A X Platform Analysis of The Brand Torku By Means of A Text Mining Method

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ARTICLE INFO	ABSTRACT
Keywords: Sentiment Analysis Text Mining Food Industry Received 24 April 2024 Revised 10 December 2024 Accepted 15 December 2024 **Article Classification:** Research Article	**Purpose** – Consumers in all sectors, and especially in the food and beverage sector, make evaluations about the products and services of businesses, and these opinions have an impact on the preferences of different consumers. The main problem of the research is how businesses can transform this multidimensional and complex big data from social media into useful insights.This study aims by means of text mining to analyze the posts shared on X platform by Torku, a brand owned by Konya Şeker, a top 50 company in Turkey operating in the food industry, using the hashtag #torku. **Design/methodology/approach** – For this purpose, 8208 tweets shared in Turkish on X platform were accessed using the programming language Python. The BERT model was used for the sentiment analysis. **Findings** – As a result of sentiment analysis, 4283 of 7212 posts were positive and 2929 were negative. The word cloud is shown that the most frequently repeated three words out of all the posts to be domestic (yerli), national (milli), and nice (güzel). **Discussion** – An analysis of the posts involving these related words show the most frequently highlighted facts in positive reviews to be that the brand is domestic, is national, and uses halal products, while the most frequently mentioned posts for negative reviews were that the prices are high

1. INTRODUCTION

A new era emerged defying the geographical borders, where people who are independent of one another can establish communications using forming groups or with hashtags under specific headings on the Internet, thanks to communication systems that have become more technological upon the transition to Web 2.0. (Weinberg, 2011: 1; Zafarani et al., 2014: 16). A quick increase in the volume of e-sales and that consumers frequently use social media channels to review services and brands have brought a substantial size of complex and embedded data to business companies. It is now a proven fact that the contents created by users on social networks contain crucial information for both users and organizations/corporations. This is because this makes it possible for people to share their opinions in an unlimited and unbiased environment on one hand and for corporations to get helpful information that affects the decision they make on the other hand (Fersini, 2017: 92). However, most of these business companies have a limited volume of knowledge on how to use this giant data stack, transform it into insights from consumers, and thus, how to increase profitability. Therefore, analyzing the data obtained from social networks becomes even more critical.

X platform is the third most popular worldwide Online Social Network (OSN) after Facebook and Instagram. Compared to other OSNs, it has a simple data model and a straightforward data access API. Therefore, X platform has become a significant research platform utilized in more than ten thousand research articles over the last ten years (Antonakaki, 2021: 1).

The most used techniques for analyzing the data obtained in the digital environment are data mining and text mining. Text mining makes it possible to analyze all textual contents such as reviews, critics, and suggestions about products and services of a business company on social media (Savaş et al: 2., 2012; Bayrakcı, 2015: 54). With this information, business companies inevitably increase their profitability levels using developing marketing strategies in line with the complaints and requests of consumers. Consequently, the data obtained from the digital environment will significantly contribute to the development of business companies, the regions, and finally, the country's economy.

Social media is mainly used to get information concerning products and services and inform campaigns. Consumers are affected by the reviews and even misinformation concerning products and services posted on social media while choosing business companies engaging in the food & beverage industry and may change the brands they use accordingly (Yılmaz et al., 2007: 13; Ibiş and Engin, 2016: 333; Sağlam and Gümüş, 2019: 161); therefore, the brands would be able to enhance their success rates if they can share such posts that are appeal to the eye and that results in them being talked about on social media, follow the consumer trends, respond to those requested and design their marketing methods based on customer relations on social media (Alyakut, 2017: 231; Seçer and Boğa, 2017: 318). Content on social networks offers businesses unique information about consumers' perceptions and feedback about the brand. However, it is often discussed how businesses can transform the complex and multidimensional big data stacks coming from social media into useful insights (Yang et al., 2022). Thus, the main problem of the research is how businesses can transform multidimensional and complex structured big data stacks coming from social media into useful insights. Businesses that can provide this will be able to achieve higher customer satisfaction and profitability. The results of this research can both guide businesses on how to transform their own brands' social media data into useful information and present researchers with the example of Torku, an important brand in Turkey, on the use of big data analytics techniques.

From this point of view, this study will analyze the reviews about Torku, a brand of the company Konya Şeker, on X platform. Konya Şeker is among the top 50 companies on the List of Turkey's Top 500 Industrial Enterprises as prepared by the Istanbul Chamber of Commerce (ICC) ("Konya Chamber of Industry", 2021). Torku, a strong brand of Konya Şeker, is mentioned in thousands of reviews on social media, and thus it is a brand about which there is a lot of digital data. The main objective of this study is to analyze the posts shared by consumers on X platform under hashtag #torku using the sentiment analysis and word clouds as text mining methods and turn the results thereof into meaningful outputs that can contribute to the profitability of the business company. Research shows that many business companies do not know how to turn data obtained from social media into meaningful outputs (Weinberg, 2009: 6; Zafarani et al., 2014: 17). The data obtained using analyzing the digital data of a large-sized enterprise that contributes to the region's economic development would also be used to offer a roadmap for Small and Medium-Sized Enterprises (SMEs) in the region.

Unlike the similar research in the literature, this research aims to obtain understandable and summary information from thousands of data carrying out a sentiment analysis and word cloud using the X platform data about the brand Torku collected in 10 years. This research aims to carry out a sentiment analysis and word cloud on the respective social media data in Turkish using the programing language of Python, obtain information that would contribute to the business profitability, and then set an example for future research that can support the economic development in the region. The fact that the study considers only the tweets with the hashtag #torku and that the reviews about the brand are collected from X platform is the restriction of this research.

2. PRELIMINARIES

2.1. Big Data

Technological advancements make it possible for almost all transactions to be conducted online. The sizes of the data generated, stored, and processed from these transactions expand day by day. As of 2019, Internet users generate 2,5 quintillion bytes of data per day, which is expected to increase day after day (Kara, 2021). The data type is also diversified as the data quantity gets increases. An increase in data stacks and the inclusion of new ones into variables frequently used for statistics require the development of dynamic, multidimensional algorithms and robust against noise and missing values. (Gülpınar Demirci and Kaplan,

2020: 254). The leading technique associated with big data processing is data mining and text mining. Data mining is based on statistics, and, together with big data, it has contributed significantly to the development of data science (Bayrakcı, 2015: 54; Ergen, 2018: 56).

