Talk of the Town: Is Emotional Connection the Secret Ingredient to a Brands' Success?

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Abstract

Purpose - This study aims to analyse the emotional connections between consumers and some of the leading food and beverage brands using sentiment analysis, highlighting how these connections impact customer brand loyalty and engagement.

Design/methodology/approach – This study analysed over 8,000 tweets from some of the leading food and beverage brands globally from 2019 - 2024, which include Nestle, PepsiCo, and Coca-Cola. Using advanced sentiment analysis techniques such as the DistilBERT and Twitter roBERTa-base models.

Findings - The results show a rich emotional profile of consumer interactions with leading food and beverage brands, suggesting that brands can use positive emotions to reinforce marketing efforts and negative comments to enhance customer satisfaction. Strong emotional attachment plays significantly important role in brand loyalty, leading to repeat purchases and spreading of positive word-of-mouth.

Originality - This paper contributes to the theoretical framework of emotional branding by offering actionable takeaways for marketers. It emphasizes the significance of understanding consumer emotions within a severely competitive environment. The study highlights the importance of emotional connection with target consumers for sustainable brand development and reinforce brand loyalty.

Research Limitations/Implications - The study's reliance on sentiment classification models simplifies the complex nature of human emotions, potentially leading to a loss of nuanced insights. Additionally, the recent rebranding of Twitter to X has introduced challenges in data collection, affecting the quality of insights derived from consumer behavior analysis.

Theoretical Implications - This study enhances the theoretical model of emotional branding by illustrating the powerful influence of emotional connections on brand loyalty and consumer behaviour. Emotional branding builds strong connections by appealing to consumers' emotions, using experiences that align with their desires,

fostering loyalty and positive feelings.

Managerial Implications – This study offers valuable insights to practicing marketers and brand managers. Marketers can use sentiment analysis tools to make informed decisions, enhance marketing strategies and customer experiences through consumer feedback.

Keywords - emotional branding, sentiment analysis, customer loyalty, food and beverage industry, social media, NLP.

Introduction:

In today's highly competitive market, where brands must work tirelessly to gain recognition, loyalty, and popularity, the importance of creating an emotional connection with consumers has become increasingly significant. There is a growing interest among the researchers and practitioners on exploring how emotional bonds contribute to the brand's success, showcasing the power of meaningful connections in long-term growth and also driving consumer loyalty. Over the past decade, the food and beverage industries have undergone a seismic shift with marketers gradually and increasingly relying on different social media platforms like Twitter, Instagram, Facebook to generate buzz, foster emotional connections and build deeper conversations with consumers. Access to information and communication between peoples from many countries and subcontinents is no longer an issue (Fitzpatrick, N., 2018). Furthermore, social media users freely express their opinions on various political and social topics, without reluctance or fear. Unlike traditional media, which is a one-way means for communication, social media users become the fundamental entity of the network, acting as both consumers and producers of information (T. M. Ali, Nawaz, and Ur Rehman, 2021). Consumers often prioritize emotional experiences over functional benefits (Huang, 2017). But how much of an impact do these interactions have on a brand's emotional factor with its audience? Can the sentiments expressed in a tweet or a product review affect customer loyalty or even modify sales? This research explores these crucial questions by analyzing consumer sentiments and emotional tone for the leading food and beverage companies.

Research has shown that despite utilitarian qualities like price, packaging, distribution, a brand has a symbolic meaning which is called brand personality (Aaker, 1996; Aaker, 1997; Kotler & Keller, 2006). The idea of emotional marketing, which began in the 80's and 90's is utilized and widely accepted globally. The importance of emotional connection is as a vital link between consumer and brand has been explored in marketing literature. Previous studies have examined the role of emotional connection in the creation, development and maintenance of strong brands (Sirgy, 1982; Malhotra, 1988; Biel, 1997; Fournier, 1998; Kim et al., 2001; Kapferer, 2008; Lin, 2010). 65% of consumers are affected by positive experiences throughout their purchase journey as stated by eMarketer (2020). Thus, various brands are designed to provide consumers with impressive experiences such as Nike's “Just Do It” campaign. Nike ensures its collaboration with athletic excellence that inclines empowerment and personal achievement. By associating this company's products with motivation, overcoming hurdles and success, there is a strong sense of relationship between consumers and the brand itself.

