Ca' Foscari University of Venice

Department of Management

Laurea Magistrale in Management

Innovation and Marketing curricula

WHEN A COMPANY MAKES AN UNPOPULAR STATEMENT

Historical cases and analysis of the most significant outcomes.

A thesis submitted for being awarded the

Master's Degree in Management

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Venice, 2023

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INTRODUCTION

As humanity has evolved, new concepts have been created that often require correction or expansion. This is true for marketing theories, which have continuously expanded in response to changes in society. This expansion can be likened to the incorporation of technology into daily life, which was a disruptive change that ultimately transformed communication through the creation of new channels of interaction.

But even though technology has taken a fundamental part in our lives, it has not replaced existing necessities, it has rather made them more intricate. Based in the notorious hierarchy of needs (Maslow, 1943), it is possible to explain all the necessities that technology assists satisfying nowadays, starting from support in physiological needs to even play a role in the esteem and cognitive needs.

Following that comparative we encounter marketing once more, as a product of the evolution of humanity and social interaction. Marketing, just as human necessities, has developed itself with time, expanding its number of tools, benefiting from the channels that technology opened but never completely leaving the basic principle that founded it (Drummond & Ensor, 2006).

There are a great number of concepts for describing marketing, the most accurate one according to my experience is the definition proposed by Kotler & Armstrong (2017): "Marketing is a social and managerial process by which individuals and groups obtain what they want and need through creating and exchanging products and value with others", which seems to gain even more legitimacy nowadays due to the importance that nontangible value had taken into our world.

Going deeper into this concept, Drummond & Ensor (2005) state that exchanges must be mutually beneficial to be sustainable, given that "Economic prosperity depends on the generation of such exchanges".

Exchanging products and value is something we have been doing for thousands of years. Since the roots of civilization, we have had this profound connection to marketing and even branding, an apparently new concept that has been implicit for a long time. As humans, we have expressed fragments of branding within our art, music, and culture. "In 2700 BCE the

Egyptians branded oxen with hieroglyphics. Likewise, the ancient Greeks and Romans marked livestock and slaves" (Bastos & Levy, 2012)

Explaining the bases of branding could be considered reductive, however, in this case it is necessary for understanding the thinking process I employed for conducting this research. Bastos & Levy's interpretation aids to understand how branding is conceived: "Branding starts as a sign, a way of denoting that an object is what it is and then becomes a form of naming something. But immediately, denotation is not enough and connotations arise."

As valid as this concept is, the development of branding as a field of study has derived into the expansion of its meaning due to the increased complexity on the behavior of people and companies towards it. Coming back to Bastos & Levy's research: "...the functions and thoughts related to branding evolved from ownership and reputation to brand image, symbolic values, fantasy, and relationship partner".

The nowadays role of branding is intricate, it shapes the communication strategy, the company's values, and philosophy to satisfy the minimum social, environmental, and overall philosophical demands of society (explicit or implicit), taking into consideration economic and financial performance.
It is at this point where connotation becomes so vital, branding needs to regulate the public perception as much as possible using all the available tools to preserve the brand image, as it will be the one representing the company, while delivering a tangible return on its investment (Kartajaya, Kotler, & Setiawan, 2017).

It is also important to mention that in the product / service market, sustainable longevity and economic growth are the primary goals for all companies. Although is not obvious at first sight, to accomplish this objective marketing and branding are necessary to say the least (their level of importance varies depending on the industry and the size of the company). They are responsible for separating the offer from commodity products and services.

To further understand how a commodity behaves I will use the methodological argumentation of Gordon, Hannesson, & Kerr (1999) "...a product whose markets do not move independently of its competitors in the long-run and whose prices quickly return to a long-run relationship after a price shock should not be amenable to promotion activities".
To stay apart from a commodity product in the search for differentiation is crucial for the goals of the company. Some industries appreciate differentiation better than others, but since it has been proven that there is a significant competitive advantage with differentiation

and starting from the premise that a commodity product is built in perfect competition, and that perfect competition is only theoretical (not feasible on a realistic market), companies have a hypothetical starting point for them to distance themselves as much as possible from conceiving their products / services as “commodities”.

Delving further into the topic, there must be a difference in objectives considering the industry and the size of the companies. Under a study of SMEs (Small and medium-sized enterprises) executed in three different countries, empirical findings confirmed that: “CRM practices, lean practices, and health and safety practices are positive predictors of SME business growth” (Malesios, et al., 2018). Moreover, the research revealed that companies were unlikely to adopt sustainable practices if they negatively impact their economic performance. This was also observed with respect to expenditures on marketing and branding.

The effectiveness in the budget allocation determines the success of the outcome. With an adequate knowledge on the field, companies can achieve outstanding results without incurring into unnecessarily expensive marketing campaigns. A good budget allocation into the used marketing activities (social media, television advertisement, product sampling, in-store promotion, etc.) can save the company a significant amount of money (Kumar, Choi, & Greene, 2016).

Given that there are different marketing objectives and multiple variables into consideration (like the ones before mentioned), a sole budget allocation that works for all companies is not accurate. For perfecting their budget allocation, successful companies measure the ROI (Return of investment) of each activity individually and as a group (Hoffman & Fodor, 2010). This is a classic optimization problem, if companies understand the variables correctly, it is possible to reach the best cost-effective solution from all the feasible alternatives.

As for the marketing department, in the path to reach its optimal budget allocation, one of the instruments that companies have often used and that has proven to be effective is social media marketing. It is preferred over traditional marketing specially by Start-ups and SMEs because the cost is significantly lower. Additionally, there is the opportunity to build a community, obtain direct feedback from customers and segment properly based on specific demographics if a social media campaign is needed (Saravanakumar & SuganthaLakshmi, 2012)

On top of that, there is a considerable variety of tools and a vast quantity of information stored in the social media servers that make possible to gather and interpret critical data to further understand trends, online costumer behavior, public perception, etc. These tools are available to companies but very often they find themselves struggling to unleash their full potential (Hammerl, Leist, & Schwaiger, 2019).

In this investigation I will focus on a social media like Twitter to evaluate real cases of branding statements that were perceived negatively by the public or that were followed up by significant controversy. An evaluation of the sentiment towards the statement will be done to assess the level of influence unpopular statements have with respect to brand perception. Furthermore, this research will permit to understand the evolution of such perception performing a sentiment analysis on people's feedback.

Choosing the social platform: Twitter

In today's digital age, social media platforms have become crucial tools for businesses to communicate with their audience. Among these platforms, Twitter has emerged as one of the most effective channels for studying a company's communication strategy.

Twitter can be described as a platform "real-time", the period for companies to receive feedback on their communications is reduced compared to other social networks. Twitter can also be used to study the "temporality and immediacy" of communication strategies, which is particularly useful for companies that need to respond quickly to market changes.

In addition, Twitter allows companies to reach a wider audience than other social networks. With over 330 million monthly active users, it has a large and diverse user base that includes people from all demographics. Consequently, the platform can be used to study social reach, especially for companies that want to understand the impact of their messages on different segments of the population (Bruns & Weller, 2016).
Other social networks, such as Facebook or Instagram, may have a larger overall user base, but they tend to be more niche-focused and not as effective in reaching a broad audience (Dijck, Nieborg, & Poell, 2018).

Furthermore, Twitter is a platform that encourages engagement between companies and their audience. This means that companies can use Twitter not only to broadcast their messages but also to start conversations publicly. According to research by Kietzmann, Hermkens, McCarthy, & Silvestre (2011), Twitter can be used to study "conversational dynamics", an important feature that allows the user to understand how the company's audience responds to their messages. By evaluating the conversations, it is possible to gain insights on the audience's preferences, needs, and pain points.

When compared to other social networks, Twitter's conversational nature tallies in a better way the objectives of this investigation. While other platforms may allow for some different levels of engagement, they often lack the real-time and conversational aspects that Twitter provides. Instagram was also considered, nevertheless it is primarily focused on visual content which may not lend itself as well to conversation. Similarly, Facebook's algorithmic feed does not fit for this research since the objective is the evaluation of the impact in a communicated message, and on a platform like Facebook multimedia is more important than the message per se.

Choosing Twitter signifies a more evolved communication analysis because of the continuously generated feedback, and the tools the platform facilitates for research purposes. Considering every tweet like a piece of information that can be put together by using proper coding, it is possible to build a reliable dataset. Furthermore, by monitoring companies' activities on-site, is possible to identify trends, gaps, and opportunities. And more importantly, a sentiment towards a brand.

The main reason Twitter was chosen as the designed platform for the research is the option to use Twitter API. API stands for Application Programming Interface and can be described as: "Mechanisms that enable two software components to communicate with each other using a set of definitions and protocols." (Amazon, Inc., 2023). By designing these protocols there is the possibility to explore Twitter in a deeper way, obtaining more complex data and enabling the investigation to become profounder. This programmatic access is legitimated by Twitter because this service is provided by the platform itself, not a third-party business that could be biased.

For accessing Twitter API, Twitter needed to grant research access to this investigation. Given that this is a thesis for graduating from a master course and that the research objective was well defined, I was designated as a researcher by Twitter and the full archive of data they hold was made available to me. "Academic Research access grants access to historical and real-time public Twitter data, helping advance research objectives for nearly any discipline." (Twitter, Inc., 2023).

The Academic Research access allows me to use my own coding to scrape databases with the information I require, making the information obtained more precise and unbiased. Up to 10 million tweets a month could be extracted. Another advantage is the vast documentation available supporting various programming languages compatible with Twitter API.

Branding on a company

Brand identity plays a crucial role in the success of modern companies, as evidenced by a wealth of research in the field of marketing and consumer behavior. A brand is more than just a logo or a name, it is the essence of a company that communicates its values, personality, and unique proposition to its target audience. With the rise of global competition and the increasing importance of digital media, branding has become an essential tool for companies to differentiate themselves and create a strong and lasting relationship with their customers.

Research by Keller (1993) found that brand identity has a significant impact on consumer behavior, as it influences their perception of the product, their attitude towards it, and their loyalty towards the brand. Another study by Aaker (1996) highlighted the importance of creating a unique and compelling brand identity that resonates with the target audience, as it can lead to increased brand equity and higher financial performance.

In today's digital age, branding has become even more critical for companies to stand out in a crowded marketplace. Specifically, digital branding enhances customer engagement and loyalty, as it enables companies to create personalized experiences for their customers and build relationships with them through social media and other digital channels.

Moreover, branding has been shown to have a significant impact on a company's financial performance. A study by Tepeci (1999) found that brand identity can increase a company's market share, improve price premium, and reduce price sensitivity among consumers. Another study by Kim, Kim, & An (2003) found that companies with strong brand identity tend to have higher profitability and better long-term financial performance.

Brand identity essentially transforms companies into living entities with their own distinct personality, which is subject to constant public scrutiny. As companies strive to position their brand, they often seek to align with their customers' preferences and values. However, in today's age of rapid information dissemination, it is imperative for companies to ensure that their messaging is consistent with a well-defined strategy. Failure to do so could lead to negative perceptions, with the company being viewed as engaging in "image washing".

The role of branding in modern companies is well-established in the academic literature. It is a powerful tool that enables companies to differentiate themselves, build trust with their customers, and improve their financial performance. As competition continues to intensify, companies that invest in building a strong brand identity will have a greater chance of success in the marketplace (Kapferer, 2008).

METHODOLOGY

Evaluation of the cases to study

The primary focus of this research revolves around the private sector, specifically emphasizing companies with a distinct identity due to the effectiveness of their branding strategy. In order to evaluate public perception following a disruptive statement, a careful selection process was implemented to assess and eliminate unsuitable alternatives.

For deciding which cases were used in this research, an evaluation of several scenarios was made to determine how impactful each case was and its link with branding theory. Articles and official reports were used to determine the timeline of events and their outcome.

The cases were evaluated under a short-, medium- and long-term perspective. For standardization of the results the short-term evaluated the first 6 months before and after the disruptive statement. The medium-term focused on a 2-year window starting as well from the 6 months prior to the statement. And the long-term evaluated 5 years following the statement again starting from the 6 months prior to it. The periods were adjusted when necessary.

Because this research feeds on social media data, it was not possible to consider cases that happened after 2018 as they do not fit the periods before stated. Furthermore, and having Twitter's database as the principal information supplier in this investigation, the cases were considered for evaluation if they happened after 2006 (the year Twitter was launched).

Creating the code on Python

The creation of the code that will allow me to extract the databases from Twitter was done in Python, a programming language largely used in the world due to its readability and consistency. “Python provides a large standard library which can be used for various applications for example natural language processing, machine learning, data analysis etc.” (Gupta, et al., 2017).

The codes were written using software libraries imported to Python. The principal library was Tweepy, an open-source package that engages with Twitter API by using the access codes and tokens provided by Twitter’s research account. It essentially acted as an intermediary, giving commands to Twitter for extracting the information in a more categorized way.

```
tweet_list = []
query = ' Starbucks lang:en -from:Starbucks -is:verified -is:nullcast -
has:links -has:media -has:images -has:video_link'
user_fields = ['username', 'public_metrics', 'description', 'location',
'name', 'verified']
tweet_fields = ['created_at', 'geo', 'public_metrics', 'text', 'id']
expansions = ['author_id', 'referenced_tweets.id']
start_time = '2022-12-05T00:00:00Z'
end_time = '2022-12-10T23:59:00Z'
max_results = 400
limit = 1

for response in tweepy.Paginator(client.search_all_tweets,
                                 query=query,
                                 user_fields=user_fields,
                                 tweet_fields=tweet_fields,
                                 expansions=expansions,
                                 start_time=start_time,
                                 end_time=end_time,
                                 max_results=max_results,
                                 limit=limit):
    time.sleep(1)
    tweet_list.append(response)
```

Figure 1. Fragment of the code employed in Python showing the Tweepy implication.

The second most important software library used was Pandas, which allowed me to manipulate the data to make it more structured, converting the dictionaries of Tweepy into a data frame. This data frame is then saved as a .csv document, finalizing the extraction process. Other libraries used in this code were “time” and “configparser”.

```
df = pd.DataFrame(result)

df['test'] = df['short_text']
df['text'] = df["test"].str.extract(r'(RT @\w+: )')
df['text'] = df['text'] + df['full_text']
df.loc[~(df["type"] == "retweeted"), 'text'] = df[~(df["type"] ==
"retweeted")]['short_text']
df.drop(columns=['short_text', 'full_text', 'test'], inplace=True)
```

Figure 2. Code extract demonstrating the usage of Pandas and the .csv conversion.

The following is a simplified example of how the final table looks once the codes are utilized. The table used in this research had 23 columns containing the crucial data used for creating the graphs.

username	author_location	author_name	created_at	language	text
thordora	New Brunswick, Canada	Jada D	2009-01-14 01:25:33+00:00	en	I won a Starbucks GC! Free soy latte's-NOTHING is better. :)
Abundantfood	Roseville, California	Abundant Food Saving	2009-01-14 01:24:08+00:00	en	Free Starbucks Coupon for a tall tea drink in the Safeway ad mailed to homes in Sacramento area tonight and in the Bee tomorrow
DeanOuellette	Chandler, AZ	Dean Ouellette	2009-01-14 01:21:48+00:00	en	hanging out at the starbucks around 4100 N Scottsdale Rd, Scottsale
AsburyYouth	Livermore, CA	Asbury Youth Group	2009-01-14 01:18:43+00:00	en	Come to Starbucks by the theater on Thurs. from 3-5:30. We are making a movie and I'm sure you want to be in it.
seanwashbot	Santa Cruz	Sean Washington	2009-01-14 01:16:11+00:00	en	Starbucks
christyscronce	Marina Del Rey, CA	Christy Scronce	2009-01-14 01:11:41+00:00	en	is wondering what band is playing at Starbucks on the Third Street Promenade...
skinnycrazed	NY	Lisa S	2009-01-14 01:11:25+00:00	en	Overthe holidays i didnt want to just send regular cards. So I sent Starbucks acrds to my vendors. They really appreciated it #WEdchat
AngelMercury	√úT: 34.048425,-118.410539	ES	2009-01-14 01:11:20+00:00	en	Stopping at starbucks to chill before the Siggraph LA meeting. I feel a little

					nervous for some reason. Henson studio should be cool though.
Pampelmoose	Portland, Oregon	Dave Allen	2009-01-14 01:10:05+00:00	en	@JulieMa wish that was Stumptown not Starbucks...

Table 1. Simplified table containing the information obtained from the initial data extraction from Twitter.

Sentiment analysis

The sentiment analysis is done using the .csv file containing the extracted Tweets. For performing the sentiment analysis, it was necessary to import a tool to python. The tool chosen is VADER that stands for Valence Aware Dictionary and sEntiment Reasoner. It is open sourced under the MIT license and is especially effective in this investigation because its text analysis is programmed specially for identifying the sentiment of microblogging in social networks, making it ideal for evaluating tweets.

The effectiveness of VADER has been proven in multiple articles, its accuracy is highlighted under social network contexts, and its systematic development and evaluation make it an asset in this research. "VADER performed as well as (and in most cases, better than) eleven other highly regard-ed sentiment analysis tools." (Hutto & Gilbert, 2014).

VADER assigns a number from -1 to 1 to a determined text, being 1 a text with a positive sentiment and -1 a text with a negative sentiment. The closer the value comes to 0 the more neutral the text is. VADER access a database with lexicons (a dictionary of words assigned with a positive or negative score indicating its sentiment and strength) to start evaluating the sentiment of a tweet. Then it combines these lexical features considering grammatical and syntactical conventions that people use when expressing themselves and the intensity of their sentiment implicit in their texts. In this case, tweets (Duyu, Wei, Qin, Zhou, & Liu, 2014).

In this investigation, for a tweet to be defined as positive the sentiment value needed to be above 0.05. For the tweet to be negative the value needed to be below -0.05, an extract of the code showing this specification is shown below.

```python
def overall_sentiment_scores(sentence):
    sid_obj = SentimentIntensityAnalyzer()
    sentiment_dict = sid_obj.polarity_scores(sentence)

    if sentiment_dict['compound'] >= 0.05:
        overall = "Positive"
    elif sentiment_dict['compound'] <= - 0.05:
        overall = "Negative"
    else:
        overall = "Neutral"
    return overall
```

Figure 3. Code extract showing the values considered for the sentiment determination.

This code acts on the .csv file of extracted tweets and assigns a sentiment to each one of them. Then generates a .csv file with 5 additional columns showing scores for how negative, positive, and neutral the tweet is, a compound number is calculated (which is the one considered for determining the overall sentiment of a tweet) and used for determining the final string (positive, negative or neutral). A simplified example of the outcome table is shown below.

username	created_at	text	compound_sentiment	overall_sentiment
demmalition	2009-01-14 01:58:17+00:00	I think they put crack in my Starbucks, how nice of themmmm. =]	0.6597	Positive
hmsvs	2009-01-14 01:57:56+00:00	@hippyco Starbucks	0	Neutral
createthegood	2009-01-14 01:57:13+00:00	@Starbucks it's awesome that they're getting into the Renew America Together Initiative! Check it!	0.6892	Positive
jerrit	2009-01-14 01:52:06+00:00	Starbucks with the dudes	0	Neutral
iheartrocknroll	2009-01-14 01:51:23+00:00	@Starbucks thanks for joining in the crusade to make a difference~!	0.4926	Positive
jordynface	2009-01-14 01:51:19+00:00	Maybe I'll go to Starbucks anyway. It'll make me happy, somewhat, and I'll be productive.	0.5719	Positive

Table 2. Sample table exemplifying the sentiment determination.

Extraction of the data to excel and the Love-hate index.

With the file in .csv format, all the databases were exported to Excel to finalize the data analysis. On Excel, a data curation was performed manually. The datasets were then merged taking into consideration the periods before mentioned (short, medium, and long term).

A third code was used in Python to perform this operation, this code merged .csv files based on their name. Considering every database obtained had the same column names, the data frame found the column name and placed the information in the proper cells. The complete code can be found down below.

```
import os, glob
import pandas as pd

path = "/Users/PycharmProjects/Twitter/venv/Twitter_explo"
all_files = glob.glob(os.path.join(path, "4Y_SA_*.csv"))
df_from_each_file = (pd.read_csv(f, sep=',') for f in all_files)
df_merged = pd.concat(df_from_each_file, ignore_index=True)
df_merged.to_csv("4Y_SA_merged.csv")
```

Figure 4. Complete code employed for merging files containing the datasets.

For understanding the inherent sentiment of the period, having the datasets correctly interrelated, it was necessary to create a value that would demonstrate the evolution of public perception. For that reason, the love-hate index was created. Just as the sentiment analysis, this is a value that oscillates between -1 and 1, being -1 a negative sentiment and 1 a positive sentiment.

There was the consideration to directly use the compound sentiment for determining the evolution of public perception but finally it was discarded because even though it considers the intensity of the tweets based on the VADER lexicon, there are expressions used specifically to praise the brand that will not be determined with the correct intensity. For example, in this real tweet: "Just got a free Mocha at Starbucks for no reason. Maybe there's something to the prosperity Gospel after all..." VADER correctly determined the sentiment of the text as positive but gave it a value of 0.2732 which is low for the intention the tweet had.

Just like in the before shown example, in microblogging the sentiment can be accurately determined most of the times, but the intensity is only accurate when more information is provided. It is even more difficult with tweets like "Starbucks!!" or "Starbucks and chill for me today" where there is not enough information for determining the intensity although the sentiment is evident. Hence it was decided that for avoiding the inaccuracies, the value used for determining the love-hate index needed to be the string of the compound sentiment.

A numeric value was then given to the string, there were 3 possibilities: 1 for positive, 0 for neutral and -1 for negative. No decimal value was assigned because the goal was to accurately understand acceptance and rejection towards a brand or a specific marketing campaign. The logic behind the love-hate index is that the closer the value comes to 1 (or 100%), the more positive the perception of the brand is. On the other hand, if the value is negative, it means the quantity of negative tweets towards a brand or marketing campaign is surpassing the positive ones. Hence, having a negative brand perception.

Moreover, to understand better the evolution of public perception, it was necessary to express development graphically, for this I used the datasets with the numeric value of the strings to create a table that would allow to visualize progression and calculate a tendency. Table 2 and its variations made possible to create most of the graphs employed in this research.

Reduced date	overall_sentiment	Numeric value	Sentiment dev.
2009-05-01	Negative	-1	-1
2009-05-01	Positive	1	0
2009-05-01	Neutral	0	0
2009-05-01	Neutral	0	0
2009-05-01	Positive	1	1
2009-05-01	Positive	1	2
2009-05-01	Positive	1	3
2009-05-01	Negative	-1	2
2009-05-01	Negative	-1	1

Table 3. Numeric value of the sentiment and sentiment development calculation.

The fourth column named “Sentiment dev.” has a simple addition that sums up the values before it. To prove all values are considered, the row “Total” column “Numeric value” must have the same quantity as the last row of “Sentiment dev.”. This is a very common accounting method to understand the progression of values and contains part of the information needed for obtaining the love-hate index.

The love-hate index (LH index hereinafter) is a more complex value than the compound sentiment because it also takes into consideration the total population, the other fundamental piece of data needed for its calculation. This means that the index appreciates magnitude in the sense that the periods with a higher tweet quantity will have more weight in determining the final love-hate index.

For creating it, once the numeric value of the string was assigned and placed in a table like Table 3, a calculation of the total population of tweets needed to be made. The number of total tweets is adjusted depending on the scenario by employing all the necessary constraints for filtering the data. Constraints possibilities are time, account it comes from, text it contains, language, location, etc.

The query (piece of data containing all the constraints) is first defined in base at the desired outcome and tested multiple times analyzing the data results. The final quantity of tweets under the query is calculated with Postman, a Twitter approved site that allows API handling and interpretation.

Having the total population of Tweets per month, the sample quantity is calculated to determine how many tweets needed to be extracted with the code made on Python. The sampling technique was adjusted depending on the desired margin of error and intended proportion. An explanation of the sampling technique used can be found in every case.

Since one of the goals of this study was to determine how public perception developed with time, there was at least one extraction of data per month satisfying the sampling requirements. This facilitated the extrapolation of the sample data to the population, allowing to reach an understanding of the evolution of the sentiment towards a brand, and the relevancy it had considering the quantity of tweets mentioning it. The following is the formulation of the created index considering everything mentioned before.

$$LH = \frac{\sum_{m=1}^{x} f(m)}{N}$$

$$f(m) = (r_p(m) * h(m)) - (r_n(m) * h(m))$$

$f(m)$ = The function of m when m is the numeric value assigned to each month

$r_p(m)$ = Percentage of positive tweets of the sample of the month

$r_n(m)$ = Percentage of negative tweets of the sample of the month

$h(m)$ = Total quantity of tweets posted in the month

x = Number of months in the study

N = Total population, total number of tweets in the desired period

For understanding in a better way the process for calculating the love-hate index, the following table expresses more graphically the application of the formulas.

	m	*rp(m)*	*rn(m)*	*h(m)*	*f(m)*
Jan-23	1	49%	17%	15,701	4913
Feb-23	2	49%	19%	26,332	7915
Mar-23	3	48%	17%	39,399	12211

Table 4. Process for the f(m) calculation

Considering the data displayed before, the formulas are applied.

$$LH = \frac{[(49\% * 15{,}701) - (17\% * 15{,}701)] + [(49\% * 26{,}332) - (19\% * 26{,}332)] + [(48\% * 39{,}399) - (17\% * 39{,}399)]}{15{,}701 + 26{,}332 + 39{,}399}$$

$$LH = 0{,}3075$$

In this case we can say that the love-hate index for the first 3 months of year 2023 was 30,75% or 0,3075. Is important to remember that the value can oscillate between -1 and 1 so a negative percentage is possible. Another specification is that the formula created intends for an analysis of a determined period by assigning a weight into the population (total number of tweets under the desired query) and associating that weight with the distribution of the sentiment (percentage of positive, negative, and neutral tweets on the sample). When these conditions are met, the love-hate index was called weighted love-hate index (weighted LH index). This specification was made to differentiate it from the LH index obtained from the sample, which is still relevant and important for evaluating the development of public perception but must be interpreted in a different way.

