DOI: 10.30519/ahtr.1116172

Advances in Hospitality and Tourism Research (AHTR) 2023
An International Journal of Akdeniz University Tourism Faculty Vol. 11 (4)
ISSN: 2147-9100 (Print), 2148-7316 (Online) 443-475
Webpage: https://dergipark.org.tr/en/pub/ahtr

ASSESSING DESTINATION BRAND ASSOCIATIONS ON TWITTER: THE CASE OF ISTANBUL

Cihangir KASAPOĞLU [1]
Department of Marketing and Advertising, Bartin University, Turkey
ORCID: 0000-0002-7664-5927

Ramazan AKSOY
Department of Business, Zonguldak Bulent Ecevit University, Turkey
ORCID: 0000-0002-6205-8334

Melih BAŞKOL
Department of Business, Bartin University, Turkey
ORCID: 0000-0002-5257-9160

ABSTRACT

The development of data mining has paved the way for studies that identify brand associations from user-generated content (UGC). However, the number of studies investigating destination associations with social media is limited. The aim of this study is to explore destination associations with UGC on Twitter and to show how data mining and sentiment analysis methods can be applied to destinations to elicit brand associations. In this study, 33,339 English-language tweets containing the word #Istanbul were collected over one year and analyzed using text mining (association rule analysis) and sentiment analysis. As a result of the study, a brand concept map (BCM) of what Twitter users associate with Istanbul was created and compared to other studies that measure associations using conventional methods. The main results show that users have positive associations with tourism in Istanbul. Unique and interesting associations (such as "cats") were observed compared to other previous studies that measured associations to destinations. Based on the study results, a method was proposed for measuring the image of a place brand by observing electronic word of mouth in social media.

Article History
Received 13 May 2022
Revised 23 January 2023
Accepted 3 April 2023
Published online 8 May 2023

Keywords
association rule
brand concept map
brand image
destination branding
sentiment analysis
text mining

INTRODUCTION

Social media is an effective platform for shaping consumers' destination perception and travel decisions (di Pietro et al., 2012). Word of mouth (WOM) plays an important role in building a destination's brand image

[1] Address correspondence to Cihangir Kasapoğlu (PhD), Department of Marketing and Advertising, Bartin University, Turkey. E-mail: cihangir@bartin.edu.tr; cihangirkasapoglu@gmail.com

with the widespread use of social media on electronic platforms. Social media has created a new environment for social interaction that makes WOM visible and accessible. The most important advantage of WOM is being spontaneous and free expression (Alzate et al., 2022). UGC contains large amounts of data about users' thoughts and feelings which is also a powerful and valuable source for researchers (Wong & Qi, 2017). For this reason, UGC is preferred by many researchers in determining brand associations.

Data mining offers great opportunities to obtain meaningful results from unstructured social media data. The fact that UGC is big and unstructured data makes data analysis very difficult (Kiran & Vasantha, 2016). With the development of data mining, unstructured social media data can be configured in accordance with the analysis (Diaz-Garcia et al., 2022). Currently, sentiment analysis techniques allow us to determine favorability (consumers' positive or negative feelings toward brand associations) (Mitra & Jenamani, 2020). Recent technologies in Big Data analytics have paved the way for faster data collection, processing, and analysis (Oliverio, 2018). A limited number of studies have attempted to investigate the perception of destination brands on Twitter. However, there is still a significant gap for new studies to measure destination associations on social media. Therefore, this gap was the starting point for this study.

Brand Concept Maps (BCM) are an effective way to measure and visualize the strength, uniqueness, and favorability of brand associations. Thanks to text mining techniques, BCMs can be created from unstructured social media content. Therefore, this study attempts to add a new dimension to the BCM technique, which is rarely used in the tourism literature, by measuring the association network of destination brands using Twitter data. This method can play a key role in crafting messages for use in brand communication strategies and in decision making by showing destination managers which associations to use to position their brand and which negative associations to eliminate.

Understanding associations is an important issue for brand communication plans of destination marketing organizations. Marketers use brand association to differentiate, position, and extend the brand, as well as to develop positive attitudes and emotions toward it (Low & Lamb, 2000). In recent years, many destinations have been promoted through social media. In order to conduct an advertising campaign on social media, data measured through social media is required. This study will also allow to determine the concepts that can be used in creating the messages that practitioners need for brand communication. Traditional methods such as surveys have been used in previous studies of destination association, but few studies were found that used social media data.

In this study, Twitter users' perceived associations with travel destinations are determined. A method was proposed to measure the associations with a destination's brand by observing WOM in social media. The objective of this study is to (1) demonstrate that the BCM technique can be applied in evaluating travel destination brand associations by using unstructured data sources; (2) draw attention to the fact that social media is a powerful data source in exploring travel destination associations; (3) demonstrate how to explore a travel destination's brand association network using data mining and sentiment analysis on Twitter. It is expected that mining data from Twitter and creating a BCM in accordance with the analysis performed by the data mining and sentiment analysis method will provide a new perspective for destination branding researchers.

LITERATURE REVIEW

Conceptual and Theoretical Background

Associations have long been a topic of interest in brand research. Aaker (1991, p. 109) defines brand associations as everything that is associated with the brand in the consumer's mind. To generate favorable feelings for a brand, highlight the advantages of utilizing it, and market a specific brand, brand managers employ brand associations in brand positioning and brand extension strategies (Low & Lamb, 2000).

The cornerstones of consumer-based brand equity and brand image are brand associations. (Christodoulides & de Chernatony, 2010). Biel (1992, p. 71) describes a brand's image as a collection of traits and connections that customers connect with the name of the company. According to Keller (2013, p. 549), a positive brand image is created by associating strong, favorable and unique associations to the brand in the mind. This statement allows to depict brand image as a network of brands and associations in the customer's mind (Dirsehan & Kurtuluş, 2018). Brand associations are theoretically based on Associative Network Theory. According to the theory, memory is a network of interconnected nodes that activate in related contexts and these nodes are linked to each other in a network of relationships (Anderson & Bower, 1980). Concepts are represented as nodes in this network, and the relationship of concepts to each other is represented as links (Collins & Loftus, 1975; Teichert & Schöntag, 2010). Whether brand associations are positive or negative, their uniqueness is a process that needs to be well managed. Therefore, an in-depth exploration of consumers' association networks provides brand managers with valuable insights.

Measuring Brand Associations

Previous studies measuring brand associations have used a traditional approach, collecting data directly from the respondent, and an approach using data derived from content generated by internet users (Gensler et al., 2015). Nam et al., (2017), on the other hand, classified these approaches as primary data-based approaches (survey-interview, ZMET, BCM, sorting), text mining approaches, and social tag-based approaches. Text mining and social tagging are approaches that use UGC.

Many qualitative, quantitative, and mixed methods have been proposed in traditional studies to measure brand associations (Vriens et al., 2019; Zenker & Braun, 2015). Qualitative techniques used in measuring brand associations are "free association" (e.g., Cornwell et al., 2022; Keller, 2013; Kim, 2017; Rahman & Areni, 2016; Shams et al., 2015), and projective techniques (e.g., Cian & Cervai, 2011; Hofstede et al., 2007; Pich et al., 2015; Spry & Pich, 2021). Likert scale (Chen, 2017; Cho et al., 2015; Gorin et al., 2022; Koll et al., 2022; Phong et al., 2020; Plumeyer et al., 2019), semantic differential scale (Alexandris et al., 2008; Ciabuca, 2015), dichotomous scale (e.g., Hsieh, 2018; Lim & O'Cass, 2001), rating scales (e.g., Dillon et al., 2001; Romaniuk, 2014), sorting task (Blanchard et al., 2017) and "Pick Any" (Dolnicar et al. 2012) are quantitative methods. However, it is known today that these scales cannot be standardized and generalized to different cultural backgrounds or different contextual factors (Başfırıncı, 2016; Gensler et al., 2015). Lastly, Repertory Grid (Bell, 2005) and BCM (Goffin et al., 2010; John et al., 2006; Schnittka et al., 2012) are examples of mixed methods.

All of the methods mentioned above place more emphasis on the relationship between an attribute and a brand than on the brand associations as a network. Therefore, these approaches are insufficient to measure the strength, favorability and uniqueness of brand associations (Brandt et al., 2011). Therefore, examining brand associations as a network structure will provide a clearer understanding of brand perceptions (French & Smith, 2013).

There are two approaches to the analysis of the brand association network: analytic techniques (network analysis) and mapping techniques

(BCM-Zaltman Metaphor Elicitation Technique) (John et al., 2006). A mathematical technique called network analysis examines the connections between concepts using the parameters of centrality, cohesion, position, density, and equivalence (Henderson et al., 1998). The Zaltman Metaphor Elicitation Technique (ZMET) is a method in which a network of brand associations is revealed, especially through metaphors located in the subconscious of consumers (Zaltman, 1995). Metaphors can be explored using images such as paintings and objects to help express conscious and unconscious thoughts and emotions (Matheson & McCollum, 2008).

One of the effective methods of assessing the structure of the consumer association network is the original brand concept maps (John et al., 2006). Important contributions of the BCM method are the set of rules for collecting brand association network data created individually by each individual in a consensus map (Böger et al., 2017). Three steps make up the BCM process: elicitation, mapping, and aggregation (John et al., 2006). At the elicitation step, brand associations are derived from responses to open-ended questions in which at least 50% of the participants cited a specific brand. Each respondent is required to create a map by connecting the concepts with one to three lines, depending on the strength of the associations, during the mapping stage. The original BCM, which shows the strength and uniqueness of brand associations, does not reflect how associations are evaluated by the consumer. Schnittka et al. (2012) further extended the scope of BCM, which measures the strength and uniqueness of associations, and developed the brand association network value metric to show the favorable associations on the map. In this mapping, the degree of negative evaluation of associations is stated by the darkness of the color of the circles surrounding the association (Schnittka et al., 2012).

Mapping techniques using qualitative and quantitative methods have weaknesses such as the tendency to choose answers that respondents believe are more socially desirable or acceptable, the validity and reliability problems of the survey and interview method, and the laboriousness and vapidity of individual data collection (Nam et al., 2017). UGCs, on the other hand, are powerful data sources where users generate data voluntarily, without influence or intervention from the researcher (Culotta & Cutler, 2016; Divakaran & Xiong, 2022).

Approaches Using User-Generated Content

Currently, data collection has evolved into an understanding in which responders are personally observed in the interaction environment without any guidance. Digital transformation also manifests itself in brand research. Therefore, researchers are seeking brand associations not in the answers that the consumer gives to questionnaire or interview questions, but in the content that the consumer creates herself/himself.

Web 2.0 provides gathering platforms for internet users in social media. Consumers leave an enormous footprint in these platforms about their thoughts, beliefs, experiences, and even interactions (Netzer et al., 2012). Customers voluntarily use social networking websites and share pertinent information in public. The publicly sharing of UGC has opened a door for researchers to hear the voice of the consumer (Klostermann et al., 2018). UGC is generally a useful information source because it is unbiased and reflects unofficial consumer advice (East et al., 2008). Since consumers' opinions and sentiments about brands are readily available online, researchers can quickly gather data. Data obtained from UGC are gathered by content analysis conducted for consumers' brand associations. But manual analysis of UGC datasets is a difficult process due to the size of the data and its unstructured nature (Elsayed et al., 2019; Yan et al., 2022).

