

100✅😊: Positive Emoji Usage from Companies

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Introduction

The way brands and companies have utilized Twitter has changed over time. While some use the platform solely to promote press and interact with users, answering questions and responding to feedback, some companies are using it to promote themselves in a different light. By interacting with other companies (who would typically be considered their rival) responding to users in a joking way, and even using sarcasm, there has been an entirely new way of branding themselves in an interactive and relatable way. One theory is that this could be an attempt to appeal to an entirely different audience, and for free (McShane et al., 2020). If a tweet of theirs goes “viral” or they can directly interact with consumers in an impactful way, it would offer promotion and positive brand messaging.

A paper written by Cody Baker (2018) examines how a popular brand has gone “viral” through social media usage and interacting with other brands. This type of exposure and free marketing is a big attraction for brands to have an online personality and following base. They also point out a big aspect of Twitter: the dialogic loop that is part of the nature of the social media site (Cody Baker, 18). This loop includes interacting with users through conversations between users as well as less obvious communications, including retweets, quote tweets, and likes. All of this stimulates conversation and interaction between not just them but the people that are seeing these interactions.

Part of relating to younger audiences and getting across positive emotions and feelings includes the usage of emojis. This can be done in several ways, including choosing emojis that relate or represent what they are promoting, replacing words with emojis, or attempting to convey a specific sentiment using them. In particular, the emotion of the emoji is something that plays a part in our research question. If they rely mostly on emojis that convey specific emotion—joy, positivity, etc.—we can assume they may be using emojis with intention to convey that feeling or image to their audience.

By examining the emoji usage for 6 major companies on Twitter, we may be able to get insight on if this is in fact the case. We are looking at the brands/companies which all represent a slightly different industry and hopefully also have slightly different consumers. Additionally, they range in follower count, from 33.9k followers to 9.5M followers. Their own twitter interactions range greatly. Some companies largely respond to users while others use the site to promote their content. By scraping 100 of each of their tweets and filtering for emoji usage, we are hoping to be able to categorize if a portion of the emojis used convey positive emotions. Furthermore, human annotation will ideally allow us to double check our methods used and alter this for the future. If using filtering techniques proves to not be enough, this could inform how we approach this going forward.

Background

Emojis’ have a vital role in communication online today. Emoticons are used to react to statuses and posts, used in text to convey emotions, and can replace whole words or thoughts. The ways that this is studied has a few different motivations and methods to go about it. From a

branding perspective, utilizing emojis in direct communication or even promotions could point to an attempt at seeming relatable and putting forth a specific persona. This leads to sentiment analysis attempts that work to classify exactly what the author meant when using specific emojis—is it just a happy looking emoji or is there more to be read?

The first aspect to consider is why emoji usage is prevalent and how it plays into everchanging brand interactions. Consumer impression must certainly be a factor when deciphering the intention behind companies advertising as well as the platforms utilized. We have seen a decided shift in not only the types of advertising put forth but also the passive forms of advertising, such as using brand Twitter account and maintaining a certain level of direct consumer engagement. This is referred to as a dialogic loop, as explained in the paper written by Cody Baker. This increased level of discourse as well as accessibility for consumers to be passively observing advertising while on social media is of note to how branding has changed. In hand with this is the attempt to relate broadly to users on social media, which includes using more casual speech and using a range of emojis (Baker, 17). With this increase in emoji usage for brands comes a wider look into the trends and usage in gender, some of which is replicated in our study. Brandwatch published the 2017 Emoji Report, which was a comprehensive study analyzing emoji usage over the span of 2 years. It illustrated the importance of emojis in our current culture. They presented that emojis depicting a face have an inherent emotion—either positive or negative—that they portray and discussed how they are used amongst branding and in everyday interactions between people. For example, they can classify that this :flushed_face: emoji, 😊, conveys the emotion of surprise. They put forth the trends of businesses and how emojis play a part in their interactions, which helps set the stage for beginning to assume intention behind emoji usage.