Going back to the example, the result of LH means that there was a higher number of positive tweets than negative or neutral ones. With 30,75% it can be said that there was a positive public perception. However, there is still a significant percentage of negative tweets ($r_n(m)$) and a high percentage of neutral tweets ($100\% - r_p(m) - r_n(m)$). In this hypothetical case those quantities represent a possible issue that must be acknowledged by the company to reach for a sentiment improvement.
Later in this investigation, a deeper interpretation of the LH index and its potential as a sentiment analysis formula will be presented.

CASES TO STUDY

Starbucks

"Starbucks or nothing" and "It's not just coffee, it's Starbucks" were the principal slogans used in this branding campaign that was the largest in company history at the time. The main objective was to assert the value of their product and reassure clientele that the extra price they would pay in their company was worth paying (The Wall Street Journal, 2009).

Given the introduction of the branding campaign towards the end of April 2009, data extraction for the campaign was initiated in May 2009 to ensure greater precision in monthly representation. As for the general perception of the brand at the time the campaign was present, an evaluation of the calendar year was employed to make a comparative. Both scenarios involved the utilization of varying date ranges to comprehend the campaign's effects on short-, medium-, and long-term outcomes.

Figure 5. Illustration used in the "Starbucks or nothing" campaign, retrieved from the Wall Street Journal article published on May 1st, 2009.

The motives behind this campaign were not only to reinforce the brand, but to recaptivate customers to reach for a premium experience. This was necessary from the marketing point of view because, at the time, Starbucks was struggling due to the economic recession underwent in the United States.

By briefly exploring Maslow's hierarchy, one can infer that Starbucks does not solely focus on fulfilling physiological needs, despite the primary product being coffee which is classified as a food item. Instead, Starbucks places greater emphasis on occupying the self-esteem and love/belonging segments in the hierarchy. The fact that their product is not a commodity, let alone a necessity, implies that the company's revenues are directly affected by fluctuations in disposable income.

When faced with limited consumption expenditures, individuals tend to prioritize essential products and evaluate the perceived value of goods or services before deciding on where to place their disposable income, thus further complicating Starbucks' challenge during the recession.

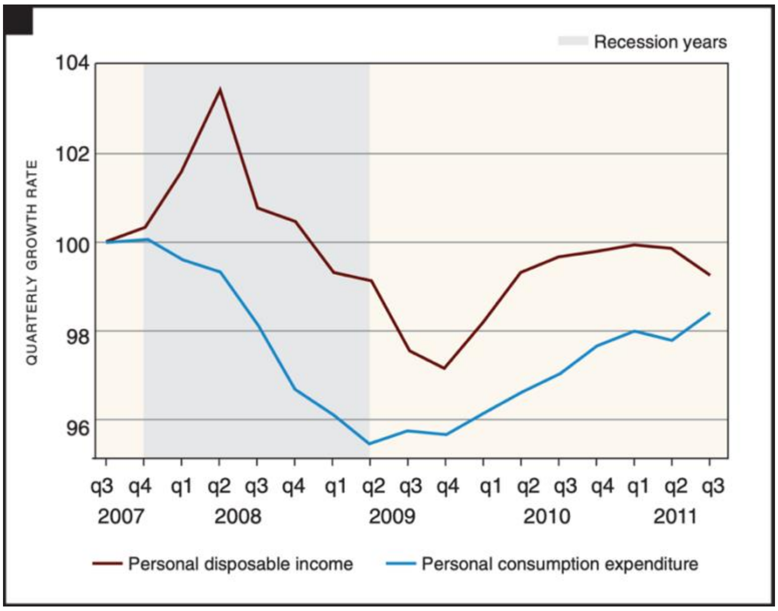

Figure 6. Comparative between the personal disposable income and personal consumption expenditure in the US during the recession years. Illustration retrieved from the report published by the Stanford Center on Poverty and Inequality (Petev, LSQ-Crest, & Pistaferri, 2012).

Compelling people with a good marketing strategy was not enough for attaining improvement. The internal structure of Starbucks needed to be rearranged thoroughly. For that reason, the company brought back Howard D. Schultz who returned as a CEO after being apart of the company for eight years (Husain, Khan, & Mirza, 2014). In a letter sent to employees the year he came back to Starbucks, it reads:

“The company must shift its focus away from bureaucracy and back to its customers, reigniting the emotional attachment with customers. The company shouldn't just blame the

economy: Starbucks' heavy spending to accommodate its expansion has created a bureaucracy that masked its problem."

- Howard 2008

There was a clear aspiration for progress and the bases for it were influenced deeply by the community. In 2008, Howard set in motion the initiative: "My Starbucks Idea", a crowdsourcing that collected until 2013 more than 150.000 ideas, out of which 277 were successfully implemented. The ideas followed a quality process, getting measured by a team of idea partners on how innovative they were and if it was feasible to implement them. Later, key decision makers in the company evaluated how to put ideas into work under Starbuck's strategy. This initiative created significant value and increased clients' engagement (Harvard University - MBA Student Perspectives, 2015).

As a result of the strategic measures adopted and internal changes made by the company before and after the launch of the marketing campaign, there was a noticeable increase in customer engagement. For companies, it is crucial to exhibit consistency, and Starbucks' implementation not only demonstrated this but also showed a commitment to ongoing improvement.

Extraction – "Starbucks or nothing" campaign

For the tweet extraction 2 scenarios were analyzed individually and later in comparative. One was based specifically on the branding campaign "Starbucks or nothing" and its outcome, and the other one based on the brand perception at the same time the campaign was present bearing in mind users in the same area.
Specific tweets of the campaign were extracted for the specific branding campaign under the parameters described in the following code extract (the time frame was modified according to the desired period):

```
query = ' "Starbucks or nothing" OR "it\'s not just coffee. it\'s
starbucks" OR its not just coffee it\'s starbucks OR "it\'s not just coffee
it\'s starbucks" lang:en -from:StarbucksNews -from:Starbucks -
from:Starbucks_usa -from:StarbucksCare -is:reply -is:quote'

start_time = '2009-05-01T00:01:00Z'
end_time = '2009-12-31T23:59:00Z'
```

Figure 7. Query employed for the tweet extraction of the "Starbucks or nothing" campaign.

In this scenario, the focus relies on the slogans or phrases employed in the campaign from the month it was introduced until the last day of December of the same year. It is not relevant to study the months prior to the campaign since there were no tweets that would satisfy the query. The official accounts of Starbucks were also excluded from the analysis to make the tweets extracted unbiased. Retweets are also considered because they represent a replication of a thought without adding any input. It is not possible to accept quotes or replies as they represent just a part of a thought complemented with the original tweet.

Short term perspective – Specific campaign

For the short time frame, the total of tweets extracted under the parameters before stated was 104 from which 51 were assigned as "neutral" under VADER's measurement. However, the tool is not considering that replicating phrases from the campaign, that would appear neutral or negative like "it's not just coffee. it's starbucks", implicitly means the person is demonstrating support and approbation. Given that it is not possible to access VADER's code to program it to detect these phrases as positive specifically for this research, a manual check was done on all the extracted tweets.

In the categorization employed, a tweet was considered positive when it expressed acceptance towards the campaign or replicated the phrases employed on it. For being considered negative, the tweet needed to question or criticize the campaign, or replicate the phrases adding some mockery or signs of disapproval. The tweets are considered as neutral when there is no sentiment expressed, the sentiment is difficult to interpret, or it analyses the campaign from a research point of view. By curating the data, a more representative and accurate dataset was obtained, reducing the quantity of neutral tweets to 21. Some "positive" and "negative" categorizations were corrected as well.
Attached here the tables counting the prevalence for the short time frame:

Sentiment counted	
Positive:	34
Negative:	19
Neutral:	51
Total:	104

Table 5. Tweet sentiment based on the initial Sentiment analysis.

Curated sentiment	
Positive	41
Negative	42

Neutral	21
Total:	104

Table 6. Tweet sentiment after the manual curation

Is possible to see that there was a big increase in the quantity of negative tweets, this is because they were initially considered as neutral but when analyzed, the tweets replicated either links with articles negatively viewing the marketing strategy of Starbucks or pieces of content making fun of the branding campaign. Hence, the negative categorization.

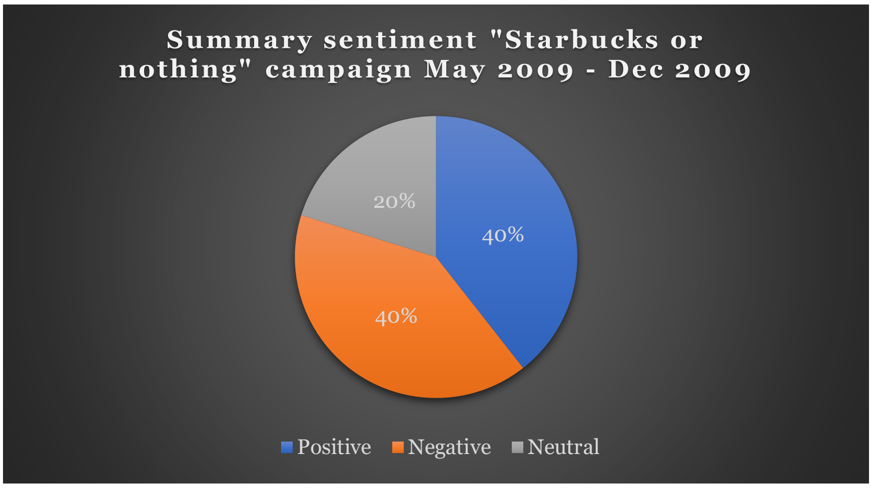

Figure 8. Sentiment proportion of the analyzed tweets in the short term for the "Starbucks or nothing" campaign. May 2009 – Dec 2009.

In the performed sentiment analysis, the opinions about this marketing proposal for the first eight months were balanced, without a clear positive or negative outcome.
Table 3 represents a short version of the table used for creating Figure 9. It was necessary to display the values in a graphic way to evidence more visually the evolution of the sentiment.

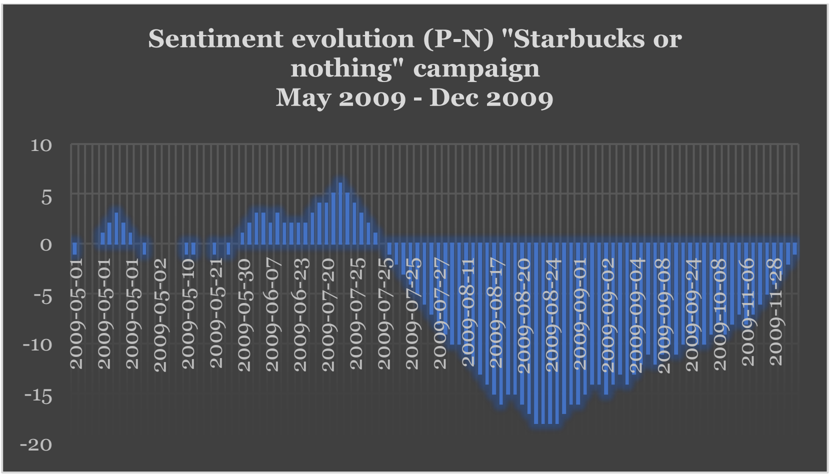

Figure 9. Evolution of Positive - Negative tweets in the short term for the "Starbucks or nothing" campaign. May 2009 – Dec 2009.

Figure 9 by itself displays an analysis of the progressive sentiment of the branding campaign, it shows the public perception's development for arriving to the final value that will be the one employed for calculating the LH index of the period. Since it's progressive, the values cannot be interpreted individually, it is necessary to take into consideration that the first date works as a pivot. Possible interpretations to this graph are: From the beginning of the campaign (May) until August 2009, there were more negative tweets than positive, showing a drastic change from the positive tendency seen from May until mid-July, there is the possibility that an event at the end of July 2009 triggered this change; or, by November 2009 the public perception about the "It's not just coffee, it's Starbucks" campaign was recovering a positive tendency, however the year still finished with a negative value, showing higher negative tweets than positive in the period May - December 2009.
Every deduction needed to use the pivot value (May) for the correct interpretation. In this graph and all the other of this style seen in this study the pivot value will always be the first introduced date.

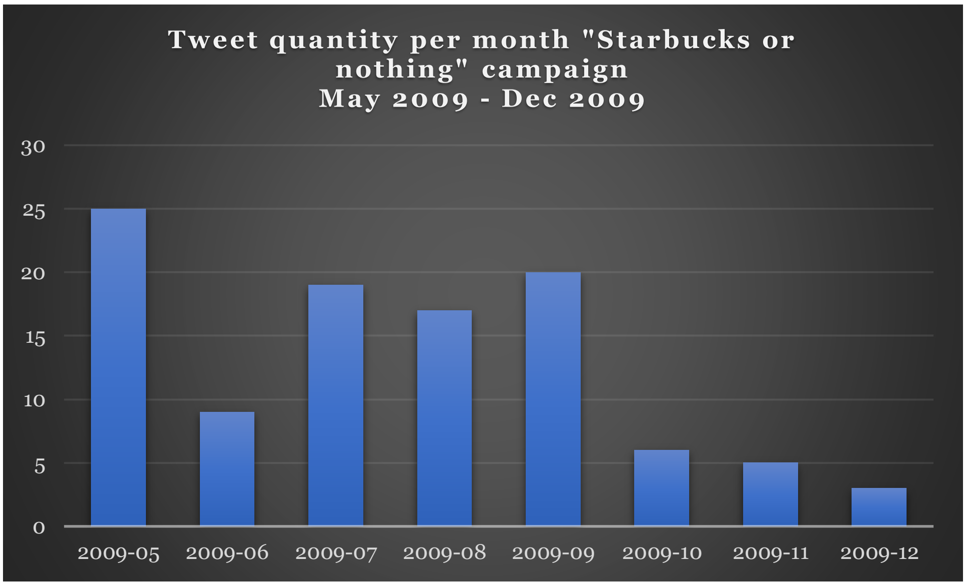

Figure 10. Quantity of posted tweets referring to the "Starbucks or nothing" campaign per month. May 2009 – Dec 2009.

Figure 10. shows the quantity of tweets posted per month talking specifically about the campaign's slogans. There was a greater reach in the beginning that started descending. The campaign then resurfaced for the months July, August and September and ended the year with less relevancy. The comparison of the LH index per month is not used in this case because the quantity of tweets is not enough to be representative, they reach a representative quantity only when analyzed as a whole in the period May – December 2009.

Finally, applying the proposed formulas, the LH index was obtained for the period. With a value of -1% it is possible to conclude that the campaign generated mixed opinions on the public that remained unconvinced on its execution. Even though the LH index is negative, the value comes close to 0 which demonstrates neutrality in this time frame.

Medium term perspective – Specific campaign

It is considered medium term, the period between the release of the campaign (May 2009) and December 2010. With 165 tweets mentioning it, the following graph describes the distribution of the sentiment towards the branding campaign.

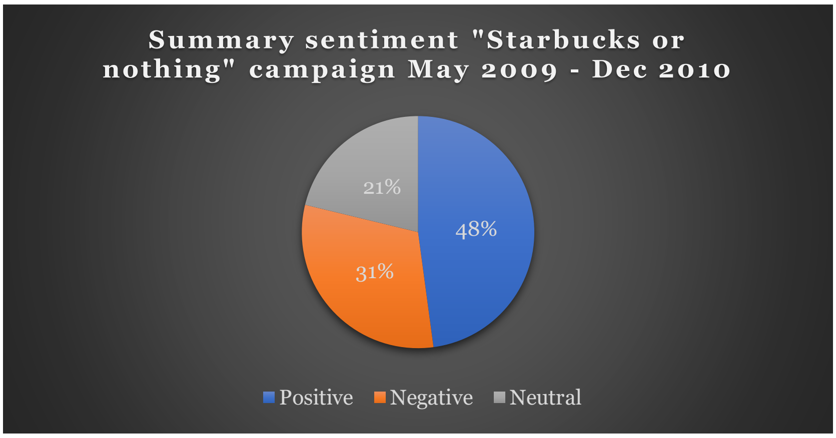

Figure 11. Sentiment proportion of the analyzed tweets in the medium term for the "Starbucks or nothing" campaign. May 2009 – Dec 2010.

Compared to the short-term summary sentiment, there is a significant reduction in the percentage of negative tweets, and an increase in the quantity of positive tweets. The quantity of neutral tweets variated by 1%.

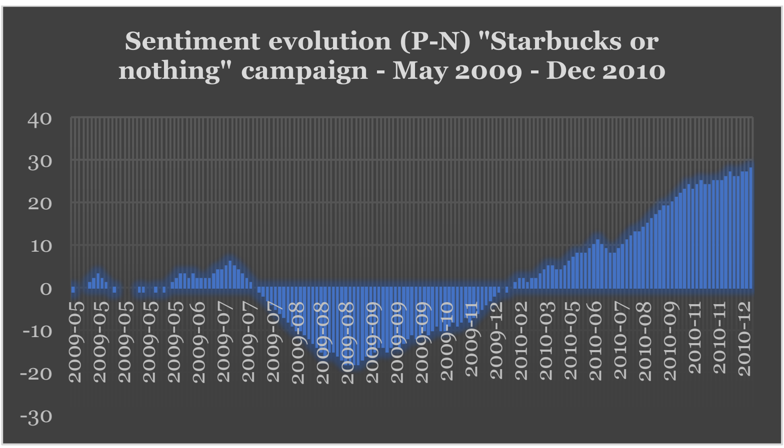

Figure 12. Evolution of Positive - Negative tweets in the medium term for the "Starbucks or nothing" campaign. May 2009 – Dec 2010.

After closing the year 2009 with a negative love-hate index. For the year 2010 the evolution of the sentiment towards the campaign showed a very positive tendency. A tendency that grew exponentially. Is possible to see in Figure 12. that positive tweets surpassed negative by 28 from a total quantity of 165 extracted tweets in the period May 2009 – December 2010.

The love-hate index of the medium-term perspective (May 2009 – December 2010) for the specific branding campaign was 17%, which shows a significant improvement from the short-term perspective. However, even though the campaign gained more acceptance, its relevance decayed with time. Figure 13. shows the number of extracted tweets per month using the code with the before explained query.

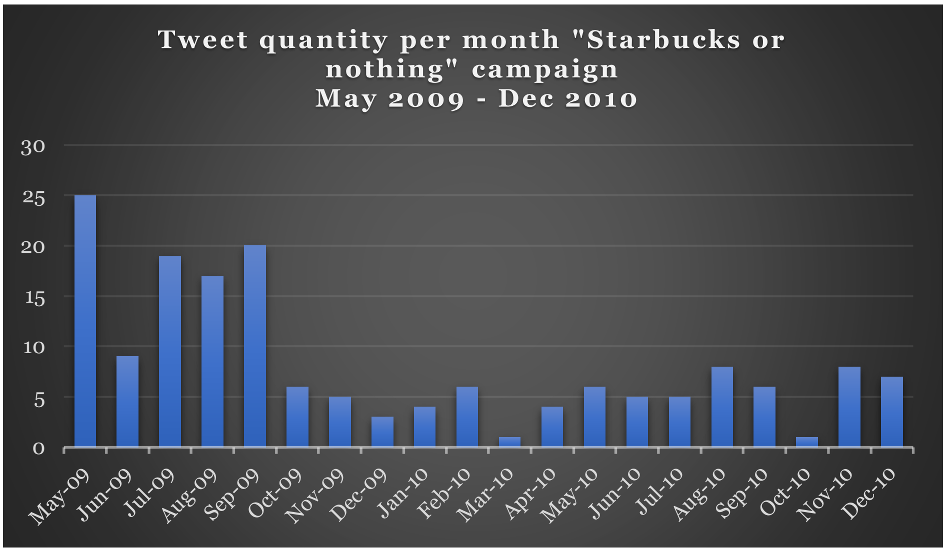

Figure 13. Quantity of posted tweets referring to the "Starbucks or nothing" campaign per month. May 2009 – Dec 2010.

Long term perspective – Specific campaign

For the long-term analysis, the quantity of tweets mentioning the campaign's phrases and their sentiment were measured yearly based on the designed query. The datasets were manually curated as well to obtain an accurate analysis.

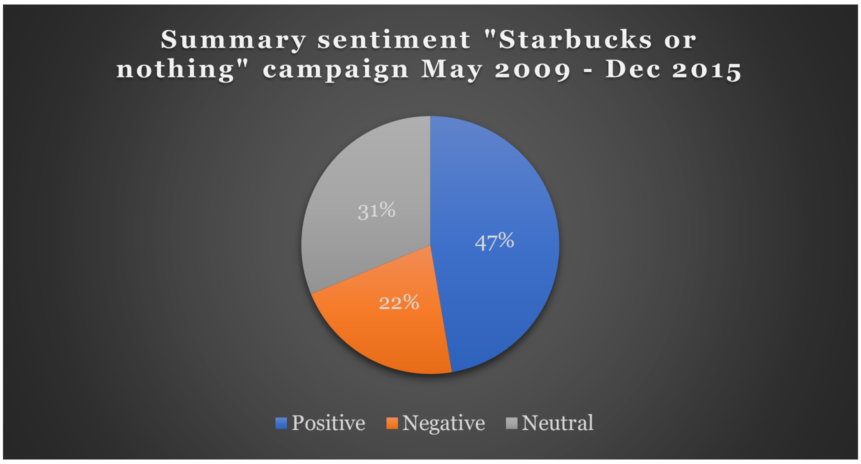

Figure 14. Sentiment proportion of the analyzed tweets in the long term for the "Starbucks or nothing" campaign. May 2009 – Dec 2015.

Making a comparison to the medium-term analysis there a 1% decrease in the percentage of positive tweets, and a significant increase in the percentage of neutral tweets that went from 21% to 31%. The quantity of negative tweets decreased by 9%.

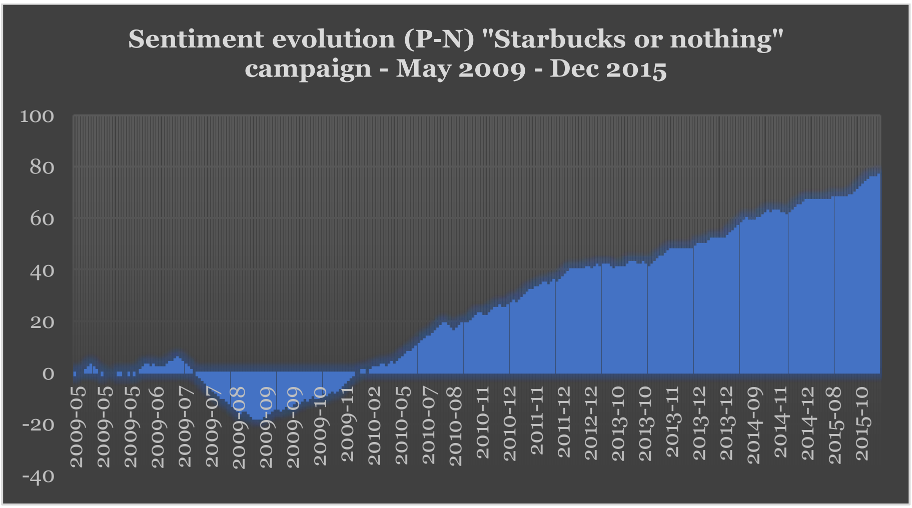

Figure 15. Evolution of Positive - Negative tweets in the long term for the "Starbucks or nothing" campaign. May 2009 – Dec 2015.

Based on the sentiment evolution, it is possible to see a sustained positive trend since September 2009. Such trend starts after the month with the highest percentage of negative tweets, August 2009. Furthermore, after January 2010 the quantity of positive tweets was never outnumbered by the quantity of negative tweets again.

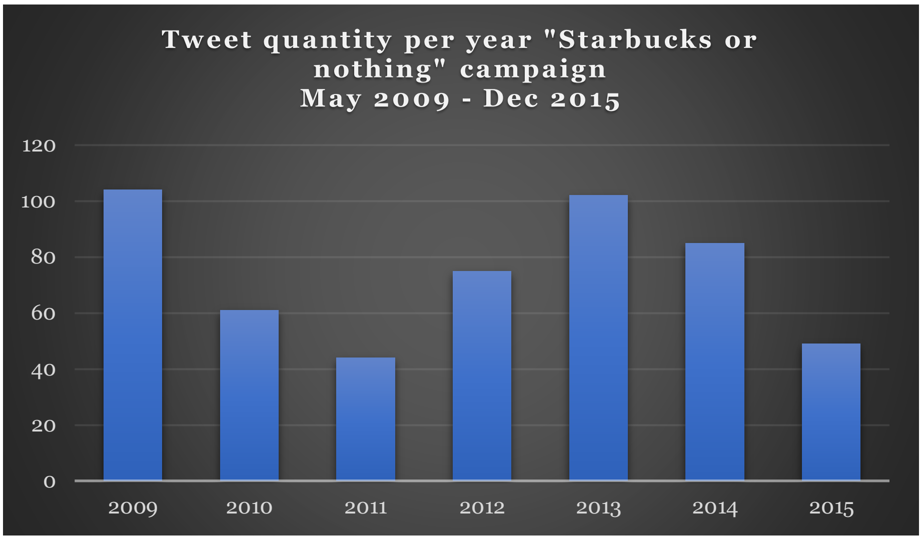

Figure 16. Quantity of posted tweets referring to the "Starbucks or nothing" campaign per year. May 2009 – Dec 2015.

