



Analysing Food Image Branding of Turkey From Instagram Social Media Platform

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Abstract

The main purpose of this study is to discover the most popular foods in Turkish cuisine by analysing user-generated content (UGC) and analysing Instagram posts to determine the most popular themes within a gastronomical context. Photographs, likes, and hashtags of 1167 posts shared with “#turkishfood” hashtag are analysed due to the representative power of this hashtag for the Turkish cuisine. Photography and text mining techniques are used under data mining. Findings for photographs and likes show that users have high and low perceived images for certain food categories. Hashtag findings support the user’s positive attitude towards Turkish cuisine. The study will help the destination develop future social media strategies by revealing the strengths and weaknesses of user-generated content (UGC) in the destination's food image branding. This study offers theoretical and practical implications by showing existing and possible image elements for destination food branding with social media.

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INTRODUCTION

Food is regarded as an important element to make the travel experience unique or to increase general travel experience as an effective factor for tourism product generation and consumption (Björk & Kauppinen-Raisanen, 2016; Henderson, 2009). Destination marketing professionals regard food as an attractive factor to guide potential tourists within a constantly changing structure of the tourism industry (McKercher et al., 2008). Within this context, food can be seen as a strategic management tool that can form the basic image of a destination and contribute to the existing image (Cohen & Aviele, 2004; Kivela & Crofts, 2006). Positive food image is considered as a differentiation factor for the destinations. According to Rozin and Rozin (1981), factors such as local food, cooking techniques, and taste properties differentiate the cuisine of a destination from others. For example, the destination image of France is often linked with culture, fashion, romanticism, and primarily with gastronomy and wines (Frochot, 2003). As unique food and cuisine increase the destination image, they can turn this destination into an important attraction centre (Long, 2004). Over time, the positive food image of a destination contributes to destination marketing (Lai, et al., 2017; Lai et al., 2018).

Since tourism activities are experience-focused and show abstract properties, tourists tend to constantly search for information to decrease the predicted and perceived risks (Luo & Zhong, 2015). Tourists create a mental model (image) of the destination through the information they collect (Tapachai & Waryszak, 2000). Perceived image is regarded as more important by the tourists in the decision-making processes (Gallarza et al., 2002). Therefore, it can be seen that information sources are an important factor for creating an image (Baloğlu, 1997; Baloğlu, 2001; Baloğlu & McCleary, 1999; Gartner, 1993; Govers et al., 2007; Ji & Wall, 2014; Rodriguez-Santoz et al., 2011; Stabler, 1993).

With the development of information and communication technologies (ICT), tourists consult user-generated content (UGC) on social media to plan their travels and make decisions (Fotis et al., 2012). UGC can be described as the content such as photographs, video, music, and blogs that are created and updated by online participants (Fatanti & Suyadnya, 2015). Destinations use UGC to interact with online users and reflect unique service and travel experiences (Narangajavana et al., 2017). In recent years, social media (Instagram, Facebook, Twitter, etc.) with user-generated dynamic information is more preferred than traditional information sources (television, radio, banners, etc.) (Varkaris & Neuhofer, 2017).

“One photo is worth one thousand words” (Hanan & Putit, 2014). Instagram (Zadeh & Sharda, 2014) as one of the new and popular UGC platforms in digital tourism highly impacts tourists’ decision-making processes (Varkaris & Neuhofer, 2017). Investigating UGC to effectively assess the interest and attention of the tourists on social media provides insights and information to destinations for their activities.

Destination marketing, branding, and e-tourism topics are widely discussed in the literature. The majority of the studies in the literature analyse UGC by using Facebook (Isacsson & Gretzel, 2011; Sabate et al., 2014), Twitter (Hay, 2010; Sotiriadis & Van Zyl, 2013), TripAdvisor (Amaral et al., 2014; Ayeh et al., 2013) and YouTube (Kim, 2012) platforms or compare different applications (Smith et al., 2012). Although Instagram is important as a marketing tool (Djafarova & Rushworth, 2017), there are only a few studies in terms of destination food marketing and branding (Ye et al., 2017; Yu & Sun, 2019; Wong et al., 2019). There are limited information and ambiguity about the effective role of social media to promote and market local cuisine. Therefore, the purpose of this study is

to analyse user-generated content (photographs, likes, and hashtags) on social media platform Instagram to discover the most popular foods in the Turkish cuisine and to determine the most popular themes in a gastronomic sense. Obtained findings can present important data to effectively position and reposition Turkey's food image as an important tourism destination.

Literature Review

Food Image and Branding

Tourists might have positive, negative or neutral emotions towards a destination as their expected experience and image formed in their mind matches (Gartner, 1989) since human behaviours are based on subjective judgments (Tapachai & Waryszak, 2000) and perceptions rather than reality (Boulding, 1956). The image might influence the tourists at selection and purchasing stages as a guiding factor. In the touristic context, destinations can create a competitive advantage by reflecting high positive images (Pike & Ryan, 2004). Therefore, various destinations attempt for branding to create a reputation by using an image (Qu et al., 2011). It can be seen that branding is effective to develop a positive destination image for tourists (Blain et al., 2005).

Branding involves sketching the broad lines for a product and management process to develop a positive image to attract and maintain consumers (Low & Fullerton, 1994). Destination brands might contain elements such as symbols, logos, words, or differentiation graphics that define the destination (Blain et al., 2005). For example, Blinfelbt and Halkier (2013) found that Logstor, which is a small town in North Jutland, Denmark, symbolized brand image with "mussels". Within this context, it is important for individuals, society, and local governments to carry out successful activities in the creation and protection of the destination brand (Chen, 2012).

Food is regarded as a cultural destination element among the components that form the destination image (Beerli & Martin, 2004; Echtner & Ritchie, 2003). Additionally, food plays an important role to shape the destination image (Lai et al., 2018). Although food is a physiological need (Frochot, 2003), it can be seen as an element that supports the travel experience or the main motivation of travel (Quan & Wang, 2004). Accordingly, various studies in the literature have confirmed the relationships between food image and tourists' behavioural intention (visiting intention, re-visiting intention or intention to recommend to others) (Ab Karim et al., 2010; Leong et al., 2010) and the relationship between food image and tourist satisfaction (Ab Karim et al., 2010; Qing-Chi et al., 2013). Therefore, food image is effectively considered as a strategic management tool by the destinations with the importance of touristic travels.

In general, food image is investigated from the tourist perspective (demand) or destination perspective (supply) (Lai et al., 2018). As can be predicted, messages that represent the food image (encouraging new food ideas, strengthening some food consumption) can be intentionally reflected by the destination marketers via various information sources to attract potential tourists (Fisher et al., 2012). With the development of information technologies and more effective internet use by individuals for finding information, decreasing ambiguities and perceived risks (Gretzel & Yoo, 2008; Mackay & Vogt, 2012), social media use by destination is highly important to reflect the images online that might help destination branding. Social media is regarded as a transparent platform with more participants compared to traditional information sources (Ukpabi & Karjaluota, 2018; Zhou & Wang, 2014). Social media has capabilities such as attracting individuals with content, attracting social interactions,

maintaining by communicating with other members, and managing mutual relationships (Wang & Fesenmaier, 2004). Therefore, local administrations and destination marketers should be encouraged to use social media platforms effectively to accurately reflect a positive food image for destination marketing.

Method

Turkey welcomes tourists all around the world with the various popular destinations that have a historical and natural attraction. Generally, it can be seen that the international tourist profile is mainly sea-sand-sun (Türkben et al., 2012). However, Turkey has an important place among world cuisines. It is emphasized that one of the main reasons of re-visit intentions and general satisfaction of international tourists is the Turkish cuisine (Rimington & Yüksel, 1998). Gaziantep, Hatay, and Afyonkarahisar have been listed in “UNESCO Creative Gastronomy City” since 2015, 2017, and 2019 respectively (UNESCO, 2020). Therefore, Turkey as a tourism destination needs positioning and re-positioning works to be distinguished within the food branding context, which is an important cultural attraction element.

