Exploring customers' perceptions toward green restaurants using user-generated content

by

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B.S., Chungbuk National University, 2012
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AN ABSTRACT OF A DISSERTATION

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Abstract

Many restaurants have incorporated sustainable or “green” practices to minimize environmental harm and to build a positive brand image. However, customers may not always appraise such efforts but rely on their existing images to implicitly process what they perceive, resulting in differences between the images that a company seeks to communicate and what customers actually perceive. Therefore, the purpose of this study was to identify green images from the free-recalled user-generated content (UGC) of certified green restaurant customers. First, the salient image categories were extracted, and effects of reviewer and restaurant characteristics on the recalled green image were examined. Then, the image network structures including both higher- and lower-level image elements and their characteristics were investigated.

Post-visit online reviews (*N*=25,098) of 70 certified green restaurants, written between March 2014 to February 2019, were selected from TripAdvisor.com to capture the free-recalled green restaurant images expressed in unstructured texts. After typical data preprocessing, 51 salient image categories were identified using the structural topic model (STM) algorithm followed by a factorial MANCOVA and LSD post hoc analysis to estimate the effects of reviewer and restaurant characteristics on the green image. A topic-level network was drawn based on topic proportion correlation matrix, and a green image network structure was examined based on the co-occurrence of the unique words found in the UGC. For both networks, a community detection algorithm was applied to discover the subgroups from the image associations. In addition, the image nodes were classified into three groups (i.e., core, semi-periphery, or periphery) based on eigenvector scores, and sentiment and emotion scores were assessed for each image node.

Both general restaurant attributes (e.g., food, service, atmosphere, and value) and green attributes emerged from the STM. Some specific restaurant attributes (e.g., employees' attire) used in previous studies did not emerge as a relevant topic. The extent of green practice implementation ($p<.001$) and the duration of the certification program ($p<.001$) were significantly associated with the likelihood of the customers mentioning a green practice topic, and female customers mentioned more about sustainable foods than males ($p<.001$). In the topic-level network, positive image categories (e.g., T44, satisfaction and T5, good flavor) tended to have higher eigenvector scores (>0.99) than negative categories (e.g., T6, T46 related to bad service; eigenvector scores<0.22), indicating that positive topics were more easily recalled among customers. Similarly, the green image network and image associations relevant to green attributes contained positive sentiment scores (>0.95). While the majority of food-focused green image associations were classified as core or semi-periphery, environment-focused green image was classified as periphery. The results demonstrated that the food-focused green image associations were more tightly connected to other image associations and more likely to be activated than environment-focused images.

This study tested the category-based perspective and associative network model with the free-recalled UGC to conceptualize the green restaurant image. Various machine-learning based approaches and network analysis improved reproducibility and overcame subjectivity in traditional qualitative analysis. Based on the findings, restaurateurs may develop green marketing strategies to gain competitive advantages.

Words: 497

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Chapter 1 - Introduction

With increasing public awareness of environmental issues, more customers demand sustainable business practices and purchase products with less negative impacts on the environment than before (Dangelico & Vocalelli, 2017; Polonsky & Rosenberger III, 2001). Many hospitality companies have implemented green practices to respond to customers' requests and to build the positive brand image by differentiating themselves from their competitors (Aragon-Correa, Martin-Tapia, & de la Torre-Ruiz, 2015). Many researchers have found the positive effects of green practices on the customers' attitudes (Gao & Mattila, 2014; Slevitch, Mathe, Karpova, & Scott-Halsell, 2013), evaluation of restaurant performance (Namkung & Jang, 2013), and customers' behavioral intention to select certain restaurants (Lee, Conklin, Bordi, & Cranage, 2016; Lee, Conklin, Cranage, & Lee, 2014).

Green practices are unique functional attributes of restaurants that influence customers to form a green restaurant "image" and generate positive outcomes, such as increased customer satisfaction, revisit intention, or willingness to pay more (Chen, 2010; Lee, Hsu, Han, & Kim, 2010). However, a restaurateur's commitment to creating a green image by implementing green attributes may not always lead to the aforementioned positive outcomes, if these green attributes are not communicated with customers (Dodds & Kuehnel, 2010; Yadav, Kumar Dokania, & Swaroop Pathak, 2016). The discrepancy between the green image that a company seeks to convey to stakeholders and the stakeholders' actual perceptions may be greater in restaurants partly than other business sectors because many sustainable practices pertain to back-of-the-house operations (Brown, Dacin, Pratt, & Whetten, 2006; Namkung & Jang, 2013). Therefore, restaurateurs may need to evaluate the effectiveness of green practices by uncovering the green attributes that customers recognize and appreciate.

An image associative network model conceptualizes that an image exists in a network structure in human memory (Anderson, 1983). The basic unit of the image network is an informational node, also known as an image association (Keller, 1993) or an image attribute (Fiske, Neuberg, Beattie, & Milberg, 1987), and a set of informational nodes are interconnected with the relational links (Anderson, 1983). An image network structure has a hierarchical structure that includes both the higher-level image *categories* and the lower-level image *attributes* (Anderson, 1983; Fiske et al., 1987). The higher-level image category constitutes multiple semantically coherent image attributes, and the attributes under the category are organized according to the importance and relationship between the attributes (Fiske & Pavelchak, 1986a).

The formation of an image is primarily influenced by subjective judgments of an individual who evaluates the stimulus (Dichter, 1985; James, Durand, & Dreves, 1976). For example, the respondents' personal traits (e.g., involvement or motivation) associated with the stimuli influence the likelihood of the particular information nodes to be recalled (Goodstein, 1993; Petty, Cacioppo, & Schumann, 1983). Thus, customers who experience the same attributes incorporated or expressed by a company may remember these attributes differently depending on their personal traits (Lynch, Marmorstein, & Weigold, 1988). To address this issue, this study attempted to understand the actual image that customers have formed from specific restaurant attributes to help operators understand what their customers care about and consider important.