Figure 16. depicts the number of tweets per year resulting from the specified query. Even though the campaign was not reintroduced, there is a noticeable increase in the number of tweets mentioning the campaign starting from 2012. This phenomenon of reigniting interest was examined in the study's findings.

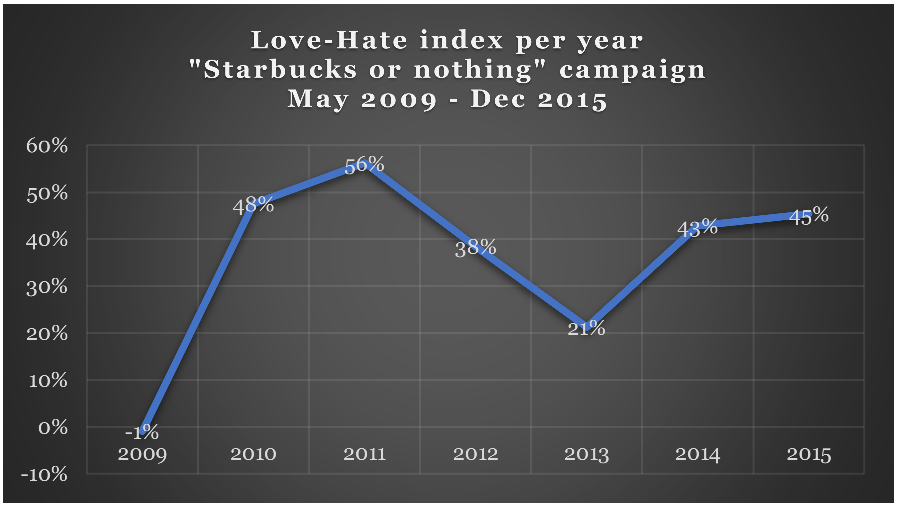

Figure 17. Comparative of the love hate index values per year for the "Starbucks or nothing" campaign. May 2009 – Dec 2015.

The graph demonstrates the long-term Love-Hate Index for the "It's not just coffee, it's Starbucks" campaign. It is noteworthy that only the first year showed a neutral index rating. However, from 2009 onwards, all subsequent years exhibited a positive Love-Hate Index. The evidence presented suggests that the campaign's Love-Hate Index increased significantly from the medium-term index of 17% to a long-term index of 25.8%. Based on the analysis methods used, it can be concluded that the campaign had a positive impact in the long run.

Initial findings

Starbucks' phrase "It's not just coffee, it's starbucks" was considered by 11% of people on the first eight months of the campaign to be a rip-off of the famous HBO phrase: "It's not TV it's HBO". It represents 26% of the negative tweets of 2009. The other issues that this campaign faced was the public perception of their pricing choices, 19% of their negative comments expressed their concern about the high prices compared to the competition.

Branding in companies was still developing at the time, it was even less known from the side of the demand. That could be one of the reasons why some critics of the campaign categorized Starbucks as "only a store that sells coffee" and expressed their disapproval of the slogan "it's not just coffee, it's starbucks" given that for them it was indeed only about the coffee. Now we know experience is a focus point for the marketing strategy of Starbucks and this ad campaign was a precedent for reaching higher branding awareness.

In 2009 Starbucks was still struggling because of the recession, it had to close shops and modify their organization, reducing the number of workers in the search for future economic sustainability. A move that was criticized by Brent Sandmeyer, a political activist who wrote an article stating that in top of the actions taken by Starbucks to prevent their loses, their strategy to become a massive chain caused 3 coffee places to close in Portland, United States in 2008 (Sandmeyer, 2009). His goal was to animate people to consume in local shops to modify the money flow from big chains. This article passed to be the biggest opponent Starbucks' branding campaign faced, with 33% of the negative tweets replicating it in the short term.

The impact of the before mentioned article published on July 25 was seen in the following months as graph Figure 15. shows. Because of it, August and September were months with a higher quantity of negative tweets.

In 2012 there was an increase in the usage of slogans. Users started replicating again tweets mentioning the campaign even though it was not relaunched. Exploring this behavior, the explanation behind it can be attributed to 2 factors. The first one is the role of media, there was an important rose in the quantity of neutral tweets due to a higher number of tweets replicating articles talking about the campaign, which reactivated the conversation. The second and more influential factor is that the quantity of tweets mentioning Starbucks grew drastically in those years as seen in Table 10. With a bigger universe, the group of people that mentioned phrases of Starbucks's specific campaign grew as well.

Despite these challenges this campaign faced, there was still a portion of the public who appreciated it from the beginning, viewing Starbucks as a premium experience that set it apart from other coffee businesses. These polarized opinions help to explain the campaign's neutral short-term results.

Based on these preliminary findings, which reveal a long-term Love-Hate Index of 25.8% and a preceding medium-term index of 17%, it can be concluded that the campaign was positively perceived overall, with an upward trend, despite the challenges it encountered.

Extraction – General perception of Starbucks

For making a comparative and understanding if there was a modification in brand perception due to the branding campaign, another exploration was needed. Tweets from the year of the campaign (2009) were extracted to perform a sentiment analysis. Since the campaign was introduced in May, the months before were considered to further understand brand perception evolution.

This time the general commentary on starbucks is needed, per consequence there is a greater quantity of tweets introduced. Because of that, it was necessary to sample the population for the analysis. Before the sampling, more filters were applied so that the information becomes more accurate. Below this paragraph there is the used query with the filters that will be explained later in this paper.

```
query = ' Starbucks - ("Starbucks or nothing" OR "it\'s not just coffee.
it\'s starbucks" OR its not just coffee it\'s starbucks OR "it\'s not just
coffee it\'s starbucks") lang:en -from:Starbucks -from:Starbucks_usa -
from:StarbucksCare -from:Starbucksindia -from:Starbucks_j -
from:StarbucksCanada -from:StarbucksUK -from:StarbucksMY -
from:SBWorkersUnited -from:StarbucksJobs -from:SbuxIndonesia -
from:starbucksph -from:starbucksbrunei -from:starbucksuae -
from:starbucks_SA -from:StarbucksIE -is:reply -is:quote -is:verified -
is:nullcast -has:links -has:media -has:images -has:video_link
```

Figure 18. Detailed query used in the tweet extraction for evaluating Starbucks' brand perception.

In this case there in an omission of the before used phrases as they specifically address the campaign and were already analyzed. This exclusion is not that impactful because as shown in table 6. the total number of tweets mentioning the campaign was 104 for 2019, and the quantity of tweets with the word "Starbucks" just in June 2009 was 110.712.

For reaching a more delimitated database a great quantity of accounts that represent starbucks were excluded, English was designated as the only language for the tweets. There was an exclusion of all verified accounts as well to omit the possibility of encountering a biased commentary due to commercial interests. Another important filter used was "-is:nullcast" an efficient Twitter tool that: "Removes Tweets created for promotion..." (Twitter Inc., 2023)

Finally, and following the logic applied for excluding quotes and replies, all tweets with media attached to them were not considered because media represented a part of a thought that needed to be considered together with the text to calculate the sentiment of the tweet. Given that the code used is limited to text analysis only, the sentiment determination of tweets with attached media was not accurate enough for this study. Among the excluded media there is: links, images, videos, and GIFs. This exclusion was not done in the specific campaign analysis since the quantity of tweets made possible to do a thorough manual check. Because of the large dataset, random manual checks were done to assert the quality of the sentiment determination.

After applying all the possible filters that allowed to reduce the population, it was important to focus the research on people that were living in the area where the branding campaign was introduced. Since it was not possible to apply a location filter because at the time Twitter did not store this kind of information, the chosen alternative was to extract tweets based on the usage time of Twitter and the time zone of the place where the campaign was introduced. According to a study the range between 12:00 and 22:00 is the most active among users in Twitter, with a peak of tweet production at 21:00 (Liang & Fu, 2015).

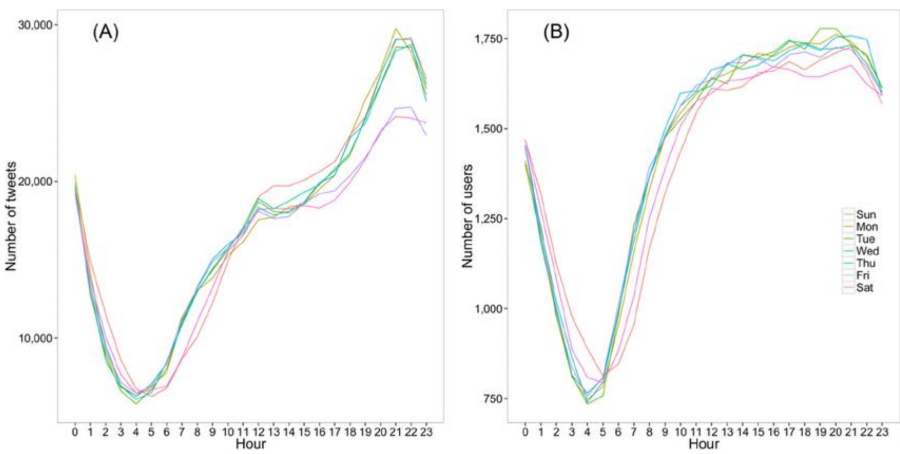

Figure 19. Image retrieved from the investigation performed by Liang & Fu (2015) describing Twitter activity.

The usage of this hour range is translated into a higher probability of getting a tweet from the target zone, hence making the extraction more accurate. In the United States there are 6 different time zones, the earliest one is the Hawaii Standard Time (HST) and the latest one is the Eastern Daylight Time (EDT). There is a difference of 6 hours between each. Bearing in mind this information, the hour range of the query was reduced to increase the effectiveness of the results. The chosen starting time for the tweet extraction is 12:00 HST and the ending time 22:00 EDT.

Hour ranges for tweet extraction			
Place		**Starting time**	**Ending time**
United States' time zones	HTS	12:00	16:00
	AKDT	14:00	18:00
	PDT	15:00	19:00
	MDT	16:00	20:00
	CDT	17:00	21:00
	EDT	18:00	22:00
Coordinated universal time	UTC	22:00	2:00

Table 7. Time zones of the United States (where the campaign was launched) fluctuating between the highest Twitter usage time.

As we can see in Table 7., using a range of 4 hours for the extraction of tweets between 22:00 and 2:00 UTC reduces the probability to encounter a tweet from a different location on earth due to the superior activity in the preferred zones. The starting time and the ending time of the time zones in the United States variates inside the hour range of higher activity on Twitter (12:00 and 22:00). Since the Twitter query needs to be built only on the coordinated universal time (UTC), this information was included to have a comparative.

Regarding the sampling process, a random sample could have been used if the population displayed a homogeneous behavior. However, since a random sample of the population itself was not adequately representative in this case, a more sophisticated sampling technique was employed.

$$n_0 = \frac{z^2pq}{e^2}$$

$$n = \frac{n_0}{1 + \frac{(n_0 - 1)}{N}}$$

The formulas displayed before are the ones employed in this study. The first one (n_0) is used to calculate the sample of a large population. The second one (n) uses n_0 to calculate the sample of a finite population, it includes into the calculus the quantity of the population (N). The larger the population is, the closer n gets to n_0 (Israel, 1992). In this case, and with a population of 807.236 (All the tweets of the year 2009 mentioning Starbucks after applying the filters before mentioned), n_0 can be used to determine the sample given that any population with a quantity above 100.000 will encounter a minimal difference between the results of n_0 and n. Here are all the values that needed to be determined for the calculus:

z = critical value of the normal distribution related to the desired confidence level
p = proportion, the percentage of the values associated with the study
q = 1-p
e = desired margin of error

For this kind of research, the desired confidence level is 98%. Considering that the values are displayed in a standard normal distribution (shaped like a bell), is possible to traduce the desired confidence level into z using the z score table. In this case, the value of z is 2,1.

The purpose of the sampling formulas, besides reducing the number of tweets to analyze, was to diminish to a minimum the possibility to include in the investigation people that did not by any means acknowledge the branding campaign conducted by Starbucks. For achieving this, a proportion needed to be found.

For calculating this proportion there was an evaluation of the quantity of stores Starbucks had in the United States (where the campaign was launched as a way of overcoming the recession) compared to the number of stores Starbucks had around the world in the year 2009. The information and calculations of the proportion are described in the table below.

2009	**Nº stores**	**Proportion**
US	11128	66.90%
Internationally	5507	33.10%
Total	16635	100%

Table 8. Number of Starbucks stores in the US and outside the US and their respective proportion (Statista, 2022).

Afterwards, it was established that the required margin of error for this investigation, bearing in mind the dataset and the reliability of the techniques used, was 4% (Fuller, 2011). Having all the needed values, the formula was used to determine the sample. As a comparative, n was employed for calculating the sample of different smaller populations with the same proportion, confidence level and margin of error. Making more visually explanatory how a large population has similar results for n_0 and n.

Population (N)	Confidence level in value (Z)	Sample proportion	Margin of error	no	n
807.236	2.1	66.90%	4%	**610.39**	**609.93**
100.000	2.1	66.90%	4%	**610.39**	**606.69**
50.000	2.1	66.90%	4%	**610.39**	**603.04**
5.000	2.1	66.90%	4%	**610.39**	**544.08**
500	2.1	66.90%	4%	**610.39**	**275.10**
50	2.1	66.90%	4%	**610.39**	**46.28**

Table 9. Calculation for determining the number of extracted tweets and sample examples considering different populations.

A calculation of the total number of tweets posted was done as well. Employing Postman, it was possible to obtain the number of tweets mentioning Starbucks from 2009 until 2015 under the query specifications. The information in table 10. is the population and was used together with the results of the sample to determine the evolution of the sentiment towards the brand under different periods, as well as the weighted LH index.

Month/ Year	2009	2010	2011	2012	2013	2014	2015
January	15,701	72,244	143,220	335,817	620,408	695,392	313,923
February	26,332	97,341	176,383	358,539	661,434	660,375	357,007
March	39,399	114,092	196,066	390,858	637,816	587,733	381,786
April	52,587	118,327	207,700	376,332	648,849	580,845	316,469
May	61,478	121,813	227,093	426,594	626,355	555,101	328,129
June	66,176	113,109	215,258	406,674	621,573	467,750	283,319
July	83,876	117,194	224,344	450,296	659,088	453,720	270,695
August	76,170	121,974	237,624	443,678	653,364	480,127	273,861
September	87,514	145,012	298,392	589,327	831,331	548,876	296,503
October	92,910	151,027	303,516	654,197	795,868	441,714	267,954
November	101,848	182,851	400,738	710,713	949,086	526,281	442,958
December	103,245	169,894	376,787	630,855	725,408	399,400	234,723
Total	807,236	1,524,878	3,007,121	5,773,880	8,430,580	6,397,314	3,767,327

Table 10. Total quantity of tweets posted per month considering the query shown on figure 18.

Short term perspective – General perception of Starbucks

To trace the evolution of Starbucks' brand perception, a comprehensive analysis of the entire year 2009 was necessary to compare dates and gauge the impact of the campaign. The initial evaluation is presented in the following graph.

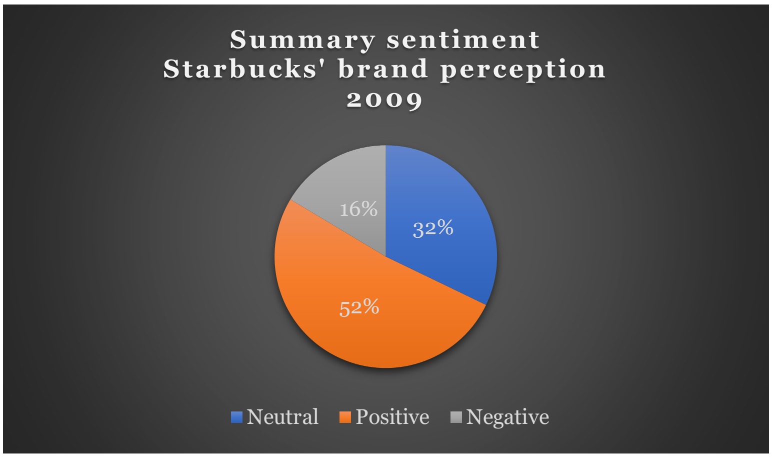

Figure 20. Sentiment proportion of the analyzed tweets in the short term, brand perception analysis. 2009.

There is an important difference in the values displayed in figure 20. compared to the ones in figure 8. In the short-term outcome of the specific campaign the quantity of positive and negative tweets was practically the same, both of 40%. In this case the public perception was better, with 52% of the tweets posted in 2009 demonstrating a positive sentiment. The monthly distribution of the sentiment towards the brand in the year 2009 can be found on figure 21.

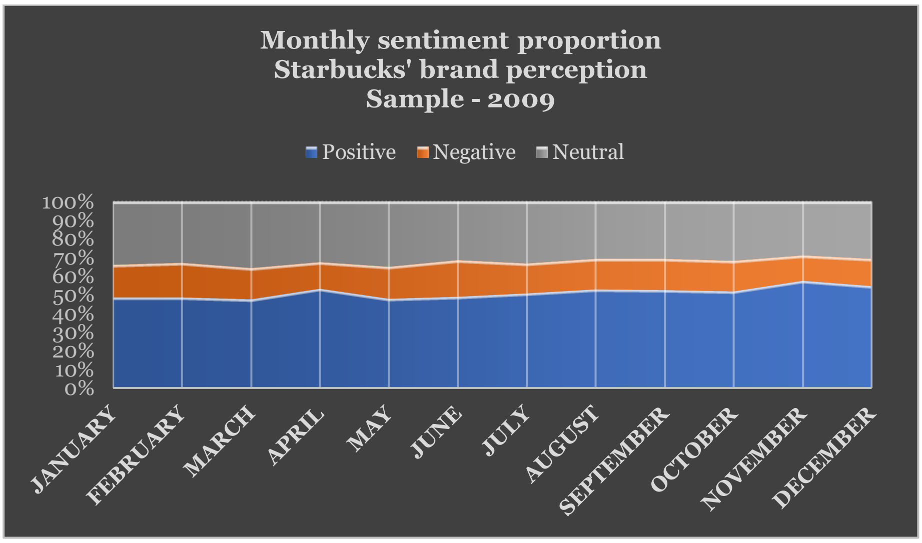

Figure 21. Negative, positive, and neutral sentiment proportion of the tweets posted in 2009. Brand perception analysis.

Using the code, it was possible to extract a sample of each month that had at least 650 tweets, the quantity required by the assigned sampling technique. For determining the love-hate index, a comparative between the positive and negative tweets needed to be done taking into consideration the population. The table below calculates the love-hate index of the sample each month and of the entire year (2009).

2009	Nº of extracted tweets	P-N	Love-hate index
January	652	204	31%
February	702	211	30%
March	855	265	31%
April	874	340	39%
May	873	273	31%
June	859	252	29%
July	862	301	35%
August	878	324	37%
September	870	310	36%
October	879	310	35%
November	883	387	44%
December	874	348	40%
2009	**10061**	**3525**	**35%**

Table 11. love hate index calculation per month. Brand perception analysis, 2009.

Based on the extracted information displayed on table 11, the graph below was generated.

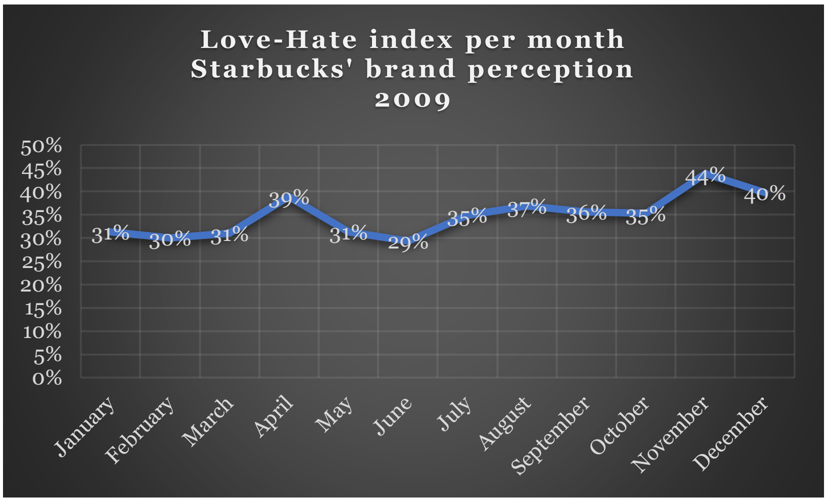

Figure 22. Comparative of the love hate index values per month. Brand perception analysis, 2009.

In figure 22. it is possible to see the love hate index evolution per month in a more visual way. It is important to keep in mind that May was the month when the branding campaign was introduced, and that at the end of July the article that became the worst critic of the campaign was published.

Since the dataset is large and representative, and the sampling technique was well applied, it is possible to extrapolate the values of the sample to the population using the obtained percentages.

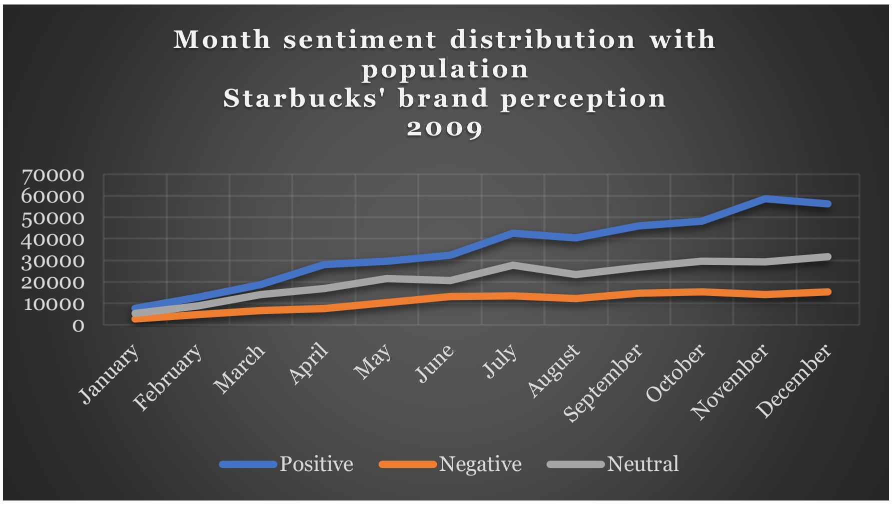

Figure 23. Sentiment distribution of the population per month. Brand perception analysis, 2009.

Employing the values of the population, the weighted love-hate index was calculated for the year 2009. With a value of 36% it is possible to affirm that the public perception towards the brand was positive, and that the actions performed in the year created greater awareness, increasing drastically the quantity of tweets posted.

Medium term perspective – General perception of Starbucks

The medium-term perspective considers the period between January 2009 and December 2010, with over 19 thousand tweets analyzed, the following graph describes de distribution of the sentiment in these 2 years.

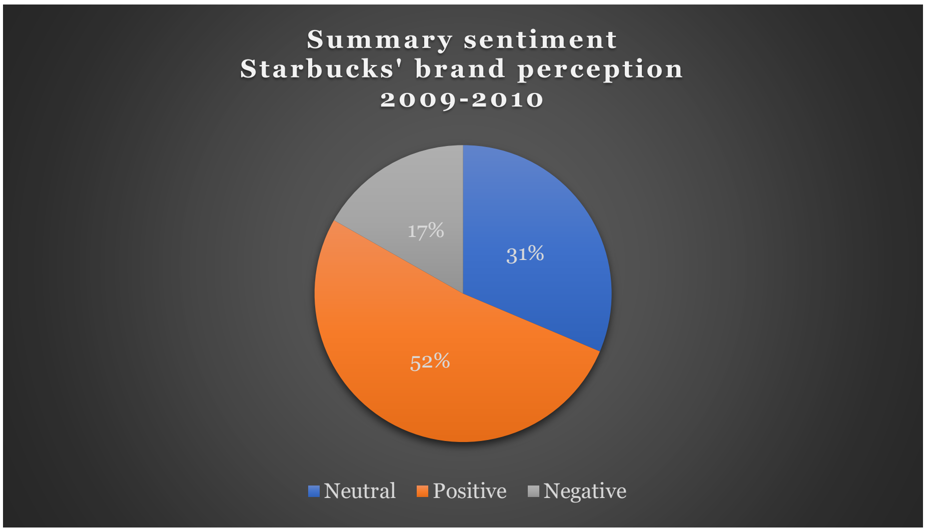

Figure 24. Sentiment proportion of the analyzed tweets in the medium term. Brand perception analysis, 2009 – 2010.

In the medium term, the percentage of positive tweets remained the same as in the short term (52%), the only difference is that the quantity of negative tweets increased by 1% and the quantity of neutral tweets decreased by 1%. The monthly distribution of the sentiment towards the brand from January 2009 until December 2010 can be found on figure 25.