Text mining has become one of the preferred methods for uncovering brand association networks in recent years. The main reason is that the qualitative analysis and interviewing methods used in traditional methods are time-consuming and tedious, require expertise, represent a limited period of time because they are applied over a period of time, have a small sample size, and simply focus on uncovering brand associations (Nam et al., 2017).

Divakaran and Xiong (2022) qualitatively analyzed users' online comments on a movie brand, measured the uniqueness, strength, and favorability of associations, and displayed them on the BCM. The BCM was created by measuring the frequency (strength) of associations, the level of difference of associations compared to competing brands (uniqueness), and the number of associations coded as positive-negative (favorability). However, this method is much more difficult and laborious for manual coding of more UGC. Advances in text mining can overcome these challenges.

Finding hidden information in textual data is a process known as text mining, a particular type of data mining (Feldman & Sanger, 2006; Miner et al., 2012). Chen (2012), on the other hand, describes text mining as the process of obtaining interesting information or insights from unstructured text. Data sources used in text mining are unstructured data obtained from expressions freely used by people in daily life (Marchand et al., 2017).

Naturel Language Processes (NLP) are the language used in daily life regardless of terms and transforms spoken words into structured data (Miner et al., 2012). Text mining mainly involves clustering, association rule analysis, trend analysis, pattern discovery, and other knowledge discovery algorithms (Zhang et al., 2015). Association Rules is a technique used in text mining to determine the causal relationships between two concepts (Lopes et al., 2007; P. C. Wong et al., 1999). A conceptually similar study was performed by Diaz-Garcia et al. (2022) who emphasized that association rule mining provides interpretability of the research model and results in social media mining.

Sentiment Analysis, an important area of text mining, is the detection of some text to be positive, neutral, or negative in meaning (Howells & Ertugan, 2017) and currently preferred in many studies to determine the favorability of brand associations (Karayılmazlar et al., 2019; Mishra & Sharma, 2019; Mitra & Jenamani, 2020; Yang et al., 2022). Sentiment analysis is therefore a functional method for measuring the favorability of brand associations.

There is an increasing trend toward the use of text mining in brand association research. For example, Netzer et al. (2012) used the frequency of co-occurrence of concepts and lift value to reveal brand associations and to measure the strength of the relationship between associations. Mitra and Jenamani (2020) proposed measuring the favorability, strength, and uniqueness of brand associations from consumer reviews using the text mining technique. According to Culotta and Cutler (2016), text mining offers a reliable, adaptable, and scalable method for tracking brand perceptions. Similarly, Liu et al. (2017) proposed a framework that automatically extracts brand topics and classifies brand sentiment by applying sentiment analysis and text mining to tweets about 20 brands in 5 different industries from UGC on social media. Blasi et al. (2020) examined the brand perceptions of fashion consumers from Twitter data using data mining method and pointed out that the survey approach has weaknesses such as the prejudices and reluctance of the respondents, and that Twitter contains more reliable opinions about brands. In another study, Park et al. (2023) used network analysis to compare the relationship between associations and different aspects of brands, to compare the differences between brands, and sentiment analysis to measure the attributes that users consider important in the product and users' evaluations. Using Latent Dirichlet Allocation and dictionary-based sentiment analysis, Alzate et al. (2022) analyzed brand image and brand positioning from online consumer reviews. In previous studies, it is seen that measuring the strength of associations, the co-occurrence of concepts in the text, and sentiment analysis were preferred in examining the favorability of associations. In this study, unlike previous studies, association rule analysis is used to calculate the strength of associations. Association rule analysis successfully applies an unsupervised data mining method and is one of the methods for detecting interesting associations from big data.

Measuring destination brand associations: from conventional methods to user-generated content

The measurement of brand associations is particularly found in studies of destination image and destination brand equity. The main reason for this is that the second fundamental element of brand equity is brand association (e.g. Aaker, 1992; Christodoulides & de Chernatony, 2010; Keller, 1993). Another approach is to use brand associations as a substitute for brand image. For example, Cai (2002) defines destination brand image as the perception reflected by the place-related associations in the memory of tourists. Kladou and Kehagias (2014) suggest that destination brand association is generally used in place of or represents brand image, while Bianchi et al. (2014) emphasize that destination brand associations relate to the image of the destination brand. In addition, Stepchenkova and Li (2014) argue that destination associations are one of the key elements of destination brand image.

In the traditional methods used to measure destination association, standardized questionnaires and free association techniques are mainly used. In these studies of tourism destinations, image is generally conceptualized as a structure consisting of two dimensions: the affective image and the cognitive image (Baloglu & McCleary, 1999; Gartner, 1994; Gartner & Ruzzier, 2010; Huete-Alcocer & Hernandez-Rojas, 2022). Pike (2009) proposed that destination associations should be measured as part of the cognitive, affective, and behavioral components of the image. Furthermore, Qu et al. (2011) pointed out that uniqueness should be included in addition to these aspects to measure destination brand association. Sahin and Baloglu (2011) analyzed the brand image of Istanbul based on common image components or characteristics, expected atmosphere, unique and popular tourist attractions, tourist activities, with an approach similar to the BCM technique. However, measuring destination associations with standardized questionnaires is limited to defined dimensions (Zenker & Braun, 2015). The common conclusion of these approaches is that positive or negative assessments of associations and uniqueness of associations are important factors that must be assessed when measuring a destination's brand. However, these studies did not focus on the direct eliciting of destination associations and associative network structures.

Different customer groups have different expectations and complex structured destination brand associations. Due to this problem, previous studies tend to use BCMs, which are an effective method to measure the association network structure of destination brands (Zenker & Braun, 2017). Another approach used in measuring destination associations are association network mapping techniques. For example, Zenker (2014) measured the strength, favorability and uniqueness of associations using the Advanced BCM technique, which is based on the Keller's (1993) approach. Brandt and de Mortanges (2011) tested the applicability of the BCM technique to place brands by measuring city brand associations. Using BCMs and network analysis, Ci and Choi (2017) proposed a method for comparing a place's image and place identity. Ivanov et al. (2010), combining the destination brand molecule and BCM techniques, examined the brand perception of two different destinations and argued that this technique reflects the dominant perceptions of the participants. By examining three different destinations with a BCM, Ibrahim and Elborsaly (2022) also show that it closes the gap in traditional measurements and provides a valid tool to explore the strengths and weaknesses of brand associations.

Recently, there has been an increasing interest in UGCs as a data collection method in destination associations retrieval. For example, Alarcón-Urbistondo et al. (2021) have suggested using UGC in destination image research, as it contains rich current information, is easily accessible, and is a low-cost data source. Marine-Roig and Anton Clavé (2015) analyzed the UGC in travel blogs by text mining and stated that it provides interesting results for brand architecture in a complex destination. Költringer and Dickinger (2015) also argue that the UGC is the richest and most diverse online source of information. Choi et al. (2015) and Mak (2017) applied content analysis with the help of text mining to reveal the destination image from websites and blogs. Liu et al. (2021) analyzed the tourists' comments about Macau on travel blogs by using text mining techniques.

Moreover, measuring the favorableness of travel destination associations through sentiment analysis is becoming more widespread (Clarke & Hassanien, 2020; Jiang et al., 2021; Nadeau et al., 2021; Park et al., 2020; Ren & Hong, 2017; Surugiu et al., 2021; Tseng et al., 2015). Kim et al.

(2017) observed that sentiment analysis in destination brand research is a more economical and less time-consuming method than survey method in predicting the favorability of brands. Jiang et al. (2021) measured the destination image of Hong Kong from the reviews of tourism websites and suggested that sentiment analysis provides a deeper understanding of the destination image. However, studies measuring travel destination associations using UGC data are generally focused on forum sites and travel blogs, and few studies used Twitter.

Measuring Destination Brand Associations on Twitter

The realization of conventional WOM communication in an electronic environment further increases the importance of social media in place branding. Kavaratzis (2004) argues that the brand of the city is transmitted in primary, secondary, and tertiary ways. Primary communication is the physical and managerial characteristics of the place. Secondary communication is formal brand communication such as marketing communications. Tertiary communication is WOM communication that occurs as a result of primary and secondary communication (Kavaratzis, 2004). WOM communication is an important component that affects the brand image and cannot be controlled by city managers. Therefore, analyzing the data obtained from WOM communication or tertiary communication of the place branding will provide more accurate results for the destination image. Social media has a significant impact on destination branding via its eWOM communication feature.

Twitter is an important E-WOM platform that enables brands to get insight (Burkhalter et al., 2014; Hodeghatta & Sahney, 2016). Twitter gives an idea of how users react to critical decision-making and to purchasing products by showing immediate sensitivity to a topic (Jansen et al., 2009) and provides researchers with big data on how much and how a brand interacts. The identification of intriguing, unexpected, or noteworthy structures from large datasets is the key component of data mining (Hand, 2007). On the other hand, as a platform of thought sharing, Twitter is an open-source database and its feature of sharing based on the text enables researchers to collect and analyze data more easily and quickly (Nadeau et al., 2021).

The use of Twitter as a data source, which has a significant impact on tourists' decision-making, is rapidly increasing in tourism research (Curlin et al., 2019). Table 1 shows that studies measuring Twitter users' perceptions of destinations focus on destination perception or satisfaction rather than measuring brand associations. Machine learning and dictionary-based sentiment analysis are considered prominent among the methods used in these studies. In recent studies, sentiment analysis on Twitter has become a growing trend. Three different sentiment analysis methods are used in the tourism literature: machine learning, dictionary-based, and hybrid (Alaei et al., 2017). In the case of machine learning-based methods, the system is trained with pre-labeled training data and emotion classification is performed with the trained system (Flores-Ruiz et al., 2021; Paolanti et al., 2021; Shimada et al., 2011; Viñán-Ludeña & de Campos, 2022). The dictionary-based approach relies on the sentiment dictionary, which is a set of known and precompiled sentimental terms (Becken et al., 2020; Zhang et al., 2022). The hybrid approach is based on a combination of a machine learning approach and a dictionary-based methods, which is used together with the sentiment dictionary in procedures (Claster et al., 2013). Moreover, deep learning has gained popularity in recent years. It should also be noted that sentiment analysis was used to track changes in users' perception of Twitter between cyclical and normal time periods.

However, the BCM evaluation model was not used to visualize the concepts emerging from the analyses. Instead of measuring the strength-favorability and uniqueness of associations, the articles focused on thematic analysis. There are few studies that aim to elicit destination associations. For example, Andéhn et al. (2014) applied a thematic analysis based on word frequency and occurrence to measure the brand equity of Stockholm on Twitter. This study classified brand associations of the destination to specific themes. However, this study did not focus on the strength and favorableness of associations.

Unlike others, Nautiyal et al. (2022) classified the hashtags shared by Twitter users and the destination management organization into different topics and analyzed the content of the regional tourism organization and locals and international Twitter users in comparison. In some previous studies, visual content was used as data in addition to text. Bui et al. (2022) argue that textual data is not sufficient to explain the destination brands. For this reason, the visual and textual data collected from social networks (Flicker, Twitter, etc.) via API set and web crawling tool were classified by popularity, sensitivity, time and location characteristics using the developed classification module.