To capture the distinctive image stored in one's memory, free-recall methods (e.g., open-ended questions or interviews) have been adopted with people who have high involvement in the particular stimulus (Christensen & Olson, 2002; Teichert & Schöntag, 2010). However, accessing free-recalled content may be difficult if there is no obvious data repository. 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. Thus, this study analyzed the green restaurant customers' responses about their dining experiences expressed in their own words – user-generated content (UGC) found in TripAdvisor. Today's customers are used to and motivated to share their honest opinions about their experiences with the public through social networking or online review sites, and therefore, a vast amount of UGC is freely available for researchers. UGC is unstructured textual data that include users' natural opinions, information, and feelings based on attributes that customers recognize, appreciate, and recall (Johnson, Sieber, Magnien, & Ariwi, 2012; Pang et al., 2011). In writing an online review, customers recall their experiences and retrieve the memory structure relevant to their experiences (Fang, 2014). Therefore, UGC is a rich source for understanding the image that is formed from their memory.

Considering the availability of the massive amount of UGC created based on the customers' actual experiences, it may be beneficial to utilize the UGC to uncover the green image. However, analyzing the unstructured data manually can be time-consuming and is challenged by the human coders' subjectivity (Rourke, Anderson, Garrison, & Archer, 2001). In order to overcome the drawbacks of manual data analyses of unstructured data, machine learning algorithms such as topic modeling have been applied to discover the latent topical categories or themes from large collections of texts (Blei, 2012; Griffiths & Steyvers, 2002; Griffiths, Steyvers, & Tenenbaum, 2007). In topic modeling, the topics are discovered by arranging the semantic relatedness of words given the particular topic, which is similar with the image categories in memory network that consist of semantically coherent attributes (Collins & Loftus, 1975; Griffiths et al., 2007). Therefore, this study aims to discover the green restaurant image expressed in UGC by applying a topic modeling algorithm.

Problem Statement

Although green practice implementation has become a significant trend in the restaurant industry (National Restaurant Association, 2019a), the systematic review of sustainability studies revealed that research related to green practices in the restaurant context remains limited (Kim, Lee, & Fairhurst, 2017). It is important to examine the effectiveness of green restaurant practices in forming a positive customer image in the foodservice context because consumers' interests in sustainable business practices has increased and positively affected intention to purchase products (DiPietro, Cao, & Partlow, 2013; Hu, Parsa, & Self, 2010). Moreover, there is a lack of hospitality literature that has examined the restaurant image encoded in memory by analyzing the freely recalled customer responses. The majority of previous literature related to green practices used the predetermined structured measurement items with various scales, such as semantic differential scales or Likert-type scales to assess customers' responses to green practices (Jeong, Jang, Day, & Ha, 2014; Kwok, Huang, & Hu, 2016; Slevitch et al., 2013). However, the attempts to discover the semantic representation of the user-generated text data have been limited (Yu, Li, & Jai, 2017).

Purpose of the Study

The purpose of this study was to examine green restaurant image expressed in the form of unstructured text data (i.e., UGC) to identify the green image stored in customers' memory without being prompted. In Phase I, this study aims to identify salient image categories from green restaurant UGC using topic modeling based on the category-based processing perspective (Fiske et al., 1987). The specific research questions for Phase I are as follows:

1. What are the salient image categories stored in customers' memory who visited green restaurants?
2. What are the image categories frequently mentioned by the green restaurant customers?
3. What are similarities and differences between the image categories discovered from UGC and findings of previous research?
4. What are the effects of the length of green certification participation and the level of engagement in green practices on the customers' green image?
5. What are the effects of the customers' demographic backgrounds on the green image?

In Phase II, the green image network structure was explored based on the associative network model (Anderson, 1983) and the green image dimensions were examined (Keller, 1993). The specific research questions of Phase II are as follows:

1. How can the green image network structures that represent the memory structure be visualized?
2. What are the characteristics of the higher- and lower-level green image networks?
3. What are the types of image associations in the green image network?
4. What is the degree of favorability of image associations that indicate the customers' emotional connections with the specific attributes?
5. What is the strength of image associations that estimates the likelihood of the specific attributes to be recalled?

Significance of the Study

In order to uncover the hierarchical image network structures stored in green restaurant customers' memory, this study combined the category-based processing perspective and the associative network model (Anderson, 1983). To do so, the probabilistic topic models (Roberts et al., 2014) and network analysis (Teichert & Schöntag, 2010; Wang et al., 2018) were applied with a large number of UGC generated by green restaurant customers. The current study captured various elements of image, such as cognitive evaluation of restaurant attributes, stereotypes, emotional responses, and holistic images (Echtner & Ritchie, 1991; Keaveney & Hunt, 1992).

The findings of this study may benefit practitioners by demonstrating which green attributes are well communicated and memorable to the customers. Also, the results may uncover the emotional responses toward the green restaurant attributes, which help the restaurateurs understand their performance compared to the customers' demands. As the customers rely on their existing images to evaluate an entity, the restaurateurs may be able to identify which green attributes they need to implement strategically (Keller, 1993). Moreover, the restaurateurs may focus on promoting the restaurant attributes that have strong connections with the other image nodes and generate positive emotions to provide more memorable products and services (Wang et al., 2018).

Limitations

This study explored only certified green restaurants as certified by the Green Restaurant Association, which are actively engaged in green practices. Thus, the results may not be directly applicable to restaurants with low engagement in sustainable restaurant practices. Including non-green restaurants in future research may improve the ability to compare customers' green images and their impact on attitudes in restaurants with different levels of engagement in sustainable practices.

Previous studies found that customers perceive green practices differently, depending on customers' personal characteristics, such as gender, income, and self-perceptions (Kwok et al., 2016). Although TripAdvisor publishes the demographic information of those who agree to disclose such information, only limited information is available. Therefore, future research may explore ways to include customers' demographic information and other covariates in topic modeling.

Although customers' natural reactions of experiencing green practices were analyzed with more than 20,000 online reviews, the customers who did not write online reviews were not assessed in this study. The future study is recommended to use other types of data sources, such as survey or integrating both methods, as appropriate.

