

What Are the Salient and Memorable Green-Restaurant Attributes? Capturing Customer Perceptions From User-Generated Content

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Abstract

This study aims to survey user-generated content (UGC) from diners in certified green restaurants, discover the green images they recall, and demonstrate the usefulness of applying a probabilistic topic model to comprehend customers' perceptions. Postvisit online reviews ($N = 28,098$), in the form of unstructured texts from the TripAdvisor.com website, were used to find freely recalled green-restaurant images. These data were preprocessed with a structural topic model (STM) algorithm to select 51 relevant categories of images. These image categories were compared with the findings of previous studies to discover unique restaurant attributes. Furthermore, a topic-level network and a green-restaurant network were drawn to discover the most easily recallable image categories and their attributes. This machine-learning-based approach improved the reproducibility of unstructured data analyses, overcoming the subjectivity of qualitative data analysis. Theoretical and practical implications are offered for topic modeling methodology along with marketing strategies for restaurateurs.

Keywords

freely recalled responses, green-restaurant image, user-generated content, topic modeling, TripAdvisor

Introduction

Hospitality firms have implemented sustainable—or “green”—practices to respond to customers' demands for proenvironment corporate action (Aragon-Correa et al., 2015). However, a restaurateur's commitment to creating a green image by implementing sustainable practices may not always lead to positive outcomes if such practices are not communicated to or noticed by customers (Yadav et al., 2016). The discrepancy between the green image a company seeks to convey to stakeholders and those stakeholders' actual perceptions may be greater in the restaurant sphere than in other business sectors, partly because many sustainable practices occur back-of-house (Brown et al., 2006). Therefore, restaurateurs may need to isolate and focus on their most effective green practices by uncovering the specific green attributes that customers recognize and appreciate. More importantly, due to limited cognitive capacity, people often do not process all potential attributes at the same time, but rather sort newly acquired information into general image categories within their memories (Fiske & Pavelchak, 1986). Therefore, to understand customers' true green images, it is required that one first identify whether customers perceive the green attributes and salient

green-image categories that are stored in their memories (Keaveney & Hunt, 1992).

Grouping freely recalled responses into various categories can be useful when trying to understand customer-image categories and the attributes relevant to specific stimuli and emotional responses (Wang et al., 2018). In other words, operationalizing images using recalled texts allows researchers to capture comprehensive image elements that go beyond the objective evaluations of predetermined attributes (Andrews, 2017). However, accessing free-recall content may be difficult if there is no obvious data repository. That is, asking participants to recall their experiences about green practices may influence customers' responses by encouraging them to think about the topic—despite a generalized lack of interest.

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Today's customers are motivated to share their stories about their consumption experiences with the public through social networking and online review sites. Thus, this study analyzed green-restaurant customers' responses about their dining experiences expressed in their own words by accessing user-generated content (UGC) found on TripAdvisor. This UGC serves as a rich source of company images collectively formed by customers based on their actual experiences.

Extending this background, this study took as its purpose examining customers' images of certified green restaurants to identify customers' perceptions without prompting specific green-restaurant attributes. We analyzed customers' opinions expressed in the form of unstructured text data (i.e., UGC) with topic modeling to discover topical categories or themes from massive amounts of text (Chuang et al., 2014). Moreover, we extended our findings to identify images that can be easily recalled based on the image associative network theory. The specific research questions addressed in this study are as follows:

Research Question 1: What are the salient image categories stored in the memories of customers who visited certified green restaurants?

Research Question 2: What are the image categories frequently mentioned by green-restaurant customers?

Research Question 3: How are the specific image elements associated with the categories relevant to green practices?

Literature Review

Green Image and Consumers' Restaurant Selection Attributes

Jeong et al. (2014) further defined the green image of a restaurant as "the function of green practices that are important for the evaluation of the greenness of the restaurant" (p. 13). Such images may be influenced by customers' experiences or their prior knowledge about the company (Han et al., 2009). However, Han et al. (2009) focused only on the emotional responses of green-hotel customers and did not consider salient attributes to operationalize the green image. Therefore, this study proposes to conceptualize green images in the restaurant context and recommends a new approach to operationalizing the green-image concept.

A green image has a positive effect on individuals' perceptions and decision-making, such as their attitudes and satisfaction. However, this aspect remains under debate in the hospitality literature. For example, Han and Kim (2010) argue that customers may not always prefer green facilities due to uncertain or skeptical attitudes toward corporate environmental claims or other service quality attributes, which outweigh green attributes in customers' minds. Manaktola and Jauhari (2007) also demonstrated that tourists prioritized

sanitation over green-business practices, especially when evaluating hospitality offerings.

Consumers consider a multifaceted assortment of service elements in assessing the quality of selected restaurants (Johns & Pine, 2002), and it is vital for restaurateurs to classify these attributes. In existing studies (Liu & Tse, 2018), these attributes have largely coalesced into five categories: food-related, service-related, price/value, atmosphere/convenience, and other.

Review of Green Restaurants

Green restaurants are defined in a variety of ways: they may be those that reduce pollution, implement recycling and composting, target water and energy efficiency, employ sustainable waste management, or provide healthy, locally grown, or organic food options on their menus (Jang et al., 2011). Namkung and Jang (2013) classified restaurants' green practices into two sectors: food-focused and environment-focused. Despite the environmental impact of the restaurant industry, the majority of hospitality sustainability research has focused on the hotel and lodging industry (Line & Runyan, 2012).

Previous researchers used the theory of reasoned action, theory of planned behavior (Jang et al., 2015), norm activation model (Han & Hwang, 2016), and value-belief-norm theory (Han, 2015) as their theoretical bases for research. These studies have primarily investigated factors or antecedents of customers' perceptions, satisfaction and attitudes, intentions to visit or to continue patronizing or recommending proenvironmental hospitality operations, and willingness to pay more (Han et al., 2020). The discordant result is that while the number of green restaurants has grown steadily, the scholarship on green-restaurant customers has remained mired in the hypothetical, with actual green diners being largely ignored.

Furthermore, the existing research has mostly employed the traditional qualitative, quantitative, and mixed-method approaches (focus groups, individual interviews, online/offline surveys, scenario-based experimental research). Some of these approaches have been limited because of small sample sizes, leading to a lack of generalizability, while their researcher-derived questions have undermined their capacity to examine subjects' true motivations and feelings (Namkung & Jang, 2013). The possibility of respondents' unintentionally reporting inflated ethical drives due to social desirability bias has also been noted (Auger & Devinney, 2007). In addition, it can be hard to generate the latent structures of data sets using traditional content analyses. These challenges can contribute to discrepancies between behavioral intentions and actual behaviors (Kim et al., 2013), with the hypothetical scenarios presented in survey instruments being poor stand-ins for actual customer events. An overview of green-restaurant research is presented in Table 1.

Table 1. Overview of Recent Relevant Literature on Green Restaurants in the Hospitality Industry.

