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ORIGINAL RESEARCH

Can Google Trends data provide information on consumer's perception regarding hotel brands?

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Abstract
Previous studies show that search engine query data is a valuable predictor for tourism demand forecasting. The goals of this study are to identify the current positions of hotels in the perception of the customer and to propose a method for practitioners to increase the visibility of consumer's mind perception of hotel brands. The study used volume of travel queries 30 hotel chains in the Turkey constructed from Google Trends and analyzed search query time series data (2014–2018). To visualize the position of brands was conducted social network analysis techniques. The results show that search engine query data regarding hotels reveal the positioning consumer's mind of hotels. The study offers that Google Trends data is useful. In addition, the study proposes a method for practitioners. Tourism businesses could use search engine data to reveal its place in the consumer's mind and change the consumer perception over the years.

Keywords Search engine data · Google Trends · Tourists' perception · Perceptual mapping · Social network analysis (SNA)

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1 Introduction

In recent years, consumers' searches on the Internet have played an important role in their purchasing decisions. Searching for information on search engines reduces consumers' uncertainty in purchase-related decision-making, maximizes their satisfaction, and takes less time (You et al. 2015). Google's search engine gathers the web search traffic information of individuals and provides it in Google Trends. Google Trends launched by Google in 2006. It can be filtered by category, search type, geographic location and time range. Google Trends provides unfiltered sample of actual search requests made to Google. It shows the relative search volume of popular search terms over time and so reflects individuals' interest by particular search terms across different regions and topical domains (Höpken et al. 2019). Search engine data have helped researchers to investigate a variety of past and now issues and to forecast future trends (Padhi and Pati 2017). Google Trends makes an index for user's search intensity based on over the time period requested in a geographical area. It is scaled from 0 to 100. Zero shows that searches made by very few people. However, 100 shows that the day had the most searches for the specific term. A search-term query returns searches for an exact search-term (in any language). However, a topic query returns related search-terms.

The search query data are important for both researchers and practitioners because they provide more information about consumer search behaviors. Therefore, the data attract their attention (Jun and Park 2017; Dinis et al. 2019). Yang et al. (2014) stated that search engine data offer important advantages such as revealing preferences in real time, providing data at a relatively high frequency, and tracking changes in consumers' preferences.

Search engine actively used by most people at least a few times. People have done 40.000 search every second on average, 3.5 billion searches per day and 1.2 trillion searches per year worldwide on Google (Livestats 2020). People have used search engines to get information about brands, services, campaigns and customer comments in the many sectors such as food, health, transportation, banking, tourism. This study was conducted on the tourism sector.

Tourism sector is also important it in Turkey as it is important in many countries (France, Italy, Spain etc.). Currently, Turkey generates only a small share of the world's tourism, yet there is tourism potential in Turkey. Although Turkey's total tourism income was \$13.854 billion in 2003, this figure was \$29.512 billion in 2018 (TÜRSAB 2019). The figure was \$34.5 billion in 2019 (Anadolu Ajansı 2020). The number of tourists in Turkey rank it eighth in the world and fourteenth in terms of tourism revenue (T.C. Kültür ve Turizm Bakanlığı 2019). When the global tourism movements are examined, it reached 1.5 billion people with an increase of 3.8% compared to the previous year (in 2019) while the number of people participating in international tourism movements in 2005 was 807 million (World Tourism Organization 2020a). In addition, Murugan (2013) forecasts a global shift in opted destination of global tourism by 2030 (specifically, a 27% growth in emerging economies).

Currently, the COVID-19 pandemic has negative impact on tourism sector around the world. According to The World Travel and Tourism Council (WTTC)'s

Economic Impact Report; the travel and tourism sector suffered US$4.5 trillion Travel Tourism GDP loss in 2020. This is relative to a 3.7% GDP decline of the global economy. In addition, domestic traveler spending decreased by 45% while international visitor spending decreased by 69.4% as a result of COVID-19. Moreover, 62 million jobs were lost around the world (− 18.5%). In Turkey, total travel and tourism GDP change (in 2020) is 54.2%, share of total travel and tourism spending 2020 is 47.2% for domestic and 52.8% for international. The sector spending change 2020 is for domestic 41.8% and for international 65.2% (WTTC 2021). UNWTO Panel Experts foresee a rebound in tourism, in the third quarter of 2021 and a return to before pandemic 2019 levels not before 2023 (World Tourism Organization 2020b).

This study deals with both the visualization of a brand and the change of a brand in the consumer's mind. The main objective of the study is to evidence that consumers' web search traffic information can be operating to derive relationships among brands. This is the first study to try investigating consumer's brand perception based on search volume time series (Turkey location) of Google Trends and perhaps to use social network analysis in perceptual mapping in tourism. Its contribution helps both researchers and practitioners. It demonstrates that search engine query data can be used to microscopically evaluate the positions of hotel brands and their relationship in consumers' minds. The study distinguishes itself from previous literature because prior studies show that search engine query data can be used to macroscopically evaluate. The present study also offers a method for practitioners.

2 Literature review

2.1 Search engine and positioning

Researchers in different fields examine search engines in terms of design, evaluation, user behavior, marketing, and implications (Ginsberg et al. 2009; Jun et al. 2014; Jun and Park 2016). Information scientists focus on user behavior, whereas computer scientists focus on the algorithms for ranking (Pan 2015). The global search engine market share of Google is 92.41% in March 2021(StatCounter 2021). Google is widely used by people because the search algorithm of Google is superior (Youn and Cho 2016).

Online search data represent the attention individuals pay to specific topics (Li and Law 2019). Previous research show that search engine query data has been used to forecast a variety of things, such as unemployment (Choi and Varian 2012; Suhoy 2009), housing (McLaren and Shanbhogue 2009; Wu and Brynjolfsson 2009), gun sales (Scott and Varian 2013), automobile purchases (Carriere-Swallow and Labbe 2011; Jun 2012), tourist inflow (Park et al. 2017; Artola and Martinez Galán 2012), diseases (Ginsberg et al. 2009; Althouse et al. 2011), auto, house, retail and tourism (Choi and Varian 2009), feature films, video games and rank of song on the Billboard Hot 100 chart (Goel et al. 2010), private consumption (Schmidt and Vosen 2011), TV market (Youn and Cho 2016), algorithm offer (Fang and Chen 2016) and more. As can be seen from the above studies, many studies started to pay attention to Internet search data in terms of forecasts. This is because the Internet is the main source for consumers. Thus, Internet search keywords may be strongly correlated with consumer's current and future purchase behavior (Park et al. 2017).

When entering their research words on a browser, a consumer may use a single keyword to that end, but also often enter more than one keyword to look for related information (a simultaneous search). The reason why a consumer carries out a simultaneous search is because they want to compare two brands in order to get information about the similarities and differences, or achieve to have more detailed information on certain aspects of a brand. According to web search traffic information, the quantity of simultaneous searches by means of using certain keywords gets increased when the consumer thinks that the relationship is closer, and it is possible to derive the relationship between the keywords by means of collecting this relational data and, making them subject to a SNA (Jun and Park 2017).