Table 1. *Previous studies on measuring destination associations on Twitter*

Authors (Year)	**Research Tools/ Method**	**Data Type**	**Objective**	**Data reporting and visualization**
Bui et al. (2022)	Construct popularity measurement / Word frequency, text classification, topic analysis Textual and visual sentiment analysis / aspect-oriented sentiment analysis	Textual and visual	To measure tourism destination image from unstructured big data and develop a holistic measurement framework.	heat-map, semantic graph, charts, and tables
Leelawat et al. (2022)	Term frequency Sentiment Analysis / Machine learning-based	Textual data	To monitor tourists' moods and visit intentions towards Thailand during the Covid 19 pandemic period.	WordCloud, graph, charts, and tables
Nautiyal et al. (2022)	Content analysis/ Classifying hashtags according to their attributes and location using cross-tabulation	Hashtags	To categorize the hashtags shared by Twitter users and the destination management organization into different topics and analyzed the content of the regional tourism organization and locals and international Twitter users in comparison	tables and charts
Viñán-Ludeña & de Campos (2022)	Sentiment Analysis/ Deep learning based	Textual data	By utilizing sentiment analysis techniques on the information gathered from Twitter and Instagram, to develop an information infrastructure for managers to enhance the perception of a tourism destination.	figures, tables
Zhang et al. (2022)	Latent Dirichlet Allocation Term Frequency-Inverse Document Frequency Sentiment Analysis/ Dictionary based	Textual data	Assessing Beijing's international image on Twitter and providing data support for destination managers' communication strategies	graph, charts, and tables
Flores-Ruiz et al. (2021)	Sentiment Analysis / Machine learning-based	Textual data	Matching current Twitter users' perceptions of the destination with the results of the Destination Management Organization's survey in the Covid-19 pandemic and observing the change in destination image.	Word cloud charts, figures, tables
Paolanti et al. (2021)	Sentiment Analysis/ Deep learning	Textual data	To compare the performances of four different classification algorithms used in sentiment analysis.	statistical graphics, plots, information graphics
Becken et al. (2020)	Sentiment Analysis / Dictionary based	Textual data - Meta data	Analyzing metadata, testing Twitter's reliability in measuring destination satisfaction.	figures, tables
Yan et al. (2020)	Sentiment analysis/ Dictionary based Latent dirichlet Allocation	Textual data	Evaluating the recovery level of tourism destinations after a disaster.	charts, figures, tables
Garay (2019)	Quantitative content analysis/ Coding	Textual data	To evaluate the relationships between destination image on Twitter by separating them according to cognitive and affective characteristics.	Word cloud

Perez Cabañero et al. (2020)	Sentiment Analysis/dictionary based (Meaning Cloud)	Textual data	To show how the photos, links, hashtags, and bookmarks in a tweet can be used to anticipate eWOM activity.	table
Andéhn et al. (2014)	Leximancer/ content (thematic-semantic) analysis	Textual data	To present an approach that reveals how Twitter is influential in the formation of place brand equity and its relational structure in a concept map by revealing place brand associations.	concept map
Claster et al. (2013)	Sentiment Analysis / hybrid -based	Textual data	Demonstrate the utility of reliable and real-time shares in tweets by current and potential consumers in market intelligence with sentiment analysis.	self-organizing map
Shimada et al. (2011)	Sentiment Analysis / Machine learning-based	Textual data	To propose a method for the information system analysis of a destination	charts, figures, tables

Twitter data is also used to track seasonal or cyclical changes to destination imagery. The destination image of the two cities was evaluated by Nadeau et al. (2021) using text mining and sentiment analysis methods throughout the Covid 19 pandemic era and the pre-pandemic period on Twitter. They found that the destination image is flexible despite a noticeably higher level of fear projections for both locations. Garay (2019) categorizes the affective and cognitive attributes of Spain's destination image by creating a codebook that describes emotional states for tweets containing #visitspain.

In summary, the above literature review reveals these important gaps in the current literature:

- Although studies analyzing brand associations on Twitter through text mining have multiplied, Twitter is still a new source of data in the field of destination branding and requires new research.
- In previous studies, researchers focused more on UGC in travel blogs, but research on destination brands on Twitter received less attention.
- Previous studies have generally focused on categorizing content into different topics using content analysis. However, research is lacking to elicit the destination's brand association network and the strength of these associations.
- The BCM approach is rarely used in studies to measure the destination brand associations.

METHODOLOGY

The empirical case of Istanbul

This study focused on the city of Istanbul to demonstrate the utility of the BCM method and UGC. Istanbul is an important city in Europe as an economic, touristic, financial, educational, cultural, artistic, and historical heritage. As one of Europe's most populous metropolises (Statista, 2020), Istanbul is a melting pot of both Eastern and Western cultures. It possesses the historical and cultural heritage of the Byzantines and the Ottomans. Thus, Istanbul will be a suitable case for measuring the destination brand from social media, and deeper and unique associations can be reached about the destination.

Procedure

The associations are the building blocks of the brand image which take place in the mind of the consumer as interrelated concepts. These associations with the target brand can be strong or weak, positive or negative. Associations can be related to each other apart from the target brand. Therefore, every association in the human mind is in a network and has a complex structure. One of the important tasks in the development of brand strategies is to reveal the associations and to determine how strong and positive the associations are brand and other associations.

Therefore, the association network was revealed in a similar way to the approach of the BCM technique, which is a mixed method that measures brand associations (John et al., 2006; Schnittka et al., 2012). Today, text mining methods provide the opportunity to determine the positive or negative states of expressions with the sentiment analysis technique. In this study, the favorability of associations was determined by applying dictionary-based sentiment analysis, one of the text mining methods, to tweets tagged Istanbul and shown in the BCM. The research process is shown in Figure 1.

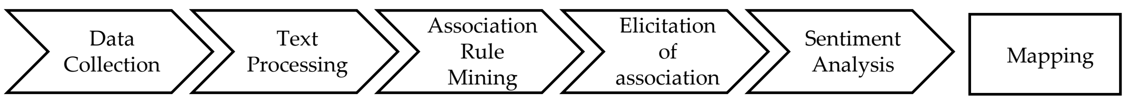

Figure 1. *Procedure*

Data Collection

English tweets that contain #Istanbul on Twitter and that were shared between June 1, 2018-31 May 2019 were collected using Rapidminer software and a total of 42.740 tweets were obtained. This number was reached by filtering retweets, posting tweets shared by robot accounts called “bot”. Bot accounts increase the access to tweets by frequently retweeting tweets. This adversely impacts the reliability of the data. In addition, tweets containing the phrases “like us”, “follow us” etc. were also removed from the data set due to their nature of ad. Two elections were held in Turkey namely presidential and national elections on June 24 March 2018 as well as local elections on March 31, 2019. Therefore, tweets on the election agenda were also shared in the range of the data collection date. Because the study focused on the associations of Istanbul's city and the statements reflected only the agenda of that year, 9189 tweets on politics and the agenda were excluded from the data set. Finally, 33.339 tweets were attained to be analyzed.

Preparing Data for Analysis

Text mining is the process of revealing hidden and useful information from text-based data (Jo, 2019). Data sources used in text mining are unstructured data obtained from expressions freely used by people in daily life. Unstructured data is complex and difficult to analyze. Text mining can analyze datasets with unstructured text content thanks to natural language processing. For this purpose, text mining can extract significant numerical indexes from text by processing the unstructured data (Özyirmidokuz, 2014). Another method used in preparing the data for analysis is to convert some words that are frequently repeated but expressed differently into a single word. Therefore, this process was carried out manually. For example, "Istanbul third airport", "Istanbul 3rd airport", "Istanbul 3rd Airport", "Istanbul's 3rd airport", "Istanbul Grand international airport", "Istanbul airport" were merged into "istanbulairport". "Blue Mosque", "Sultan Ahmet Mosque", "Sultan Ahmed Mosque", "Sultan Ahmad Mosque", are merged as "bluemosque". "Aya Sophia", "Haya Sophia", "Hagia Sophia", "Agia Sophia", "St. Sophia", "Saint Sophia", "Hagya Sophia" are merged as "hagiasophia"; "Grand Bazaar", "Grand Market" are merged as "grandbazaar"; "Spice Bazaar", "Spice Market" are merged as "spicebazaar"; "bosporus", "bosphorus" are merged as "bosphorus".

The text flow is divided into statements, words, symbols, or other significant elements by tokenization in the decomposition process, also called text pre-processing. Then, through the “transform cases” operator, all the text is converted into lower case. Prepositions, pronouns, punctuation marks and conjunctions that do not make sense alone were removed from the data set via the “Stopwords” process. In this way, the data are cleared of unnecessary words and made ready for analysis. With the help of the "Stem (snowball)" operator, words with the same root are converted into root cases. Words consisting of less than 2 to more than 25 characters are removed from the data set using the filter tokens by the length operator. The text preprocessing process applied via RapidMiner is indicated in Figure 2. Data are structured and ready for analysis with text preprocessing.

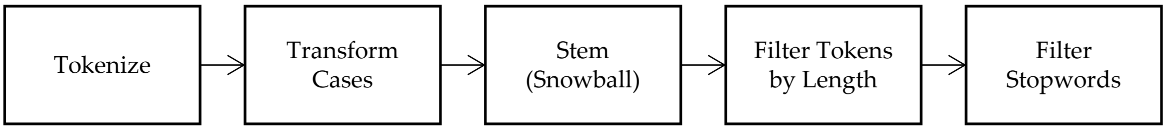

Figure 2. *Text preprocessing*

Association Rule Mining

By using association rule analysis and sentiment analysis, it is crucial to measure the strength and favorability of brand associations. In a manner similar to the BCM, associations from big data will also be shown in this manner (Schnittka et al., 2012) . The association rule, also known as market basket analysis in marketing research, is used to reveal the frequency and probability of selling products in a market together (Wong et al., 1999). In this study, the probability and the values of the words co-occuring were calculated using the association rule analysis. The association rule analysis is also similar to "contingency analysis"(Osgood, 1959). The concept of counting the co-occurrence of a word with another word as opposed to the quantity of times a word appears gave rise to contingency analysis.

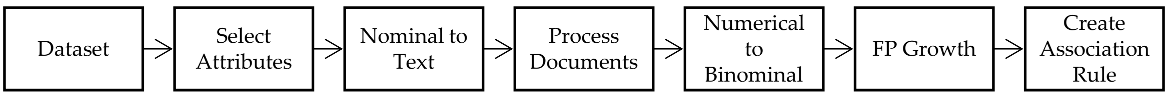

Figure 3. *Association Rule Analysis Process in Rapidminer*

The tweets were analyzed via Rapid Miner software with association analysis (Figure 3). In the association rule, the co-occurrence of two elements is symbolized as X→Y. The meaning of this rule is the probability that operations in a database containing X contain Y (Agrawal et al., 1996). The association rule is a commonly used technique for studying relationships and outcomes between subjects or descriptive concepts used to characterize structured text (Cherfi et al., 2003; Lopes et al., 2007; Rajman & Besançon, 1998). In association rule mining, two measures are used, namely "support" and "confidence". The support determines the rate at which a relationship repeats throughout the data. In an association rule, the support is defined as the percentage of document containing X∪Y in the total number of documents in the database. In Formula 1, N (X∪Y) refers to the number of documents in which X and Y contain together, and N refers to the total number of documents. So, Support (X ⇒ Y) refers to the frequency with which the concepts of X and Y in tweets coexist in all tweets. In this direction, support states the strength of the relationship between associations. Support (X ⇒ Y) is calculated as in Formula 1.

$$\text{Support } (X \Rightarrow Y) = \frac{n(X \cup Y)}{N} \qquad (1)$$

The confidence reveals the probability of customers who buy product "X" to buy product "Y". Confidence (X ⇒ Y) implies the frequency of the number of tweets where X and Y are together in tweets where X is present. For example, a result with confidence (X ⇒ Y) = 0.40 means that 40 percent of tweets containing the word "X" also contain the word "Y".

$$\text{Conf } (X) = \frac{n(X \cup Y)}{X} \qquad (2)$$

In other words, the support measure shows how frequent this correlation is in the dataset whereas the confidence measure shows the probability of the use of Y in tweets with the concept of X. Rules with a high confidence and support are called strong rules. Association rule mining requires obtaining strong patterns of co-occurrence from big databases. In association rule analysis, all frequent item sets of products must be established above a minimum support previously determined by the researcher, and strong association rules created from frequent item sets must be above a minimum support and confidence threshold determined by the user (Agrawal & Srikant, 1994). For this reason, a threshold is required for support and confidence. X⇒Y the association rule is created by the user to provide the lowest value of support and confidence (Han et al., 2012). When the minimum support is high, valuable rules cannot be obtained because they are not repeated frequently, and when the minimum support value (minsup) is low, both the number of rules increases excessively, and the importance and interestingness of the obtained rules decrease. Therefore, if the minsup is kept high, very few rules will be obtained, but if it is kept low, a large number of rules will be obtained, which occur very rarely (Lai & Cerpa, 2001). For this reason, "0.02" as the minsup threshold value and "0.7" as the minimum confidence value is preferred.