It is important to investigate how social media can be used effectively to promote the elements that contribute to the destination image. Therefore, the main purpose of this study is to discover the most popular foods in the Turkish cuisine by analysing UGC and analysing Instagram posts (photographs, likes, and hashtags) to determine the most popular themes within a gastronomical context. In other words, user-generated food posts, as well as likes and hashtags for these posts on Instagram, were analysed and the perceived food image of Turkey was evaluated from the user perspective.

In this study, “#turkishfood” hashtag was analysed since this hashtag had the highest number of posts and the power of presenting user perception towards Turkish cuisine was high. This study applied content analysis method among qualitative research methods, and answers for three main problems and sub-problems were investigated by using text mining and photo mining techniques under data mining.

1. What is the category frequency created by the photographs with “#turkishfood” hashtag posted by the users?
2. What is the like level in the “#turkishfood” hashtag post categories?
3. What is the other hashtags level in the “#turkishfood” hashtag post categories?
 - 3a. What is the relationship level between “#turkishfood” hashtag and other hashtags in the post categories?
 - 3b. What is the other hashtags usage frequency with the “#turkishfood” hashtag post categories?
 - 3c. What are the themes created by the other hashtags in the “#turkishfood” hashtag post categories?

Content analysis is used for transforming data into systematic and clear information (Schreier, 2014). Content analysis can be used for processing non-text data such as photographs (Billore et al., 2013). Content analysis is important for research as this method is suitable for large samples, provides systematic information, and provides validation and repetition under similar conditions. To analyse the UGC, data mining methods are used to help content analysis from online platforms (social media, websites, etc.) (Al-Daihani and Abrahams, 2016). Using innovative data mining techniques in data collection and analysis processes decrease the time and errors compared to traditional methods.

Model of Study

In today's world, it is necessary to obtain a high amount of information from the most resources and discover value-added information to make critical decisions (Aksu & Güzeller, 2019). Within this context, big data that represents a low cost, large volume, high-speed, and various information is important among data processing methods (Gandomi & Haider, 2015). While it is possible to obtain big data from various sources, social media data is highly important due to the unbiased representation of individual ideas, attitudes, and emotions. Therefore, to answer the problems and sub-problems expressed in the previous section, the social media platform Instagram was investigated, and the flowchart process is given in Fig. 1 by considering the social media analysis process (Fan & Gordon, 2014; Gandomi & Haider, 2015).

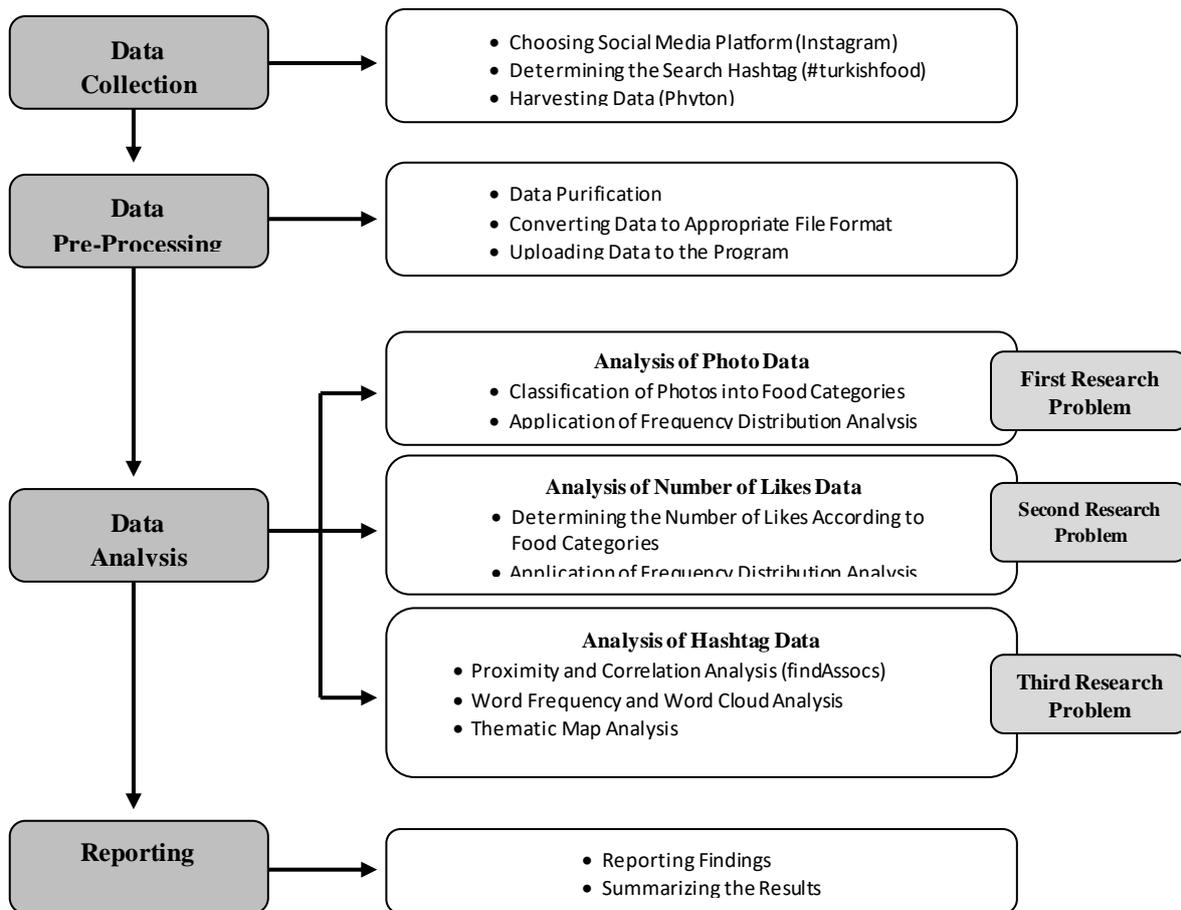


Fig 1. Study Flowchart Process

The study consists of four stages including data collection, data pre-processing, data analysis, and reporting (Fig. 1). The first two stages (data collection, data pre-processing) represent data methods including data obtaining, data storage, and preparing the data for analysis with supportive technologies. The last two stages (data analysis and reporting) represent techniques used in big data analysis and logical analysis representing the process for findings (Gandomi & Haider, 2015). These stages are explained in detail in the following sections.

Population and Sample

The study population is the user-generated contents on popular social media platform Instagram that represents Turkish cuisine. This study considered post content with frequently-used “#turkishfood” hashtag due to the

representative power of this hashtag of Turkish cuisine. This study used purposive sampling method among non-random sampling method since content related to foods representing Turkish cuisine were included and promotion-related (discount, draws, promotions, and ads) contents were excluded. Purposive sampling represents intention selection that does not include the entire population for the research problem due to participant properties (Pamuk, 2017). Within this context, 846051 posts created by users with the "#turkishfood" tag were reached on April 27, 2020. 1167 posts meeting the specified criteria were examined within the scope of the research. It was seen that 691 of these posts met all the criteria while 476 contained irrelevant photographs.

Data Collection Tool

Data collected from the social media platform Instagram was analysed by using the "Python" open-code program "Selenium", "BeautifulSoup", and "Pandas" packages. "Selenium" is a package that enables operating desired operations on internet browsers (Firefox, Google Chrome, etc.) to automatize these activities (Selenium, 2020). "BeautifulSoup" helps to separate HTML and XML data and data extraction (Mitchell, 2018). "Pandas" is a Python package for data processing, data extraction, and data storage (McKinney, 2012).

