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Mapping Tourists' Destination (Dis)Satisfaction Attributes with User-Generated Content

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Abstract: Although the tourism industry has increasingly used social media, there has been little empirical research in terms of the attributes of tourist satisfaction and dissatisfaction with user-generated contents. The purpose of this study is to explore the attributes of tourist satisfaction and dissatisfaction through user-generated contents. We collected data from online review platforms. Our data include historical online reviews, names of reviewers, ratings, location, helpful votes, date of visits, and contributions. In terms of results, the study found 30 key topics related to tourist satisfaction and dissatisfaction. Additionally, we found three clusters (i.e., holiday experience, attractions and facilities, and food experience). Lastly, we that suggested rating levels are different based on the type of tourists (i.e., domestic and international). This study provides discussions and implications for tourism research and industry practices.

Keywords: user-generated content; satisfaction; dissatisfaction; text mining; big data

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1. Introduction

The advent of social media has increasingly altered the hospitality and tourism landscape and now plays a critical role in promotion, advertising, and marketing [1]. The use of social media is already a mainstream practice in the tourism industry, and it has already become a topic of recent study within the tourism industry [2,3]. Typically, these reviews are composed of textual data, which accrues into "big data" motherlodes of information—so much information that longstanding statistical methods are often incapable of analyzing it [3]. In order to investigate such big data, today's academics have to use, in addition to traditional statistics, advanced techniques such as web crawling, computational linguistics, and text mining [4].

The dimensions of tourist satisfaction and dissatisfaction in a destination are oft-studied topics in the literature, but few of these studies have been conducted using user-generated content. For example, Park, et al. [5] examined dimensions of customers' revisiting behavior in the hotel industry using textual data. Moro, et al. [6] suggested dimensions of guest satisfaction using textual data in the hotel industry. Few researchers, however, have traced tourist (dis)satisfaction through online textual reviews written by authentic customers [7], and the lack of such studies within the tourism and destination contexts is clear.

Therefore, the purpose of this study is to explore the attributes of tourist satisfaction and dissatisfaction with user-generated content. More specifically, the objectives of this study are twofold: (1) to explore the attributes of tourist satisfaction and dissatisfaction based on user-generated content, and (2) the relationship among attributes of satisfaction and dissatisfaction, rating, and tourist type.

The scope of this research is the set of attractions located in Incheon, South Korea. Incheon is the second largest port city in Korea and was the main gateway to commercial and cultural exchange in the late 19th century. Moreover, it is now home to Incheon International Airport and hosts Korea's best music festivals and concerts. As such, Incheon is rapidly developing into a modern cultural capital.

2. Literature Review

2.1. Customer Satisfaction and Dissatisfaction

An organization's prior, current, and potential success are all embodied in its degrees of customer satisfaction [8]. Customer-satisfaction levels reflect such critical consumption concepts as attitude change, repeat purchasing, and consumer loyalty [9]. Satisfaction's criticality is amplified by the fact that dissatisfied customers complain and demand reparative action in compensation for their disappointed expectations [10].

In the tourism and hospitality context, Herzberg's two-factor theory has been used in a variety of research settings to assess each attribute's disparate impact that contributes to individual satisfaction and dissatisfaction [11]. Even though customer satisfaction and dissatisfaction have been commonly investigated in the relevant hospitality and tourism context (e.g., [12,13]), limited studies have considered them separately [14], in spite of the fact that individuals' dissatisfaction and satisfaction are different constructs [15]. This tendency to amalgamate is a critical error, as customer satisfaction and dissatisfaction need to be conceptually different [15]. For example, previous research has often employed overall satisfaction scores to examine customer satisfaction, failing, in the process, to distinguish low satisfaction from dissatisfaction. However, as the two-factor theory reveals, satisfaction and dissatisfaction are not mutually exclusive and may both be present in a customer's experience [16]: certain aspects of a service encounter may produce satisfaction while others simultaneously lead to dissatisfaction [17]. Finally, few hospitality-industry studies discuss customer dissatisfaction compared with satisfaction [18], leaving this vital construct underexamined.

2.2. Attributes as Determinants of Customer (Dis)Satisfaction in Hospitality and Tourism Research

A plethora of dimensions are known to influence customer (dis)satisfaction [10]. Most relevant researchers have indicated that hotel and restaurant attributes are causes of tourist satisfaction and dissatisfaction. Such studies (e.g., [18,19]) have shown that customer (dis)satisfaction toward hotels derives from numerous factors. These can include infrastructure elements (Wi-Fi, parking, room conditions), services (transportation, food and beverages, housekeeping and cleanliness), intangibles (quality of management, attitude of staff, peacefulness), and more. Sezgen, et al. [20] indicated that, in the airline industry, friendliness and helpfulness of staff, product value, and low price were the major elements driving satisfaction. Correspondingly, they also showed that service attributes such as seat comfort and legroom, luggage care, flight disruptions, and staff behaviors were the major factors behind passengers' dissatisfaction. Furthermore, previous research [21] has shown that in restaurants, different dimensions—such as food, environment, service, interpersonal interaction, and diner motivation—decide customer (dis)satisfaction.

One complication in tourism research is that both tangible and intangible features exist in and define a destination [22]. These multiple attributes of a tourism destination are major factors driving tourist satisfaction. Prior research ([23]) has focused on destination attributes ranging from tourism activities (cultural attractions, recreational facilities, shopping, restaurant culture) to local amenities (hospitality infrastructure, natural environment, climate, security and safety, and quality of accommodations) to grasp tourists' perceptions of their destination visits. Similarly, relevant research has revealed the key dimensions of the typical cruise experience, such as staff, entertainment, and value [24].