The use of support and confidence measures along with interestingness measures is recommended by many authors (McNicholas et al., 2008; Tan et al., 2018). In other words, although the rules of association show that the greater the values of support and confidence are, the stronger the relationship is, this may not always reflect the truth. Lift is the ratio of co-occurrence of two terms to the frequency expected to see them together. Therefore, when the lift value is calculated, there are three possibilities. If the lift is greater than 1, the correlation is positive, when it is less than 1, the correlation is negative. When equal to 1, the correlation is independent (Hussein et al., 2015).

Sentiment Analysis

Two approaches are used in sentiment analysis; lexicon-based and machine learning-based (Feldman & Sanger, 2006; Liu, 2010; Liu & Zhang, 2012). Machine learning approaches are supervised approaches as they perform learning over labeled training data. On the other hand, lexicon -based approaches are semi-supervised approaches that are implemented by constructing a set of terms into a sentiment dictionary. The lexicon-based approach takes advantage of a dictionary where there are known and pre-compiled terms of emotion (Medhat et al., 2014). The dictionary-based approach to sentiment analysis has been used by many researchers (Han et al., 2018; Kumar & Babu, 2021; Lopez et al., 2020). For dictionary-based sentiment analysis, it is necessary to use a dictionary that describes mood states. This study used AFINN, an English Dictionary of emotion containing 2477 words rated between -5 (negative) and 5 (positive) (Nielsen, 2011). Analysis was carried out using Phyton software.

FINDINGS

In this part of the study, the findings obtained from the association rule and sentiment analysis of English tweets containing #Istanbul are visualized in a way similar to the advanced BCM (Schnittka et al., 2012) method. As a result of the association rule analysis, 50 rules (relationships) were identified. Table 2 indicates the results for this analysis which consists of the columns, premise, conclusion, confidence value, support value, normalized support value, and lift value, respectively. If the premise is present, the probability of the conclusion is shown. Since the word "Istanbul" has been mentioned at least once in each tweet, all of the results have been included in the conclusion column. For this reason, in conventional market basket analysis, support value has become a more important measure than a confidence value because the frequency of words used together is decisive in assessing the strength of the relationship between associations. Support values are low because they are obtained from the unstructured data.

Table 2. *Findings of the association rule mining*

Associations with Istanbul	Support	Normalized Support	Confidence	Lift
Turkey	0.3237	1.0000	0.9943	1.0040
travel	0.1323	0.3802	0.9946	1.0043
turkey, travel	0.0820	0.2173	0.9975	1.0072
love	0.0728	0.1876	0.9976	1.0073
city	0.0666	0.1674	0.9942	1.0039
world	0.0532	0.1241	0.9835	0.9931
photography	0.0505	0.1154	1.0000	1.0097
turkish	0.0482	0.1077	0.9872	0.9968
time	0.0452	0.0982	0.9902	0.9999
life	0.0442	0.0950	0.9980	1.0077
visit	0.0424	0.0891	0.9986	1.0083
beautiful	0.0392	0.0787	0.9985	1.0082
bosphorus	0.0354	0.0664	0.9992	1.0089
view	0.0319	0.0550	0.9963	1.0060
street	0.0296	0.0478	0.9990	1.0087
cats	0.0285	0.0442	0.9938	1.0035
europe	0.0285	0.0442	0.9938	1.0035
great	0.0283	0.0436	0.9958	1.0055
hotel	0.0266	0.0380	0.9978	1.0075
trip	0.0263	0.0368	0.9977	1.0075
bluemosque	0.0260	0.0359	1.0000	1.0097
food	0.0259	0.0358	0.9966	1.0063
design	0.0247	0.0316	0.9952	1.0049
turkey, love	0.0246	0.0316	0.9988	1.0085
turkey, city	0.0246	0.0314	0.9988	1.0085
night	0.0236	0.0281	0.9987	1.0085
hagiasophia	0.0233	0.0273	0.9962	1.0059
turkey, photography	0.0225	0.0248	1.0000	1.0097
mosque	0.0221	0.0235	1.0000	1.0097
turkey, turkish	0.0215	0.0214	0.9918	1.0014
amazing	0.0212	0.0206	0.9944	1.0041
turkey, world	0.0208	0.0192	0.9873	0.9969
turkey, visit	0.0198	0.0158	1.0000	1.0097
people	0.0188	0.0127	0.9953	1.0050
happy	0.0185	0.0116	0.9968	1.0065
history	0.0184	0.0115	0.9984	1.0081
music	0.0181	0.0104	1.0000	1.0097
tour	0.0172	0.0076	1.0000	1.0097
summer	0.0171	0.0070	1.0000	1.0097
good	0.0170	0.0069	0.9983	1.0080
turkey, life	0.0170	0.0068	1.0000	1.0097
turkishairlines	0.0170	0.0067	0.9330	0.9421
turkey, bosphorus	0.0168	0.0061	1.0000	1.0097
travel, photography	0.0165	0.0051	1.0000	1.0097
turkey, bluemosque	0.0158	0.0029	1.0000	1.0097
turkey, beautiful	0.0157	0.0025	1.0000	1.0097
business	0.0152	0.0010	0.9827	0.9923
istanbulairport	0.0152	0.0010	0.0619	3.1897
east	0.0151	0.0009	0.9884	0.9980
holiday	0.0149	0.0000	1.0000	1.0097

According to these results, all support values were normalized using the min-max method to give a more significant image of the BCM and to take values between 0-1. Results point out that the lift value takes values close to 1. For this reason, there is no interestingness, but there is an expected co-occurrence.

As shown in Table 2, all the rules show the relationship with Istanbul. This is because each of the tweets in the data set contains the word Istanbul at least one time. There has been no relationship between the other concepts. The strength of associations must be demonstrated according to the values of support. Therefore, the data in Table 2 are listed by support values. The highest support value is between Turkey and Istanbul. With the "travel" association, the support value of "Istanbul" is "0.1323", while the confidence is "0.9943". Accordingly, "travel" and "Istanbul" were used together in 13 percent of all tweets. 'Travel', 'city', 'Turkish', 'visit', 'love', 'photography', 'bosphorus', 'cats', and 'beautiful' are the most common associations. The support value of all words in the dataset except "Turkey" and "travel" is less than 10 percent, but given that the analysis applies to 33,339 tweets, this is quite a big ratio.

Dictionary-based sentiment analysis findings obtained from the association rule analysis revealed whether each tweet was positive, negative or neutral statements. The results obtained from the analysis are illustrated in Table 3 which indicates frequencies for the negative, positive, and neutral tweets, the negative and positive tweet percentages. Results are ranked by decreasing from top to bottom according to the document frequency. Negative tweet percentages point out how many tweets consist of a negative statement. Of the 33,339 tweets in which the word "Istanbul" is used, which makes up the entire data set, 7.46 percent are negative, and 48.21 percent are positive tweets. 44.32 percent of all tweets are neutral statements.

Table 3**.** *Findings of the sentiment analysis*

Associations	Document Frequency	Positive tweet Frequency	Negative tweet Frequency	Neutral tweet Frequency	Percentage of negative tweets	Percentage of positive tweets
Istanbul	33339	16072	2488	14779	7.46	48.21
turkey	10337	4395	1435	4507	13.88	42.52
travel	4478	2337	244	1897	5.45	52.19
city	1858	1265	134	459	7.21	68.08
turkish	1589	844	140	605	8.81	53.12
visit	1426	851	81	471	5.68	59.68
love	1391	1356	20	15	1.44	97.48
photography	1250	786	95	369	7.6	62.88
beautiful	1210	1199	6	5	0.5	99.09
bosphorus	1173	527	27	619	2.3	44.93
cats	962	518	73	371	7.59	53.85
time	921	393	61	575	6.62	42.67
view	905	618	44	415	4.86	68.29
bluemosque	858	373	22	495	2.56	43.47
great	851	838	6	7	0.71	98.47
Istanbulairport	831	266	104	461	11.97	40.33

street	800	319	90	393	11.25	39.88
hotel	799	541	34	224	4.26	67.71
night	776	357	62	357	7.99	46.01
life	759	479	80	250	10.54	63.11
hagiasophia	747	364	83	300	11.11	48.73
tour	714	361	35	318	4.9	50.56
good	705	692	8	5	1.13	98.16
trip	703	463	46	194	6.54	65.86
europe	702	325	64	313	9.12	46.3
amazing	663	660	2	1	0.3	99.55
food	658	328	46	284	6.99	49.85
mosque	655	341	36	278	5.5	52.06
history	610	338	39	233	6.39	55.41
turkishairlines	600	242	70	288	11.67	40.33
people	595	329	98	168	16.47	55.29
happy	526	521	1	4	0.19	99.05
east	516	3	70	216	13.57	44.57
summer	474	265	23	186	4.85	55.91
holiday	469	266	21	182	4.48	56.72
design	462	238	21	203	4.55	51.52
music	455	250	27	178	5.93	54.95
business	407	216	35	156	8,6	53,07

The findings obtained from the association rule mining and sentiment analysis are visualized in a concept map in Figure 4. The dimensions of the nodes indicate the frequency values of the association while the thickness of the lines indicate the support value between the two associations, i.e., the strength of the associations. A triple line between concepts shows a high confidence value, a double line shows a medium confidence value, and single line indicates a low confidence value. The confidence value of all associations is between 98 percent and 100 percent. For this reason, all associations are connected to Istanbul, which is the main brand, with 3 lines. Therefore, confidence values are quite high. The strongest relationship with Istanbul is the concept of "travel" following "Turkey"[2]. This finding is a significant indicator that Istanbul is a tourist city. Since the values of other associations are close to each other, there is no significant difference in line thicknesses in terms of relationship strength. The difference between the frequency of these concepts can also be understood by the size of the circles of the concepts. Since the confidence value in all concepts ranges from 98 percent to 100 percent, all concepts are connected to the main brand with 3 lines. The words "city", "world" and "time" were among the top 10 concepts. The word "city" was used to emphasize that Istanbul is a city. "World" and "time" are associations that add different meanings depending on where they are used. Therefore, it is difficult to say that they are the defining association of Istanbul. For this reason, the concepts of world and time are not included in the map.