Data Collection Process

Instagram as a photograph and video-based social media application where images and comments can be shared rapidly on the platform is regarded in digital tourism as a popular tool where everyone can be a tourism expert (Hanan & Putit, 2014). Although Instagram was launched in 2010, it is one of the most popular social media platforms around the world (Benedek, 2018). 2019 statistical data show that the platform has 1 billion monthly active users and 500 million daily active users (Clement, 2019). It can be seen that Instagram is adopted and effectively used by tourists to share their travel experiences by others and destination marketers to promote the destination (Barbe et al., 2019). Kufie and Kesa (2020) found that users most commonly use Instagram to share their food experiences. A study in Portugal by Kuhzady and Ghasemi (2019) emphasized that food-beverages are among the most attractive image elements among the users.

Instagram was selected as a reference since this social media platform has the highest number of users in the digital world and it is popular among the young generation (Statista, 2020). To discover the UGC on Instagram, popular hashtags (#turkishfood, #turkishfoodie, #turkishfoodlover, etc.) were investigated. Since there were significant differences between the number of posts, user-generated content (photographs, likes, hashtags) under "turkishfood" hashtag with the highest number of posts (846051 posts) was included in the study for reliable and consistent data.

Data scraping on the web environment represents an automatic method to obtain a large amount of data from websites and social media platforms. To extract data from Instagram, codes were written on "Selenium", "BeautifulSoup" and "Pandas" packages of open-source program Python. By using Selenium package codes, automatic connections with designated Instagram accounts were obtained on the "Firefox" browser. Selenium Core runs a JavaScript code on a host computer and controls the tested web application by using the browser capabilities (Bruns et al., 2009). Data on social media platforms are referred to as unstructured data. "BeautifulSoup", which is a data scraping package, helps to collect the unstructured data from Instagram and to store it in a structured way. By using the Instagram bot created with the Selenium package, the last 1167 posts with "turkishfood" hashtag and other

contents linked to these posts (photographs, likes, and hashtags) were obtained. The data set was created under three titles such as photographs with “turkishfood” hashtag, likes, and texts (hashtags) on 27 April 2020 by using Instagram. Lastly, data collected with the “Pandas” library were processed and prepared for analysis in “xlsx” (Excel) format.

Data Pre-Processing

Photograph data were numbered (image 1, image 2 ...) and collected in a folder created for photography mining analysis. At the first stage, the data series (1167 posts) obtained under photography mining were analysed by the researchers. Researchers separated the relevant and irrelevant photographs in the data set for Turkish cuisine.

Texts with likes and hashtags were transferred to the “Excel” file as a corpus. First, all the character distortions, texts other than Latin letters, punctuations, corrupted data, and irrelevant posts outside the scope were cleared from the “Excel” data set. After the pre-cleaning process, a “tm package of the “R” package program was used (Feinerer & Hornik, 2019) to transform all capital and small letters and characters to plain text. Punctuations and figures in the data were removed and spaces were eliminated. These corrections were turned into a clean data set to be analysed with the “dplyr” package. Thus, three separate data sets which were photographs, likes, and hashtags were created before the analysis.

Data Analysis

Data mining techniques were used to interpret UGC on the popular social media platform Instagram. Two different techniques including text and photography mining were used since the analysed data set consisted of photographs and texts (likes and hashtags). After creating and cleaning the data set, data analysis was conducted in line with the research problem.

For the first research problem, by using the existing studies in the literature (Cömert & Alabacak, 2019; Eren & Çelik, 2017; Ergün & Öztürk, 2018; Şanlıer, 2005) and field knowledge of the researchers, Turkish cuisine classification categories and explanatory content were determined to classify the photographs. Photographs irrelevant with food were included under the “irrelevant photographs” title in the category to obtain interpretable findings. Categories and contents used for photograph classifications are given in Table 1. Photographs in 1167 posts in the data set were analysed by the researchers and classified in certain categories. In other words, Table 1 was used as the measurement criteria in data evaluation. Frequency distribution analysis was conducted to represent the photography data in terms of numbers and percentage and to determine the value distribution properties.

To answer the second research problem related to posting likes, the number of likes of the photographs separated into the food category in Table 1 were analysed. For each category, total likes and like levels were calculated. Frequency distribution analysis was used for the percentage of data.

Table 1. Food Categories and Contents Classifying Turkish Cuisine

Food Category	Category Content
Soups	- Cereal, pulses and dough soups, Meat and offal soups, Yogurt and milk soups, Chicken soups, Vegetable soups.
Meats	- Grills, Kebabs, Meatballs, Stews, Offals.
Seafoods	- Saltwater fish, Freshwater fish, Shellfish, Mollusk.
Vegetables	- Mousaka, Oturtma (a dish made of ground meat and vegetables), Mücver (vegetable patty), Pan Dishes, Silkme (vegetables and meat cubes first fried and then cooked in its own gravy, shaken at intervals), Olive oil Dishes, Dolma (stuffed vegetables) and Sarma (stuffed leaves).
Cereals	- Rice Dishes, Pastas, etc.
Dried Legume Foods	- Meat and Dried Legume Foods, Olive oil and Dried Legume Foods.
Salads	- Salads prepared with vegetables, Salads prepared with cereal or pasta, Salads prepared with dried legumes, Salads prepared with meat and offal, Salads prepared with seafood.
Mezes	- Hot and cold mezes.
Desserts	- Dairy desserts, Fruit desserts, Dough desserts, Cereal desserts.
Bakery and Pastry Products	- Bread, Pita, Donuts, Pies, Cakes, Cookies, Tarts and varieties.
Breakfast	- Contains photos of one or more of the breakfast products on the table (bread types, cookies types, donuts types, pastries types, cheese types, olive types, corn flakes types, salami and sausage types, jam and honey types, oil types, egg types, beverages, etc.).
Dinner	- It contains photographs of more than one food in different food categories on the table.
Irrelevant Photos	- Photos not related to food.

In line with the third research problem and sub-problems, the corpus was created by using a “tm” package to process hashtag texts, and a clean set was created and organized. The clean data set for the analysis contained text sentences written by each user for the Instagram post photograph. Since “#” was used at the beginning of a related word in hashtag use, hashtags obtained from the text sentences were created by the program to choose words with the hashtag (#) sign. To prevent any bias, “#turkishfood” hashtag in the hashtag data was determined as an exclusion criterion. 1167 posts with 100% sparsity created with “#turkishfood” hashtag and term-text matrix of 5544 obtained terms are given in Equation A1 (Appendix).

According to 3a sub-problem, proximity and correlation (findAssocs) analysis were conducted on processed data obtained with text mining by using a “tm” package on the “R” package program. “FindAssocs” statement is based on the standard “cor” function on the R statistic program (Feinerer & Hornik, 2019). With this operation, a tdm (term-document matrix) was created and numerical vector value covariances were divided to standard deviation to calculate a relationship (Shakeel & Karwal, 2016). “FindAssocs” command shows the correlation coefficient of a word and the relationship with other words in the term-document matrix. Correlation coefficients range between 0 and 1. As the frequency of having two words together increases, the correlation value is closer to 1.00 and when the frequency decreases, the correlation value is closer to 0.00. Therefore, correlation is a measurement showing how closely words are related to the corpus (Shakeel & Karwal, 2016). Codes used for the sub-problem “3a” are given in Equation A2 (Appendix). Terms with relationship ratio larger than 0.25 were investigated.