A consumer, who wants to buy a product, is inclined to search for information by means of using only a single representative keyword in an early stage, but after they get a certain amount of information, they enter more than one keywords in order to find detailed information about the features of a product. For example, when iPhone 6 was released (or when it was announced that it would be released), consumers first searched for the keyword "iPhone 6" to get a basic understanding of the features it was supposed to deliver. After a certain amount of information was obtained, they started to enter more keywords such as "iPhone 6 design" or "iPhone 6 display" in order to get more specific information about this product. A consumer from time to time concurrently entered two or more products for their search in order to compare them and, used phrases such as "iPhone 6 Galaxy S5". When the two or more keywords that a consumer is possibly to enter for search are considered, it is highly possible that they make a search for a specific product together with a term for a feature that interests them. That is to say, it is highly possible that a consumer carries out a simultaneous search which includes product features they are included to associate with a specific brand (Jun and Park 2017).

The studies on search query data can be categorized into two fields. The first field comprise of empirical evidences that indicate how search query data may be used to make forecasts social phenomena (e.g. the buying power of consumers). Second field research focuses on operating search query data to, examine consumer behavior and track changes in consumers' expectations. There are fewer studies in the second field (Jun and Park 2017). Dinis et al. (2019) have examined literature published (2006–2018), that used search engine data (Google Insights) on tourism and hospitality research. According to research findings, web search engine was used only a study while 12% of the literature was mentioned Google Trends. Besides, they find that Google Trends use has increased significantly from 2012 to 2017. Especially, the increase is observed for tourism forecasting; knowing the interest of users' searches; displaying the relationship between tourism statistics and the search volume index of Google Trends. Even though number of studies using this data in tourism and hospitality research increase, there are still them relatively scarce, remaining largely unknown to practitioners and researchers (Dinis et al. 2019).

Recently, search engines have been examined by researchers to better understand travelers' behavior (Bangwayo-Skeete and Skeete 2015; Bokelmann and Lessmann

2019; Rivera 2016; Yang et al. 2015) because travelers use search engines as a major tool in planning trips, including for accommodations, attractions, and dining (Dergiades et al. 2018; Pan et al. 2006). Research aims to accurately forecast consumer behavior through various techniques using effective resources and determining pricing strategies (Song and Li 2008). Yang et al. (2015) said that researchers adopted two main methods: time series or statistics (e.g., Bangwayo-Skeete and Skeete 2015; Bokelmann and Lessmann 2019; Rivera 2016; Yang et al. 2015) and artificial intelligence methods (e.g., Chen et al. 2005; Chen and Wang 2007; Law and Au 1999).

Studies have also examined patterns in online travel queries across destinations. Xiang and Pan (2011) found that the ratio of travel queries related to a specific city was based on the touristic popularity of the city, and keywords in travelers' queries showed their knowledge of the city and its competitors. Bokelmann and Lessmann (2019) examined the spurious patterns for several German holiday regions. Researchers evidence that the Google Trends time series they operate share specific patterns with Google Trends time series used in previous studies, involving several studies unconnected to the tourism sector. They found that artefacts as spurious patterns (downward trends and breaks in 2011 and 2016) have a negative effect on forecasting. They offer a method to sanitize Google Trends data and decrease the negative effect of spurious patterns. Moreover, Dergiades et al. (2018) examined the effect of language bias and platform bias on search intensity indices, took by search platforms. They arranged search intensity indices using bias correction approaches and compared with search intensity indices not bias correction approaches. They stated that search engine volume indices arranged for different search languages and platforms is preferable to non-arranged indices for predicting international visitor volume.

Forecasting of visitor volume through search engine query data is important. However, the data can be used to track changes in consumers' preferences in real time. Thus, businesses can indirectly evaluate the positioning of each brand in the consumer mind. Nowadays, businesses use search engine optimization technique to advance the ranking of websites based on user's keyword search on a search engine and increase their website traffic (Schultz 2020), that is to say, the technique helps businesses attract customer (Sheffield 2020). Businesses have learned about positioning of keywords in the consumer mind through search engine optimization technique.

The positioning is defined by Ries and Trout as follows: "Positioning is not what you do to a product. But what you do to the mind of the prospect. That is, you position the product in the mind of the prospect" (as cited in Saxena 2008). It is the way the target market perceives the product's place in a particular market and is the place in the perceptual map of consumers (Blythe 2014). The concept is important as it is a source of competitive advantage for businesses (Porter 1980). Lewis (1985) proposed an approach (i.e. determining perceptual difference among competing brands and examining performance of a brand based on customer) of analysis to discover positioning in the hospitality sector. Some studies conducted research on positioning in the tourism field using various techniques such as multidimensional scaling, importance-performance analysis, and factor analysis. Businesses can use brand position to determine their strengths and weaknesses through perceptual maps and can change the positions of the brands over time (Kim et al. 2007). In addition, many studies have examined the concept, using collected data with survey technique to constitute perceptual maps (Lewis 1990). The perceptual maps have been used as a tool by which to understand the characteristics and different factors that represent the perception of a business (Lewis 1984). Accurately forecasting brand position is very important for businesses. This study explored the positions of specific tourism destinations in the minds of consumers using the social network analysis (SNA) technique.

2.2 Social network analysis centrality measures

SNA is based on network theory. The theory posits a person's relationships and connections with others (Valente 2010). The SNA technique was introduced in sociology and then evolved into other usage fields over the years. The greatest advantage of the technique is used relational data. Relational data can be acquired from the contacts, ties, connections, which exist between two entities. The data show the degree of relations among people and organizations (Jun and Park 2017).

A network status is mainly intended to count, map and analyze the patterns of connections between the elements of any system, whether it is natural, artificial, social, ecological or economic, which could be modelled as an ensemble of distinct elements of players (the nodes or vertices of the network, as connected by the relationships existing between them (the links or edges), which can also carry a weight (cost, importance etc.) or be asymmetric (the connection has a direction). These studies are based on the methods of the mathematical graph theory, which, however, have had a number of improvements, variations and expansions providing a large number of metrics to measure static and dynamic features and, produce statistical models for the evolution of the systems that are considered (Baggio and Fuchs 2018; Newman 2010).

In order to elicit and analyze brand association networks from consumers, Henderson et al. (1998) applied various concepts and methods used in network analysis by means of working from the premise that consumers' brand associations also form network structures. A network analysis' greatest advantage is that consumers are allowed to compare more than one brand at the stage of identifying brand associations. We are able to concurrently elicit associations in connections with multiple brands rather than only to a single brand by means of using these types of similarities and differences. The company has to carry out an analysis on the associations which consumers have in relation to its own brand, and those associations that relate to competitors in order to set advertising and marketing strategies for a brand. A network analysis offers very useful information about how a consumer perceives the company's brand in relation to competing brands, and establishes the associations that must be aimed to ensure improvement or reinforcement in order to deal with these requirements. Besides, there is another advantage that makes this method a strong practical utility, and it is the ease through which matrices are used to create association networks (Jun and Park 2017).