[2] Since the word Turkey expresses the country where Istanbul is located, it will negatively affect the interpretation of the brand image on the map (Figure 4). Therefore, Turkey was removed from the map in order to make the map more meaningful.

Table 2 illustrates the relationship of binary concepts such as "Turkey-travel", "Turkey-love", "Turkey-city" and "Turkey-photograph" with Istanbul. Since BCMs show the relationship of a single concept with another concept, these binary associations are not included in the map. Since each tweet included "Istanbul", there was no relationship between the concepts other than Istanbul. In order to see if there is a relationship between concepts other than Istanbul, the word Istanbul was excluded from the data set, analyzed again, and no rules have been formed. No other association has occurred due to words directly related to the concept of Istanbul. If there was an association that indirectly connects to the main brand in this way, the line around words that are not connected to the main brand would be illustrated by a dashed line.

The results of sentiment analysis were also shown in the BCM, revealing the favorability of associations. In Figure 4, as the negativity level of associations increases, the color inside the circles gets darker. As a result of the sentiment analysis, the association in the highest negative expression is the concept of "people" with 16.47 percent. Therefore, the concept of "people" appears to be darker than other associations. On the other hand, 55.29 percent of the concept of people were among positive statements.

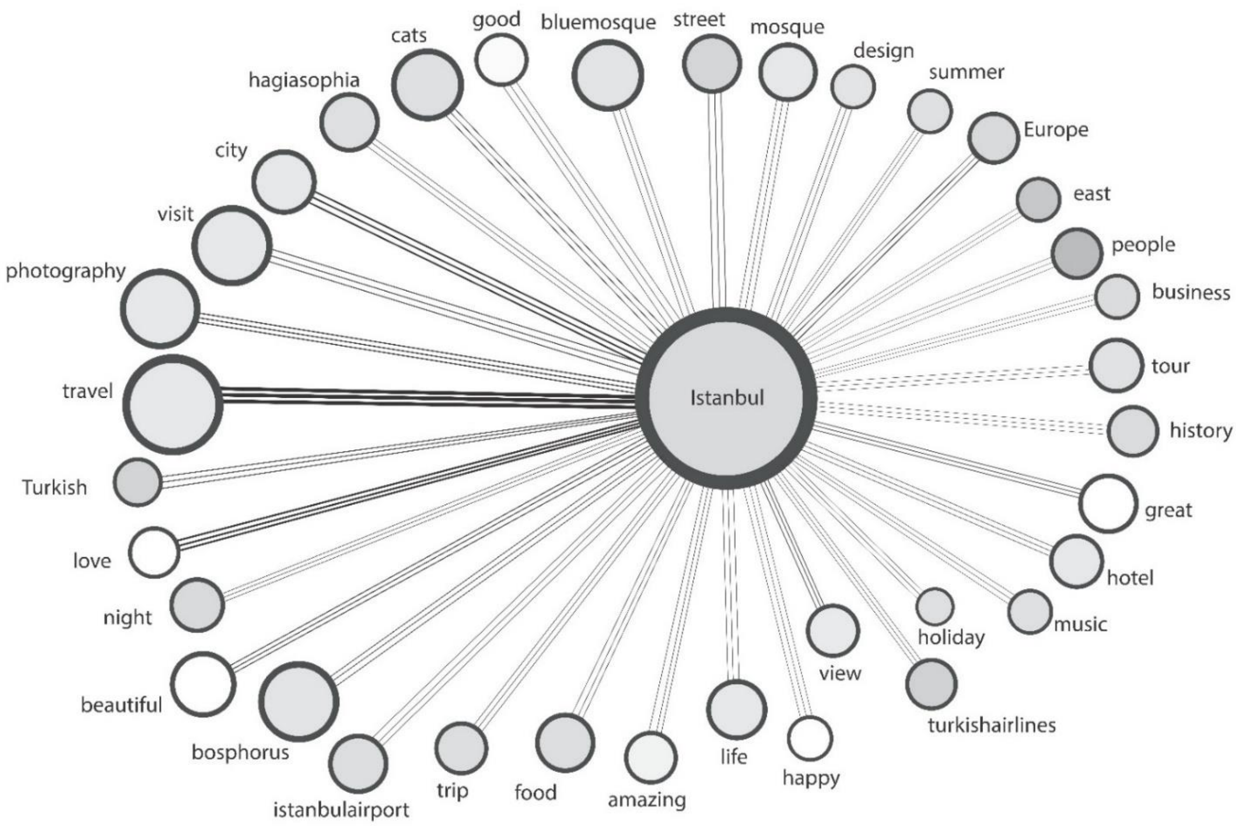

Figure 4. *The Brand Concept Map of Istanbul*

DISCUSSION AND CONCLUSIONS

In the present research, the brand associations of a destination reflected in the eWOM environment are measured and, with the help of data mining, it is indicated how meaningful information is generated from big data. Considering the influence of social media on the formation of destination branding, social media holds a unique position in destination branding research. Thus, thanks to developing data analysis technologies, social media, which was used as a secondary data source in the past, has become the primary data source. One of the most important features of the study is that the data are derived from Twitter. Destination branding practitioners can gain a better insight from research on social media data. Data mining, which many businesses are increasingly using, will also pave the way for these studies to facilitate the analysis.

This study attempted to bring a new perspective to research in this area by using text mining in the BCM to measure associations with the destination brand. BCM method is one of the mixed methods that have the common advantages of quantitative and qualitative methods. In addition, BCM is an effective method of collecting the strength, uniqueness, and favorability of associations in a visual and in revealing the network of associations in the consumer's mind. While previous BCMs were created qualitatively and on a smaller sample, in this study, the favorableness of the associations that make up the brand image and their association strength with the brand were measured and used in a larger sample group. In this context, emotions toward destination associations were determined through in-depth information extraction from the content generated by Twitter users and the connection strength of these associations was analyzed.

This paper showed that favorability dimension can also be measured from Twitter data using sentiment analysis. Text mining allows the unstructured social media data to be configured and to be transformed into significant data. One of the most important advantages of the information obtained from data on social media is that it has a very large volume of sample. Therefore, it paves the way for more reliable results. Today, developing data mining technologies can collect and analyze big data faster.

This paper also showed that unexpected and interesting results can be obtained from big data. For example, the association of “cats” is a very authentic result for Istanbul. The documentary directed by Ceyda Torun in 2016, which tells about Istanbul from the eyes of stray cats, may have played an important role in the formation of these associations. The documentary was defined as “Citizen Kane of Cats” (Kohn, 2020). The most basic result of this study is that Istanbul has a high strength of relationship with “travel”. Therefore, it can be considered that Istanbul is an important tourism destination and is mainly mentioned in terms of tourism on Twitter. However, this result may be because the tweets are in English. If Turkish tweets were collected and analyzed, different findings could be obtained. The associations of 'Travel', 'Visit', 'Trip', 'Tour', and 'Hotel' also indicate that most of the tweets are for tourism. Moreover, findings point out that orientalist elements such as the “Blue Mosque” and “Hagia Sophia” are one of Istanbul's unique tourist attractions. The concept of 'street', one of the strong associations with Istanbul, is also associated with 'photograph'. It suggests that street photographers show interest in Istanbul. The chaotic appearance of the streets of Istanbul is a feature that attracts the attention of photographers. The association of love is among the concepts that have the highest relationship with Istanbul. It is seen that “love” is also used as loving Istanbul in tweets. However, it is difficult to claim that love and romance are unique associations in terms of being able to compete with Paris, Amsterdam, Prague, Venice, and Rome.

Comparison with Previous Studies

In the studies that created the brand association network using text mining, the relationship between concepts was measured by considering word co-occurrence, but in the current study, the relationship between concepts was measured by association rule analysis. In association rule analysis, the degree of concept co-occurrence is represented by the support score. In addition to this parameter, confidence and lift scores are also important elements of the analysis. This study demonstrates the applicability of association rule mining by taking a different approach than previous studies.

Due to the dynamic and changing nature of social media, different results may be obtained from Twitter in different time periods. In this way, it provides an opportunity to observe the changes in the destination associations. For example, while some associations of a travel destination are positive in a time period, negative associations may increase in another time period. Also, if an association has a strong relationship with the destination, the relationship between them may weaken soon. However, it is very difficult and time-consuming to monitor this change in traditional studies measuring destination associations.

Implications for Practitioners

These results will play an important role in determining the content of the messages that will be created in the brand communication projects of Istanbul. The findings can guide the Destination Marketing Organizations. It is estimated that destination brand practitioners will play a key role in creating the messages to be used in brand communication strategies and making effective decisions by seeing which associations they should position their brands with and which associations they should eliminate. Based on the study findings, besides the well-known tourist attractions and the orientalist elements, the hospitality and friendship of the people of Istanbul can be emphasized in the brand communication messages. One of the significant findings of Istanbul is its association with food. It is seen that nearly half of the tweets containing the word "food" are positive tweets. In this context, it shows that food in Istanbul is an important travel motivation that makes it preferable. Thus, it is recommended to include messages about Istanbul culinary culture in promotions.

Future Research and Limitations

In future studies, revealing the brand associations of competing cities abroad simultaneously with Istanbul will allow us to determine the unique brand associations of Istanbul more clearly. This study tried to draw attention to the importance of UGC in destination image research. It will shed light on the development of new methods on the perceptions of the destination image in the online environment and new studies on the use of text mining.

There are some limitations to the study. The most obvious of these are the restrictions imposed by Twitter on the collection of data from this platform. Buying this information from Twitter poses serious costs. For this reason, the data in this study were collected weekly for a year. It is hoped that when this cost is overcome, more effective results will be achieved with larger data. Because of the size of the data, high-performance computers are also needed for data analysis.

The most important limitation of the sentiment analysis method is that it does not perform well in all languages. For example, it has been observed that sentiment dictionaries are not sufficient for Turkish language texts. For this reason, more accurate results can be achieved by applying the machine learning technique. The number of training data will positively affect the accuracy of the results of the sentiment analysis applied with the machine learning technique.

ACKNOWLEDGMENT

This article was derived from the PHD thesis entitled 'Analysis of Istanbul City Brand Image via Concept Map Method over English Social Media Shares' prepared by Cihangir Kasapoğlu.

REFERENCES

Aaker, D. (1991). *Managing Brand Equity*. New York.

Aaker, D. A. (1992). The value of brand equity. *Journal of Business Strategy, 13*(4), 27-32. https://doi.org/10.1108/eb039503

Agrawal, R, Mannila, H., Srikant, R., Toivonen, H., & Verkamo, I. (1996). Fast discovery of association rules. *Advances in knowledge discovery and data mining, 12*(1), 307-328.

Agrawal, R., & Srikant, R. (1994). Fast algorithms for mining association rules. *Proc. of 20th International Conference on Very Large Data Bases, {VLDB'94}* (Vol. 1215, pp. 487-499).