The hospitality and tourism industries aim to manage tourist 'experiences' to maximize customer satisfaction [25]. Overall, tourist satisfaction is chiefly decided by travelers' evaluations of a tourism destination's various attributes; customer (dis)satisfaction results from travelers' perceptions of all of the elements that add up to create the trip experience [26]. Xiang, Schwartz, Gerdes and Uysal [7], using a text-analytical approach, dissected hotel guests' reviews to document the connection between guests' experiences and their satisfaction levels.

Previous studies ([10]) have examined significant differences in tourism destination elements by different travel characteristics (i.e., domestic versus international travel destinations). Studies (e.g., [27]) have demonstrated differences between the travel behaviors and satisfaction evaluations of domestic and international travelers. Magnini et al. [28] also stated that customer satisfaction could be affected by customers' origins or the nature of their travel, showing differences between domestic and international hotel guests. Li, et al. [29] also separated domestic and international guests to indicate different patterns in customer-satisfaction ratings.

2.3. Examining Online Reviews

Online review platforms attract reviews and experience reports in large numbers from both satisfied and dissatisfied customers [30]. For that reason, online reviews can take researchers directly to the heart of the customer experience [31], with positive reviews detailing satisfaction and negative reviews encapsulating dissatisfaction [18]. In today's marketplace, online reviews substantially affect how destinations are perceived by potential consumers, making them remarkably important to industry operators [32]. Tourism and hospitality organizations now routinely turn to online reviews to improve their service deliveries and product sets with insights from actual customers [33,34]. Online reviews have now been used to investigate travelers' opinions on hotels, airlines, restaurants, and attractions, where most previous studies had employed reviews from this platform only to investigate tourists' hotel and dining preferences [35]. The academic evaluation of online reviews is still a young field, and so far most of the literature conceives hotels and restaurants as homogenous hospitality settings—often focusing on the hotel aspect (e.g., [7,36]). Hotel-stay satisfaction is one of the hospitality dimensions most clearly documented in online customer reviews, and academia has taken notice.

The online reviews describe tourists' experiences with products/services/destinations, and they reflect tourists' assessments and satisfaction based on staying experience [37]. Because of the popularity of using online reviews, relevant studies have investigated individuals' (dis)satisfaction from online reviews. Nonetheless, the researchers call for more research.

2.4. Social Media Analytics and Topic Modeling

Social media produces massive troves of structured and unstructured data. Analyzing this data has required the development of novel techniques, culminating in the new interdisciplinary field of social-media analytics [38]. Relevant research has explored methods such as web crawling, data mining, and machine learning to gather, investigate, and understand textual data for meaningful insights [39]. Specifically, topic modeling—which is capable of discovering topics hidden in textual data—is frequently employed. One of these big-data analytic tools, topic modeling, has been employed in different fields (e.g., [40]). Researchers have identified latent topics from a large body of content (e.g., unstructured texts) [41]. Within the hospitality and tourism context, topic modeling has been employed for different purposes such as examining different types of reviews, analysis of multiple online review platforms, tourist-satisfaction analysis of visitors of hospitality and tourism-related organizations, consumer perceptions of hospitality and tourism-related products and services, investigating the posting of reviews in social media to document travelers' experiences, and service-quality attributes from online reviews (e.g., [3,42]). Table 1 provides a summary of recent studies on topic modeling in the hospitality and tourism industry.

Table 1. Summary of recent studies of topic modeling in the hospitality and tourism industry.

Author(s), Publication Year	Description	Data Source	Methods Used	Context
Kirilenko et al. [43] (in press)	Traveler satisfaction	TripAdvisor	Topic modeling	Tourism
Wen et al. [44]	User-generated reviews and consumer perceptions	TripAdvisor	Topic modeling and content analysis	Restaurant
Chatterjee [45]	Helpfulness of online hotel reviews (i.e., TripAdvisor)	TripAdvisor	Sentiment and emotion mining approach	Hotel
Luo et al. [35]	Theme park and online review	TripAdvisor	Topic modeling	Tourism
Vu et al. [21]	Data mining, travel itinerary	Twitter	Topic modeling	Tourism
Li et al. [29]	Impacts of temporal, explanatory, and sensory cues on customers' perceived usefulness and enjoyment toward restaurant online reviews	Yelp.com	Text mining approach and econometric analysis	Restaurant

Structural topic modeling—or STM—a recent development in text analysis, has already proved itself in political science and linguistic studies, but it has not become typical in hospitality and tourism studies [46]. Even though customer-(dis)satisfaction investigations have been conducted using online reviews (e.g., [7]), scholarship utilizing STM within the tourism context is still paltry. Table 2 shows customer (dis)satisfaction-related research using (non)text analysis of online reviews.

Table 2. Consumer (dis)satisfaction-related research using text-analysis methods.