This, though, may not consider how emojis are used by the public in unexpected or ironic ways. One that exemplifies this is the :skull: (💀) emoji—while this is categorized as negative using Brandwatch and Unicode’s lists, a user on Twitter might recognize that this is used to convey that someone found a comment funny or shocking, but certainly not in a negative manner as suggested. This is where further sentiment analysis can come in to give us a more accurate dive into emoji usage.

Felbo et al. (2017) recognized this gap, which was largely due to the limitations of human annotation. In order to go around this issue, they created a model that was trained using 1246 million tweets that each contained a common emoji, which is far more than possible when using human annotation. By doing so, they were able to make the DeepMoji model which is now accessible for other to implement and gives a tool for accurate sentiment analysis of words and corresponding emojis (Felbo et al. 2017).

With the ability to categorize emojis solely using computer interference, studying human trends of usage can go even further. Kejriwal et al. (2021) explores how emojis can have regional trends, with distribution being different across different countries and even states. This is important to remember when considering the emojis analyzed in this paper. The assumed meaning/emotional response desired can be different depending on the intended audience and more importantly where the brand is located. With many of the top brands being American based and all the tweets analyzed being in English, this could have some significance when making claims.

McShane et al. (2021) takes a broader look at the relationship between brands and emoji usage on Twitter specifically. They take statistical observations about the number of tweets from brands containing emojis rising in the past couple of years and use that basis as a hypothesis for their research. Their findings exhibit that there is indeed an increase in engagement in tweets that contain emojis as compared to tweets that do not (McShane et al., 97) and develop research that

give insight into why brands may choose to use emojis. Since being active on Twitter is another method of branding and publicity, it is likely that the use of emojis is tied to how they work to put across a positive brand message and create positive interactions between brand and consumer (McShane et al., 97). They also touch on different conditions of where the emoji lies in the tweet as being a factor, which is something I considered when doing my human annotations. Emojis are found in different parts of the tweet, such as before or after specific words to emphasize ideas, to replace words, or at the beginning or ends of tweets as a whole. Based on placement they were able to categorize the level of “playfulness” that this conveyed, which in turn increased engagement. This intention is important to consider when thinking about and observing emoji usage in companies, as this could generate different uses.

Methods

I will be scraping 100 original tweets and replies from a total of six companies. These companies have been chosen to represent a wide variety of industries present in the consumer world. I had to ensure that the brand I chose would have an adequate number of tweets when put through my filter, as some companies had a large number of replies to users questions/comments that did not contain emojis. Due to this, there was some trial and error in terms of how I chose my companies to ensure I had enough consistent data. Ultimately, I ended up with the 6 companies outlined in the table below. I took note of their Twitter username and follower count since that could have an impact on the number of interactions and type of content put forward. Additionally, I categorized each of their respective industries, as this could also have an impact on they purpose they have for maintaining an active Twitter account.

Table 1

Company	Twitter Username	Follower Count	Industry
Arby's	@Arbys	847.1 K	Food & Beverage
Airbnb	@Airbnb	758.9 K	Hospitality
La Croix	@lacroixwater	33.9 K	Food & Beverage
MLB	@MLB	9.5 M	Entertainment
Powell's Books	@Powells	329.3 K	Retail
Tinder	@Tinder	207.1 K	Lifestyle

Companies Information from Twitter

In order to access their tweets, I used the Snsrape package in Python to scrape for 100 tweets from each company that I chose. These were all American companies that largely tweeted in English, though many have other accounts for different countries. That being said, all of the tweets scraped were in English. From there, I used the Csv and Pandas package to create a .csv for each company containing these tweets. I utilized the Emoji package available for Python in order to convert each emoji into a descriptive emoji form as shown on the right. This enabled me to use Regex to filter and save only the tweets that contained emojis in them. This was done using a Boolean statement.

