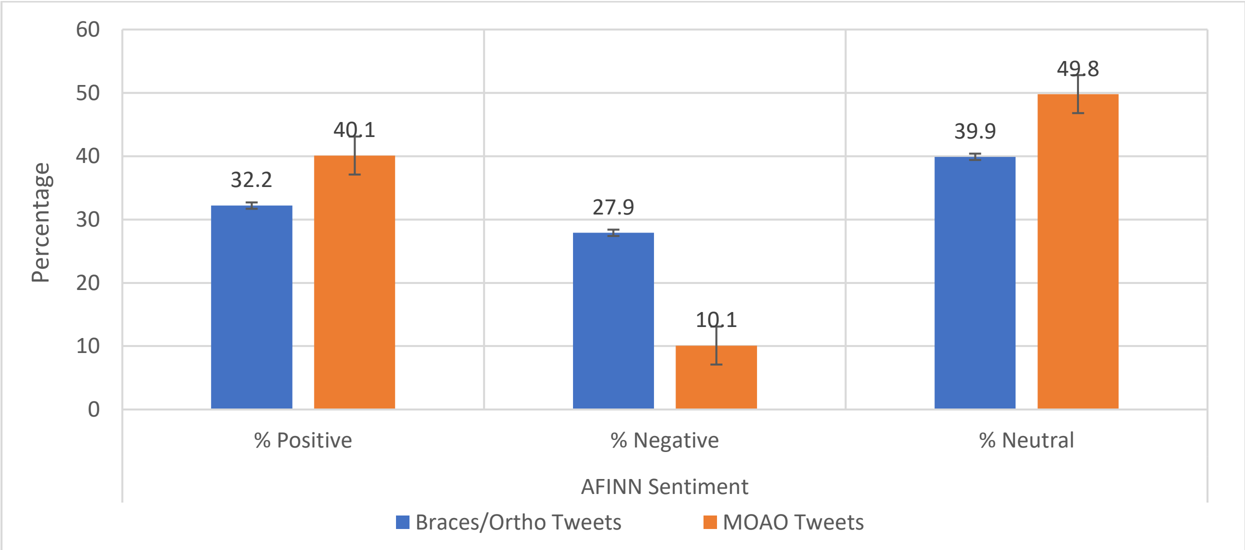

Figure 3: AFINN Analysis of Tweet Sentiment. Error bars represent 95% confidence intervals.

The distributions in sentiment were found to be statistically-significant (Chi-square = 105.156, p-value = 0.000). Tweets about MOAO were more often positive or neutral than tweets about braces/orthodontics. Additionally, tweets about braces/orthodontics were more often negative.

5. DISCUSSION

5.1 Comparison with Previous Studies

As discussed earlier, no previous study has expressly compared public sentiment about braces/orthodontics to public sentiment about mail-order aligner options (MOAO). There have been studies that compared patient experience with bonded braces to clear aligners. Since MOAO businesses offer clear tooth aligners, those studies offer an obtusely-related comparison.

One such study of braces versus clear aligners was done by Azaripour et al. in 2015.[68] These authors assessed gingival quality via examination and patient satisfaction via a custom questionnaire of 100 patients who were, on average, approximately one year into treatment with either bonded braces or with Invisalign®. They found that gingival/periodontal health was better in the Invisalign® patients than the patients with braces. They also found greater patient satisfaction in the Invisalign® group.[68] The results of the current study support the findings of Azaripour et al. Perhaps patient satisfaction with their clear aligners is the impetus for more positive and less negative sentiment among the MOAO tweets compared to braces/orthodontics tweets.

In 2016, Lin et al. published a study comparing fixed orthodontic appliances (FOA) to clear aligners on a patient's quality of life.[69] Matched and randomly-assigned groups (76 patients per group) were assessed at baseline, 6 months into treatment and 12 months into treatment. They utilized an Oral Impacts on Daily Performance (OIDP) assessment to evaluate any effects seen on patient's daily lives. They found that wearing clear aligners has less of an impact on daily life than wearing FOA.[69] If the results of this study are generalizable, then perhaps the greater negative sentiment seen in tweets about braces/orthodontics compared to MOAO can partly be explained. It should be noted that the Lin et al. study was retracted because one author did not give consent for publication and statistical errors were identified.[70]