2.2. Data Mining

Data mining makes it possible to perform several analyses such as estimations, classifications, and optimizations to reveal patterns hidden in the big data stacks (Gülpınar Demirci and Kaplan, 2020 :254). With an analysis of the products it sells, a business company can shape future campaigns and discover the connections between the products based on the data showing which products are bought together. Another benefit for a business company is that it can understand similar behaviors and trends, carry out analyses and estimations on the target market and use the information from that place for its marketing activities. Thanks to text mining, it is possible to prevent marketers from making wrong decisions under today's renewed conditions. Therefore, one can say that data mining has become an important decision-making tool (Dolgun et al., 2009: 58; Savaş et al., 2012: 18).

2.3. Text Mining

As data mining emerged during the 1990s, the efforts intended to access texts and retrieve information from that place, categorize texts, and structure text data have gained momentum. The interest in text mining has started to increase after the 2000s. Text mining makes it possible to reveal information embedded in the different formats of texts (Hearst, 2003; Hippner and Rentzmann: 288, 2006; Oğuzlar, 2011: 4-8).

The most distinctive difference between data mining and text mining is that numbers are used for the first one, and texts are used for the second one. However, this difference does not mean that data mining and text mining are separate concepts. That is to say, during the analysis performance for text mining, unstructured textual data are converted into digital data using pre-processing and then become ready for use at the stages of data mining. In this way, data mining is utilized at the stage of modeling when text mining is applied (Oğuzlar, 2011: 55-56).

Based on the research on text mining, it is possible to say that text mining generally consists of four steps. Considering today's application of the stage for the creation of a text collection that is the first step, advanced text mining software programs make it possible to download thousands of posts about the subject in question from the respective websites or social media platforms (Oğuzlar, 2011: 56; Aravi, 2014: 45; Kasapoğlu et al., 2020: 200). The stage of pre-processing texts, that is, the second step, is mainly intended to refine the unstructured textual data making it into the shortest form with no unnecessary additions so that the most appropriate format is achieved to process the data (Güven, 2007: 9; Oğuzlar, 2011: 57). The pre-processing steps can significantly affect the model's performance (Jianqiang and Xiaolin, 2017: 2879). During the third stage, clustering, classification, and association analyses are used to discover information, which analyses are also used for the conventional data mining methods (Oğuzlar, 2011: 56; Çınar, 2012: 4; Kasapoğlu et al., 2020: 200). Lastly, the results obtained from the textual data are assessed and presented to the respective users in the most clarified manner (Oğuzlar, 2011: 10).

2.3.1. Word Cloud

The reporting and data visualization methods are word clouds, word frequency distribution histogram, n-grams, word co-occurrence correlations, and heterogeneous distributions of words. As the easiest and most frequently used visualization method, word clouds aims to help find the most frequently repeated words in many datasets and form an opinion about the actual data based on those words. Frequently mentioned words are randomly distributed in an area. In contrast, the relatively more frequently used words are written using larger font sizes reflecting the main idea and subject of the respective text. A researcher defines the number of frequently used words to create the word cloud. Similarly, the researcher can define the words' colors and the cloud's shape and create text images. Since there would be many prepositions, conjunctions, and other similar phrases in the sentences within a word cloud, these words should be sorted out and then analyzed accordingly (Demir et al.: 64, 2019; Atan, 2020: 232; Küçükkartal, 2020: 11).

2.3.2. Sentiment Analysis

A business company that is aware of positive or negative opinions of consumers concerning the products and services it offers would take an excellent opportunity to increase the functionalities offered by these products and services, compete with other companies and carry out efficient marketing analyses. For this reason, despite analyses carried out to get these conclusions through customer satisfaction surveys for many years, it has not been possible to get good results from these surveys or similar approaches due to the restriction in the sample sizes and the difficulties in the preparation of an efficient survey. In response to the need to identify positive or negative meanings in extensive data, Tetsuya and Jeonghee came up with the concept of sentiment analysis in 2003 and presented an application example in this respect (Nasukawa and Yi, 2003: 70-77).

It is possible to gather posts that are shared about various subjects through virtual environments and identify the central theme of a text consisting of thousands of words using text mining methods and sentiment analyses. As a result of analyses of a text, the sentiments of the words used in the text are calculated by specific computer programs resulting in a map of sentiments. In order to conduct this analysis on a computer, one should define positive, negative, and neutral words using specific dictionaries that contain sentiment words for each respective language. This makes it possible to map the words used in the text and the sentiment words found in the dictionary, reveal the dominant sentiment therein, and thus analyze the sentiments and thoughts embedded in the text as positive, negative, and neutral (Şeker, 2015: 32; Akcayol and Özyurt, 2018: 690; Demir et al.: 65, 2019; Atan, 2020: 229; Küçükkartal, 2020: 12; Beşbekirli et al., 2021: 22).

2.3.3. Tools Used for Text Mining

There are paid and free tools used to convert the textual contents obtained using a text mining method into data that are sufficiently summarized to understand at a single glance. Among free software programs as strong as paid alternatives and commonly used in the field are R application, Python, Weka, Orange, and Google Sentiment API applications. With these applications, one can conduct analyses such as word frequency distribution, word cloud, and sentiment analyses (Çınar, 2012: 5-6; Atan, 2020: 229-230). Python is used for the text analyses within the scope of this research.

Python is a programming language, the first release of which was published by Guido van Rossum in 1991 without any particular area-related restriction (Malkoç, 2021: 201). Python is not only a robust programming language, but it is also easy to read and understand the applications thereof. This application that supports data mining and text mining is an open-source language, making it possible to prepare machine learning algorithms (Atan, 2020: 230).

3. LITERATURE AND BACKGROUND

Konya Şeker is a company that operates in the province of Konya. Konya has Turkey's most significant farmland ("Konya Population", 2021; "TÜİK- Agricultural areas", 2020). Thanks to this extensive farmland, Konya has been suitable for agricultural production since the beginning of human history and has become one of the regions where the food industry overgrows. Some manufacturers gathered under the roof of cooperation to establish Konya Sugar Factory in the 1950s. All the products from Konya Şeker are collected under the roof of the brand Torku. The number of people directly employed by Torku is more than 10 thousand, while those indirectly employed are more than 100 thousand. Torku put into service Direct Agricultural and Food Markets, which exclusively sell products from Torku, in 2007 and chains of restaurants, where meals are prepared using the products from Torku, in 2018 ("Torku", 2021; "Torku Official Website", 2021).