Several studies on marketing analysis in the past focused mainly on managing brand reputation, trust and customer satisfaction. Yet, with social media platforms such as Twitter and others, understanding consumer emotions and their emotional attachments is now more feasible. But there is a lack of research specifically into the emotional connection people have with various brands using advanced NLP models like DistilBERT and Twitter RoBERTa. Moreover, prior studies often used simple classification techniques, missing the subtle shades of brand emotion. Our paper fills in these gaps through comparing sentiments among popular and trusted companies, thus giving knowledge on how different brands touch the emotions of consumers.

RQ1: Understand how sentiment analysis enhances the understanding of consumer emotions.

RQ2: Examine significance in strengthening brand loyalty across various industries.

RQ3: Analyse how sentiment analysis of consumer tweets can provide actionable insights for brand engagement and marketing strategies.

Understanding emotions and sentiments in individuals has always been a key area of interest in psychology, sociology, and marketing. In the earlier times, the most common approaches to measuring sentiment were based on surveys and interviews where direct questions were asked about one's feelings or attitudes towards certain topics. Such surveys were aimed at measuring certain audiences' emotions such as happiness, sadness, anger, and satisfaction (Batterton et al., 2017). These methods were effective but had challenges due to such factors as small sample size, response bias, and lengthy procedures. As Natural Language Processing technologies advanced, the possibility of utilizing computational tools to analyse sentiments in a more or less automatic way implied the domain of sentiment analysis or "opinion mining" (Pang & Lee, 2008). As a result, it became possible for the scholars to work with large quantities of unorganized data, for instance, customer reviews in a much faster and effective way. Sentiment analysis, also known as opinion mining, involves the use of computational methods to determine the emotional tone behind a body of text (Liu, 2012).

It is a powerful tool that unlocks the emotional undertone behind various digital interactions, enables companies to determine how they are perceived by their consumers and audience. Sentiment analysis can evaluate and capture these feelings, enabling brands to touch the nerve of their buyers, whether it is customers who are thrilled at the release of a new product, or those who are dissatisfied and raving about a product service. Sentiment analysis is important in that it can afford businesses the opportunity to gather data that can be used immediately and decisively to customer perception and satisfaction, thus affecting strategic decisions (Pang & Lee, 2008). For big companies like Nestle, Coca Cola, Pepsi, and others, emotional connections and sentiment analysis allow them to have a glimpse into consumer's hearts and minds. The research is focused on the application of sentiment analysis to globally leading companies in the food and beverage sector, which is a novel method to merge actionable insights with the brands' customer engagement, in addition to an increase in sales and competitive edge.

Literature Review:

The significance of brand emotional connection in the food and beverage industry has garnered increasing attention in past few years, leading to deep connections with consumers with the help of emotional engagement through social media. Emotional branding being a major strategy and consumers navigating through hugely crowded marketplaces saturated with options nowadays, the brands capacity to build a deep emotional connection has now become a critical differentiator (Loureiro et al., 2012). Over the years researchers have become aware of how strong emotional ties enhance brand loyalty, persuading repeated purchases and positive word-of-mouth recommendations from consumers (Thomson et al., 2005).

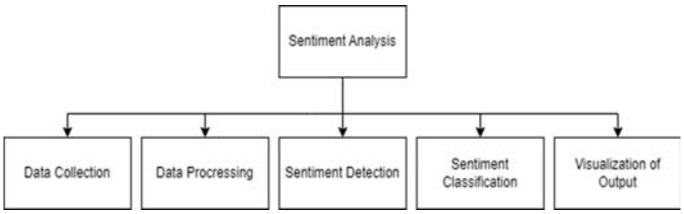
Memories play an important role for a brand to capture its consumers, thus emotional dynamics is crucial for marketers in the food and beverage industry to guide initiatives that increase consumer engagement and develop long-term relationships through the use of storytelling and sensory experiences (Albert et al., 2008; Brakus et al., 2009). This stimulates sentiments that resonate with consumer's values and memories. (Brakus et al., 2009). For instance, brands like Nestle and PepsiCo have successfully integrated emotional branding strategies by creating unforgettable impressions that fit the goals and lifestyles of the consumers (Iglesias et al., 2011).