Rosvall et al. compared metal braces to other “more esthetic” options, including clear aligners.[71] They utilized photos of the smile of a model with various metal brackets, ceramic brackets, an Essix® tray (to simulate clear aligners) and no appliances (to simulate lingual appliances). These photos were shown to 50 adults who were asked to evaluate the photos, rate attractiveness and acceptability of various options, and offer a price difference that they would be willing to pay for a more attractive/acceptable option (with metal braces as the baseline). While the fact that the questions in this study were designed to guide the 50 subjects to the assumption that the metal braces were the least valuable and least attractive may have introduced bias into the study, the subjects consistently rated the smiles with no brackets (lingual) and essix trays as the most attractive options for their treatment. Over 90% of the adults found clear trays or lingual braces to be acceptable forms of treatment and would pay a mean amount of $610 more for those appliances instead of traditional metal twin brackets. The adults felt this way when considering treatment for themselves or for their children.[71]

The results of the current study are partially consistent Rosvall et al.[71] The greater proportion of positive sentiment in tweets about MOAO (clear aligners) in comparison to braces/orthodontics could be an indicator that people find the clear aligners significantly more attractive and a more acceptable appliance to wear. However, based on the marketing efforts of the MOAO businesses, their customers are at least partly motivated to pay less than the cost of traditional metal braces. This nuance is somewhat contradictory to the findings of Rosvall et al.

It is worth noting that Walton et al. found that children between 12-14 years old preferred metal brackets with colored ties to clear aligners or ceramic brackets.[72] This preference reversed in older children, but it did demonstrate that clear aligners are not inherently more attractive than metal braces. Perhaps the attractiveness of appliances is not the only reason why there is a difference in tweet sentiment between the braces/orthodontics group and the MOAO group in this study.

Pacheco-Periera et al. evaluated patient satisfaction and quality of life before and after treatment with Invisalign®.[73] They did not compare Invisalign® with any other modality of treatment. They found increased patient satisfaction after treatment was mostly associated with improved esthetics and function (chewing). The doctor-patient relationship was also found to be important.[73] This component of their results is somewhat contradictory to the present study. People who elect to try a MOAO for orthodontic treatment will have little to no relationship with a doctor. The Pacheco-Periera et al. study would suggest that this might reduce patient satisfaction. That was not seen in the current study's results. Pain and food impaction were commonly cited sources of dissatisfaction in the Pacheco-Periera et al. paper. This finding is consistent with common themes present in negative tweets collected for the current study.

Miller et al. designed a study to evaluate the pain level and quality of life of adult patients with Invisalign® and adults with FOA over the first week of their treatment.[74] They reported that the patients with Invisalign® experienced less pain, took fewer analgesics, and described fewer negative impacts on their quality of life during their first week in treatment.[74] Fujiyama et al. also found that Invisalign® patients reported less pain over the course of treatment when compared to traditional braces.[75] Others have found similar pain-related results between removable and fixed orthodontic appliances.[76,77] If the pain and quality of life differences remain true throughout treatment, then this could explain some of the difference in tweet sentiment found between tweets about braces/orthodontics and those about MOAO. Indeed, a large number of negative tweets about braces referred to painful teeth.

The findings of Miller et al., Fujiyama et al., and others were somewhat contradictory to the findings of Shalish et al.[78] The latter followed adults for the first 14 days after appliance insertion (fixed buccal braces, Invisalign®, or fixed lingual braces). Shalish et al. found no difference in pain, analgesic use, or speech dysfunction after 14 days between buccal appliances and Invisalign®. They found the Invisalign® group to have greater pain than the braces group in the first day or two after appliance insertion.[78] The combination of these studies further obfuscates the role pain plays in patient experience between clear aligner patients and patients with FOA/braces. It is even less apparent how this would affect tweet sentiment shared about braces/orthodontics and about MOAO.