The analysis provides useful information in terms of defining brand associations about multiple brands rather than only single in the minds of consumers (Jun and Park 2017). Based on search query data, this research examined consumer perception in relation to hotels and the changes in this perception over the years.

The SNA centrality measures were used to analyze the networks. The centrality analysis allows us to observe the importance and effect of each node and, the ability to bind the other nodes of the network and thus helps us identify the importance of each actor in the entire network (Baggio and Fuchs 2018). This study focuses on the degree, betweenness, closeness and the eigenvector centralities.

2.3 Degree centrality

With respect to a social network, the incoming connection represents a connection from i to j, while the outgoing connection represents a connection from j to i. Considering the scope of the research, the in-degree of the Hilton hotel corresponds to the total number of searches for X Hotel Hilton Hotel at Google Trends. And the out-degree of the Hilton hotel corresponds to the search frequency for "Hilton Hotel X Hotel". The all degree centrality, on the other hand, is the sum of the in-degree and out-degree centralities. As is seen, the in-degree and out-degree centrality, which is an important concept for a friendship network, is not as important as for hotel searches. As a matter of fact, the sums of the input and output searches were considered due to a great level of similarity. This value is important since it will show us how many searches are made for the Hilton hotel together with the other hotels.

The node degree is the number of the direct connection that a node has (Newman 2010), i.e. the degree of a hotel on the network shows the number of searches for it together with the other hotels. The normalized degree centrality preferred by the SNA software programs such as Pajek and Ucinet represents the connections in terms of percentages. A higher degree centrality means a stronger actor (David-Negre et al. 2018). The degree centrality of the different nodes in a network indicates the difference of connectivity with a wider target system and, thus the popularity of various positions (Van Der Zee and Bertocchi 2018). The degree centrality equals to the number of connections of an actor with the other actors (Otte and Rousseau 2002). On a non-directional binary chart, the actor degree centrality measures the extent of the connection of a node with the other nodes in the social network. On a non-directional chart with the actor *n*, the degree centrality for the actor *i* is calculated by means of adding the direct connections of the *i* with the other $n - 1$ actor.

$$C_{Di} = \text{the degree of the node } i$$

The calculation of the value C_D is based on the sum of all the cell inputs in the rows and columns on the sociomatrix of each actor *i*. The actor degree centrality does not only reflect the connectivity of each node with the other nodes, but also is based on the value *n* (the network size). That is to say, the bigger the network is, the higher the possible maximum degree centrality value gets. Therefore, a certain degree centrality value indicates that either an actor has a lot of connections in a small network or it has only a few connections in a large network. A normalized measure is suggested by Wasserman and Faust (1994) to eliminate the effect of the variability of the network size in terms of the degree centrality:

$$C'_{Di} = \frac{C_{Di}}{n-1}$$

2.4 Closeness centrality

Defined as the distance measure from an edge to the other edges, the closeness centrality is completely different from the other centrality measures (Newman 2010). The closeness centrality has been developed as to reflect how close a node in a social network is to the other nodes therein. The closeness is of more general since it takes into account the structural position of the actors in the entire network. A higher closeness for an actor means that the actor is connected to the others with a fewer number of ways (Otte and Rousseau 2002). The closeness and distance indicate how fast an actor establishes an interaction with the others. Considering the binary search networks for hotels, the closeness centrality represents the centrality in terms of accessibility.

Considering a geodesic distance from i to j (the shortest path), which means the number of the edges across the path, as d_{ij}, the closeness centrality is calculated using the following formula:

$$C_C = \frac{1}{\sum_j d_{ij}}$$

Since the average distance C_C represents lower values for more central edges and, higher values for less central edges unlike the other measures, it is not the centrality measure in the same meaning as the other measures mentioned in this section. Therefore, the researches in the SNA literature generally calculate the opposite of the value C_C instead of itself. And this is called the closeness centrality C_{C_i}: (Newman 2010):

$$C_{C_i} = \frac{1}{C_C} = \frac{n}{\sum_j d_{ij}}$$

2.5 Betweenness centrality

The betweenness centrality is an important indication of the control of the excessive information exchange or source flow in a network (Knoke and Yang 2008). This measure is based on the number of the shortest paths through an actor. An actor with a higher betweenness centrality value plays a role to connect different groups and acts as an "intermediary" (Otte and Rousseau 2002). A hotel with a higher betweenness centrality is the key point of a network since it is on the shortest path between the other node pairs and thus connects different groups to one another (David-Negre et al. 2018).

Considering the cluster of all the geodesic paths available in a network, the betweenness centrality of the edge i is defined as the number of the said paths through the edge i. (Newman 2010). The number of geodesic paths from n^i_{st}, s to t through i and, g_{st} the number of geodesic paths from s to t, the betweenness centrality of the edge i is calculated using the following formula (Newman 2010).

$$C_B = \sum_{st} \frac{n^i_{st}}{g_{st}}$$

where, if both the value n^i_{st} and the value $\mathrm{g_{st}}$ is zero, then $\mathrm{n^i_{st}/g_{st}} = 0$. In some cases, it is appropriate to normalize the betweenness centrality value. There are many standard computer programs concerning network analyses such as Pajek and UCINET to carry out these normalizations. It is generally normalized by means of dividing the number of paths by the sum of the (regulated) edge pairs n^2 (Newman 2010).

2.6 Eigenvector centrality

In numerous cases, a connection to a popular person is more important than the one to an alone person. The eigenvector centrality network metric considers not only the number of connections that a vertex has (ie. its degree), but also the centrality of the vertices connected thereto (Hansen et al. 2020). Referring to the idea that a player is more central if the player has a relationship with the players that are themselves central, one could argue that the centrality of some nodes do not only depend on the number of adjacent notes, but also on the value of centrality pertaining thereto (Ruhnau 2000).

The calculation of the eigenvector centrality is shown by Bonacich (1972) as follows: A_{ij} To show the contiguity matrix, the x_i centrality of the edge i being proportional to the sum of the i contiguity centralities, the eigenvector centrality.

$$x_i = \kappa_1^{-1} \sum_j A_{ij} x_j$$

3 Methodology

The study uses the simultaneous searches for hotels obtained through the Google Trends. A simultaneous search is when a user makes a search on Google, e.g. typing 'Hilton Hotel Radisson Hotel' and, these search statistics are measured on the Google Trends.