Finally, this study analyzed online reviews of certified green restaurants in the U.S. Restaurants in other countries may also engage in different degrees of sustainable "green" restaurant practices. Hence, results from this study may not be generalized to restaurants outside the U.S.

Chapter 2 - Literature Review

Corporate Social Responsibility and Green Practices

The concept of corporate social responsibility (CSR)

With the growing public awareness of the negative impacts of human activity on the environment, the importance of corporate social responsibility (CSR) has been increasingly emphasized in business operations (Li, Fang, & Huan, 2017). CSR is defined as “the responsibility of enterprises for their impacts on society and outlines what an enterprise should do to meet that responsibility” (European Commission, 2011, p. 6). McWilliams and Siegel (2001) defined CSR as “actions that appear to further some social good, beyond the interests of the firm and that which is required by law” (p. 117). The CSR definitions denote the corporations’ role of performing business practices that contribute to positive changes in the society beyond making the financial performance (Cronin, Smith, Gleim, Ramirez, & Martinez, 2011).

CSR is a multidimensional concept that includes different components, and many studies have attempted to identify various dimensions. For example, Carroll (1991) conceptualized CSR as a concept pertaining to legal, economic, ethical, and philanthropic or voluntary responsibilities. According to the proposed concept, a business is not only required to be economically profitable and obedient to the law, but also has ethical and philanthropic responsibilities to enhance community well-being (Carroll & Shabana, 2010). By analyzing the existing CSR definitions, Dahlsrud (2008) identified the following five dimensions that are predominant in many available definitions of CSR: the environmental, economic, social, stakeholder, and the voluntariness dimensions. The multiple categories of CSR highlighted the social, environmental, and economic impacts that a business can make while dealing with regulations and balancing the different opinions among stakeholders (Dahlsrud, 2008).

Many firms have engaged in CSR activities to respond to the various stakeholder groups and satisfy their expectations toward the company (Colleoni, 2013). Through CSR activities, the companies attempt to align the corporate practices with the stakeholder demands so they can obtain legitimacy, which is essential for survival of the business (Du & Vieira, 2012). Legitimacy is conceptualized as "a generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions" (Suchman, 1995, p. 574). However, social norms or values can be potentially contradictory among multiple stakeholder groups (Guthey & Morsing, 2014). Thus, a firm's CSR activities that advocate a certain value may dissatisfy a certain group of stakeholders and create a potential crisis (Coombs & Holladay, 2015). As the stakeholders' expectations and social norms may change over time, understanding the stakeholders' needs is critical for companies to establish a successful CSR strategy.

The effects of CSR activities can also vary because each industry has unique situations and features. For example, oil companies, which are criticized for their immoral business practices, tend to have difficulty in building legitimacy through their CSR actions due to stakeholders' high level of skepticism (Du & Vieira, 2012). Although establishing a comprehensive and accepted framework for CSR is important (Carroll, 1999; Dahlsrud, 2008), the general and interdisciplinary concept of CSR may ignore the underlying characteristics of the industry (Banerjee, 2001). Therefore, a context-specific definition of CSR should be developed to address different situations and practical issues within the particular context (Farrington, Curran, Gori, O'Gorman, & Queenan, 2017; Van Marrewijk, 2003).

Based on the multidimensional concept, CSR describes a situation when a company chooses the sustainable practices that align with its own mission as well as stakeholders' values (Van Marrewijk, 2003). The hospitality industry has had an increasing demand to adopt more sustainable business practices, especially environmentally sustainable practices (Xu, Xiao, & Gursoy, 2017). Common sustainable practices in the hospitality industry include recycling or using eco-friendly chemicals (Namkung & Jang, 2013). The more detailed discussion about these green practices implemented in the hospitality industry is presented in the next section.

Green practices in the hospitality industry

Green practices, which are often conceptualized under the concept of CSR (Kwok, Huang, & Hu, 2016; Singal, 2014), are defined as "things that organizations can do to minimize their carbon footprint and the negative impact that their organization has on the environment" (DiPietro & Gregory, 2012, p. 2). The hospitality industry heavily depends on the natural environment and resources and needs close relationships with their customers in local communities, and thus, gaining legitimacy through green practices is critical for business success (Kim, Thapa, & Holland, 2018; Serra-Cantallops, Peña-Miranda, Ramón-Cardona, & Martorell-Cunill, 2018). For example, the hotel industry has the large number of operations all over the world, and many hotel corporates engage in sustainable practices make a significant influence on the socioeconomic conditions of the local community (Serra-Cantallops et al., 2018). Also, stakeholders in the casino industry, which is considered as controversial due to undesirable consequences to the society (Du & Vieira, 2012), often demand advanced ethical performance beyond legal requirements and business interests (Vong & Wong, 2013). Hence, gaming companies have strategically used green attributes to reduce its unfavorable public image as well as firms' risk (Jo & Na, 2012; Vong & Wong, 2013).

Likewise, the restaurant industry participates in the green movement. There are approximately one million restaurant operations and 15.3 million employees in the U.S. restaurant industry alone (National Restaurant Association [NRA], 2019a), and the local community is important for them as it creates demands and provides the labor pool for their operations. As customers become more health- and environment-conscious, implementing green practices has become a major tactic to create a positive brand image and subsequently leads to increased customer satisfaction (Namkung & Jang, 2013; Wang, Chen, Lee, & Tsai, 2013).

The hospitality industry outperforms other business sectors with regard to investments in sustainable practices (Singal, 2014). Hospitality companies, especially large corporations, are committed to implementing green practices to meet high expectation of their customers, who demand positive changes in society (Kang, Lee, & Huh, 2010). For example, a sustainability report by the Marriott corporation stated that 73% of Marriott operations use high-efficiency lighting, 65% of their operations participate in recycling programs, and 99.2% of its contracted suppliers have a sustainability policy (Marriott, 2017). In addition to reducing the negative environmental impacts, Marriott announced their commitment to positive social changes, such as supporting local communities, protecting human rights, and providing equal opportunities to all people (Marriott, 2017). Many hospitality companies implement similar sustainable practices, not only to respond to customers' requests, but to gain competitive advantage by differentiating themselves from their competitors (Aragon-Correa et al., 2015; Namkung & Jang, 2013).