Related Study	Data Source	Methods	Setting
Hu et al. [43]	TripAdvisor	Topic modeling (Structural Topic Model)	Hotel
Park et al. [47]	Yelp.com	Topic modeling (Structural Topic Model)	Restaurant
Boo and Busser [48]	Online reviews of hotels	Leximancer tool with manual work	Hotel
Guo et al. [3]	Online reviews of hotels	LDA	Hotel
Xu and Li [18]	Customer review	LSA topic model, dissatisfaction with airline service	Airline
Büschken and Allenby [49]	Hotel review	LDA	Hotel
Mankad et al. [50]	Hotel review	LDA	Hotel

3. Methods

3.1. Data Collection

To examine tourists' perceptions, online reviews from two major online review platforms, i.e., Google and TripAdvisor, were collected with Python-based crawlers in July

2019. The following seven most popular attractions in Incheon were used as keywords to search online reviews: Incheon China town, fairytale town, Wolmido, the memorial hall for Incheon landing operation, Incheon Jayu park, and Sinpo international market. As a result, 6822 online reviews were collected. In addition to online reviews, the date the online reviews were written, name of reviewers, ratings, location (if available), helpful votes (if available), date of visits (if available), and contributions (if available) were collected.

3.2. Online Review Translation

One of the challenges of using user-generated content is the limited amount of metadata publicly available from which researchers can infer different patterns of tourist behavior by demographics or personal traits, which leads to another quest for researchers: discerning metadata from available information. We found Google reviews to have limited metadata compared to dedicated online review platforms (e.g., TripAdvisor and Yelp). However, due to their growing popularity among tourists around the globe, Google reviews have quite a large volume of reviews written in multiple languages. Similarly, TripAdvisor is one of the most popular review sites that lists a vast number of travel destinations throughout the world. Since we targeted the popular tourism destinations in Incheon, South Korea, most of the implicated online reviews were composed in foreign languages. Instead of selecting online reviews written in one language, different languages were identified to create new metadata: the apparent "nationality" of tourists. Due to the large number of data, this study adopted automated translation by using the R package "googleLanguageR." Although human translation is optimal to capture the nuance of the sentence and intended meaning, the use of machine translation has been found to be suitable for topic modeling [51]. Grounded on the bag-of-words assumption, topic modeling ignores the order of vocabularies within a document [52]. Thus, topic modeling performs well regardless of the differences in language structures from multiple languages [51].

The following steps were followed to translate reviews. First, the original language of the online reviews was automatically detected. As a result, we found the online reviews were written in 13 different languages (e.g., Korean, English, and Chinese). Based on these language detection results, online reviews written in the same language were combined to create separate files, and each of these data files was used as an input to be translated into English. De Vries et al. [53] confirmed that machine translations using Google Translate can produce highly similar topic-modeling results to human translations. Still, to ensure the quality of translation and topic modeling results, two researchers whose first language is Korean and who are fluent in English reviewed the machine-generated Korean–English translation, and both researchers agreed on the adequacy of the machine translation. After removing online reviews whose language the machine process failed to detect, 6439 English-language online reviews remained for further data preprocessing.

3.3. Data Preprocessing and Structural Topic Modeling

Python was used for data preprocessing before text mining. All reviews were lowercased, and non-English characters, special characters, and common words (i.e., NLTK stop words) were removed. Based on the discussion of researchers, the list of additional stop words was created, and they were used for data cleaning. Python package "Gensim" was used to create bigrams and trigrams and lemmatize data. Data cleaning resulted in 210 short reviews, and finally, 6229 online reviews were used for text mining.

R-based probabilistic topic modeling, a form of structural topic modeling (STM), was performed to extract the latent themes from the online reviews [54]. Due to the probabilistic nature of topic modeling, the machine process generates different topics and values at each run. To ensure the reliability of the results, researchers set seeds in the line to make consistent results possible. Based on STM-generated indices, 30 topics were selected to build the model. Two researchers manually reviewed the top words and actual online reviews and discussed them to label the topics. Unlike in classification models or Latent Semantic Analysis where each document belongs to only one category, the probabilistic topic model (including STM) generates the probabilistic distribution of each document to all topics. Therefore, this approach can discover the associations of each document with multiple topics.

To examine associations among topics, the topic network was explored with a cutoff point of 10%. Additionally, eigenvector centrality scores were calculated for each topic node [55]. After comparing modularity scores of community detection algorithms, Greedy community detection was applied to identify clusters within topic correlation. Ratings and tourist types were used as metadata to estimate the effects of metadata on topic proportions. Based on the languages used for reviews, tourists were categorized as domestic tourists and international tourists. Specifically, all reviews written in Korean were recoded as "1 (domestic tourist)," and reviews in other languages were recoded as "0 (international tourists)". To simplify the estimation with ratings, a new dummy variable was created with original rating scores ranging from 1 to 5; high rating scores (4 or 5) were converted to 0, and low rating scores (1, 2, or 3) were converted to 1. The implemented methodology is summarized in Figure 1.