Author(s), (publication year)	Title	Description	Subjects	Methodology
Wu et al. (in press)	What drives green experiential loyalty towards green restaurants?	Quality, satisfaction, and loyalty	Green-restaurant customer	SEM and regression analysis
Han et al. (2020)	Uncovering the determinants of pro-environmental consumption for green hotels and green restaurants: A mixed-method approach	Mixed-methods, green hotels, and green restaurants	Hotel and restaurant patrons	Qualitative and quantitative approaches
Hwang & Lee (2019)	Pride, mindfulness, public self-awareness, affective satisfaction, and customer citizenship behaviour among green restaurant customers	Green restaurant and customer citizenship behavior	Green-restaurant customer in Seoul	Survey questionnaire and PLS method
Kwok & Huang (2019)	Green attributes of restaurants: Do consumers, owners, and managers think alike?	Stakeholder theory and sustainability	Consumers, restaurant managers, and owners	Survey questionnaire, ANOVA, and MANOVA
Xu & Jeong (2019)	The effect of message framings and green practices on customers' attitudes and behavior intentions toward green restaurants	Restaurant type and message type	U.S. consumers	Experimental design and ANOVA
Park et al. (2020)	The structural topic model for online review analysis: Comparison between green and non-green restaurants	UGC and topic modeling	Yelp.com reviews	Structural topic modeling
Kwok et al. (2016)	Green attributes of restaurants: What really matters to consumers?	Green practices and restaurant	Consumers	Survey questionnaire and quantitative analysis
Line et al. (2016)	Sustainability communication: The effects of message construals on consumers' attitudes towards green restaurants	Information processing theory and green restaurants	U.S. consumers	ANOVA

Note. ANOVA = analysis of variance; MANOVA = multivariate analysis of variance; UGC = user-generated content; SEM = structural equation modeling; PLS = partial least-squares.

Structural Topic Modeling (STM)

The hospitality and tourism research contexts, when employing big-data approaches, have commonly used word-frequency analysis, geovisualization, and sentiment analysis to examine the massive tomes of unstructured UGC made available by the advent of social media (Lu & Stepchenkova, 2015). Among these approaches, topic modeling remains one of the most frequently employed by industry and social-science investigators as they search for latent topics (Kaplan & Vakili, 2015).

A generative probabilistic model has been applied to understand the semantic memory, a mode of memory in which informational nodes are arranged according to their semantic similarities (e.g., Griffiths et al., 2007; Griffiths & Steyvers, 2002, 2003). Topics, which consist of a list of words with a different degree of relevance to a particular target, are considered to be image categories (Griffiths & Steyvers, 2002). Furthermore, the probability distribution of the words indicates the likelihood of particular informational nodes being activated and recalled (Griffiths & Steyvers, 2002). Accordingly, the topics discovered in probabilistic

topic modeling are considered to be image categories in memory, and the words belonging to each topic act as the specific attributes relevant to each image category (Griffiths & Steyvers, 2003).

A probabilistic topic model enables the discovery of latent topic structures by analyzing observed vocabulary in documents (Blei et al., 2003). Topic modeling algorithms are applications of machine-learning techniques that produce major themes from large amounts of text data. The algorithm generates collections of semantically coherent words, often called top words, each one an array of words consistent with a certain topic. Topic modeling can also calculate the prevalence of the extracted topics (i.e., topic weights) and the probabilistic association between top words and each topic.

Relevant studies introduced an STM that includes meta-data in the estimation model to measure systematic differences in topic proportions and topical content depending on observed covariates (Roberts et al., 2014). This approach takes UGC as an unstructured data set and mines it for unrevealed topics (Roberts et al., 2016). STM attempts to obtain additional strength and enhance predictive power by

replacing a global prior with a more flexible distribution (Roberts et al., 2016). This result is to be expected as STM was developed by social scientists, who are mostly interested in testing hypotheses by examining relationships among variables. STM has been popularly adopted in social science literature (Gilardi & Wüest, 2017; Hu et al., 2019). In hospitality and tourism studies, for example, existing studies have used STM to discern relevant service quality elements buried in unstructured customer reviews (Ding et al., 2020), as well as to analyze employees' online reviews to assess job satisfaction (Stamolampros et al., 2019) and perform satisfaction analyses of hotel visitors. This study implemented STM to discover the salient image categories.

The Image Associative Network Theory

The image associative network theory has been applied widely to understanding the image structure stored in memory and the process of retrieving information encoded in the human mind (Keller, 1993). According to this model, memory is stored in the form of an associative network, which consists of nodes containing information and concepts and relational links connecting these nodes (Anderson, 1983). When the retrieval cues are presented, the informational nodes stored in the human memory network are activated to be recalled (Collins & Loftus, 1975).

"Node" is used to denote the basic element of the memory network, with each node containing a concept related to an entity (Wang & Horng, 2016). A node can be created not only by the direct experience of a product or services but also via vicarious means, including marketing materials and word-of-mouth communication (Keller, 1993). Moreover, the existing nodes tend to be sustained in memory and influence the process of evaluating any new stimulus (Henderson et al., 1998). As mentioned, the informational nodes in the memory network are connected with the relational links. If a node is linked to a high number of other nodes, its associated image can easily be recalled, whereas loosely connected image associations are further out of mind (Anderson, 1983; Keller, 1993). Therefore, the strength of image association indicates the likelihood of image nodes being activated from memory (Teichert & Schöntag, 2010).

According to a spreading activation theory, when a particular image association is activated, the activation spreads to other image associations to which it is strongly connected through relational links (Anderson & Pirolli, 1984). As the strength of these relational links determines the quality and quantity of spreading activations from activated image association to other image associations, it also determines the likelihood of an image association being activated and recalled (Gensler et al., 2015). Wang et al. (2018) incorporated a concept called core periphery into the destination image network map to discover which image nodes have the highest likelihood of being recalled.

The application of this network mapping on freely recalled texts shared by actual customers is useful for discovering the specific attributes that are memorable to customers. Still, most previous studies regarding green restaurants chose to use predetermined measurements. In contrast, this study used stories shared by actual restaurant customers to capture their memorable experiences and reshape them into a network formed from unstructured texts.

Method

Sample

This study examined postvisit reviews of green restaurants. Customer reviews of green restaurants that have been certified by the Green Restaurant Association (GRA). GRA is an international nonprofit organization with comprehensive certification standards, including both food- and environment-focused green practices (Schubert et al., 2010). For the restaurants to be certified, they must have implemented a certain degree of green practices according to various sustainability standards. Most of the green restaurants certified by GRA are located in the United States, particularly in California, Illinois, Pennsylvania, Texas, and New York, the states with most green restaurants. A list of 618 certified green restaurants (as of August 22, 2018) was obtained from the GRA website (www.dinegreen.com). Among various consumer review websites, this study chose TripAdvisor, the largest travel review site worldwide, as its data source because it boasts more than 859 million reviews (TripAdvisor, 2020). Out of 618 certified green restaurants, 128 commercial, noncatering restaurant operations were available on TripAdvisor. All 37,052 UGC reviews written for these 128 restaurants were collected from TripAdvisor in February 2019 using a Python-based web crawling tool. Among these, reviews written before March 2014 (i.e., those more than 5 years old) were removed. To ensure the reviewers had experienced a green-restaurant practices, only reviews written after a particular restaurant achieved certification with the GRA were included in the final sample. Furthermore, restaurants with fewer than 50 reviews were excluded from the sample to ensure the effects of the green-restaurant characteristics were derived from a sufficient number of reviews. Consequently, the final data set stretched across 60 months (March 2014 and February 2019) and featured 25,098 customer-produced reviews covering 70 GRA-certified restaurants. The sampling procedure is displayed in Figure 1.