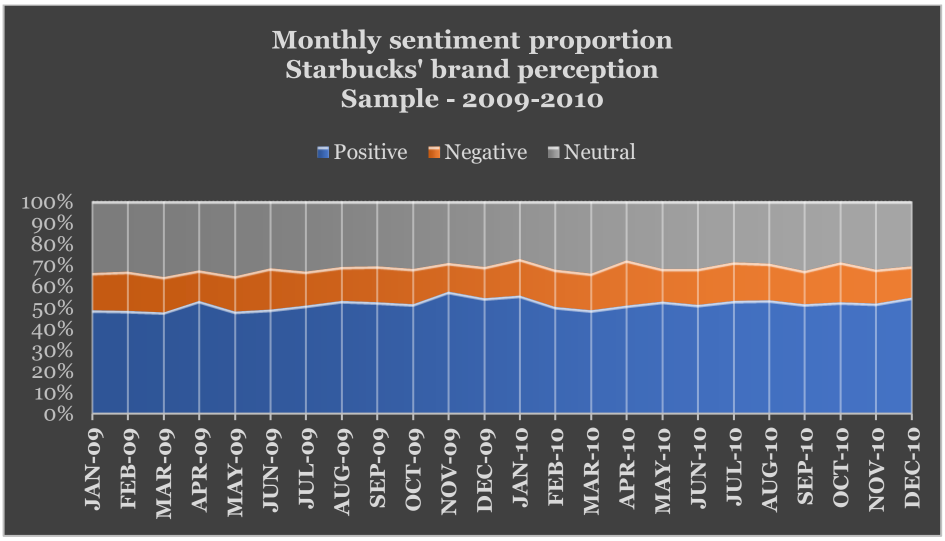

Figure 25. Negative, positive, and neutral sentiment proportion of the posted tweets. Brand perception analysis 2009 - 2010.

Table 12. includes the calculation of the love-hate index of the sample per month and of the medium-term period without considering the population.

	Nº of extracted tweets	**P-N**	**Love-hate index**
Jan-09	652	204	31%
Feb-09	702	211	30%

Mar-09	855	265	31%
Apr-09	874	340	39%
May-09	873	273	31%
Jun-09	859	252	29%
Jul-09	862	301	35%
Aug-09	878	324	37%
Sep-09	870	310	36%
Oct-09	879	310	35%
Nov-09	883	387	44%
Dec-09	874	348	40%
Jan-10	777	301	39%
Feb-10	774	255	33%
Mar-10	765	241	32%
Apr-10	765	227	30%
May-10	781	291	37%
Jun-10	761	263	35%
Jul-10	769	268	35%
Aug-10	767	279	36%
Sep-10	779	282	36%
Oct-10	762	257	34%
Nov-10	770	275	36%
Dec-10	774	307	40%
2009-2010	**19305**	**6771**	**35%**

Table 12. love hate index calculation per month on the sample of the 2009 – 2010 period.

Based on the extracted information displayed on table 12, the graph showing the evolution of the monthly LH index was generated.

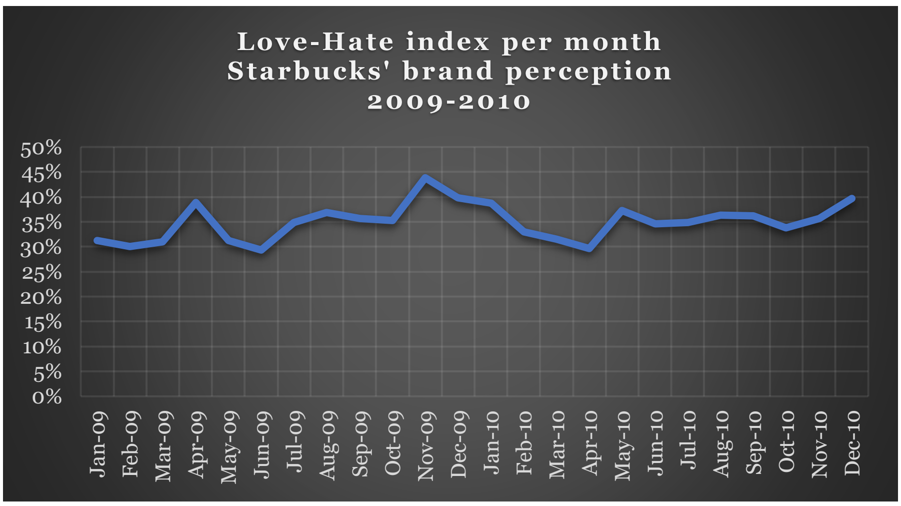

Figure 26. Comparative of the love hate index values per month. Brand perception analysis, 2009 – 2010.

Extrapolating the data of the sample to the population (total quantity of published tweets per month), the distribution of negative, positive, and neutral tweets is estimated to be as displayed in figure 27.

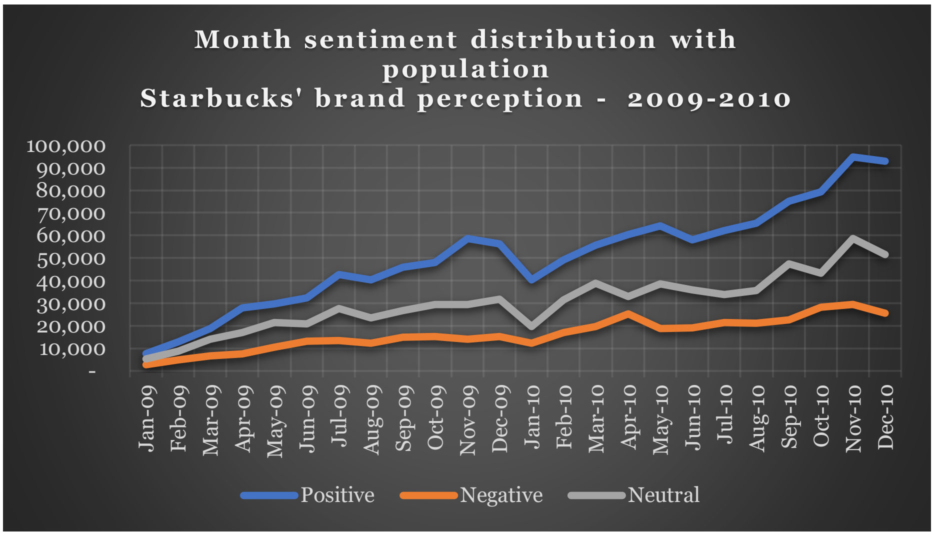

Figure 27. Sentiment distribution of the population per month. Brand perception analysis, 2009 – 2010.

Considering all the data gathered and performing the formula created, the weighted love – hate index for the medium-term period (2009-2010) is 0,3551 or 35,51%. A slightly lower value than the weighted love-hate index for 2009 (36,08%).

Long term perspective – General perception of Starbucks

The long-term perspective comprises the period between January 2009 and December 2015. Over 60 thousand tweets were extracted and analyzed. The result of the distribution of the sentiment does not vary much from the past retrieved results, but it shows for a first time a decrease of 1% in the percentage of positive tweets in the sample.

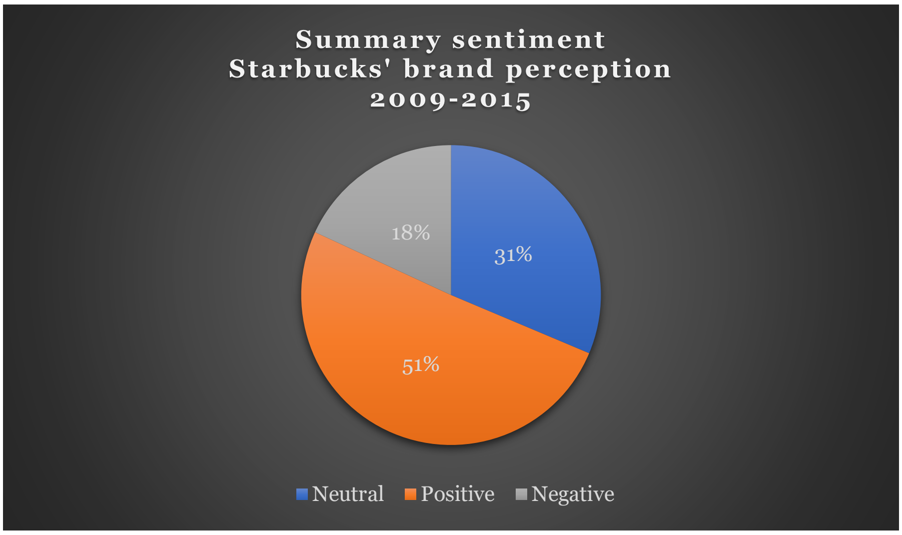

Figure 28. Sentiment proportion of the analyzed tweets in the long term for the brand perception analysis, 2009 – 2015.

The distribution of the sentiment towards the brand from January 2009 until December 2015 divided by year can be found figure 29.

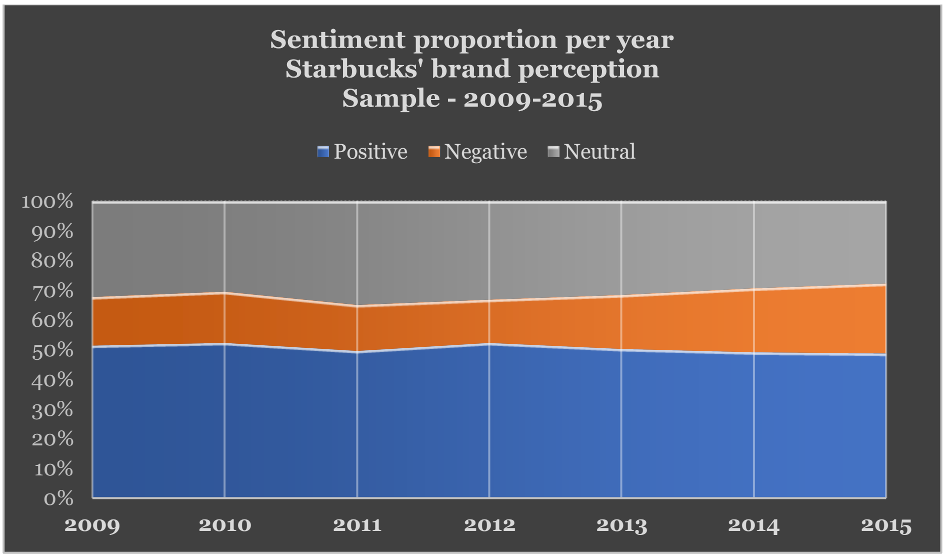

Figure 29. Negative, positive, and neutral sentiment proportion of tweets. Brand perception analysis, 2009 - 2015.

To gain insights into the relevance of the brand and the public sentiment towards it, the sentiment distribution was incorporated into the population analysis. The resulting graph provides an understanding of these aspects.

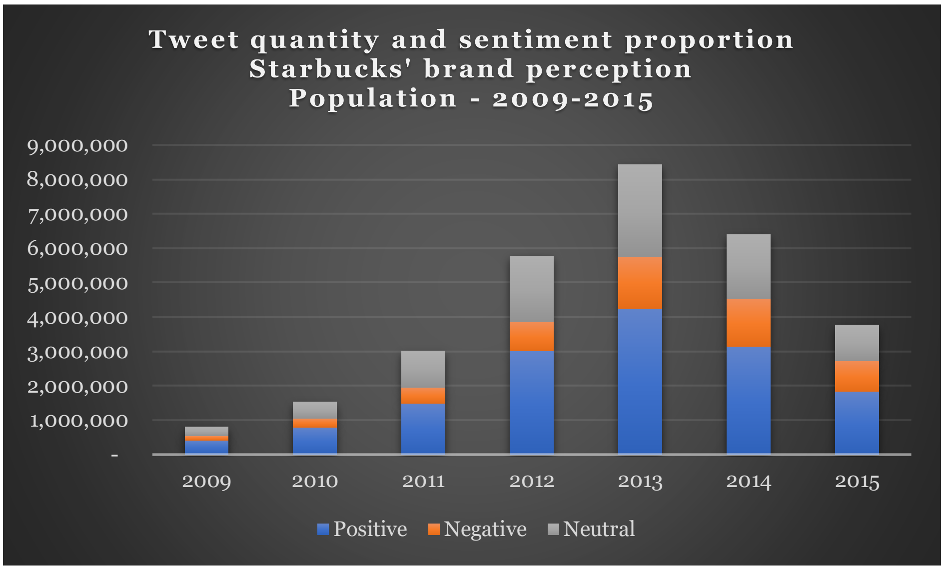

Figure 30. Quantity of tweets and sentiment proportion per year. Brand perception analysis, 2009 - 2015

For reaching a better understanding of the sentiment variation, a semester analysis was performed.

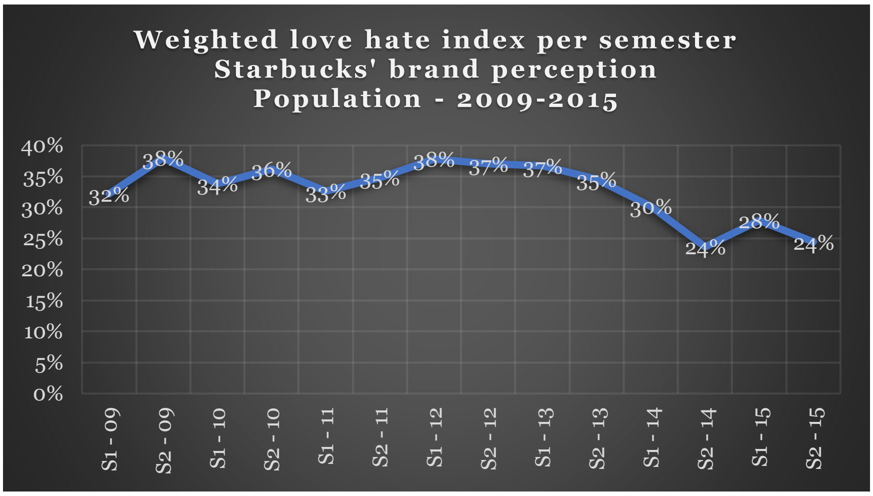

Figure 31. Comparative of the love hate index values per semester. Brand perception analysis, 2009 – 2015.

The values displayed in figure 31 are weighted by the quantity of tweets present by semester in the population. They do not differ significantly from the love-hate index by semester obtained from the sample (2% is the maximum difference). Extrapolating the data of the sentiment distribution to the population, it is possible to perceive the evolution of public perception by semester, as well as how relevant Starbucks was in the long-term period.

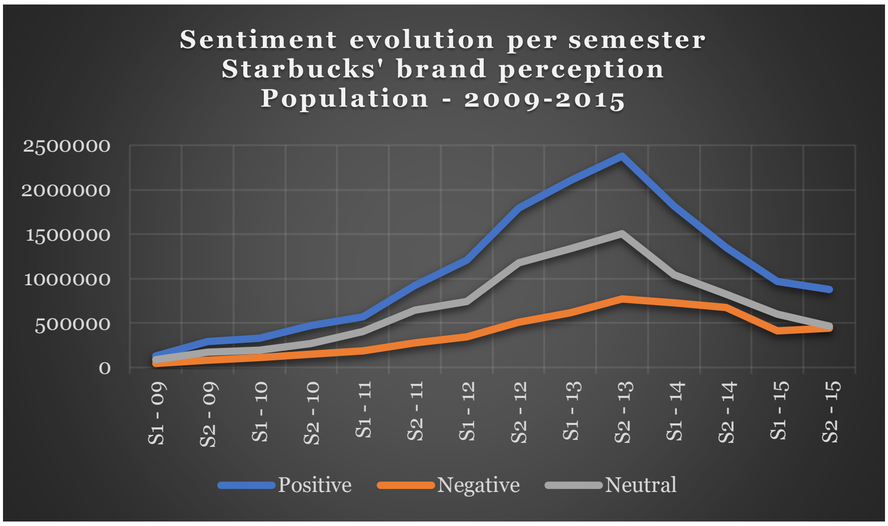

Figure 32. Sentiment distribution of the population per semester. Brand perception analysis, 2009 – 2015.

Figure 32. shows a clear rising on the percentage of negative tweets about Starbucks in the last semesters of the study, this quantity comes close to the quantity of neutral tweets in the second semester of 2015. There is also a noticeable decrease in relevancy (quantity of tweets posted about Starbucks) in the latest semesters. For isolating the crucial dates influencing this outcome, an expansion into a monthly analysis was made.

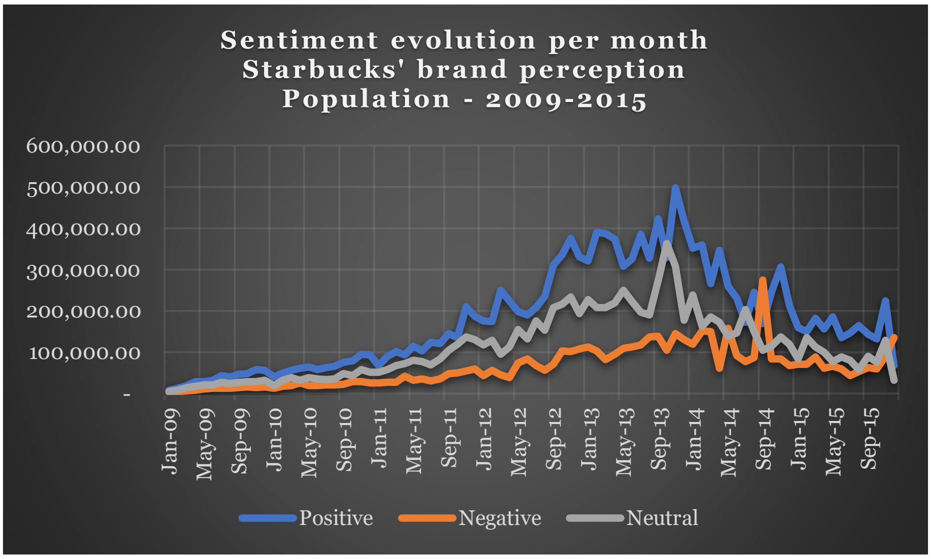

Figure 33. Sentiment distribution of the population per month. Brand perception analysis, 2009 – 2015.

There is a critical rising in the quantity of negative tweets from March 2014 and a decrease in relevancy of Starbucks that same year. A more detailed analysis of this outcome can be found on the findings.

Based on the information obtained, a weighted love-hate index was computed for the period 2009-2015, yielding a result of 0.3278 or 32.78%, indicating a positive brand perception in the long term. However, the graph reveals a negative trend in the latest semesters of the long-term period, suggesting weaknesses in Starbucks' branding strategy. The analysis of the graph suggests that there was a trend towards a neutral or negative brand perception in the years following 2015.

Findings of the case

As evidenced by the initial investigation, the branding campaign was not implemented in isolation; there was a preexisting strategy that provided coherence to it, resulting in an increase in the number of positive tweets mentioning Starbucks. The weighted love-hate index for the first four months of 2009 (prior to the campaign's launch) was 33,9%, while from May until December 2009 it was 36,5%, indicating a slight improvement.

Table 11. demonstrates that in 2009 the campaign, in conjunction with the marketing strategy, had a positive impact, increasing the proportion of positive tweets and improving the brand perception of Starbucks. Additionally, the reach of the brand increased as well. Prior to the campaign, the average number of tweets posted per month was 33,504, while the average number of tweets posted per month after the campaign launched was 84,152.

The campaign strategy's objective was to perceive Starbucks as a company that differentiated their products from the rest, proposing quality rather than choosing a low pricing strategy. The message was well adopted in their actions, but the phrases used in their communication were not effective. Considering the queries used, in 2009 the quantity of tweets mentioning Starbucks was over 800,000 and the quantity of tweets mentioning the specific phrases of the Starbucks campaign were 104, which leads to conclude that the impact of the phrases was minimum in comparison to the vast reach achieved by the branding strategy.

In the middle-term period, it was possible to understand that the weighted love-hate index for only 2009 was slightly better (36,08%) than the weighted love-hate index for only 2010 (35,21%.). Furthermore, the weighted love-hate index for the medium-term period (2009-2010) was 35,51%, evidencing the weight influence 2010 had due to the high quantity of tweets mentioning Starbucks.

Considering all the data, from January 2009 until December 2015, the month with the highest quantity of positive tweets was March 2012. It is also the month with the best LH index (52%).

Another important outcome is that even though the articles posted in July 2009 criticizing Starbucks caused the percentage of negative tweets to increase significantly in the "Starbucks or nothing" campaign, it had no influence on the general brand perception of Starbucks that presented a love hate index of 35% and 37% for July and August respectively.

Until the month of January 2014 there was a sustained growing in the tweet quantity and a positive sentiment towards the brand, with November 2013 being the month with the highest quantity of posted tweets (949,086) in the long-term period. Nevertheless, from March 2014 the positive sentiment towards the brand decreased, reaching a critical point in September 2014, the first month with a significant negative love-hate index (-19,19%).

The loss of relevancy of Starbucks on Twitter and the irregular sentiment fluctuation of the public sentiment indicates flaws in the long-term branding strategy. Furthermore, during this research it was possible to perceive the impact influencers have on brand perception.

Overall, there were over 30 million tweets posted between 2009 and 2015 under the specified query, their sentiment distribution was: 50% positive, 18% negative and 31% neutral. During this period the average number of tweets posted per month was 357,433. Two months, September 2014 (with a love-hate index of -19.19%) and December 2015 (with a love-hate index of -28.25%), had a higher quantity of negative tweets than positive, negative tweets also outnumbered neutral tweets in those cases.

The month with the highest percentage of positive tweets was March 2012 when 64% of the tweets were positive, which signified a 52% LH index. The month with the lowest percentage of negative tweets was April 2012 with 10%, 60% were positive tweets and 30% neutral. December 2015 was the month with the highest percentage of negative tweets with 57%.

The comparison of the love hate index in the short medium and long term demonstrates a slight progressive decrease. For the short-term the love hate index value was 36,08%, for the medium term it was 35,51% and 32,78% for the long term. Consequently, it is possible to assume that there was a deterioration of the brand image of Starbucks in the long term even though the sentiment towards the branding campaign adopted a positive tendency.

Tweets specifically mentioning the specific campaign had a neutral love-hate index for the short term (-1%), slightly positive for the medium term (17%) and positive in the long term (25,8%). Performing a comparison of the love hate indexes in the same periods for both cases (branding campaign and brand perception) it is possible to see how even with an initial neutral sentiment towards the campaign, its launching was beneficial for the company for increasing its reach, and how the positive acceptance of the phrases used in the campaign in the long term did not influence positively in the brand image, which showed progressive decadence.

Conclusively, and despite the slight deterioration in the brand perception of Starbucks the last two years of the study (2014, 2015), the employment of the "Starbucks or nothing" campaign can be considered as a positive. The sentiment distribution towards the brand was almost constant, the long-term value of the love hate index was positive, and the reach the campaign had increased brand awareness considerably.

Nike

The American company is recognized worldwide by its great logo and motivational personality. In 2022 it was chosen by Brand Finance to be the first one in the Apparel 50 ranking (Brand Finance, 2022). Keeping the leading position for the 8th consecutive year.

2022	2021	Logo	Name	Country	2022
1 =	1		Nike		$33,176M
2 ^	3	LOUIS VUITTON	Louis Vuitton		$23,426M
3 v	2	GUCCI	GUCCI		$18,110M
4 ^	5	CHANEL	Chanel		$15,260M
5 v	4	adidas	Adidas		$14,636M
6 ^	10		Hermès		$13,499M
7 v	6	ZARA	ZARA		$12,997M

Figure 34. Illustration indicating the apparel 50 ranking of 2022 retrieved from the Brand Finance ranking (2022).

The steps Nike had taken in the past and, more importantly, their convictions had led them into a path of continuous growing. But Nike is not only reflected on the products they sell and the personality they project. The company is also famous for sponsoring thriving athletes, making them carry Nike's logo and values into every sport venture or competition they have.

The human component is risky because at some level it is unpredictable. Athletes like Many Pacquiao or Lance Armstrong had been removed from the company's list of brand ambassadors because Nike considered that their actions did not represent the brand and their values (ESPN, 2016) (Forbes, 2012).

Historically, there are multiple examples on how the brand chose to make personality statements. In February 1995 Nike featured in their TV advertisement Ric Muñoz, an HIV-positive runner they incorporated into the "Just do it" campaign (first launched in 1988) (Kessler, 2018).

In December 2007, Nike launched the "No excuses" campaign featuring Matt Scott, a paralympic medalist, and in 2012 gender equality was addressed with their ad "Voices". The repercussion of this campaigns signified greater revenue for the brand, more visibility, and the solidification of their brand personality.

But advertisement choices Nike have had were not always welcomed in a positive way by the public. In this case I will evaluate the impact on the brand perception on Twitter of the advert "Dream Crazy", a campaign led by the former NFL athlete and current activist Colin Kaepernick.

Kaepernick is a former player of the San Francisco 49ers, an American football team in the U.S. National Football League (NFL). He played in the quarterback position and managed to take the team to the Super Bowl XLVII where they would lose against the Baltimore Ravens. Colin is most famous for taking a knee during the U.S. national anthem in September 2016 as a protest for the oppression and violence black people were suffering at the time.

"I am not going to stand up to show pride in a flag for a country that oppresses Black people and people of color. To me, this is bigger than football and it would be selfish on my part to look the other way. There are bodies in the street and people getting paid leave and getting away with murder."

- Kaepernick

(History.com Editors, 2021)

Kaepernick's departure from the 49ers in 2017 was controversial, and his period as a free agent even more. Because of his political stand, Colin was blackballed by the NFL teams. In October 2017 he filed a grievance against the NFL that reached a confident settlement in February 2019.

