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Demonstration of exponential random graph models in tourism studies: Is tourism a means of global peace or the bottom line?

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ABSTRACT

Most social network analyses conducted in hospitality and tourism studies are merely descriptive. Despite the recent popularity of exponential-family of random graph models (ERGMs) in various scientific investigations, no studies have utilized these inferential methods of network analysis in hospitality and tourism studies. In some contexts, the power of these methods is undeniably superior to those of conventional statistical tests. Accordingly, in the current study, by using the controversial subject of tourism-peace, I demonstrated how ERGMs can be used in hypotheses testing and statistical modeling in hospitality and tourism context. The results of this study suggest that a change of perspective in tourism-peace discourse from tourism as a peacemaker to tourism as a peacekeeper can be a valid approach concerning the long-lasting debates on the relationship between tourism and peace.

Introduction

> *"No one is born hating another person because of the color of his skin. People learn to hate. They can be taught to love, for love comes more naturally to the human heart."*
>
> Nicholson, W. in 'Mandela: Long Walk to Freedom'

The origin of network analysis in social science (Social Network Analysis (SNA)) dates back to early 20th century. Although probabilistic models (i.e., inferential network models) were developed in late 1950s, traditional methods of network analysis, which are merely descriptive, were the dominant, widely used approaches until recently (Harris, 2014). Part of the resistance to using inferential statistics in network analysis is due to the nature of data. Relational data, which is the main type of data used in network analysis, violates one of the basic assumptions of statistical techniques, independence of observation (Snijders & Borgatti, 1999). As a result, almost all classic inferential statistics tests including parametric and nonparametric approaches cannot be employed in network analysis studies. Major developments in probabilistic models emerged two decades after the introduction of the initial models, which resulted in emergence of exponential random graph models (ERGMs) (Harris, 2014). Over the course of the past 30 years, ERGMs have substantially developed and have become the main inferential statistical method in network analysis. Specifically, for the past 10 years, ERGMs have been considered as the main statistical modeling and hypothesis testing method in network analysis (Robins, Pattison, Kalish, & Lusher, 2007).

The use of SNA is not limited to sociology or social science in general. There are abundant examples concerning the applications of SNA in physics, biology, neuroscience, chemistry, psychology, information technology, computer science, and management and marketing (e.g., de-Marcos et al., 2016; Qiu, Zhao, Wang, Wang, & Wang, 2016; Sinke, Dijkhuizen, Caimo, Stam, & Otte, 2016; Sung-Hyuk, Soon-Young, Wonseok, & Sang Pil, 2012). Similar to other disciplines and fields of studies, in hospitality and tourism, SNA has

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been employed in various studies (e.g. Benckendorff & Zehrer, 2013; Casanueva, Gallego, & García-Sánchez, 2016; Stienmetz & Fesenmaier, 2015; For more information on SNA in tourism, see Scott, Baggio, & Cooper, 2008). Most of these studies, however, are limited to the applications of traditional descriptive methods except for a few recent ones (e.g., Liu, Huang, & Fu, 2017) To the best of my knowledge, however, no study has used the flexible and powerful ERGM techniques to test the structural hypotheses of hospitality and tourism networks. Utilizing Markov Chain Monte Carlo (MCMC) method, ERGMs can produce different fit indices and accordingly, allow researchers to measure how well the employed theory explains a social network's structure. The ability to measure and provide model fit along with the capacity to take on variables with various measurement levels make the ERGMs family unique and powerful in analyzing social networks.

In psychology and economic literature, cognitive mapping has been employed in various contexts to elucidate and map sophisticated, interrelated mental concepts such as risk (van Winsen et al., 2013). Cognitive mapping is built upon the three fundamental assumptions that 1) 'meaning' is created with human making sense of the surrounding world through contrast and similarity, 2) human attempts to explain and justify his world-why is it this way and what underlying factors have made it so, and 3) human organizes the concepts hierarchically to find the significance of the world surrounding him and identify the priority of constructs and outcomes (Eden, 1988). The initial implications of cognitive mapping were mostly in the areas of spatial memory, knowledge of distance, and location (Evans & Pezdek, 1980). The initial implications of cognitive mapping within the above-mentioned areas formed a specific type of cognitive mapping known as mental mapping (Sommer & Aitkens, 1982). Later on, researchers used the technique of cognitive mapping in studies of brand mapping, which unlike previous studies, were mostly focused on associative memory (Henderson, Iacobucci, & Calder, 1998). Brand mapping studies also formed a specific type of cognitive mapping known as concept mapping which are very common in marketing (John, Loken, Kim, & Monga, 2006). Taking the cognitive mapping technique from the realm of spatial memory to associative memory caused Human Associative Memory (HAM) models to be adopted in cognitive mapping studies. Some researchers of cognitive psychology and neuroscience have started using network analysis through the lenses of HAM models (Teichert & Schöntag, 2010). According to HAM models, human memory is a network of interconnected nodes (vertices) which activate each other in relevant situations (Teichert & Schöntag, 2010). Each node (vertex) is a basic unit of a network and contains information and meanings. Accordingly, it is possible to map the interconnections and spot the critical vertices that activate a great part of the network. Recently, several studies in branding and marketing have used the network analysis technique based upon HAM models' doctrines to map the knowledge structure and associations of brands (e.g., Gensler, Völckner, Egger, Fischbach, & Schoder, 2015; Teichert & Schöntag, 2010). This approach can be used in any types of cognitive mapping studies, specifically in destination image and travel de/motivation contexts. Hence, to study the social capital of non-travelers, the current study uses the network analysis to apply the HAM models' principles within these contexts. Current study considers destinations as primary nodes that are connected to different attitudinal attributes (secondary nodes); therefore, each time a destination is recalled from memory, related attitudes get activated to form an image of the destination.