Word frequency and word cloud analysis were then conducted with a “word cloud” package for the sub-problem 3b (Fellow, 2018). Analysis inputs were transformed into a matrix. After transformation, term-document matrix counting and ranking processes were completed. Following this stage, hashtags with less than 40 repetitions were excluded from the analysis by considering the importance levels of the words. Word frequency code for sub-problem “3b” is given in Equation A3 and word cloud code is given in Equation A4 (Appendix).

Lastly, the “bibliometrix” package in R program was used to discover the social structure for the hashtags to better answer sub-problem 3c (Aria & Cuccurollo, 2020). Thematic map analysis was applied to the data by using this package.

Findings

Based on the main purpose of this study, Instagram posts were analysed to discover the most popular foods in the Turkish cuisine by analysing UGC and to determine the most popular themes within gastronomical context. Within this context, photographs, likes, and hashtags with “#turkishfood” hashtag were investigated. Photographs, likes, and hashtags were considered under different sections, and findings were presented.

Findings for Photographs

Instagram offers an effective role to collect and share photographs of food that reflect a destination (Ye et al., 2017). Photographs are interpreted more attractively, lively, and strongly than explanatory words and enrich the content (Guidry et al., 2014). In other words, photographs contain richer content than texts to share food experience (Hu et al., 2014). Within this context, 1167 photographs with “#turkishfood” hashtag with the highest number of posts reflecting Turkish cuisine were investigated. Photographs were clustered as user-generated content among created food categories (Table 1). Photograph frequency and percentages are given in Table 2.

Table 2. Clustering Results of Photographs Shared with “#Turkishfood” Hashtag

	Food Category	Frequency (f)	Percent (%)	Valid Percent (%)
Valid Data	Meats	187	16.02	27.06
	Bakery and Pastry Products	180	15.42	26.05
	Desserts	74	6.34	10.71
	Vegetables	68	5.83	9.84
	Cereals	58	4.97	8.40
	Breakfast	28	2.40	4.05
	Dinner	22	1.89	3.18
	Soups	19	1.63	2.75
	Seafoods	19	1.63	2.75
	Salads	16	1.37	2.32
	Mezes	11	0.94	1.59
	Dried Legume Foods	9	0.77	1.30
	Total Valid Data	691	59.21	100
Missing Data	Irrelevant Photos	476	40.79	
	GRAND TOTAL	1167	100	

When Table 2 shows Instagram photographs shared by users with “#turkishfood” hashtag is analysed, it can be seen that the majority of these photographs (40.79%) were lost data (irrelevant photographs) that are not related to food. Findings show that the relationship between used hashtags and shared photographs is weak. Users might use the irrelevant hashtag in the photographs to show them to and share them with more users. Therefore, hashtag and content match should be considered when user-generated content hashtags are investigated.

When the photograph clusters obtained from the popular relevant Turkish cuisine data (59.21%) was analysed (Table 2), it can be seen that the users share meat 27.06% (n=187), bakery and pastry products 26.05% (n=180), desserts 10.71% (n=74), vegetables 9.84% (n=68) and cereals 8.40% (n=58) on Instagram. On the other hand, food photographs in the other categories (breakfast, dinner, soups, seafoods, salads, mezes, and dried legume dishes) were

shared less frequently by the users (less than 5%). This shows that the users have developed higher and more positive images towards meats, bakery and pastry products, desserts, vegetables, and cereals in Turkish cuisine. At the same time, less frequent food shares in various categories might show that the users have a negative or neutral image or they have limited or no knowledge about the foods in these categories. It is important to investigate the reasons for the categories with limited photograph sharing.

Findings for Likes

A high number of likes on a social media post reflects the interest of the consumer (Sabate et al., 2014). It is necessary to consider the number of likes created as the user reaction to achieve successful branding and marketing strategies, and these likes show the popularity of the post on social media (Kumar & Mirchandani, 2012). The popularity of the post (likes) might have a positive impact on a brand (brand awareness etc.) or consumer behaviour (purchasing decision, customer loyalty, etc.) (Lin et al., 2017; Rapp et al., 2013). In this context, like levels of photographs in 1167 posts with “#turkishfood” hashtag in the food categories (Table 1) were analysed. Post like frequency and percentages are given in Table 3.

Table 3. Like Level of Posts Shared with “#Turkishfood” Hashtag for Categories

	Food Category	Number of Photos (f)	Number of Likes (f)	Average Likes (\bar{x})	Percentage of Average Likes (%)
Valid Data	Meats	187	14345	76.71	8.52
	Bakery and Pastry Products	180	25986	144.37	16.04
	Desserts	74	4791	64.74	7.20
	Vegetables	68	3343	49.16	5.46
	Cereals	58	4409	76.02	8.45
	Breakfast	28	2205	78.75	8.75
	Dinner	22	1756	79.82	8.87
	Soups	19	1462	76.95	8.55
	Seafoods	19	663	34.89	3.88
	Salads	16	906	56.63	6.29
	Mezes	11	954	86.73	9.64
	Dried Legume Foods	9	676	75.11	8.35
	Total Valid Data	691	61496		100
Total Average Likes			$\bar{x}=89.00$	$\bar{x}=8.33$	
Missing Data	Irrelevant Photos	476	38790	$\bar{x}=81.49$	
GRAND TOTAL		1167	100286	$\bar{x}=85.93$	

When the valid data findings for likes of posts shared with “turkishfood” hashtag were analysed (Table 3), it can be seen that average likes and frequency in food category shares did not have a parallel increase. While the meats have the highest frequency level, it can be seen that the average like level was 8.52% ($\bar{x}=76.71$). While bakery and pastry products have the second-highest frequency, the average like level of this category was at the highest level with 16.04% ($\bar{x}=144.37$). Mezes have the second-highest like percentage of 9.64% ($\bar{x}=86.73$) and share the frequency value of this group had the lowest value after dried legume food. Dinner (8.87%, $\bar{x}=79.82$), breakfast (8.75%, $\bar{x}=78.75$), soups (8.55%, $\bar{x}=76.95$), cereals (8.45%, $\bar{x}=76.02$) were the other food categories with relatively lower likes than average (8.33%, $\bar{x}=89.00$). Dried legume had the lowest frequency value while the like value was closer to the average likes (8.35%, $\bar{x}=75.11$). Desserts (7.20%, $\bar{x}=64.74$), salads (6.29%, $\bar{x}=56.63$), vegetables (5.46%, $\bar{x}=49.16$), and sea products (3.88%, $\bar{x}=34.89$) had the lowest like levels respectively.

Findings for Hashtags

Instagram hashtags help users to classify the photographs and reflect their emotions about these photographs (Hu et al., 2014). At the same time, hashtags enable users with similar interest areas to communicate. Hashtags are distinguished as an important element to develop the online personality of a user (Lang & Wu, 2011). Within this context, analysing the existing popular hashtags in UGC is important to increase content visibility and transferring the content to more users. Within this context, other hashtags used in photographs with “#turkishfood” hashtag that reflect the foods in the Turkish cuisine were analysed.

To provide information to more users and increase interaction, it is important for users to use hashtags highly related to the hashtags in the post. While this increases destination food recognition by the users, it can also support a positive perception of the food. Therefore, the relationship between other hashtags used with “#turkishfood” hashtag was analysed for sub-problem “3a”, and the results are given in Table 4.