Alaei, A. R., Becken, S., & Stantic, B. (2017). Sentiment analysis in tourism: Capitalizing on big data. *Journal of Travel Research*, *58*(2), 175–191. https://doi.org/10.1177/0047287517747753

Alarcón-Urbistondo, P., Rojas-de-Gracia, M. M., & Casado-Molina, A. (2021). Proposal for employing user-generated content as a data source for measuring tourism destination image. *Journal of Hospitality & Tourism Research*, 10963480211012756. https://doi.org/10.1177/10963480211012756

Alexandris, K., Douka, S., Papadopoulos, P., & Kaltsatou, A. (2008). Testing the role of service quality on the development of brand associations and brand loyalty. *Managing Service Quality*, *18*(3), 239–254. https://doi.org/10.1108/09604520810871865

Alzate, M., Arce-Urriza, M., & Cebollada, J. (2022). Mining the text of online consumer reviews to analyze brand image and brand positioning. *Journal of Retailing and Consumer Services*, *67*, 102989. https://doi.org/10.1016/J.JRETCONSER.2022.102989

Andéhn, M., Kazeminia, A., Lucarelli, A., & Sevin, E. (2014). User-generated place brand equity on Twitter: The dynamics of brand associations in social media. *Place Branding and Public Diplomacy*, *10*(2), 132–144. https://doi.org/10.1057/pb.2014.8

Anderson, J. R., & Bower, G. H. (1980). *Human associative memory*. Psychology Press. https://doi.org/10.2307/1421672

Baloglu, S., & McCleary, K. W. (1999). A model of destination image formation. *Annals of Tourism Research*, *26*(4), 868–897. https://doi.org/10.1016/S0160-7383(99)00030-4

Başfırıncı, Ç. (2016). Analysing brand image through social network analysis: A research on Turkcell and Vodafone brand. *İstanbul Gelişim Üniversitesi Sosyal Bilimler Dergisi*, *3*(2), 25–50.

Becken, S., Alaei, A. R., & Wang, Y. (2020). Benefits and pitfalls of using tweets to assess destination sentiment. *Journal of Hospitality and Tourism Technology*, *11*(1), 19–34. https://doi.org/10.1108/JHTT-09-2017-0090

Bell, R. C. (2005). The repertory grid technique. In F. Fransella (Ed.), *International Handbook of Personal Construct Psychology* (pp. 95–103). John Wiley & Sons Ltd. https://doi.org/10.1002/0470013370.ch9

Bianchi, C., Pike, S., & Lings, I. (2014). Investigating attitudes towards three South American destinations in an emerging long haul market using a model of consumer-based brand equity (CBBE). *Tourism Management*, *42*, 215–223. https://doi.org/10.1016/J.TOURMAN.2013.11.014

Biel, A. (1992). How brand image drives brand equity. *Journal of Advertising Research*, *32*(6), 6-12.

Blanchard, S. J., Aloise, D., & Desarbo, W. S. (2017). Extracting summary piles from sorting task data. *Journal of Marketing Research*, *54*(3), 398–414. https://doi.org/10.1509/jmr.15.0388

Blasi, S., Brigato, L., & Sedita, S. R. (2020). Eco-friendliness and fashion perceptual attributes of fashion brands: An analysis of consumers' perceptions based on twitter data mining. *Journal of Cleaner Production*, *244*, 118701. https://doi.org/https://doi.org/10.1016/j.jclepro.2019.118701

Böger, D., Kottemann, P., Meißner, M., & Decker, R. (2017). A mechanism for aggregating association network data: An application to brand concept maps. *Journal of Business Research, 79*, 90-106. https://doi.org/10.1016/j.jbusres.2017.05.025

Brandt, C., de Mortanges, C. P., Bluemelhuber, C., & van Riel, A. C. R. (2011). Associative networks: A new approach to market segmentation. *International Journal of Market Research, 53*(2), 187-207. https://doi.org/10.2501/ijmr-53-2-187-208

Brandt, C., & de Mortanges, C. P. (2011). City branding: A brand concept map analysis of a university town. *Place Branding and Public Diplomacy, 7*, 50-63. https://doi.org/10.1057/pb.2010.37

Bui, V., Alaei, A. R., Vu, H. Q., Li, G., & Law, R. (2022). Revisiting tourism destination image: A holistic measurement framework using big data. *Journal of Travel Research*, *61*(6), 1287–1307. https://doi.org/10.1177/00472875211024749

Burkhalter, J. N., Wood, N. T., & Tryce, S. A. (2014). Clear, conspicuous, and concise: Disclosures and Twitter word-of-mouth. *Business Horizons*, *57*(3), 319–328. https://doi.org/10.1016/J.BUSHOR.2014.02.001

Cai, L. A. (2002). Cooperative branding for rural destinations. *Annals of Tourism Research*, *29*(3), 720–742. https://doi.org/https://doi.org/10.1016/S0160-7383(01)00080-9

Chen, H. (2012). Dark Web: Exploring and mining the dark side of the web. *2011 European Intelligence and Security Informatics Conference*, Athens, Greece, (pp. 1-2). 10.1109/EISIC.2011.78.

Chen, Y. C. (2017). The relationships between brand association, trust, commitment, and satisfaction of higher education institutions. *International Journal of Educational Management*, *31*(7), 973–985. https://doi.org/10.1108/IJEM-10-2016-0212

Cherfi, H., Napoli, A., & Toussaint, Y. (2003). Towards a text mining methodology using frequent itemsets and association rule extraction. In E. SanJuan (Ed.), *Journées d'informatique Messine - JIM'03* (pp. 285--294). HAL-Inria. https://hal.inria.fr/inria-00107723

Cho, E., Fiore, A. M., & Russell, D. W. (2015). Validation of a fashion brand image scale capturing cognitive, sensory, and affective associations: Testing its role in an extended brand equity model. *Psychology & Marketing*, *32*(1), 28–48. https://doi.org/10.1002/MAR.20762

Choi, S., Jeon, J., Subrata, B., & Kwon, O. (2015). An efficient estimation of place brand image power based on text mining technology. *Journal of Intelligence and Information Systems*, *21*(2), 113–129. https://doi.org/https://doi.org/10.13088/jiis.2015.21.2.113

Christodoulides, G., & de Chernatony, L. (2010). Consumer-based brand equity conceptualisation and measurement: A literature review. *International Journal of Market Research*, *52*(1), 43-66. https://doi.org/10.2501/S1470785310201053

Ci, C., & Choi, S. (2017). How to manage a city's image using the brand concept map and network analysis: A case of Seoul. *Quality and Quantity*, *51*(6), 2441–2456. https://doi.org/10.1007/s11135-016-0402-6

Ciabuca, A. (2015). The development of a semantic differential scale for assessing the perceived image of citizens about Romanian Police Forces. *Procedia - Social and Behavioral Sciences*, *187*, 28–33. https://doi.org/https://doi.org/10.1016/j.sbspro.2015.03.006

Cian, L., & Cervai, S. (2011). The Multi-Sensory Sort (MuSeS). *Qualitative Market Research: An International Journal*, *14*(2), 138–159. https://doi.org/10.1108/13522751111120666

Clarke, H., & Hassanien, A. (2020). An evaluation of Toronto's destination image through tourist generated content on Twitter. *International Journal of Customer Relationship Marketing and Management*, *11*(2), 1–16. https://doi.org/10.4018/IJCRMM.2020040101

Claster, W., Pardo, P., Cooper, M., & Tajeddini, K. (2013). Tourism, travel and tweets: Algorithmic text analysis methodologies in tourism. *Middle East J. of Management*, *1*(1), 81-99. https://doi.org/10.1504/mejm.2013.054071

Collins, A. M., & Loftus, E. F. (1975). A spreading-activation theory of semantic processing. *Psychological Review*, *82*(6), 407–428. https://doi.org/10.1037/0033-295X.82.6.407

Cornwell, T. B., Humphreys, M. S., & Kwon, Y. (2022). Shared brand equity. *Journal of Advertising*, 1-19. https://doi.org/10.1080/00913367.2022.2131656

Culotta, A., & Cutler, J. (2016). Mining brand perceptions from twitter social networks. *Marketing Science, 35*(3), 343-362. https://doi.org/10.1287/mksc.2015.0968

Curlin, T., Jaković, B., & Miloloža, I. (2019). Twitter usage in tourism: Literature review. *Business Systems Research: International Journal of the Society for Advancing Innovation and Research in Economy, 10*(1), 102–119. https://doi.org/10.2478/bsrj-2019-0008

di Pietro, L., di Virgilio, F., & Pantano, E. (2012). Social network for the choice of tourist destination: attitude and behavioural intention. *Journal of Hospitality and Tourism Technology*, *3*(1), 60–76. https://doi.org/10.1108/17579881211206543

Diaz-Garcia, J. A., Ruiz, M. D., & Martin-Bautista, M. J. (2022). A survey on the use of association rules mining techniques in textual social media. *Artificial Intelligence Review, 56*(2), 1175-1200. https://doi.org/10.1007/s10462-022-10196-3

Dillon, W. R., Madden, T. J., Kirmani, A., & Mukherjee, S. (2001). Understanding what's in a brand rating: A model for assessing brand and attribute effects and their relationship to brand equity. *Journal of Marketing Research*, *38*(4), 415–429. https://doi.org/10.1509/jmkr.38.4.415.18910

Dirsehan, T., & Kurtuluş, S. (2018). Measuring brand image using a cognitive approach: Representing brands as a network in the Turkish airline industry. *Journal of Air Transport Management*, *67*, 85–93. https://doi.org/https://doi.org/10.1016/j.jairtraman.2017.11.010

Divakaran, P. K. P., & Xiong, J. (2022). Eliciting brand association networks: A new method using online community data. *Technological Forecasting and Social Change*, *181*, 121769. https://doi.org/https://doi.org/10.1016/j.techfore.2022.121769

Dolnicar, S., Rossiter, J. R., & Grün, B. (2012). 'Pick Any' measures contaminate brand image studies. *International Journal of Market Research*, *54*(6), 821–834. https://doi.org/10.2501/IJMR-54-6-821-834

East, R., Hammond, K., & Lomax, W. (2008). Measuring the impact of positive and negative word of mouth on brand purchase probability. *International Journal of Research in Marketing, 25*(3), 215-224. https://doi.org/10.1016/j.ijresmar.2008.04.001

Elsayed, M., Abdelwahab, A., & Ahdelkader, H. (2019). A proposed framework for improving analysis of big unstructured data in social media. *14th International Conference on Computer Engineering and Systems (ICCES)*, 61–65. https://doi.org/10.1109/ICCES48960.2019.9068154

Feldman, R., & Sanger, J. (2006). *The text mining handbook: Advanced approaches in analyzing unstructured data*. Cambridge: Cambridge University Press. https://doi.org/10.1017/cbo9780511546914

Flores-Ruiz, D., Elizondo-Salto, A., & Barroso-González., M. D. L. O. (2021). Using social media in tourist sentiment analysis: A case study of Andalusia during the Covid-19 Pandemic. *Sustainability*, *13*(7), 1–19.

French, A., & Smith, G. (2013). Measuring brand association strength: A consumer based brand equity approach. *European Journal of Marketing, 47*(8), 1356–1367. https://doi.org/10.1108/03090561311324363

Garay, L. (2019). #Visitspain. Breaking down affective and cognitive attributes in the social media construction of the tourist destination image. *Tourism Management Perspectives*, *32*, 100560. https://doi.org/10.1016/J.TMP.2019.100560

Gartner, W. C. (1994). Image Formation Process. *Journal of Travel & Tourism Marketing*, *2*(2–3), 191–216. https://doi.org/10.1300/J073v02n02_12

Gartner, W. C., & Ruzzier, M. K. (2010). Tourism destination brand equity dimensions: Renewal versus repeat market. *Journal of Travel Research, 50*(5), 471–481. https://doi.org/10.1177/0047287510379157

Gensler, S., Völckner, F., Egger, M., Fischbach, K., & Schoder, D. (2015). Listen to your customers: Insights into brand image using online consumer-generated product reviews. *International Journal of Electronic Commerce, 20*(1), 112-141. https://doi.org/10.1080/10864415.2016.1061792

Goffin, K., Lemke, F., & Koners, U. (2010). Repertory Grid Technique. In *Identifying Hidden Needs: Creating Breakthrough Products* (pp. 125–152). Palgrave Macmillan UK. https://doi.org/10.1057/9780230294486_6

Gorin, A., Nedelko, A., Kosonogov, V., Vakhviyainen, M., Tugin, S., Moiseeva, V., Klucharev, V. & Shestakova, A. (2022). N400 correlate of brand associations. *Journal of Economic Psychology*, *90*, 102506. https://doi.org/https://doi.org/10.1016/j.joep.2022.102506

Han, H., Zhang, J., Yang, J., Shen, Y., & Zhang, Y. (2018). Generate domain-specific sentiment lexicon for review sentiment analysis. *Multimedia Tools and Applications*, *77*(16), 21265–21280. https://doi.org/10.1007/S11042-017-5529-5

Han, J., Kamber, M., & Pei, J. (2012). Data Mining Trends and Research Frontiers. *Data Min*, 585-631.