Case demystified

Debates concerning the effect of tourism on global peace and mutual understandings started in 1920s (Becken & Carmignani, 2016). The common sense is that tourism is a catalyst for peace, promoting courtesy and cross-cultural understanding (Gunce, 2003; Jafari, 1989). The conceptualization of tourism contribution to global peace is based on democratic peace theory, which was developed according to the principles of Immanuel Kant's essay entitled "Project for Perpetual Peace" (Edgell, Allen, Smith, & Swanson, 2008). According to democratic peace theory, mutual trust and respect result in peace, which then peace leads to political stability. Consequently, political stability results in safety and security. Safety and security, then, cause tourism to flourish which enhances cultural understanding. Finally, cultural understanding increases mutual trust and respect, and the cycle repeats all over again (Fig. 1). According to the figure below, not all relationships are definite. To be specific, the impact of tourism on cultural understanding and the influence of cultural understanding on democratic peace are indecisive (Edgell et al., 2008). Furthermore, Edgell et al. (2008) proposed system is a causal chain in which a broken link disrupts the entire process. The right-side chain (hereafter,

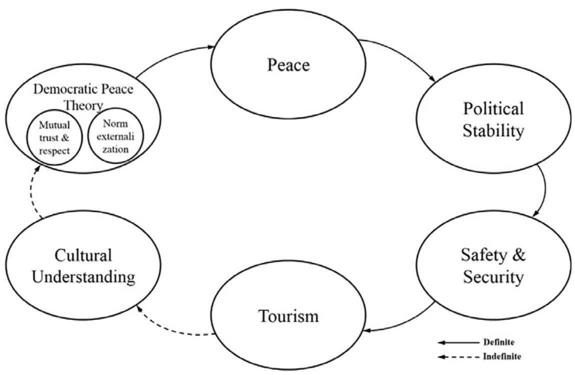

Fig. 1. The relationship between tourism and peace .
reproduced from Edgell et al. (2008, p. 164)

right-chain) can be interpreted as 'tourism as the bottom line of peace', while the left-side chain (hereafter, left-chain) can be taken as 'tourism as a means of peace (peacemaker)'.

Supporting the notion of left-chain, contact theory introduces tourism as an instrument to reach peace (Becken & Carmignani, 2016). Although the right-chain notion that tourism enjoys stability and peace and does not flourish in conflictual environments is well-supported in the literature (Farmaki, 2017), the controversial, divergent findings of left-chain empirical studies are the evidence that the notion of tourism as an instrument for peace and as a peacemaker is not well-articulated and conclusive (Sirakaya-Turk, Nyaupane, & Uysal, 2014). For instance, while Carlson and Widaman (1988) and Taft (1977) reported that tourism exerts a positive influence on visitors' attitudes, Pizam, Jafari, and Milman (1991) reported no significant change in visitors' attitudes. On the other hand Anastasopoulos (1992) stated that after tourists visit the host community, they form a negative attitude towards the host community which underlies the notion that tourism has a negative impact on visitors' attitudes. Additionally, other studies reported a combination of positive and negative impacts (e.g., Litvin, 2003; Nyaupane, Teye, & Paris, 2008). On top of these findings, unexpectedly, Sirakaya-Turk et al. (2014) recently reported that some visitors' prejudicial beliefs towards the host community were intensified/developed after their visit.

According to normative theory, individuals' opinions are under the influence of group interactions (Farmaki, 2017). Simply put, individuals consciously or unconsciously reflect the values of the group to which they belong. However, it seems that the normative theory has been ignored in studies which consider tourism as a peacemaker (left-chain) since they do not take the social capital of non-travelers into account. A review of left-chain empirical studies shows that these studies are based on the assumption that *potential visitors will visit a destination regardless of their negative attitudes towards the destination*. In other words, previous studies have only investigated "travelers" which means that the previous findings are based on "travelers' " point of view only. Hence, the left-chain studies are questionable with regards to the credibility of their assumption. Based on the above-discussion, the main question that the current study seeks an answer for is whether or not, an individual with high conflicting opinions (i.e., negative attitude) towards a specific destination would visit the destination. Following the HAM models' principles, this study employed a bipartite network ERGMs to study the emergence of terms together (i.e., destination and attitudes) in order to investigate the structure of non-travelers' belief systems. In addition, this study will address the association between destinations and their respective attitudinal variables. Hence, the purpose of the current study is two-fold: 1) to *demonstrate* the use of ERGMs in studying relational data to infer the attributes and structure of local network to the population of interest, and 2) to investigate the assumption of left-chain tourism-peace studies in the context of conflictual regions.

Hypotheses

In order to investigate the assumption that '*potential visitors will visit a destination regardless of their negative attitudes towards the destination'*, I will focus on the indecisive relationship between tourism and cultural understanding of the left chain. Based on the Edgell et al. (2008) model (Fig. 1), it is possible to infer that tourism is an *active* element (actuality state) of the system that should result in cultural understanding. The term, "should", is used here because of the indecisive relationship between tourism and cultural understanding (Fig. 1). This means that in case of non-travelers, tourism is still in a state of potentiality that may or may not become actual (active). The three hypotheses below will be tested as the possible reasons for which tourism's state of potentiality might not change to state of actuality.