Table 4. Relationship Between “#Turkishfood” and Other Hashtags

#turkishfoodinqatar 0.72	#turkishfoodfestival 0.70	#turkishfoodindubai 0.70
#turkishfoodlove 0.70	#turkishfooddrink 0.70	#turkishfoodromania 0.69
#turkishfoodblogger 0.68	#turkishfoodbucharestaurant 0.68	#turkishfoodmelbourne 0.66
#turkishfoodie 0.62	#turkishfoodporn 0.59	#turkishfoodiftar 0.32
#chickenmeatball 0.31	#danakofte 0.31	#danakoftemenu 0.31
#danakoftesi 0.31	#fatihyemekleri 0.31	#istanbulgurme 0.31
#istanbulgurmesi 0.31	#istanbulgurmesiii 0.31	#turkeymeatball 0.31
#turkishfoodinkuwait 0.31	#turkishfoodschannel 0.31	#atpazari 0.30
#yemekburdayenir 0.30	#baranetmangal 0.29	#bbq 0.29
#kebab 0.29	#fatih 0.28	#turkishfoodisthebest 0.28
#gurme 0.27	#turkishfoodculture 0.26	#mangal 0.25

When Table 4 is analysed, high relationship with “#turkishfoodinqatar” (0.72), “#turkishfoodindubai” (0.70), “#turkishfoodromania” (0.69) and “#turkishfoodmelbourne” (0.66) show the positive image of Turkish cuisine in other destinations. Additionally, this can show that using these hashtags can indicate Turkish cuisine food consumption in these destinations. The high relationship between “#turkishfoodfestival” (0.70) and “#turkishfood” hashtag might show the positive image of Turkish cuisine festivals. Additionally, the lack of negative hashtags shows that general image perception for Turkish cuisine is positive.

Popular hashtags used by the users represent the user attitudes towards food. By using the frequently used hashtags, destinations can generate positive images for food branding. For this purpose, the usage frequency of other hashtags with “#turkishfood” hashtag for sub-problem “3b” is shown in Table 5. Words in the term-document matrix are listed in descending order.

Table 5. Frequency of Other Hashtags Used with the “#Turkishfood” Hashtag

#Hashtag	Frequency (f)	#Hashtag	Frequency (f)	#Hashtag	Frequency (f)
#turkishfoodrecipe	570	#turkishfoodisthebest	487	#food	340
#turkishfoodlove	276	#foodie	260	#turkish	249
#foodlove	171	#foodphotography	153	#foodporn	142
#delicious	138	#turkishfoodporn	137	#yummy	121
#instafood	119	#turkey	117	#foodstagram	113
#eat	107	#turkishcuisine	105	#istanbul	99
#foodblogger	90	#turkishfoodie	86	#foodgasm	84
#deliciousfood	75	#homemade	70	#kebab	69
#restaurant	67	#turkishfoodblogger	65	#meat	64
#yemek	64	#foodpic	62	#turkishfoodindubai	60
#turkishfooddrink	59	#turkishfoodfestival	56	#borek	55
#turkishfoodchef	55	#turkishfoodinqatar	55	#turkishkitchen	54
#daphnerestaurant	52	#turkmutfagi	52	#atasehirevyemekleri	51
#healthyrecipe	51	#daphnecaferestaurant	50	#homemadefood	49
#kofte	49	#turkishfoodromania	49	#turkyemekleri	49
#atasehirdaphnecaferestaurant	48	#turkishfoodbucharestaurant	48	#aysenuraltan	47
#recipe	47	#instagood	46	#turkishfoodmelbourne	46
#dessert	45	#evyemekleri	45	#turkiye	43
#breakfast	41	#cook	41	#healthyfood	41
#subscribe	41	#salad	40		

When Table 5 is analysed, it can be seen that the top 5 hashtags used with “#turkishfood” hashtag were “#turkishfoodrecipe” (n=570), “#turksihfoodisthebest” (n=487), “#food” (n=340), “#turkishfoodlove” (n=276) and “#foodie” (n=260). The findings show that users use emotional hashtags (#turkishfoodlove etc.) that reflect their feelings, mood, and emotions with non-emotional hashtags (#food) that give data, information, answer object, value or concepts (Scherer, 2005; Stephen & Saejoon, 2003). At the same time, positive word usage shows that users developed positive attitudes towards Turkish cuisine.

Word cloud analysis after frequency count plays an important role in data mining. Word cloud is a visualization tool that shows how frequently a word is used in the text body (Carter et al., 2014). Word cloud was generated to show the words with at least 20 repetitions and to show at most 100 words to prevent the high number of words and structural problems. The analysis presents an image that shows the dominant aspects of the general structure of other hashtags used with “#turkishfood” hashtag (Fig. 2).

Themes on the top right corner of the thematic mapping are known as “motor themes” and represent both high centrality and density. This means these themes are important for the research field (Estrada, 2017). When Fig. 3 is analysed, it can be seen that “#turkishfood” and “#nefisyemektarifleri” hashtags are in this quarter and these are among the important themes. It can be seen that “#turkishfood” theme and hashtags were more dominant since it involves the most repeated hashtag themes. Themes on the bottom right corner are known as “basic themes” and this represents high centrality and low density. Fig. 3 shows that the “#food” theme and hashtags related to this theme are in this quarter. Since foods are the main research area, this finding is natural. Themes on the top left corner are known as “very special themes” or “niche themes”, and this represents well-developed connections (high density) but irrelevant outer connections (low centrality). Therefore, elements in this quarter have limited importance (Estrada, 2017). Analysis results showed that the “#foodphotography” theme and contents were in this quarter and had limited importance. Themes in the bottom left are known as “emerging and disappearing themes”, and this represents less developed and extreme elements, which mean low centrality and density. “#turkishisthebest” and “#restaurant” themes were among the emerging and disappearing themes.

Keyword analysis forms the first indicators for user destination food image with the increasing importance of certain hashtags over time. It is important to use hashtags with themes that have high centrality and density (#turkishfood) to use destination foods on Instagram to use it as a branding element for current images of the users or to shape the images in the positive direction. Additionally, “#food” and “#foodphotography” themes contain the hashtags that have a development potential. While the identified hashtags increase the destination food recognition by the users, they can also support the positive images. At the same time, effective usage of hashtags can help to create destination food image or to increase this image for less-known foods.

Result

In this study, user-generated content (photographs, likes, and hashtags) on the social media platform Instagram was analysed to discover the most popular foods in the Turkish cuisine and to determine the most popular gastronomic themes. User posts shared with “#turkishfood” hashtag that represents the Turkish cuisine as a popular hashtag were analysed with photograph mining and text mining techniques among data mining methods. This study determines the user image perception for Turkish cuisine food and obtained data provides insights to destination marketing professionals to use reflected food image as a branding element.

In today’s world, communication with social media seems inevitable (Narangajavana et al., 2017). While Instagram meets the social needs of individuals for communication and self-representation (Ye et al., 2017), it is one of the easiest platforms for multi-dimensional communication (Wang et al., 2016). Additionally, users use social media to strengthen social relationships, create their images, reflect their feelings, archive themselves and to share information (Liu et al., 2019; Wang et al., 2016; Wong et al., 2019). Compared to the advertisement with mass communication tools, UGC is considered more reliable (Fotis et al., 2012). Within this context, information obtained from social media platforms are important for destinations to define hidden risks and potential opportunities, evaluate the performance and create competitive advantage (Mirzaalian & Halpenny, 2019). Destinations should well reflect their food-related images on social media as a branding element.

Analysis results obtained in this study with photography mining techniques showed that users share more photographs in meats, bakery and pastry products, desserts, vegetables, and cereals. This finding shows that the foods

in these categories are more popular and have a high positive image (Table 2). Additionally, likes assessed based on the photographs in the same category showed that bakery and pastry and mezes categories had high like levels. The non-linear relationship between photography sharing frequency and likes in categories other than bakery and pastry products might be caused by the social media platform structure. Still, the lack of negative hashtags in the results obtained with text mining showed that Turkish cuisine food generally had a positive food image among users. Accordingly, using highly related hashtags, frequently used hashtags, and hashtags with highly important motor themes by the destinations can positively impact food image and help to distribute the information faster and to larger masses.