There are several instances of Twitter™-based studies on patient sentiment concerning braces. As reviewed earlier, the New Zealand study by Henzell et al. suggested thematic elements that patients tweet about their braces.[56] They did not seek to compare patient sentiment about braces to any other options. Additionally, their study was purely qualitative. However, the same themes identified in the Henzell et al. study were present in the tweets collected for the current study. Henzell et al. did suggest that "although some patients may hold negative views during treatment, these are often counterbalanced by more positive thoughts as treatment approaches completion and the final esthetic result is realized."[56] They did not expressly state that they found more positive than negative comments about braces because their analysis was qualitative. But the suggestion that, in tweets about braces, the positives outweigh the negatives (in terms of sentiment frequency) is supported by the current study.

The Noll et al. study offers the most interesting comparison to the current study.[57] Both are Twitter™-based. Both offer comparisons of tweet sentiment. The major difference is that Noll et al. compared tweets about braces to tweets about Invisalign® and this study compared tweets about braces/orthodontics to those about MOAO. The Noll et al. study analyzed differences in orthodontic appliance types and this study analyzed differences in business models.

Noll et al. found no difference between positive and negative sentiment in tweets about braces compared to tweets about Invisalign®.[57] This finding does not align with the significant differences found in the present study. Noll et al. did find that negative tweets often focused on pain and positive tweets on excitement about braces removal. Those findings are consistent with the current study. Additionally, Noll et al. found mostly positive sentiments expressed about both braces and Invisalign®. The current study did not find a majority of tweets to be positive but did find more positive than negative sentiment expressed about braces/orthodontics and about MOAO.

Overall, a comparison to Noll et al.'s results and the current studies results suggests that there is something attractive about the MOAO business model (not just the appliance offered) when compared to the traditional braces/orthodontics model. Perhaps the convenience of ordering from home and never (or rarely) visiting a dentist or orthodontist is leading to more positive tweet sentiment. Or perhaps Twitter™ users are more inclined to be pleased when discussing MOAO because they are happy about the money they believe they are saving. The current results leave open these types of interpretations.

The existing literature does not offer many firm explanations for the present results. Perhaps an expansion on this research will allow for more interesting comparisons.

5.2 Significance of Results

The results of this study have many implications. Overall, they suggest that, proportionally, MOAOs enjoyed more positive and less negative attention than braces/orthodontics on Twitter™ in 2018. This suggests that their business model may be gaining acceptance online, at least in this one social network. The public is more likely to tweet a negative sentiment about traditional orthodontic treatment (braces).

It is worth noting the huge disparity between the volume of tweets sent about MOAOs and the volume sent about braces/orthodontics. There were approximately sixty times more tweets collected about braces/orthodontics. One may conclude from this that the saturation on the public consciousness about MOAOs is significantly overshadowed by the traditional braces/orthodontics model.

Nonetheless, it would be prudent for the orthodontic community to be aware of the content shared online about new modalities of delivering orthodontic treatment. The legality of certain MOAO business models is being debated in specific states and across the country.[4,79–82] As the profession waits for legal opinions to be rendered, it would be wise to pay attention to public opinion. This study offered one means to assess public opinion. The orthodontic community may want to investigate this research question further and possibly direct a public awareness campaign toward Twitter™ users.

5.3 **<u>Study Limitations</u>**

There are a number of limitations to the present study. Firstly, the collection of tweets based off of keywords is inherently imperfect. The keywords selected for this study were aimed at collecting tweets about either braces/orthodontics or about mail-order aligner options. Eliminating unrelated words/phrases, duplicates, and tweets falling into both categories eliminated almost 20% of the original sample (9915/49,989 = 19.8%). A 20% error rate in collecting target data is inefficient.

Another keyword to consider using would have been “Invisalign.” Since Invisalign® was only a dentist- or orthodontist-provided product in 2018, the collection of tweets about that product would have given this study more insight into public sentiment about the range of services provided by orthodontists and dentists. The inclusion of this keyword could help narrow the data interpretation in this study. One could no longer assume that tweets about MOAOs might be expressing more positive sentiments because their customers feel that clear aligners are superior to more traditional FOA.

Additionally, only 675 tweets were collected about MOAOs. This is less than 2% of the total number of tweets used in the analysis. It may be that people tweeted about braces/orthodontics almost sixty times more often than they tweeted about MOAOs in 2018, or the initial keyword search may have been flawed. Perhaps searching for “smile direct club” in addition to “smiledirectclub” (and similar variations of the other MOAO keywords) would have generated more results and a more representative sample. Finding more creative ways to capture tweets about MOAOs would have been beneficial.