According to the literature, there are three main drivers of conflict: "ethnic divisions, economic factors and resource competition, and political and institutional factors" (Farmaki, 2017, p. 530). Moreover, prejudicial attitudes against the host community are not uncommon in tourism studies (Sirakaya-Turk et al., 2014). Studies have shown that a lack of mutual understanding, historical injustice, and asymmetrical access to prosperity and opportunity are resulted from co-existence of different ethnic groups that facilitate conflicts (Becken & Carmignani, 2016). The combination of the facilitators and drivers of conflict can easily trigger racism among conflictual ethnic groups, especially if conflicts last for a long time. In regions with a history of conflict and hostility, in-group interactions can result in negative prejudice and racist attitudes towards an out-group. In tourism, these attitudes impact travel decisions of in-group communities (in this study: tourist-generating countries/regions), as shown in different studies carried out in Cyprus, the Korean peninsula, Israel, Ireland, etc. (Farmaki, 2017). Based on this information, it is possible to propose:

H_1. Non-travelers have more conflictual attitudes towards destinations with which their country of residence shares ethnic groups.

H_2. Prejudicial attitudes dominate the attitudinal network of non-travelers.

The rich literature of animosity in consumer behavior can explain the reasoning of the third hypothesis. In consumer behavior, the negative impacts of ethnocentrism-as a combination of patriotism and negative internationalism (Ishii, 2009)-and cultural animosity on consumers' intention to buy foreign products is vastly studied (Annie Peng, Theresa, & Michael, 2012; Narang, 2016; Shoham & Gavish, 2016). Conflict is a major cause of animosity (Annie Peng et al., 2012), and it seems that the duration of conflict and the type of conflictual event (a vast spectrum from a bloodshed war to a simple football match) influence consumers' judgment of products. Interestingly, animosity and ethnocentrism will continue to decrease consumers' purchase intention of the products of the other country even when the conflict is indirect. All these relationships, however, are relevant to ongoing conflict(s); this means that if the conflict has been concluded, depending on how long it has been since conflict resolution, most of these factors (i.e. animosity and ethnocentrism) will become insignificant. This is due to the idea that the two parties will gradually 'forgive' each other which is in accordance with the explanation of forgiveness theory on how attitude changes over time. That being said, in the initial stages of forgiveness, depending on the level of conflict involvement, factors such as self-enhancement and personal characteristics would still decelerate consumers' willingness to buy the other country's products (Ben Mrad, Mangleburg, & Mullen, 2014). If we replace "consumers" with "non-travelers", and "product of a specific country" with "a trip to a specific country", then all the above-mentioned concepts will become applicable to the context of this study (i.e., tourism-peace). Concerning the findings of studies on forgiveness, however, one should note that individuals with prejudicial beliefs will not forgive easily because beliefs (cognitive attitudes) are more difficult to change compared to other components of attitudes (i.e., affective and conative) (Heslop, Lu, & Cray, 2009). Drawing on this idea, accordingly, that beliefs take a longer time to change compared to conative and affective, as well as the findings of Becken and Carmignani (2016) that peace is time-dependent, which means that the longer a country (region, area) remains at peace, the lower is the risk of conflict, in addition to the notion that as peace-specific capital accumulates in places with a long history of peace, conflict-specific capital depreciates, it is possible to test the following hypothesis:

H_3. Non-travelers have more conflictual attitudes towards destinations with which their country of residence has/had a history of conflict.

Methodology

Sample and study context

With the adoption of purposing sampling method, forty Iranian participants were selected based on their international travel experience and their sense of belonging to different socio-cultural and political groups to ensure the reflection of various norms and values. Iran was selected because of its geographic location. To be more specific, as the aforementioned drivers of conflicts are typically found in Middle Eastern countries and the facilitating conditions of conflict are usually provided in this region, Iran is an appropriate study context to address the purpose of this study on tourism-peace. There are also other factors that make the Middle East an appropriate region for studies about tourism-peace. For instance, in the Middle East, there are at least four ethnic groups that are shared between Iran and the neighboring countries. Furthermore, the entire region in general and Iran in particular compete with adjacent countries over scarce resources, such as water, and abundant resources, such as petroleum and gas. Additionally, the region has a long history of conflict, and peace is not very well-established. Particularly, countries in the Middle East are usually involved in national (inside the country) or regional (between two or more countries) conflicts, such as revolutions, movements, wars, coups, and social unrest.

Procedures

Semi-structured interviews were conducted according to participants' convenient time and desired location. The average duration of each interview was 9′:36″. Participants were first asked to name four destinations where they would *never* choose to spend their vacation. Next, they were questioned as to why they would not travel to these destinations. The responses were recorded and transcribed for the analysis. To extract the attitudinal variables (demotivation) related to their respective destinations a quantitative/qualitative approach to content analysis was employed by using the RQDA package (Huang, 2014) under the R platform (Core Team, 2015) as the primary analytical tool. To ensure the reliability of the coding process, a second coder, who has experience and knowledge in cultural tourism (i.e., credibility), reviewed the extracted codes first; consequently, the codes with intercoder-reliability of less than 0.85 were dropped from the analysis.

After extracting the countries and their related attitudinal variables, data were placed in a two-mode (bipartite) incidence matrix to quantitatively explore the relationships among destinations and their respective attitudes (Eq. (1)). Matrix A shows the number of times ($a_{n,n}$) that each attitudinal variable (columns) is allocated to each destination (rows). The graph (network) which is the result of this incidence matrix can be treated as an attitudinal map for the sample of study.

$$Matrix\ (A) = \begin{bmatrix} & att_1 & att_2 & \dots & att_n \\ dst_1 & a_{1,1} & a_{1,2} & \dots & a_{1,n} \\ dst_2 & a_{2,1} & a_{2,2} & \dots & a_{2,n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ dst_n & a_{n,1} & a_{n,2} & \cdots & a_{n,n} \end{bmatrix} \tag{1}$$

in which dst is the destination, att is the attitudinal variable, n is the number of destinations in rows or the attitudinal variables in columns respectively, and $a_{n,n}$ is the number of times that a specific attitudinal variable was assigned to a specific destination.