Hand, D. J. (2007). Principles of data mining. *Drug-Safety*, *30*(7), 621-622.

Henderson, G. R., Iacobucci, D., & Calder, B. J. (1998). Brand diagnostics: Mapping branding effects using consumer associative networks. *European Journal of Operational Research*, *111*(2), 306–327. https://doi.org/10.1016/S0377-2217(98)00151-9

Hodeghatta, U. R., & Sahney, S. (2016). Understanding Twitter as an e-WOM. *Journal of Systems and Information Technology*, *18*(1), 89–115. https://doi.org/10.1108/JSIT-12-2014-0074

Hofstede, A., van Hoof, J., Walenberg, N., & de Jong, M. (2007). Projective techniques for brand image research. *Qualitative Market Research: An International Journal*, *10*(3), 300–309. https://doi.org/10.1108/13522750710754326

Howells, K., & Ertugan, A. (2017). Applying fuzzy logic for sentiment analysis of social media network data in marketing. *Procedia Computer Science*, *120*, 664–670. https://doi.org/10.1016/j.procs.2017.11.293

Hsieh, M. H. (2018). Measuring global brand equity using cross-national survey data. *Journal of International Marketing*, *12*(2), 28–57. https://doi.org/10.1509/JIMK.12.2.28.32897

Huete-Alcocer, N., & Hernandez-Rojas, R. D. (2022). Does local cuisine influence the image of a World Heritage destination and subsequent loyalty to that destination? *International Journal of Gastronomy and Food Science*, *27*, 100470. https://doi.org/10.1016/j.ijgfs.2022.100470

Hussein, N., Alashqur, A., & Sowan, B. (2015). Using the interestingness measure lift to generate association rules. *Journal of Advanced Computer Science & Technology, 4*(1), 156-162. https://doi.org/10.14419/jacst.v4i1.4398

Ibrahim, M. M., & Elborsaly, A. A. (2022). Measuring tourism destination brand equity by using associative networks. *European Journal of Business and Management Research*, *7*(3), 224–235. https://doi.org/10.24018/ejbmr.2022.7.3.1450

Ivanov, S. H., Ilium, S. F., & Liang, Y. (2010). Application of destination brand molecule on destination image and brand perception: An exploratory study. *Tourism*, *58*(4), 339–360. https://doi.org/10.2139/SSRN.1586263

Jansen, B. J., Zhang, M., Sobel, K., & Chowdury, A. (2009). Twitter power: Tweets as electronic word of mouth. *Journal of the American Society for Information Science and Technology, 60*(11), 2169-2188. https://doi.org/10.1002/asi.21149

Jiang, Q., Chan, C.-S., Eichelberger, S., Ma, H., & Pikkemaat, B. (2021). Sentiment analysis of online destination image of Hong Kong held by mainland Chinese tourists. *Current Issues in Tourism*, *24*(17), 2501–2522. https://doi.org/10.1080/13683500.2021.1874312

Jo, T. (2019). *Text mining: Concepts, Implementation, and Big Data Challenge*. Springer, Cham. https://doi.org/10.1007/978-3-319-91815-0

John, D. R., Loken, B., Kim, K., & Monga, A. B. (2006). Brand concept maps: A methodology for identifying brand association networks. *Journal of Marketing Research*, *43*(4), 549-563. https://doi.org/10.1509/jmkr.43.4.549

Karayılmazlar, S., Bardak, T., Avcı, Ö., Kayahan, K., Karayılmazlar, A. S., Çabuk, Y., Kurt, R., & İmren, E. (2019). Determining the orientation in choosing furniture based on social media based on data mining algorithms: Twitter example. *Turkish Journal of Forestry*, *20*(4), 447–457. https://doi.org/10.18182/tjf.609967

Kavaratzis, M. (2004). From city marketing to city branding: Towards a theoretical framework for developing city brands. *Place Branding*, *1*(1), 58–73. https://doi.org/10.1057/PALGRAVE.PB.5990005

Keller, K. L. (1993). Conceptualizing, measuring, and managing customer-based brand equity. *Journal of Marketing*, *57*(1), 1–22. https://doi.org/10.2307/1252054

Keller, K. L. (2013). *Strategic Brand Management Building, Measuring, and Managing Brand Equity Global Edition* (4th ed.). Pearson.

Kim, D. D. E. (2017). A unified measure of media brand personality: Developing a media brand personality scale for multiple media. *International Journal on Media Management*, *19*(3), 197–221. https://doi.org/10.1080/14241277.2017.1306531

Kim, K., Park, O., Yun, S., & Yun, H. (2017). What makes tourists feel negatively about tourism destinations? Application of hybrid text mining methodology to smart destination management. *Technological Forecasting and Social Change*, *123*, 362–369. https://doi.org/10.1016/j.techfore.2017.01.001

Kiran, P., & Vasantha, S. (2016). Analysing the role of user generated content on consumer purchase intention in the new era of social media and big data. *Indian Journal of Science and Technology*, *9*(43), 1-7. https://doi.org/10.17485/ijst/2016/v9i43/104754

Kladou, S., & Kehagias, J. (2014). Developing a structural brand equity model for cultural destinations. *Journal of Place Management and Development*, *7*(2), 112–125. https://doi.org/10.1108/JPMD-03-2013-0007

Klostermann, J., Plumeyer, A., Böger, D., & Decker, R. (2018). Extracting brand information from social networks: Integrating image, text, and social tagging data. *International Journal of Research in Marketing, 35*(4), 538-556. https://doi.org/10.1016/j.ijresmar.2018.08.002

Kohn, E. (2020). *"Kedi' is the 'Citizen Kane of Cat Documentaries – Review"*. Indiewire. Retrieved 4 May, 2023, from https://www.indiewire.com/2017/02/kedi-review-cat-documentary-citizen-kane-1201781292/

Koll, O., von Wallpach, S., & Uzelac, B. (2022). Stakeholder-oriented brand management: A Venn-diagram approach to monitor brand associations. *European Management Journal*. https://doi.org/10.1016/j.emj.2022.03.004

Költringer, C., & Dickinger, A. (2015). Analyzing destination branding and image from online sources: A web content mining approach. *Journal of Business Research*, *68*(9), 1836–1843. https://doi.org/10.1016/j.jbusres.2015.01.011

Kumar, C. S. P., & Babu, L. D. D. (2021). Evolving dictionary based sentiment scoring framework for patient authored text. *Evolutionary Intelligence*, *14*(2), 657–667. https://doi.org/10.1007/S12065-020-00366-Z

Lai, K., & Cerpa, N. (2001). Support vs confidence in association rule algorithms. In *Proceedings of the OPTIMA Conference, Curicó* (pp. 1-14).

Leelawat, N., Jariyapongpaiboon, S., Promjun, A., Boonyarak, S., Saengtabtim, K., Laosunthara, A., Yudha, A. K., & Tang, J. (2022). Twitter data sentiment analysis of tourism in Thailand during the COVID-19 pandemic using machine learning. *Heliyon*, *8*(10), e10894. https://doi.org/10.1016/J.HELIYON.2022.E10894

Lim, K., & O'Cass, A. (2001). Consumer brand classifications: an assessment of culture-of-origin versus country-of-origin. *Journal of Product & Brand Management*, *10*(2), 120–136. https://doi.org/10.1108/10610420110388672

Liu, B. (2010). Sentiment analysis and subjectivity. In *Handbook of Natural Language Processing* (2. Ed.) (pp. 627-666).

Liu, B., & Zhang, L. (2012). A survey of opinion mining and sentiment analysis. In *Mining Text Data* (pp. 415-463). Springer, Boston, MA. https://doi.org/10.1007/978-1-4614-3223-4_13

Liu, M. T., Liu, Y., Mo, Z., & Ng, K. L. (2021). Using text mining to track changes in travel destination image: the case of Macau. *Asia Pacific Journal of Marketing and Logistics*, *33*(2), 371–393. https://doi.org/10.1108/APJML-08-2019-0477

Liu, X., Burns, A. C., & Hou, Y. (2017). An investigation of brand-related user-generated content on Twitter. *Journal of Advertising*, *46*(2), 236–247. https://doi.org/10.1080/00913367.2017.1297273

Lopes, A. A., Pinho, R., Paulovich, F., & Minghim, R. (2007). Visual text mining using association rules. *Computers & Graphics*, *31*(3), 316–326. https://doi.org/10.1016/j.cag.2007.01.023

Lopez, A., Guerra, E., Gonzalez, B., & Madero, S. (2020). Consumer sentiments toward brands: the interaction effect between brand personality and sentiments on electronic word of mouth. *Journal of Marketing Analytics*, *8*(4), 203–223. https://doi.org/10.1057/S41270-020-00085-5/FIGURES/8

Low, G. S., & Lamb, C. W. Jr. (2000). The measurement and dimensionality of brand associations. *Journal of Product & Brand Management*, *9*(6), 350–370.