Green practices in the foodservice industry

The restaurant industry is one of the most rapidly expanding sectors in the United States, whereby the number of restaurant locations has exceeded more than one million (NRA, 2019a). With the large number of restaurant locations, negative impacts of these businesses on the natural environment are significant in conjunction with the intensive use of energy (Chou, Chen, & Wang, 2012; Hu et al., 2010). The range of environmental impacts of the restaurant industry is also wide and intensive, from excessive use of water, energy, and resources to high carbon footprints made during the production and delivery of goods, and the transportation of customers and employees (Schubert, Kandampully, Solnet, & Kralj, 2010). Due to heavy use of energy in commercial foodservice establishments (Energy Star, 2018), green practices in the restaurant industry have become a significant way to reduce operating expenses, conserve non-renewable energy use, and protect environments (NRA, 2019b). In addition to the restaurateurs' interest in the environment, serving sustainable food products (e.g., organic, local ingredients) has become a unique green practice in the foodservice sector (Hanks & Mattila, 2016; Remar, Campbell, & DiPietro, 2016). With customers' growing interest in the health and the ecological environments, the use of organic or locally sourced products has been one of the major trends in the restaurant industry (NRA, 2019b).

To reflect the restaurant customers' increasing interests in green practices, several studies have been conducted to examine the effectiveness of green practices on customer perceptions, brand image, and behavioral intention (e.g., DiPietro, Cao, & Partlow, 2013; Hu et al., 2010; Jeong et al., 2014; Namkung & Jang, 2017; Swimberghe & Wooldridge, 2014). However, a major challenge in the sustainability literature is a lack of consensus to define green attributes upon which researchers, managers, and customers can agree (Hopkins et al., 2009; Kim et al., 2017). Therefore, the green attribute frameworks proposed by scholars are illustrated in the next section.

Green attribute frameworks in foodservice

As green practices are context-specific, green attributes that can be adopted in restaurant operations should be identified (Ham & Lee, 2011). To address this issue, previous literature has attempted to conceptualize green restaurant attributes (e.g., Chen, Cheng, & Hsu, 2015; Choi & Parsa, 2006; Ham & Lee, 2011; Kwok et al., 2016). A green restaurant framework suggested the following three perspectives in green restaurant practices: health, environmental, and social (Choi & Parsa, 2006). The environment concern is regarding restaurants' responsibility to protect the natural environment and the community. It includes environmentally friendly practices, such as reducing plastic waste or recycling materials. The social concern emphasizes the restaurateurs' role in community involvement, socially responsible marketing, and fair human resource practices. The health concern highlights the approach that supports customers' healthy lifestyles by serving healthy options, such as organic, low-fat, and nutritionally-balanced foods. While other sectors heavily focus on environment-friendly initiatives or social issues, the health perspective is a unique green attribute in the restaurant industry (Choi & Parsa, 2006).

Kwok et al. (2016) proposed an alternative green attribute framework for the restaurant setting, which includes food-, environment-, and administration-focused green practices. Within this framework, food- and environment-focused green practices are similar to the health and environmental perspectives developed by Choi and Parsa (2006), respectively. Kwok et al. (2016) suggested that the social concern perspective is less relevant to the green restaurant concept. Instead of social concern perspective, Kwok et al. (2016) proposed the administration-focused green attributes that reflect the restaurateurs' efforts and commitment to operate the restaurant in the sustainable way, such as obtaining green certifications and training employees to incorporate green practices in daily operations.

Based on previous research and various green certification standards, Ham and Lee (2011) outlined eight categories of green practices (i.e., water efficiency/conservation, waste reduction and recycling, sustainable furnishings, building materials or resources, use of healthy/sustainable food, energy, disposables, chemical and pollution reduction, and organizational green practices) to evaluate restaurants' sustainability practices. Also, Chen et al. (2015) developed the GRSERV scale by conducting an extensive review of the previous literature on green restaurants and service quality and performing in-depth interviews with experts in the field. Through GRSERV, Chen et al. added two dimensions related to a sustainable environment and food on the five dimensions of DINESERVE (i.e., reliability, assurance, responsiveness, tangibles, and empathy), which was proposed by Stevens, Knutson, and Patton (1995).

Benefits of green practice implementation

Implementing green restaurant practices has a myriad of benefits that compensate for the associated costs and efforts. Saving utility costs is a major benefit. For instance, Wendy's implemented over 1,100 energy upgrade projects in more than 550 operations. With these projects, Wendy's saved about $14 million dollars in utility cost (The Wendy's Company, 2016). Another benefit of engaging in green practices is to reinforce the public image by expressing their commitment to sustainability (Namkung & Jang, 2013; Tan & Yeap, 2012). Considering the fierce competition in the restaurant industry, managing a positive brand image is particularly important for the managers to differentiate the company from the competitors (Namkung & Jang, 2013).

A number of studies have identified the positive effect of green practice implementation on various areas, such as customer attitude (Jeong et al., 2014; Swimberghe & Wooldridge, 2014), brand image (Jeong et al., 2014; Namkung & Jang, 2013), revisit intention (Giebelhausen, Lawrence, Chun, & Hsu, 2017; Hu et al., 2010; Lee et al., 2014), and willingness to pay more (DiPietro, Gregory, & Jackson, 2013; Kwok et al., 2016; Namkung & Jang, 2017; Schubert et al., 2010). These findings imply that incorporating green practices can be a marketing strategy to gain competitive advantage and improve the restaurants' financial performance (Inoue & Lee, 2011; Kang et al., 2010; Lee, Singal, & Kang, 2013).