There are seven companies from Konya on the List of Turkey's Top 500 Industrial Enterprises as prepared by the Istanbul Chamber of Commerce (ICC). Among those companies in the province of Konya, Konya Şeker ranked first on this list in 2019, just as it also achieved in the previous years. It has achieved to be the biggest 49th company in Turkey with a budget of 3 billion 544 million 617 thousand 111 Turkish Liras obtained from the sales of its products. This achievement also made it the most significant industrial enterprise in the province of Konya ("Konya Chamber of Industry", 2021; "Torku", 2021).

A view of the studies in the literature reveals that the text mining method has been used in various areas. Similarly, data concerning the food industry have been collected through online environments and analyzed accordingly. From this standpoint, under this heading of literature, we will examine 11 studies conducted in

connection with the Torku, a brand of Konya Şeker, and 16 studies conducted in connection with the food industry making use of text mining and other methods for the analysis, and mention 8 data and text mining studies out of those conducted on X platform.

The social media accounts of the brand Torku have been analyzed to see how a video with harmful content can affect the brand's reputation (Boyacı Özyurt, 2019: 1-124) and out of 5 senses, which are addressed by the posts shared on social media (Büdün Aydın, 2021: 24-43). In addition to them, an analysis was conducted to see how advertising and promotions have affected the formation of brand awareness for Torku, resulting in the finding that this has been a powerful effect (Bilgili and Özkul, 2015: 89-106). Among the findings from other studies are that the brand Torku sponsoring a football team positively affects the consumers (Temel and Şirin, 2017: 241-253), and it has become successful with specific steps such as it indicates that it uses sugar beets in its products, it sells its products at its direct stores, it gives Turkish names to its products, etc. (Oğuz and Mete, 2017: 386-424). On the other hand, it has been observed that consumers mainly pay attention to the headings of an advertisement (Köylüoğlu and Tekin, 2017: 469-475). An analysis of the brand in respect of marketing strategies resulted in a conclusion that it is a localized brand that uses modern marketing strategies mainly for national markets (Sezgin and Şenel, 2017; Türk et al., 2019) and that how old a company is or how many trademark applications a company submits does not add value to the company (Gümüş and Algül, 2018: 183-195). On the other hand, the brand Torku has won the consumers' trust with corporate social responsibility activities (Karaboğa et al., 2020: 347-366) and contributed to the regional development (Bahar and Nas, 2021: 63-82).

With marketing activities conducted on social media, the company will be able to engage the customers in its activities, use the information obtained from them for the benefit of the company, increase the brand recognition, ensure the brand loyalty and improve customer relations (Çelimli and Adanacıoğlu, 2020: 493-498; Kara, 2020: 165-175). This shows that companies' efficient use of social media may positively affect sales (Say, 2015 :19-39). For this reason, analyses have been frequently conducted on the social media posts of business companies. During these studies, analyses were conducted on the websites of the same brand in different countries to get a general opinion (Su Le et al., 2015: 2-4). Another study was about women engaging in natural food production in Kartepe, who have promoted their products through social media and thus achieved to sell them on social media (Alyakut, 2016: 125-149). Another study analyzed the consumers who purchase conventional products on social media, concluding that these products are preferred mainly by married people. (Sarı, 2017: 1-144). Social media is also used to analyze the consumers' opinions about a particular brand or brands (Dolan and Goodman, 2017: 23-30; Lynch et al., 2019: 120-141; Cheng, 2020: 1-62); to analyze the awareness created by brands in respect of sustainable consumption and the role of brands in this respect (Erkan, 2019: 170-182); and to analyze the effect of fear on the purchasing sensitivity (Sarıyer, 2019: 1-23). Studies conducted with sentiment analyses through different methods on X platform data concerning the food industry were used to understand the customers' opinions (Nawaz et al., 2019 :110-115), and identify the most favorite and popular brands (Ali et al., 2018: 225-232; El Rahman et al., 2019: 1-4), determine how a brand is affected when a celebrity consumes the products of that brand (Ramdhani et al., 2018: 123-127) and conduct a social media competitive analysis for three companies (Trivedi and Singh, 2021: 891-910).

In 2023, Rodríguez-Ibanez et al. They evaluated sentiment analysis studies conducted on social media platforms together. In the study where more than 2300 articles were evaluated, it was seen that the X platform was examined the most, and the reason for this was "the opportunity for a very large and diverse population to comment on current issues on a daily basis". The most frequently used areas of sentiment analysis are; They are listed as marketing, politics, economy, and health.

Among the studies conducted with text mining analysis on X platform are: a sentiment analysis to get opinions about Jet Airway (Ahuja and Shakeel, 2017: 17-24), a sentiment analysis and word cloud on posts concerning Apple, Samsung, and Huawei (Akundi et al., 2018: 87-94), the relationship between the social media addresses and the actual brand values of 100 Turkish brands (Uyar et al., 2019: 287-306), a sentiment analysis and word cloud on social media concerning vaccines (Küçükkartal, 2020: 10-13) and on posts shared at different times concerning vaccines (Beşbekirli et al., 2021: 21-25).

4. METHODOLOGY

4.1. Population and Sample of the Research

During the data collection phase, research was conducted using various hashtags on X platform. However, it has been seen that the #torku tag gives the most data on the subject. In this direction, all correspondence, opinions, thoughts, and shares related to the research subject were examined to examine the public opinion of the Torku company on social media and determine the reasons for positive/negative opinions. All these data were included in the research, and various analyzes were made with text mining methods. In addition, the identity of the people sharing the posts is kept confidential in order to comply with ethical principles. At this point, the research universe consists of 8208 X platform posts written in Turkish with the hashtag #torku on the X platform between 01.01.2011 and 01.01.2021. Between these dates, 39 tweets with the same text content were deleted, and analyzes were made on 8169 tweets.

4.2. The Method of the Research

X platform shares were obtained using the Python programming language and the twint library. The data were pre-processed before being analyzed. During the pre-processing, posts with precisely the same text content were cleaned. In addition, many links, mentions, hashtags, RT expressions, and numeric characters in the shares were cleaned from the shares, and raw text with emotion was obtained. Emojis and punctuation marks that affect expressing emotions are preserved in this step. Then, the entire text was converted to lowercase letters, and standardization was achieved. In addition, due to the tendency to write words that are frequently seen in social media shares using repeated letters, an arrangement was made in words with more than two-letter repetitions so that the letter repetition is 2. Although it is often used in a language, words that do not cause significant changes in meaning when removed from the sentence are called stopwords. As a traditional pre-processing step in text mining applications, texts are cleaned from stop words to ease the processing load and reduce deviations (Oğuzlar, 2011: 42-44). The list of stop words created by the researchers within the scope of the study consists of 408 stop words in total. These words have been cleaned from X platform posts.