With this information and a narrowed down .csv file, I referenced the Brandwatch 2017 Emoji Report to guide my next steps. The goal was to see whether companies were using emojis with easily distinguishable intention, such as using positive tweets rather than negative ones. My

Table 2

Demojize Description	Emoji
:face_blowing_a_kiss:	😘
:goat:	🐐

Emoji Description

starting point was the emotion lists provided from Brandwatch. Their process behind determining these emoji lists is described in their “Methodology” section and was based on the emotion information available from MIT’s DeepEmoji API.

In order to double check their lists and add updated emojis, I followed their method of using Unicode’s list of emojis with the corresponding emotion. This, though, only included one’s that contained a face. The full list of emojis I decided on for my filtering purposes is in the Appendix below.

When filtering, I used the scraped tweets file I had for each individual company that contained only their tweets with emojis. I wrote code that counted the occurrence of all emojis as well as the emojis that were in my positive/negative emoji list. This was appended to a file but somewhere during this process it got a little messy, so I ended up having duplicates of the main emoji and count list in my .csv file. This was easily fixed in Google Sheets. This gave me an outline of the total number of emojis and how many of those were positive or negative for each brand. In order to determine how accurate this was as well as decide if I was missing anything in terms of emoji usage for the companies, I had to go through each emoji with my own annotation. This was so I could independently classify each one. This was done using the scraped tweets .csv that I had generated earlier and adding in columns “Emotion (+, -, O)” and “Place in Sentence (B, E, M, R, A)”. Through these columns I had a guideline and key for my human annotations. The goal was to use the context from the tweet combined with my own knowledge of emoji meaning from being a user of Twitter myself to determine the emotions. Tweets with emojis adding a positive feeling were given a “+”, negative feelings “-”, and neutral were given “O”. This raised some issues, as some emojis were adding playfulness to the tweet but was not decidedly positive. Additionally, the “Place in Sentence” column was added with the intention to allow us to look at two things in particular: how many tweets contained only emojis and how many instances occurred of a word being replaced with a tweet. Having the knowledge of how current emojis are used and being able to determine the meaning intended, even if it contradicted what the emoji may have initially represented, was useful and differentiated my human annotations from the negative/positive lists generated using Unicode.

In Table 3 below, we have laid out how specific tweets contain emojis that must be interpreted different than initially expected due to cultural usage as opposed to intended usage. This type of context is critical in emoji discussions but difficult to address on a rating system or even with simple filtering. As for the placement in the sentence, this could help determine whether the emojis were being used as a word replacement or if majority of them are being added on the end as emphasis.

Table 3

Tweet	Author	Reason
@lyft omg do we make this official? 🤖	Tinder	Emoji is playful but not necessarily pos/neg
@wtfsmamruddhiiii @Tinder_India i— 😭	Tinder	Crying emoji is negative but in this context it’s used in a positive way

Sending SO MUCH love and support to my Tinder match starting a conversation after I said “hey” 3 days ago with no response. You got this. ❤️⚡	Tinder	Sarcastic contents of tweet changes the meaning of the heart
@FunnySupply 🐐	Arby's	The emoji replaces the word “goat” and has a positive connotation
Kansas City's new unis are looking colddd. 🥶	MLB	Cold has a negative connotation, but in this usage it is positive

Special Instances of Emoji Usage

I realized after I had annotated half of the emoji's that I had made an error in how I was categorizing the tweets and emojis as positive/ negative. Some tweets contained more than one emoji, and those emojis put across different emotions. For example, the :sparkles: emoji (✨) or :backhand_index_pointing_down: emoji (👉) are often used to direct towards content or emphasize something, but not necessarily associated with a specific emotion. In our tweets, they were often found alongside the :sparkling_heart: emoji (💖), which does have a positive connotation. I ended up going back and editing my work, instead having the base tweet and then going through in the order the emojis occur in the tweet to independently categorize each emoji. This way, my final count included the rating for each emoji individually. This can be seen in the github linked in the Appendix.