Text Preprocessing and Data Analysis

To uncover the major categories underpinning this massive amount of UGC, STM (a topic modeling technique) was employed (Roberts et al., 2014). Before conducting STM, text preprocessing was conducted to prepare the corpus for text mining, all in line with the model set forth by Park et al.

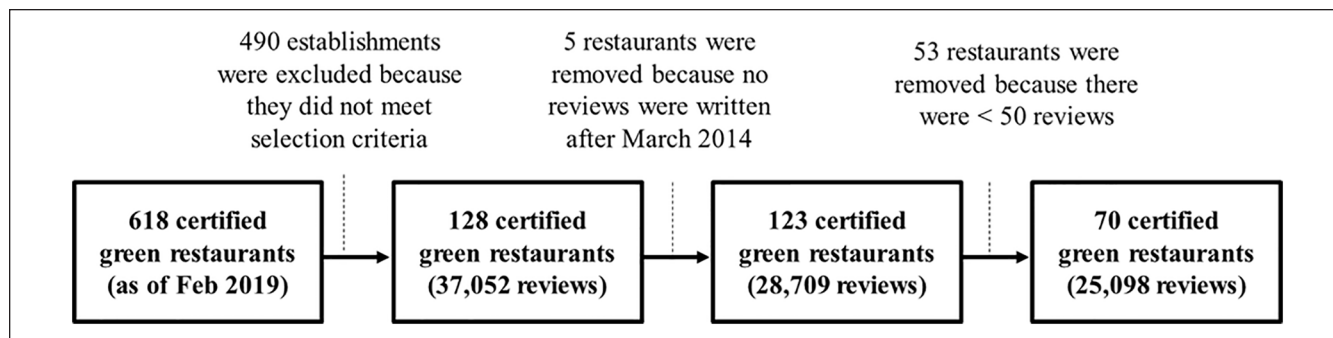


Figure 1. The process of sampling.

(2018). Creating context-specific stop words was necessary to improve the topic quality of the data set by removing words that appeared frequently but were not meaningful (Wallach et al., 2009). Word frequency was conducted with online reviews to come up with these stop words. For example, due to nature of restaurant reviews, food names frequently appeared in reviews, which led many topics related to types of menus, not green-restaurant practices. Since this study aims to discover salient perceptions about restaurants attributes, including green practices, researchers decided to remove menu item and food names. Along with these stop words, the authors reviewed a list of other frequent stop words, such as prepositions (e.g., across, over) and adverbs (actually, however), and removed them. The four quantitative indices (i.e., held-out likelihood, residuals, semantic coherence, and lower bound) were compared to determine the optimal k value. Based on a rough approximation, the performances of topic models with a varying number of k were compared, and $k = 51$ was determined to be optimal.

Content Analyses

Topic modeling automatically generates a collection of vocabulary with different probabilistic associations for each selected topic; however, topics generated by the topic modeling need to be labeled manually. Previous studies using topic modeling have usually labeled topics based on top words only. To improve comprehension of the topics, this study conducted additional manual content analyses. Two researchers independently reviewed 20 top words and 20 documents closely related to each topic (i.e., the reviews with the highest topic proportion in each topic) to determine the preliminary labels. After the researchers separately named the preliminary label for each topic, the initial labels were compared. If the topic labels were not consistent between the two researchers, the researchers discussed them until they reached consensus on the labels.

Network Analysis

To test spreading activation with freely recalled responses among green-restaurant customers, a topic-level image

network was created using the topic proportion correlation matrix ($N = 25,098$ reviews, 51 topics). The *igraph* software package in R was used to visualize and obtain the network statistics. The threshold for the topic correlation was set at 0.1, and the edges below the threshold were dropped for the network visualization (Roberts et al., 2016).

The low-level green-image networks ($N = 696$) were examined by creating a green-image network with online reviews closely related to two green topics (T10 and T37). To create this green-image network, the appearances of unique terms in multiple green-restaurant reviews were tabulated and evaluated. In the green-image network, the nodes are the unique words that represent low-level image associations, and the ties connecting nodes represent the associations among these unique words. Gephi software was used to visualize the green-image network with the unique terms that appeared more than 50 times in the corpus.

Based on the understanding of how nodes flow in the network, an appropriate centrality metric should be chosen to measure the strength of the image association (Wasserman & Faust, 1994). Eigenvector centrality counts the circuitous trajectories and paths nodes visit multiple times (Borgatti, 2005) and enables researchers to measure the influences of long-term and indirect links (Wang et al., 2018). Therefore, this study selected the eigenvector to measure the strength of image association among various centrality measures. The process of data analysis was summarized in Figure 2.

Results

Data Profile

Descriptive characteristics for certified green restaurants ($N = 70$) and customer reviews ($N = 25,098$) were identified. The majority of certified green restaurants ($N = 58$) averaged 4.0 or 4.5 stars in their TripAdvisor ratings. On average, the restaurants had been certified for 6 years ($M = 6.2$, $SE = 3.1$), with the longest period of certification being 12 years. To be certified, the restaurant must earn green points by meeting certain environmental standards, and GRA's star ratings are dependent on these green-point totals.

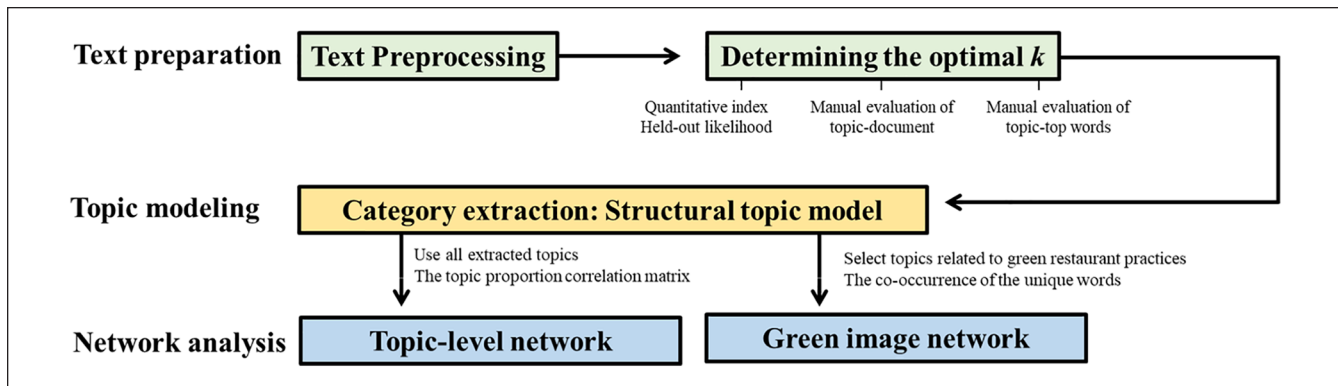


Figure 2. The process of data analysis.

The majority of the certified restaurants ($N = 35$) attained GRA's three-star rating.

Topic Modeling: Discovery of Image Categories

Topic modeling was applied to the 25,098 reviews of certified green restaurants to discover salient and frequently noted image categories. Among 51 salient topics discovered from STM, multiple topics represent the same attributes but contained different emotional states. Therefore, the topics were categorized into the following high-level dimensions: four general restaurant attributes (i.e., value, service, atmosphere, and food), green attributes, overall restaurant experience evaluation, and behavioral intentions. A summary of topics is presented in Table 2.