The action of taking the knee during the national anthem on a country where in that year (2017) 75% of adults declared to be extremely or very proud of being from the U.S. was an act of bravery and had an important backlash (Brenan, 2022). "At one point in 2017, more than 200 NFL players knelt, sat or raised their fists during the anthem" (CNBC, 2019).

Nike decided to promote the campaign "Dream Crazy" with Kaepernick as the principal spokesman from September 2018. Kaepernick's post on Twitter with the phrase "Believe in something, even if it means sacrificing everything." has at the time almost 800 thousand likes and more than 300 thousand retweets.

Given that the figure of Kaepernick was controversial, Nike's decision to support him together with the campaign message generated boycotts against the athlete and Nike. Even the president at the time, Donald Trump, gave declarations stating his rejection to any action that would demonstrate a protest during the national anthem and criticizing the brand for choosing such strategy. In a tweet posted by him in September 2018 it reads: "What was Nike thinking?".

On Twitter, the main trend the following days after the post was #NikeBoycott and the company stock closed the day decreasing 3.2% (CNBC, 2018). However, even though there was a patriotic movement condemning fiercely the branding campaign, according to CNBC the company's online sales increased by more than 25% in the short run. At the time there was a contrast of supporting Nike (by buying their products) and rejecting the statement made with the campaign (by burning Nike's merchandise on Twitter). The final outcome was positive for both athlete and the brand when in 2019's Creative Arts Emmy Awards the ad was awarded as "outstanding commercial" (CNN, 2019). In this case, this research will clarify the initial polarity and analyze the brand perception impact the ad had on different periods.

Extraction – "Dream Crazy" campaign

Just like in the extraction in the Starbucks case, 2 scenarios were analyzed individually and later in comparative. The first one is based on the branding campaign

"Dream Crazy" and its outcome, and the other one based on the general brand perception of Nike at the same time the campaign was present bearing in mind users in the same area. Considering the phrases used, specific tweets of the campaign were extracted for the specific branding campaign under these parameters (the time frame was modified according to the desired period):

```
query = ' ((Nike Colin) OR (Nike kaepernick) OR ("Dream crazy" nike)) -
(Geragos OR Avenatti) lang:en -is:reply -is:quote -is:verified -is:nullcast
-has:links -has:media -has:images -has:video_link '
start_time = '2018-09-16T00:00:00Z'
end_time = '20218-09-21T23:59:00Z'
```

Figure 35. Query employed for the tweet extraction of the "Dream crazy" campaign.

The query is designed to exclude tweets that are not directly related to the branding campaign. It also limits the language to English, excludes quotes and replies, and does not consider any tweet with media, links or that was promoted commercially. By filtering this data is possible for VADER to have a better and unbiased analysis of the dataset, hence a more accurate assessment of it. The dates are adjusted for every period.

There was another adjustment done in the query, during the extraction there were multiple variations on the tweet quantity because of a scandal involving Nike and Michael Avenatti. Avenatti, a former lawyer (who was sentenced to over 2 years in prison in 2021), tried to extort the company and at the time this scandal became public (United States Attorney's Office, 2021). There were connections between Avenatti and Mark Geragos, who was the lawyer of Colin Kaepernick in his case against the NFL presidents.

Multiple tweets mentioning Kaepernick, Nike, Geragos and Avenatti were posted. For this investigation, is important to exclude these tweets because they do not represent the sentiment towards Nike, Kaepernick or the campaign, the query was then adjusted accordingly.

Short term perspective – Dream Crazy campaign.

For the short-term perspective 6 months after the launching of the campaign were analyzed. The specificity of the query makes it difficult to find tweets before the launching of the campaign. For this case the methodology was adjusted just like in the Starbucks case, omitting the tweet extraction for the months prior the launching.

The advert was launched in September, on the graph below is possible to understand its reach and the relevancy development over the short term.

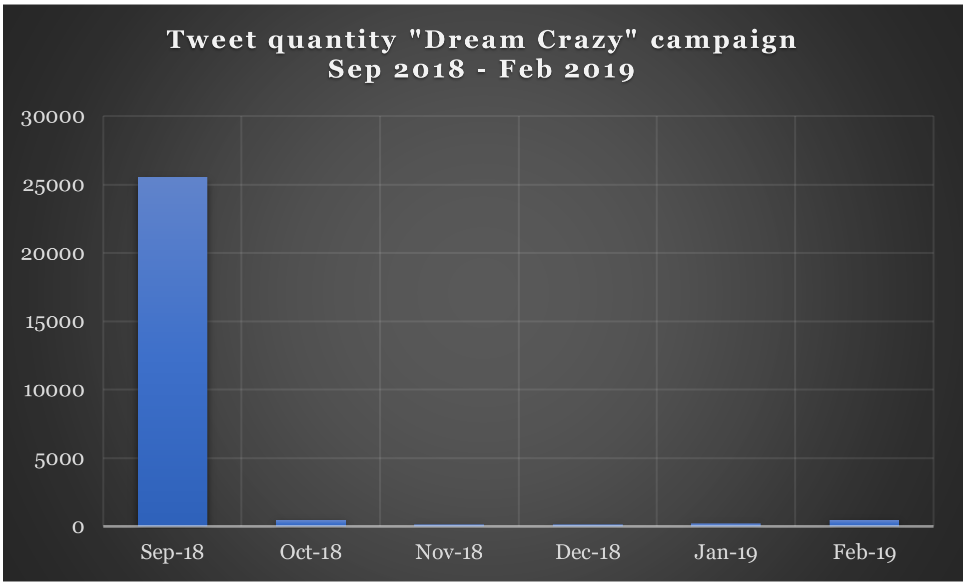

Figure 36. Quantity of tweets posted per month under the query of the "Dream crazy" campaign. Sep 2018 – Feb 2019.

Figure 35 is based on Table 13. It is possible to visualize the instant impact that the campaign had in the month of September. The tweets before September are not significant enough to be considered in Figure 36. In Table 13, the exact quantity of tweets posted considering the query before explained can be seen.

	Number of tweets
Mar-18	3
Apr-18	6
May-18	4
Jun-18	2
Jul-18	5
Aug-18	0
Sep-18	25505
Oct-18	437
Nov-18	134
Dec-18	131
Jan-19	188
Feb-19	443
TOTAL	**26858**

Table 13. Quantity of tweets per month under the query chosen for the "Dream crazy" campaign. Sep 2018 – Feb 2019.

For the month of September, when the campaign was launched, a sampling was done to reduce the quantity of analyzed tweets. The sampling procedure was the same one used in the Starbucks case, the desired confidence level was still 98%, making the value of z 2,1, and the desired margin of error was 4%.

The proportion needed to be adjusted to be representative. For this sample, the proportion was calculated in base at the revenues perceived by the company in the U.S. in 2018. Nike perceived 14,855 millions of U.S. dollars in revenues in north America, and 34,485 millions of U.S. dollars in revenues worldwide (Statista, 2022). An adjustment of the proportion was performed to fit the month of the sample when needed.

2018	Revenues (M)	Proportion
US	14,855	43,1%
Internationally	19,630	56.9%
Total	34,485	100%

Table 14. Nike revenue quantity in the US, Internationally and worldwide in 2018.

With a proportion of 43,1% it is possible to calculate in base at the sampling formula before mentioned that the value of the sample for the month of September is 658. The sentiment analysis was performed in the entire quantity of tweets for the other months as their quantity allowed it.

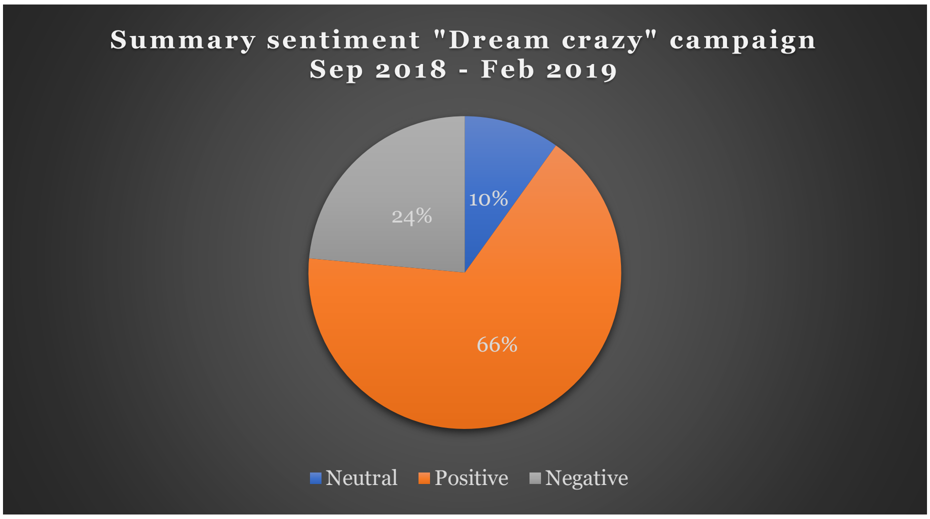

Figure 37. Sentiment proportion of the analyzed tweets in the short term for the "Dream crazy" campaign, September 2018 – February 2019.

With more than 3 thousand tweets analyzed, the sentiment expressed by people on Twitter on the period September 2018 – February 2019 was mostly positive (66%).

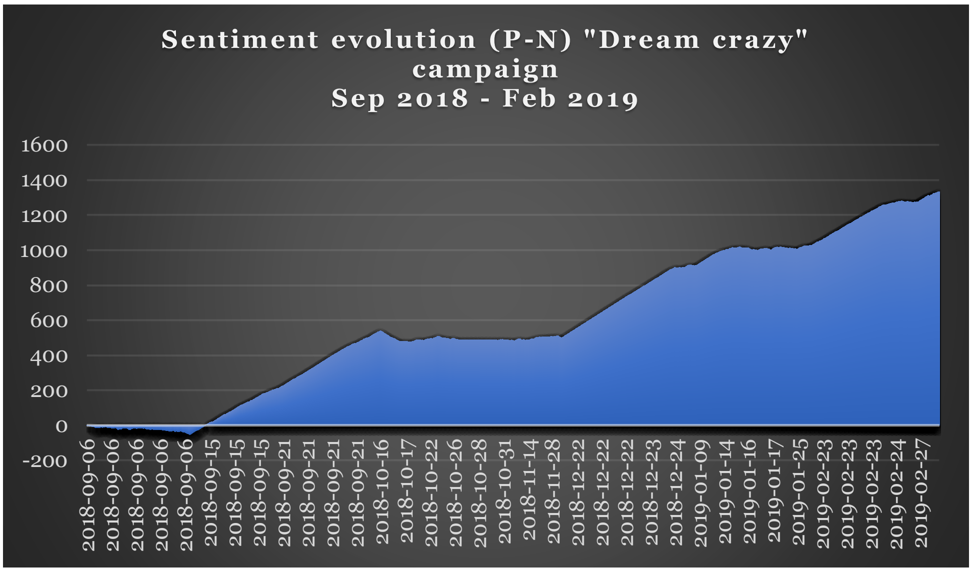

Figure 38. Evolution of Positive - Negative tweets in the short term. "Dream crazy" campaign. September 2018 – February 2019.

Figure 38. shows the sentiment evolution of the campaign, every tweet analyzed becomes a numeric data entry that either increases, decreases, or maintains the direction of the graph. The outcome of the graph needs to be considered as a whole, always taking into consideration the pivot date (September 2018). This graph uses the information from the extracted tweets; it does not take into consideration the population (total quantity of tweets under the query), a posterior analysis will include the population. The total amount of tweets extracted was 3,100, from which 730 were negative, 2063 positive and 307 neutral. Hence, by the end of the period (February 2019) the quantity of positive tweets was almost 3 times higher than the quantity of negative tweets.

It is also possible to see on figure 38. that there was a negative backlash at the beginning of the campaign, this backlash however was never significant enough to demonstrate rejection towards the brand in the overall sentiment analysis, but it did demonstrate a polarization of opinions that were balancing each other. Finally, 10 days after the introduction of the campaign, a positive tendency appeared. Other period when the quantity of positive and negative comments was almost the same started from the beginning of October 2018 and extended until the 22 of December 2018. Afterwards, a new positive tendency appeared and did not change significantly until the end of February 2019.

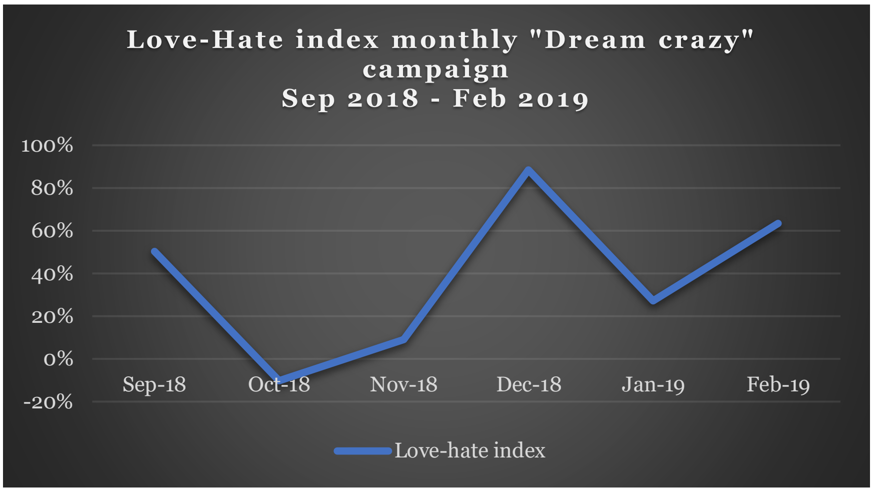

Figure 39. Comparative of the love hate index values per month, "Dream crazy" campaign, Sep 2018 – Feb 2019.

On figure 39 is possible to see the love hate index per month, October corresponds to the results before shown, with an index close to 0% demonstrating balance between the positive and negative tweets. The exact values of the love- hate index can be seen down below.

1Y	Nº of extracted tweets	P-N	Love-hate index
Sep-18	1068	537	50%
Oct-18	450	-46	-10%
Nov-18	208	19	9%
Dec-18	459	406	88%
Jan-19	451	123	27%
Feb-19	464	294	63%

Table 15. Values of the love hate index per month, sample results. "Dream crazy" campaign Sep 2018 – Feb 2019.

To better understand the opinions of tweeter users, the following graph shows the monthly distribution of the sentiment towards the "Dream crazy" campaign, starring Colin Kaepernick.

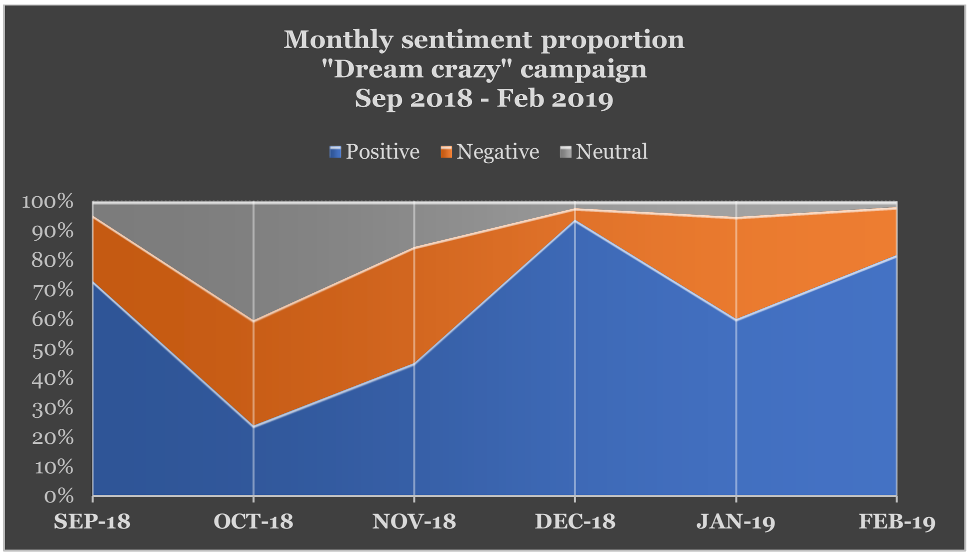

Figure 40. Negative, positive, and neutral sentiment proportion of the tweets posted about the "Dream crazy" campaign, Sep 2018 - Feb 2019.

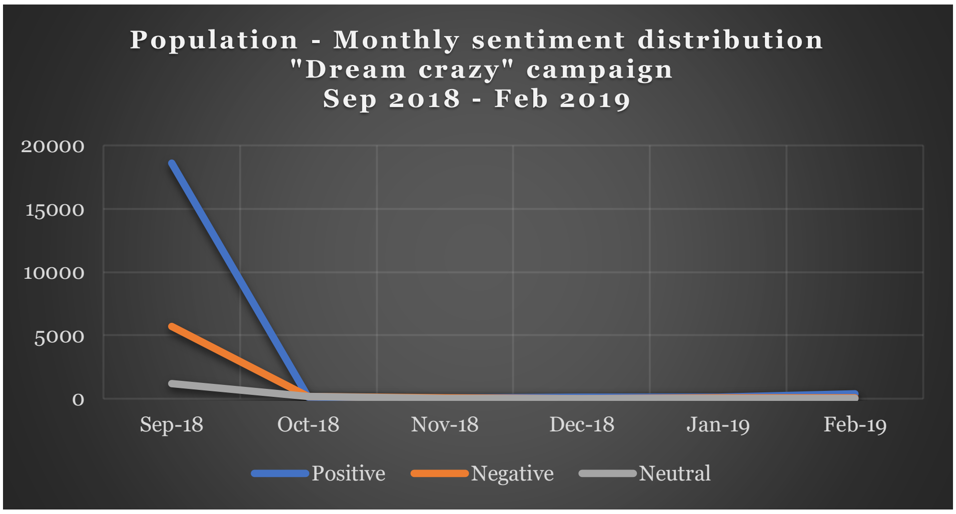

Figure 41. Total quantity of posted tweets per month distributed by sentiment, "Dream crazy" campaign, Sep 2018 - Feb 2019.

Figure 41. shows how significant the first impact about the campaign was and how fast people stopped talking about it. Is possible that the effect of the campaign faded, or that there is a behavior on social networks that limits conversations to a short lifetime.

To better comprehend the sentiment distribution, figure 42. was created excluding September (the extreme value).

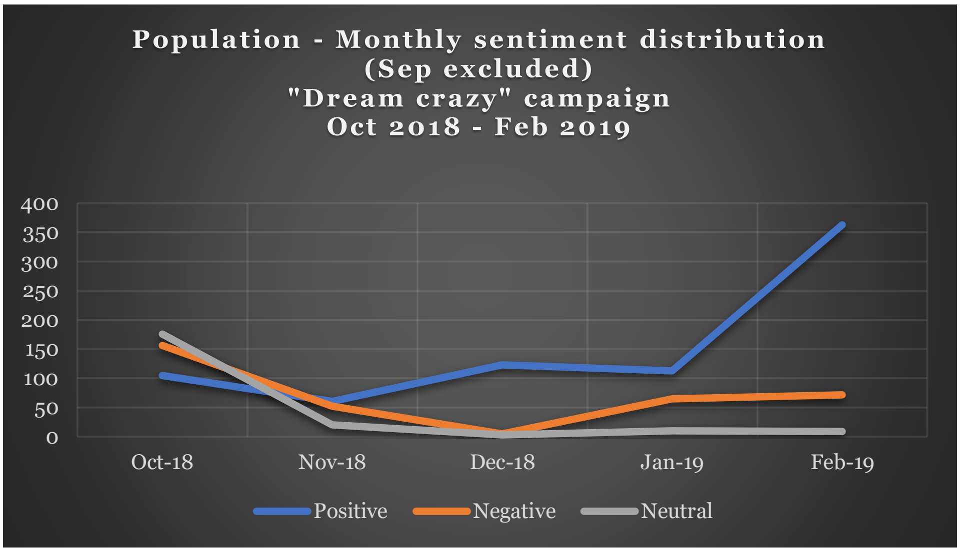

Figure 42. Total quantity of posted tweets per month distributed by sentiment and excluding September "Dream crazy" campaign, Oct 2018 - Feb 2019.

Finally, the weighted love hate index for this period (considering the population) is 49,6%.

Medium term perspective – Dream Crazy campaign.

The medium term corresponds to the period between September 2018 and February 2020. Tweets were extracted with the query before explained.

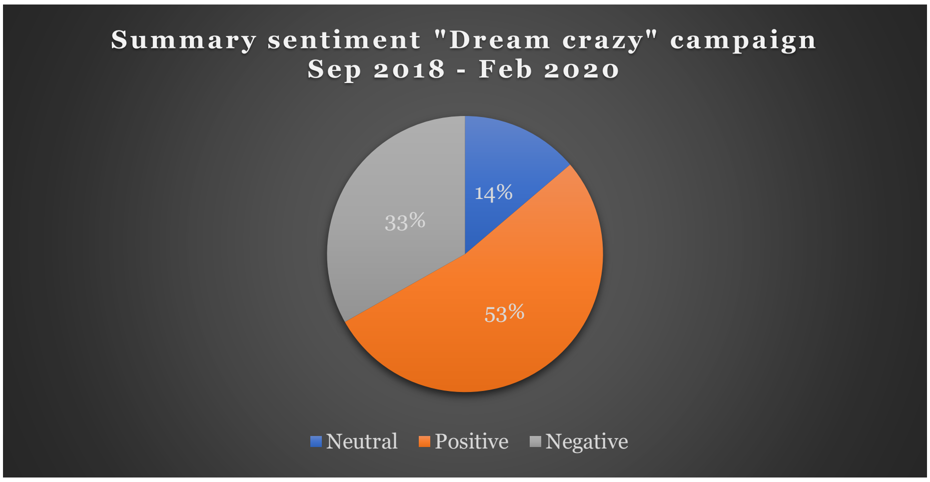

Figure 43. Sentiment proportion of the analyzed tweets in the medium term for the "Dream crazy" campaign, September 2018 – February 2020.

There is a significant reduction in the percentage of positive tweets, falling from 66% in the short term to 53% in the medium. The quantity of neutral tweets increased by 4% and the quantity of negative tweets increased by 9%.

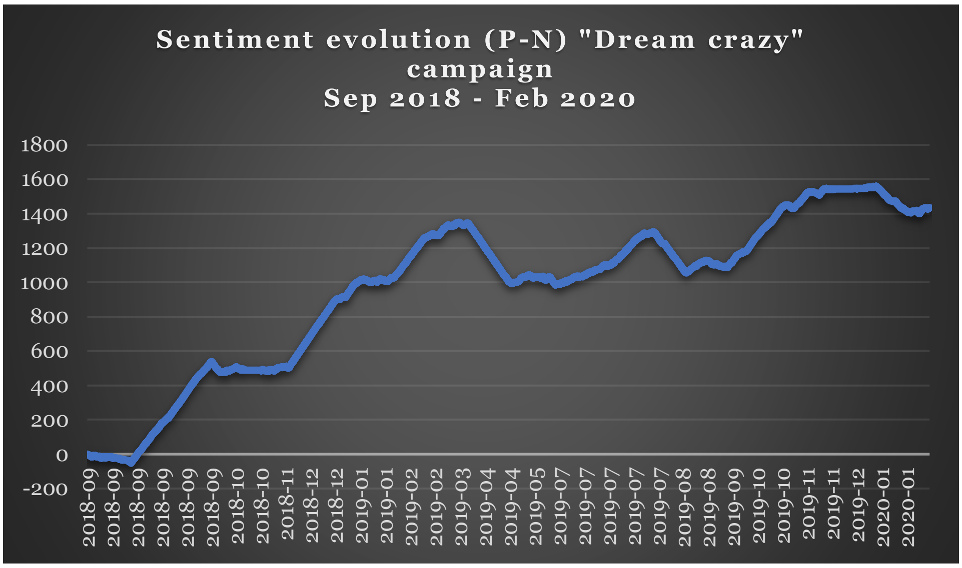

Figure 44. Evolution of Positive - Negative tweets in the medium term. "Dream crazy" campaign, September 2018 – February 2020.

As for the sentiment evolution, the before reflected positive tendency of the short term is now more horizontal, with periods of negative balance like in the months of April 2019 or August 2019. The total amount of tweets extracted was 7,230, from which 2,399 were negative, 3,835 positive and 996 neutral. Hence, by the end of the period (February 2020) the quantity of positive tweets was almost the same as the sum between negative and neutral tweets.

To better understand the fluctuations between positive and negative perception towards the campaign, figure 45. shows the love-hate index per month.