Results

In terms of positive emoji usage compared to negative emoji usage, there was overwhelmingly more positive than negative emojis across the board for each company. For Arby's, there was a total of 194 emojis found in 79 tweets. Using the filtering tools from my code, 24 of these emojis were labeled as positive and 1 negative. From my human annotation, 47 were decided to be positive and 2 negative. That is a 12.37% positive rate compared to 24.23% positive, respectively. Both counts were less than 3 percent for negative emojis.

In contrast, out of 223 tweets from La Croix Water, the computer counted 55 positive emojis and I counted 108 positive. There were 0 negative emojis present. This represents a 24.66% positive rate compared to 48.43% positivity rate. This is also a 0% negativity rate across the board. This was our highest number of positive emojis counted out of all of the companies. MLB tweets contained the least number of emojis with 33. Of these, the code determined 1 to be positive (3.03%) and 1 to be negative. Through annotation, 11 were determined to be positive (36.67%) and 1 negative. Powell's 81 tweets contained a filtered 4 positive (4.94%) and 1 neg (1.23%), though when annotated this became 20 positive and (24.69%) 0 negative.

Tinder had the second most positive tweets annotated with 43 being positive at 37.7% and 3 negative at 2.63%. The code, though, gave us counts of 11 positive at 9.65% and 8 negative at 7.02%.

Some were found to use emojis in a very different way. For Airbnb, the code found 0 positive and negative emojis out of 45. My annotations did not detect a big difference, with 2 positive (4.44%) and 0 negative emojis. This is due to a difference in the purpose of the emoji usage, where Airbnb used them often as a way to emphasize a word or topic in the tweet using associated figures. For example, a location would get a :round_pushpin: emoji (📍) or a tweet about sustainability would get a :recycling_symbol: emoji (♻️). Instead of eliciting positive interactions through using positive tweets, they focused on further illustrating or representing their ideas or product.

The pattern of replacement for words is important to consider as well. Overall, there was

Figure 1

Positive Emojis

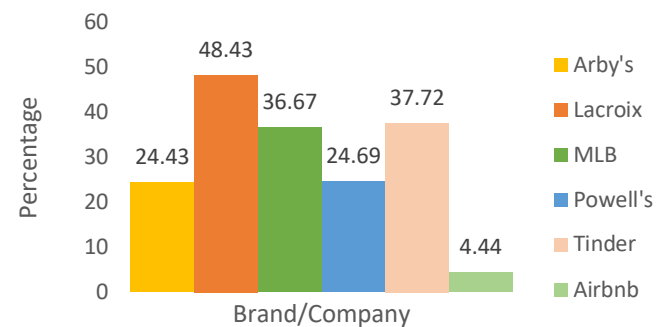
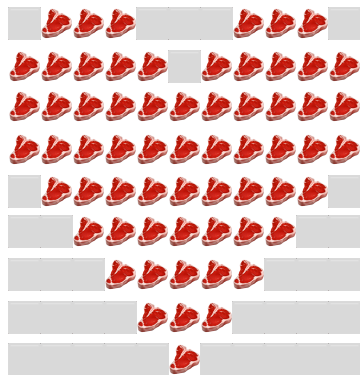


Figure 2

Tag a real Arby's fan in this love letter ❤️



significantly more instances of emojis being used within the words to illustrate a point. However, there were a total of 12 occurrences of replacement across all of the tweets scraped. These occurred both on their own (as the only text in the tweet) as well as found amongst complete sentences and other whole words.

In addition to replacement being of note, instances of the emoji being the entire text of the tweet should be considered as well. In total, there were 51 occurrences of emoji's being the whole tweet. Arby's contained the most of these, having 25 and La Croix contained the second most with 15. In some of these, such as the tweet shown in Table 3, occurrences of replacement and the emoji being the whole tweet occurred together. Another thing to note is that when emojis were the entire tweet, it often included two emojis together rather than one emoji alone.

I also got some interesting variation in terms of total emoji count and total number of tweets containing emojis out of the 100 scraped. Considering this data can point towards a specific industry using more emojis in their tweets overall and can also show how concentrated

some emoji counts are in specific tweets. This is also relevant due to some companies using emoji's to create a "picture" of sorts, as we saw with both Arby's and Tinder. This looked like the tweet above in Figure 2, which is an example from Arby's. The total counts for these can be seen below in Table 4 below.