The text data in the unstructured format has been converted to the structured format after the text pre-processing phase and is ready for the data mining phase. At this stage, sentiment analysis was carried out through the BERTTürk language model, and word cloud was carried out with the Wordcloud library for knowledge discovery from structured texts.

Below, brief information about common and suitable social media applications will be given.

Today, users use social media applications such as X, Facebook, and Instagram to obtain or share information. One of the most popular applications among these, X platform is one of the most popular microblogging services with more than 1.3 billion user accounts and an average of 152 million daily active users. In 2021, 353 million active users were reached. It is known that 42% of the users of this service visit the platform every day and share an average of 500 million posts per day (Giachanou and Crestani, 2016: 5; Antonakaki et al., 2021: 1; "Digital 2021 July Global Statshot Report", 2021: 132-133). X platform allows its users to share their feelings, thoughts, and opinions with the public in textual posts called "tweets" with a maximum length of 280 characters. There is also a command to like the posts. Various words are written together within the shares with the # (hashtag) expression, and the content is tagged with the relevant subject or person. This process allows the shares to be classified. Thanks to these features of X platform, it is possible to reach the conversations by searching for various keywords and to access information such as how much a post has spread and how much impact it has on people. In these respects, the X platform application is suitable for the study. When examined in terms of the Torku firm's data, it was decided that the most appropriate word and research style was #torku. By using this hashtag, the shares made in virtual environments related to the research subject were reached.

4.3. Research Questions

In this research, emotion and word cloud will be done with the Python program on the data stack on X platform. As a result of the inferences, it aims to contribute to the literature in terms of how digital data can be used to increase the profitability of the company and the economic development of the region. From this

point of view, the first stage of the research consists of determining the questions that guide the determination of the research details.

The questions of research are:

a. How many tweets have Torku customers on X platform tweeted about Torku over the years?

b. How many of the comments about Torku products are positive or negative?

c. What are the most frequently used words in all the posts concerning the brand Torku?

d. What are the most frequently expressed words among the positive comments about Torku products?

e. What are the most frequently expressed words among the negative comments about Torku products?

5. FINDINGS

In the study, a two-step analysis, the first step of which was sentiment analysis, was carried out for the Torku company, specifically for X platform shares. The X platform shares to be analyzed were subjected to various pre-processing for sentiment analysis, an intensely studied subject in the natural language processing field. Then the classification as positive or negative was automatically performed with the BERT model with high accuracy rates. In the next step, unique words in the shares that were separated according to the emotional state were determined, their frequencies were calculated, and word clouds were created using the Python programming language, Wordcloud library. Visualization of the followed steps is shown in Fig.1. The results of these analyzes will be discussed under different headings.
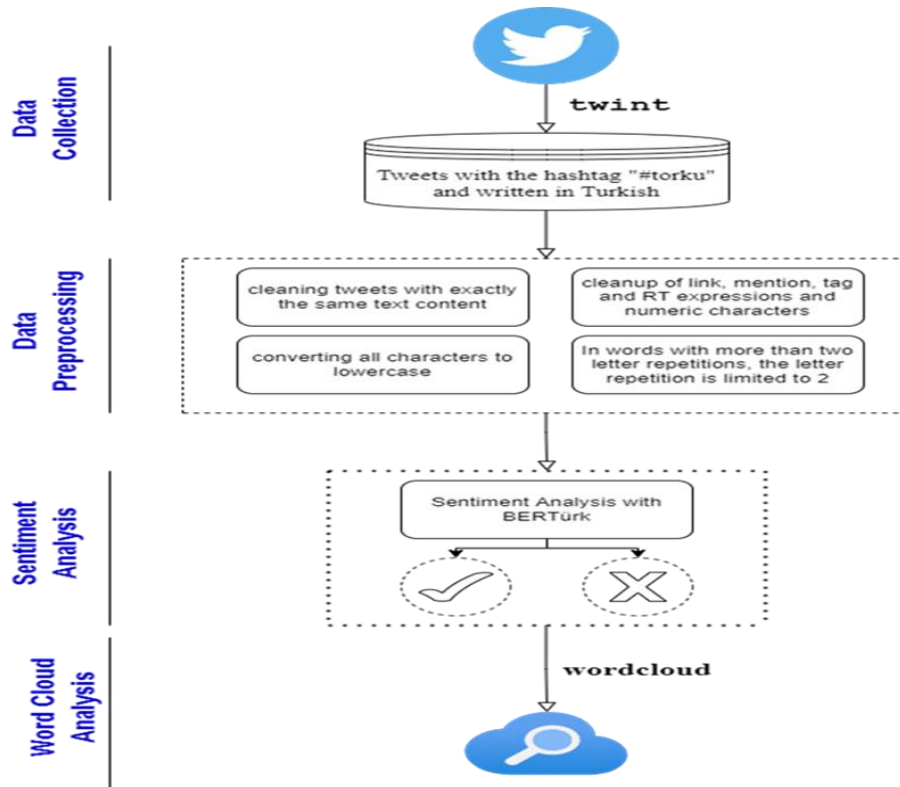

Figure 1. Stages of The Sentiment Analysis and Word Cloud of The X platform Posts Containing Hashtag #torku

Sentiment Analysis on Turkish X Platform Posts with BERT (Bidirectional Encoder Representations from Transformers) Language Model

BERTurk, which is a pre-trained BERT Base model in Turkish, was used as a language representation model in the presented study. BERTurk has been trained with a 35 GB corpus containing 4 404 976 662 tokens and has been shared for the use of researchers ("BERTürk", 2021). For the sentiment analysis subtask of this significant language representation model, a fine-tuned BERT model by Dr. Savaş Yıldırım was used ("Bert-based Turkish emotion model", 2021). For this purpose, in addition to two different sentiment analysis

datasets used in the study presented by Demirtaş and Pechenizkiy (2013), X shares a sentiment analysis dataset compiled for the study of Hayran and Sert (2017) was used. The combined datasets for fine-tuning include 48 290 samples, of which 32 000 are to be used in training, and sentiment analysis is classified as binary positive and negative. The BERT model, published by Yıldırım and fine-tuned for the sentiment analysis problem, can classify a sentence with a success rate of over 95% as positive or negative (Yıldırım, 2020:315-318; Bert-based Turkish sentiment model, 2021). According to this model, 5057 of the 8169 X shares analyzed were classified as positive and 3112 as negative.