Some bias was likely introduced in the manual sorting of 1,400 tweets. These were all sorted by the primary author who is an orthodontic resident. It is conceivable that his interpretations of tweet sentiment was affected by his background in the profession of orthodontics. For example, many tweets included a variation of, “I can’t wait to get my braces off!” In the manual sorting, these were always categorized as positive because the tweeter was interpreted as excited to finish treatment. One could argue that a negative sentiment is being expressed in this type of tweet because the person tweeting may be lamenting the fact that they still have braces on their teeth. However, the author who did the sorting chose to label that type of tweet as positive.

This potential bias had very little impact on the results. In the end, the 1,400 tweets were only used to help select AFINN as the lexicon for sentiment analysis. There were minimal differences between AFINN and the other lexicons evaluated (Supplemental Figure 1, Appendix B), so the choice of lexicon had minimal impact on the final results.

One further step to reduce bias in the manual sorting of tweets would be to have a non-orthodontist, non-dentist reviewer manually-sort the 1,400 tweets. The introduction of someone outside the profession would decrease the likelihood of the introduction of bias into the study methods.

The amount of text present in each tweet is limited. The API only allows collection of the first 140 characters of a tweet. Twitter™ originally limited all tweets to 140 characters. This policy officially changed in November, 2017 when that character limit doubled for all users.[83] Unfortunately, the Twitter™ API still truncates tweets at 140 characters. Some of the tweets collected for this study were thereby incomplete. An estimated 30% of the tweets collected were greater than 140 characters and so data was lost at the end of those tweets.

The end of a tweet can contain emotive words/phrases. For example, “Dog these braces really ruining my life my mouth hurt so bad” or “Aww so cute…........OMG!!! No Braces!!! YAY!!! :D” both contain significant emotion near the end of the tweet. This loss of data in ~30% of tweets could be a significant limitation. It is possible that the lost content was particularly meaningful to overall tweet sentiment and could have affected our results.

Lastly, Twitter™ is an imperfect tool from which to generalize the entirety of public sentiment. In 2018, only 24% of adults reported using Twitter™ regularly.[15] Additionally, some researchers have cautioned against using tweet content in research because the content of a tweet can be very difficult to discern.[84] A large amount of message content shared on Twitter™ is contained in photos, videos, and links to other websites. Photos and videos were not collected via the Twitter™ API, and links to other websites were not investigated in this study, so in some instances context may have been lost.

5.4 **Future Studies**

Future studies should utilize the lessons learned in this study to refine search parameters/keywords to obtain a larger and more-refined set of tweets that are representative of the target subjects. To combat the loss of data at 140 characters, future studies could be designed prospectively. A prospective study can gather the full Twitter™ data utilizing any number of social media listening tools.[85] In this way, several of the limitations of the present study could be reduced.

Data could also be collected on the public profiles of the people sending the tweets. An interesting question to ask would be "*Who* is tweeting about mail-order aligner options?" A demographic survey through publicly-available Twitter™ data would help orthodontists and MOAOs understand who their patients/customers are.

Other questions pertinent to the orthodontic community could be asked utilizing similar methods as the present study. For example, the acceptability of premolar extractions, headgear compliance, or patient opinion of interproximal reduction.

Outside of social media platforms, future studies could analyze the language used in online reviews (like Yelp® or Google™) concerning MOAO businesses and orthodontic practices. The sentiment shared in online review website may differ from what people choose to share on social media. On a review website people know that their words are meant to inform other consumers. This type of study could provide very useful data.

We know that the internet contains a large amount of data. The volume of data grows larger each day. Sampling from that well of information in thoughtful ways could help the orthodontic profession answer some critical and timely questions about the way the profession is perceived online, how patients feel, and what patients want.

6. CONCLUSIONS

- In 2018, tweets about braces/orthodontics or about mail-order aligner options (MOAO) were generally more positive than negative.
- Tweets about MOAO expressed significantly more positive or neutral emotion than tweets about braces/orthodontics.
- Tweets about braces/orthodontics expressed significantly more negative emotion than tweets about MOAO. Words indicating anxiety, anger and sadness were more often found in tweets about braces/orthodontics.
- Both orthodontists and businesses offering mail-order aligners should be aware of how they are perceived online.
- More research needs to be done to refine Twitter™ search parameters and generate data from which to draw stronger conclusions.