Table 4

Company	Scraped Tweets (out of 100)	Total Emoji Count
MLB	22	33
Airbnb	26	45
Powell's	34	81
Arby's	52	194
Tinder	55	114
La Croix	91	223

Company Scraped Tweet and Emoji Totals

Discussion

Overall, I did find that many companies use positive emojis rather than negative ones. This is consistent with the assumptions made around *why* they tweet—to reach a broader consumer base—as well as thinking about emoji trends. Additionally, it is probable that social media accounts for brands would tweet about more positive topics than negative. I would also like to note that I began scraping tweets before the events with Ukraine began. When looking at companies that I considered for my research since, I have seen a large uptick in tweets revolving around current events, which may have impacted my results had I started scraping tweets later.

I found some things surprising, such as the usage of only emojis to respond to other users as well as the patterns of emojis I did not anticipate in my initial filtering. Emojis such as the :check mark: (🟢) before lists, or instances when points or statements were preceded with emojis corresponding to their sentiment or meaning. I think that updating the positive/negative list to include those that are not just face-based would add benefit to the filters as well. With current emoji trends across social media platforms, many emojis that would not be assumed to have those a specific connotation or meaning attached to them now do. This is mentioned briefly above, but emojis such as :goat: (🐐) and others have taken on an independent meaning across social media. This type of usage could be factored in or even studied on their own.

Additionally, if I had gone the route of using a larger base of brands or taken a broader look at finding specific brands based on revenue or follower count, as some studies such as the Brandwatch Emoji Report (2017) or McShane et al. (2021) did, then my results could have been different and provided a broader view. A large sample size through more tweets is probably always a positive thing when considering usage and language trends, as Felbo et al. (2017) exhibited in their DeepMoji AI training with a large dataset for training. Looking further at how the emojis embedded within the tweets and creating conditions from that, also as McShane et al. (2021) exhibited, would have given me more of a linguistic perspective on the topic.

One thing that did surprise me was the use of neutral emojis to go along with the content of their tweet and/or their brand and user base. For example, tinder used 11 fire (🔥) emojis, which correlate to both the trending usage of their consumers as well as correlates to their logo. This was not factored into my research, and would be interesting to look into in the future. This usage of “neutral” emojis could point towards two things in particular with reference to my research: that they see it as something that fits into the content of their tweets to further illustrate their points, or it goes along with what they believe consumers like to see on social media.

The usage of neutral emojis and their varying purpose can be vaguely seen in Table 3 above, though the correlation between number of tweets containing emojis and number of emojis does seem to increase at a steady rate. That being said, with Arby’s have the 4th most scraped tweets containing emojis and the 5th most number of emojis, though that could have been impacted by the tweet in Figure 2.

Conclusion

Further implementations of studies like these have largely been done. Emoji usage has been studied extensively, through machine learning training and applications of business to observe customer relation techniques. Scraping tweets from over a period of time, such as three different time periods, could be an interesting way to observe broad changes of social media usage and in particular emoji usage.

As mentioned above, the extended route that McShane et al. (2021) took to examine emoji usage through direct company behavior combined with further studies to look at factors of

playfulness through placement of emojis through engagement is an interesting route to go. In combination with this is the thesis paper from Cody Baker (2018), which discussed “viral” or trending tweets from companies, this could provide significant insight. Becoming viral is solely based on user interactions and likeability of the content of the tweet or video, so examining trends in these behaviors could provide particularly interesting data.

One factor to consider with these types of studies, which I have not seen mentioned frequently, is that it is likely one person or potentially a team hired specifically to run these accounts. Companies with more followers or higher revenue may have collected data on what is pleasing to consumers or what increases interaction and visibility, but ultimately it is a person doing the tweeting. Due to this, the number of emojis used as well as the manner in which they are used could be dependent on the individual running the account or the instructions they were given. Emoji usage trends differ depending on factors such as age and gender, as exhibited in the Brandwatch Emoji Report (2017) and this could also have an impact on the decision on emoji usage.

