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Social Network Analysis as a Valuable Tool for Understanding Tourists' Multi-Attraction Travel Behavioral Intention to Revisit and Recommend †

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Abstract: In order to better understand tourists' multi-attraction travel behavior, the present study developed a research model by combining the social network analysis technique with the structural equation model. The object of this study was to examine the structural relationships among destination image, tourists' multi-attraction travel behavior patterns, tourists' satisfaction, and their behavioral intentions. The data were gathered via an online survey using the China panel system. A total of 468 respondents who visited multiple attractions while in Seoul, Korea, were used for actual analysis. The results showed that all hypotheses are supported. Specifically, destination image was an important antecedent to multi-attraction travel behavior indicated by density and degree indices. In addition, the present study confirmed that density and degree centrality, the indicators of tourists' multi-attraction travel behavior, were positively related to tourist satisfaction. The current study represented theoretical and practical implications and suggested avenues for future research.

Keywords: multi-attraction travel; social network analysis; degree centrality; density; tourist behaviors; tourism destination image; behavioral intention; Chinese tourist

1. Introduction

Tourism destination image is a pivot from tourism destination branding, and every successful tourism destination has a uniquely appealing image that distinguishes it from others [1]. According to tourist behavior literature, tourism destination image consists of the image features of a destination, which subsequently affect tourists' destination choice, trip planning, and post-trip evaluation of visited destinations [2]. Therefore, developing and managing a positive tourism destination image is a critical step before planning, policy-making, and marketing communication for tourism destinations.

Pleasure travel is based on a whole experience at a very personal level involving many elements, such as spatial/temporal durations, breadth and depth of experiential deeds, intensity (e.g., relaxation and engagement), social/individual interactions, senses, meaning, symbol, and the functionality of the consumptive target [3,4]. Travelers undergo a series of complex spatial/temporal experiential stages, which involve a relatively high level of psychological involvement compared to buying consumption goods. According to Lee, Petrick, and Crompton [5], satisfaction is a consumer's experience occurring as the end condition of a psychological procedure. Most tourism research supports the significance of satisfaction as an evaluation of an experience or service [6]. The evaluation

of tourists' satisfaction has been adopted by destination marketing organizations (DMOs) not only to monitor its comprehensive performance but also to explore opportunities for and to amend problems with tourism organizations [7]. Therefore, it is of prime interest for destination management companies, travel agencies, the government, and private enterprises to continuously monitor visitors' satisfaction score [8].

In general, tourists tend to travel to multiple attractions, destinations, or cities when they travel to a foreign country [9,10]. Despite these common practices of multi-attraction travel behavior, quite a few empirical studies of tourist behavior heavily relying on traditional statistical procedures, often linear modeling techniques, are based on the unrealistic premise that tourists visit a single destination. A number of scholars have argued that although one-destination selection models have contributed consistently to the understanding of the behaviors of tourists, the single-destination framework is too simple to fully capture tourists' travel behavior of visiting multiple travel routes [9,10]. Thus, relying on a single-destination framework does not allow researchers to have a more complete understanding of tourists' complex travel pattern of visiting multiple attractions. To overcome the obstacle of the traditional statistical technique, some scholars have tried mapping spatial movements by means of the geographic information system (GIS) technique [4,11]. The drawbacks of such GIS-based analysis arise from its constraint in identifying only the spatial movement patterns of visitors. In order to solve the problems of both traditional analytical analysis and the GIS technique, scholars have adopted social network analysis (SNA) techniques to discover the multiple attraction travel behavior patterns of tourists [12–16]. However, even though studies adopting SNA techniques have provided in-depth knowledge and snapshot pictures about tourists' multi-attraction travel behavior pattern, these SNA-based studies are very limited in explaining the holistic relationship between the antecedents (e.g., attraction image) and consequences (e.g., tourist satisfaction and future behavior intention) of tourists' multi-attraction travel behavior. Furthermore, to the knowledge of the authors, studies incorporating SNA with traditional statistical analysis to understand tourists' multi-attraction travel behavior do not exist in tourist behavior research.

Thus, to address the literature gap and better understand tourists' multi-attraction travel behavior, the present study developed a research model by combining the SNA technique with the structural equation model (SEM). The primary purpose of this study is to examine the structural relationships among tourism destination image, tourists' multi-attraction travel behavior patterns, tourists' satisfaction, and their behavioral intentions.

2. Theoretical Background, Research Hypotheses, and Model

2.1. Tourism Destination Image

Tourism destination image has been an important topic of study since the 1970s because tourism has become more and more dependent on destination image [17]. Due to the reciprocal relation between destination image and destination choice behavior, interest has arisen in destination image studies because the aforementioned are predictor variables in the destination choice model [1]. In addition, since tourism destination as a product possesses a unique image, the importance of destination image is commonly acknowledged in tourism studies as it affects tourists' perception and destination decision making [2].

Baloglu and McCleary [2] used a two-dimensional model of destination image, which included affective and cognitive image components. The cognitive image was defined by Gartner [18] as an assessment of known attributes of the goods. From a cognitive image viewpoint, destination image is evaluated based on a set of attributes that correspond to physical attributes, such as attractions and resources, that the destination offers [19]. Affective image relates to motivation in feeling and/or emotion, which is how a subjective entity values the object under consideration. From an affective image viewpoint, destination image represents overall feelings about a destination [20]. This study

used an overall destination image consisting of cognitive and affective images to investigate the relationship between destination image and tourists' multi-attraction travel behavior patterns.