Word Cloud on Turkish X Posts

Torku brand sponsored Konyaspor between 2012- 2016 and 2020-2021 ("Konyaspor", 2021). After Konyaspor sponsored the Torku brand, it was seen that the word Torku was often associated with the word Konyaspor in the posts on X platform. In this respect, in order not to overshadow the findings of the study and to see the consumer preferences more straightforwardly, this word was added to the stop word list in order to remove the tweets containing the word Konyaspor from a total of 8169 posts during the analysis phase, and the posts containing this word were not processed. At this stage, 7212 tweets that did not contain the word Konyaspor were composed of 93 222 characters and 148 579 words. As a result of the pre-processing, 78 753 words were obtained. When the stop words were removed, 55 419 words were obtained. When sentiment analysis was applied to 7212 posts, it was seen that 4283 of them were positive, and 2929 of them were negative. Word cloud analyzes will be made first on the words in all posts, then on the words at the intersection of positive and negative words, and finally on positive and negative posts separately. First, among 7212 tweets that did not contain the word Konyaspor, the most frequently repeated words were included in graphic form. In the light of this information, according to the finding related to the first research question (a), 7212 posts were shared in connection with Torku between 01.01.2011 and 01.01.2021. On the other hand, a sentiment analysis was carried out on all the posts and, 4283 positive statements and 2929 negative statements were found according to the finding related to the second research question (b).
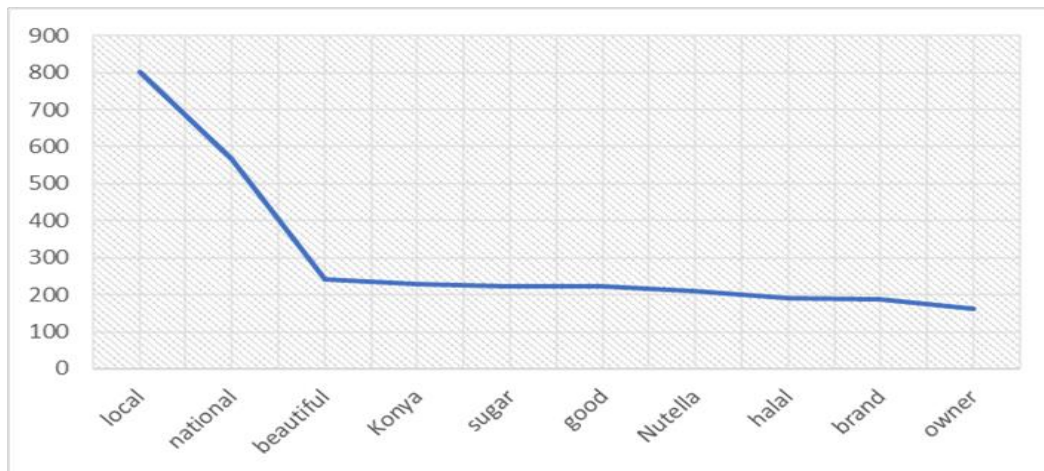

Figure 2. Distribution Chart of All Tweets by Frequency

The findings related to the third research question (c) were obtained as follows: the ten most repeated words and the number of repetitions seen in the distribution chart of all tweets by frequency are the word "Yerli (local)" 803 times, the word "milli (national)" 567 times, the word "güzel (beautiful)" 243 times, the word "Konya" 229 times, the word "şeker (sugar)" 223 times, the word "malı (good)" 222 times, the word "Nutella" 211 times, " The word "helal (halal)" is repeated 192 times, the word "marka (brand)" 189 times, and the word "sahip (owner)" 163 times. The data were visualized thanks to word cloud, which has a positive relationship between the frequency of repetition of the words and the size of the font size among all words.

Figure 3. Word Cloud of All Tweets

Keywords at the İntersection of Positive and Negative

As a result of the analysis made on positive and negative tweets, it was seen that some words were frequently repeated both in positive words and in negative words. It was also needed to analyze the words in the intersection set, and it was thought that it would be helpful for the study. At this stage, these words were excluded from the analysis for positive and negative words. Three different analyzes were performed: only positive words, only negative words, and words in the intersection set. Thus, the most frequently repeated ones among the familiar words were also graphed and expressed with numbers, and examples of how they were used in positive and negative sharing were given.
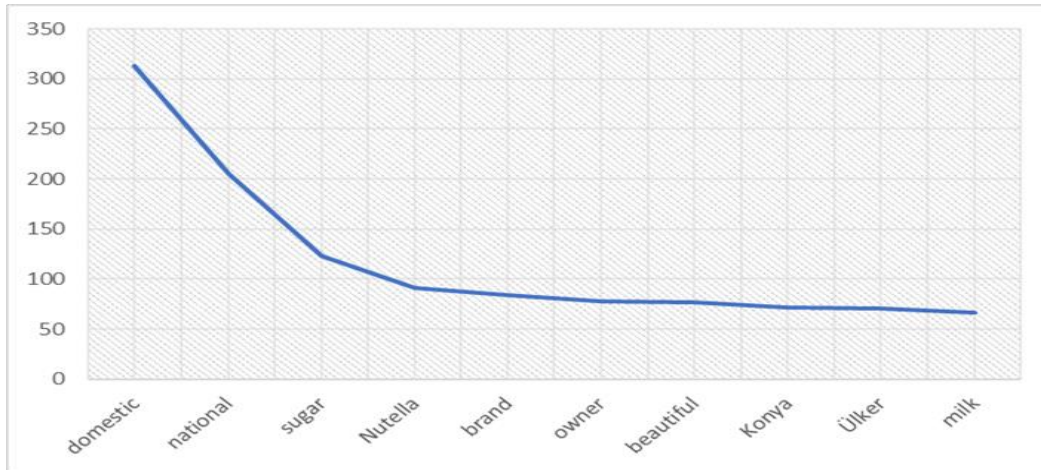

Figure 4. Distribution Graph of Tweets at The Intersection of Positive and Negative Words According to Frequencies

When looking at the ten words that are most frequently repeated among the keywords in the intersection of positive and negative, the word "yerli (domestic)" 313 times, the word "milli (national)" 205 times, the word "şeker (sugar)" 123 times, the word "Nutella" 91 times, the word "marka (brand)" 84 times, the word "sahip (owner)" 78 times, the word "güzel (beautiful)" 77 times, the word "Konya" 72 times, the word "Ülker" 71 times, and the word "süt (milk)" is repeated 67 times. Examples of how these words are used in positive and negative sharing will be given in the tabular form to make them more understandable. Table 1 gives examples of positive and negative use of words in tweets.