The process to obtain data for the research is as follows: On Google Trends, the following options are ticked off: date, region (Turkey) and "travel". Then, hotels are searched simultaneously and as binaries. Google Trends provide weekly search

Table 1 Simultaneous search percentages for the hotels Radisson and Hilton in 2014

Date	Percent	Date	Percent	Date	Percent	Date	Percent
5.01.2014	31	6.04.2014	0	6.07.2014	34	5.10.2014	35
12.01.2014	0	13.04.2014	62	13.07.2014	45	12.10.2014	62
19.01.2014	29	20.04.2014	32	20.07.2014	34	19.10.2014	93
26.01.2014	30	27.04.2014	31	27.07.2014	41	26.10.2014	0
2.02.2014	43	4.05.2014	0	3.08.2014	72	2.11.2014	0
9.02.2014	31	11.05.2014	64	10.08.2014	52	9.11.2014	30
16.02.2014	93	18.05.2014	100	17.08.2014	34	16.11.2014	31
23.02.2014	45	25.05.2014	0	24.08.2014	34	23.11.2014	29
2.03.2014	30	1.06.2014	31	31.08.2014	33	30.11.2014	0
9.03.2014	30	8.06.2014	33	7.09.2014	0	7.12.2014	29
16.03.2014	0	15.06.2014	34	14.09.2014	0	14.12.2014	44
23.03.2014	30	22.06.2014	35	21.09.2014	33	21.12.2014	29
30.03.2014	40	29.06.2014	0	28.09.2014	0	28.12.2014	29
Total for 2014: 1677							

trends. The values shown on a weekly basis are expressed in percentages. Therefore, a weekly search frequency could be of 100 at maximum. Google Trends provides information on the number of searches for a certain term in relation with the total number of searches that are performed on Google. On a scale from 0 to 100 where each point on the graph is divided by the highest point or 100, the data is normalized and presented accordingly. A line trending downward means that the relative popularity of a search term is getting decreased, not necessarily that the total number of searches for that term is getting decreased, but that compared to other searches, the popularity is shrinking (Google News Initiative 2021).

The values for all the weeks obtained were summed up and gathered together in a matrix where binary searches are shown for all the hotels. For example, the value 1677, which shows the simultaneous search values for the hotels Radisson and Hilton in 2014, was obtained as follows: As seen on the Table 1, the percentages of the simultaneous searches for the hotels Radisson and Hilton in 2014 are obtained separately on a weekly basis. And the sum of all the weeks resulted in the value 1677. This value is recorded on the intersection for Radisson*Hilton on the matrix for simultaneous searches in 2014. For the search for Hilton and Radisson, the same was repeated and resulted in the value 1754. This matrix is not symmetric. This provided a directional network. Therefore, this value is on the intersection for Hilton*Radisson. Repeating the same for all the binary hotel searches, the matrixes created for each year were analyzed by SNA.

The article's research method is based on the frequency of binary searches made over Google Trends. Therefore, each node within the social network represents a hotel brand. On the other hand, the connection (weight) between two nodes is related to the search frequency of words and it is calculated as follows:

Considering the year of 2018, let's assume that the first node represents the X hotel and the second node represents the Y hotel. By selecting the "travel" option in the year of 2018 over Google Trends, "X Hotel Y Hotel", "Y Hotel X Hotel", "X Hotel Y", "Y Hotel X", "X Y Hotel" and "Y X Hotel" searches were obtained separately.

The data were obtained through two phases when identifying the hotel brands used for simultaneous binary searches as obtained on the Google Trends. The total number of chain hotels was 60, 44 of which were local, in Turkey as of 2018 (Horwath 2019). The first 30 hotels on the list of domestic and foreign chain hotels in 2020 issued by the Hotel Associations of Turkey (TUROB) were considered, and a new list was created consisting of the chain hotels with more facilities. For example, the hotels Novotel, Ibis and Rixos under the Accor hotel chains were included into the study as the sub-brands according to the number of facilities thereof. Therefore, the 30 brands with the highest number of facilities in Turkey were analyzed under this study.

This study selected 30 chain hotels (see Table 2)—those with the highest number of hotels in Turkey—and analyzed them.

The research was made in both Turkish and English. Although it is not possible to identify whether the searcher is a Turkish citizen or foreign national, the IP address used for the search is in Turkey, i.e. the searches were made within the borders of Turkey. In other words, a limitation was set in terms of country to Turkey while choosing the Google searches on the Google Trends. The searches from abroad were excluded. In order to make sure that the sample cluster is appropriate for the SNA, only the chain hotels serving in Turkey are considered in order to avoid the formation of a sparse network consisting of a great number of chain hotels operating in different countries. The second reason is that we attempt that the results are turned into meaningful information that would increase the profitability levels of the hotels. That is to say, a hotel brand in Turkey would like to identify its position among the hotel brands serving within the borders of Turkey.

Binary searches were made over Google Trends. The reason is that the adjacency matrix used in social network analysis is a nxn dimension square matrix where: each i line and each j column represents a node, and the cell shown with (ij) represents a connection made from i to j (Newman 2010). The matrix is therefore two-dimensional and each cell, which is located on the junction point of the lateral and horizontal axes, shows the weight between two nodes. In this case, it is impossible to obtain these results using network analysis even one looks at the search frequency between more than two hotels.

The data were collected within a period of 3 months between June and August in 2019. However, it should be stated that the search frequencies on the Google Trends are valid for the entire year. That is to say, the result of the search "X Hotel Y Hotel" on the Google Trends for 2018 was not restricted to certain months, and it covers all the days in 2018.

The centrality measures that are the most frequently used ones in the literature were taken into considered in the scope of the research: degree, closeness, betweenness and eigenvector centralities (David-Negre et al. 2018), and the hotels with the highest centrality measures were ranked accordingly. The similar practices are adopted in the literature. During a study when David-Negre et al. (2018) analyzed the use by European tourists of the e-tourism platforms, they put in order the

Table 2 Characteristics of hotel chains

Hotel group	Hotel chain type	The hotel number of chains	The number of rooms
Amara	Domestic chain	5	2496
Anemon	Domestic chain	18	1919
Barut	Domestic chain	12	3716
Cactus	Domestic chain	7	1189
Crowne Plaza	Foreign chain	8	2251
Crystal	Domestic chain	14	7769
Dedeman	Domestic chain	17	2737
Delphin	Domestic chain	7	3918
Divan	Domestic chain	19	2512
Eftalia	Domestic chain	7	2858
Elite World	Domestic chain	7	1632
Euphoria	Domestic chain	4	1522
Grand Park	Foreign chain	4	–
Hilton	Foreign chain	63	12,674
Holiday Inn	Foreign chain	16	2097
Ibis	Foreign chain	15	2003
Kaya	Domestic chain	12	3745
Larissa	Domestic chain	14	3856
Limak	Domestic chain	9	3007
Novotel	Foreign chain	6	–
Orka	Domestic chain	6	1031
Paloma	Domestic chain	8	2585
Radisson	Foreign chain	10	2590
Ramada	Foreign chain	33	8319
Rixos	Domestic chain	23	8908
Sentido	Foreign chain	12	3300
Sheraton	Foreign chain	7	–
The Green Park	Domestic chain	7	1811
Titanic	Domestic chain	13	3546
Voyage	Domestic chain	6	1950

platforms used by the tourists according to the degree, betweenness and closeness centralities. On the network analyses made use of by Van Der Zee and Bertocchi (2018) to understand how the relational data analysis of the content created by the TripAdvisor Users facilitates the decision-making on a tourism destination, they put in order the locations with the highest degree centralities. In order to assess the basic characteristics of a tourist destination, Éber et al. (2018) analyzed the websites of the tourism stakeholders by means of a hyperlink network analysis, and identified the most effective (prominent) plays on the multi-target network by means of using an 'importance index' defined as the geometric average of the (normalized) centrality metrics such as degree, eigenvector and clustering coefficients. As is seen, the important actors on a network are identified by means of putting in order the nodes with the highest centrality measures. The hypothesis tests are used when an analysis is carried out on the relations of the centrality measures of the actors and the different variants on a SNA (Francalanci and Hussain 2016). Since the analyzed network is in fact an observation and, this is in general a research environment for a network analysis, we may not rely on sampling from multi observations and, subsequent probability and statistical meaningfulness statements. Therefore, a network analysis is based on the idea of permutation and on the possibility of an observed network appearing if there are many networks created with the same basic data (Farine 2017).