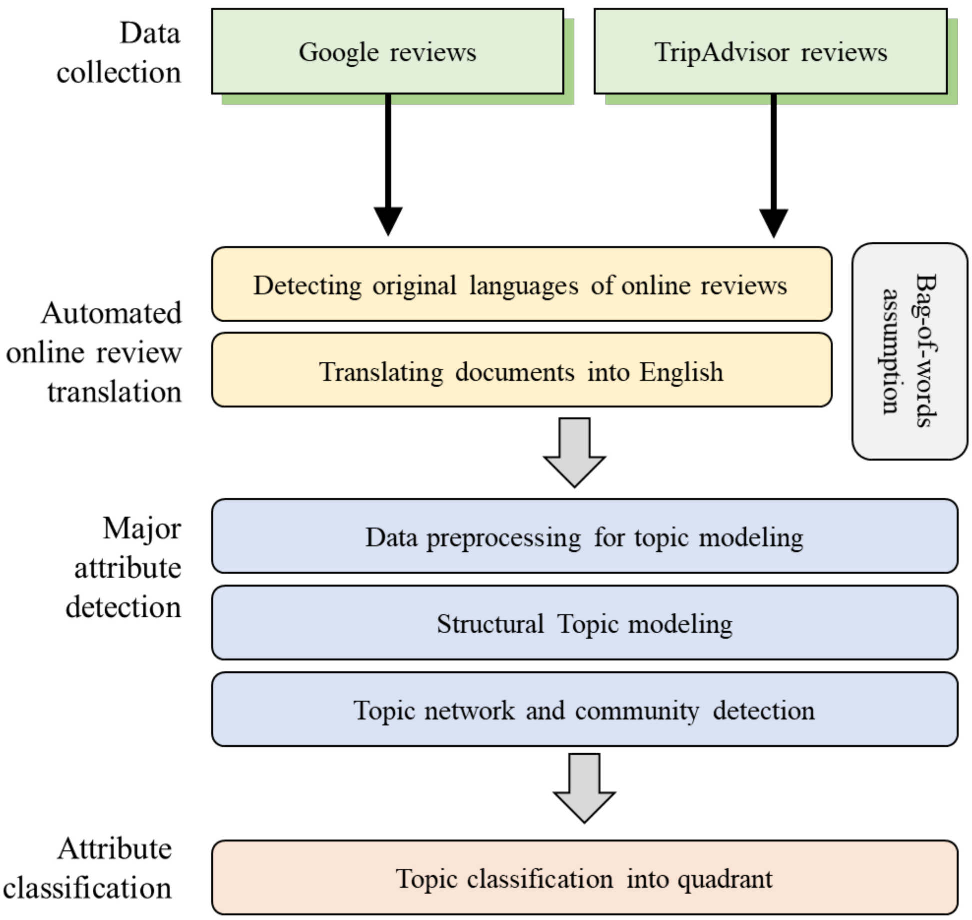

Figure 1. Summary of data analysis.

4. Results

The majority of online reviews were written in 2018 (43.3%) and 2019 (35.8%). Nearly 70% of reviewers had four- or five-star rating scores, and Korean reviews accounted for the highest proportion among the reviews. Table 3 provides descriptive statistics of samples.

Table 3. Descriptive statistics of samples.

Variable	Frequency	%
Year		
2019 (As of July)	2232	35.83
2018	2696	43.28
2017	587	9.42
2016	330	5.3
Prior to 2015	384	6.16
Rating		
1-star	175	2.81
2-star	296	4.75
3-star	1463	23.49
4-star	2265	36.36
5-star	2030	32.59
Language		
Korean	4839	77.69
English	667	10.71
Chinese	351	5.63
Japanese	179	2.87
Russian	64	1.03
Thai	46	0.74
German	21	0.34
Spanish	19	0.31
Indonesian	15	0.24
French	13	0.21
Vietnamese	8	0.13
Portuguese	7	0.11

4.1. Identifying Salient Attributes

By applying STM, the 30 most salient topics were identified. Average topic weights represent the popularity of the topics. For the topics with high topic weights, travelers mentioned them more frequently than other topics with low topic weights. Topic 14, related to a special Korean dish called Chicken Ganjeong, was the most popular, accounting for about 6.2% of the total topic weight. Topic 17, regarding a variety of restaurant options, had the second-highest topic weight, accounting for nearly 4.7% of the total topic weight. The eigenvector centrality score indicates how strongly each topic is related to others. Topics related to food and restaurants, such as topics 17 (restaurant variety), 28 (food experience), and 14 (chicken dish), had high eigenvector centrality scores. Table 4 illustrates an overview of the 30 topics.

As a result of community detection, three clusters were discovered among the 30 topics (Figure 2). Topics that share common themes and have similar keywords are tightly connected in the topic network and thus more likely to be in the same cluster. Therefore, the tight topic correlation implies that these topics have overlapping keywords, or they were mentioned by the same person. Based on the 30 topics, 11 topics were grouped together in cluster 1. Twelve topics were included in cluster 2, and seven topics were classified together in cluster 3. Figure 1 shows the topic network. The clusters are as follows:

Cluster 1. A group of holiday experiences;
Cluster 2. A group of attractions and facilities;
Cluster 3. A group of food tourism.

Cluster 1 (e.g., holiday experiences) is mostly about tourists' emotional expression (e.g., topic 13: positive experience) and behavior intention (e.g., topic 24: recommendation) while they are spending leisure time in the destinations. Topics that belonged to cluster 2 are more related to infrastructure and tangible facilities (e.g., topic 2: museum, topic 29: park). While clusters 1 and 2 are typical topics that can be found in many destinations, it is worth noting that one cluster is mostly about tourists' experiences related to food.

Table 4. Overview of 30 topics.