Table 1: The Positive and Negative Use of Words in Tweets

Keyword	Positive	Negative
'domestic'	During these times when even those, who used to sweep aside domestic products claiming that "These are domestic, but of poor quality" preventing national companies from growing and making better products, find no negative words to tell about the quality of the products from #Torku, we will always support Torku which is domestic, national and ours all the way.	We buy and consume your products since they are domestic and cooperative goods, but you have #foreigners starring in your commercials! #torku
'sugar'	I've tried it for the first time and it is pretty nice… it tastes like the mixture of coke, jelly tots and fizzy drink… it is a plus that it does not contain colorant and artificial sugar, but TL 2.95 is too expensive for such a small box… it is successful in general @torku #torku	@torku noon! It would be so nice if you would make it sugar-free or less sugar! #noon #torku
'nutella'	Very successful; I liked it very much as a #nutella fan; it is natural and made in Turkey, what else do you expect? #torku	After #nutella declared that it is not halal, those who make mistakes by not buying from our farmers such as Torku Banada, Fiskobirlik should from now on know which brand they should buy #Torku #Banada #fiskobirlik
'own'	One of my teachers from elementary school who is about to retire post a review for facede nutella reading long live #Torku. We protect what is our own :)	Protect what is your own #torku #TorkuIsthePrideofKonya
'ülker'	Since #ülker has become a cruel capitalist monster, let them be a world's brand. We will get #torku in Turkey.	#torku in ülker out
'halal'	Nutella said they are not halal. We have already chosen our side, right friends? We stand by Torku forever :) Nutella mine your business #Nutella #torku	#Torku failed to get halal certificate from #gimdes despite all instance, evaded questions in this respect claiming that they had submitted an application waiting the result etc. and thus destroyed its own credibility; if they have confident, they should get a certificate from gimdes!
'oil'	We fully sport and have complete trust on #Torku, which is the only brand that does not let any glucose syrup and palm oil be used in their products.	Shame on you. I thought you were using date seed oil, but in fact you are using Palm Oil too #torku

Positive Tweets

The number of positive tweets is 4283 and consists of 510,177 characters and 85,788 words. As a result of the pre-processing, 40,591 words were obtained. When the stop words were removed, 28,781 words were obtained, and analyses were made on these words' amounts.
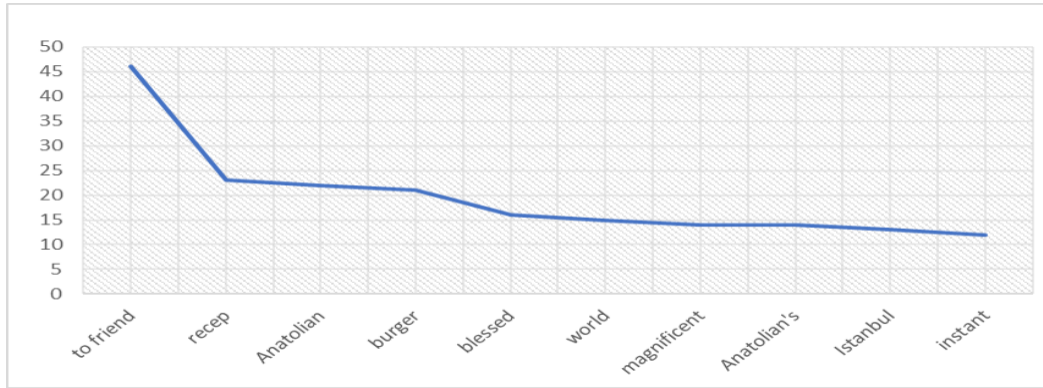

Figure 5: Distribution Graph of Positive Tweets by Frequency

The findings related to the fourth research question (d) were as follows: the ten most repeated words and the number of repetitions seen in the distribution graph of positive tweets by frequency are the word "Dosta (to a friend)" is 46 times, the word "Recep" 23 times, the word "Anadolu (Anatolian)" 22 times, the word "burger" 21 times, the word "kutlu (blessed)" 16 times, the word "dünyanın (world)" 15 times, the word "muhteşem (magnificent)" 14 times, the word "anadolunun (Anatolian)" 14 times, the word "Istanbul" 13 times, the word "anında (instant)" is repeated 12 times. These repetitive words will be visualized with a word cloud.

Figure 6: Word Cloud of Positive Tweets

When the posts about these most repetitive words are examined, it is seen that the word "dosta (to a friend)" is shared many times using the slogan "dosta torku, düşmana korku (Torku to a friend, fear to the enemy)". Looking at the posts about the word "Recep", it is seen that it is related to Recep Konuk, who started his duty in 1999 and is still the president of the institution today. For tweets containing the word "Anadolu (Anatolia)", posts such as "#Torku candır. @torku biraz pahalıdır ama, yerli malıdır, anadolu emeğidir..torku milli ve yerlidir.sahip çıkmalıyız (#Torku is sweet. @torku is a bit expensive, but it is a local product, it is Anatolian labor. Torku is national and local..we must protect it.)" can be given as an example. The fact that the word "burger" is among the frequently repeated words is because Torku opened Torku Banquet restaurants in 2018 in response to consumers' demand for both delicious and reliable food for ready-to-eat consumption ("Torku Ziyafet", 2021). In this respect, it has been the subject of posts about campaigns in restaurants or positive tweets where consumers express their opinions. The word "dünyanın (world)" is used in posts like "#TORKU dünyanın heryerinde (#TORKU is everywhere in the world)". The word "muhteşem (fabulous)" is primarily included in the comments made by people who consume the products. Repeated words like these and tweets about these words can increased.