The data were limited to the travel search option of Google Trends and to online searches conducted from 2014 to 2018 by consumers in Turkey. The data were collected year by year by the researchers without any programs using browser's incognito mode. Browser does not store one's browsing history, cookies, site data, and so on, in incognito mode. However, incognito mode does not offer complete privacy. Your IP address and other information can be recorded and seen by the websites you visit (Haberturk 2021). Thus, some steps were carried out to provide privacy. Firstly, the browsing data were cleared from the browser. Secondly, the study was used a virtual private network (VPN). VPN can be defined as a service that protects your internet connection and online privacy. It creates an encrypted tunnel for your data, protects your online identity by hiding your IP address, and allows you to securely use internet. We used to Avast SecureLine VPN. The study was hidden IP address, was created virtual IP and was determined location as Istanbul, Turkey by VPN. Lastly, antivirus program was used for internet security and privacy. The study used SNA to reveal the perception of the network among the hotel brands. SNA was conducted on a time series (2014–2018) to track the changes in status of each hotel brand over time. The Gephi software package was used to analyze the social network relationships. The Gephi software allows the visualization and analysis of networks of various sizes using network metrics (Nuss et al. 2016).

4 Results

The results of the SNA performed using the volume of simultaneous searches for hotel brands are shown in Table 3. Although some hotels are located centrally, others fall outside the network depending on the degree of weakness of the connections. The Hilton, Ramada, Rixos, and Radisson brands have more intense connections in the network compared to other brands. Hilton (26,840), Ramada (22,716), and Rixos (18,368) are the hotel brands with the highest output (outgoing) connection weights of SNA in 2014. This means that there are 26,840 searches for the Hilton hotel together with another hotel chain in 2014 in Turkey. The connection numbers of the other hotels are interpreted in a similar manner.

The input (incoming) connection weights are Hilton (24,207), Ramada (22,352), and Rixos (21,920), respectively. The total link weight for 2014 is 235,657. As shown in Table 3, the Ramada, Hilton, Dedeman, and Radisson brands have more

Table 3 Total outgoing and incoming connections in the networks

Hotels	2014		2018		2014–2018	
	Outgoing connection	Incoming connection	Outgoing connection	Incoming connection	Outgoing connection	Incoming connection
Amara World	2416	3494	5734	4158	21,366	23,839
Anemon	4219	4506	8528	9182	32,463	33,119
Barut	7735	7122	11,414	13,867	49,105	54,363
Cactus	0	0	0	0	0	0
Crowne Plaza	7012	5763	6714	4947	30,223	30,223
Crystal	14,775	13,153	18,647	15,898	84,117	73,173
Dedeman	11,828	14,889	14,155	13,905	64,875	71,272
Delphin	4827	5418	6157	5987	31,293	29,970
Divan	8184	9044	10,660	11,154	45,606	48,975
Eftalia	737	899	1105	1758	4391	5404
Elite World	1733	1733	2690	2745	10,049	11,394
Euphoria	0	963	0	791	0	4212
Grand Park	3031	4268	9105	7603	24,864	29,807
Hilton	26,840	24,207	34,994	34,313	145,085	142,008
Holiday Inn	8450	7010	10,933	8563	45,948	40,768
Ibis	7209	7530	8666	10,878	39,616	41,985
Kaya	5883	5191	4279	5975	25,564	26,426
Larissa	0	0	0	0	0	0
Limak	11,465	11,453	12,072	11,260	57,146	56,904
Novotel	3204	4284	6539	7100	22,581	23,579
Orka	436	349	1162	1162	5233	5348
Paloma	3123	2708	5409	5708	25,683	23,662

Table 3 (continued)

Hotels	2014		2018		2014–2018	
	Outgoing connection	Incoming connection	Outgoing connection	Incoming connection	Outgoing connection	Incoming connection
Radisson	14,391	12,130	20,891	19,908	87,150	78,550
Ramada	22,716	22,352	29,942	30,530	125,996	122,763
Rixos	18,368	21,920	16,440	21,069	90,965	97,026
Sentido	5553	3323	5683	6157	26,011	25,461
Sheraton	12,828	13,073	15,291	15,053	70,117	69,984
The Green Park	3808	3278	6773	5678	27,932	24,375
Titanic	15,562	16,296	17,412	17,414	80,278	82,781
Voyage	9324	9301	10,638	9270	51,495	47,781
Total	235,657		302,033		1,325,152	

Table 4 Comparison of general properties of networks

	2014	2015	2016	2017	2018	2014–2018
Density	0.230	0.240	0.237	0.262	0.254	0.262
Average degree	6.660	6.960	6.860	7.600	7.360	7.600
Average weighted degree	7776.460	8335.760	7724.030	10,106.000	9955.100	43,604.730
Average cluster coefficient	0.569	0.582	0.580	0.597	0.587	0.604
Average path length	1.940	1.930	1.940	1.890	1.910	1.900

intense connections in the network compared to the other brands. Hilton (34,994), Ramada (29,942), and Radisson (20,891) are the hotel brands with highest output (outgoing) connection weights of SNA in 2018. The input (incoming) connection weights are Hilton (34,313), Ramada (30,530), and Rixos (21,069), respectively. The total link weight for 2018 is 302,033 (Table 3).

The network views for 2014–2018 show that very close networks were obtained. Hilton (145,085), Ramada (125,996), and Rixos (90,965) are the hotel brands with highest output (outgoing) connection weights of SNA in 2014–2018. The input (incoming) connection weights are Hilton (142,008), Ramada (122,763), and Rixos (97,026), respectively. The total link weight for 2014–2018 is 1,325,152 (Table 3).

Table 4 shows the general characteristics of the networks for simultaneous searches by years.

Considering the density values, which are the ratio of the number of actual connections with the number of possible connections as shown in the Table 4, it is seen that the simultaneous search network for 2017 is the densest network (0.262). This means that this year was the year when the highest number of searches were made for the respective hotels. On the other hand, the average degree represents the number of binary searches and, it is seen that this had the highest value in 2017 on the networks as an analysis by years. The average weighted degree is a measure that takes into consideration not only the number but also the weights of the connections. In other words, in case of a search for the Hotel X and the Hotel Y simultaneously, it gives this degree (1) and, the number of simultaneous searches for the Hotel X and the Hotel Y (e.g. if they are searched together for 100 times) gives this weighted degree. It is also seen that the average weighted degree values are higher in 2017. The average path length, which is defined as the average number of steps across the shortest paths for all the possible node pairs in the network topology, and the clustering coefficient, which is a measure of how an actor in the network is interlocked with the adjacent actors, show similarity in terms of years.