Green restaurant certifications

To promote environmental sustainability to restaurateurs, several certification programs have been established, such as Green Restaurant Association (GRA), Green Seal, and Green Kitchen certifications (DiPietro, Cao, & Partlow, 2013). These certification programs help operators who recognize the benefits of implementing green practices, but are still unaware of how to improve their sustainable practices (Jang, Zheng, & Bosselman, 2017). The GRA offers a nationally recognized certification program, which encourages a green movement in the foodservice industry based on the following seven environmental standards: sustainable food, energy use, water efficiency, waste reduction and recycling, sustainable durable goods and building materials, reusables and environmentally preferable disposables, and chemical and pollution reduction (GRA, 2018). Researchers contend that these certification standards reflect the green attribute frameworks for the restaurant industry (Schubert et al., 2010). GRA standards include both health-(food) and environment-related categories, while social requirements are absorbed under the food and environmental categories (Kwok et al., 2016).

Based on the extant understanding of green restaurant practices in the literature and industry standards, this study primarily focused on two dimensions of green practices: *food*- and *environment-focused* green attributes. *Administration*-focused green practices were addressed by selecting the restaurants that participated in the formal green restaurant certification program as the study sample.

The Concept of Images

In this section, the previous literature on green image and more general image concept is reviewed to provide an understanding of the fundamental characteristics and theories relevant to the image and the conceptualization in the restaurant context. Among various conceptualizations of an image, researchers agree that an image is a global or overall impression toward an entity based on the evaluation of its attributes. For example, Oxenfeldt (1974) proposed that an image exists like a picture that combines various impressions of an object. He also emphasized that an image is more than a factual description of objective reality, and thus, an image is greater than the sum of its parts. Similarly, Zimmer and Golden (1988) described an image as a global impression that transcends the responses to specific attributes. Dichter (1985) denoted that an image comprises one's total impressions about an entity rather than a description of specific features or qualities.

Keller (1993) defined a brand image as a set of associations related to a brand that individuals hold in their memory. Keller asserted that each image association contains the personal meaning of the brand, which is identified by customers. The formation of an image is primarily influenced by the subjective judgment of an individual assessing the stimulus, whether using factual information or inaccurate stereotypes (Dichter, 1985; James et al., 1976). The argument is supported by the fact that images once formed in the previous experiences tend to sustain and influence responses to a new stimulus (Keaveney & Hunt, 1992). That is, an image created by the same physical stimulus may vary according to a variety of individual factors, such as personal biases, opinions, feelings, and prior experiences (Greenwald & Banaji, 1995).

Based on the conceptualization of an image, a green image has been defined in different contexts. For example, Chen (2010, p. 309) defined a green brand image as “a set of perceptions of a brand in a consumer’s mind that is linked to environmental commitments and environmental concerns.” Also, Jeong et al. (2014, p. 13) 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.” These definitions implied that the environmental commitments of a company play a vital role in building a green image (Mayer, Ryley, & Gillingwater, 2012). While these definitions above highlighted the importance of functional and physical attributes of an image, they did not consider overall or holistic features.

According to Han, Hsu, and Lee (2009, p. 520), an overall image of a green hotel is defined as “hotel customers’ overall perceptions of a green hotel, formed by processing information and by prior or vicarious knowledge about a green hotel and its attributes.” The proposed definition of the overall image of a green hotel includes both functional attributes and general impressions of the image. This conceptualization is consistent with the previous literature that an image contains more than evaluations about functional attributes (Echtner & Ritchie, 1993; Keaveney & Hunt, 1992). Some researchers also acknowledged that the image might be influenced by customers’ experience of a green hotel as well as customers’ prior knowledge about the hotel (Han et al., 2009). However, these researchers focused only on the emotional responses of green hotel customers and did not consider the salient attributes to operationalize the green hotel image.

There have been several attempts to conceptualize a green image. However, previously proposed conceptualizations of a green image did not capture all of the various components, such as functional, holistic, and unique impressions (Echtner & Ritchie, 1993; Stylos, Vassiliadis, Bellou, & Andronikidis, 2016). Also, there is an inconsistency between the green image conceptualization and operationalization, and thus, the rich insight of a green image may not be made (Keaveney & Hunt, 1992; Zimmer & Golden, 1988). Therefore, this study aims to conceptualize the green image in the restaurant context and recommend a new approach to operationalize the green image concept. Specifically, the hierarchical structure of an image and the network structure of a green restaurant image are illustrated below.

The hierarchical structure of an image

Scholars hypothesized that the hierarchical structure of the memory includes both the higher-level categories and the lower-level attributes. As shown in Figure 2.1 below, Fiske et al. (1987) proposed the memory structure that includes both categories at a higher-level and a set of multiple attributes associated with each category at a lower-level. The higher-level category constitutes the multiple semantically coherent attributes that represent a common feature (Fiske & Pavelchak, 1986a). The attributes under the category are organized according to the relatedness among the attributes (Collins & Loftus, 1975; Fiske & Pavelchak, 1986a). For example, Collins and Loftus (1975) argued that the tightly interconnected nodes have the common property that differentiates from other groups of the informational nodes. For example, a set of nodes related to different colors or vehicles are more likely to be interconnected with more links due to semantic similarity. Anderson (1983) also denoted that the memory network consists of the superordinate cognitive units, which are linked to the lower-level informational nodes.

The basic unit of informational nodes in the memory network corresponds to the lower-level image attributes in the category-based perspective, and the superordinate cognitive unit corresponds to the higher-level image categories (Fiske et al., 1987). The hierarchical structure of the memory structure can be also understood as the basis of the brain function; that is the nodes (i.e., neurons) in different brain regions are interconnected with the links (i.e., synapses) to construct a comprehensive memory (Teichert & Schöntag, 2010). Given the understanding about the memory structure, scholars have explored a higher-level entity in a memory structure that combines lower-level elements (e.g., attributes) sharing commonality (Teichert & Schöntag, 2010; Wang et al., 2018). Therefore, this study attempts to test the hierarchical memory structure to examine both the higher-level image categories and the lower-level image elements.