Negative tweets

2929 negative tweets were composed of 383,044 characters and 62,791 words. As a result of the pre-processing, 38,162 words were obtained. When the stop words were removed, analyzes were made with the remaining 26,638 words.
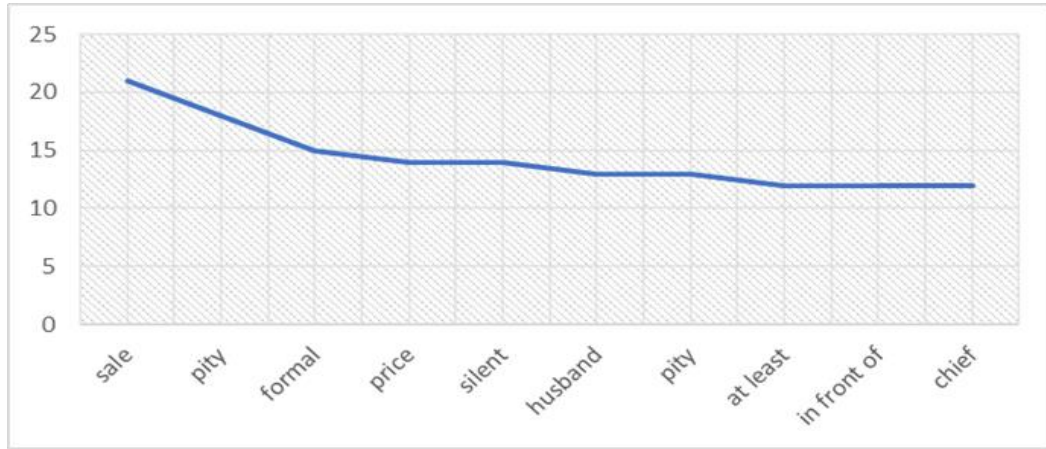

Figure 7: Distribution Graph of Negative Tweets by Frequency

The findings related to the fifth research question (e) were as follows: the ten most repeated words and the number of repetitions seen in the distribution graph of negative tweets by frequency are the word "satış (sale)" 21 times, the word "yazık (pity)" 18 times, the word "resmen (formal)" 15 times, the word "fiyatı (price)" 14 times, the word "sessiz (silent)" 14 times, the word "koca (husband)" 13 times, the word "yazıklar (pity)" 13 times, the word "bari (at least)" 12 times, the word "önüne (in front of)" 12 times, the word "şefi (chief)" is repeated 12 times. These repetitive words will be visualized with a word cloud.

Figure 8: Word Cloud of Negative Tweets

Looking at the tweet sharing examples of some of the negative keywords that are frequently used in the word cloud, it is seen that the most frequently repeated word "sales" is caused by persistently sharing a negative experience. a salesperson by one of the consumers. The word "yazık (pity)" was used in posts such as "Ne yazık ki üretim yaptığımız pek fazla birşey yok ülkece. Bari tüketimden elde ettiğimiz gücü akıllıca kullanalım. #Torku ya sahip çıkalım (Unfortunately, there is not much we produce in the country. Let's use the power we get from consumption wisely. Let's take care of #torku)", which contains negative words but not negative things about the brand. The word "resmen (officially)" was used in the posts about various inferences made about the products. For example, "Desteklemesine destek olalım tabi ki ancak yerli ve milli dediğiniz şey ucuz olması gerekirken yayıldıkça fiyatları kademeli artırıldı ve milli duygularla kazıklanmaya başladık resmen. Fiyatlandırma Türkiyeye göre olmalı dolara göre değil. Hem düşük fiyat rekabeti artırır. #Torku (Let's support it, of course, but what you call domestic and national should be cheap, but as it spread, its prices gradually increased, and we started to be ripped off with national feelings. Pricing should be according to Turkey, not dollars. Besides, low price increases competition. #Torku)". The word "fiyatı (price)" is mainly used in the posts about the high price. For example, "#torku diyorsunuz tamam da, Torku da fiyatları kırsın

bi zahmet. Destek olayım diye almaya niyetleniyorum bakıyorum fiyatına almıyorum. (You say #torku, okay, but do not bother with Torku to lower the prices. I intend to buy it so that I can support you. However, I don't buy it for the price.)". The word "bari (at least)" is also mentioned in the posts about the inferences, as in the post "Üretmeyen bir ülkede bari #Torku gibi üreten kuruluşları koruyup sahip çıkalım. (Let's protect and own the producing organizations like #Torku in a country that does not produce)".

Comparison of the Obtained Findings

Table 2: Comparison of the Most Frequently Used 10 Words in Tweets

Positive tweets	Negative tweets	Intersection of positive and negative	All tweets
"Dosta (to a friend)" "Recep" "Anadolu (Anatolian)" "burger" "kutlu (blessed)" "dünyanın (world)" "muhteşem (magnificent)" "anadolunun (Anatolian)" "Istanbul" "anında (instant)"	"satış (sale)" "yazık (pity)" "resmen (formal)" "fiyatı (price)" "sessiz (silent)" "koca (husband)" "yazıklar (pity)" "bari (at least)" "önüne (in front of)" "şefi (chief)"	"yerli (local)" "milli (national)" "şeker (sugar) " "Nutella" "marka (brand)" "sahip (owner)" "güzel (beautiful)" "Konya" "Ülker" "süt (milk)"	"Yerli (local)" "milli (national)" "güzel (beautiful)" "Konya" "şeker (sugar)" "malı (good)" "Nutella" "helal (halal)" "marka (brand)" "sahip (owner)"

When the frequently used words in Table 2 are analyzed, it is seen that some important findings are obtained. Analyzes of Torku brand's customer comments on X platform indicate that the most repeated words in all the posts are domestic, national, nice, halal, natural, good, our brand, quality and advertising, all of which are classified as positive. Previous studies also suggest that the main message in the advertisements, promotions and images for the brand Torku is about natural and pure products, and there is a brand personality (Bilgili and Özkul, 2015: 103). Accordingly, it is understood that consumers positively respond to the message 'naturally one of us' on which the brand attempts to position itself and designs the advertising media based on this idea. This is because the phrase "naturally one of us' used as an advertising copy refers to the fact that this is a national brand and the products are natural. Additionally, as mentioned in the study carried out by Ibiş and Engin (2016: 333), consumers are affected by positive reviews posted on social media when choosing business companies engaging in the food & beverage industry. That is to say, there is a cycle that positive reviews increase the number of consumers and, as the number of consumers increases, the number of reviews also increases. An analysis on the reviews concerning the brand Torku shows that people suggest the products they use and the brand to other consumers with their positive reviews, and other reviews posted with hashtags containing words I tried and suggest.