The results for all degree centralities by year are shown in Table 5. According to the table, all degree centralities are, respectively, Hilton (40; 40; 39; 40), Ramada (34; 34; 34;38), and Radisson (28; 29; 28; 31) in 2014, 2015, 2016 and 2017; Hilton (41), Ramada (35), and Titanic (29) in 2018; and Hilton (40), Ramada (39), Radisson (29), and Titanic (29) in 2014–2018. The hotel names between 2014 and 2018 are sized as per height of the degree centrality values in the network and, shown in Fig. 1.

Table 5 All degree centralities

Hotels	All degree centrality					
	2014	2015	2016	2017	2018	2014–2018
Amara	5	4	8	9	8	10
Anemon	13	14	14	13	15	14
Barut	14	15	16	20	19	19
Cactus	0	0	0	0	0	0
Crowne Plaza	10	10	10	10	10	10
Crystal	22	25	24	27	26	27
Dedeman	23	24	22	26	25	26
Delphin	6	8	9	10	10	10
Divan	18	18	18	18	19	19
Eftalia	2	2	2	2	2	2
Elite World	5	5	4	6	5	6
Euphoria	1	1	1	1	2	1
Grand Park	12	13	6	14	14	14
Hilton	40	40	39	40	41	40
Holiday Inn	14	14	16	16	15	16
Ibis	18	18	18	18	16	18
Kaya	9	10	8	8	8	9
Larissa	0	0	0	0	0	0
Limak	14	14	14	18	15	17
Novotel	10	9	10	12	11	11
Orka	1	2	2	2	2	2
Paloma	5	9	9	10	10	9
Radisson	28	29	28	31	28	29
Ramada	34	34	34	38	35	39
Rixos	23	22	23	25	24	24
Sentido	7	8	8	8	8	8
Sheraton	20	20	22	22	22	22
The Green Park	8	10	7	11	10	12
Titanic	25	26	26	27	29	29
Voyage	13	14	14	14	14	15

Although brands such as Hilton, Ramada, Radisson, and Titanic have very strong connections in the network, brands such as Larissa, Cactus, and Euphoria have very weak connections in Fig. 1.

The results of closeness centrality are shown in Table 6. According to Table 6, the hotel brands with the highest closeness centrality are; Hilton (0.771; 0.771; 0.771; 0.771), Ramada (0.710; 0.710; 0.750; 0.710), and Crystal (0.658; 0.658; 0.675; 0.675) in 2015, 2016, 2017 and 2018; Hilton (0.771), Ramada (0.710), and Titanic (0.642) in 2014; and Hilton (0.771), Ramada (0.750), Titanic and Crystal (0.658) in 2014–2018. Although brands such as Hilton, Ramada, Crystal, and Titanic have very strong closeness centrality values in the network, brands such as Larissa, Cactus, and Orka have

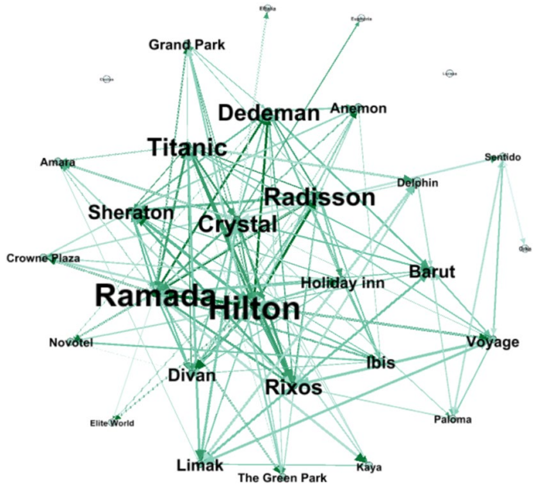


Fig. 1 Degree centrality in 2014–2018

very weak closeness centrality values. The hotel names between 2014 and 2018 are sized as per height of the closeness centrality values in the network and, shown in Fig. 2.

The results of betweenness centrality are shown in Table 7. According to Table 7, hotel brands with the highest centrality are Hilton (0.206; 0.195; 0.206), Crystal (0.159; 0.188; 0.185), and Ramada (0.111; 0.103; 0.115) in 2014, 2015, and 2016; Crystal (0.192), Hilton (0.155), and Ramada (0.137) in 2017; and Hilton (0.199), Crystal (0.188), and Ramada (0.108) in 2018. The SNA ranking of betweenness centrality of the total connections is Crystal (0.193), Hilton (0.169), and Ramada (0.134) in 2014–2018. Although brands such as Crystal, Hilton, and Ramada have very strong betweenness centrality in the network. The hotel names are sized as per the height of the betweenness centrality values in the network and, shown in Fig. 3.

The results of eigenvector centrality SNA coefficients is shown in Table 8. According to Table 8, the ranking of the hotel brands with the highest SNA eigenvector centrality in each other year and in 2014–2018, based on the total number of connections over the 5 years, is the same for all years. Accordingly, Hilton is the hotel brand with the highest eigenvector centrality (1; 1; 1; 1; 1; 1). The Hilton brand is followed by Ramada (0.878; 0.898; 0.942; 0.957; 0.917; 0.958), and Radisson (0.776; 0.766; 0.759; 0.748; 0.700; 0.749), respectively. The hotel names between 2014 and 2018 are sized as per the height of the eigenvector centrality values in the network and, shown in Fig. 4. Although brands such as Hilton, Ramada, and Radisson have a very strong eigenvector centrality in the network in Fig. 4.

Table 6 Closeness centralities

Hotels	Closeness centrality					
	2014	2015	2016	2017	2018	2014–2018
Amara	0.421	0	0.519	0.540	0.540	0.540
Anemon	0.500	0.500	0.500	0.500	0.500	0.500
Barut	0.562	0.562	0.574	0.600	0.586	0.600
Cactus	0	0	0	0	0	0
Crowne Plaza	0.482	0.482	0.482	0.482	0.482	0.482
Crystal	0.627	0.658	0.658	0.675	0.675	0.658
Dedeman	0.551	0.562	0.551	0.586	0.574	0.586
Delphin	0.421	0.473	0.473	0.473	0.473	0.473
Divan	0.529	0.529	0.529	0.529	0.529	0.529
Eftalia	0.391	0.402	0.402	0.409	0.409	0.402
Elite World	0.450	0.465	0.450	0.465	0.465	0.465
Euphoria	0	0	0	0	0	0
Grand Park	0.482	0.562	0	0.562	0.562	0.562
Hilton	0.771	0.771	0.771	0.771	0.771	0.771
Holiday Inn	0.500	0.500	0.509	0.509	0.509	0.509
Ibis	0.519	0.519	0.519	0.519	0.509	0.5191
Kaya	0.529	0.540	0.482	0.529	0.473	0.540
Larissa	0	0	0	0	0	0
Limak	0.551	0.562	0.562	0.586	0.574	0.574
Novotel	0.482	0.473	0.482	0.490	0.490	0.490
Orka	0	0.306	0.306	0.310	0.310	0.306
Paloma	0.421	0.465	0.457	0.465	0.465	0.457
Radisson	0.586	0.600	0.600	0.613	0.613	0.600
Ramada	0.710	0.710	0.710	0.750	0.710	0.750
Rixos	0.613	0.613	0.613	0.627	0.613	0.613
Sentido	0.428	0.435	0.435	0.442	0.442	0.435
Sheraton	0.540	0.540	0.551	0.562	0.562	0.551
The Green Park	0.473	0.482	0.473	0.500	0.500	0.500
Titanic	0.642	0.642	0.642	0.642	0.658	0.658
Voyage	0.574	0.551	0.551	0.551	0.551	0.586