Sentiment analysis allows the identification, extraction and quantification of feelings and emotions expressed in a text, thus gaining relevance in the marketing domain (Liu, Burns, & Hou, 2017; Pang & Lee, 2008; Rana & Cheah, 2016). To tabulate emotions, scholars need to select an appropriate codebook that is specific to the word-feeling association, and create an algorithm or use a pre-existing one (Lee & van Dolen, 2015; Medhat, Hassan, & Korashy, 2014; Pathak & Pathak-Shelat, 2017). In the present study 'sentiment' is conceived and used only for polarized emotions (Frijda, 1994). Positive and negative sentiments have been defined as polar emotions.

After comparison of few pre-existing algorithms used for coding emotions on tweets, we selected the DistilBERT model and Twitter-roBERTa-base for emotion classification because it showed the best overall emotions recognition performance. In particular, this instrument: (i) has been trained on more than 124 million tweets for self-supervised natural language processing with six basic emotions (love, joy, anger, sadness, surprise, fear) and three sentiments (positive, negative and neutral); (ii) is tailored for long tweets regardless of the language used; (iii) has been validated by Meta research team.

Sentiment Analysis consists of five processes for data processing: data collection, data processing, sentiment detection, sentiment classification, and visualization of output as seen in Figure 1.

Figure 1. Steps of Research Methodology



(Source: Adaptation of various references)

Machine learning is a popular technique in natural language processing (NLP), particularly sentiment analysis (Hasan et al., 2021). The availability of massive amounts of labelled data has increased the usefulness of machine learning in real-world problems in recent years. The use of supervised learning is more than unsupervised and semi-supervised learning. Supervised learning is also widely used for Twitter sentiment analysis (Shyamasundar et al., 2016; Siddiqua et al., 2016; Mehta et al., 2021; Chen, et al., 2020).

We conscientiously directed our research by comprehensive review of industry rankings and insights from reputable sources which lead us for the final selection of leading food and beverage companies for this analysis. Utilization of data from "Food Digital", which provides an overview of the leading global food and beverage companies, importantly highlighting their market presence and influence within the industry. Additionally, a detailed list of the largest food and beverage companies as of 2024 was offered by "Culinary Coverage", which catered us to identify main players based on their revenue and global reach. Furthermore, valuable information regarding the operational scale and market strategies of these companies was contributed by "Thomson Data", which corroborated that our selection not only based on financial metrics but also considered their impact on consumer behaviour and brand loyalty. By incorporating information and data from these authoritative sources, we verified that our analysis focuses less on the company's leadership in terms of sales and more on companies emphasising in shaping consumer sentiments and emotional connections within the food and beverage sector.

Sentiment analysis serves as a major tool for evaluating emotional connections between consumers and brands (Liu, 2012). This analysis aids brands with deeper understanding of the emotional tone behind consumer perspective, which significantly influences brand perception and loyalty (Pang & Lee, 2008). Consumer sentiment analysis and emotional connection are interconnected, playing a vital role in understanding how brands engage with their consumers. Firstly, categorization of consumer opinions into positive, negative and neutral sentiments, which allows brands to access overall consumer viewpoint towards their products or services. After identification of the emotional drivers behind these sentiments, brands can deduce what aspects of their offerings resonate with consumers (Pang & Lee, 2008). Moreover, changes in consumer sentiments over time can be tracked down with the help of continuous monitoring of sentiment across different social media platforms. Thereby enabling them to decipher evolving trends and potential issues before they scale up. Timely strategic adjustments are thus executed (Cambria et al., 2017).

Furthermore, important facts deduced from sentiment analysis acts a foundation for creation of marketing strategies, highlighting different aspects of improvement. Promotion of brand strengths can be leveraged by positive sentiments while negative sentiment can guide brands in monitoring weaknesses (Hutto & Gilbert, 2014). Finally, sentiment analysis also contributes to enhancing customer engagement. For fostering strong relationships with customers, engagement strategies are tailored by understanding emotional connect of consumers with their brand. Identification of key memories that influence consumer emotions such as exceptional consumer service experience can be analysed by brands through sentiment analysis (Godes & Mayzlin, 2004). Thus, the value of brand emotional connection cannot be overemphasized, as it serves as a foundation for building loyalty and driving consumer behaviour in the competitive landscape of the food and beverage sector (Albert et al., 2008).