Cluster	Topic Number & Label	Eigenvector Centrality	Average Weight	Top Five Words
1: Holiday experience	T13 Positive experience	0.192	0.046	good, time, day, quiet, spend
	T4 China town	0.151	0.044	china_town, china, great, love, first
	T8 Picture	0.195	0.043	nice, its_good, take_picture, picture, pretty
	T1 Fairytale village	0.084	0.041	fairytale, village, beautiful, wall, character
	T9 Weekend experience	0.044	0.039	weekend, many_people, parking, car, enough
	T16 Child	0.183	0.038	child, photo, walk, great place, it's great
	T22 Diverse experience	0.341	0.035	see, close, dont, many_thing, many_place
	T24 Recommendation	0.071	0.033	visit, recommend, want, good_place, weekday
	T10 Mural	0.065	0.032	street, mural, well, dong, way
	T30 Place	0.355	0.030	place, come, little, normal, develop
	T21 Neighborhood	0.561	0.020	the neighborhood, expect, next, shopping, something
2: Attractions and facilities	T29 Park	0.105	0.035	park, view, course, macarthur, tour
	T25 Restaurants in China town	0.547	0.032	restaurant, town, chinese_restaurant, jajangmyeon, incheon_china
	T27 Chinese building	0.134	0.032	Chinese, people, building, style, change
	T2 Museum	0.001	0.030	museum, history, memorial, Incheon_lande, operation
	T12 Local shops	0.037	0.030	shop, area, local, try, store
	T18 Public transportation	0.001	0.029	walk, station, interesting, Seoul, hour
	T7 Freedom park	0.173	0.025	freedom_park, cherry_blossom, cheap, watch, high
	T15 Nearby facility	0.053	0.024	look, nearby, worth, bad, hill
	T5 Tourist attraction	0.007	0.024	tourist, make, noodle, attraction, spot
	T23 Trivia	0.012	0.024	small, price, japanese, easy, compare
	T19 Mediocre experience	0.014	0.024	feel, atmosphere, nothing, exotic, special
	T20 Restaurant facilities	0.224	0.019	sell, big, lunch, meal, business
3: Food experience	T14 Chicken dish	0.774	0.063	eat, chicken_gangjeong, famous, gangjeong, line
	T17 Restaurant variety	1.000	0.047	food, lot, snack, crowd, many_restaurant
	T28 Food experience	0.834	0.041	taste, fun, chinese_food, enjoy, expensive
	T26 Traditional market	0.403	0.037	old, house, alley, bread, traditional_market
	T6 Market	0.225	0.031	market, family, memory, play, taking_picture
	T3 Gourmet	0.681	0.027	delicious, thing, clean, around, gourmet
	T11 Chinese foods	0.714	0.027	jjajangmyeon, dumpling, sinpo_market, jjajang, cake

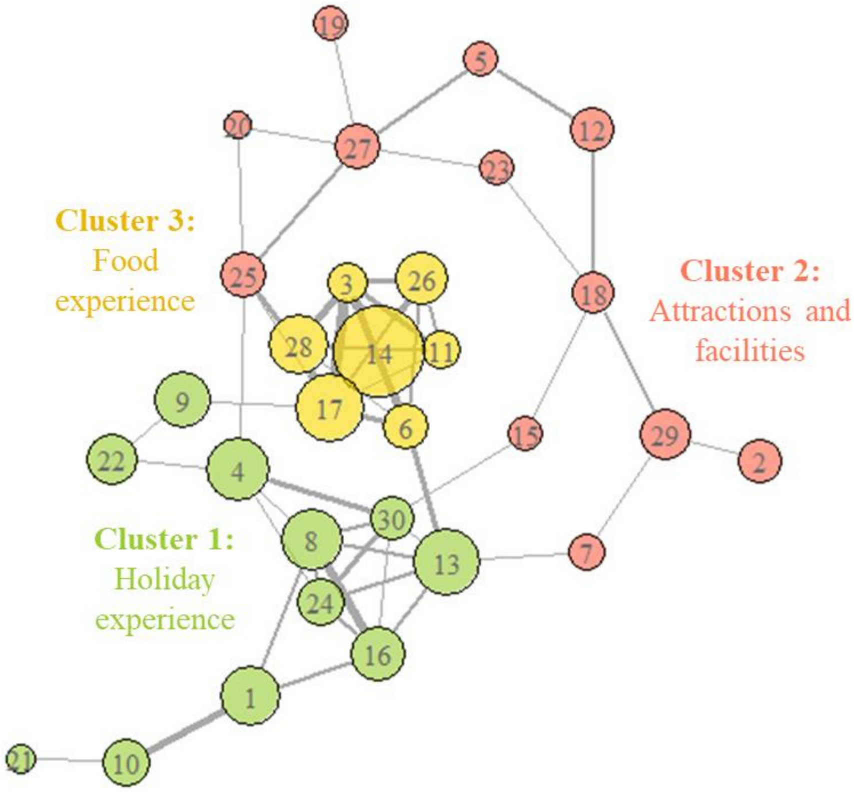

Figure 2. Topic network (Node size represents topic weight and edge thickness represents topic correlation degree).

Based on the topic network, centrality scores of topics were calculated to identify the most influential topics in the network, more specifically, a topic that has more dense connections with other topics. Among topics with the highest centrality scores, many of them belonged to cluster 3, such as topic 17 (Restaurant, centrality: 1.00), topic 28 (food experience, centrality: 0.83), and topic 14 (chicken dish, centrality: 0.77). Since these topics are tightly connected with other topics, they are more likely to be mentioned or recalled together with such other topics. Particularly, topic 14 (chicken dish) had the highest topic weight. More specifically, this is related to the characteristics of Incheon as a destination. Since the representative food of Incheon is a chicken dish which has appeared in the media frequently, tourists have mentioned it a lot, and it has served as a hub for Incheon tourism.