Destination management organizations and marketing professionals should use user-generated content more effectively to create strategies to make their brands more visible and reliable (Ana & Istudor, 2019). Within this context, destinations should maintain strong sides and improve weak sides within the strategies to present a better image for the users. Destinations should use the information obtained from social media to create new content. Active, comfortable, and effective interaction of the users with destinations (Wang et al., 2016) impact the purchasing decision as well as the general satisfaction level (Narangajavana et al., 2017). The analysis showed that there are no official social media accounts for Turkish cuisine. Creating and developing an official social media account is important to create or improve the food brand image for Turkish cuisine. Findings obtained from user-generated content analysis in this study contribute to this purpose and provide information for strategic branding works on destination food. Activities play a vital role in destination success (Kuhzady & Ghasemi, 2019).

The limitation of this study is the assessment of Turkish cuisine food on Instagram and content created with “#turkishfood” hashtag (photographs, likes, and hashtags) on a certain date. The data obtained from photography mining and data analysis on likes are limited with the created categories. Also, this study only considered individual users for UGC. Since internet users above 50 years old tend to not enjoy social media platforms and 83% of the users are between 18-29 years old (Hanan & Putit, 2014), this study reflects the views of generation Y and Z. Due to the impossibility of distinguishing real and fake accounts on Instagram, users were assumed as real individuals. It is important to analyse other content (comment texts, comment numbers, etc.) in addition to photographs, likes, and hashtags created by the users to determine the image elements reflecting the Turkish cuisine. User content from other platforms (Instagram, Facebook, Twitter, etc.) for destination foods should be compared and their contribution to the image should be discussed. Additionally, future studies should investigate the shares by considering the cultural differences and demographic properties of the users, and these shares should be classified.

Conflict of Interest

None of the authors has received research grants from any Company toward the submitted manuscript or have any conflict of interest.

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REFERENCES

- Ab Karim, M. S., Lia, C. B., & Salleh, H. (2010). Malaysia as a culinary tourism destination: International tourist's perspective. *Journal of Tourism, Hospitality and Culinary Arts*, 1(3), 63-78.
- Aksu, G., & Güzeller, C. O. (2019). Büyük veri: Sosyal bilimler ile eğitim bilimlerinde kullanımı ve uygulama alanları. *Mediterranean Journal of Humanities*, 9(1), 13-26.
- Al-Daihani, S. M., & Abrahams, A. (2016). A text mining analysis of academic libraries' tweets. *The Journal of Academic Librarianship*, 42(2), 135-143.
- Amaral, F., Tiago, T., & Tiago, F. (2014). User-Generated content: Tourists' profiles on tripadvisor. *International Journal of Strategic Innovative Marketing*, 1(3), 137-45.
- Ana, M. I., & Istudor, L. G. (2019). The role of social media and User-Generated-Content in millennials' travel behavior. *Management Dynamics in the Knowledge Economy*, 7(1), 87-104.
- Aria, M., & Cuccurullo, C. (2020). Package 'bibliometrix'. <https://cran.r-project.org/web/packages/bibliometrix/bibliometrix.pdf>, (Date of access: 18.06.2020).
- Ayeh, J. K., Au, N., & Law, R. (2013). Predicting the intention to use Consumer-Generated media for travel planning. *Tourism Management*, 35, 132-43.
- Baloğlu, S. (2001). Image variations of Turkey by familiarity index: Informational and experiential dimensions. *Tourism Management*, 22(2), 127-133.
- Baloğlu, S., & Brinberg, D. (1997). Affective image of tourism destinations. *Journal of Travel Research*, 35(4), 11-15.
- Baloğlu, S., & McCleary, K. W. (1999). A model of destination image formation. *Annals of Tourism Research*, 26(4), 868-897.
- Barbe, D., Neuburger, L., & Pennington-Gray, L. (2019). Follow us on Instagram! Understanding the driving force behind following travel accounts on instagram. *e-Review of Tourism Research (eRTR)*, 17(4), 592-609.
- Beerli, A., & Martin, J. D. (2004). Factors influencing destination image. *Annual of Tourism Research*, 31(3), 657-681.
- Benedek, I. (2018). Instagram as a tool for destination Branding –Case study on the major cities of Romania. *Journal of Media Research*, 11(2), 43-53.
- Billore, S., Billore, G., & Yamaji, K. (2013). The online corporate branding of banks – A comparative content analysis of Indian and Japanese banks. *Journal of American Business Review*, 1(2), 90-96.
- Björk, P., & Kauppinen-Räsänen, H. (2016). Local Food: A source for destination attraction. *International Journal of Contemporary Hospitality Management*, 28(1), 177-194.
- Blain, C., Levy, S. E., & Brent Ritchie, J. R. (2005). Destination branding: Insights and practices from destination management organizations. *Journal of Travel Research*, 43(4), 328-338.

- Blichfeldt, B. S., & Halkier, H. (2013). Mussels, tourism and community development: A case study of place branding through food festivals in rural North Jutland, Denmark. *European Planning Studies*, 22(8), 1587-1603.
- Boulding, K. E. (1956). *The image: Knowledge and life in society*. Ann Arbor MI: University of Michigan Press, United States.
- Bruns, A., Kornstadt, A., & Wichmann, D. (2009). Web application tests with selenium. *IEEE Software*, 26(5), 88–91.
- Büyüköztürk, Ş. (2018). *Sosyal bilimler için veri analizi el kitabı*. Ankara: PEGEM Akademi.
- Callon, M., Courtial, J. P., & Laville, F. (1991). Co-Word analysis as a tool for describing the network of interactions between basic and technological research: The case of polymer chemistry. *Scientometrics*, 22, 155–205.
- Carter A. Hunt, J. G., & Lan X. (2014). A visual analysis of trends in the titles and keywords of Top-Ranked tourism journals. *Current Issues in Tourism*, 17(10), 849-855.
- Chen, N. (2012). Branding national images: The 2008 beijing summer Olympics, 2010 Shanghai World Expo, and 2010 Guangzhou Asian Games. *Public Relations Review*, 38(5), 731–745.
- Clement, J. (2019). *Instagram – Statistics & Facts*. <https://www.statista.com/topics/1882/instagram/> (Date of access: 20.05.2020).
- Cobo, M. J., López-Herrera, A. G., Herrera-Viedma, E., & Herrera, F. (2011). “An approach for detecting, quantifying, and visualizing the evolution of a research field: A practical application to the fuzzy sets theory field”. *J Informetrics*, 5(1): 146–66.
- Cobo, M. J., Martínez, M. A., Gutiérrez-Salcedo, M., Fujita, H., & Herrera-Viedma, E. (2015). 25 Years at Knowledge-Based systems: A bibliometric analysis. *Knowl-Based Syst*, 80, 3–13.
- Cohen, E., & Aviele, N. (2004). Food in tourism: Attraction and impediment. *Annals of Tourism Research*, 31(4), 755-778.
- Cömert, M., & Alabacak, C. H. (2019). Türk mutfağına ait yemeklerin özelliklerinin değerlendirilmesi: Ankara ili örneği. *Journal of Tourism and Gastronomy Studies*, 7(3), 2123-2143.
- Djafarova, E., & Rushworth, C. (2017). Exploring the credibility of online celebrities’ Instagram profiles in influencing the purchase decisions of young female users. *Computers in Human Behavior*, 68, 1–7.
- Echtner, C. M., & Ritchie, J. R. B. (2003). The meaning and measurement of destination image. *Journal of Tourism Research*, 14(1), 37-48.
- Eren R., & Çelik M. (2017). Çevrimiçi gastronomi imajı: Türkiye restoranlarının tripadvisor yorumlarının içerik analizi. *Turizm Akademik Dergisi*, 4(2), 121-138.
- Ergün, Ö. Ö., & Öztürk, B. (2018). An ontology based semantic representation for Turkish cuisine, *26th Signal Processing and Communications Applications Conference (SIU)*, Izmir, 1-4.
- Estrada, S. (2017). Qualitative analysis using R: A free analytic tool. *The Qualitative Report*, 22(4), 956-968.
- Fan, W., & Gordon, M. D. (2014). The power of social media analytics. *Communications of the ACM*, 57(6), 74–81.