Among the four general restaurant attributes, the number of topics assigned to the food-quality dimension was the highest, accounting for 19.1% of the total topic weight, followed by the service quality dimension, which represented 16.4% of the total topic weight.

In the food-quality dimension, which boasted 10 topics, several topics (Topics 5, 15, and 50) regarded customers' perceptions about good flavor, but their latent intentions or perceptions associated with these topics were varied. For instance, the top words associated with topic 15 were *sweet*, *satisfy*, *rich*, and *creamy*. These top words contained vocabulary to describe food flavors and tastes, capturing people's positive evaluations toward their flavor. In the case of Topic 50, the top words were *love*, *eat*, *yummy*, and *place*. These words were closely related to people's emotional satisfaction with flavor and their choice of restaurant selection. Finally, top words for Topic 5 included *delicious*, *back*, and *went*, indicating that this topic is associated with good flavor stimulating customers' willingness to come back in the future. Topic 11 was also related to food flavor, but included top words related to poor-quality foods, such as *dr(y)*, *burnt*, and *overdone*.

Within the service dimension, there were several topics regarding service quality, which contained positive sentiments

(e.g., knowledgeable employees [T32], attentive staff [T38]) and negative sentiments (e.g., slow service [T6], inattentive service [T46]). The topic model also extracted topics regarding restaurant atmosphere, such as location (T47) and background music (T20). The value-related topics demonstrated that customers' evaluation of value was often situation specific.

Two topics related to green practices also emerged, such as local/organic ingredients (T10) and vegetarian/healthy option (T37). GRA notes that serving vegan or vegetarian dishes may reduce harmful environmental impacts (GRA, 2020), and, therefore, this study considered the vegetarian/healthy option (T37) as a pertinent green topic.

To find contrasts within the image categories discovered from UGC and findings of the previous research using the traditional research methods, the topics extracted from STM were compared with the restaurant attributes identified from previous studies (see Table 3).

Topic-Level and Image-Level Networks

The associations among topics were estimated by creating a topic network (see Figure 3). According to the topic proportion correlation matrix, the average eigenvector centrality for the 51 topics was 0.24. The size of nodes and labels of the image network were proportional to the eigenvector centrality scores, and the detailed information about the topic network can be found in Table 4. Two topics had centrality scores greater than 0.9, Topic 44 (customer satisfaction) and Topic 5 (good flavor). There were 17 topics with eigenvector centrality scores between 0.8 and the average centrality score, 0.24. These topics pertain to customers' evaluations of general restaurant attributes (e.g., good service [T32 and T38] and good flavor [T50]) and overall evaluation of restaurants (e.g., positive experience [T51] and satisfaction [T4]). Finally, we found 32 topics with centrality scores lower than the average centrality, which were related to objective descriptions of specific restaurant attributes (e.g., building [T36], location [T47]). Specialized topics related to

Table 2. Overview of Topics: Top Words and Topic Weights.

Dimension	Topic number and labels	Top words (highest probability)	Topic weight
Food	T5: Good flavor	Delici, back, definit, went, stop	0.029
	T25: Excessive portion size	Order, appet, portion, entre, larg	0.024
	T27: Small plates	Excel, small, plate, share, favorit	0.024
	T12: Menu variety	Men, item, interest, differ, select	0.022
	T50: Overall good flavor	Love, eat, ate, yummi, place	0.020
	T11: Bad flavor	Tast, serv, dri, season, light	0.019
	T14: Accommodation for diet restrictions	Like, free, gluten, felt, normal	0.016
	T30: Unique flavor	Flavor, top, uniqu, mix, combin	0.013
	T45: Disappointing food characteristics (flavor, portion size, temperature)	Come, hot, big, cold, spici	0.013
	T15: Good flavor	Sweet, satisfi, yes, rich, creami	0.011
Service	Subtotal		0.191
	T6: Bad service (slow service)	Wait, tabl, minut, arriv, seat	0.027
	T32: Good service (knowledgeable employees)	Wonder, help, outstand, select, list	0.026
	T40: Good service (prompt seating)	Reserv, waiter, tabl, made, busi	0.025
	T46: Bad service (inattentive service)	Ask, came, manag, waitress, order	0.024
	T26: Good service (quick, friendly service)	Staff, friend, quick, super, fast	0.022
	T38: Good service (attentive staffs)	Server, perfect, attent, cook, start	0.022
	T21: Bad service (long wait)	Line, park, crowd, long, open	0.018
Atmosphere	Subtotal		0.164
	T9: Atmosphere (seating area)	Nice, atmospher, area, view, pleasant	0.028
	T47: Convenient location	Kitchen, locat, corner, villag, stay	0.025
	T20: Background music	Enjoy, meal, live, music, charm	0.016
	T13: Excessive noise	Room, group, parti, tabl, loud	0.015
	T36: Building exterior	Outsid, beauti, insid, patio, head	0.013
	T2: Décor	Decor, warm, space, vibe, brown	0.010
Value	Subtotal		0.107
	T23: Overprice with poor quality	Food, servic, averag, expens, disappoint	0.020
	T34: Fair value	Price, reason, qualiti, food, fair	0.018
	T29: Pricey choices (good value)	Dinner, littl, pricey, expens, romant	0.017
	T24: Good value (time and money)	Well, worth, prepar, wait, drive	0.015
Green attributes	Subtotal		0.070
	T10: Local/organic ingredients (sustainable sourcing)	Fresh, local, ingredi, farm, creativ	0.020
	T37: Vegetarian/healthy option	Mani, choic, option, green, vegetarian	0.017
Overall restaurant experience evaluation	Subtotal		0.037
	T42: Repeat customer experience (consistency)	Time, everi, disappoint, never, last	0.030
	T39: Not meeting expectation	Better, expect, think, noth, bad	0.021
	T4: Overall satisfaction	Best, ever, meal, eaten, far	0.020
	T44: Exceptional experience	Amaz, everyth, fabul, absolut, incred	0.019
Behavioral intention	Subtotal		0.090
	T: Revisit intention	Visit, return, next, trip, recent	0.016
	T3: Restaurant recommendation	Recommend, high, anyon, end, highlight	0.014
	T19: Menu recommendation	Tri, must, give, won, foodi	0.014
	Subtotal		0.044

green-restaurant practices had low centrality scores, and they were separated from the common restaurant attributes that shaped a tight and sizable subgroup (Figure 4).

In the green-image network, positive words—such as good, excellent, great, and wonderful—frequently appeared and had the highest eigenvector centrality. Especially,

customers related to green practices as healthy and fresh, which can be related to health-related benefits. Also, people found the green menus as delicious. In the green-image network, terms regarding ingredient sourcing (e.g., local, farm [to] table) and vegetarian/healthy options also had high eigenvector centrality. According to the topic-level and the

Table 3. A Comparison of Topics Derived From STM and Measurement Items Found in Previous Studies.