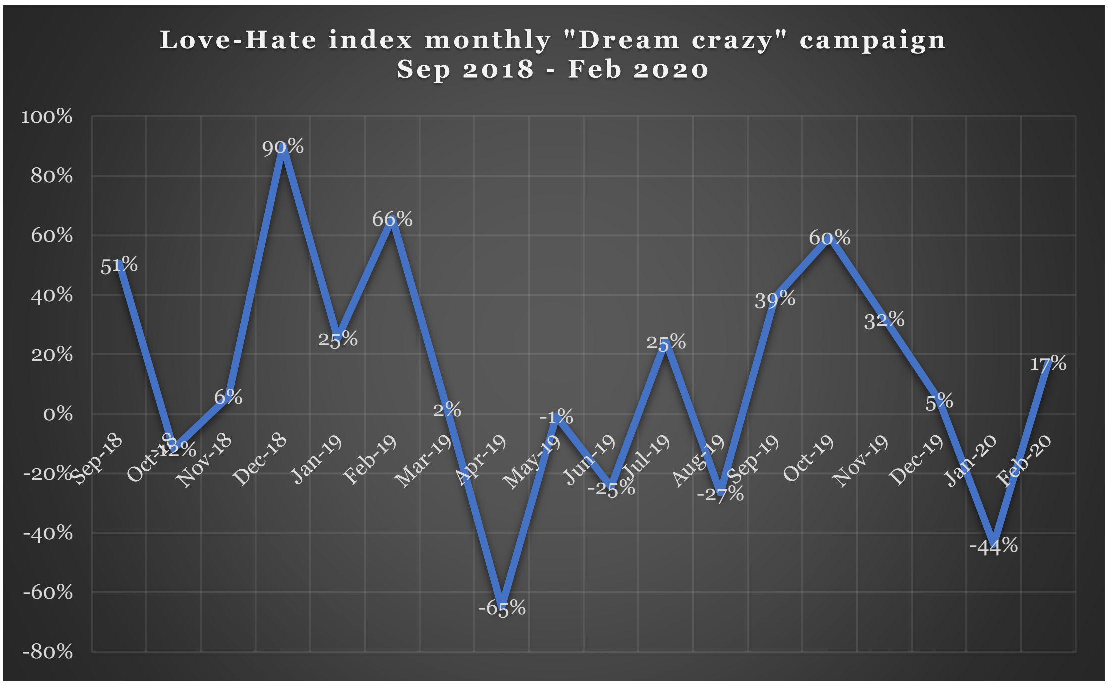

Figure 45. Comparative of the love hate index values per month, "Dream crazy" campaign, Sep 2018 – Feb 2020.

Unlike the starbucks case, it is possible to see here an extreme polarity of opinions. Is also important to mention that the quantity of tweets analyzed here is not sufficient to be considered an individual opinion. In the sense that even though the query represents public opinion specifically on the Colin Kaepernick campaign, September was the only month with a big population of tweets (more than 25 thousand), all the other months had less than 1,000 tweets. With a small quantity of tweets, this research found that the conversations started in Twitter by "influencers" were impactful on determining the brand perception for certain months. This means that the results here showed are legitimate because they address Tweets indiscriminately but in certain scenarios the love hate index could be influenced by the opinions of the community of the influencer reigniting the conversation.

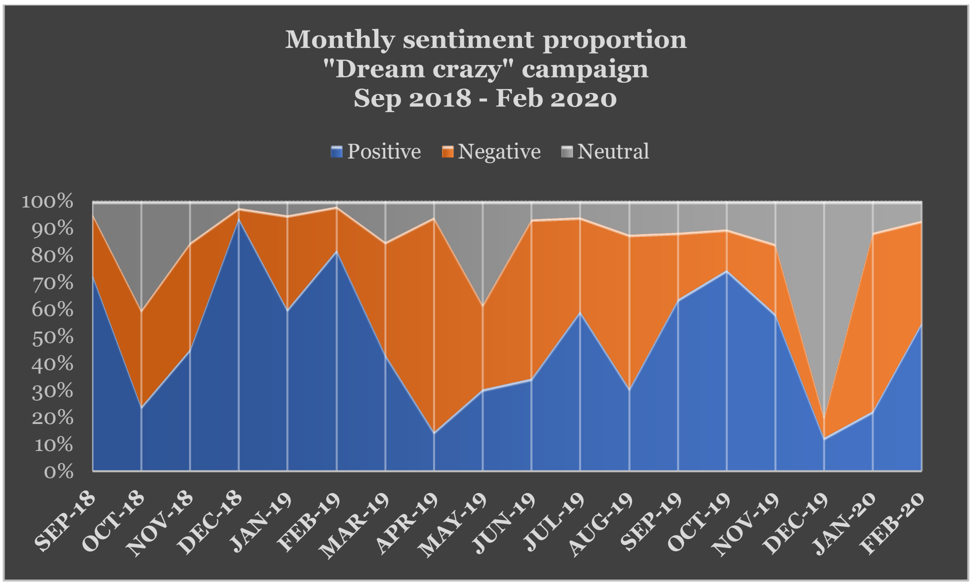

Figure 46. Negative, positive, and neutral sentiment proportion of the tweets posted about the "Dream crazy" campaign, Sep 2018 - Feb 2020.

Figure 46. shows the proportion of positive, negative, and neutral tweets in the medium term. There is a big quantity of neutral tweets in December 2019, and an alarming proportion of negative tweets between March and August of 2019.

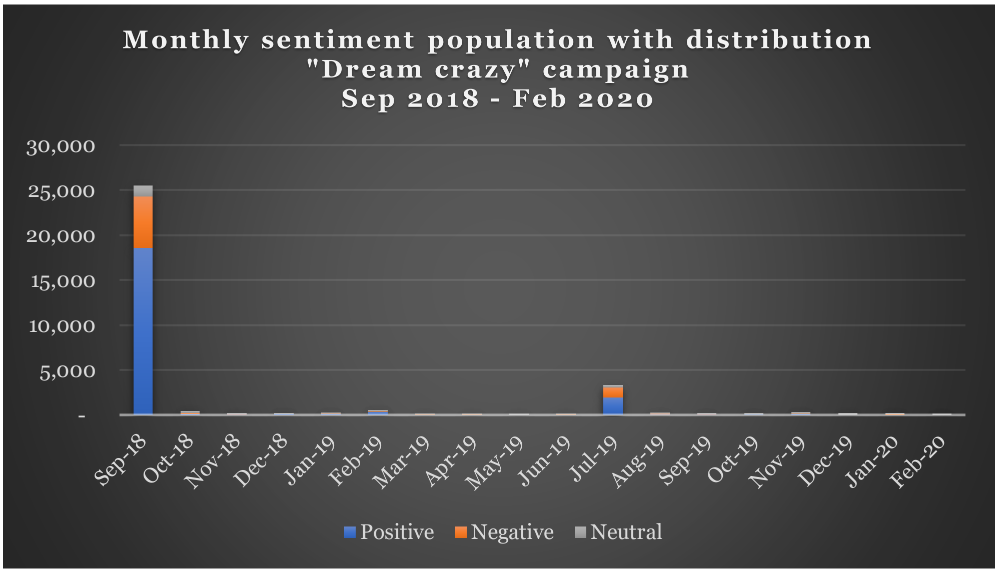

Figure 47. Quantity of tweets and sentiment proportion per month. "Dream crazy" campaign, Sep 2018 - Feb 2020.

Figure 47. shows the great impact that the campaign gained from the beginning and how it was impossible for it to maintain or even come close to its starting relevance. The month of July demonstrates a reignition of the conversation. Figure 47. is based on the population exploration done for determining the quantity of tweets, the results of this exploration are shown in Table 16.

	Total tweet count	Positive	Negative	Neutral
Sep-18	25505	18,603	5,708	1,194
Oct-18	437	105	156	176
Nov-18	134	61	53	21
Dec-18	131	123	5	3
Jan-19	188	113	65	10
Feb-19	443	363	72	9
Mar-19	93	40	39	14
Apr-19	67	10	53	4
May-19	56	17	18	21
Jun-19	54	19	32	4
Jul-19	3297	1,954	1,145	198
Aug-19	185	57	106	23
Sep-19	142	91	35	17
Oct-19	108	80	16	11
Nov-19	246	143	64	39
Dec-19	190	24	15	152
Jan-20	157	35	104	18
Feb-20	50	28	19	4

Table 16. Quantity of tweets per month under the employed query. . "Dream crazy" campaign, Sep 2018 - Feb 2020.

The weighted love hate index for this period was 44,98%

Long term perspective – Dream Crazy campaign.

For the long-term perspective, the dates analyzed correspond from September 2018 until February 2023.

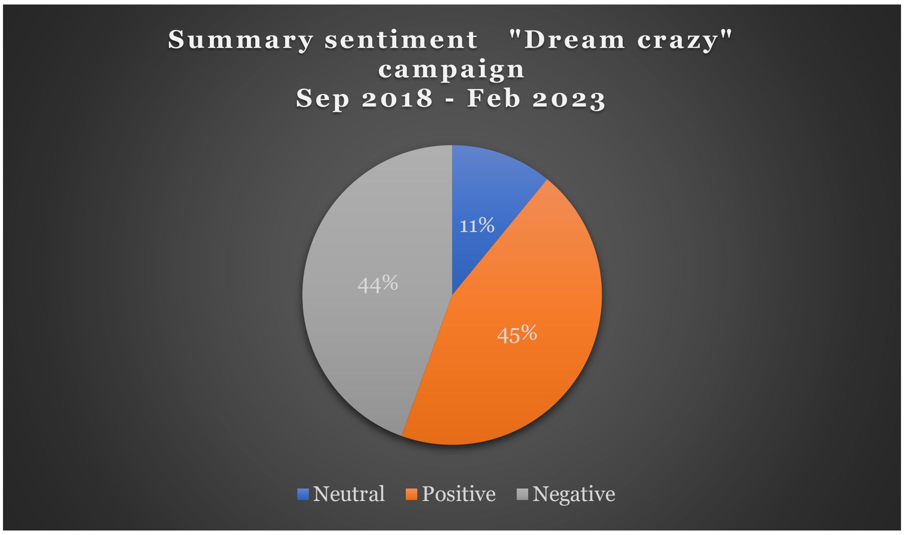

Table 17. Sentiment proportion of the analyzed tweets in the long term for the "Dream crazy" campaign, September 2018 – February 2023.

The quantity of negative tweets in this period is alarming, it almost equated the percentage of positive tweets. The total amount of tweets extracted was 14,390 from which 6,406 were negative, 6,410 positive and 1,574 neutral. Hence, by the end of the period (February 2023) the quantity of positive and negative tweets was almost the same.

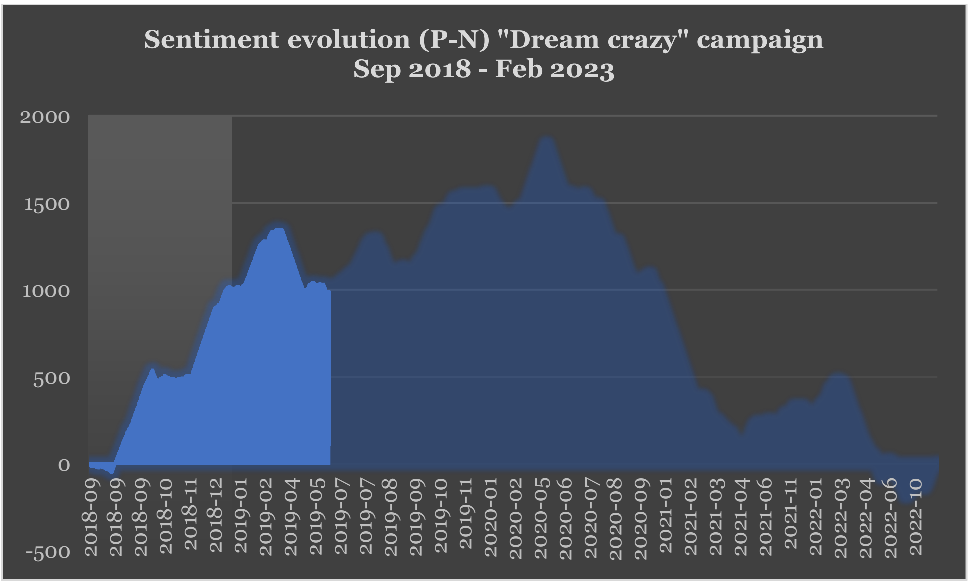

Table 18. Evolution of Positive - Negative tweets in the long term. "Dream crazy" campaign. September 2018 – February 2023.

After reaching the highest point in May 2020, the following months the campaign had a higher quantity of negative tweets than positive. For that reason, there is a negative tendency on the direction of the graph. With a constant monthly negative love-hate index, the campaign reached its critical point in 2022, when for the first time after September 2018, there was a higher quantity of negative tweets than positive about the "Dream crazy" campaign on Twitter.

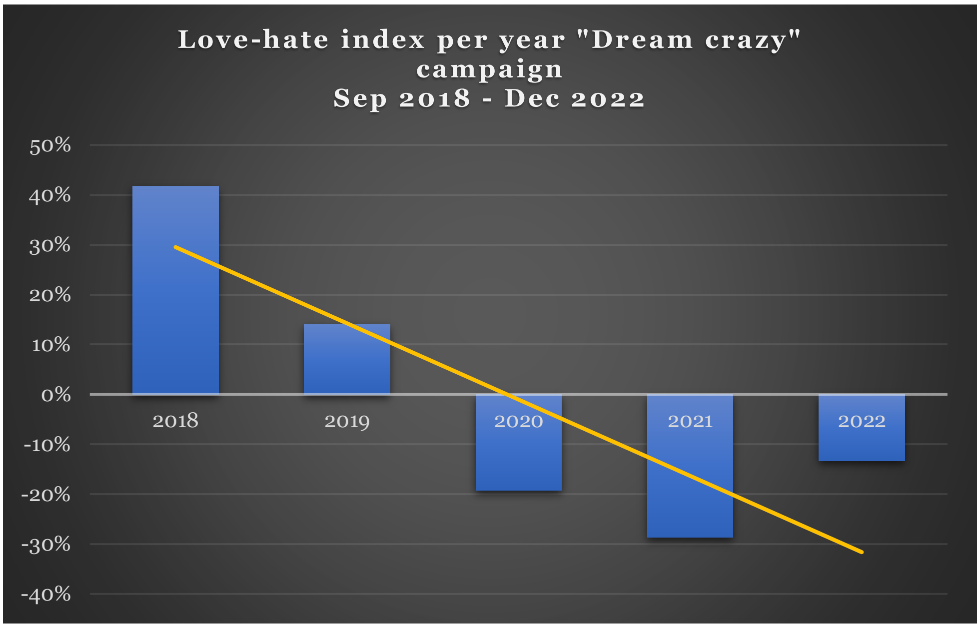

Figure 48.Comparative of the love hate index per year and predictive trendline. September 2018 – December 2022.

Figure 48. shows the love hate index per year (taking into consideration that 2018 was only analyzed from September until December) of the branding campaign featured by Colin Kaepernick. In yellow, the calculated trendline that helps to highlight the overall direction of the data and the mathematical future prediction.

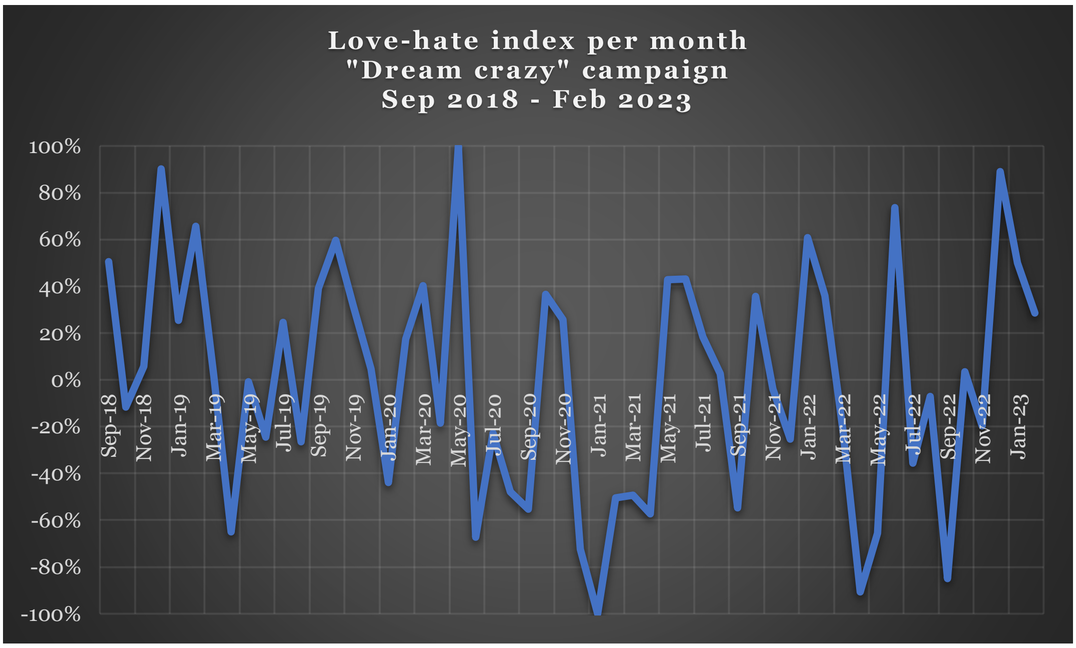

Figure 49. Comparative of the love hate index values per month, "Dream crazy" campaign, Sep 2018 – Feb 2023.

In figure 49. there is a visualization of the big fluctuations of the love hate index for the "Dream crazy" campaign per month. Months with extreme values were tracked to understand and explain their behavior. It is important to notice how until September 2020 the fluctuations were mostly over 0% and after September 2020 until December 2022 the fluctuations were mostly under 0%, demonstrating more specifically the negative tendency before seen.

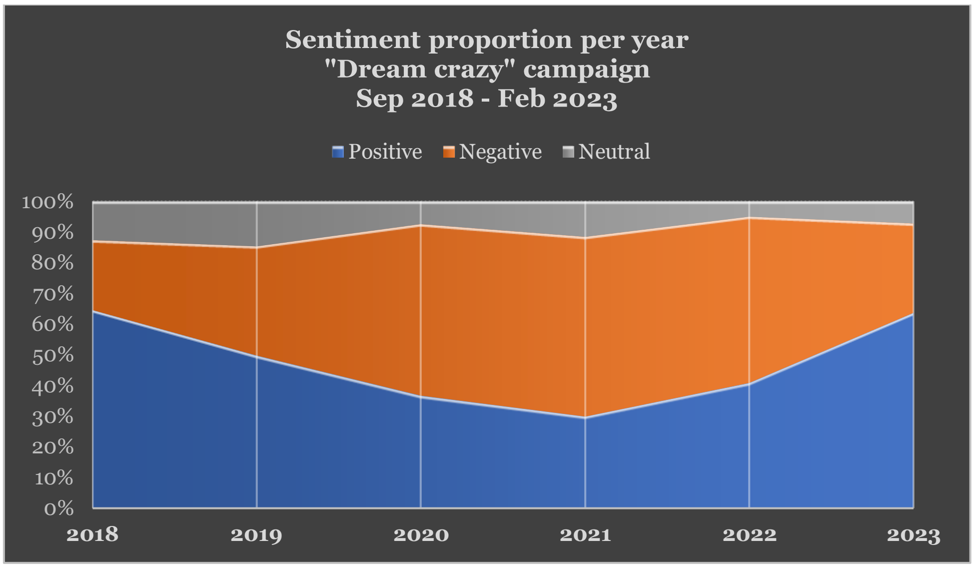

Figure 50. Negative, positive, and neutral sentiment proportion of the tweets posted about the "Dream crazy" campaign, Sep 2018 - Feb 2023.

The sentiment proportion per year is shown in figure 50. Extrapolating this information to the population is possible to understand its sentiment.

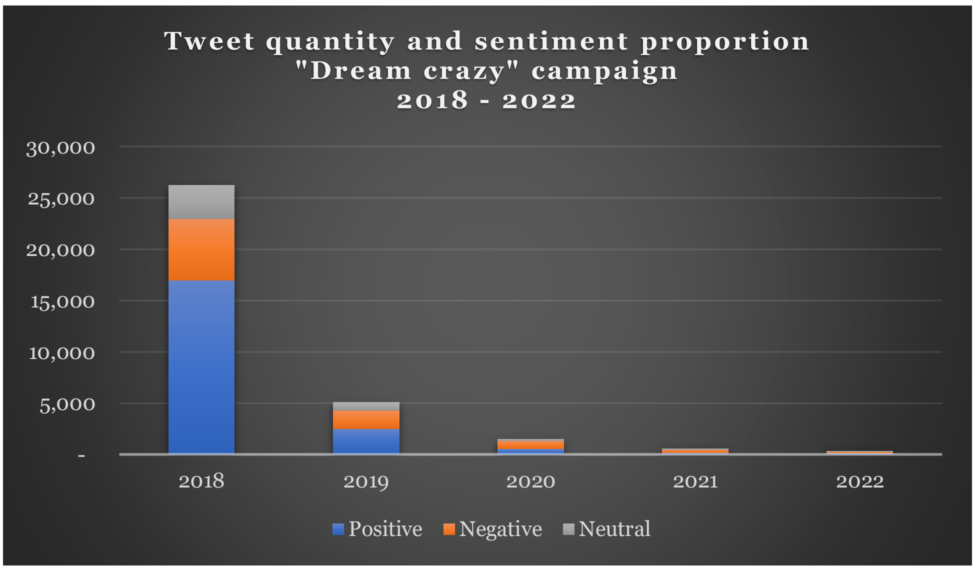

Figure 51. Quantity of tweets and sentiment proportion per year. "Dream crazy" campaign, 2018 – 2022.

As seen in figure 51. the relevancy of the marketing campaign decreased progressively with time. The first feedback was significant, generating more than 26 thousand tweets. Not even the sum of the tweets of all the other years reaches the quantity of tweets shared in 2018. Because of that and considering that the weighted love hate index considers population into the equation. The weighted love hate index for the long-term period is 33,4%.

Initial findings

Figure 52. Timeline of events that influenced the outcome of the "Dream crazy" campaign.

The “Dream crazy” campaign had a great impact when it was launched, the first month it generated over 25 thousand tweets. The quantity of tweets dropped to almost zero (just as before the campaign was published) the months after but it did not disappear. Without counting the month when it was launched (September 2018) the average tweets mentioning the campaign the following 5 months was 266 per month.

There is an interesting phenomenon unveiled in this case. Companies have the power to start a conversation with a great initial repercussion. However, this great initial impact is not maintained for a long period of time. In fact, in this short-term analysis of the “Dream crazy” campaign” the impact lasted less than a month for Nike, having more than 25,000 tweets the first month and the second month reaching only to 437 tweets. This behavior indicates that nowadays the ephemeral nature of social media discussions has reduced the lifetime of the conversation topics.

Just as Nike did a statement supporting Colin Kaepernick and his initiatives, some stores decided to join the boycott movement against Nike. It could be considered that they also performed a branding strategy by making a statement for their stores and their values. This decision however made store owners lose money, with some stores even closing because of it (The Guardian, 2019). The lack of Nike products in a sport store and the monetary loss of not selling those products was described to be the main reason for closing the stores. This exemplifies how powerful the brand is in the United States.

Furthermore, situations like the trial and public scandal between Nike and Avenatti influenced public opinion. There is evidence that, apart from the quantity of tweets getting incremented, there is a polarization of the sentiment towards the brand during controversies. The more popular and controversial these situations are, the more intense the sentiment was towards the brand.

As seen in the medium-term period, the relevancy of this campaign was reignited in July 2019. It did not reach the same level of the launching month, but it was significant enough to provoke a deeper exploration. On that month, Candace Owens, a conservative political activist posted a tweet against Nike and Colin Kaepernick. In this tweet she stated that the campaign was “advocating for segregation”.

Even with this critical point of view from a very influential figure, the love hate index for that month reached 24,54%, denoting that influencers are indeed able to reignite conversations but that these conversations are less controlled by the influencer when they achieve a great reach. Hence, the higher the reach is, the more objective and unbiased the sentiment of the conversation is.

As for the long term, even though there was a negative tendency in the last years of the study, the weighted love hate index remained positive due to the vast quantity of initial tweets and their high positive proportion. With a love hate index of 33,4%, this campaign even allowed Nike to win the “outstanding commercial” Emmy award in September 2019.

The reach of this specific campaign was not influenced by the killing of George Floyd or the support Nike gave to the BLM (Black Lives Matter) movement at the time.

Although the initial impact of the campaign was significant, it proved to have a limited lifespan, with sentiment towards it shifting dramatically over time. The variation of the weighted love-hate index from 49.6% in the short term, to 44.98% in the medium term, and finally 33.4% in the long term, illustrates how the positive initial response became increasingly diluted with time. Possible reasons for this decline include the controversial figure of Kaepernick and the perception of "image washing" activities by Nike.

Even in the years 2020, 2021, and 2022, the long-term analysis indicates a negative love-hate index and a trendline that declined progressively. However, it is reasonable to suggest that the initial success of the campaign continues to overshadow the negative perception in recent years. Consequently, the campaign may still be regarded as successful from a financial point of view.

Extraction – Nike brand perception

In this scenario the general brand perception of Nike on Twitter at the same time the campaign was present will be analyzed, bearing in mind users in the same area.
Considering the phrases used, specific tweets of the campaign were extracted for the specific branding campaign under these parameters:

```
query = ' Nike - ((Nike Colin) OR (Nike kaepernick) OR ("Dream crazy" nike)
OR (Geragos OR Avenatti)) lang:en -is:reply -is:quote -is:verified -
is:nullcast -has:links -has:media -has:images -has:video_link '
user_fields = ['username', 'public_metrics', 'description', 'location',
'name', 'verified']
tweet_fields = ['created_at', 'geo', 'public_metrics', 'text', 'id']
expansions = ['author_id', 'referenced_tweets.id']
start_time = '2018-09-16T00:00:00Z'
end_time = '2018-09-21T23:59:00Z
```

Figure 53. Code extract to measure Nike brand perception, excluding the query used for the "Dream crazy" campaign.

The design of the query intends the exclusion of all the tweets that were analyzed before employing the first query for this Nike case. All the rest, from the language English until the exclusion of quotes and replies remains the same. The dates and time are adjusted for every period.