5 Discussion

The aim of this study was to explore not only the usefulness of obtained data from search engine both also applicability of social network analysis in revealing perception in the consumer mind. In the analysis, data were collected Google Trends and analyzed using social network analysis.

Many consumers make a search on search engine prior to purchase decision. The search behavior is a sign of consumer's real interest. Thus, search engines are an important channel for businesses in terms of communicating with current and potential consumers. Currently, many businesses use search engine marketing as part of

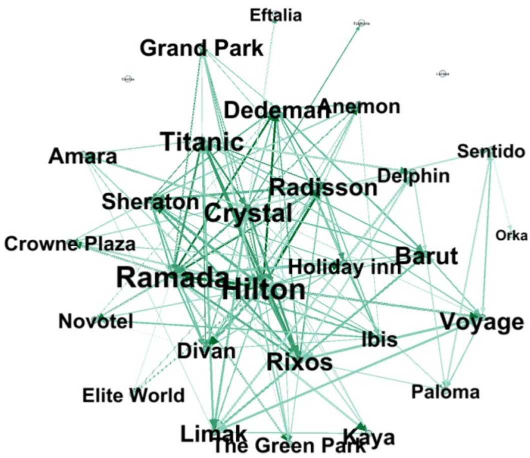


Fig. 2 Closeness centrality in 2014–218

their online marketing. They must understand consumers' web search behaviors to be successful at search engine marketing (Schultz 2020; Pan 2015; Xiang and Pan 2011).

Considering the findings together, Hilton and Ramada are those that are searched for together with other hotels the most (David-Negre et al. 2018), their accessibility on the hotel network is very high, they have a more frequent connection and, also they are associated with the significant hotel brands with a key position in the network (Ruhnau 2000). Besides, Crystal connects different groups in the network with one another, it has a key role (David-Negre et al. 2018). Hilton and Ramada are the most popular brands in the network. The results show that consumers think that these brands have a central position in the market (Jun and Park 2017). This type of information could not be obtained by the sales volume by itself, and serves as an important source for the estimation of the market leadership in the future (Jun and Park 2017). On the other hand, it is known that a "web search" is an action carried out with the intention to fulfill the duty to get prepared for purchases or future purchases (Jun and Park 2017). From this point of view, the results show that the chain hotel brands included in the study are able to identify their brand positions and gain important information for the estimation of the market leadership in the future using the inexpensive environment available on the Internet.

There are many different search engines such as Google, Yandex, Badu, Yaani, Bing. Google is the most widely used search engine. The individual goes into search engine using particular terms and phrases known as keywords, upon which the search engine submits them with a search engine results page (SERP). SERP is served to users when individuals search for something using a search engine. The keywords using by individuals actually show the relative importance (position) of each brand or product in the consumer mind. The study used Google as search engine and data (a time series from 2014 to 2018) was collected on Google Trends. This way, this study reveals changes their position in consumer minds relative to competitors over time.

Table 7 Betweenness centralities

Hotels	Betweenness centrality					
	2014	2015	2016	2017	2018	2014–2018
Amara	0	0	0	0	0	0
Anemon	0	0	0	0	0	0
Barut	0.039	0.019	0.022	0.023	0.022	0.026
Cactus	0	0	0	0	0	0
Crowne Plaza	0	0	0	0	0	0
Crystal	0.159	0.188	0.185	0.192	0.188	0.193
Dedeman	0.026	0.024	0.16	0.024	0.022	0.023
Delphin	0	0	0	0	0	0
Divan	0.003	0.003	0.003	0.003	0.004	0.003
Eftalia	0	0	0	0	0	0
Elite World	0	0	0	0	0	0
Euphoria	0	0	0	0	0	0
Grand Park	0.004	0.008	0	0.007	0.007	0.007
Hilton	0.206	0.195	0.206	0.155	0.199	0.169
Holiday Inn	0.001	0.001	0.001	0.001	0.001	0.001
Ibis	0.003	0.003	0.002	0.002	0.001	0.001
Kaya	0	0	0	0	0	0
Larissa	0	0	0	0	0	0
Limak	0.011	0.008	0.01	0.011	0.005	0.009
Novotel	0	0	0	0	0	0
Orka	0	0	0	0	0	0
Paloma	0.002	0.004	0.004	0.006	0.006	0.003
Radisson	0.038	0.038	0.037	0.032	0.032	0.029
Ramada	0.111	0.103	0.115	0.137	0.108	0.134
Rixos	0.071	0.04	0.039	0	0.043	0.036
Sentido	0.036	0.062	0.062	0.063	0.063	0.063
Sheraton	0.011	0.009	0.011	0.047	0.011	0.009
The Green Park	0	0	0	0	0	0
Titanic	0.057	0.054	0.057	0.055	0.065	0.059
Voyage	0.026	0.038	0.041	0.032	0.035	0.037

One of the greatest struggles meeting marketers is positioning (Pike 2012). The positioning concept is important for businesses. Positioning is done by using the marketing mix. It is the process of accessing a desired place in the consumer's mind. As a marketing research tool for positioning, perceptual mapping is used by marketing managers. It indicates how consumers perceive product as regards the most important attributes. In addition, businesses can see perceptions rather than features in a perceptual map; they can understand how consumers perceive their products and their competitors' products (Bovee et al. 1995).

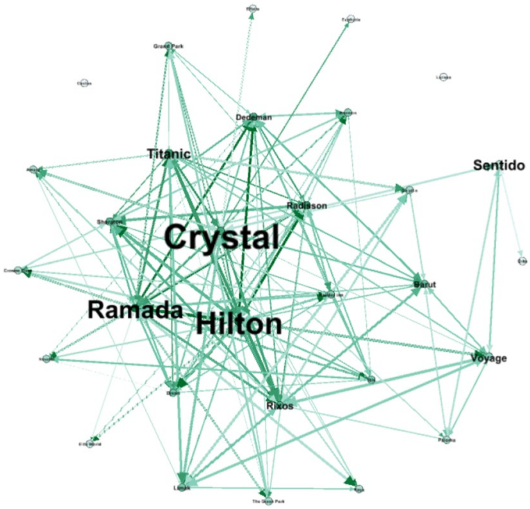


Fig. 3 Betweenness centrality in 2014–2018

In recent years, web search traffic information has been provided by Google. Google Trends provide big data that can be reconstituted to understand consumers' interest in products and businesses (Kim and Hanssens 2017). Marketers use Google Trends to get information about how consumers use search engines to find out about products and businesses in which they are concerned (Schmidt and Vosen 2011). The data are used to develop forecasts on the consumption of various products. However, Google Trends data still little explored academically (Dinis et al. 2019). The goal of this study was to examine the consumer perceptions of hotel brands through SNA using data provided by Google Trends.