2.2. Tourists' Multi-Attraction Travel Behavior Patterns

In general, tourists tend to visit various attractions located within the one destination during their travel. This type of travel is called as multi-attraction travel [14,21]. Multi-attraction travel is defined as a tourist visit of two or more attractions within the same tourism destination that are on the same travel route [14]. Understanding tourists' multi-attraction travel behavior is essential for destination management strategies concerning attraction planning, designing and developing accommodations and tourism products, transportation, and infrastructure and superstructure to support tourism [4]. Thus, the concept of visiting multiple attractions within one destination has attracted researchers in various fields, such as tourism, hospitality, marketing, geography, and transportation [9,21]. Considering the importance of multi-attraction travel of tourists, previous researchers have tried to apply various techniques to understand the multi-attraction travel behavior of tourists.

Some research endeavors are based on more traditional methods, such as interview and survey questionnaires, as in Smallwood, Beckley, and Moore [22]. Similarly, Yang, Fik, and Zhang [23] analyzed data using multivariate statistical procedures, including logistic regression, a logit model, and a Markov model in understanding tourist movement patterns. On the other hand, in mapping tourist movement patterns, a plethora of researchers has used various new approaches. For instance, some researchers have applied GIS [4,11,24]. Recently, SNA, for its part, has slowly but steadily gained approval from tourism researchers for its usefulness in explaining tourism destination network. Researchers examined and visually presented tourism destination networks using SNA methodology to extend our understanding of tourist movement patterns and the structural characteristics of tourism destination [12–16,25]. The results of those studies provide tourism industry practitioners with implications for marketing strategies and researchers with directions for future research.

2.3. Hypothesis Development

2.3.1. Tourism Destination Image and Tourists' Multi-Attraction Travel Behavior Patterns

Previous image studies demonstrated that destination image has a strong association with tourists' length of stay [26–28]. More specifically, Gokovali et al. [27] confirmed that the overall image of Turkey stimulates travelers' length of stay. De Menezes et al. [26] categorized the 25-item scale of destination image into six dimensions—cultural heritage; nature and landscape; availability of packages and flights; safety and hospitality; quality and price; weather and ultra-periphery. They found that out of the six dimensions, the primary reasons for tourists' longer length of stay in a leisure destination originate from their favorable perceptions of two dimensions: Weather and remoteness; and nature and landscape. Machado [28] reported that tourists who had a favorable destination image of Madeira Island tended to stay for longer periods.

On the other hand, previous researchers attempted to identify the relation between the length of stay and tourists' travel pattern. Oppermann [29] indicated that when tourists stay for longer periods of time in a destination, they are more likely to visit more places and attractions. Asero et al. [12] indicated that network density is used as a way to connect tourist routes among attractions. Suppose a multi-attraction network has a high density score within its overall network structure. This implies that tourists tend to travel to multiple attractions within one trip. Based on the aforementioned literature, this study proposes that long-term tourists' travel pattern displays a more extensive pattern than short-term tourists' travel pattern.

In sum, the better the destination image, the longer tourists tend to stay, which in turn allows them to visit more complex routes and diverse attractions, leading to high network density. Based on this literature background, the authors propose the following hypothesis:

Hypothesis 1 (H1). *Destination image has a positive influence on network density.*

Tourism destination image is commonly defined as tourists' overall perception of a tourism destination [30]. Destination image, one of the most important factors influencing destination preference and consequent behaviors, is diverse feelings about, overall evaluation of, and attitudes toward a destination [2]. Most image studies suggest that destination image is one of the most influential predictors of tourists' destination choice behavior and a pivot of destination branding [31,32]. More specifically, according to Sirakaya et al. [32], cognitive evaluation of destination attractiveness and tourist services of attractions are predictors for increasing the probability of a tourist's choice to visit the destination. Mussalam and Tajeddini [31] confirmed that the perception of a destination's infrastructure (e.g., accessibility, accommodation facilities, and transportation facilities) and the perception of a destination's popularity have a significant effect on the frequency of visits to the destination.

From an SNA perspective, according to Wasserman and Faust [33], Asero et al. [12], and Chung, Chung, and Nam [13], destinations with a high degree centrality are connected with many other destinations and places. Consequently, they tend to be influential attractions, often serving as an anchor-point within a larger city system. For that reason, they serve as a core attraction, which attracts a large number of visitors for its popularity and distributes visitors to a few connected destinations. Therefore, a typical destination with a high degree centrality is a famous hub of tourism infrastructures, superstructures, and public transportation. In our study, those destinations with highdegree centrality, including Myeongdong, Dongdaemun Market, Namsan/N Seoul Tower, and Lotte World, have all these qualities. Asero et al. [12] suggested that if many tourists visit a specific destination, the specific destination can be influential and become popular within the network. Most of the popular destinations have a well-established infrastructure: Accommodation, convenient transportation facilities, easy accessibility, and unique attractiveness (e.g., heritage, mountain, and activities) [34].