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APPENDICES

Appendix A – UIC IRB Exemption

UIC

Notice of Determination of Human Subject Research

November 27, 2018

20181455-118966-1

Benjamin Youel
Orthodontics

RE: **Protocol # 2018-1455**
What are people tweeting about mail-order aligner options?

Sponsor(s): None

Dear Benjamin Youel:

The UIC Office for the Protection of Research Subjects received your "Determination of Whether an Activity Represents Human Subjects Research" application, and has determined that this activity **DOES NOT meet the definition of human subject research** as defined by 45 CFR 46.102(f).

Specifically, data will be collected by searching through publicly available tweets and retrieving applicable content.

You may conduct your activity without further submission to the IRB.

If this activity is used in conjunction with any other research involving human subjects or if it is modified in any way, it must be re-reviewed by OPRS staff.

cc: Jennifer Caplin

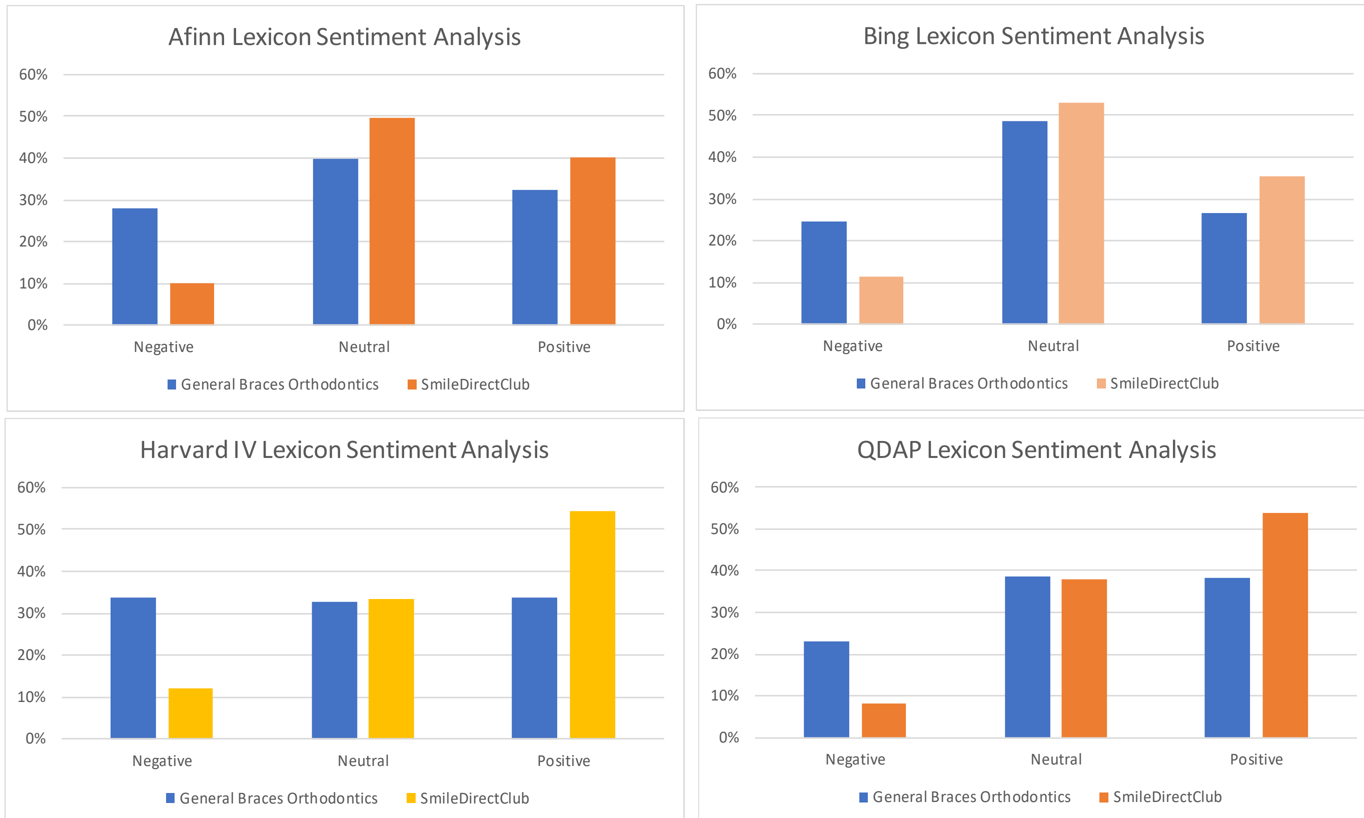
UNIVERSITY OF ILLINOIS AT CHICAGO
Office for the Protection of Research Subjects
201 AOB (MC 672)
1737 West Polk Street
Chicago, Illinois 60612
Phone (312) 996-1711