Dimensions	Specific aspects	Topic number and labels	References
Food	Flavor	T5: Good flavor T11: Bad flavor T15: Good flavor T30: Unique flavor T50: Overall good flavor	Han & Hyun (2017); Jang & Namkung (2009); Jang et al. (2011); Jin et al. (2012); Ryu et al. (2012)
	Portion size	T25: Excessive portion size T27: Small plates	DiPietro & Gregory (2012)
	Menu variety	T12: Menu variety	Jin et al. (2012); Ryu et al. (2008); Ryu et al. (2012); Wu & Mohi (2015)
	Healthy (nutritious) options	T37: Vegetarian/healthy option ^a	Jang & Namkung (2009); Jang et al. (2011); Ryu et al. (2012)
	Fresh foods	T10: Local/organic ingredients (sustainable sourcing) ^a	Jang & Namkung (2009); Jang et al. (2011); Ryu et al. (2012)
	Accommodation for diet restrictions	T14: Accommodation for diet restrictions	Not found
	Food presentation	Not found	Jang & Namkung (2009); Jang et al. (2011); Jin et al. (2012); Ryu et al. (2012)
Service	Food smell	Not found	Ryu et al. (2012)
	Willingness to help	T32: Good service (knowledgeable employees)	Jang & Namkung (2009); Jang et al. (2011); Ryu et al. (2012)
	Speed of service	T6: Bad service (slow service) T21: Bad service (long wait) T26: Good service (quick, friendly service) T40: Good service (prompt seating)	Ryu et al. (2008, 2012)
	Comfortable/friendly staffs	T38: Good service (attentive staffs) T46: Bad service (inattentive service)	Ryu et al. (2012)
	Instill confidence	Not found	Jang & Namkung (2009); Jang et al. (2011)
	Best (specific) interests	Not found	Jang & Namkung (2009)
	Accurate service	Not found	Jang et al. (2011); Ryu et al. (2012)
Atmosphere	Interior design	T2: Décor	DiPietro & Gregory (2012); Han & Hyun (2017); Jang & Namkung (2009); Jang et al. (2011); Ryu et al. (2008, 2012); Wu & Mohi (2015)
	Background music	T20: Background music	Jang & Namkung (2009); Ryu et al. (2012)
	Location	T47: Convenient location	DiPietro & Gregory (2012); Jang et al. (2011); Ryu et al. (2008)
	Building exterior	T9: Atmosphere (seating area) T36: Building exterior	
	Comfort for socializing	T13: Excessive noise	Jang et al. (2011)
	Cleanness	Not found	Ryu et al. (2008, 2012); Wu & Mohi (2015)
	Employees' attire (appearance)	Not found	Jin et al. (2012); Ryu et al. (2008, 2012)
	Colors	Not found	Jang & Namkung (2009)
	Facility layout	Not found	Jang & Namkung (2009); Wu & Mohi (2015)
	Lighting	Not found	Jang & Namkung (2009)
	Value	T23: Overprice with poor quality T24: Good value (time and money) T29: Pricey choices (good value) T34: Fair value	DiPietro & Gregory (2012); Jang et al. (2011); Jin et al. (2012); Ryu et al. (2008, 2012)
Green attributes	Food	T10: Local/organic ingredients (sustainable sourcing) ^a T37: Vegetarian/healthy option ^a	Choi & Parsa (2006); DiPietro & Gregory (2012); Ham & Lee (2011); Jang et al. (2011); Kwok et al. (2016); Schubert et al. (2010)
	Environmental	T37: Vegetarian/healthy option ^a	Choi & Parsa (2006); Ham & Lee (2011); Jang et al. (2011); Jeong et al. (2014); Kwok et al. (2016); Schubert et al. (2010)
	Social	T10: Local/organic ingredients (sustainable sourcing) ^a	Choi & Parsa (2006)
	Administrative (organizational)	Not found	Ham & Lee (2011); Kwok et al. (2016)

Note. STM = structural topic model.

^aTopics related to green attributes.

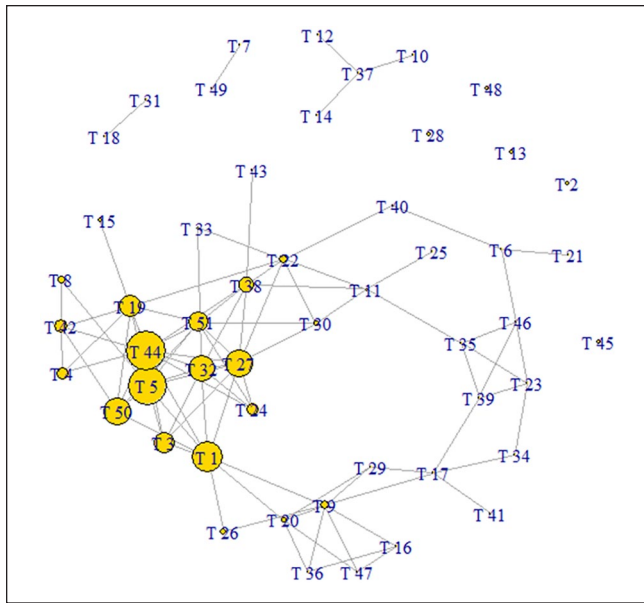


Figure 3. The topic-level image network.

green-image networks, green-restaurant practices serve as a unique restaurant attributes that are distinct from the common restaurant attributes, but they tend to trigger positive sentiment.

Conclusion and Implications

To advance scholarly inquiry, this study analyzed freely recalled customers' postvisit green-restaurant reviews to capture green-restaurant images that are context specific. To answer its first research question, which sought to identify salient image categories about green restaurants, the study sampled UGC written by actual green-restaurant customers and analyzed it using topic modeling to discover prevalent themes shared across customers. The prevalent themes discovered from green-restaurant reviews may represent most memorable image categories in relation to their green-restaurant experiences. This study found that most online review content consisted of customer appraisals of specific restaurant attributes. To answer the second research question, which focused on the image categories frequently mentioned by green-restaurant customers, the topic weights were compared. A topic modeling algorithm can generate topic weights, which indicate how frequently each topic was mentioned in each review. Each review-level topic weight can be converted into a document-level topic weight to demonstrate topic popularity. In other words, topics with high topic weights were more likely to be mentioned by green-restaurant customers. This quantified index of topic weight can represent the image categories that many green-restaurant customers are likely to perceive. Among the core restaurant attributes, the topic weights related to food quality were the highest and had high topic centrality, indicating that food

quality was the most salient core restaurant attribute, as suggested by Ryu et al. (2012). Finally, the last research question, which inquired into the specific image elements associated with the categories relevant to green practices, was answered by discovering topics related to green practices. Although the certified green restaurants in the sample implemented various environment-focused green practices (i.e., recycling, waste reduction), only food-focused green practices appeared in UGC. This finding is in line with prior research that showed food-focused attributes to be prioritized by restaurant customers (Jang et al., 2011). In a similar way, reviewers were less likely to mention restaurants' participation in green certification programs. Less than 3% of customers who visited a certified green restaurant were later able accurately to identify the eatery's certification information, indicating a lack of customer interest in certification programs and/or a lack of visibility for certification participation (DiPietro et al., 2013). DiPietro et al. (2013) also found that customers perceived the implementation of green practices in a restaurant operation to be more important than attaining any official green certification.