Data analysis

A local network model was built based on the data of incidence matrix A. Using the information of both the local network model and ERGM method, an equivalent global network model was simulated to test the hypotheses and answer the main question of study. Global network is a random graph that is produced based on the attributes of local network model. In network analysis, ERGM is similar to logistic regression, as it predicts the probability of the existence of a tie (edge/link) between a pair of nodes (vertices) based on the properties (attributes) of nodes. ERGMs was fit to the local network data using Monte Carlo Markov Chain (MCMC) maximum-likelihood estimation. To estimate the statistical parameters, hundreds of thousands of models were simulated for the local network.

A basic ERGMs model is (Luke, 2015):

$$P(y_{ij} = 1|Y_{ij}^c) = \left(\frac{1}{c}\right) exp\left\{\sum_{k=1}^{K} \theta_k z_k(y)\right\}, \tag{2}$$

in which the model predicts the probability of the existence of a tie between the nodes i and j, which is conditioned to the existence of all other ties. θ_k is the coefficient of the network statistics of interest for each K, including statistics of $Z_k(y)$. $(1/c)$ is a normalizing constant to ensure that probability remains between 0 and 1.

In addition to inferential analysis, descriptive measures of degree and betweenness centralities were calculated for the local network's vertices. Degree centrality is the number of direct edges that connects one vertex to others:

$$Degree\ (v_i) = \sum_{j=1}^{n} E_{i,j}, \tag{3}$$

in which v_i is the vertex of interest, j is a vector of all vertices in the network except i, and E is the edge value that takes the values of 1 for every existence and 0 for every absence.

Betweenness centrality shows how strongly a vertex is shared among others in the network. The existence of vertices with high betweenness is crucial for a network, since these vertices hold the network together and act like bridges among different clusters in a network:

$$Betweenness\,(v_i) = \sum_{m \neq v \neq p} \frac{\sigma_{mp}(v_i)}{\sigma_{mp}}, \tag{4}$$

In which v_i is the vertex of interest, σ_{mp} is the number of the shortest paths between vertices m and p, and σ_{mp} (v_i) is the number of shortest paths between vertices m and p that include the vertex of v_i.

Statnet (Handcock, Hunter, Butts, Goodreau, & Morris, 2008), sna (Butts, 2014), network (Butts, 2015), ggplot2 (Wickham, 2009), and ergm (Handcock et al., 2016) packages developed for the R platform (Core Team, 2015) were employed for data analysis. More information on the use of ERGMs, statistical, and mathematical modeling with R-based network analysis packages can be found in Luke (2015), Kolaczyk and Csárdi (2015), and Harris (2014).

Model demonstration and results

Participants named 47 destinations that they would never visit. Most of the destinations were country names, but regions, ethnicities, and geographical areas were also mentioned. In terms of frequency, Afghanistan (18), Iraq (15), Saudi Arabia (15), Pakistan (14), and Israel (8) were the top five countries that the sample of respondents said they would never visit. As a result of sentence by

Table 1
Destinations' and individuals' attitudes' codes and frequencies.

Destination	Code	Frq	Destination	Code	Frq	Destination	Code	Frq
Afghanistan	**AF**	18	*Indonesia*	**ID**	1	*Qatar*	**QA**	1
African	**AFR**	6	*Iraq*	**IQ**	15	*Russia*	**RU**	3
Australia	**AU**	1	*Israel*	**IL**	8	*Saudi Arabia*	**SA**	15
Azerbaijan	**AZ**	1	*Italy*	**IT**	1	*Serbia*	**RS**	2
Bahrain	**BH**	2	*Kuwait*	**KW**	1	*Singapore*	**SG**	1
Bulgaria	**BG**	1	*Kyrgyzstan*	**KG**	2	*Somalia*	**SO**	1
Canada	**CA**	2	*Lebanon*	**LB**	1	*Sri Lanka*	**LK**	1
Chad	**TD**	1	*Libya*	**LY**	1	*Syria*	**SY**	7
Chile	**CL**	1	*Malaysia*	**MY**	3	*Thailand*	**TH**	3
China	**CN**	4	*Mexico*	**MX**	3	*Turkey*	**TR**	2
Columbia	**CO**	1	*Mongolia*	**MN**	2	*Turkmenistan*	**TM**	1
Cyprus	**CY**	1	*Netherlands*	**NL**	1	*UAE*	**AE**	3
Eastern Europe	**EEU**	2	*North Korea*	**KP**	1	*UK*	**UK**	2
Germany	**DE**	4	*Pakistan*	**PK**	14	*USA*	**US**	7
Hungary	**HU**	1	*Poland*	**PL**	1	*Zimbabwe*	**ZW**	1
India	**IN**	2	*Portugal*	**PT**	1			
Antagonism	**ANT**	6	*Lack of Interest*	**LOI**	24	*Poor Hospitality*	**PHS**	4
Climate	**CLM**	10	*Lack of Security*	**LOS**	12	*Previous Experience*	**PEX**	2
Crime Rate	**CRM**	1	*Least Developed*	**UDV**	13	*Racism*	**RCM**	14
Crowded	**CRW**	2	*Life Style*	**LST**	6	*Religious Issues*	**RLI**	11
Cuisine	**CSN**	2	*Negative Attitudes*	**NAT**	24	*Terrorism*	**TRM**	1
Expensive	**CST**	2	*Negative WOM*	**NWM**	1	*War*	**WAR**	2
Health Issues	**HLI**	2	*Personal Reason*	**PRS**	1			
Hostility	**HST**	21	*Political Issues*	**PTI**	12			

Frq: Frequency.