- Fatanti, M. N., & Suyadnya, I. W. (2015). Beyond user gaze: How Instagram creates tourism destination brand?. *Procedia - Social and Behavioral Sciences*, 2(11), 1089–1095.
- Feinerer, I., & Hornik, K. (2019). *Package 'tm'*. <https://cran.r-project.org/web/packages/tm/tm.pdf>, (Date of access: 27.05.2020).
- Fisher, H., Du Rand, G., & Erasmus, A. (2012). The power of food images to communicate important information to consumers. *International Journal of Consumer Studies*, 36(4), 440-450.
- Fotis, J., Buhalis, D., & Rossides, N. (2012). Social media use and impact during the holiday travel planning process. *Information and Communication Technologies in Tourism*, 13–24.
- Frochot, I. (2003). An analysis of regional positioning and its associated food images in French tourism regional brochures. *Journal of Travel & Tourism Marketing*, 14(3-4), 77-96.
- Gallarza, M. G., Saura, I. G., & Garcia, H. C. (2002). Destination image towards a conceptual framework. *Annals of Tourism Research*, 29(1), 56-78.
- Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, 35(2), 137–144.
- Gartner, W. (1993). Image formation process. *Journal of Travel and Tourism Marketing*, 2(2/3), 191-215.
- Gartner, W. C. (1989). Tourism image: Attribute measurement of state tourism products using multidimensional techniques. *Journal of Travel Research*, 28(2), 16-20.
- Govers, R., Go, F. M., & Kumar, K. (2007). Promoting tourism destination image. *Journal of Travel Research*, 46(1), 15-23
- Gretzel, U., & Yoo, K.H. (2008). Use and impact of online travel reviews, in En O'Connors, P., Hopken, W. y Gretzel, U. (Eds), *Information and Communication Technologies in Tourism*, Springer, Vienna, 35-46.
- Guidry, J. D., Messner, M., Jin, Y., & Medina-Messner, V. (2015). From #McDonalds Fail to #Dominossucks: An Analysis of Instagram Images About The 10 Largest Fast Food Companies. *Corporate Communications: An International Journal*, 20(3), 344-359.
- Hanan, H., & Putit, N. (2013). Express marketing of tourism destinations using instagram in social media networking. *Hospitality and Tourism*, 471–474.
- Hay, B. (2010). Twitter Twitter – But who is listening? a review of the current and potential use of Twittering as a tourism marketing tool. *Paper presented at the 20th International Research Conference: 'Challenge the Limits'*, University of Tasmania, Australia, February 8-11
- Henderson, J. C. (2009). Food tourism reviewed. *British Food Journal*, 111(4), 317-326.
- Hu, Y., Manikonda, L., & Kambhampati, S. (2014). What we Instagram: A first analysis of Instagram photo content and user type. *8th International Conference on Weblogs and Social Media*, 34(3), 21-24.
- Isacsson, A., & Gretzel, U. (2011). Facebook as an edutainment medium to engage students in sustainability and tourism. *Journal of Hospitality and Tourism Technology*, 2(1), 81-90.

- Ji, S., & Wall, G. (2014). Understanding supply- And Demand-Side destination image relationships. *Journal of Vacation Marketing*, 21(2), 205–222.
- Kim, J. (2012). The institutionalization of YouTube: From user- generated content to professionally generated content. *Media, Culture & Society*, 34(1), 53-67.
- Kipper, L. M., Furstenau, L. B., Hoppe, D., Frozza, R., & Iespen, S. (2019). Scopus scientific mapping production in industry 4.0 (2011–2018): A bibliometric analysis. *International Journal of Production Research*, 1–24.
- Kivela, J., & Crofts, J.C. (2006). Tourism and gastronomy: Gastronomy's influence on how tourists experience a destination. *Journal of Hospitality and Tourism Research*, 30(3), 354-377.
- Kuhzady, S., & Ghasemi, V. (2019). Pictorial analysis of the projected destination image: Portugal on Instagram. *Tourism Analysis*, 24(1), 43–54.
- Kumar, V., & Mirchandani, R. (2012). Increasing the ROI of social media marketing. *MIT Sloan Management Review*, 54(11), 55–61.
- Lai, M. Y., Khoo-Lattimore, C., & Wang, Y. (2017). Food and cuisine image in destination branding: Toward a conceptual model. *Tourism and Hospitality Research*, 0(0), 1-14.
- Lai, M. Y., Khoo-Lattimore, C., & Wang, Y. (2018). A perception gap investigation into food and cuisine image attributes for destination branding from the host perspective: The case of Australia. *Tourism Management*, 69, 579-595.
- Lang S., & Wu, F. (2011). Anti-Preferential attachment: If I follow you, Will you follow me?. *2011 IEEE third international conference on social computing (socialcom)*, 339–346.
- Leong, Q. L., Ab Karim, M. S., Othman, M., Mohd, A. N., & Sridar, R. (2010). Relationships between Malaysian food image, tourist satisfaction and behavioral intention. *World Applied Sciences Journal*, 10(10), 164-171.
- Lin, H.-C., Swarna, H., & Bruning, P. F. (2017). Taking a global view on brand post popularity: Six social media brand post practices for global markets. *Business Horizons*, 60(5), 621–633.
- Liu, X., Mehraliyev, F., Liu, C., & Schuckert, M. (2019). The roles of social media in tourists' choices of travel components. *Tourist Studies*, 20(1), 27-48.
- Long, L. M. (2004). Culinary tourism: A folkloristic perspective on eating and otherness. L. M. Long (Ed.), *Culinary Tourism*. The University Press of Kentucky, USA, 20-50.
- Low, G. S., & Fullerton, R. A. (1994). Brands, brand management, and the brand manager system: A critical-historical evaluation. *Journal of Marketing Research* 31(2), 173–190.
- Luo, Q., & Zhong, D. (2015). Using social network analysis to explain communication characteristics of travel-related electronic Word-Of-Mouth on social networking sites. *Tourism Management*, 46(0), 274–282.
- Mackay, K. Y., & Vogt, C. (2012). Information technology in everyday and vacation context. *Annals of Tourism Research*, 39(3), 1380-1401.