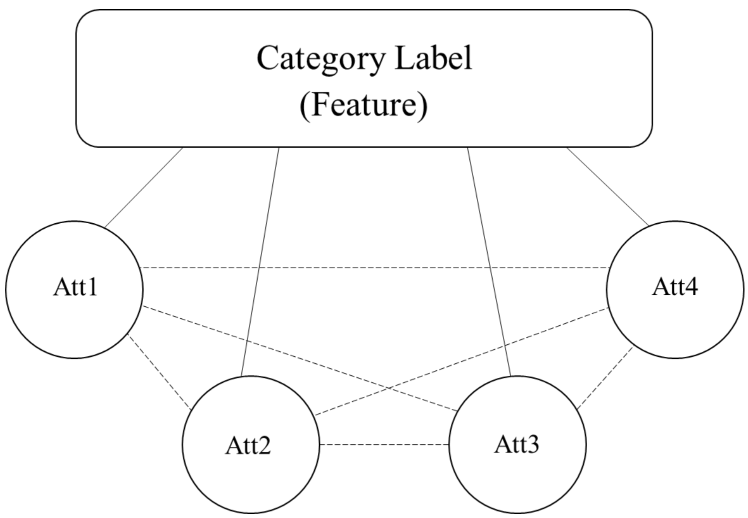

Figure 2.1. The graphic representation of memory structure (Fiske et al., 1987)

When encountering a stimulus, people tend to engage in cognitive processing to incorporate the new stimulus into the existing mental structures (Teichert & Schöntag, 2010). Similarly, the emotional reactions to an encountered object can be determined depending on the personal relevance or preference that has already been established in past experiences (Christensen & Olson, 2002). According to Fiske et al. (1987), affective meanings are attached to the higher-level categories and the lower-level memory elements in the memory structure (Figure

2.2). If a new stimulus fits into an existing category, the affective tags stored in the category are automatically retrieved to generate an instant affective response toward the stimulus (Sujan, 1985). On the other hand, if the new stimulus fails to fit the previously defined category, the emotional response to the object is determined based on the sum of the affective responses to each attribute relevant to the object (Fiske et al., 1987).

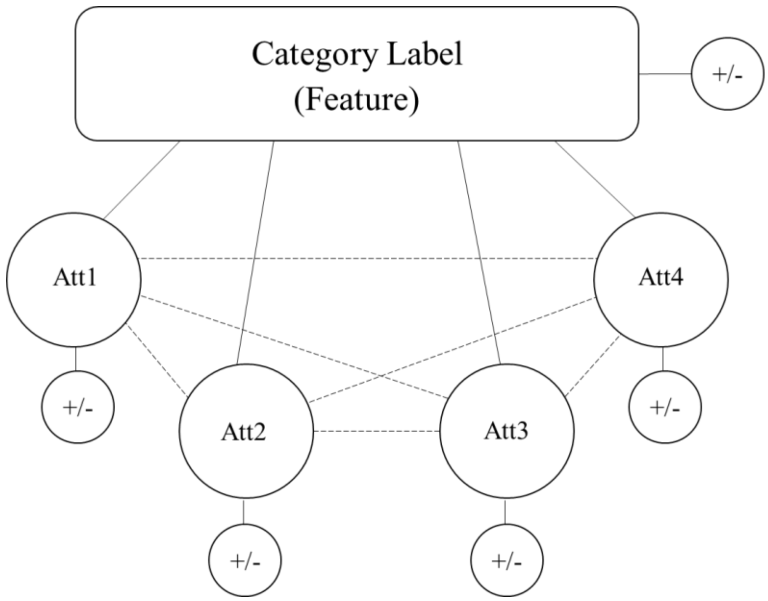

Figure 2.2. The graphic representation of memory structure with affective tags (Fiske et al., 1987)

Mapping an image network structure

The image categories and associated attributes are considered to exist as a network structure in memory (Anderson, 1983; Fiske et al., 1987). The image associative network theory has been widely applied to understand the image structure stored in memory and the process of retrieving information encoded in the human mind (Cattaneo & Guerini, 2012; Keller, 1993). According to this model, memory is stored in the form of an associative network, which consists of nodes containing information and concepts as well as the relational links connecting the nodes (Anderson, 1983; Srull & Wyer, 1989). The multiple informational nodes that are semantically associated tend to be strongly connected with the relational links, and these multiple nodes develop higher-level cognitive units (Collins & Loftus, 1975; Teichert & Schöntag, 2010). With the retrieval cues presented, the informational nodes stored in the human memory network can be activated to be recalled (Collins & Loftus, 1975).

For example, when a person experiences an entity, such as McDonald's, all encounters related to the brand are stored in memory as informational nodes that are interconnected with the relational links. As shown in Figure 2.3 (Aaker, 1996), there are multiple higher-level categories directly connected to the McDonald's brand, such as value, meals, service, and social involvement. The higher-level image categories (e.g., service) include specific image attributes, such as pricing, portion size, promotion.