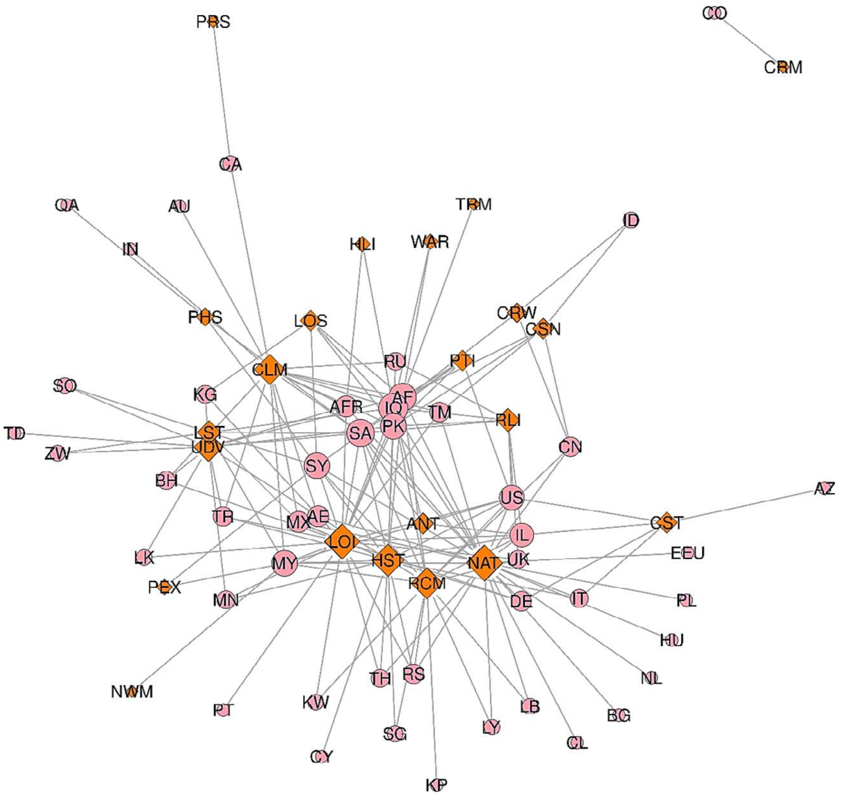

Fig. 2. Destinations and their respective attitudes assigned by participants. Light colored circle vertices show the destinations and dark colored diamond vertices show the attitudinal variables attached to destinations. The network above is drawn by using Fruchterman-Reingold force directed algorithm. Sizes of the shapes are a function of vertices' degree of centrality (size = $\sqrt[3]{(\text{degree}/10)}$).

sentence open coding process, 22 codes were extracted from the reasons that participants explained as to why they would not travel to a particular destination (Table 1).

Upon the completion of coding process, while reviewing the coding schema, five levels of prejudicial content, reflecting undesirable attitudes, were emerged based upon their conceptual definitions. On the first level, attitudes with no or low prejudicial content such as "lack of interests", "ongoing war", "crowded", etc. were categorized. On the second level, attitudes with low/medium prejudicial content such as "negative attitudes", "crime rate", "lack of security", "poor hospitality", etc. were coded as negative attitudes. The third level showed medium, passive prejudicial attitudes of "hostility" and "religious issues". The fourth level, unlike the third level, was an active level of hostility, opposition, and unfriendliness which is labeled as "antagonism". Finally, the fifth level, which encompassed the highest explicitness of prejudicial content, was labeled "racism". Other codes were rather neutral codes, such as "climate" and "expensive". The following examples depict different levels of prejudicial content found in responses. Accordingly, "*They may have many attractions, but none of them is attractive to me*" was coded as lack of interest, or "*[…] especially men behavior with women is awful, women use Hijab* [i.e. a kind of Islamic code of dressing for women] *which I don't like it either*" was coded as negative attitudes. "*I think they are against us*" was coded as hostility, and "*I hate Iraq and Iraqi people, because of their role in the eight years of war between Iraq and Iran* [i.e. Iran-Iraq war 1980–1988]" was coded as antagonism. Finally, "*I am a racist person, I do not like Arabs especially Saudi ones*" was coded as racism. The coding process and codes are presented in detail in the first supplementary document, named 'Cod'.

The network presented in Fig. 2 shows the relationships among destinations and their attitudinal variables. This network is a local network that is drawn based on the collected data.

As shown in Fig. 2, there is an inner circle of attitudes and destinations that are highly tied and connected together. These attitudes and destinations have higher values of degree and betweenness centralities (Table 2) compared to those in peripheral areas of the network. In terms of degree, Iraq (26), Afghanistan (22), Saudi Arabia (22), Malaysia (18), Pakistan (18), and Syria (18) were among the top destinations to which participants of this study would not travel, with negative attitudes (50), lack of interest (46), hostility (36), racism (32), and climate (30) being among the top attitudinal reasons (Table 2). With regards to betweenness, Saudi Arabia (435.4), Afghanistan (420.7), Iraq (419.3), Malaysia (313.7), and Syria (245.1) were among the top destinations where participants of this study would not spend holidays, with negative attitudes (1232.3), lack of interest (807.8), climate (662.1), hostility (522.3), and racism (464.2) being among the top attitudinal reasons (Table 2). A sortable Excel file of the centrality values can be accessed through the second supplementary document, named 'Cent'.

The results showed that attitudinal variables like political issues, which had relatively high frequencies, were not critical

Table 2
The degree and betweenness centralities of destinations and attitudes.