Research Methodology:

Data collection:

The dataset used for the experimentation is obtained from using a web extension called X Twitter Scraper to extract the tweets needed for our analysis. Our dataset comprises of over 8,000 tweets that record interactions between the Leading Food and Beverage companies from all over the world and their consumers. We are focusing on 10 food and beverage companies, which includes Nestle, PepsiCo, Coca-Cola Company, Unilever, Tyson Foods, Mars, Anheuser-Busch InBev, JBS, Archer Daniels Midland (ADM), and Mondelez International. These companies were listed on the basis of their significant market presence and consumer engagement, which was highlighted in various industry analyses, such as Food Digital, Culinary Coverage, and Thomson Data. The period ranges from January 1 2019 to August 31 2024. The consumers reactions to the brand are pretty diverse, reflecting on the different sentiments. The extracted tweets are described in Table 1:

Table 1. Data Collection

Data Type	Content
Date	Date of the respective tweets
Post type	image, video, text
Content	Tweet text
Like	Number of likes
Retweet	Number of retweets
Reply	Number of replies

(Source: Creation of Author)

Data Processing:

To begin with the data pre-processing steps firstly we analyse sentiments and emotions, focusing on the content column slicing the actual text data of the tweet. After loading the dataset, we identify and select the content column. This column contains the primary data needed for sentiment and emotion analysis. The next step involves converting the content column to a list. Each entry in the list corresponds to an individual tweet, enabling easy transformation of applying text processing models in subsequent steps. Moving on, once the list of tweet content is prepared, it is passed through two predefined sentiment analysis models designed to evaluate the emotional content of the text. The models process the text and output a list of dictionaries. Each dictionary contains two key pieces of information: label and score. At this stage the model output, the primary focuses is on extracting the label and its corresponding score. The label (emotion or sentiment) is predicted by the models and the score determines the strength or likelihood of the predicted emotion. This results in a list of dictionaries where each dictionary contains a label (emotion) and a corresponding score. When the list of dictionaries encompassing various emotion labels and their scores has been retrieved, a program counter is operated to count the frequency of different emotions. This counter iterates through the list, calculating how many times each emotion appears. This step evaluates the emotional patterns detected in the tweets, giving us a clear understanding of the distribution of emotions within the dataset.

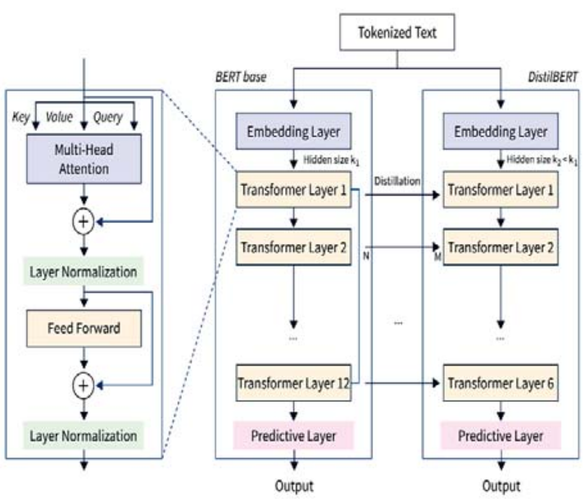
Sentiment Classification:

The techniques used for classification of consumer sentiments are described below:

1) DistilBERT Model:

DistilBERT is a distilled version of BERT (Bidirectional Encoder Representations from Transformers), which has proved that it is possible to reduce the size of a BERT model by 40%, while retaining 97% of its language understanding capabilities and being 60% faster (Victor Sahn al et., 2020). It was developed by Hugging Face and performs several key functions. It maintains the core transformer architecture of BERT but reduces the number of layers from 12 to 6, which eventually results to fewer parameters and faster inference times as shown in Figure 2 (Victor Sahn al et., 2020). Knowledge distillation approach was used to train this smaller model which learns to mimic the behaviour of a larger, pre-trained model (BERT) through teacher-student framework. This approach includes minimization of the difference between the outputs of the two models for a given task (Victor Sahn al et., 2020). Various NLP tasks such as text classification, sentiment analysis, named entity recognition and question answering can be performed efficiently using this model. This model proves to be efficient for applications where computational resources are limited or where quick response times are critical (Victor Sahn al et., 2020).