Appendix B – Supplemental Figures/Tables

SUPPLEMENTAL TABLE I

100 DAYS SELECTED TO GENERATE TWEET SAMPLE. THESE DAYS WERE SELECTED VIA AN ONLINE RANDOM NUMBER GENERATING APPLICATION.

1/1/2018	3/1/2018	5/2/2018	7/25/2018	10/13/2018
1/3/2018	3/6/2018	5/3/2018	7/26/2018	10/14/2018
1/12/2018	3/7/2018	5/5/2018	7/29/2018	10/16/2018
1/16/2018	3/9/2018	5/8/2018	8/6/2018	10/19/2018
1/18/2018	3/13/2018	5/21/2018	8/10/2018	10/26/2018
1/19/2018	3/14/2018	5/30/2018	8/21/2018	10/27/2018
1/22/2018	3/21/2018	6/10/2018	8/24/2018	11/4/2018
1/27/2018	3/22/2018	6/12/2018	8/27/2018	11/8/2018
1/28/2018	3/26/2018	6/17/2018	9/2/2018	11/9/2018
2/2/2018	3/27/2018	6/18/2018	9/8/2018	11/18/2018
2/4/2018	3/31/2018	6/21/2018	9/9/2018	11/19/2018
2/5/2018	4/3/2018	6/27/2018	9/10/2018	11/29/2018
2/11/2018	4/5/2018	7/2/2018	9/11/2018	12/2/2018
2/12/2018	4/13/2018	7/6/2018	9/12/2018	12/9/2018
2/15/2018	4/17/2018	7/9/2018	9/14/2018	12/13/2018
2/16/2018	4/19/2018	7/12/2018	9/17/2018	12/14/2018
2/17/2018	4/22/2018	7/13/2018	9/24/2018	12/18/2018
2/21/2018	4/23/2018	7/14/2018	9/27/2018	12/21/2018
2/24/2018	4/29/2018	7/15/2018	9/28/2018	12/29/2018
2/27/2018	5/1/2018	7/21/2018	10/10/2018	12/31/2018



Supplemental Figure 1: Analysis of Four Sentiment Lexicons. Note how minimally the results of these lexicons varied. The AFINN lexicon was ultimately utilized because it most accurately matched the 1400 manually-categorized tweets.

Appendix C – Raw Data

SUPPLEMENTAL TABLE II

LIWC2015 OUTPUT.

Filename	Segment	WC	Analytic	Clout	Authentic	Tone	WPS	Sixltr	Dic
Ortho Keywords Corpus.txt	1	542787	44.73	29.97	67.50	36.63	25.04	12.68	77.70
Other Keywords Corpus.txt	1	8695	59.13	60.49	25.29	99.00	18.74	35.20	70.60

Filename	function	pronoun	ppron	i	we	you	shehe	they	ipron
Ortho Keywords Corpus.txt	46.68	17.41	13.88	9.86	0.27	1.83	1.11	0.81	3.53
Other Keywords Corpus.txt	36.99	12.42	9.50	5.41	0.83	2.23	0.29	0.75	2.92

Filename	article	prep	auxverb	adverb	conj	negate	verb	adj	compare
Ortho Keywords Corpus.txt	3.47	10.50	6.81	5.45	5.37	1.29	16.05	4.19	2.04
Other Keywords Corpus.txt	3.38	7.80	6.07	5.32	3.73	0.90	11.88	3.40	1.47