To sum up, a favorable image of destination regarding its infrastructure, attractiveness, and reputation is more likely to contribute high tourists' traffic flow of a tourism destination, which in turn is accompanied by high degree centrality. Based on this literature background, the following hypothesis is proposed:

Hypothesis 2 (H2). *Destination image has a positive influence on degree centrality.*

2.3.2. Tourists' Multi-Attraction Travel Behavior Patterns and Tourist Satisfaction

Generally speaking, tourist satisfaction is an important parameter in assessing the quality of tourism services. According to Lue et al. [10], potential tourists tend to travel to various destinations due to their rational behavior that could decrease their time and expenditure related to their travel itineraries and maximize their benefits. On the other hand, Tussyadiah, Kono, and Morisugi [35] attempted to explain tourists' multi-attraction travel behavior patterns from another perspective. They argued that the primary motivation of travelers' behavior is to satisfy various needs of tourists that cannot be accomplished by visiting a single destination.

According to Kang et al.'s [14] studies on tourist attraction, if a multi-attraction network has a high density score, it indicates that tourists cohesively visited the multi-attraction. On the other hand, if a multi-attraction network has a low density score, it shows that the attraction visit patterns of tourists tended to be hierarchical. In other words, the network's high density score can be derived from the centralized pattern in which tourists visit a multi-attraction to enhance their satisfaction with the experience of various travels in a single trip. Based on this literature background, the authors propose the following hypothesis:

Hypothesis 3 (H3). *Network density is positively related to tourist satisfaction.*

In tourism literature, satisfaction refers to the emotional condition reflected in tourists' post-experience evaluation of a tourism destination [36]. Previous studies have empirically confirmed that the experience of destination has a positive association with satisfaction from tourists [37].

From an SNA perspective, an attraction with high degree centrality is interpreted as a famous and popular tourist place located at a geographic center within an overall destination network structure [14,16]. In addition, these studies confirmed that attractions with high degree centrality are fully equipped with positive reputation, convenient transportation, easy accessibility, and well-established shopping centers.

On the other hand, several empirical studies have identified the relationship between tourism facilities and tourist satisfaction. Araslı and Baradarani [38] categorized the 23-item scale of destination facilities into five factors—shopping and tourist attraction; food; lodging and restaurants; environment and safety; and transportation. They demonstrated that out of five factors, three dimensions—shopping and tourist attraction, environment and safety, and food—have a positive effect on tourist satisfaction. Thompson and Schofield [39] argued that positive relationships were revealed between transport facilities and tourist satisfaction.

In sum, the attraction with high degree centrality, which is assumed to have abundant tourism-related facilities, such as transportation, accessibility, and well-established shopping/dining centers, is likely to tempt tourists, which can in turn induce tourists' satisfaction. Accordingly, the authors propose the following hypothesis:

Hypothesis 4 (H4). *Degree centrality is positively related to tourist satisfaction.*

2.3.3. Tourist Satisfaction and Behavioral Intentions

Tourist satisfaction is defined as a function of pre-tour expectation and post-tour experience [37]. Without any doubt, tourism researchers and most practitioners in the tourism industry would agree that tourism success depends on the level of tourist satisfaction [40].

The present study uses three behavioral intention variables, revisit intention, word-of-mouth (WOM) intention, and intention to recommend, to examine the outcomes of tourists' satisfaction. In tourism literature, revisit intention, serving as a strong indicator of future behavior, is defined as a tourist's willingness or eagerness to revisit the same destination [30]. Intention to recommend is closely associated with tourists' satisfaction levels [30]. WOM is defined as informal communication between sender and receiver about a product or service [41].

Numerous tourism studies suggest an important relationship between tourist satisfaction and behavioral intentions [6,42]. Moreover, satisfied tourists are more inclined to recommend the attraction they visit to others and to revisit those places [30,43]. Previous studies demonstrated the significant positive effect of tourist satisfaction on WOM [41,43]. Thus, the authors derive the following hypothesis from the literature:

Hypothesis 5 (H5). *Tourist satisfaction has a positive influence on behavioral intentions.*

Figure 1 displays the hypothesized research model that is composed of the interrelationships among research variables.

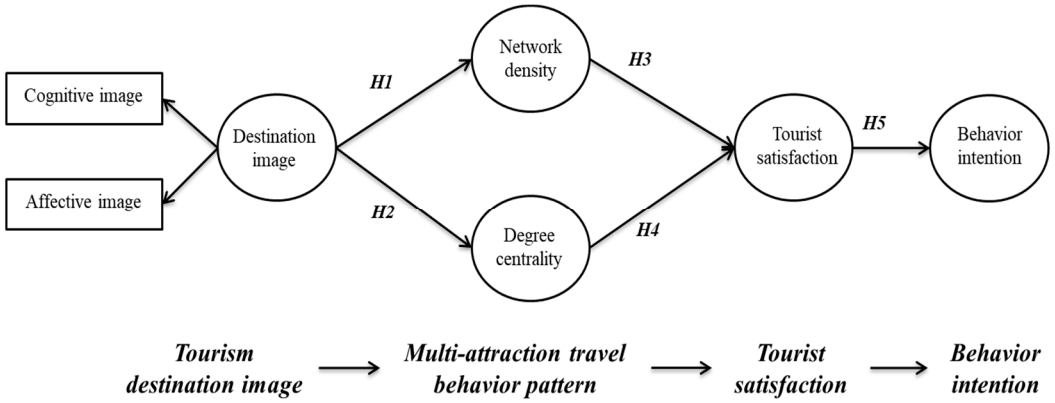

Figure 1. A research model for the structural relationships of tourism destination image, multi-attraction travel behavior pattern, tourist satisfaction, and behavior intention. Notes: Destination image construct (i.e., second-order factor structure) is manifested by cognitive image and affective image.