Figure 2. DistilBERT Model Architecture

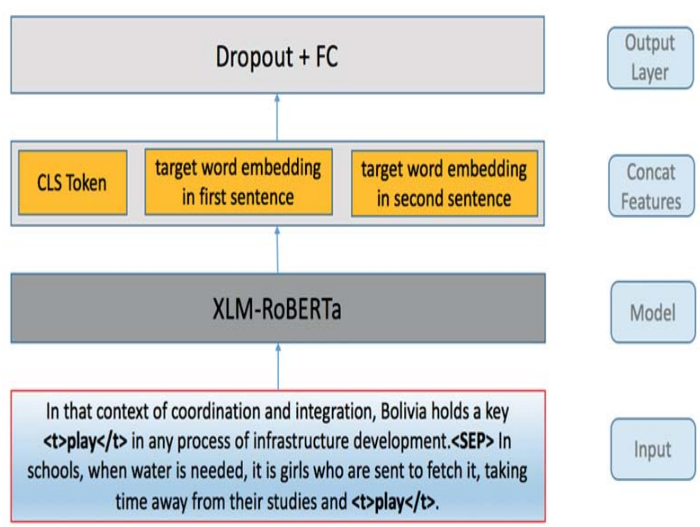


(Source: HuggingFace DistilBERT - Scaler Topics)

2) Twitter roBERTa base:

Twitter RoBERTa model focuses on its application in tweet classification tasks within the TWEETEVAL benchmark. RoBERTa , which is stands for "Robustly optimized BERT approach" and represents a transformer-based language model has demonstrated superior performance in various NLP tasks (Barbieri et al., 2020). This was also developed by the Hugging Face team to serve several key functions such as, due to its strong performance in the General Language Understanding Evaluation (GLUE) benchmark and ideally suitable for handling typically short and noisy nature of tweets, often consisting of single sentences, this model was chosen (Barbieri et al., 2020). Three types of variants were trained for this model. Initially it was trained on RoB-Bs which is a base model pre-trained on large corpus of textual content. Next came the RoB-RT which was similar model further trained to adapt to some specific characteristics of social media texts and ultimately was trained on RoB-Tw which was a variant trained from scratch using twitter data only. These models were trained on a substantial corpus of 60 million tweets, for ensuring that the model is well-versed in the languages and nuances of Twitter (Barbieri et al., 2020). For the reduction of output dimensions, a dense layer was added to the RoBERTa model as shown in Figure 3 to match the number of labels in each classification tasks involved. This model was also fine-tuned on various tweet classification tasks such as sentiment analysis, emotion recognition and hate speech detection (Barbieri et al., 2020).

Figure 3. RoBERTa Model Architecture

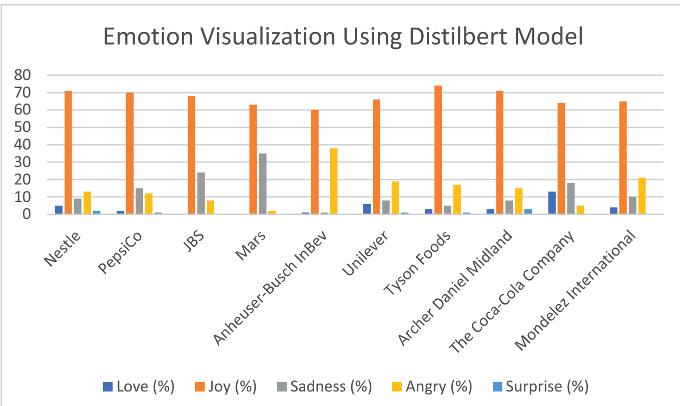


(Source:https://www.researchgate.net/Figureure/Fine-tuned-XLM-RoBERTa-model architecture_Figure1_351046950)

Visualization and Output:

After Data Collection, Data Processing, and Sentiment Classification, we move onto the next part which is Sentiment Visualization for which we decided to use donut chart for efficient distribution of love, joy, surprise, anger, and sadness emotions. Also, we used 100% stacked bar graph for distribution of positive, negative, and neutral sentiments. Figure 4 shows the outputs we derived using DistilBERT Model. (Source: Creation of Author)

Figure 4. Visulization of DistilBERT Model results for all companies



The emotional connections these brands foster with consumers are critical in today's competitive landscape, where emotional branding strategies are increasingly recognized as essential for driving customer loyalty and engagement. So, taking consumer responses into considerations for these companies, we have ranked these companies as shown in Table 2 keeping "joy" as the primary factor, while anger and sadness adjust the ranking necessarily.