Since in this case the tweet quantity is vast, a sampling is necessary for every extraction. The sample is determined using the proportion before explained, as well as the margin of error and confidence level. For the accuracy of the sample, at least 3 extractions were performed per month.

Short term perspective – Nike general perception

Since in this case it is possible to evaluate brand perception 6 months before and after the launching of the advert, the stated methodology is applied. The starting date for the tweet extraction is March 2018, and the ending date is February 2019 for this period.

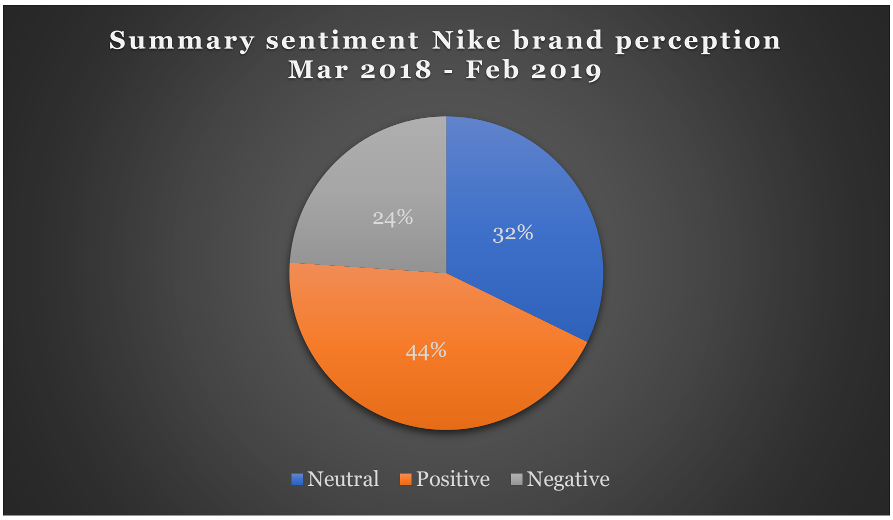

Figure 54. Sentiment proportion of the analyzed tweets in the short term. Nike brand perception, Mar 2018 – February 2019.

In this period, there is a higher percentage of neutral tweets compared to the "Dream crazy" campaign analysis. The total amount of tweets extracted was 8,487 from which 2,031 were negative, 3,720 positive and 2,736 neutral.

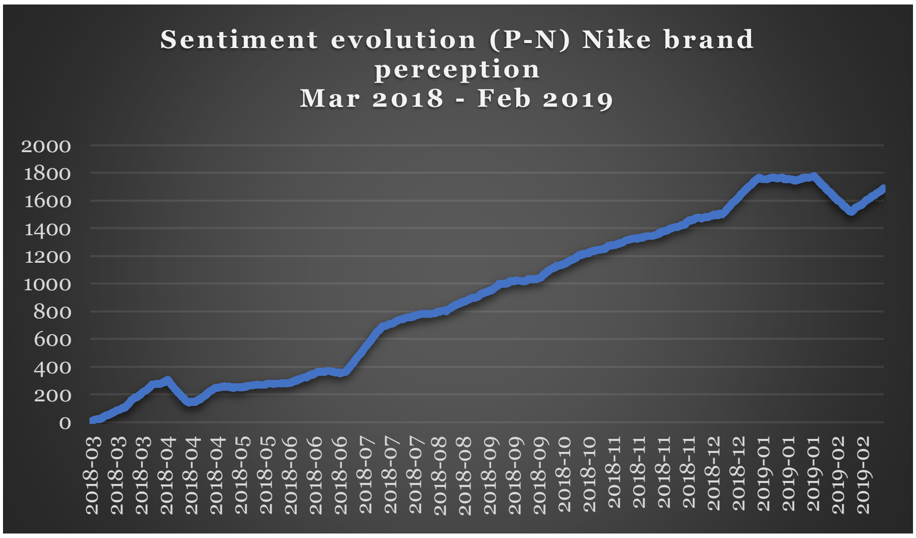

Figure 55. Evolution of Positive - Negative tweets in the short term. Nike brand perception, Mar 2018 – February 2019.

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The sentiment evolution for this period shown on Figure 55. demonstrates that there was not a significant positive or negative backlash in public opinion regarding the "Dream crazy" campaign. To understand better the evolution of the sentiment, a monthly love hate index was calculated and displayed in figure 56.

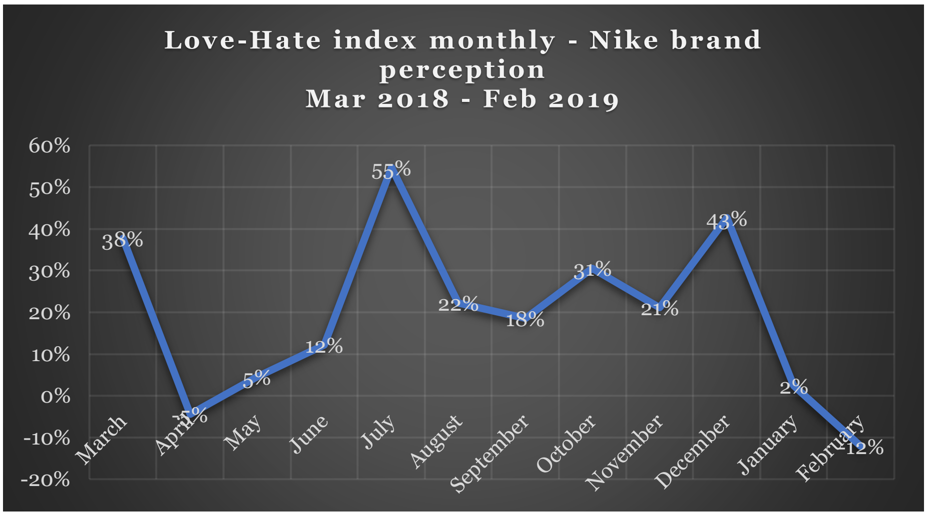

Figure 56. Comparative of the love hate index values per month, Nike brand perception Mar 2018 – February 2019..

The monthly LH index shown in this graph demonstrates mostly positive values, which means there is a higher number of people that have a positive sentiment towards Nike. However, these fluctuations prove a high volatility in the perception of the brand. In branding, these changes in public perception are reactive. They respond to an action taken by the company directly or indirectly. They even respond to an independent trend sometimes.

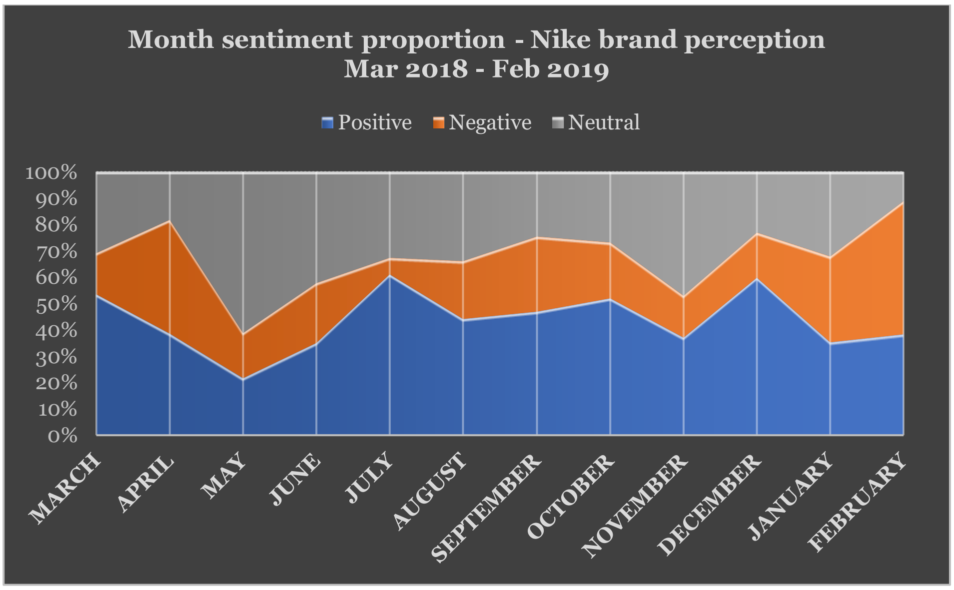

Figure 57 Negative, Positive, and Neutral sentiment proportion of the tweets posted. Nike brand perception on the short term, Mar 2018 – February 2019.

Figure 57. shows the proportion of the sentiment of the extracted tweets, it does not include into consideration the quantity of tweets posted. There are two important peaks in the percentage of positive tweets in July and December 2018. Even though the month of the "Dream crazy" campaign was September, it still displays (together with the months around it) a very average behavior. With no significant visible change in the brand perception.

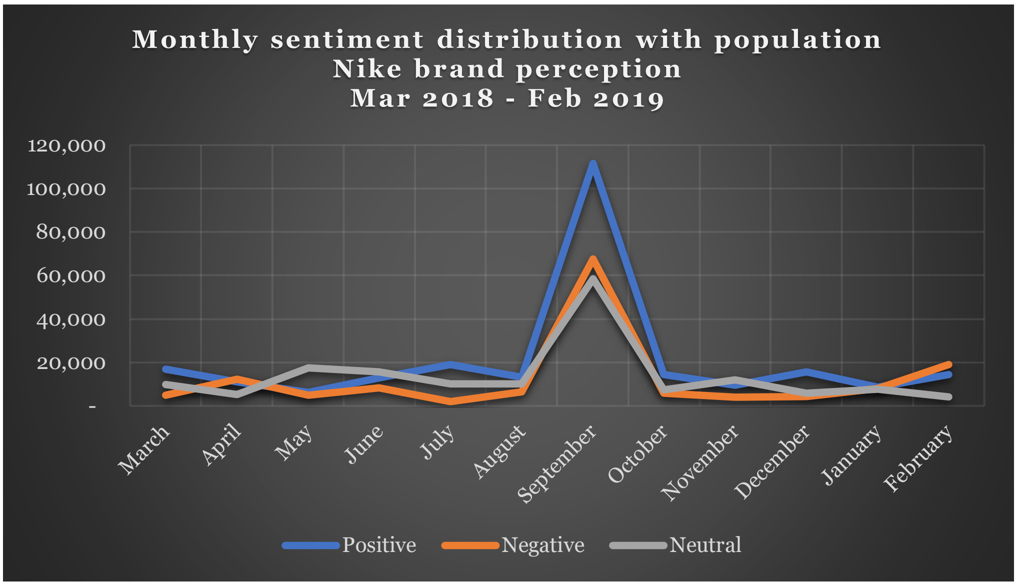

Figure 58. Quantity of tweets and sentiment proportion per month. Nike brand perception, Mar 2018 – February 2019..

On the other hand, there an undoubted impact due to the advert, being September the month with the highest quantity of tweets posted in this period. The total quantity of tweets mentioning Nike was 253,190 from which 111,586 were posted in September.

The 6 months before the campaign there was an average of 31 thousand tweets per month, the 6 months after there was an average of 63 thousand tweets per month. The campaign undeniably generated awareness and demonstrated a great initial impact. On the other hand, the weighted love hate index for the 6 months before the campaign was 21,46%, and for the 6 months after the campaign was 17,15%. This decrease is the first evident impact this campaign proves to have in this research. The weighted love hate index for the short term, including 6 months before and after the campaign, is 18,6%

Medium term perspective – Nike general perception.

For this period the tweets from March 2018 until February 2020 will be analyzed under the query before stated.

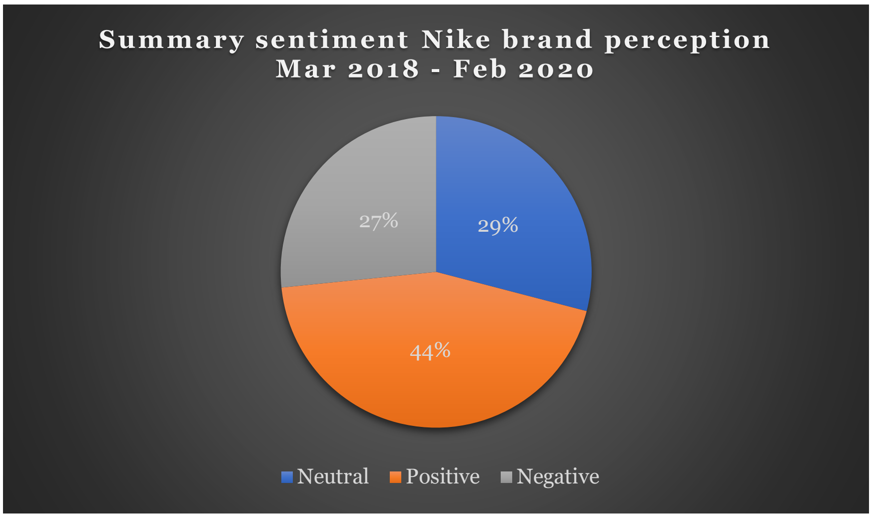

Figure 59. Sentiment proportion of the analyzed tweets in the medium term. Nike brand perception, Mar 2018 – February 2020.

As seen in Figure 59. there are no significant variations on the sentiment distribution towards Nike. The percentage of positive tweets is the same compared to the short term, and there is a slight reduction on the quantity of negative tweets. The total amount of tweets extracted was 17,178 from which 4,570 were negative, 7,617 positive and 4,991 neutral.

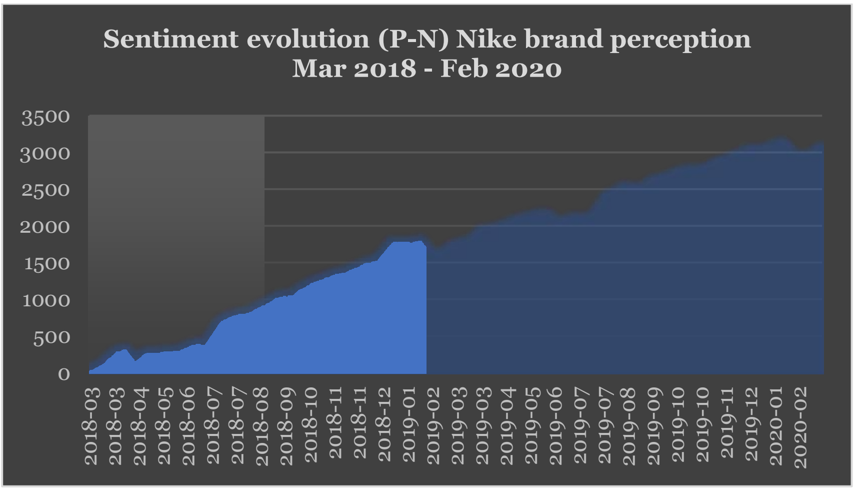

Figure 60. Evolution of Positive - Negative tweets in the medium term. Nike brand perception, Mar 2018 – February 2020.

The sentiment evolution in Figure 60. shows some important decreases in February and June 2019, and January 2020. Therefore, it means that in these dates there was a higher number of negative tweets than positive. Apart from that, there is a positive tendency for Nike's brand perception.

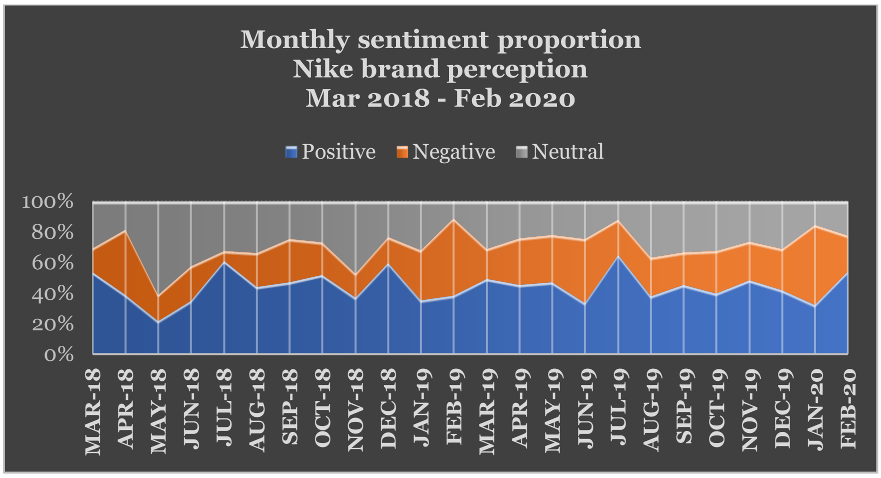

Figure 61. Negative, Positive, and Neutral sentiment proportion of the tweets posted. Nike brand perception for the medium term, Mar 2018 – February 2020.

Figure 61. shows the monthly sentiment distribution of the sample. On it, it is possible to recognize some patterns comparing it with Figure 46. like the peaks in the percentage of positive tweets in December 2018 and July 2019.

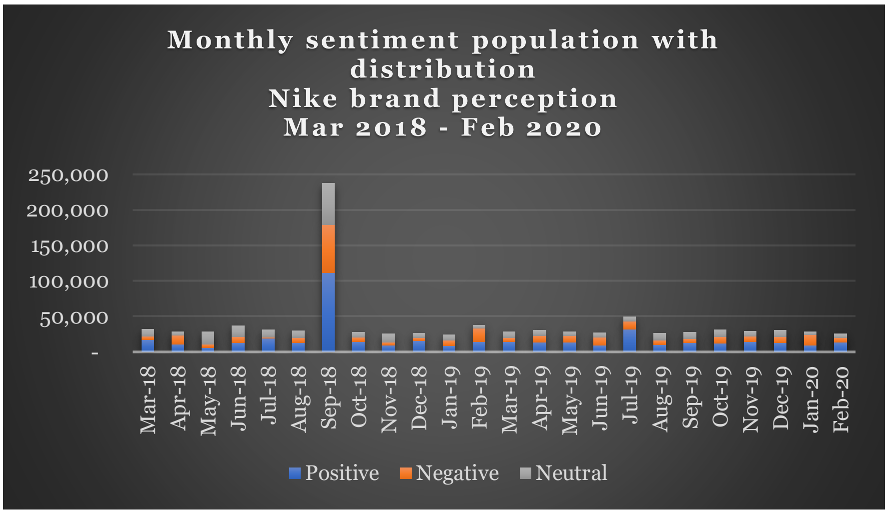

Figure 62. Quantity of tweets and sentiment proportion per month. Nike brand perception, Mar 2018 – February 2020..

As for Figure 62, it shows the quantity of times Nike was mentioned and the sentiment towards it. Just as in the medium term for the "Dream crazy" campaign there is a great reach attained in the marketing campaign launching month (September) and an instant normalization on the quantity of tweets posted in the following months. There is however another similitude, on the month of July there is an odd increase in the tweet quantity.

The weighted love hate index just for the second year of the analysis (from March 2019 until February 2020) is 17,4%, there is not a great variation from the love hate index of the 6 months after the campaign. The weighted love hate index for the medium-term period is 18,1%.

Long term perspective – Nike general perception.

For this period the tweets from March 2018 until December 2022 will be analyzed under the query before stated.

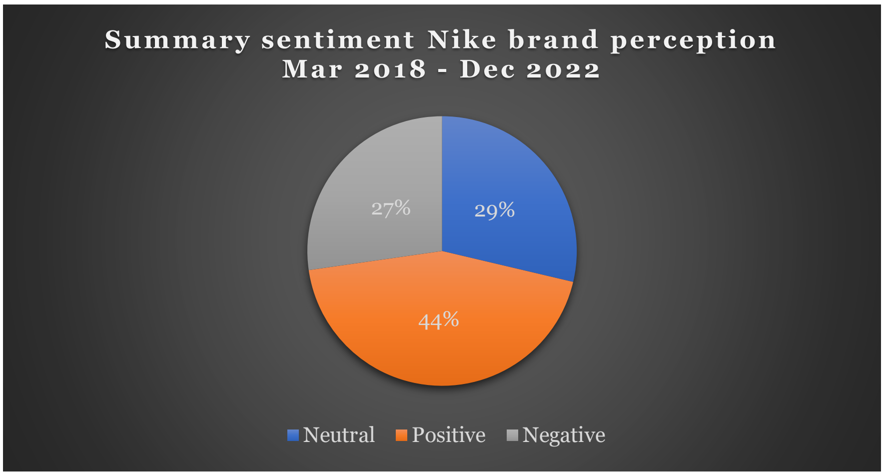

Figure 63. Sentiment proportion of the analyzed tweets in the long term. Nike brand perception, Mar 2018 – Dec 2022.

As seen in figure 63. the percentage of positive, negative, and neutral tweets remained the same as in the medium term even though there was a greater quantity of tweets evaluated. The total amount of tweets extracted was 43,037 from which 11,734 were negative, 18,957 positive and 12,346 neutral.

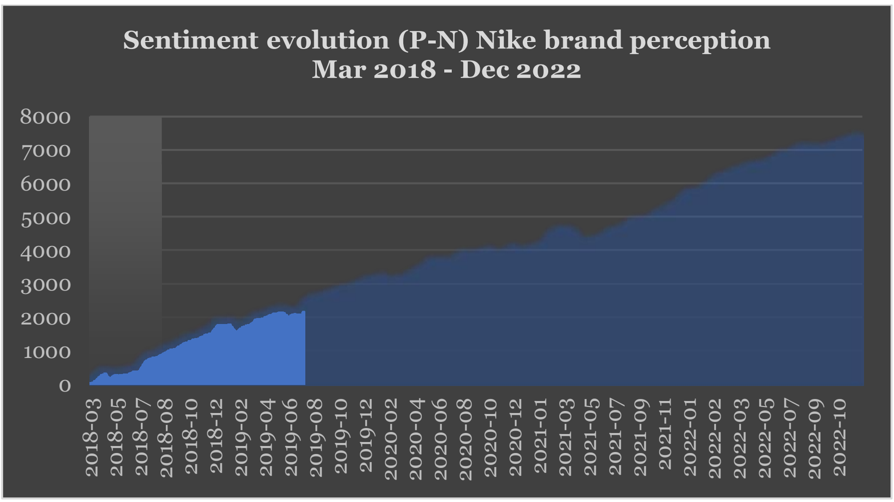

Figure 64. Evolution of Positive - Negative tweets in the long term. Nike brand perception, Mar 2018 – Dec 2022.

As for the sentiment evolution, April 2021 was a period with a significant reduction in the line tendency, which means it had a greater quantity of negative tweets than positive. To further understand the LH index variations figure 65 was created.

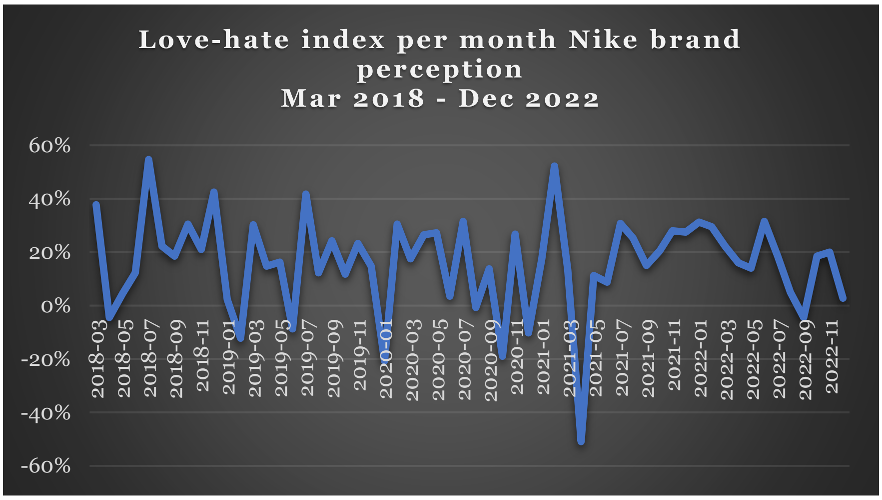

Figure 65. Comparative of the love hate index values per month, Nike brand perception, Mar 2018 – Dec 2022.

Even though most of the percentages are over 0% which indicates a positive relation with the public and the brand, the volatility of these values indicates a high sensitivity of people's opinion towards Nike.

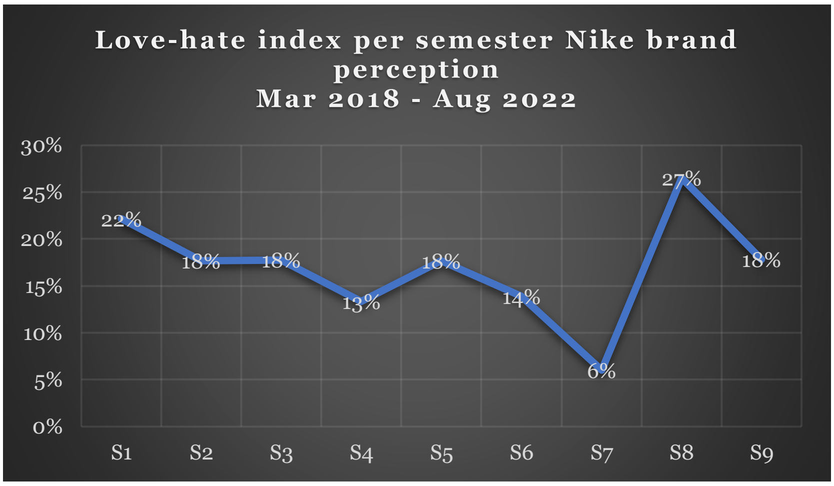

Figure 66. Comparative of the love hate index values per Semester. Nike brand perception, Mar 2018 – Aug 2022.