3. Methodology

3.1. Sample and Data Collection

The rapid increase in the number of Chinese tourists visiting Korea shows that Chinese tourists are highly interested in South Korea tourism [44]. Considering the importance of China as the number one originating country to the Korean inbound market, the present study selected Chinese free independent travelers (FITs) for its subject.

The researchers conducted an online survey for over ten days from 1 May 2015 to 12 May 2015 through "Wen Juan Xing" (www.sojump.com), an online survey company in China. This company is the number one online research and development agency with the largest panel members in China. Target panel members were Chinese tourists who were eighteen years or older and stayed at least one night in Seoul mainly for leisure purposes. When the panel members consented to participate in the online survey, they received an e-mail that contained an online survey site link.

The survey used two screening questions: Whether the respondents were 18 or older and if they had visited Seoul for an overnight stay mainly for leisure purposes (e.g., "Have you visited to Seoul for an overnight within the last 12 months for leisure purpose?"). If respondents answered "no", the survey immediately stopped. Next, the questionnaire randomly evaluated the study's scale items. Further, in order to minimize common method bias, the questionnaire administered separate cover stories for each scale. The final part of the questionnaire was composed of respondents' demographics.

The authors collected a total of 484 questionnaires through the online survey. Prior to analyzing the data, the researchers eliminated data that were not appropriate for the purpose of the study. More specifically, the purpose of this study was to measure tourists' multi-attraction travel behavior by constructing a multi-attraction network based on the relationship between attractions and then analyzing a multi-attraction network. Thus, the authors deleted the sample that visited single attractions because it was not suitable for constructing a multi-attraction network. After eliminating the abovementioned 16 samples, the researchers used a total of 468 responses for this study.

3.2. Measurement

3.2.1. Scale Items

The researchers used scale items from diverse sources in the literature to operationalize the key constructs of destination image (cognitive image and affective image), tourist satisfaction, and behavioral intentions. These variables produced the attribute data as shown in Table 1, and a total of 18 measurement items were used based on previous studies. The current study measured all scale

items of the attribute data on a five-point Likert scale, with answer options ranging from 1 (strongly disagree) to 5 (strongly agree). The theoretical basis of the variables is displayed in Table 1.

Table 1. Constructs in the research model.

Construct	Measurement Items	References
Destination image		
Cognitive image (CI)	I feel Seoul has good shopping facilities I feel Seoul has a beautiful nature I feel Seoul has a diversity of foods I feel Seoul has a good accommodation system I feel Seoul has a clean environment	Beerli and Martin [19]
Affective image (AI)	I feel Seoul is a safe I feel Seoul is exciting I feel Seoul is peaceful I feel Seoul is exotic I feel Seoul is vital	
Tourist satisfaction (TS)	I am satisfied with my decision to visit Seoul (TS1) I feel good about my choice to visit Seoul (TS2) Overall, I am satisfied with my decision to visit Seoul (TS3) I am satisfied with the cost for the tour experience (TS4)	Eid and Gohary [45]
Behavioral intention (BI)	I will recommend Seoul to my friends (BI1) I intend to revisit Seoul (BI2) I will say positive things about Seoul to my friends and relatives (BI3) I will visit Seoul again (BI4)	Zabkar, Brencic, and Dmitrovic [46]

3.2.2. Measurement of Network Variable

Social Network Analysis

SNA describes the structure of relations between given entities, such as people, place, and information, and then applies quantitative measurements to find relevant indicators for the features of the network structure and the role of its components [16]. Two main mathematical functions are available in SNA: Network density and centrality measures for explaining the structural characteristics of a network [14]. Network density is defined by de Nooy, Mrvar, and Batagelj [47] as a proportion of the maximum possible linkage in a network. It measures the relative number of connections in the network [47]. The more nodes linked to another node, the denser the network will be [14]. Meanwhile, centrality is defined with reference to the whole network that an individual structure has [48]. It refers to the positioning of a specific network node linked to other network nodes; a given node is more or less central than other nodes, a primary concern in SNA [48]. Wasserman and Faust [33] defined degree centrality as the number of nodes directly connected to a particular node. According to Wasserman and Faust [33], the number of links indicates 'connectedness' of one node to other nodes, and it is a function of influence and power it has within the network.

Network Variables Derived from SNA

The network variables utilized in this study, such as network density and degree centrality, explain the multi-attraction travel behavior of tourists. In order to measure the network variable, the authors used the questionnaire items about "Which attractions did you visit while traveling in Seoul? Please select the appropriate place from the suggested attraction list" (as shown in Appendix A).

However, according to Liu, Huang, and Fu [49], social network data gained via a survey are attribute data and should be transformed to relational data for SNA. Thus, in order to convert attribute data to relational data, we created a matrix showing the relationships between tourists and tourist attractions using a sociometric choice matrix that shows whether a relationship between entities existed or not. The details of how this study created the matrix are outlined in Appendix B (See Table A1 in Appendix B). More specifically, in order to measure density, we converted the aforementioned

tourist–tourist attraction matrix to a tourist attraction–tourist attraction matrix to calculate the density scores (See Table A2 in Appendix B). As a result, the 468 tourists by 23 attractions matrix was transformed to a matrix of 23 attractions by 23 attractions for the density score. The details of how this study calculated the density indices are outlined in Appendix C. In terms of network structure, the nodes mean each tourist attraction, and the link indicates tourist attractions sharing the relationship.