Table 2. Ranking of the companies based on their tweet responses

Rank	Brand	Joy(%)	Anger(%)	Sadness(%)
1	ADM	68.7	14.9	8.1
2	Nestle	52.7	9.9	6.8
3	PepsiCo	51.3	8.6	11.2
4	Tyson Foods	47.0	11.1	3.1
5	Mars	51.6	1.3	28.5
6	Coca-Cola Company	47.1	3.8	13.1
7	Mondelez International	49.4	15.7	7.8
8	JBS	48.3	6.0	16.7
9	Anheuser-Busch InBev	53.5	34.5	1.1
10	Unilever	50.8	14.7	5.9

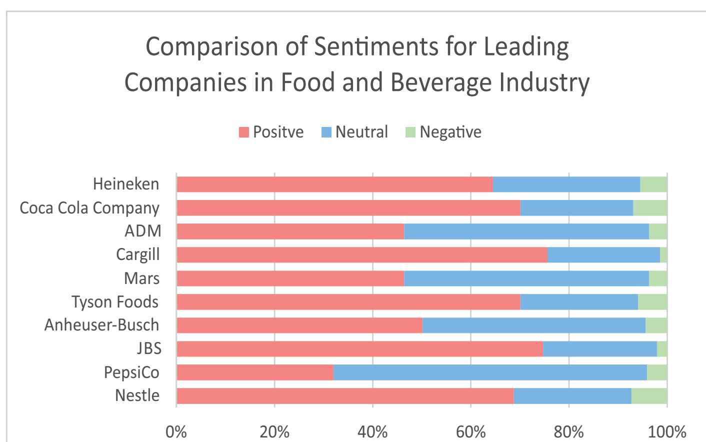
(Source: Creation of Author)

The sentiment analysis of customers towards the leading food and beverage companies based on their Twitter responses appears to have a varied emotional landscape among consumers. Archer Daniel Midland is first with the highest percentage of joy being as high as 68.7% which suggests a strong positive engagement with their customers. Mars on the other hand records the highest sadness level at 28.5%, which is likely to indicate worry or dissatisfaction in the customer interactions, though joy levels are moderate. Anheuser-Busch InBev and Nestle also have a high joy percentage of 53.5% and 52.7% respectively.

Anheuser-Busch InBev's has a strikingly high anger proportion of 34.5%. This suggests that a few of the responses might have caused some degree of discontent or controversy among their consumers. The three companies that showcases moderate joy levels but exhibit varying degrees of sadness and anger levels indicating mixed responses which could be from unresolved issues are PepsiCo, Tyson Foods, and JBS. The discontented score of Mondelez International is rather high at 15.7% which might suggest customer frustration. Overall, these findings bring out the fact that certain organizations can effectively induce positive feelings, however, others struggle at alleviating the adverse experiences, thus suggesting the need for some engagement efforts to be more balanced.

Figure 5 represents the output we derived using Twitter RoBERTa-base Model:

Figure 5. Comparative Sentiment Analysis of Leading Food and Beverage Companies



(Source: Creation of Author)

Implications:

Theoretical Implications

The study suggests that building emotional connections influence brand loyalty and consumer behavior significantly and thereby strengthen the theoretical framework of emotional branding. This orients with the findings of Aaker (1996) and Fournier (1998) who emphasize the significance of brand personality and emotional ties in different consumer-brand relationships. The body of research on consumer behavior is expanded by the use of sentiment analysis as a methodological approach in understanding consumer emotions. It stands by the idea that computational methods can effectively quantify emotional responses, as discussed by Pang & Lee (2008) and Liu (2012). Thus, future research can explore sentiment analysis in various industries other than food and beverage with the help of this contribution. The findings point to emotional experiences playing an important role in influencing consumer perception in line with the research on sensory experiences and storytelling in marketing by Brakus et al. (2009).