Filename	interrog	number	quant	affect	posemo	negemo	anx	anger	sad
Ortho Keywords Corpus.txt	1.46	1.62	1.43	6.31	3.45	2.83	0.21	1.21	0.59
Other Keywords Corpus.txt	0.97	2.17	1.17	13.70	12.69	0.99	0.06	0.23	0.21

Filename	social	family	friend	female	male	cogproc	insight	cause	discrep
Ortho Keywords Corpus.txt	7.39	0.40	0.25	0.93	1.02	8.66	1.39	1.43	1.57
Other Keywords Corpus.txt	7.56	0.18	0.26	0.26	0.30	7.52	1.06	1.09	1.05

Filename	tentat	certain	differ	percept	see	hear	feel	bio	body
Ortho Keywords Corpus.txt	1.73	1.27	2.30	2.63	1.27	0.38	0.85	4.61	2.11
Other Keywords Corpus.txt	1.39	2.22	1.48	1.96	0.94	0.39	0.41	1.87	1.16

Filename	health	sexual	ingest	drives	affiliation	achieve	power	reward	risk
Ortho Keywords Corpus.txt	1.45	0.40	0.62	6.43	1.04	0.81	1.47	3.22	0.40
Other Keywords Corpus.txt	0.32	0.02	0.15	5.72	2.06	1.06	1.29	1.68	0.24

Filename	focuspast	focuspresent	focusfuture	relativ	motion	space	time	work	leisure
Ortho Keywords Corpus.txt	4.02	10.58	1.35	12.86	1.50	5.43	6.09	0.79	0.74
Other Keywords Corpus.txt	2.38	8.38	1.18	10.40	1.64	4.13	4.89	1.83	0.62

Filename	home	money	relig	death	informal	swear	netspeak	assent	nonflu
Ortho Keywords Corpus.txt	0.11	0.50	0.22	0.11	3.91	1.28	2.31	0.27	0.21
Other Keywords Corpus.txt	0.08	1.09	0.08	0.01	3.08	0.17	1.13	1.61	0.17

Filename	filler	AllPunc	Period	Comma	Colon	SemiC	QMark	Exclam	Dash
Ortho Keywords Corpus.txt	0.08	17.56	3.90	1.56	0.34	0.35	0.95	1.48	0.36
Other Keywords Corpus.txt	0.00	42.45	3.67	1.78	0.18	0.28	0.86	3.20	0.63

Filename	Quote	Apostro	Parenth	OtherP
Ortho Keywords Corpus.txt	3.21	0.79	0.34	4.29
Other Keywords Corpus.txt	3.54	1.01	0.25	27.04

VITA

NAME: Benjamin C. Youel

EDUCATION: B.S., Chemistry, North Central College, Naperville, IL, 2009

D.D.S., Dentistry, University of Illinois at Chicago, Chicago, IL, 2013

Certificate, General Practice Residency, Advocate Illinois Masonic Medical Center, Chicago, IL, 2014

HONORS: American College of Dentists Fellowship, 2017

Omicron Kappa Upsilon Honor Society, 2013

The International College of Dentists Leadership Award, 2013

Chicago Odontographic Society Walter E. Dundon Award for Clinical Excellence and Leadership, 2013

UIC Frances Best Watkins Award for Outstanding Leadership Skills and Academic Excellence, 2013

UIC Dr. Gerson Gould & Mr. Sol H. Gould Memorial Scholarship for Professional Growth in Managerial skills and Outstanding Performance in Four-Handed Dentistry, 2013

UIC John and Grace Nuveen International Award for Guatemala Dental Rotation, 2012

Academy of General Dentistry Scholarship to attend AGD 2012 Leadership Conference, 2012

UIC Frances Best Watkins Award for Outstanding Leadership Skills and Academic Excellence, 2012

NCAA Post Graduate Scholarship, 2009

Outstanding Chemistry Major, North Central College, Naperville, IL, 2009

ESPN The Magazine/CoSIDA Academic All-America Team, First Team, Men's At-Large, 2009

PROFESSIONAL	American Dental Association
MEMBERSHIPS:	American Dental Political Action Committee
	Academy of General Dentistry
	Chicago Dental Society
	Illinois State Dental Society
	Delta Sigma Delta International Dental Fraternity – Rho Chapter
	Omicron Kappa Upsilon Honor Society – Sigma Chapter
	American Association of Orthodontics
	American College of Dentists