Mak, A. H. N. (2017). Online destination image: Comparing national tourism organisation's and tourists' perspectives. *Tourism Management*, *60*, 280–297. https://doi.org/10.1016/j.tourman.2016.12.012

Marchand, A., Hennig-Thurau, T., & Wiertz, C. (2017). Not all digital word of mouth is created equal: Understanding the respective impact of consumer reviews and microblogs on new product success. *International Journal of Research in Marketing*, *34*(2), 336–354. https://doi.org/10.1016/J.IJRESMAR.2016.09.003

Marine-Roig, E., & Anton Clavé, S. (2015). Tourism analytics with massive user-generated content: A case study of Barcelona. *Journal of Destination Marketing & Management*, *4*(3), 162–172. https://doi.org/10.1016/J.JDMM.2015.06.004

Matheson, J. L., & McCollum, E. E. (2008). Using metaphors to explore the experiences of powerlessness among women in 12-step recovery. *Substance Use and Misuse*, *43*(8-9), 1027-1044. https://doi.org/10.1080/10826080801914287

McNicholas, P. D., Murphy, T. B., & O'Regan, M. (2008). Standardising the lift of an association rule. *Computational Statistics and Data Analysis*, *52*(10), 4712-4721. https://doi.org/10.1016/j.csda.2008.03.013

Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal*, *5*(4), 1093–1113. https://doi.org/10.1016/j.asej.2014.04.011

Miner, G. D., Elder, J., & Nisbet, R. A. (2012). Practical text mining and statistical analysis for non-structured text data applications. In *Practical Text Mining and Statistical Analysis for Non-structured Text Data Applications*. Elsevier Inc. https://doi.org/10.1016/C2010-0-66188-8

Mishra, M. S., & Sharma, R. W. (2019). Brand crisis-sentiment analysis of user-generated comments about @Maggi on Facebook. *Corporate Reputation Review*, *22*(2), 48–60. https://doi.org/10.1057/s41299-018-0057-4

Mitra, S., & Jenamani, M. (2020). OBIM: A computational model to estimate brand image from online consumer review. *Journal of Business Research*, *114*, 213–226. https://doi.org/10.1016/J.JBUSRES.2020.04.003

Nadeau, J., Wardley, L. J., & Rajabi, E. (2021). Tourism destination image resiliency during a pandemic as portrayed through emotions on Twitter. *Tourism and Hospitality Research*, *22*(1), 60–70. https://doi.org/10.1177/14673584211038317

Nam, H., Joshi, Y., & Kannan, P. K. (2017). Harvesting brand information from social tags. *Journal of Marketing*, *81*(4), 88–108. https://doi.org/10.1509/jm.16.0044

Nautiyal, R., Albrecht, J. N., & Carr, A. (2022). Can destination image be ascertained from social media? An examination of Twitter hashtags. *Tourism and Hospitality Research*. https://doi.org/10.1177/14673584221119380

Netzer, O., Feldman, R., Goldenberg, J., & Fresko, M. (2012). Mine your own business: Market-structure surveillance through text mining. *Marketing Science*, *31*(3), 521-543. https://doi.org/10.1287/mksc.1120.0713

Nielsen, F. Å. (2011). A new ANEW: Evaluation of a word list for sentiment analysis in microblogs. *CEUR Workshop Proceedings*.

Oliverio, J. (2018). A survey of social media, big data, data mining, and analytics. *Journal of Industrial Integration and Management*, *3*(03), 1850003. https://doi.org/10.1142/S2424862218500033

Osgood, C. E. (1959). The representational model and relevant research methods. In I. Pool (Ed.), *Trends in Content Analysis* (pp. 33–38). Illinois Press.

Özyirmidokuz, E. K. (2014). Mining unstructured Turkish economy news articles. *Procedia Economics and Finance, 16*, 320-328. https://doi.org/10.1016/s2212-5671(14)00809-0

Paolanti, M., Mancini, A., Frontoni, E., Felicetti, A., Marinelli, L., Marcheggiani, E., & Pierdicca, R. (2021). Tourism destination management using sentiment analysis and geo-location information: A deep learning approach. *Information Technology & Tourism*, *23*(2), 241–264. https://doi.org/10.1007/s40558-021-00196-4

Park, J., Yang, D., & Kim, H. Y. (2023). Text mining-based four-step framework for smart speaker product improvement and sales planning. *Journal of Retailing and Consumer Services*, *71*, 103186. https://doi.org/10.1016/J.JRETCONSER.2022.103186

Park, S. B., Kim, J., Lee, Y. K., & Ok, C. M. (2020). Visualizing theme park visitors' emotions using social media analytics and geospatial analytics. *Tourism Management*, *80*, 104127. https://doi.org/10.1016/J.TOURMAN.2020.104127

Perez Cabañero, C., Bigne, E., Ruiz Mafe, C., & Cuenca, A. C. (2020). *Sentiment Analysis of Twitter in Tourism Destinations*, 1–3. https://doi.org/10.4995/carma2020.2020.11621

Phong, L. T., Nga, T. H., Hanh, N. T., & van Minh, N. (2020). Relationship between brand association and customer loyalty: The case of online retail industry. *Management Science Letters*, *10*(7), 1543–1552. https://doi.org/10.5267/j.msl.2019.12.012

Pich, C., Armannsdottir, G., & Dean, D. (2015). The elicitation capabilities of qualitative projective techniques in political brand image research. *International Journal of Market Research*, *57*(3), 357–394. https://doi.org/10.2501/IJMR-2015-033

Pike, S. (2009). Destination brand positions of a competitive set of near-home destinations. *Tourism Management*, *30*(6), 857–866. https://doi.org/10.1016/J.TOURMAN.2008.12.007

Plumeyer, A., Kottemann, P., Böger, D., & Decker, R. (2019). Measuring brand image: A systematic review, practical guidance, and future research directions. *Review of Managerial Science, 13,* 227-265. https://doi.org/10.1007/s11846-017-0251-2

Qu, H., Kim, L. H., & Im, H. H. (2011). A model of destination branding: Integrating the concepts of the branding and destination image. *Tourism Management*, *32*(3), 465–476. https://doi.org/10.1016/J.TOURMAN.2010.03.014

Rahman, K., & Areni, C. S. (2016). The benefits of quantifying qualitative brand data: A mixed-method approach for converting free brand associations to a brand equity index. *International Journal of Market Research*, *58*(3), 421–450. https://doi.org/10.2501/IJMR-2015-053

Rajman, M., & Besançon, R. (1998). Text Mining: Natural Language techniques and Text Mining applications BT - Data Mining and Reverse Engineering: Searching for semantics. In S. Spaccapietra & F. Maryanski (Eds.), *IFIP TC2 WG2.6 IFIP Seventh Conference on Database Semantics (DS-7) 7–10 October 1997, Leysin, Switzerland* (pp. 50–64). Springer US. https://doi.org/10.1007/978-0-387-35300-5_3

Ren, G., & Hong, T. (2017). Investigating online destination images using a topic-based sentiment analysis approach. *Sustainability, 9*(10), 1765. https://doi.org/10.3390/su9101765

Romaniuk, J. (2014). Comparing methods of measuring brand personality traits. *Journal of Marketing Theory and Practice*, *16*(2), 153–161. https://doi.org/10.2753/MTP1069-6679160205

Sahin, S., & Baloglu, S. (2011). Brand personality and destination image of Istanbul. *Anatolia*, *22*(1), 69–88. https://doi.org/10.1080/13032917.2011.556222

Schnittka, O., Sattler, H., & Zenker, S. (2012). Advanced brand concept maps: A new approach for evaluating the favorability of brand association networks. *International Journal of Research in Marketing*, *29*(3), 265–274. https://doi.org/10.1016/j.ijresmar.2012.04.002

Shams, R., Alpert, F. & Brown, M. (2015). Consumer perceived brand innovativeness. *European Journal of Marketing*, *49*(9/10), 1589–1615. https://doi.org/10.1108/EJM-05-2013-0240

Shimada, K., Inoue, S., Maeda, H., & Endo, T. (2011). Analyzing tourism information on Twitter for a local city. *2011 First ACIS International Symposium on Software and Network Engineering*, 61–66. https://doi.org/10.1109/SSNE.2011.27

Spry, L., & Pich, C. (2021). Enhancing data collection methods with qualitative projective techniques in the exploration of a university's brand identity and brand image. *International Journal of Market Research*, *63*(2), 177–200. https://doi.org/10.1177/1470785320943045

Statista. (2020). *Largest cities in Europe in 2020*. https://www.statista.com/statistics/1101883/largest-european-cities/.

Stepchenkova, S., & Li, X. (Robert). (2014). Destination image: Do top-of-mind associations say it all? *Annals of Tourism Research*, *45*, 46–62. https://doi.org/10.1016/j.annals.2013.12.004

Surugiu, C., Tudorache, D. M., Aștefănoaiei, R. M., & Surugiu, M. R. (2021). Bucharest cultural heritage through the eyes of social media users. *Anatolia*, *33*(4), 576-587. https://doi.org/10.1080/13032917.2021.1984960

Tan, P. N., Steinbach, M., & Karpatne, K. (2018). Association analysis: Basic concepts and algorithms. In P.-N. Tan, M. Steinbach, A. Karpatne & V. Kumar (Eds.), *Introduction to Data Mining* (2nd ed., pp. 357–449). https://www-users.cs.umn.edu/~kumar001/dmbook/ch5_association_analysis.pdf

Teichert, T. A., & Schöntag, K. (2010). Exploring consumer knowledge structures using associative network analysis. *Psychology and Marketing*, *27*(4), 369-398. https://doi.org/10.1002/mar.20332

Tseng, C., Wu, B., Morrison, A. M., Zhang, J., & Chen, Y. (2015). Travel blogs on China as a destination image formation agent: A qualitative analysis using Leximancer. *Tourism Management*, *46*, 347–358. https://doi.org/10.1016/j.tourman.2014.07.012

Viñán-Ludeña, M. S., & de Campos, L. M. (2022). Discovering a tourism destination with social media data: BERT-based sentiment analysis. *Journal of Hospitality and Tourism Technology*, *13*(5), 907–921. https://doi.org/10.1108/JHTT-09-2021-0259

Vriens, M., Chen, S., & Schomaker, J. (2019). The evaluation of a brand association density metric. *Journal of Product and Brand Management*, *28*(1), 104–116. https://doi.org/10.1108/JPBM-02-2018-1768

Wong, C. U. I., & Qi, S. (2017). Tracking the evolution of a destination's image by text-mining online reviews - the case of Macau. *Tourism Management Perspectives*, *23*, 19–29. https://doi.org/10.1016/J.TMP.2017.03.009

Wong, P. C., Whitney, P., & Thomas, J. (1999). Visualizing association rules for text mining. *Proceedings of the IEEE Symposium on Information Visualization*. https://doi.org/10.1109/infvis.1999.801866

Yan, H., Ma, M., Wu, Y., Fan, H., & Dong, C. (2022). Overview and analysis of the text mining applications in the construction industry. *Heliyon*, *8*(12), e12088. https://doi.org/10.1016/J.HELIYON.2022.E12088

Yan, Y., Chen, J., & Wang, Z. (2020). Mining public sentiments and perspectives from geotagged social media data for appraising the post-earthquake recovery of tourism destinations. *Applied Geography*, *123*, 102306. https://doi.org/10.1016/J.APGEOG.2020.102306

Yang, F. X., Li, X., & Choe, Y. (2022). What constitutes a favorable destination brand portfolio? Through the lens of coherence. *Tourism Management*, *90*, 104480. https://doi.org/10.1016/j.tourman.2021.104480

Zaltman, G. (1995). *Metaphor elicitation method and apparatus* (Patent No. 5,436,830).

Zenker, S. (2014). Measuring place brand equity with the advanced Brand Concept Map (aBCM) method. *Place Branding and Public Diplomacy*, *10,* 158-166. https://doi.org/10.1057/pb.2014.2

Zenker, S., & Braun, E. (2015). Rethinking the measurement of place brands. In K. Mihalis, G. Warnaby & G. J. Ashworth (Eds.), *Rethinking Place Branding Comprehensive: Brand Development for Cities and Regions* (pp. 211–224). Springer, Cham. https://doi.org/10.1007/978-3-319-12424-7

Zenker, S., & Braun, E. (2017). Questioning a "one size fits all" city brand: Developing a branded house strategy for place brand management. *Journal of Place Management and Development*, *10*(3), 270–287. https://doi.org/10.1108/JPMD-04-2016-0018

Zhang, Y., Chen, M., & Liu, L. (2015). A review on text mining. *2015 6th IEEE International Conference on Software Engineering and Service Science (ICSESS)*, 681–685. https://doi.org/10.1109/ICSESS.2015.7339149

Zhang, Z., Luo, M., Luo, Z. & Niu, H. (2022). The international city image of Beijing: A quantitative analysis based on twitter texts from 2017–2021. *Sustainability (Switzerland)*, *14*(17), 10675. https://doi.org/10.3390/su141710675