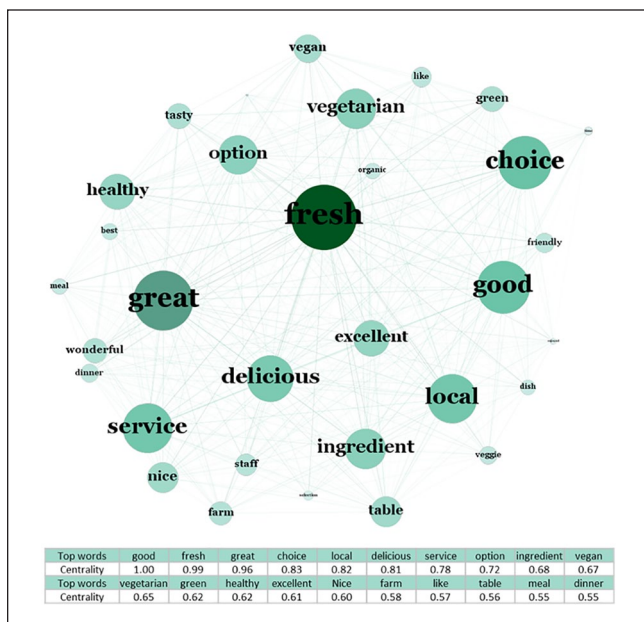
Based on the image categories discovered, the green-image network structure stored in customers' memories was identified and analyzed. In terms of the recallability of image categories by spreading activation, positive image categories tended to be retrieved more easily than negative image categories. There was an inconsistency between the frequency and the eigenvector score because some of the image categories people frequently mentioned in UGC were not central in terms of spreading activation (Wang et al., 2018). For example, the image categories containing negative sentiment, which had the relatively high topic weights, were sparsely connected to other image categories. In other words, customers who experienced service failures and expressed negative feelings tended to focus on the negative aspects and rather than talk about other restaurant attributes.

Only a limited number of studies have targeted UGC related to green-restaurant customers at online review sites. Compared with previous studies that used qualitative and quantitative approaches (e.g., surveys, interviews, and focus groups), this study was able to feature far more review texts from a much greater number of actual customers. Postvisit online reviews contain freely recalled experiences shared by actual customers without being prompted by researchers, which may inadvertently stimulate participants' responses. Hence, the sample of this study may have less inherent selection biases than a convenience sample may entail (Grimmer, 2015; Roberts et al., 2016).

This study used its topic modeling algorithm to investigate green-restaurant customers' cognitive processes and memorable attributes and emotions. Topic proportion was used as a proxy of the popularity and importance of the topic (Guo et al., 2017). In addition, the topic-level image network was drawn to understand spreading activation among the high-level cognitive units (Anderson, 1983). The spreading

Table 4. Topic Weights and Eigenvector Centrality of Image Categories in the Topic-Level Network.

Label	Centrality	Weights	Label	Centrality	Weights
T1: Good food and service and atmosphere	0.079	0.706	T34: Reasonable value	0.018	0.036
T17: Good food with dissatisfying factor	0.045	0.081	T31: Bar	0.018	0.007
T42: Repeat customers	0.030	0.393	T29: Overprice	0.017	0.203
T5: Good flavor	0.029	0.995	T37: Vegetarian/healthy option	0.017	0.020
T9: Outdoor, indoor seating	0.028	0.248	T8: Revisit intention	0.016	0.364
T6: Bad service (slow service)	0.027	0.018	T22: Online review	0.016	0.452
T32: Good service (knowledgeable staffs)	0.026	0.740	T33: Fine dining	0.016	0.150
T40: Good service (reservation)	0.025	0.103	T20: Background music	0.016	0.296
T47: Location	0.025	0.084	T14: Dietary restriction	0.016	0.002
T27: Small plates	0.024	0.669	T24: Good value	0.015	0.366
T25: Big portion size	0.024	0.085	T43: Special occasions	0.015	0.109
T46: Bad service (employees' attitude)	0.024	0.021	T13: Noise	0.015	0.006
T38: Good service (attentive staffs)	0.022	0.546	T19: Menu recommendation	0.014	0.571
T26: Good service (professional employees)	0.022	0.321	T3: Recommendation	0.014	0.483
T12: Menu selections	0.022	0.092	T35: Mixed dissatisfying factors	0.014	0.039
T39: Disappointment	0.021	0.065	T30: Unique flavor	0.013	0.391
T50: Good flavor	0.020	0.697	T36: Building	0.013	0.092
T4: Satisfaction	0.020	0.494	T45: Portion size	0.013	0.033
T23: Overprice	0.020	0.035	T49: Good service	0.012	0.047
T16: Touristic place	0.020	0.060	T15: Good flavor	0.011	0.204
T10: Local/organic ingredients	0.020	0.103	T51: Positive experience	0.010	0.523
T44: Satisfaction	0.019	1.000	T41: Brewing company	0.010	0.015
T11: Bad flavor	0.019	0.178	T18: Bar	0.010	0.001
T7: Iconic place	0.019	0.024	T2: Décor/ambiance	0.010	0.009
T21: Crowded, popularity	0.018	0.010	T28: Happy hour	0.007	0.003
			T48: Course meal/gourmet	0.006	0.062

**Figure 4.** The image network related to green-restaurant practices.

activation model suggested the strength of image associations determined the likelihood of image retrieval (Lai & Li,

2012). The strength of image associations measured by the eigenvector centrality allowed authors to discern what restaurant attributes were more important and readily recallable than others (Wang et al., 2018).

The customer review content analyzed here provides a series of practical implications for the restaurant industry. The findings of this study show how restaurant operators can influence their customers to shape a positive image by understanding the salient and recallable images. For example, the number of online reviews containing environment-focused green practices was significantly lower than that for reviews of food-focused green practices, suggesting the low visibility of and/or low interest in environment-focused green practices. This confirmed supposition of previous studies about the low visibility of environment-focused green practices in restaurants (Namkung & Jang, 2013). Arguably, restaurant practitioners interested in harnessing the power of green trends should, therefore, focus on green-food innovations to create and sustain a customer-pleasing green image. Considering the significant efforts required for green-restaurant certification through environment-focused green practices, restaurateurs should publicize such efforts as recycling or composting through various media, social networking, in-restaurant displays, or employee training. Given that customers tend to shape an image even before they visit

a restaurant (Bae et al., 2017), promoting environmentally friendly initiatives on social media or via review platforms can improve customers' awareness. Once customers, drawing on preexposure information, form the impression that a restaurant operates in a sustainable manner, they may maintain a positive stereotype about that restaurant, intensifying customers' personal attention to environmentally friendly practices (Reynolds & Oakes, 2000).

Because this study's sample of reviews was gathered from only one website (TripAdvisor.com), the findings of this study are limited to that online platform's base of patrons. Future studies could combine review data from multiple online review platforms for a more broad-based data analysis. We can also recommend using other types of data sources, such as open-ended surveys or the integration of both surveys and big-data analytics to overcome limitations. They may consider employing on-site surveys to broaden the sample with respondents who may not use social media or cannot access the internet. Because this research considered only reviews written in English for its data analysis, future research targeting reviews written in other languages would provide fascinating contrasts. Similarly, this study explored strictly those green restaurants certified by the GRA. Therefore, follow-on projects could include other types of certified restaurants. They may choose to explore differences in consumer attitudes and images based on further topic modeling covariates, such as demographic characteristics. Finally, this study analyzed online reviews of certified green restaurants only in the United States. Examining customer reactions to restaurants in other countries may provide broader insights into sustainable restaurant practices.