Managerial Implications

Brands can capitalize on positive sentiments to improve their marketing campaigns while addressing and analysing negative sentiments to improve customer satisfaction (Hutto & Gilbert, 2014). The findings gained from sentiment analysis can direct marketing strategies. This can be achieved by ascertaining emotional drivers that resonate with consumers. The proactive approach of monitoring and analyzing customers' reactions allows brands to constantly follow the changes in public perception as the time goes by, thus companies can quickly change the strategy in case of a need, as stated by Cambria et al. (2017). By using sentiment analysis, brand managers can detect threatening situations in an early phase and thus make corresponding resolutions. Brands can customize their communication and service experiences to the customer in order to have a closer relationship with them (Godes & Mayzlin, 2004) by acknowledging their emotional stimuli; the conclusion drawn is that brands are able to build customer loyalty on emotional connections, the support of Albert et al. (2008) which emphasizes the issue of emotional connections as the main factor in the development of consumer loyalty, is in line with the above. By identifying the emotional ties consumers feel for the brands, one can design effective ways of bringing them in. The research underlines the importance of data-driven decision-making in marketing. Managers can make informed decisions based on consumer feedback by utilizing different sentiment analysis tools leading to more effective marketing strategies and improved customer experiences.

Limitations and Future Scope:

The Twitter roBERTa-base model distinguishes the tweets into three different categories: positive, neutral, and negative. Though effective in categorizing, this classification does oversimplify the concept of human emotions that are expressed in the tweets. There exist many more significant sentiments that do not fit well into these three categories. A consumer tweet may express a mix of sentiments but the model wouldn't be able to capture and classify them into one category. It could result in a loss of relevant emotional insights affecting our study of consumer sentiment analysis towards the top companies. We made use of another pre-existing model DistilBERT that classified the tweets into five different sentiments: Love, Joy, Anger, Surprise, and Sadness. By using a broader and more detailed spectrum of emotions, it increases the accuracy of sentiment analysis.

The changes brought about by the rebranding of Twitter to X have made it so much more strenuous for people who scrape data mostly for research or analysis purpose. The new structural and policy frameworks of the platform have introduced restrictions on data collection and has made data extraction very tedious. Researchers may find it difficult in collecting a sufficient number of tweets which would help to pm thorough sentiment analysis and understanding consumer behaviour. These challenges not only make it too hard to accurately capture the consumers' feelings but also risk the quality of insights that brands rely on to connect with their target audience. It also greatly impacts how brands engage with their customers as data-driven decisions are very crucial in this day and age.

Conclusion:

Despite the fact that number of scientific articles analysing connection between brand and consumer personalities have increased recently, not all articles provide ranking of brands and companies on the basis of customer sentiments. Ranking of companies is generally provided on the basis of its annual turnover, but we have tried to rank companies on the basis of their customer emotional connection through 8000 tweets. This analysis demonstrates that brands like Archer Daniel Midland (ADM) and Nestle are leading in consumer emotional engagement criteria because their positive sentiments dominate consumer interactions.

The study emphasizes the role of emotional dynamics in marketing strategies, where storytelling and sensory experiences enhance emotional engagement (Albert et al., 2008; Brakus et al., 2009). Brands that resonate emotionally with consumers can differentiate themselves in a crowded marketplace, reinforcing the notion that emotional connections are fundamental to building strong brands (Fournier, 1998).

In the intensely competitive business environment where different brands fight to be noticed and trusted, it is important to build affective relations with customers. Emotional ties to a brand result in a two-way relationship where customers trust a brand and, in return, demonstrate trust and loyalty to the company, thus driving sustainable growth. For a brand to be successful, it needs to build a community of loyal customers whom it has brought into its inner circle. Personal Brand Power is based on the emotional tie between the brand and the consumer. A brand that is terrific is then perceived as one with which a connection is covered by feelings like trust, steadfastness, and satisfaction. The extent to which a user of a product emotionally identifies with a brand is, for example, measured by the degree to which trust and reassurance are determinant factors for being satisfied or not. The emotional connection of a brand is examined through customer surveys and other metrics such as social media engagement to assess the emotional impact of a brand on its customers.

However, limitations exist, such as the oversimplification of human emotions in sentiment analysis models (Liu, 2012). Future research could explore more sophisticated models to capture a broader range of emotional responses.

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