In addition, to calculate degree centrality, the tourist–tourist attraction matrix was converted to a tourist–tourist matrix (See Table A3 in Appendix B). As a result, the 468 tourists by 23 attractions matrix was transformed to a matrix of 468 tourists by 468 tourists for the calculation of degree centrality score. The details on the calculation of the degree centrality score are represented in Appendix C. In network structure, the node represents each tourist, and the link indicates tourists sharing the relationship.

3.3. Data Analysis Process and Analytical Tools

Two categories of data are used in this study: Multiple-item scales, including tourism destination image, tourist satisfaction, and behavioral intentions, and relational data concerning network density and degree centrality. To estimate the structural model and test the research hypotheses, we followed the data analysis process of previous studies [50,51]. First, we carried out network density and degree centrality analysis as explained above (see also Appendix B). Second, to meet the normal distribution assumption for the multivariable analysis technique, the network variables induced from SNA (i.e., NC, and DC) were normalized. Third, indices for network density and degree centrality were encoded as individual tourist-level variables. To examine the scale validity of tourism destination image, satisfaction, and behavioral intention, confirmatory factor analysis (CFA) and discriminant analysis were carried out, followed by tests of the structural relationships among all variables using SEM [52].

For data analyses, SPSS 20.0 and UCINET 6 were used to convert and compute the network density and the degree centrality scores. AMOS 20.0 packages were used for CFA, discriminant analysis, and SEM.

4. Results

4.1. Characteristics of Respondents

Table 2 summarizes respondents' profile information. Of the total respondents, 52.1% were male, whereas 47.9% were female. The respondents in their 30s were 53.4% of the total respondents, followed by those in their 20s (36.5%). Married respondents (80.3%) out-numbered single respondents (19.7%). As for educational level, a vast majority of the respondents (76.7%) completed university, followed by a completion of graduate school (12.6%). With regard to occupation, half of the respondents were white-collar workers (45.9%), followed by engineers (19.2%), and professionals (8.5%). In terms of monthly household income, 13.2% of the respondents earned between $1051 and $1120, followed by 11.8% of the respondents between $1501 and $1650, and 10.9% earned more than $2101.

Table 2. Profiles of the respondents (n = 468).

Characteristics	N	(%)	Characteristics	N	(%)
Gender			*Age (years)*		
Male	224	47.9	20–29	171	36.5
Female	244	52.1	30–39	250	53.4
Marital status			40–49	43	9.2
Single	92	19.7	50 or older	4	0.9
Married	376	80.3	*Monthly household income (US$)*		
Education			Less than 600	9	1.9
High school	4	0.9	601–750	49	10.5
2 years college	46	9.8	751–900	45	9.6
University	359	76.7	901–1050	40	8.5
Graduate school	59	12.6	1051–1120	62	13.2
Occupation			1121–1350	46	9.8
Clerical worker	215	45.9	1351–1500	30	6.4
Business executives	65	13.9	1501–1650	55	11.8
Government/military	22	4.7	1651–1800	31	6.6
Agriculture/fisheries	2	0.4	1801–1950	28	6.0
Student	7	1.5	1951–2100	22	4.7
Engineer	90	19.2	More than 2100	51	10.9
Professional related (doctor, attorney, etc.)	40	8.5			
Sales & related	3	0.6			
Service worker	19	4.1			
Other	5	1.1			

4.2. Measurement Validation

We analyzed the reliability and validity of the latent construct variables, including destination image, tourist satisfaction, and behavior intention. The Cronbach's alpha coefficients of the three structures are presented in Table 3. The Cronbach's alpha coefficients of the three structures ranged from 0.570 (tourist satisfaction) to 0.672 (destination image), which can be regarded as reliable because the three constructs are all above the acceptable threshold of 0.50 [53].

Table 3. The results of convergent validity and reliability testing.

Construct	Indicators	AVE	CR	Alpha	Std. Factor Loadings	T-Values
Destination image	AI	0.866	0.927	0.672	0.612	–
	CI				0.838	12.974
Tourist satisfaction	TS1	0.525	0.766	0.570	0.644	–
	TS3				0.481	8.938
	TS4				0.559	10.193
Behavior intention	BI1	0.532	0.771	0.618	0.681	9.845
	BI2				0.586	9.043
	BI4				0.534	–

Model fit: χ^2 [17] = 35.504, Q = 2.062; goodness of fit index (GFI) = 0.981; normed fit index (NFI) = 0.965; Tucker–Lewis index (TLI) = 0.969; comparative fit index (CFI) = 0.981; root mean square error of approximation (RMSEA) = 0.048.

The authors employed CFA to estimate the convergent validity. Following the suggestion of Hall, Snell, and Foust [54], this study adopted an item parceling procedure, aggregated individual items, and used combined items as the indicators for the higher order latent dimension to accomplish a more parsimonious model. The authors formed two parcels for the destination image: Affective image and cognitive image. The initial result of the CFA showed that the factor loadings of one item (T2) of the

tourist satisfaction and one item (B3) of the behavior intention were less than 0.40. By deleting these two items, the reliability of indicators was secured.