Destination	Code	Deg	Bet	Destination	Code	Deg	Bet	Destination	Code	Deg	Bet
Afghanistan	**AF**	22	420.7	*Indonesia*	**ID**	4	2.0	*Qatar*	**QA**	2	0.0
African	**AFR**	10	100.9	*Iraq*	**IQ**	26	419.3	*Russia*	**RU**	6	14.1
Australia	**AU**	2	0.0	*Israel*	**IL**	14	132.4	*Saudi Arabia*	**SA**	22	435.4
Azerbaijan	**AZ**	2	0.0	*Italy*	**IT**	6	36.4	*Serbia*	**RS**	8	26.5
Bahrain	**BH**	6	19.2	*Kuwait*	**KW**	4	3.9	*Singapore*	**SG**	4	3.3
Bulgaria	**BG**	2	0.0	*Kyrgyzstan*	**KG**	6	12.0	*Somalia*	**SO**	4	3.4
Canada	**CA**	4	130.0	*Lebanon*	**LB**	4	4.8	*Sri Lanka*	**LK**	4	5.0
Chad	**TD**	2	0.0	*Libya*	**LY**	4	4.8	*Syria*	**SY**	18	245.1
Chile	**CL**	2	0.0	*Malaysia*	**MY**	18	313.7	*Thailand*	**TH**	6	14.5
China	**CN**	8	46.5	*Mexico*	**MX**	10	67.9	*Turkey*	**TR**	8	36.9
Columbia	**CO**	2	0.0	*Mongolia*	**MN**	6	15.6	*Turkmenistan*	**TM**	8	58.3
Cyprus	**CY**	2	0.0	*Netherlands*	**NL**	2	0.0	*UAE*	**AE**	10	87.8
Eastern Europe	**EEU**	2	0.0	*North Korea*	**KP**	2	0.0	*UK*	**UK**	6	9.6
Germany	**DE**	8	66.1	*Pakistan*	**PK**	18	211.6	*USA*	**US**	16	156.8
Hungary	**HU**	2	0.0	*Poland*	**PL**	2	0.0	*Zimbabwe*	**ZW**	4	3.4
India	**IN**	2	0.0	*Portugal*	**PT**	2	0.0				
Antagonism	**ANT**	10	21.8	*Lack of Interest*	**LOI**	46	807.8	*Poor Hospitality*	**PHS**	6	131.5
Climate	**CLM**	30	662.1	*Lack of Security*	**LOS**	10	29.1	*Previous Experience*	**PEX**	4	1.9
Crime Rate	**CRM**	2	0.0	*Least Developed*	**UDV**	26	382.9	*Racism*	**RCM**	32	464.2
Crowded	**CRW**	8	73.2	*Life Style*	**LST**	14	130.8	*Religious Issues*	**RLI**	14	57.0
Cuisine	**CSN**	10	79.9	*Negative Attitudes*	**NAT**	50	1232.3	*Terrorism*	**TRM**	2	0.0
Expensive	**CST**	10	136.5	*Negative WOM*	**NWM**	2	0.0	*War*	**WAR**	4	1.7
Health Issues	**HLI**	4	2.0	*Personal Reason*	**PRS**	2	0.0				
Hostility	**HST**	36	522.3	*Political Issues*	**PTI**	10	21.1				

Deg: Degree; Bet: Betweenness.

concerning degree or betweenness centralities. On the other hand, interestingly, some variables such as poor hospitality that were not connected to many different destinations were critical in terms of betweenness. This is due to the connection of the majority of destinations to the network through these variables. Expensive, religious issues, and crowded were other variables with important roles in determination of betweenness centrality. Similar to attitudinal variables, some destinations such as Canada and Sri Lanka that possessed low degrees of centrality, displayed higher betweenness centrality and therefore were connected to more unique reasons, such as personal reasons. In contrast, destinations such as Indonesia, which were connected to more than one reason but located in the peripheral areas, did not connect any attitudinal variables to the network.

All high-ranked attitudinal variables (both in terms of betweenness and degree centralities), with the exception of climate, were among the attitudinal constructs with different dosages of prejudicial contents and conflictual attitudes. The results showed that the top five destinations (both in terms of betweenness and degree centralities), with the exception of Malaysia, were all in the same region as Iran, and three out of five share land borders with Iran. Drawing upon the results of local network, a random graph was simulated (i.e., global network) (Fig. 3) to test the study hypotheses.

With more variables added to the global model (random graph), it became more similar to the local model. As previously mentioned, the analysis of ERGMs is similar to logistic regression. The dependent variable is the existence of an edge (0 if there is no edge and 1 if there is an edge) between any two vertices (here, attitudinal variables). The independent variables are vertices' and edges' attributes which would be added to the model one at a time. The results of ERGM and the estimation steps of the global model are shown in Table 3. In the first step, a null model was built with the same number of vertices and edges as the local network. Second, terms appropriate for hypothesis testing were added to the null model one at a time (for the sake of parsimony, the table shows all hypotheses testing terms in one place under the column entitled "Vertex Attribute"). Accordingly, the dummy variable of ethnic group was the first term added to the model to show whether two countries (vertices) share similar ethnic groups (1) or not (0). Prejudicial content was the second term that was added to the model and was a five-level ordinal variable ranging from (1) containing no or low prejudicial content/conflictual attitude (e.g., lack of interest) to (5) containing the highest level of prejudicial content/conflictual attitude (e.g., racism). Next, conflict history, a dummy variable that indicates whether two countries had a history of conflict and hostility (1) or not (0), was added to the model. Finally, a geometrically-weighted structural term was added to the model to maximize the similarity of the simulated model and improve the model fit. In the current study, I used the geometrically-weighted degree (GWDegree) as the structural term. There are more sophisticated terms, however, such as geometrically-weighted edgewise shared partners (GWESP) and geometrically-weighted dyad-wise shared partners (GWDSP) which are more useful in larger networks (more information on structural terms in ERGMs and how to interpret them can be found in Snijders, Pattison, Robins, and Handcock (2006) and Harris (2014)).