Some topics serve as a bridge to connect clusters because these topics have overlapping attributes among the clusters. For example, topic 4 (China town) of cluster 1 is connected to topic 25 (restaurants in China town) in cluster 2. After reviewing both top words and online reviews closely related to topic 4 and topic 25, researchers found that topic 4 is more related to tourists' expression of their experiences in China town whereas topic 25 merely introduces the restaurants located in the destination. Similarly, topic 5 (tourist attraction) in cluster 2 is connected to topic 28 (food experience) in cluster 3. Topic 5 was mostly written by travelers who visited the famous tourist restaurants that have almost turned into touristic destinations, which explains why topic 5 and topic 28 are connected. Topic modeling results demonstrate that the same word (e.g., "china_town") can have different intentions and meanings in different contexts. Therefore, it is helpful to create higher units by applying community detection so that topics can be comprehended based on the broader context.

4.2. Classification of Attributes by Rating and Tourist Types

We investigated the difference between rating and tourist types. Topic weights were compared by ratings and tourist types (Table 5). In comparison to topic weights based on the rating dummy variable, positive coefficients demonstrated the number of reviews with high ratings (4 or 5) that surpassed low ratings (1, 2, or 3) for the particular topic. For example, topic 1 (fairytale village) had a positive coefficient in the rating comparison, meaning among tourists who mentioned the fairytale village, more people gave high star rating scores than low. In other words, tourists who visited the fairytale village were more likely to be satisfied with their past experiences. Therefore, the rating coefficient can demonstrate the positive or negative emotional state of a tourist, derived from the topic-related experience. A comparison of topic weights by tourist type demonstrated whether domestic or international tourists mentioned a specific topic more frequently. If domestic travelers mentioned a topic more often than international travelers, the topic had a positive coefficient and vice versa.

More specifically, in the group of holiday experiences, regarding the rating, topics with a positive coefficient for rating were fairytale village (topic 1), picture (topic 8), positive experience (topic 13), and child (topic 16), implying that tourists who had children and visited the fairytale village were more likely to be satisfied. They were also satisfied because there were many places to take pictures. However, tourists who went to the places during the weekend (topic 9) and expected more diverse experience (topic 22), and interesting neighborhood (topic 21) and diverse experience (topic 22) were dissatisfied. The comparison of topic weight by tourist type indicated most of the topics in a group of holiday experiences (e.g., topic 8: picture, topic 9: weekend experience) were more popular among domestic travelers, except for the neighborhood topic (topic 21). Therefore, within the group of holiday experience, we were able to isolate the difference between rating and tourist type.

In the group of attractions and facilities, topics related to parks and museums (topics 2, 7, and 29) had positive coefficients for rating, indicating reviews related to these topics had more high ratings than low ratings. However, six topics (e.g., topic 15: nearby facility, topic 20: restaurant) had negative coefficients for rating estimation. Specifically, domestic customers were more likely to be dissatisfied with restaurants near the attractions, whereas international customers were dissatisfied with the attractions themselves, such as a park or nearby facilities. Both domestic and international travelers were dissatisfied with Chinese buildings (topic 27) and evaluated their experiences as nothing special (topic 19). International travelers mentioned public transportation (topic 18) and local shops (topic 12) more frequently than domestic travelers. However, reviews related to these two topics had mixed ratings, and thus, the differences in topic weights by ratings were not significant.

All topics in the group of food tourism were related to foods, and domestic travelers mentioned them more frequently than international travelers. Domestic customers were satisfied because they had delicious foods (topic 3) and a variety of options (topic 17). Among topics that domestic travelers mentioned more than international travelers, the topic related to the special Korean chicken dish (topic 14), chicken gangjeong, had the greatest difference in topic weight between domestic and international travelers. Not only did domestic travelers frequently mention the chicken dish, but also, they were satisfied with their experiences and had high ratings.

Figure 3 shows the classifications of topics by satisfaction and tourist type. Domestic travelers mentioned the topics belonging to cluster 3 (food experience) more frequently than did international tourists, indicating they had greater interest in food experiences. Additionally, these food experiences tended to be evaluated positively. On the other hand, international tourists were more interested in destination attributes related to physical facilities and attractions. In particular, fairytale village, museum, and freedom park had a positive relationship with the overall satisfaction score. Both domestic and international tourists were dissatisfied with the physical building and facilities related to cluster 2. While domestic tourists were concerned about and dissatisfied with the quality of experience and intangible attributes of tourism products, international tourists were more dissatisfied with tangible attributes, such as the surrounding facilities or neighborhoods.

Table 5. Effects of metadata on topic proportions.