- Mankan, E. (2012). *Yabancı turistlerin türk mutfağına ilişkin görüşleri: Ege Bölgesi Örneği* (Doktora Tezi). Ankara Üniversitesi, Fen Bilimleri Enstitüsü, Ankara.
- McKercher, B., Okumus, F., & Okumus, B. (2008). Food tourism as a viable market segment: It's all how you cook the numbers!. *Journal of Travel & Tourism Marketing*, 25(2), 137-148.
- McKinney, W. (2012). *Python for data analysis: Data wrangling with Pandas, Numpy, and Ipython*. O'Reilly Media, Inc., United States of America.
- Mirzaalian, F., & Halpenny, E. (2019). Social media analytics in hospitality and tourism: A systematic literature review and future trends. *Journal of Hospitality and Tourism Technology*, 10(4), 764-790.
- Mitchell, R. (2018). *Web scraping with Python: Collecting more data from the modern web*. O'Reilly Media, Inc., United States of America.
- Narangajavana Kaosiri, Y., Callarisa Fiol, L. J., Moliner Tena, M. Á., Rodríguez Artola, R. M., & Sánchez García, J. (2017). User-Generated content sources in social media: A new approach to explore tourist satisfaction. *Journal of Travel Research*, 58(2), 253-265.
- Pamuk, S. (2017). Arşivsel örnekleme yöntemlerinin arşiv serileri/sınıfları üzerinde uygulanması. *Bilgi ve Belge Araştırmaları Dergisi*, 8, 1-41.
- Pike, S., & Ryan, C. (2004). Destination positioning analysis through a comparison of cognitive, Affective and conative perceptions. *Journal of Travel Research*, 42(4), 333-342.
- Qing-Chi, C. G., Chua, B. L., Othman, M., & Ab Karim, S. (2013). Investigating the structural relationships between food image, food satisfaction, culinary quality, and behavioral intentions: The case of Malaysia. *International Journal of Hospitality & Tourism Administration*, 14(2), 99-120.
- Qu, H., Kim, L., & Im, H. H. (2011). A model of destination branding: Integrating the concepts of the branding and destination image. *Tourism Management*, 32(3), 465-476.
- Quan, S., & Wang, N. (2004). Towards a structural model of the tourist experience: An illustration from food experiences in tourism. *Tourism Management*, 25(3), 297- 305.
- Rapp, A., Beitelspacher, L. S., Grewal, D., & Hughes, D. E. (2013). Understanding social media effects across seller, retailer, and consumer interactions. *Journal of the Academy of Marketing Science*, 41(5), 547-566.
- Rimington, M., & Yüksel, A. (1998). Tourist satisfaction and food service experience: Results and implications of an empirical investigation. *Anatolia: An International Journal of Tourism and Hospitality Research*, 9(1), 37-57.
- Rodriguez-Santos, M. C., González-Fernández, A. M., & Cervantes-Blanco, M. (2011). Weak cognitive image of cultural tourism destinations. *Quality & Quantity*, 47(2), 881- 895.
- Rozin, E., & Rozin, P. (1981). *Culinary themes and variations*. *Natural History*, 90(12): 6- 14.
- Sabate, F., Berbegal-Mirabent, J., Cañabate, A., & Lebherz, P. R. (2014). Factors influencing popularity of branded content in Facebook fan pages. *European Management Journal*, 32(6), 1001-1011.

- Sabate, F., Berbegal-Mirabent, J., Cañabate, A., & Lebherz, P. R. (2014). Factors influencing popularity of branded content in Facebook fan pages. *European Management Journal*, 32(6), 1001–1011.
- Şanlıer, N. (2005). Yerli ve yabancı turistlerin türk mutfağı hakkındaki görüşleri. *Gazi Eğitim Fakültesi Dergisi*, 25(1), 213-227.
- Scherer, K. R. (2005). What are emotions? and how can they be measured?. *Social Science Information*, 44(4), 695-729.
- Schreier, M. (2014). Ways of doing qualitative content analysis: Disentangling terms and terminologies. *Forum: Qualitative Social Research*, 15(1), 1-27.
- SELENIUM (2020). <https://selenium-python.readthedocs.io/> (Date of access: 20.05.2020).
- Shakeel, M., & Karwal, V. (2016). Lexicon-based sentiment analysis of Indian Union Budget 2016–17. 2016 *International Conference on Signal Processing and Communication (ICSC)*, Noida, 299-302.
- Smith, A. N., Fischer, E., & Yongjian, C. (2012). How does Brand-Related User-Generated content differ across YouTube, Facebook, and Twitter?. *Journal of Interactive Marketing*, 26(2), 102-13.
- Sotiriadis, M. D., & Van Zyl, C. (2013). Electronic Word-of-Mouth and online reviews in tourism services: the use of Twitter by tourists. *Electronic Commerce Research*, 13(1), 103-24.
- Stabler, M. (1993). The image of destination regions: Theoretical and empirical aspects. Goodall, B. ve Ashworth, G. (Ed.), *Marketing in the Tourism Industry the Promotion of Destination Regions*, Routledge, UK. 133-160.
- STATİSTA (2020). <https://www.statista.com/statistics/253577/number-of-monthly-active-instagram-users/> (Date of access: 20.05.2020).
- Stephen B. W., & Saejoon K. (2003). *Fundamentals of codes, graphs, and iterative decoding*. Springer, 135-151.
- Tapachai, N., & Waryszak, R. (2000). An examination of the role of beneficial image in tourist destination selection. *Journal of Travel Research*, 39(1), 37-44.
- Türkben, C., Gül, F., & Uzar, Y. (2012). Türkiye’de bağıcılığın tarım turizmi (Agro-Turizm) içinde yeri ve önemi, *KMÜ Sosyal ve Ekonomik Araştırmalar Dergisi*, 14(23), 47-50.
- Ukpabi, D. C., & Karjaluoto, H. (2018). What drives travelers’ adoption of User-Generated content? A literature review. *Tourism Management Perspectives*, 28, 251-273.
- UNESCO (2020). <https://en.unesco.org/creative-cities/creative-cities-map> (Date of access: 20.05.2020).
- Varkaris, E., & Neuhofer, B. (2017). The influence of social media on the consumers’ hotel decision journey. *Journal of Hospitality and Tourism Technology*, 8(1), 101–118.
- Wang, S., Kirillova, K., & Lehto, X. (2016). Travelers’ food experience sharing on social network sites. *Journal of Travel & Tourism Marketing*, 34(5), 680–693.
- Wang, Y., & Fesenmaier, D. R. (2004). Modelling participation in an online travel community. *Journal of Travel Research*, 42(3), 261-270.

- Wong, I. A., Liu, D., Li, N., Wu, S., Lu, L., & Law, R. (2019). Foodstagramming in the travel encounter. *Tourism Management*, 71, 99–115.
- Ye, Z., Hashim, N. H., Baghirov, F., & Murphy, J. (2017). Gender differences in Instagram hashtag use. *Journal of Hospitality Marketing & Management*, 27(4), 386–404.
- Yoo, K. H., & Gretzel, U. (2011). Influence of personality on travel-related consumer-generated media creation. *Computers in Human Behavior*, 27(2), 609–621.
- Yu, C.-E., & Sun, R. (2019). The role of Instagram in the UNESCO's creative city of gastronomy: A case study of macau. *Tourism Management*, 75, 257–268.
- Zadeh, H. A., & Sharda, R. (2014). Modeling brand post popularity dynamics in online social networks. *Decision Support Systems*, 65, 59–68.
- Zhou, L., & Wang, T. (2014). Social media: A new vehicle for city marketing in China. *Cities*, 37, 27–32.

APPENDIX**Equation A1.** Term-Text Matrix Related to Data Obtained from “#Turkishfood” Hashtag

```
cleanset <- tm_map(cleanset, stripWhitespace)
tdm <- TermDocumentMatrix(cleanset)
tdm
## <<TermDocumentMatrix (terms: 5544, documents: 1167)>>
## Non-/sparse entries: 17023/6452825
## Sparsity : 100%
## Maximal term length: 98
## Weighting : term frequency (tf)
```

Equation A2. Affinity and Association Analysis Equation for “#Turkishfood” Hashtag and Other Hashtags

```
findAssocs(tdm, "turkishfood", .25)
$turkishfood
```

Equation A3. Frequency Count Equation for “#Turkishfood” Hashtag and Other Hashtags

```
w <- rowSums(tdm)
w <- subset(w, w>=40 )
sort(w, decreasing = T)
```

Equation A4. Word Cloud Equation for “#Turkishfood” Hashtag and Other Hashtags

```
library(wordcloud)
w <- sort(rowSums(tdm),decreasing = TRUE)
set.seed(222)
wordcloud(words = names(w),
  freq = w,
  max.words = 100,
  random.order = FALSE,
  min.freq = 20,
  colors = brewer.pal(8, "Dark2"),
  scale = c(5, 0.3),
  rot.per = 0.3)
```