Before testing the hypotheses, the assumptions of ERGMs should be investigated to make sure no assumption is violated and results are reliable. The third supplementary document, 'Diag', shows the diagnosis of the simulated graph and the fourth supplementary document of 'Fit' includes the information of model fit. With these two supplementary documents, one can see the graph met diagnosis and model fit criteria, which makes it possible to claim that the random graph model is a proper representation of the local graph model. Model fit and specification issues in ERGMs are discussed in-depth in Snijders et al. (2006), Morris, Handcock, and

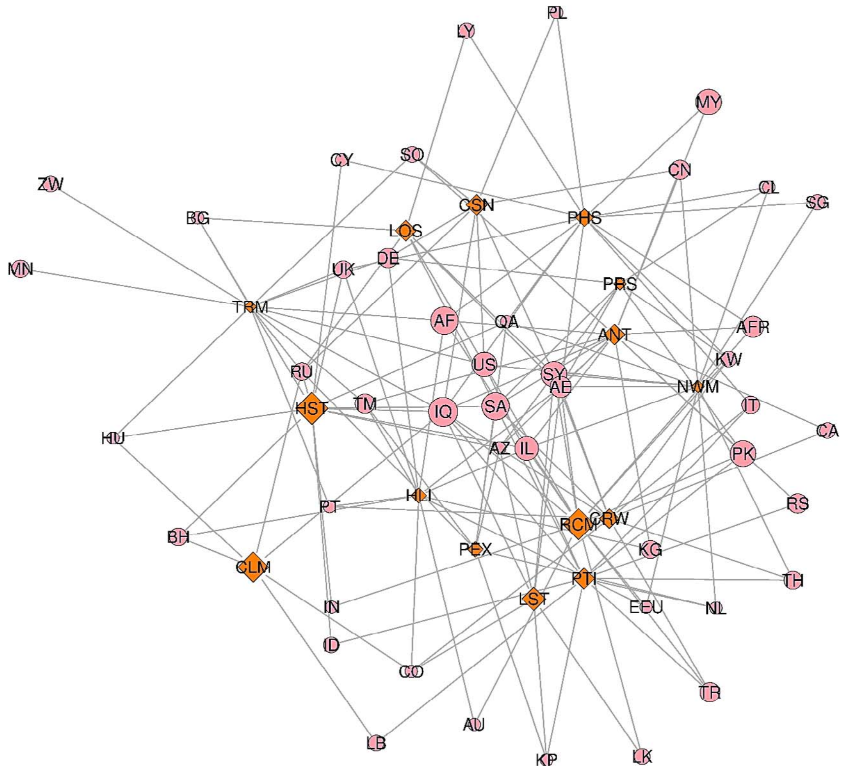

Fig. 3. Simulated Global Network based on the information of Local Network.

Table 3
Simulated model fit and terms used for hypothesis testing.

	Estimates (Standard Errors)			Odds Ratio		
	Null Model	Vertex Attribute	Structural Term	Odds	0.025 CI	0.975 CI
Edges (Constant)	−1.65** (0.085)	−2.44** (0.179)	−1.86** (0.144)	0.15	0.12	0.21
Ethnic Group		0.90** (0.184)	0.97** (0.191)	2.65	1.82	3.85
Prejudicial Content		0.17* (0.069)	0.05 (0.042)	1.05	0.97	1.14
Conflict History		0.87** (0.211)	0.95** (0.224)	2.59	1.67	4.02
GWDegree (Attitudinal)			−4.01** (0.412)	0.02	0.01	0.04
GWDegree α			Fixed to 1			
Model Fit						
AIC	913.1	859.4	808.9			
BIC	918.0	879.1	833.6			
Res. Dev. (df)	911.1 (1033)	851.4 (1030)	798.9 (1029)			
Iteration	5	5	3			

CI: confidence interval; GWDegree: geometrically-weighted degree; AIC: akaike information criterion; BIC: Bayesian information criterion; Res: residual; Dev: deviation; df: degree of freedom;

** Significant at $\alpha \le 0.01$;

* Significant at $\alpha \le 0.05$.

Hunter (2008), and Wang, Pattison, and Robins (2013).

The results of this study supported H_1 (Table 3), as countries that share ethnic groups with Iran were 2.65 times more likely to connect to one of the attitudinal variables ($\beta = 0.97$, $\rho < 0.001$). Despite high degree and betweenness centralities, results rejected the dominance of prejudicial attitudes (H_2) in the global network ($\beta = 0.05$, $\rho = 0.224$). With the odds ratio (effect size) of 1.05, however, it is possible to argue against these results considering that the lower bond of the confidence interval can be round up to 1 [$CI_{0.025} = 0.97$, $CI_{0.975} = 1.14$]. In addition, it is worth mentioning that the dominance of prejudicial attitudes was significant ($\beta = 0.17$, $\rho = 0.017$) before adding the structural term (GWDegree) to the model. Most likely, the reason that the study failed to reject the null hypothesis (H_0) of the second hypothesis (H_2) is that the sample size was relatively small which reduces the power of the test to reject the false null hypothesis (Khalilzadeh & Tasci, 2017). Despite all the arguments above, it should be noted that even if the sample size becomes larger, the effect size most likely will remain small due to the odds ratio's upper limit of 1.14. Finally, H_3 was supported according to the findings of this study. The odds of assigning an attitudinal variable to the destinations with which the non-travelers' country of residence has/had a history of conflict was 2.59 times higher compared to the destinations with which the non-travelers' country of residence had no history of conflict ($\beta = 0.95$, $\rho < 0.001$).