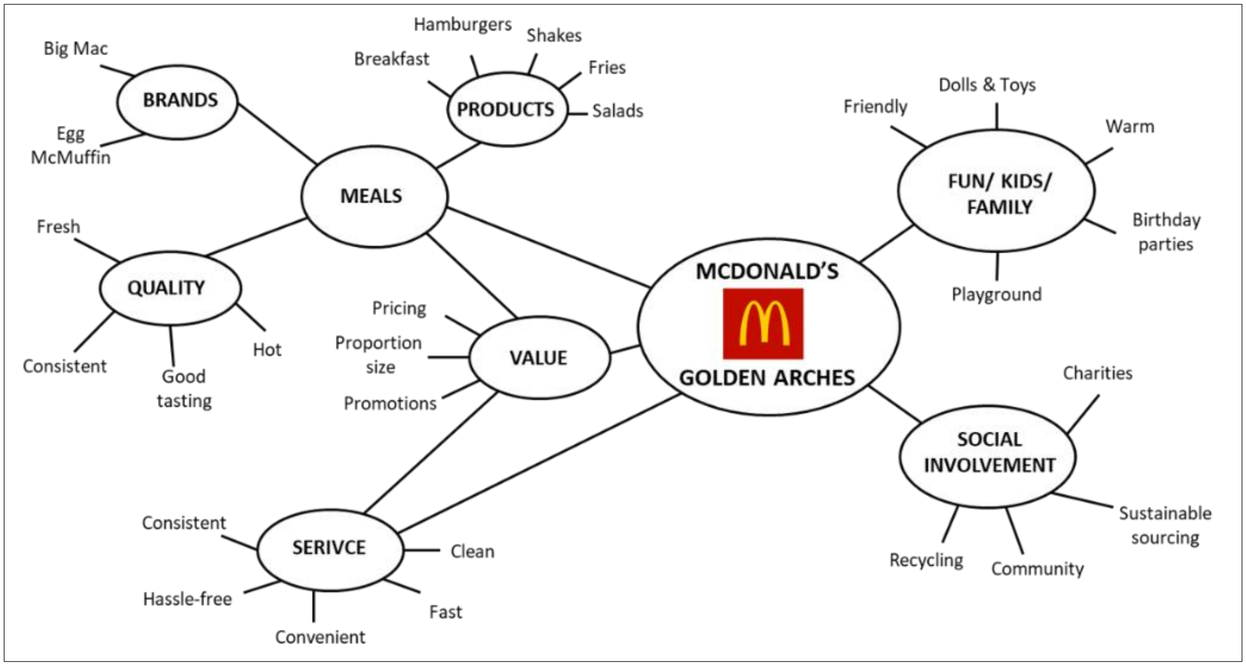

Figure 2.3. Brand image map of McDonald's (Source: Aaker, 1996)

Grounded on the associative network model, previous studies have examined the features of the two essential elements of an image network: informational nodes and relational links (e.g., Collins & Loftus, 1975; Keller, 1993; Teichert & Schöntag, 2010; Wang & Horng, 2016; Wang et al., 2018). A node is a basic unit of the memory network, and each node contains a concept related to an entity. A node can be created by not only the direct experience of an entity but also indirect experiences, such as advertising or word-of-mouth (Keller, 1993). Moreover, the existing nodes tend to sustain in the memory and influence the process of evaluating a new stimulus (Henderson, Iacobucci, & Calder, 1998). The informational nodes in the memory network are connected with the relational links. An image association strongly connected to a large number of other image nodes can be easily recalled compared to the loosely connected image associations (Anderson, 1983; Keller, 1993). Therefore, the strength of image association indicates the likelihood of the image nodes being activated from memory (Teichert & Schöntag, 2010).

The dimensions of image associations: types, favorability, strength, and uniqueness

Based on the associative network memory model, Keller (1993) conceptualized the multiple dimensions of the image associations, which includes types, strength, favorability, and uniqueness. These dimensions are useful to understand the customers' awareness and responses to an organization or relevant attributes, which later influence to build brand equity (Keller, 1993).

Previous researchers examined the different types of image associations that a person retains in his/her memory (e.g., Baloglu & McCleary, 1999; Echtner & Ritchie, 1993; Keller, 1993; Low & Lamb, 2000). For example, Keller (1993) introduced *attributes, benefits,* and *attitudes* as the elements of image associations. *Attributes* are descriptive features of a product or service that are related to customers' purchase or consumption behaviors. *Benefits* are the value customers attach to the attributes, and *attitudes* are their overall evaluations of the object. Echtner and Ritchie (1993) emphasized the importance of capturing the complex nature of images and proposed the continuum of *functional* and *psychological* characteristics of image elements. The *functional* image elements are more tangible and observable while the *psychological* image elements are more abstract and difficult to measure. Similarly, Low and Lamb, Jr. (2000) indicated that an image consists of its *functional* advantage (i.e., functional utility or qualities of a product or service) and *symbolic* perceptions (i.e., personal meaning of the product/service to customers). The *cognitive* and *affective* image components have been widely tested to identify the dynamics of image formation (Baloglu & McCleary, 1999). The *cognitive* image is the knowledge or beliefs about the objective attributes or physical features, while the *affective* image refers to the feeling or attachment to the various attributes (Baloglu & McCleary, 1999; Gartner, 1994; Genereux, Ward, & Russell, 1983). Based on the previous literature, this study attempted to identify both the *cognitive* image, which is the objective evaluation of an entity or specific attributes, and the *affective* image, which represents the personal value attached to the object.

As the image associations tend to reflect the evaluative judgment of the entity, the image associations have a different degree of favorability (Keller, 1993). Keller (1993) proposed that a person may evaluate an image association more positively when the perceived benefits associated with an attribute satisfy a customer's personal needs, or the performance of the attribute exceeds his or her expectation. In addition to the prior expectation or personal needs, the perceived importance of an attribute determines the polarity of favorability of the image associations (Keller, 1993). Simply put, customers may not have a favorable image association if they think such an attribute is not important. Therefore, the perceived importance of an attribute should also be considered to evaluate the polarity of favorability of image associations.

Strength of image associations that determines the extent of memory recall is grounded on a spreading activation (Collins & Loftus, 1975). According to Collins and Loftus (1975), the set of informational nodes (i.e., image associations in a memory network) are interconnected with the relational links of different strengths. Therefore, when a particular image association is activated, the activation spreads to the other image associations strongly connected to the activated image association through the relational links. For instance, if a person recalls a concept "computer," the prime concept node "computer" is activated, and the activation spreads to the nodes closely located to the prime node. As the memory network is organized according to the semantic relatedness, the strength of relational links varies depending on the distance between the nodes (Wang et al., 2018). The nodes sharing semantic similarities are interconnected with strong relational links, which enables the fast-spreading activation among the interconnected nodes (Collins & Loftus, 1975). Consequently, the strength of the relational links determines the quality and quantity of spreading activation from the activated image association to other image associations (Keller, 1993). In other words, the strength of image associations determines the likelihood of an image association to be activated and recalled (Gensler, Völckner, Egger, Fischbach, & Schoder, 2015; Keller, 1993). Based on the spreading activation theory, Wang et al. (2018) incorporated the concept of the core-periphery structure into the destination image network map. They categorized image associations as the core, semi-periphery, and periphery depending on the strength of the links that connect the image associations. With the application of the core-periphery structure, the researchers categorized the image depending on the likelihood of being recalled.