Table 3 shows the final result of CFA, which was composed of the three constructs. The three-factor measurement model represented an acceptable goodness of fit with χ^2 = 35.504, df = 17, χ^2/df = 2.062, p = 0.000, goodness of fit index (GFI) = 0.981, normed fit index (NFI) = 0.965, Tucker–Lewis index (TLI) = 0.969, comparative fit index (CFI) = 0.981, and root mean square error of approximation (RMSEA) = 0.048. Overall, the CFA results meet the suggested level of goodness of fit [52,55], indicating that the measurement model is generally suitable for the sample data. In addition, the standardized factor loadings score ranged from 0.481 to 0.838, and all standardized factor loadings were significant at $p < 0.001$. The average variance extracted (AVE) values (0.525: Tourist satisfaction to 0.866: Destination image) exceeded the recommended threshold of 0.50 [56]. In addition, the composite reliability (CR) values (0.771: Behavior intentions to 0.927: Destination image) were higher than the suggested threshold of 0.70 [56].

The AVE test (average variance extracted), a measure of the amount of variance captured by a construct in relation to the amount of variance due to measurement error, confirmed the discriminant validity of measurement scales. The AVE value for each construct ought to be higher than the squared correlation among the constructs [56]. Table 4 shows that the square value of all correlation coefficients does not exceed the AVE value. Thus, this result demonstrates that the measurement model meets the acceptable discriminant validity [56]. In sum, the results of convergent and discriminant validity provided strong evidence of the validity of the constructs.

Table 4. Results of the correlations and discriminant validity assessment.

Variables	1	2	3	4	5
1. Destination image	-				
2. Network density	0.104 *	-			
3. Degree centrality	0.118 *	0.905 *	-		
4. Tourist satisfaction	0.648 ** (0.420)	0.139 **	0.159 **	-	
5. Behavior intention	0.600 ** (0.360)	0.069	0.099 *	0.641 ** (0.410)	-
AVE score	0.866	-	-	0.525	0.532

Notes: Correlations among all research variables are represented in the lower off the diagonal; calculated scores of the squared correlations among constructs (i.e., destination image, tourist satisfaction, and behavior intention) are displayed in parentheses; network variables (i.e., network density and degree centrality) are excluded from the discriminant validity test, because they do not have an AVE value. Thus, network variables (network density anddegree centrality) were used only for correlation test. * $p < 0.05$, ** $p < 0.01$.

4.3. Structural Model

The authors utilized a set of fit indices to test the structural model and hypotheses using SEM as shown in Figure 2. The research model fits the statistics well with χ^2/df = 1.923, p = 0.000, GFI = 0.972, NFI = 0.961, TLI = 0.936, CFI = 0.969, and RMSEA = 0.073. Hypotheses 1 and 2 examined the relation between tourism destination image and multi-attraction travel behavior patterns. Destination image (γ = 0.157, $p < 0.05$) has a statistically significant effect on network density, and destination image (γ = 0.172, $p < 0.05$) is positively related to degree centrality. Thus, Hypotheses 1 and 2 are supported. Hypotheses 3 and 4 investigated the relation between multi-attraction travel behavior patterns and tourist satisfaction. Network density (γ = 0.176, $p < 0.001$) and degree centrality (γ = 0.185, $p < 0.001$) have significant effects on tourist satisfaction. Therefore, Hypotheses 3 and 4 are accepted. As expected, tourist satisfaction has a significant positive effect on behavioral intentions (γ = 0.913, $p < 0.001$), lending support for Hypothesis 5.

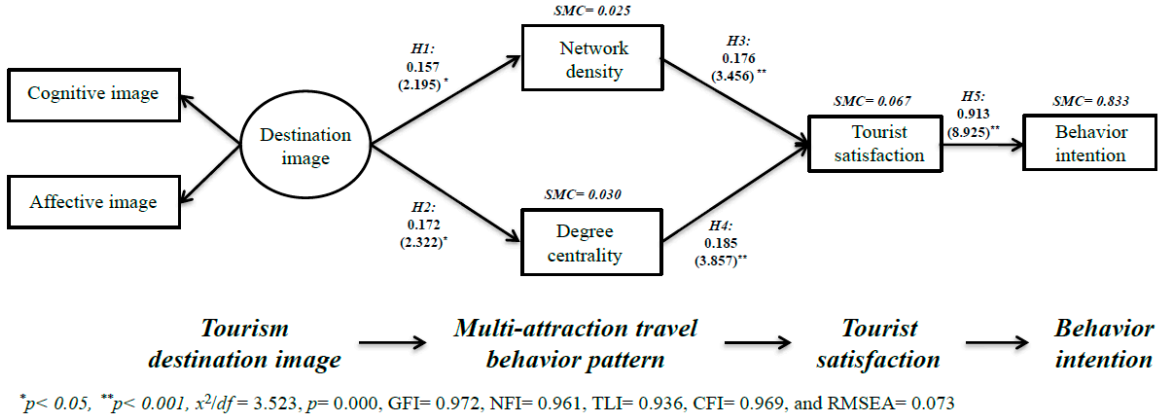

Figure 2. Structural model and hypotheses test results.

5. Discussion and Implications

5.1. Discussion

For a deeper understanding of tourist behavior, this study attempted to develop a research model fully reflecting tourists' multi-destination travel behavior by way of combining SNA techniques with multivariate linear modeling techniques.