Clusters	Topics	Rating (Low vs. High)				Tourist Type (Domestic vs. International)			
		Estimate	**Std.Error**	**Ci.Lower**	**Ci.upper**	**Estimate**	**Std.Error**	**Ci.Lower**	**Ci.Upper**
1: Holiday experience	T1 Fairytale village	0.004	−0.001	0.006	0.002	−0.019	−0.003	−0.013	−0.025
	T4 Chinatown	0.001	−0.001	0.002	0.000	0.000	−0.001	0.003	−0.003
	T8 Picture	0.003	−0.001	0.005	0.002	0.008	−0.002	0.012	0.004
	T9 Weekend experience	−0.010	−0.001	−0.008	−0.013	0.036	−0.002	0.040	0.032
	T10 Mural	0.001	−0.001	0.002	−0.001	−0.011	−0.002	−0.007	−0.015
	T13 Positive experience	0.004	−0.001	0.005	0.002	0.005	−0.002	0.008	0.002
	T16 Child	0.003	−0.001	0.005	0.001	0.001	−0.002	0.005	−0.004
	T21 Neighborhood	−0.002	−0.001	−0.001	−0.003	−0.007	−0.002	−0.004	−0.011
	T22 Diverse experience	−0.003	−0.001	−0.002	−0.004	0.021	−0.002	0.025	0.018
	T24 Recommendation	0.000	−0.001	0.001	−0.001	0.000	−0.002	0.003	−0.003
	T30 Place	0.001	0.000	0.002	0.000	−0.001	−0.001	0.001	−0.003
2: Attractions and facilities	T2 Museum	0.005	−0.001	0.008	0.002	−0.043	−0.005	−0.034	−0.052
	T5 Tourist attraction	−0.001	−0.001	0.000	−0.003	−0.013	−0.001	−0.011	−0.016
	T7 Park	0.003	−0.001	0.005	0.002	0.006	−0.002	0.010	0.001
	T12 Local shops	−0.001	−0.001	0.001	−0.002	−0.049	−0.002	−0.045	−0.053
	T15 Nearby facility	−0.002	−0.001	−0.001	−0.003	−0.012	−0.001	−0.009	−0.014
	T18 Public transportation	0.001	−0.001	0.003	−0.001	−0.069	−0.003	−0.063	−0.075
	T19 Mediocre experience	−0.005	−0.001	−0.004	−0.007	0.002	−0.002	0.005	−0.001
	T20 Restaurant	−0.005	−0.001	−0.003	−0.006	0.004	−0.002	0.008	0.001
	T23 Trivia	−0.006	−0.001	−0.004	−0.007	−0.012	−0.002	−0.008	−0.015
	T25 Restaurant	−0.004	−0.001	−0.003	−0.005	0.007	−0.001	0.010	0.004
	T27 Chinese building	−0.005	−0.001	−0.003	−0.007	−0.003	−0.002	0.000	−0.007
	T29 Park	0.004	−0.001	0.006	0.002	−0.029	−0.003	−0.023	−0.035
3: Food experience	T3 Gourmet	0.003	0.000	0.004	0.002	0.015	−0.001	0.017	0.013
	T6 Market	0.004	−0.001	0.005	0.003	0.012	−0.001	0.015	0.010
	T11 Chinese foods	0.000	−0.001	0.002	−0.002	0.033	−0.002	0.038	0.029
	T14 Chicken dish	0.004	−0.002	0.007	0.001	0.055	−0.003	0.060	0.049
	T17 Restaurant	0.002	−0.001	0.004	0.001	0.016	−0.001	0.019	0.013
	T26 Traditional market	0.001	−0.001	0.003	−0.001	0.027	−0.002	0.031	0.024
	T28 Food experience	0.000	−0.001	0.001	−0.001	0.020	−0.002	0.024	0.017