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References

- Anderson, J. R. (1983). A spreading activation theory of memory. *Journal of Verbal Learning and Verbal Behavior*, 22(3), 261–295.
- Anderson, J. R., & Pirolli, P. L. (1984). Spread of activation. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 10(4), 791–798.
- Andrews, M. (2017, July 16–29). *A Bayesian account of memory for text* [Conference session]. 39th Annual Meeting of the Cognitive Science Society, London, England.
- Aragon-Correa, J. A., Martin-Tapia, I., & de la Torre-Ruiz, J. (2015). Sustainability issues and hospitality and tourism firms' strategies: Analytical review and future directions. *International Journal of Contemporary Hospitality Management*, 27(3), 498–522.
- Auger, P., & Devinney, T. M. (2007). Do what consumers say matter? The misalignment of preferences with unconstrained ethical intentions. *Journal of Business Ethics*, 76(4), 361–383.
- Bae, S. J., Lee, H., Suh, E.-K., & Suh, K.-S. (2017). Shared experience in pretrip and experience sharing in posttrip: A survey of Airbnb users. *Information & Management*, 54(6), 714–727.
- Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of Machine Learning Research*, 3, 993–1022.
- Borgatti, S. P. (2005). Centrality and network flow. *Social Networks*, 27(1), 55–71.
- Brown, T. J., Dacin, P. A., Pratt, M. G., & Whetten, D. A. (2006). Identity, intended image, construed image, and reputation: An interdisciplinary framework and suggested terminology. *Journal of the Academy of Marketing Science*, 34(2), 99–106.
- Choi, G., & Parsa, H. (2006). Green practices II: Measuring restaurant managers' psychological attributes and their willingness to charge for the "Green Practices." *Journal of Foodservice Business Research*, 9(4), 41–63.
- Chuang, J., Wilkerson, J. D., Weiss, R., Tingley, D., Stewart, B. M., Roberts, M. E., Poursabzi-Sangdeh, F., Grimmer, J., Findlater, L., Boyd-Graber, J., & Heer, J. (2014, December). *Computer-assisted content analysis: Topic models for exploring multiple subjective interpretations* [Conference session]. Montreal Canada: Advances in Neural Information Processing Systems Workshop on Human-Propelled Machine Learning.
- Collins, A. M., & Loftus, E. F. (1975). A spreading-activation theory of semantic processing. *Psychological Review*, 82(6), 407–428.
- Ding, K., Choo, W. C., Ng, K. Y., & Ng, S. I. (2020). Employing structural topic modelling to explore perceived service quality attributes in Airbnb accommodation. *International Journal of Hospitality Management*, 91, Article 102676.
- DiPietro, R., Cao, Y., & Partlow, C. (2013). Green practices in upscale foodservice operations customer perceptions and purchase intentions. *International Journal of Contemporary Hospitality Management*, 25(5), 779–796.
- DiPietro, R., & Gregory, S. (2012). Customer perceptions regarding green restaurant practices: A comparison between fast food and upscale casual restaurants. *FIU Hospitality Review*, 30(1), 1–22.
- Fiske, S. T., & Pavelchak, M. A. (1986). Category-based versus piecemeal-based affective responses: Developments in schema-triggered affect. In R. M. Sorrentino & E. T. Higgins (Eds.), *Handbook of motivation and cognition: Foundations of social behavior* (pp. 167–203). Guilford Press.
- Gensler, S., Völckner, F., Egger, M., Fischbach, K., & Schoder, D. (2015). Listen to your customers: Insights into brand image using online consumer-generated product reviews. *International Journal of Electronic Commerce*, 20(1), 112–141.
- Gilardi, F., & Wüest, B. (2017, June 8–10). *Newspaper coverage of female candidates during election campaigns: Evidence from a structural topic model* [Conference session]. European Conference on Politics and Gender: Annual Meeting, Lausanne, Switzerland.
- GRA. (2020). Green Restaurant Certification Standards. <https://www.dinegreen.com/>
- Griffiths, T. L., & Steyvers, M. (2002). A probabilistic approach to semantic representation. In W. D. Gray & C. D. Schunn (Eds.),

- 24th Annual Meeting of the Cognitive Science Society (pp. 381–386). Cognitive Science Society.
- Griffiths, T. L., & Steyvers, M. (2003). Prediction and semantic association. In S. Thrun, L. K. Saul, & B. Schölkopf (Eds.), *Advances in neural information processing systems 16 (NIPS 2003)*. <https://proceedings.neurips.cc/paper/2002/file/cb8da-6767461f2812ae4290eac7cbc42-Paper.pdf>
- Griffiths, T. L., Steyvers, M., & Tenenbaum, J. B. (2007). Topics in semantic representation. *Psychological Review*, 114, 211–244.
- Grimmer, J. (2015). We are all social scientists now: How big data, machine learning, and causal inference work together. *Political Science & Politics*, 48(1), 80–83.
- Guo, Y., Barnes, S. J., & Jia, Q. (2017). Mining meaning from online ratings and reviews: Tourist satisfaction analysis using latent dirichlet allocation. *Tourism Management*, 59, 467–483.
- Ham, S., & Lee, S. (2011). US restaurant companies' green marketing via company websites: Impact on financial performance. *Tourism Economics*, 17(5), 1055–1069.
- Han (2015). Travelers' pro-environmental behavior in a green lodging context: Converging value-belief-norm theory and the theory of planned behavior. *Tourism Management*, 47, 164–177.
- Han, H., Hsu, L.-T. J., & Lee, J.-S. (2009). Empirical investigation of the roles of attitudes toward green behaviors, overall image, gender, and age in hotel customers' eco-friendly decision-making process. *International Journal of Hospitality Management*, 28(4), 519–528.
- Han, H., & Hwang, J. (2016). Cruise travelers' environmentally responsible decision-making: An integrative framework of goal-directed behavior and norm activation process. *International Journal of Hospitality Management*, 53, 94–105.
- Han, H., & Hyun, S. S. (2017). Impact of hotel-restaurant image and quality of physical-environment, service, and food on satisfaction and intention. *International Journal of Hospitality Management*, 63, 82–92.
- Han, H., & Kim, Y. (2010). An investigation of green hotel customers' decision formation: Developing an extended model of the theory of planned behavior. *International Journal of Hospitality Management*, 29(4), 659–668.
- Han, H., Moon, H., & Hyun, S. S. (2020). Uncovering the determinants of pro-environmental consumption for green hotels and green restaurants: A mixed-method approach. *International Journal of Contemporary Hospitality Management*, 32(4), 1581–1603.
- Henderson, G. R., Iacobucci, D., & Calder, B. J. (1998). Brand diagnostics: Mapping branding effects using consumer associative networks. *European Journal of Operational Research*, 111(2), 306–327.
- Hu, N., Zhang, T., Gao, B., & Bose, I. (2019). What do hotel customers complain about? Text analysis using structural topic model. *Tourism Management*, 72, 417–426.
- Hwang, K., & Lee, B. (2019). Pride, mindfulness, public self-awareness, affective satisfaction, and customer citizenship behaviour among green restaurant customers. *International Journal of Hospitality Management*, 83, 169–179.
- Jang, S. S., & Namkung, Y. (2009). Perceived quality, emotions, and behavioral intentions: Application of an extended Mehrabian–Russell model to restaurants. *Journal of Business Research*, 62(4), 451–460.
- Jang, Y. J., Kim, W. G., & Bonn, M. A. (2011). Generation Y consumers' selection attributes and behavioral intentions concerning green restaurants. *International Journal of Hospitality Management*, 30(4), 803–811.
- Jang, Y. J., Kim, W. G., & Lee, H. Y. (2015). Coffee shop consumers' emotional attachment and loyalty to green stores: The moderating role of green consciousness. *International Journal of Hospitality Management*, 44, 146–156.
- Jeong, E., Jang, S. S., Day, J., & Ha, S. (2014). The impact of eco-friendly practices on green image and customer attitudes: An investigation in a café setting. *International Journal of Hospitality Management*, 41, 10–20.
- Jin, N., Lee, S., & Huffman, L. (2012). Impact of restaurant experience on brand image and customer loyalty: Moderating role of dining motivation. *Journal of Travel & Tourism Marketing*, 29(6), 532–551.
- Johns, N., & Pine, R. (2002). Consumer behaviour in the food service industry: A review. *International Journal of Hospitality Management*, 21(2), 119–134.
- Kaplan, S., & Vakili, K. (2015). The double-edged sword of recombination in breakthrough innovation. *Strategic Management Journal*, 36(10), 1435–1457.
- Keaveney, S. M., & Hunt, K. A. (1992). Conceptualization and operationalization of retail store image: A case of rival middle-level theories. *Journal of the Academy of Marketing Science*, 20(2), 165–175.
- Keller, K. L. (1993). Conceptualizing, measuring, and managing customer-based brand equity. *The Journal of Marketing*, 57(1), 1–22.
- Kim, H. J., Park, J., Kim, M.-J., & Ryu, K. (2013). Does perceived restaurant food healthiness matter? Its influence on value, satisfaction and revisit intentions in restaurant operations in South Korea. *International Journal of Hospitality Management*, 33, 397–405.
- Kwok, L., & Huang, Y.-K. (2019). Green attributes of restaurants: Do consumers, owners, and managers think alike? *International Journal of Hospitality Management*, 83, 28–32.
- Kwok, L., Huang, Y. K., & Hu, L. (2016). Green attributes of restaurants: What really matters to consumers? *International Journal of Hospitality Management*, 55, 107–117.
- Lai, K., & Li, Y. (2012). Core-periphery structure of destination image: Concept, evidence and implication. *Annals of Tourism Research*, 39(3), 1359–1379.
- Line, N. D., Hanks, L., Zhang, L. (2016). Sustainability communication: The effects of message construals on consumers' attitudes towards green restaurants. *International Journal of Hospitality Management*, 57, 143–151.
- Line, N. D., & Runyan, R. C. (2012). Hospitality marketing research: Recent trends and future directions. *International Journal of Hospitality Management*, 31(2), 477–488.
- Liu, P., & Tse, C.-Y. (2018). Exploring factors on customers' restaurant choice: An analysis of restaurant attributes. *British Food Journal*, 120(10), 2289–2303.
- Lu, W., & Stepchenkova, S. (2015). User-generated content as a research mode in tourism and hospitality applications: Topics, methods, and software. *Journal of Hospitality Marketing & Management*, 24(2), 119–154.
- Manaktola, K., & Jauhari, V. (2007). Exploring consumer attitude and behaviour towards green practices in the lodging industry