To conclude this section, I believe it is imperative to note that the results of hypothesis testing of this study are not generalizable due to the non-probability nature of the sampling technique and the study's small sample size. In other words, the main purpose of hypotheses testing in this study is to *only* demonstrate as to how ERGM can be used in tourism and what useful information it can provide that traditional descriptive SNA can't.

Conclusion

Mark Twain may not be correct in saying, "Travel is fatal to prejudice" (Jafari, 1989, p. 439), as, apparently, prejudicial attitudes are fatal to travel. The results of this study support the idea that the tourism industry's complex, dynamic, and power-driven environment, as well as the contextual factors which shape the nature of conflicts, make peace-through-tourism a challenging goal (Farmaki, 2017). The current study casts doubt on the assumption of most tourism-peace studies that *potential visitors would visit a destination despite their negative attitudes against the destination*. In other words, it seems that this assumption does not always hold for different destination/residences, especially for "traditional enemies" (The term is borrowed from Farmaki, 2017, p. 532). This study showed that prejudicial attitudes are significant reasons for which visitors do not travel to a particular destination, at least for some countries in conflictual areas of the Middle East. This means that even if we accept that the interaction of host and guest, in the tourism context, nurture mutual understanding and trust between them, it's a lost opportunity because the host-guest interaction would not even occur in the first place. Furthermore, the two supported hypotheses of the current study (H_1 and H_3) suggest that non-travelers never travel to a specific destination because of their ethnocentrism, regions' accumulated animosity, and history of conflict. As a result, the link that connects tourism to mutual understanding in the left-chain is broken (Fig. 1). In other words, in the context of this study, the indecisive impact of tourism on mutual understanding, is evidenced as non-existent which means that the state of potentiality in the relationships of the left chain of system would not always become actual. This study's findings are in-line with the previous literature and arguments about tourism as peacemaker (Becken & Carmignani, 2016; Farmaki, 2017). Accordingly, the discourse of tourism as peacemaker should be revised and the argument should shift from the left-chain of Fig. 1 to the right-chain with its definite relationships that also have been empirically supported (Farmaki, 2017). The bottom line of this study is that tourism is not the cause of peace, mutual understanding, and trust (left chain); rather, it is an outcome of these situations. Particularly, tourism, as the symbol of return to normality (Becken & Carmignani, 2016), is a *peacekeeper* than a *peacemaker*.

One of the main implications of this study is for policy makers; changing the discourse from tourism as a peacemaker to tourism as a peacekeeper signifies the importance of planning based upon the conflictual background of a destination, as well as travelers' country of residence. Careful interpretation of history of peace is a necessity in tourism development process of conflictual parties in order to avoid the re-emergence of past and present fundamental animosities (Becken & Carmignani, 2016).

The future of network analysis seems to be promising with the recent introduction of probabilistic models that can handle both random variables' edges and vertices attributes. These new models can be explained as a combination of the latent space model and the Gaussian graphical model (Cai, 2017). Furthermore, network analysis not only provides the opportunity of studying complex systems that were not investigable before, but also provides cutting edge knowledge on dynamism and sophistication of problems with which the researchers deal with. That being said, as explained in the introduction, despite the prominence and immense acceptance of ERGMs in statistical modeling of networks in many contexts, the applications of these models are neglected in hospitality and tourism studies. To be specific, the application of network analysis in tourism and hospitality is limited to the applications of descriptive social network analysis (SNA) although ERGMs are more advanced and can provide more relevant information. Accordingly, the current study is an attempt to introduce ERGMs to hospitality and tourism scholars and inform them about the added-value information that ERGMs can provide. ERGMs are one of the advanced versions of the SNA family and can be used in any contexts where SNA is applicable. For instance, collaboration and cooperation among different organization, collaboration and cooperation within tourism destinations, composition of attractions in terms of geographic dispersion, branding efforts, destination image, stakeholders' relationships, resource allocation and optimization, economic development, sustainability, marketing, trust, communication, preferences, risk analysis, contagious behaviors, social capitals, proximity, homophily, evolutions, governance, complex systems (Scott et al., 2008), strategic management, game theory, technology acceptance, balance of trade, dissemination of happiness, well-being, and rumors, and value distributions (Jackson, 2013) are among the topics and areas to which ERGMs can contribute.

The main strength of ERGMs is the power of this technique for handling unconventional hypotheses that are not testable with conventional statistical tests. ERGMs not only handle relational data, in forms of networks, but also can be applied to transformed data, such as memberships, which can be treated as a network. Nevertheless, similar to other SNA techniques, ERGMs have their own weaknesses and advantages. Four main disadvantages of ERGMs are model degeneracy, model convergence issues, run-time, and structural terms' interpretation (Harris, 2014). Model degeneracy occur when the network is close to a complete or empty network, or a dense part of the network occupies a small part of it. Usually degeneracy either results in lack of convergence or biased estimation of the coefficients. Generally, ERGMs perform better when density is less than 50%. Model convergence issues can be due to the size of the network (with very large networks, it is more likely that this issue occurs), or the number of parameters to be estimated (when a large variety of attributes are tested simultaneously), which in case of the latter, it means that estimations are not reliable. Model run-time is the third issue with ERGMs. Depending on the number of parameters to estimate, number of structural terms in the model, size of the networks, sample sizes and intervals for MCMC, ERGMs can take from a few minutes to many days to run. Only stronger commercial mega-computers can reduce this time significantly. Finally, the interpretations of the structural terms need plenty of time, expertise, and clear understanding of the SNA as well as problem under study. Generally, interpretation of ERGMs' terms are difficult compared to classical statistics test because of the dyadic nature of the relationships. More importantly, structural terms (e.g., GWESP, GWDSP, etc.) require a deep understanding of the geometric distribution of different types of relationships (transitivity, triangles, clusters, etc.) (Harris, 2014).

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.annals.2017.12.007.

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