The first major finding of this study is that the image of Seoul had a positive effect on density, which is defined as the connectivity of tourist attractions. Therefore, this finding can be interpreted as: If the Chinese tourists perceived the image of Seoul more positively, they tended to visit more of the tourist attractions within Seoul, which increased the connectivity of tourist attractions. This result confirms Kang et al.'s [14] previous studies. Second, destination image had a positive influence on degree centrality. If a destination has an overall positive image, tourists presume that it is equipped with favorable publicity and reputation, locational advantages, and convenient transportation facilities that are drawing factors to the attraction selection. Third, network density was positively related to tourist satisfaction. Travel to multiple attractions affects tourist satisfaction. According to a study by Xiang [57], Chinese FITs tend to spend a lot of time in a large geographic area by searching for information on multiple attractions and selecting multiple attractions based on obtained information. Based on these FITs' travel behavioral characteristics, one can interpret the result of the study that Chinese FITs improve satisfaction by meeting their needs based on gained experience through multi-attraction travel. Fourth, degree centrality, one of the indicators of tourists' multi-attraction travel behavior, exerted a positive influence on tourist satisfaction. In other words, well-known places and/or geographically advantageous tourist attractions, which are positioned to have a high pulling effect, lead to greater tourist satisfaction. Finally, tourist satisfaction had a positive impact on behavioral intentions. This result is consistent with previous findings [42,46] showing that tourist satisfaction is an important antecedent of behavioral intention to revisit. In other words, the higher the tourists' satisfaction, the higher their revisit intention, favorable WOM, and destination recommendations.

5.2. Academic Implications

The uniqueness of this study is in its approach to tourist behavior model. This study makes a methodological contribution to the literature on the topics of tourism destination management and marketing by amalgamating overall network structure, which reflects visitors' movement patterns and the composition of places/attractions within a destination system, with SEM dealing with the behavioral intention and its key precursors. Findings of the present study suggest a few methodological implications for sustainable tourism marketing and development. Most of all, this study overcomes the limitations of existing research, which were mainly concerned with spatial movement patterns of tourism

phenomena [4,11,24], or tourists' individual behavioral characteristics in a single destination [9,10]. This study will serve as a catalyst for extending the realms of researchers tackling this topic.

Unlike the diverse empirical findings of the GIS and traditional statistical technique-based studies, this study collected survey data from actual tourists visiting multiple attractions and applied SNA techniques to incorporate their actual visit patterns. Adopting this approach, we found an important association between destination image perceived by visitors and their movement patterns within the destination, as indicated by the network density and degree centrality of SNA. Another interesting point to note is that both indices of network density and degree centrality exerted positive influences on tourist satisfaction. As far as the authors' knowledge goes, the present study is the first that investigated actual multi-attraction travel behavior using SNA and then transformed it as attribute level variables to examine the structural relationship between SNA indices and tourist satisfactions. Thus, we rendered a strong empirical support to Hwang et al. [9] and Lue et al.'s [10] theoretical proposal about the relationship between tourists' multi-attraction travel behaviors and tourist satisfaction. Apart from the fact that the research methodology is only at its initial stage, this study has made significant advances in this topical area; as the first empirical example, it demonstrates an innovative methodological approach by amalgamating two different techniques from different disciplines. Therefore, the current study contributed to developing the destination choice behavior model for sustainable tourism. This study will trigger new attempts for furthering the applications and expansion in tourism research. In addition, there are several practical implications of the study as discussed below.

5.3. Practical Implications

First, this study verified that the destination image is a significant variable that affects tourists' multi-attraction travel behavior. Thus, in order to induce the multi-attraction travel of tourists, DMOs may utilize the following methods to implant a positive destination image in them. For example, DMOs may utilize various sources of social media, such as YouTube comments, blogs, Twitter, and online discussions, to identify which types of attractions (e.g., restaurants with good food, tourist attractions, nearby attractions, attractions that are easily accessible using local means of transportation) tourists are interested in. This knowledge can be helpful in developing a composed attractive image related to the accommodation, food, landmarks, and transportation. Further, advertising these appealing qualities via television ads, print ads, and social media can lure tourists to visit multiple attractions, which in turn could promote economic vitalization by inducing those tourists to spend money at those attractions.

Lastly, the current study confirmed that the multi-attraction travel of tourists has a positive influence on the level of tourist satisfaction. Thus, in order for DMOs to provide a higher level of satisfaction for tourists through diverse attractions and memorable experiences, the following multilateral efforts are needed: (1) DMOs need to establish a smart tourism plan. For example, from an information-providing perspective, DMOs have to provide information regarding the destination to satisfy the needs of tourists using social media. Using that method, tourists can receive up-to-date information on the destination, attraction diversity, traffic, and lodging; (2) DMOs need to make an effort to provide guidance to multi-attraction tourists regarding the facilities and services that are available for traveling between destinations. For instance, tourism product developers can create a city tour bus program so that tourists who are planning to visit multiple attractions within a destination can comfortably travel between sites, which can increase tourist satisfaction.

5.4. Limitations and Avenues for Future Research

This study, by using survey data for tourists' multi-attraction travel behavior and applying it to SNA, elucidates an in-depth analysis of tourist behavior and suggests constructive ways for local governments, related companies, or tourism destination marketers who organize tourism destinations. However, this study has some limitations. First, there are shortcomings in unveiling the causal relationships among variables by incorporating SNA, which has been utilized by researchers on tourist

behavior patterns, with measurement factors, such as destination images or tourist satisfaction into the structural model. Furthermore, the failure to convey meaning for a small number of specific items resulted in data loss. More specific measurement metrics need to be used in future studies.

Second, due to the nature of the data (i.e., undirected data), tourists' multi-attraction travel behavior patterns are only measured by network density and degree centrality in this paper. Future studies will employ additional metrics that can describe the structural characteristics of the network, such as closeness centrality and concentration, to understand multi-attraction travel in a more detailed manner.