- in India. *International Journal of Contemporary Hospitality Management*, 19(5), 364–377.
- Namkung, Y., & Jang, S. S. (2013). Effects of restaurant green practices on brand equity formation: Do green practices really matter? *International Journal of Hospitality Management*, 33, 85–95.
- Park, E., Chae, B., & Kwon, J. (2018). Toward understanding the topical structure of hospitality literature: Applying machine learning and traditional statistics. *International Journal of Contemporary Hospitality Management*, 30(11), 3386–3411.
- Park, E. O., Chae, B. K., & Kwon, J. (2020). The structural topic model for online review analysis: Comparison between green and non-green restaurants. *Journal of Hospitality and Tourism Technology*, 11(1), 1–17.
- Reynolds, K. J., & Oakes, P. J. (2000). Variability in impression formation: Investigating the role of motivation, capacity, and the categorization process. *Personality and Social Psychology Bulletin*, 26(3), 355–373.
- Roberts, M. E., Stewart, B. M., & Airoidi, E. M. (2016). A model of text for experimentation in the social sciences. *Journal of the American Statistical Association*, 111(515), 988–1003.
- Roberts, M. E., Stewart, B. M., Tingley, D., Lucas, C., Leder-Luis, J., Gadarian, S. K., Albertson, B., & Rand, D. G. (2014). Structural topic models for open-ended survey responses. *American Journal of Political Science*, 58(4), 1064–1082.
- Ryu, K., Han, H., & Kim, T. (2008). The relationships among overall quick-casual restaurant image, perceived value, customer satisfaction, and behavioral intentions. *International Journal of Hospitality Management*, 27(3), 459–469.
- Ryu, K., Lee, H., & Kim, W. (2012). The influence of the quality of the physical environment, food, and service on restaurant image, customer perceived value, customer satisfaction, and behavioral intentions. *International Journal of Contemporary Hospitality Management*, 24(2), 200–223.
- Schubert, F., Kandampully, J., Solnet, D., & Kralj, A. (2010). Exploring consumer perceptions of green restaurants in the us. *Tourism and Hospitality Research*, 10(4), 286–300.
- Stamolampros, P., Korfiatis, N., Chalvatzis, K., & Buhalis, D. (2019). Job satisfaction and employee turnover determinants in high contact services: Insights from employees' online reviews. *Tourism Management*, 75, 130–147.
- Teichert, T. A., & Schöntag, K. (2010). Exploring consumer knowledge structures using associative network analysis. *Psychology & Marketing*, 27(4), 369–398.
- TripAdvisor. (2020). *About us*. <https://tripadvisor.mediaroom.com/IN-about-us>
- Wallach, H. M., Mimno, D. M., & McCallum, A. (2009, December 7–10). *Rethinking lda: Why priors matter* [Conference session]. Advances in Neural Information Processing Systems, Vancouver, British Columbia, Canada.
- Wang, H. J., & Horng, S. C. (2016). Exploring green brand associations through a network analysis approach. *Psychology & Marketing*, 33(1), 20–35.
- Wang, Y., Li, X., & Lai, K. (2018). A meeting of the minds: Exploring the core-periphery structure and retrieval paths of destination image using social network analysis. *Journal of Travel Research*, 57(5), 612–626.
- Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications* (Vol. 8). Cambridge university press.
- Wu, H.-C., Cheng, C.-C., & Ai, C.-H. (in press). *What drives green experiential loyalty towards green restaurants?* *Tourism Review*.
- Wu, H. C., & Mohi, Z. (2015). Assessment of service quality in the fast-food restaurant. *Journal of Foodservice Business Research*, 18, 358–388.
- Xu, Y., & Jeong, E. (2019). The effect of message framings and green practices on customers' attitudes and behavior intentions toward green restaurants. *International Journal of Contemporary Hospitality Management*, 31(6), 2270–2296.
- Yadav, R., Dokania, A. K., & Pathak, G. S. (2016). The influence of green marketing functions in building corporate image: Evidences from hospitality industry in a developing nation. *International Journal of Contemporary Hospitality Management*, 28(10), 2178–2196.