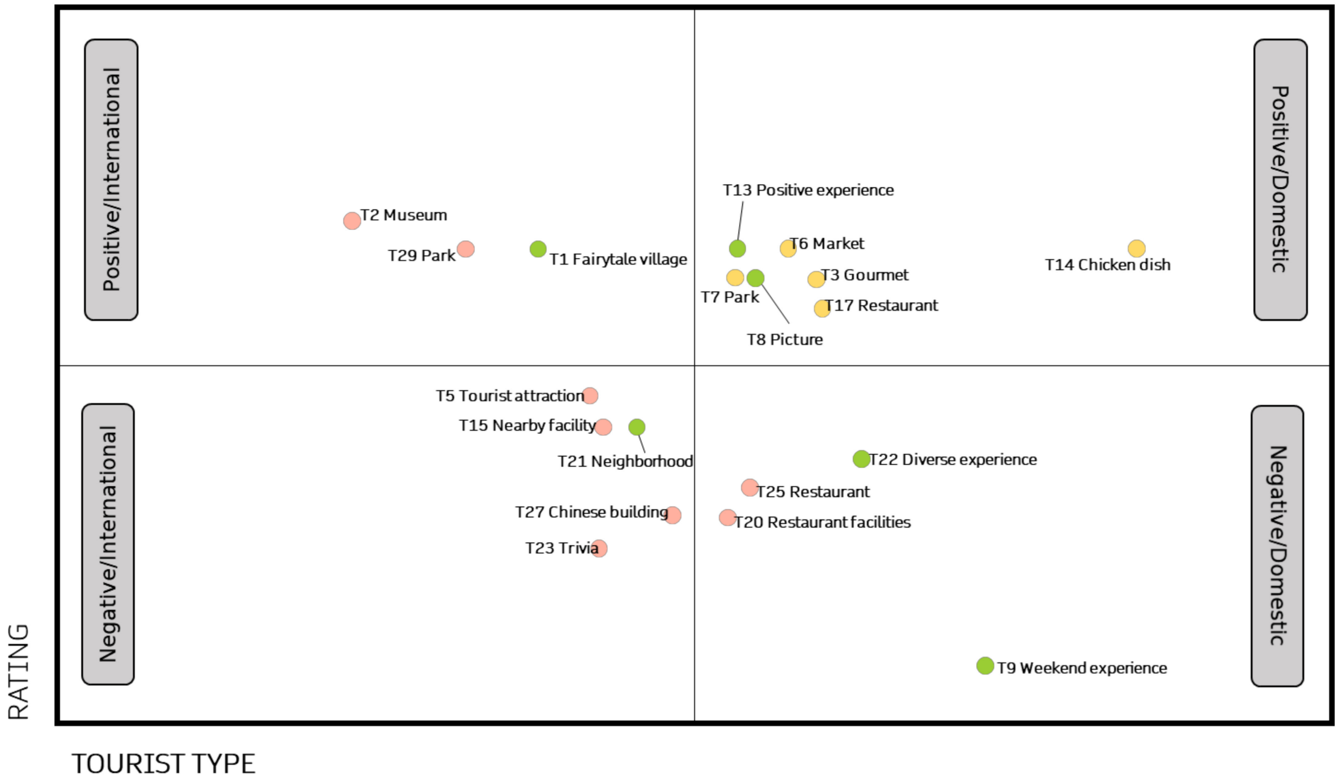

Figure 3. Classifications of topics by satisfaction and tourist type (green dots: cluster 1 (holiday experience), light red dots: cluster 2 (attractions and facilities), yellow dots: cluster 3 (food experience)).

5. Discussion and Conclusions

Although the tourism industry has increasingly adopted user-generated content as a source of data on customer experiences, there have been few empirical studies identifying the dimensions of tourist satisfaction and dissatisfaction using user-generated content [13,47]. This study explored text mining as a means of identifying the key aspects shared by tourists in their online reviews. First, we found key topics such as topics 17 (restaurant variety), 28 (food experience), and 14 (chicken dish) from user-generated content. This finding is aligned with that of previous studies [56]. Second, based on the topic-correlation results, three clusters of topics frequently mentioned by travelers were identified (i.e., holiday experience, attractions and facilities, and food experience). This finding is related to some previous studies [57]. This may suggest that the group of holiday experiences was satisfied regarding family, pictures, and positive experience. In the group of food tourism, they were satisfied with the restaurant variety and food experience. Third, by comparing the topic proportion between the high- and low-rating reviews, the satisfying and dissatisfying aspects were discovered. This study compared topic proportions between domestic and international travelers to see whether they have different interests or expectations in various aspects.

In terms of implications, first, we found hidden key topics and three clusters from user-generated content. In other words, this study provides a new market segmentation approach based on user-generated content. Most previous studies have focused on market segmentation based on traditional methods (e.g., surveys). However, this research provides new insights regarding market-segmentation approaches [58]. More specifically, marketers can obtain user-generated content and hidden topics from consumers' perceptions as revealed in online reviews. For instance, this approach could provide market segmentation effectively in order to identify existing tourists and potential tourists based on real data. This implies that destination marketing organizations (DMOs) and governmental tourist agencies might consider these topics in order to attract more potential tourists to their destinations [59]. For example, destination marketing plans can be divided into three groups (e.g., holiday experience, attractions and facilities, and food experience) for future marketing plans; this concept is directly related to market segmentation [57]. Thus, in order to satisfy consumer needs and wants, marketers might provide specific attractions and services based on their needs by analyzing data [60]. For example, marketers could consider focusing on positive experiences for the group of the holiday experience. For a group of attractions and facilities, marketers might provide more tourism destinations. In terms of the group of food experiences, marketers could consider providing more of a variety of food experiences for them.

Second, destination marketing organizations could consider personalization based on the nationalities of tourists (i.e., domestic tourists and international tourists) [61]. Personalization is, overall, already mainstream in the tourism industry. Destination marketers could consider the cultural background of tourists as these backgrounds can influence their tourism selections [61]. For instance, in terms of the group of the holiday experience, international tourists might require a more authentic travel experience compared to domestic tourists. Therefore, the destination marketing organization could consider preparing an authentic travel experience for international tourists.

Third, marketers might consider using and developing guidelines to connect customer relationship management (CRM). There are some prior research projects that have investigated the relationship between impacts of user-generated content and customer relationship management (i.e., online customer reviews) in the context of the tourism industry [13]. This is because customer-relationship management can affect firm performance. Typically, customer-relationship management presents two issues: management response and proactivity. For instance, marketers can respond to customers' needs and wants by monitoring and verifying social media proactively. In addition, marketers might track textual data to predict emerging issues related to the destination [62].

Lastly, there is still a lack of scholarship identifying the attributes of user-generated content [32]. This study used user-generated data for analyzing text-based content in a tourism destination. Advanced text-mining techniques could complement traditional methods [63]. In other words, adopting user-generated-content approaches has some benefits compared with traditional methods for data collection and data analysis [64]. This implies that this study might contribute to filling the absence of utility among tourism destinations and user-generated content. Thus, this approach provides benefits to researchers for capturing the most commonly emerging and important topics and determining how these are changing and evolving in different areas [65].

Although there are advantages in adopting and analyzing big data using user-generated content, this study has some limitations. First of all, this study focuses on a specific destination, so a generalization of the findings should be approached with prudence. Future studies might consider extending this study's approach to other cities or countries or other opinion-gathering websites and platforms. This is because the utilization of textual data could encompass cultural information (e.g., locations). In addition, although this study encompassed, in the form of more than 6800 online reviews, travelers' natural reactions to their destination visits, this study's methods did not sample travelers who did not write online reviews. Therefore, future research could consider leveraging mixed methods (e.g., interviews, surveys) to understand more detailed responses and behavioral intentions in relation to the overall destination experience.

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