In terms of how my own data could be altered, I initially made the mistake of labeling the whole tweet as positive/neutral/negative based on the emojis found within. In this case, tweets containing a combination of emojis such as with this tweet from Tinder: “@awfulannouncing Bill Walton is the 🐕 for this 🔥🔥”, which would have been labeled as positive. This type of generalization may be important in research, too, as the entire sentiment of the tweet could be changed based on the types of emojis used. Sometimes, emojis that have no meaning alone can have one when combined, such as: “@delia_cai all you had to do was ask queen 🙄👉👈” and “@CaucasianJames imagine our joint slay... jkjkjk..... unless? 🙄💋🙄” from Tinder. These combinations are often used culturally on Tinder and have their own meaning.

Additionally, the content of the tweet or who the tweet is in reply to could impact this as well and change the meaning of the emoji itself, which would represent a change from the intended meaning of the emoji. All of these are factors to be considered when formulating further research options.

For my purposes of exploring the bounds of my ability with code as a novice, I found this project to be rewarding and fun. Going forward I would have changed a lot of small things: better formed csv files, harnessing NLPK abilities to derive further sentiment, and having a more sincere goal in mind. Overall, though, I found it exciting to be able to do this type of project on my own. Even if at such a small scale and proving something somewhat obvious, every step of the process utilized new steps for me and different types of applications.

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Appendix

All of my code and datasets with annotations can be found at this github repository:

<https://github.com/madmmich/emoji-final-project>

Table 5

Emoji Type	List Emoji	List Demojize	Total
Positive		:grinning_face:, :grinning_face_with_big_eyes:, :grinning_face_with_smiling_eyes:, :beaming_face_with_smiling_eyes:, :grinning_squinting_face:, :grinning_face_with_sweat:, :rolling_on_the_floor_laughing:, :face_with_tears_of_joy:, :slightly_smiling_face:, :upside-down_face:, :winking_face:, :smiling_face_with_smiling_eyes:, :smiling_face_with_halo:, :smiling_face_with_hearts:, :smiling_face_with_heart-eyes:, :star-struck:, :face_blowing_a_kiss:, :kissing_face:, :smiling_face:, :kissing_face_with_closed_eyes:, :kissing_face_with_smiling_eyes:, :smiling_face_with_tear:, :face_savoring_food:, :face_with_tongue:, :winking_face_with_tongue:, :zany_face:, :squinting_face_with_tongue:, :smiling_face_with_open_hands:, :money-mouth_face:, :smiling_face_with_sunglasses:, :relieved_face:, :drooling_face:, :smiling_face:	33
Negative		:frowning_face:, :face_with_medical_mask:, :face_with_thermometer:, :face_with_head-bandage:, :nauseated_face:, :face_vomiting:, :sneezing_face:, :hot_face:, :cold_face:, :woozy_face:, :exploding_head:, :confused_face:, :worried_face:, :slightly_frowning_face:, :frowning_face:, :face_with_open_mouth:, :hushed_face:, :astonished_face:, :flushed_face:, :pleading_face:, :frowning_face_with_open_mouth:, :anguished_face:, :fearful_face:, :anxious_face_with_sweat:, :sad_but_relieved_face:, :crying_face:, :loudly_crying_face:, :face_screaming_in_fear:, :confounded_face:, :persevering_face:, :disappointed_face:, :downcast_face_with_sweat:, :weary_face:, :tired_face:, :yawning_face:, :face_with_steam_from_nose:, :pouting_face:, :angry_face:, :face_with_symbols_on_mouth:, :smiling_face_with_horns:, :angry_face_with_horns:, :skull:, :skull_and_crossbones:, :grimacing_face:, :face_with_crossed-out_eyes:	44

Complete positive and emoji lists used in my filtering