The study contributes to the literature about data-based decision-making and to managers. It confirms that consumers' search engine information can be used to visualize the relatively position of brands in consumers' minds microscopically. Previous research has stated that the data can be used to forecast in various fields (e.g. economics, retail, tourism) macroscopically. In addition, previous research has demonstrated that search engine data are useful in providing meaningful and managerially valuable insights in different fields (Ginsberg et al. 2009; Schmidt and Vosen 2011; Youn and Cho 2016; Höpken et al. 2019). In addition, search engine data could be used by businesses to better understand the decision-making process of individuals when preferring a particular business, e.g. which businesses and attractions are most heavily searched and, so, is of particular relevance for individuals (Fesenmaier et al. 2010).

6 Conclusion

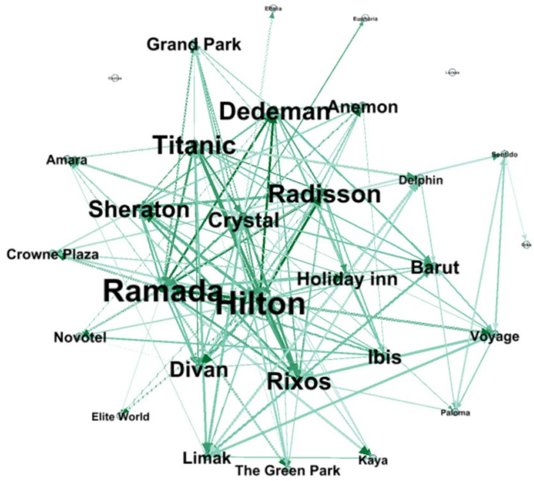
The study proposes an application of network analysis to examine brand perception. Based on a social network perspective, this study analyzed hotel brand perception in the consumer mind using SNA. Measures of centrality of SNA help to determine

Table 8 Eigenvector centralities

Hotels	Eigenvector centrality					
	2014	2015	2016	2017	2018	2014–2018
Amara	0.196	0.267	0.281	0.320	0.210	0.324
Anemon	0.439	0.508	0.532	0.487	0.515	0.487
Barut	0.384	0.413	0.432	0.562	0.558	0.517
Cactus	0	0	0	0	0	0
Crowne Plaza	0.375	0.369	0.394	0.359	0.354	0.358
Crystal	0.485	0.516	0.498	0.577	0.539	0.603
Dedeman	0.721	0.712	0.718	0.741	0.729	0.736
Delphin	0.161	0.164	0.226	0.285	0.278	0.285
Divan	0.612	0.613	0.648	0.626	0.621	0.627
Eftalia	0.049	0.052	0.051	0.054	0.052	0.057
Elite World	0.262	0.172	0.173	0.248	0.160	0.248
Euphoria	0.049	0.052	0.051	0.054	0.052	0.057
Grand Park	0.479	0.417	0.414	0.473	0.466	0.478
Hilton	1	1	1	1	1	1
Holiday Inn	0.488	0.480	0.571	0.520	0.469	0.520
Ibis	0.587	0.584	0.618	0.562	0.476	0.561
Kaya	0.287	0.343	0.302	0.277	0.340	0.294
Larissa	0	0	0	0	0	0
Limak	0.352	0.362	0.376	0.451	0.366	0.452
Novotel	0.391	0.385	0.396	0.367	0.359	0.367
Orka	0.010	0.012	0.012	0.011	0.012	0.011
Paloma	0.049	0.140	0.143	0.218	0.217	0.149
Radisson	0.776	0.766	0.759	0.748	0.700	0.749
Ramada	0.878	0.898	0.942	0.957	0.917	0.958
Rixos	0.593	0.589	0.648	0.710	0.695	0.704
Sentido	0.088	0.104	0.105	0.112	0.110	0.107
Sheraton	0.656	0.657	0.743	0.685	0.681	0.686
The Green Park	0.310	0.369	0.266	0.360	0.290	0.360
Titanic	0.650	0.697	0.719	0.751	0.761	0.777
Voyage	0.310	0.331	0.347	0.356	0.355	0.346

the strongest subjects in the network and can demonstrate the position (Borgatti and Everett 1997; Gajdošík 2015; Casanueva et al. 2016; Peng et al. 2014). According to our findings, Hilton is the brand with the greater degree, closeness and eigenvector. The findings show that Hilton is most influential in the network and has an advantageous position in the consumer mind. Similarly, the brand is the nearest brand to tourists. Crystal, Hilton, and Ramada have a high betweenness centrality, which means that they act as connectors between tourists who search different brands. The findings can be considered as direct indicator of the effectiveness and success of brand positioning strategies. In addition, the results show that search engine data reveal the positioning of consumer's perceptions of hotels.

Fig. 4 Eigenvector centrality in 2014–2018



From a methodological perspective, this study, based on social network theory, presents an analysis method and solution for practitioners. The results of this study demonstrate that search engine data can be used by researchers and practitioners in the tourism industry. The study offers a method that hotels can use to determine consumers' perception of their brands through search query data provided by Google Trends. The method is both cheap and simple for determining brand position and marketing strategies.

From a theoretical perspective, the results of this study add to the emerging literature on data-based decision-making and the existing brand positioning literature by exploring the relationship between search engine query data and consumer's mind perception of hotel brands. In addition, using social network theory, this study provides information about the relative importance of tourist destinations, the structure and relations among brands in the network. This paper highlights the importance of a social network approach for revealing the brand's place in the consumer's mind.

This study has some limitations. First, the sample for this study was limited to the travel search option of Google Trends and examined 30 hotel chains. Therefore, future research should be conducted on different hotel types and different Google Trends search options. Second, search engine data were used to visualize customer perception of hotel brands. Future research can be conducted exploring different factors using consumers' web search behaviors. Moreover, future research can examine consumers' perceptions of different businesses in the tourism industry and study various types of data, such as social media, to reveal consumers' perceptions of brands. Considering that the probability that a consumer performs a simultaneous search that includes the attributes of a product they tend to associate with a certain brand is high (Jun and Park 2017), it is suggested that analyses are carried out in the next studies with search records that include simultaneous comparisons of different attributes of hotels such as price, review scores etc., e.g. 'Hilton Hotel price, Ramada Hotel price'.

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Declarations

Conflict of interest The authors declare that they have no confict of interest.

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