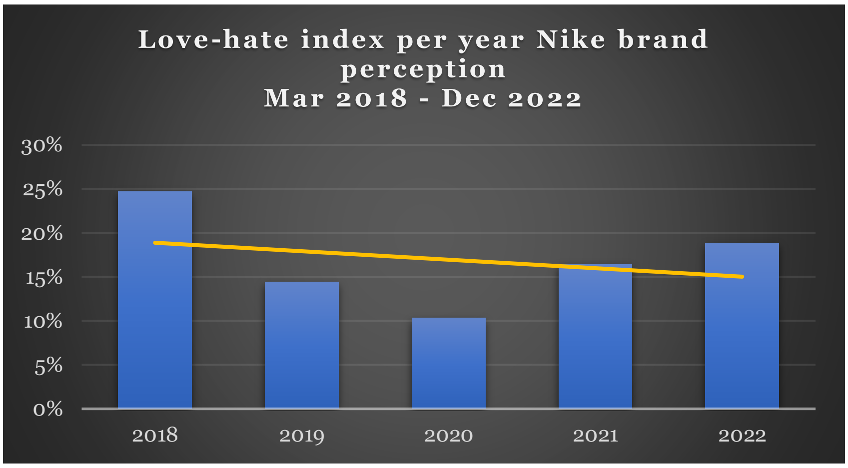

Figure 67. Love hate index comparative per year and predictive trendline. Mar 2018 – Dec 2022.

Figure 67. and 66. depict the sentiment trend towards Nike during various periods, with Figure 67. displaying a trendline based on the analysis of more than 43,000 tweets. Notably, the year of the campaign launch (2018) coincided with the highest brand perception score for Nike, with a love-hate index of 25%. In contrast, all other years examined did not exceed a love-hate index of 20%, with 2022 emerging as the second-best year with a score of 19%.

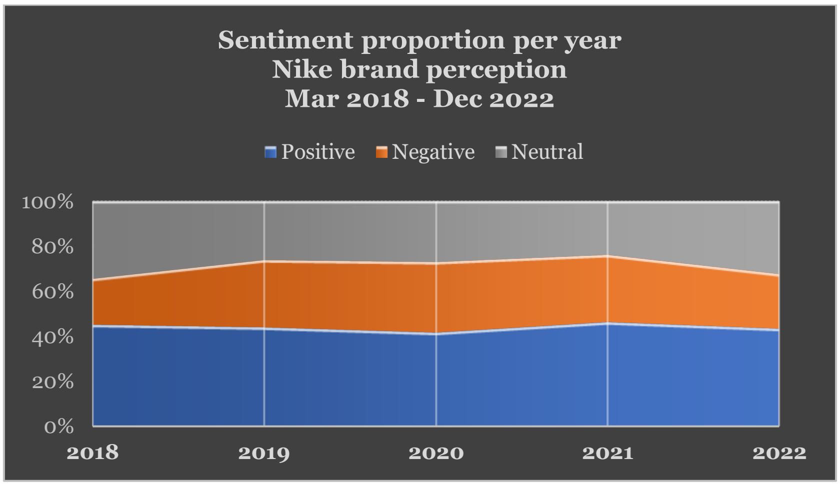

Figure 68. Negative, Positive, and Neutral sentiment proportion of the tweets posted on the long term. Nike brand perception, Mar 2018 – Dec 2022.

Finally, the sentiment proportion proves to be constant over the years, with slight inconsequential changes as shown on Figure 68. By extrapolating this information into the population is possible to determine the sentiment towards the brand considering the reach as well.

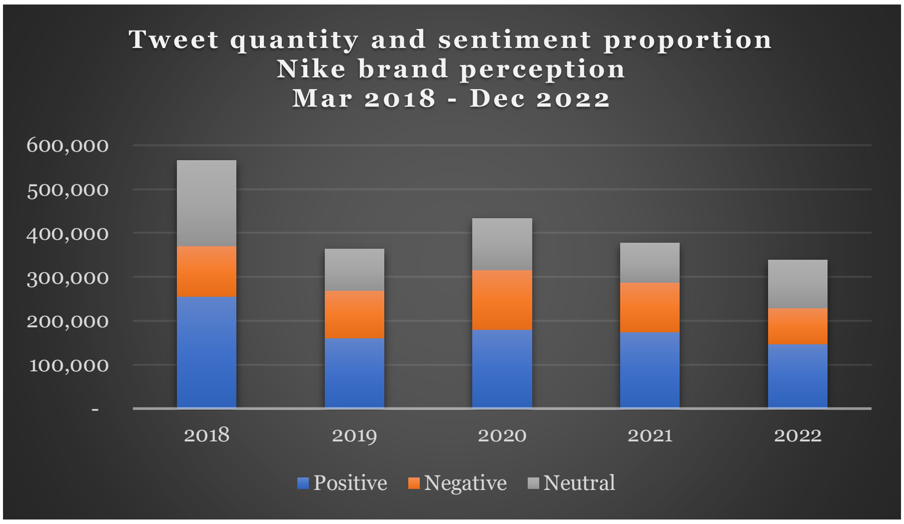

Figure 69. Quantity of tweets and sentiment proportion per year. Nike brand perception, Sep 2018 – Dec 2022..

As shown in Figure 69, there was a great reach in the year 2018 due to the "Dream crazy" campaign, the quantity of tweets for the following years then decreased but not as significantly as in the case of the extraction specifically done for the "Dream crazy" campaign. In this case, the relevancy of the brand prevailed even when the campaign was long forgotten by the users.

The number of tweets posted mentioning Nike considering the before stated query, as well as the calculation of positive, negative, and neutral tweets contained in the population based on the sample can be found in the following table.

	Positive	**Negative**	**Neutral**	**Total**
2018	255,081	115,479	194,890	565450
2019	160,561	107,974	95,517	364053
2020	180,400	135,684	116,703	432787
2021	174,870	112,849	89,843	377562
2022	146,700	82,810	108,994	338504

Table 19. Number of tweets mentioning Nike under the designed query and follow calculation per year. Nike brand perception 2018 – 2022.

Finally, the weighted love hate index for the Nike brand perception in the long term is 17,46%.

Findings of the case

By analyzing the short-, medium- and long-term values of the love hate index, it is possible to conclude that there is a stable brand perception with a slight decrement in the latest years. In the case of the short term, a 18,6% love hate index shows a slightly positive sentiment towards the brand that, as seen in the short-term results, was influenced by the marketing campaign in terms of reach. On the other hand, the sentiment towards the brand was also affected by the campaign but in a negative way. Even though the investigation proved that the tweets directly mentioning the campaign had a positive love hate index initially (49,6%), the brand perception of Nike the 6 months before the campaign showed a higher love hate index (21,56%) than the 6 months following the camping (17,15%).

This dichotomy shows how a branding statement that seems to have received a positive outcome could affect the overall perception of the brand indirectly.

Regarding the monthly variation of the love-hate index, there was little change in September and its surrounding months. This is noteworthy because during that time, there were boycott movements against Nike, yet the overall sentiment remained relatively consistent, denotating a strong brand image. The main difference, however, was the quantity of tweets posted. Before the campaign, there was an average of 31,000 tweets per month, which doubled to 63,000 in the six months following the launch of the campaign.

Similar to the results of the specific campaign, July 2019 is also a noteworthy month due to a substantial increase in the number of tweets. The reason behind this can be found in the findings of the "Dream crazy" campaign. Moreover, the fact that there was a reactivation of a conversation with a topic that apparently was not relevant anymore, and how it managed to generate more relevancy and generate repercussions in a branding level, shows the power influencers have on social networks.

The conversation was reactivated with a critic against Nike and even under that circumstances the proportion of positive tweets in that month managed to be the highest one of all the months considered in the medium-term analysis. This proves that the role of influencers activating conversations and generating reach is important, and that the sentiment distribution of these conversations is less biased by the shared opinion of the influencer's community when there is a greater reach.

Analyzing the long-term love hate index on a monthly basis reveals a notable volatility in the public perception of Nike's brand. This indicates that the sentiment of the public towards Nike is highly sensitive and can change rapidly in the short term. Figure 65. also shows a higher number of negative monthly LH index values in the latest years, indicating failures of Nike in maintaining a positive brand perception.

Considering years from 2018 until 2022, The year of the advert proved to be the most effective one in terms of reach, and the most successful one considering the love hate index. The best years for Nike's brand perception on Twitter were 2018, 2022 and 2021. With love hate indexes of 24,7%, 18,9% and 16,4% respectively. The worst year for Nike's brand perception was 2020 with a love hate index of 10,3%.

On March 2020 George Floyd was killed. Following the activist personality of the company, Nike created a series of posts protesting violence and animating people to participate into "taking action". This generated significant feedback, making it the second year with the highest quantity of tweets posted and the second year with the best love hate index considering the period 2018-2022.

Until 2022, Nike did not reach the level of relevancy on Twitter that was accomplished in 2018 with the launching of the "Dream crazy" advert.

Finally, the sentiment distribution displayed on the short, medium, and long term proved to be almost similar, demonstrating consistency towards the brand. The quantity of published tweets per year under the query did not have the drastic variation the specific campaign had but it showed important increments following important events. The average of tweets posted from 2019 to 2022 was 378,227 and the number of tweets posted in 2018 (year of the campaign) was 565,450.

As for the love hate index, with 18,6% in the short term, 18,1% in the medium term and 17,5% in the long term, there is an evident decreasing tendency that proves a failure of the company to maintain a positive public perception towards the brand in the US market in the years following the launching of the campaign.

CONCLUSION

The Love-Hate Index formula has proven to be a reliable marketing tool that yields accurate results. It gains validation considering the quality of the extracted database due to the Academic Research access granted by Twitter. Its development is first based on sociological theories that consider norms and dominant values within reference groups. The theory suggests that when individuals face these norms, they have the option to adopt and perpetuate these beliefs in their own thoughts, behavior, and interactions with others or to challenge and oppose them by thinking and behaving in ways that deviate from them (Crossman, 2021).

Similarly, the proposed index categorizes tweets as negative and positive for determining acceptance or rejection towards the reference group that in this case is the company. An inclusion of a neutrality is done as well for making the values more complex and representative. A mathematical approach is then opted for assigning a quantifiable value to public perception, the outcome of this process is a useful index that can be replicated for measuring marketing choices' impact and brand perception.

Using the love index formula allows for the assessment of a marketing campaign's effectiveness in the short, medium, and long term, including measuring sentiment towards the campaign, its impact on the brand sentiment, and quantifying brand perception over time. Additionally, this formula enables chronological evaluation and identifies the effect of media and influencers.

In 1952, Harold Kelley recognized two distinct types of reference groups based on the functions they serve. These are normative reference groups and comparative reference groups (Kelley & Volkart., 1952). As Influencers belong in the comparative kind of reference groups they function as a standard of comparison for people during self-appraisal. This research showed that the fluctuations of the love hate index are not directly related to the company or their actions all the time, instead, important increases in the produced tweet quantity and sentiment variations were tracked to influencers starting conversations on Twitter, demonstrating the power they behold.

In this investigation such power (or influence) proved to be more effective in terms of reach for the short term, ineffective for the sentiment variation of the brand in the short term, slightly effective for modifying brand perception in the long term and very effective for determining the sentiment of a specific marketing campaign in the short term.

Another important outcome of this investigation is the understanding of the behavior of conversations on Twitter. For both cases required the design of a special query that only extracted tweets specifically regarding the chosen campaign. Such campaign implicitly generated a conversation with an original thematic. Both Nike and Starbucks had instant feedback after the campaign was launched, and in both cases such feedback decreased in the short term.

The Starbucks case showed a gradual decrease in the proportion of tweets related to the "Starbucks or nothing" campaign, while in the Nike case the proportion of tweets related to the "Dream crazy" campaign dropped significantly during the second month. One possible explanation for this discrepancy, considering the number of conversations available on Twitter at the time, is that the lifespan of social media conversations is reliant on the number of ongoing conversations available for users to participate in.

As for the proposed sentiment evolution graph (ex. Figure 55.), it allows to understand how public perception fluctuates in a determined period. It is useful from a visual point of view because it illustrates important variations that were studied in the findings of each case. There are however 2 important limitations. The first one is that this graph does not consider the population, so the sentiment determination is not fully accurate until is weighted. The second one is that the longer the period is the more difficult it is to perceive sudden changes in public perception.

On the other hand, the love hate index represents accurately public perception under the desired period and it can be extrapolated to the population by employing the weighted love hate index to project relevancy and sentiment. Its limitation is that it fails to explain the intensity of a feeling.

Another observation is that media has the characteristic of prolonging conversations with the articles they chose to publish. When these articles are inclined towards a sentiment, they can significantly affect the perception of a marketing campaign, but they have little influence in brand perception in the short term. On the medium and long term however, there is an impact on both brand and campaign perception that is directly proportional to the relevancy and reach the article had.

Specifically for the Starbucks case, it can be concluded that after the initial negative feedback and rejection of the campaign, the complete branding strategy together with the mass communication incursions proved to be effective for improving brand perception and increasing brand awareness in the short term. The changes on the LH index under different periods suggest a growing acceptance of the branding campaign and deficiencies of the company on maintaining positive brand perception in the long term. Since the sentiment towards the campaign improved while the brand image deteriorated, it is not possible to presume a mutual influence in the long term.

"Starbucks or nothing"	
Period	LH index
Short	-1.0%
Medium	17.0%
Long	25.8%

Table 20. "Starbucks or nothing" love hate index comparison.

Brand perception Starbucks	
Period	LH index
Short	36.1%
Medium	35.2%
Long	32.8%

Table 21. Starbucks' brand perception, love hate index comparison.

On the other hand, the Nike case showed a positive sentiment towards the "Dream crazy" campaign initially. With a love hate index of 49,6% and an increase of 692% in the number of tweets posted, the campaign undoubtably benefited the brand in the short term. In spite of that, the comparison of the love hate index under different periods showed a gradual decrease in the proportion of positive tweets about both Nike as a brand and the "Dream crazy" campaign.

"Dream crazy"	
Period	LH index
Short	49.6%
Medium	45.0%
Long	33.4%

Table 22. "Dream crazy" love hate index comparison.

Brand perception Nike	
Period	LH index
Short	18.6%
Medium	18.1%
Long	17.5%

Table 23. Nike brand perception, love hate index comparison.

The case of Nike serves as evidence that an unpopular statement, while it may be advantageous in terms of short-term revenue growth, awareness, and positive sentiment, ultimately has negative effects on the brand perception in the medium and long term. Both companies examined in this research failed to maintain a consistent sentiment towards their brand after the initial boost provided by the campaign.

Based on the presented evidence, it can be inferred that unpopular statements serve as a potent instrument for companies. Utilizing such statements enables them to swiftly attain visibility, expand their reach, and generate immediate revenue, as evidenced by the cases investigated in this study. However, it is crucial to acknowledge the considerable detrimental effect unpopular statements have on brand perception, particularly in the medium and long term. As sown on Tepeci's research (1999) this impact could significantly influence prospective purchasing decisions and affect consumers' sensitivity to price.

A future study in the field of marketing could use the LH index to evaluate how convenient sentiment volatility is for companies and if there is a correlation between such volatility and a strong brand personality.

BIBLIOGRAPHY

Aaker, D. A. (1996). *Building strong brands.* New York: New York: Free Press.

Amazon, Inc. (2023, March 19). *What Is An API (Application Programming Interface)?* . Retrieved from Amazon Web Services (AWS) : https://aws.amazon.com/what-is/api/#:~:text=APIs%20are%20mechanisms%20that%20enable,weather%20updates%20on%20your%20phone.

Bastos, W., & Levy, S. J. (2012). *A history of the concept of branding: practice and theory.* Journal of Historical Research in Marketing.

Brand Finance. (2022). *Apparel 50 2022 - The annual report on the most valuable and strongest apparel brands.* Brand Finance.

Brenan, M. (2022, June 29). *Record-Low 38% Extremely Proud to Be American*. Retrieved from GALLUP: https://news.gallup.com/poll/394202/record-low-extremely-proud-american.aspx

Bruns, A., & Weller, K. (2016). Twitter as a first draft of the present: and the challenges of preserving it for the future. . *In Proceedings of the 8th ACM Conference on Web Science (WebSci '16)* (pp. 183–189). New York: Association for Computing Machinery.

CNBC. (2018, Sep. 04). *Nike shares fall as backlash erupts over new ad campaign featuring Colin Kaepernick* . Retrieved from CNBC: https://www.cnbc.com/2018/09/04/nike-shares-tumble-after-company-reveals-new-ad-campaign-featuring-colin-kaepernick.html#:~:text=Nike%20shares%20fall%20Tuesday%20after,from%20consumers%20on%20social%20media.

CNBC. (2019). *How Nike Turns Controversy Into Dollars* . Retrieved from YouTube: https://www.youtube.com/watch?v=Yvkf88eSTrI&t=260s

CNN. (2019, Sep. 15). *Colin Kaepernick's Nike ad wins Emmy for outstanding commercial* . Retrieved from CNN entertainment: https://edition.cnn.com/2019/09/15/entertainment/nike-ad-emmy-win-trnd/index.html#:~:text=Nike's%20gamble%20to%20partner%20with,2019%20Creative%20Arts%20Emmy%20Awards.

Crossman, A. (2021, February 16). *What Is a Reference Group?* Retrieved from ThoughtCo.: https://www.thoughtco.com/reference-group-3026518

Dijck, J. V., Nieborg, D., & Poell, T. (2018). PLATFORM POWER & PUBLIC VALUE. *Paper presented at AoIR 2018: The 19thAnnual Conference of the Association of Internet Researchers.* Montréal, Canada.

Drummond, G., & Ensor, J. (2006). *Introduction to marketing concepts.* Routledge.

Duyu, T., Wei, F., Qin, B., Zhou, M., & Liu, T. (2014). Building Large-Scale Twitter-Specific Sentiment Lexicon : A Representation Learning Approach. *Proceedings of COLING*

2014, the 25th International Conference on Computational Linguistics: Technical Papers, (pp. 172-182). Dublin, Ireland.

ESPN. (2016, Feb. 17). *Nike cuts ties with Manny Pacquiao after derogatory comments*. Retrieved from https://www.espn.com/boxing/story/_/id/14793389/nike-ends-endorsement-contract-manny-pacquiao

Forbes. (2012, Oct. 17). *Nike's Disassociation From Lance Armstrong Makes Nike A Stronger Brand* . Retrieved from Forbes: https://www.forbes.com/sites/darrenheitner/2012/10/17/nikes-disassociation-from-lance-armstrong-makes-nike-a-stronger-brand/?sh=62307f396df4

Fuller, W. A. (2011). *Sampling statistics.* John Wiley & Sons.

Gordon, D. V., Hannesson, R., & Kerr, W. A. (1999). What is a Commodity? An Empirical Definition Using Time Series Econometrics. *Journal of International Food & Agribusiness Marketing*, 1-29.

Gupta, B., Negi, M., Vishwakarma, K., Rawat, G., Badhani, P., & Tech, B. (2017). Study of Twitter Sentiment Analysis using Machine Learning Algorithms on Python. *International Journal of Computer Applications, 165(9)*, 29-34.

Hammerl, T., Leist, S., & Schwaiger, J.-M. (2019). Measuring the Success of Social Media: Matching Identified Success Factors to Social Media KPIs. *Proceedings of the 52nd Hawaii International Conference on System Sciences*, (pp. 2427-2436).

Harvard University - MBA Student Perspectives. (2015, Oct 31). *My Starbucks Idea: Crowdsourcing for Customer Satisfaction and Innovation*. Retrieved from Digital Innovation and Transformation: https://d3.harvard.edu/platform-digit/submission/my-starbucks-idea-crowdsourcing-for-customer-satisfaction-and-innovation/#

History.com Editors. (2021, July 09). *Quarterback Colin Kaepernick sits during national anthem, gives interview about it for the first time*. Retrieved from HISTORY: https://www.history.com/this-day-in-history/colin-kaepernick-kneels-during-national-anthem

Hoffman, D. L., & Fodor, M. (2010). Can you measure the ROI of your Social Media Marketing? *MIT Sloan, Management review VOL.52*, 40-49.

Hsieh, H.-F., & Shannon, S. E. (2005). Three Approaches to Qualitative Content Analysis. *Qualitative Health Research*, 1277-1288.

Husain, S., Khan, F., & Mirza, W. (2014, September 28). *How Starbucks pulled itself out of the 2008 financial meltdown*. Retrieved from Business Today: https://www.businesstoday.in/magazine/lbs-case-study/story/how-starbucks-survived-the-financial-meltdown-of-2008-136126-2014-09-22

Hutto, C., & Gilbert, E. (2014). VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text . *Proceedings of the Eighth International AAAI Conference on Weblogs and Social Media216* (pp. (Vol. 8, No. 1, pp. 216-225).). Atlanta: Association for the Advancement of Artificial Intelligence.

Israel, G. D. (1992). Determining Sample Size. *University of Florida*.

Kapferer, J.-N. (2008). *The new strategic brand management.* London and Philadelphia: Kogan page publishers.

Kartajaya, H., Kotler, P., & Setiawan, I. (2017). *Marketing 4.0: moving from Traditional to Digital.* John Wiley & Sons.

Keller, K. L. (1993). Conceptualizing, Measuring, and Managing Customer-Based Brand Equity. *Journal of Marketing*, 1–22.

Kelley, H. H., & Volkart., E. H. (1952). The Resistance to Change of Group-Anchored Attitudes. *American Sociological Review*, 453-465 .

Kessler, M. (2018, Oct. 12). *The Story Of Ric Muñoz And Nike's 1995 HIV-Positive Runner Ad* . Retrieved from wbur: https://www.wbur.org/onlyagame/2018/10/12/nike-colin-kaepernick-ric-munoz

Kietzmann, J. H., Hermkens, K., McCarthy, I. P., & Silvestre, B. S. (2011). Social media? Get serious! Understanding the functional building blocks of social media. *Business Horizons*, 241-251.

Kim, H.-b., Kim, W. G., & An, J. A. (2003). The effect of consumer-based brand equity on firm's financial performance. *Journal of Consumer Marketing*, 335-351.

Kotler, P., & Armstrong, G. (2017). *Principles of Marketing (17th ed.).* Pearson.

Kumar, V., Choi, J. B., & Greene, M. (2016). Synergistic effects of social media and traditional marketing on brand sales: capturing the time-varying effects. *Academy of Marketing Science*, 268 - 288.

Liang, H., & Fu, K.-w. (2015). Testing Propositions Derived from Twitter Studies: Generalization and Replication in Computational Social Science. *PLoS ONE 10(8)*, 1-14.

Malesios, C., Skouloudis, A., Dey, P. K., Abdelaziz, F. B., Kantartzis, A., & Evangelinos, K. (2018). Impact of small- and medium-sized enterprises sustainability practices and performance on economic growth from a managerial perspective: Modeling considerations and empirical analysis results. *Bus Strat Env.*, 27: 960– 972.

Maslow, A. H. (1943). *A theory of human motivation.* Psychological Review.

Na, W. B., Marshall, R., & Keller, K. L. (1999). Measuring brand power: validating a model for optimizing brand equity. *Journal of Product & Brand Management*, 170-182.

Petev, I. D., LSQ-Crest, & Pistaferri, L. (2012). Consumption in the Great Recession.

Sandmeyer, B. (2009, July 25). *Starbucks or Nothing?* Retrieved from BlueOregon: https://www.blueoregon.com/2009/07/starbucks-or-nothing/

Saravanakumar, M., & SuganthaLakshmi, T. (2012). Social Media Marketing. *Life Science Journal*, 4444-4451.

Statista. (2022, Aug. 15). *Nike's revenue worldwide from the fiscal years of 2017 to 2022, by region*. Retrieved from https://www.statista.com/statistics/241692/nikes-sales-by-region-since-2007/

Statista. (2022, Nov. 28). *Number of international and U.S.-based Starbucks stores from 2005 to 2022*. Retrieved from Statista: https://www.statista.com/statistics/218366/number-of-international-and-us-starbucks-stores/

Tepeci, M. (1999). Increasing brand loyalty in the hospitality industry. *International Journal of Contemporary Hospitality Management*, 223-229.

The Guardian. (2019, Feb. 14). *Sports store that boycotted Nike over Colin Kaepernick ads forced to close* . Retrieved from https://www.theguardian.com/business/2019/feb/14/sports-store-owner-who-boycotted-nike-over-colin-kaepernick-ads-closes-shop

The Wall Street Journal. (2009, May 01). *Starbucks Ads Urge Consumers Not to Switch to Cheaper Coffee*. Retrieved from The Wall Street Journal: https://www.wsj.com/articles/SB124112408062074463

Twitter Inc. (2023). *Building queries for Search Tweets*. Retrieved from Twitter - Developer Platform: https://developer.twitter.com/en/docs/twitter-api/tweets/search/integrate/build-a-query

Twitter, Inc. (2023, March 22). *Twitter API - Academic Research access* . Retrieved from Developer platform: https://developer.twitter.com/en/products/twitter-api/academic-research

United States Attorney's Office. (2021, July 08). *Michael Avenatti Sentenced To Over Two Years In Prison For Attempting To Extort Nike And For Defrauding His Client* . Retrieved from PRESS RELEASE: https://www.justice.gov/usao-sdny/pr/michael-avenatti-sentenced-over-two-years-prison-attempting-extort-nike-and-defrauding#:~:text=July%208%2C%202021-,Michael%20Avenatti%20Sentenced%20To%20Over%20Two%20Years%20In%20Prison%20For,States%20District%20Judge%