On the other hand it is understood from the words Nutella, halal and Banada that are the most frequently repeated words in all the posts that consumers started to consider Banada from Torku as an alternative to Nutella (competitor of Banada, a chocolate brand from Torku) when a question of whether the chocolate manufactured by Nutella is halal on 14.09.2020 was answered by the official X platform account that "no they are not halal" ("Nutella Official X Platform Account", 2021) although this statement was later corrected indicating that the products are halal. From this standpoint, considering that the words domestic and national are frequently repeated in the reviews and the posts about chocolate, one could claim that the brand Torku is positioned on the mind of consumers with the perception of "halal food". Additionally, as a result of the analyses conducted in this respect, considering that the words domestic and national are the most frequently

used words and that the product is Made in Turkey, it is possible to claim that the brand Torku arouses nationalist feelings in consumers resulting in loyalty to the products. An analysis on the posts that contain the words domestic, national and Anatolia shows that the consumers of the products from Torku suggest other people that they should prefer the products from Torku over other products and embrace this brand indicating that the products from this brand are domestic and national products and belong to Anatolia. From this point of view, the company may prepare such contents on social media that would support the positive reviews such as domestic and national or carry out advertising companies accordingly in order to increase the profitability and thus contribute to the regional development. Another finding from the research is that the ingredients of the products are healthy and the products are halal and quality. For this reason, in particular, it is important to highlight that the ingredients of the products are not harmful to health. Therefore, they could increase the number of statements highlighting that the products are halal and the ingredients are healthy. It is possible to see the brand's visibility not only with its products but also with its employees in a holistic way through negative and positive tweets. When a negative event involving Torku's sales personnel was met with negative propaganda on social media, the frequency of words such as "satış (sale)"and "şefi (chief)" in negative tweets was quite high. Similarly, during the period when Konya Şeker assumed the presidency, the positive profile of Recep Konuk in the eyes of the public resulted in the word 'Recep' being frequently mentioned in Torku posts with a positive mood

The findings obtained from this research contain important information not only for the brand Torku but also all the brands engaging in the food industry in Turkey and even those serving the domestic market. Thanks to social media, consumers are able to state their positive, and negative opinions and requests about products and services and, companies attempt to take advantages of this feedback using them for their own benefits. In addition, an attempt may be made to ensure that people could try the new products at certain points of the direct stores where they could taste them. This is also important for experiential marketing. Similarly, an attempt may be made to ensure that people could try promotional products as a contribution to the formation of brand recognition. Some statements may be made to convince consumers about the complaints on higher prices as mentioned in the negative reviews for the products. Companies should immediately consider such positive and negative reviews, complaints and requests. In particular, quick and convincing response to negative reviews satisfying consumers or solving a problem would increase the value of the company in the eyes of consumers and maybe turn those negative reviews into positive ones. (Say, 2015: 87). Assuming that these posts are public, they would have a greater influence.

6. CONCLUSION

Given the power of social media, consumers today are quick and willing to voice their opinions. They express themselves both positively and negatively on various aspects of life, such as satisfaction with a purchase, service or product, or an economic event. The expression of opinions has increased greatly because electronic media offer the opportunity to respond while maintaining the confidentiality of personal information. For companies, crisis situations can be avoided if they respond quickly to the results of the analysis. This can help plans to be better strategies and executed in a consumer/human-friendly manner. In addition, a consumer that takes online reviews into account can help increase profits through word of mouth. For example, the movie Stree, which hit theaters in 2018, made big profits despite low advertising costs thanks to word of mouth on social media. The same is true for companies and brands. Therefore, it is high time for businesses and financial and economic planners to learn about consumer sentiments and opinions on various social websites to explore their attitudes and sentiments (Agarwal, 2019: 132). People are the goldmine of sentiment analysis, and with the explosion of information on social media, companies, and businesses can gain many advantages in making profits and planning future projects (Agarwal, 2019). Sentiment analysis also enables marketers to obtain immediate feedback on attitudes and opinions without having to invest in lengthy and costly market research activities (Rambocas and Gama, 2013: 1). In the same direction, Fan et al. (2018: 689) argue that this type of analysis can not only help manufacturers find out consumers' demands or needs, but also facilitate the development of new products and the improvement of products already on the market. In this context, sentiment analysis techniques are a useful method for analyzing opinion texts that contain consumer opinions about companies, products, brands, or events (Kauffmann et al., 2019: 2).

From this point of view, this research found out how consumers position the Torku brand in comparison with competing companies and in which aspects they evaluate it positively and negatively. This not only provides

the company with a quick, easy, and cost-effective way to determine consumer perceptions, but also helps to increase the number of consumers by including campaigns that reinforce perceptions of pure, national, and halal products in advertising and marketing. Similarly, the advantage of online word-of-mouth marketing can be benefitted in content created for social media advertising by highlighting these words that consumers perceive positively. Reducing advertising and marketing costs, increasing consumer satisfaction, and promoting online word-of-mouth marketing are the factors that will directly impact the company's profitability.

The study has theoretical and practical implications. The related works performed in this subject presented the benefits of analyses on user comments in online communities for brands and, in particular the importance of the social media platforms for e-trade (Olaleye, 2018: 85-102). This work makes it possible to utilize the posts of the people, who are free to make comments hiding their identity, on the social media instead of such other methods addressing a limited number of consumers such as consumer satisfaction surveys. This method has a flexibility making it adoptable to all the industries. An analysis of the social media data by means of text mining provides benefits for the related companies and the literature since it is possible to easily get feedbacks from customers, it is cheaper than methods such as surveys, it has lower costs of marketing, it contributes to brand recognition, and it increases the sales of products.

The work makes it possible to learn about the requests, usage experience, and comments of customers about products by mean the social media. Thus, the findings of this work give an opportunity for brands to have a better understanding of the needs, requests, suggestions and complaints of consumers, through more efficient use of the social media platforms, which are the reflection real-life, and improve their services in line with these implications resulting in satisfaction of consumers and, also increase their profitability. On the other hand, this makes it possible for brands to include consumers into the stage of production of products and services contributing to the profitability and, establishing a bond of loyalty with consumers.

During further studies, more data may be used for analyses by means of accessing all the social media data concerning the brand. It may be possible to compare posts before and after a certain event in order to analyze the effects thereof on the brand, e.g. the brand being a sports sponsor. Comparisons of various aspects may be made between competitors in the food industry. A survey may be used in addition to a text mining method to compare the conclusions thereof.

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