Lastly, we used a total of 468 responses for this study. This seems to be sufficient for this type of modeling and a reasonable level of model fit. However, other than the SEM analysis purpose, for a more conclusive confirmation of the findings of our study, a larger data set would surely be beneficial. Thus, researchers should utilize a large volume of additional data for a more conclusive confirmation of the findings in the future study.

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Appendix A. Explanation of 23 Attractions in Seoul, South Korea

Attractions	Name	Characteristics
Attraction 1	Palaces	Heritage site
Attraction 2	Museums (Memorial Halls)	Heritage site
Attraction 3	Insa-dong	Cultural & shopping place
Attraction 4	Namsan/N Seoul Tower	Landmark of Seoul
Attraction 5	Myeong-dong	Shopping place
Attraction 6	Namdaemun Market	Shopping place
Attraction 7	COEX	Convention & exhibition place
Attraction 8	Dongdaemun Market	Shopping
Attraction 9	Itaewon	Multicultural & shopping place
Attraction 10	Lotte World	Theme park
Attraction 11	Yeouido/63 Building	Entertainment building
Attraction 12	Hangang River/Ferry	Natural scenery place
Attraction 13	Cheonggyecheon	Natural scenery place
Attraction 14	Sinchon/Hongik University	Shopping place
Attraction 15	DMC/World Cup Stadium	Sports & entertainment place
Attraction 16	Hanok village(Namsan)	Cultural place
Attraction 17	Bukchon/Samcheong-dong	Cultural place
Attraction 18	Cheongdam-dong	Shopping
Attraction 19	Garosu-gil street	Shopping place
Attraction 20	Seoul National University	University
Attraction 21	Ewha Womans University	University
Attraction 22	Naksan park	Natural scenery place
Attraction 23	Gangnam station	Shopping place

Appendix B. Conversion to Relational Data from Attribute Data

Table A1, the Attraction by Tourist 2 mode matrix indicates all possible pairs of one-to-one connectedness between an attraction and a tourist.

Table A1. Attraction by Tourist, 2 mode matrix (Incidence matrix).

	Tourist 1	Tourist 2	Tourist 3	Tourist 4	Tourist 5
Attraction 1	1	1	1	1	0
Attraction 2	1	1	1	0	1
Attraction 3	0	1	1	1	0
Attraction 4	0	0	1	0	1

Table A2 (Attraction by Attraction) indicates the number of tourists who visited any pair of common attractions. For instance, Attraction 1 and Attraction 4 share one tourist who visited both places.

Table A2. Attraction by Attraction, 1 mode matrix (Adjacency matrix).

	Attraction 1	Attraction 2	Attraction 3	Attraction 4
Attraction 1	-	3	3	1
Attraction 2	3	-	2	2
Attraction 3	3	2	-	1
Attraction 4	1	2	1	-

Table A3 (Tourist by Tourist) indicates an overall connectedness between two tourists who visited the same attractions derived from the first two matrices, Tables A1 and A2. In other words, Table A3 shows the number of attractions commonly visited by any two particular tourists. For instance, Tourist 2 and Tourist 3 commonly visited Attraction 1, Attraction 2, and Attraction 3. These two tourists commonly selected three different attractions while they traveled.

Table A3. Tourist by Tourist, 1 mode matrix (Adjacency matrix).

	Tourist 1	Tourist 2	Tourist 3	Tourist 4	Tourist 5
Tourist 1	-	2	2	1	1
Tourist 2	2	-	3	2	1
Tourist 3	2	3	-	2	2
Tourist 4	1	2	2	-	0
Tourist 5	1	1	2	0	-

Therefore, a two-mode matrix is a primary input matrix showing connectedness between the same kind of nodes (either attractions or tourists). On the other hand, the two-mode matrix shows how two different categories of nodes (attraction by tourist) are connected. Converting matrices from 2-mode to 1-mode does not result in any information loss, as shown when Tables A1 and A2 is incorporated into Table A3.

Appendix C. Calculation Process of Density and Centrality Value

Density is calculated using an SNA conducted based on data from the attractions that tourists have actually visited. For instance, if an SNA conducted on 'Tourist A', who visited six of the 23 attractions in Seoul, produces a density value of 0.05, and the same analysis is conducted on 'Tourist B', who visited two out of the 23 attractions, and that produced a density value of 0.01, the density value for 'Tourist A' means that 'Tourist A' shows a wider multi-attraction visit pattern than 'Tourist B'. The authors applied this procedure in order to derive the density values to use them as a variable in the SEM. First, they constructed a 23-attractions-by-1-tourist matrix based on the responses of each respondent in order to calculate the density value, which was then converted to a 23×23 attraction matrix. Lastly, the authors created 468 attraction networks using the 1-mode matrix (attraction by attraction) and then conducted an SNA to calculate the density value for each of the 468 individuals.

In addition, a quasi-network, which is created when tourists visit an attraction at the same time, was used to calculate the degree centrality. More specifically, the authors created a 468 tourists by 23 attractions matrix to calculate the degree centrality value and then converted the matrix to a 468 tourists by 468 tourists matrix. Secondly, they conducted the SNA to calculate the degree centrality of the 468 respondents, which indicates the number of tourists directly connected to a particular tourist. Lastly, they used the degree centrality value as a variable that an attraction visited by a tourist with a high degree centrality tended to be visited simultaneously by many other tourists, which means that the particular attraction has a high degree centrality.

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