The uniqueness of image associations can be determined by the distinctive features of an entity that are not shared with the competitors (Keller, 1993). To be successful in the business, it is important to create unique image associations that are evaluated favorably (Keller, 1993).

Conceptualization and Measurement of an Image: Attribute- and Category-Based Perspectives

In order to understand how people process specific stimuli and store an image in memory, two main approaches have been proposed in psychology and consumer behavior research: an attribute-based processing approach and a category-based processing approach (Fiske et al., 1987; Keaveney & Hunt, 1992). The attribute-based perspective hypothesized that people are motivated to evaluate various attributes relevant to an entity separately and intentionally (Keaveney & Hunt, 1992). According to this approach, it is assumed that people intentionally evaluate the salient attributes and make overall judgments based on combined ratings of salient attributes (Fiske & Pavelchak, 1986b). Therefore, their overall impressions are grounded on the sum of a conscious evaluation of attributes (Goodstein, 1993).

In reality, people encounter numerous stimuli, but they exert cognitive efforts to process a small number of salient attributes due to their limited capacity of attention (Kahneman, 1973). Among numerous encounters, only stimuli that are particularly salient and have a strong impression are processed voluntarily and intentionally (Simola, Kuisma, Öörni, Uusitalo, & Hyönä, 2011). More importantly, people are involved in the cognitive processing of the particular stimuli depending on the level of motivation and involvement in the relevant attributes (Andrews, Durvasula, & Akhter, 1990; Lee & Faber, 2007). That is, the structure of the image stored in each person may vary depending on the situation and the individual values (Teichert &

Schöntag, 2010). Therefore, the unique image that each individual holds in memory should be elicited to understand what people recognize and how they respond to the attributes provided by the restaurant (Keaveney & Hunt, 1992).

The majority of previous studies examining an image used predefined attributes with a semantic differential or a Likert scale (Greenwald & Banaji, 1995). However, using predetermined measurement items makes it difficult to understand the effects of individual and contextual differences on the image processing and the image network structure. As respondents reply to the image measurement items that are selected by researchers, they have little opportunity to retrieve the salient attributes (Teichert & Schöntag, 2010). When the direct measurement is used to measure an image, attributes that are determined by researchers are presented to respondents. Therefore, such measurements may work as a "mold" to force people to answer the attributes regardless of their actual retrieval of image categories or salient attributes to process the entity (Keaveney & Hunt, 1992). In other words, the respondents may need to answer the image measurements that are "unimportant" or "irrelevant" to them (Zimmer & Golden, 1988).

Based on the argument, category-based processing theory is proposed as an alternative to the attribute-based process. The basic premise of the category-oriented perspective is that people's evaluation of a new stimulus begins with an automatic classification of the entity into the existing categories that are already in the mind (Sujan, 1985). When encountering stimuli, people start evaluating the familiarity of the stimuli based on the pre-existing memory categories (Brainerd, Wright, Reyna, & Payne, 2002). Therefore, the ability to elaborate and recall stimuli is dependent on the fit between stimuli and the attributes within the pre-existing memory category (Keaveney & Hunt, 1992). Specifically, if an encountered stimulus matches one of the existing categories, people implicitly process the stimulus by comparing the entity with the existing categories in memory and retrieving the attributes under the category to evaluate the stimulus (Fiske & Pavelchak, 1986b). However, if the preliminary classification into the existing categories fails, the person intentionally evaluates the attributes associated with the stimulus and generates a new category containing the previously uncategorized attributes. For example, Goodstein (1993) compared the extent of people's cognitive processing in evaluating the typical (or atypical) television advertisements that are consistent (or inconsistent) with the product category to test the category-based processing. Those who watched the typical ads engaged in the cognitive processing less extensively than those who evaluated the atypical ads. Moreover, the respondents' formerly shaped emotional response to the category had a more significant influence on the evaluation of the typical ads than the atypical ads. The results imply that people tend to rely on the existing categories in memory to evaluate the new entity.

The previous studies grounded on the category-based approaches analyzed open-ended surveys or free recalls by grouping them into groups to examine the categorical properties of an image (e.g., Goodstein, 1993; Greenwald & Banaji, 1995; Keaveney & Hunt, 1992; Zimmer & Golden, 1988). The benefit of utilizing unstructured and freely recalled responses is that they allow the respondents to elicit an image relevant to themselves without predetermined boundaries (Teichert & Schöntag, 2010). The specific external stimuli which are highly visible or in which people have strong involvement are more likely to be recalled (Christensen & Olson, 2002). Thus, the freely recalled and unstructured content may demonstrate key image attributes and general impressions stored in people's memories.

Unlike the attribute-based items that only capture people's evaluation of the functional attributes, the free-recall approach allows examination of the various characteristics of an image, such as the general impressions based on the personal interpretation of the stimuli (Goodstein, 1993; Petty et al., 1983). When people are asked to describe the characteristics related to an object, people tend to describe the holistic and general image dimensions beyond the descriptions of the functional attributes (Echtner & Ritchie, 1993; Wang et al., 2018). The current study adopted the category-based perspective to comprehend how people elaborate stimuli and construct green restaurant images in memory. More specifically, the current study explores free-recall, in the form of user-generated content from an online review site.

User-Generated Content and Free-Recall

The advent of web 2.0 which is utilized in review sites, blogs, and social network sites, enabled many individuals to share their opinions online in forms of user-generated content (UGC) with few barriers of time and space (Cheung & Thadani, 2012; Lu & Stepchenkova, 2015). Although the seller-created content about products or services mainly describes positive features, UGC tends to contain customers' honest opinions and subjective feelings based on their experience (Park, Lee, & Han, 2007).

UGC is written without consistent and standardized formats, and content can vary in terms of length, opinions, and emotional responses (Park et al., 2007). Thus, even people who have purchased the same product or had similar experiences may write different content in online reviews. Such variability in UGC may occur because people evaluate the target object in different ways based on their interests, beliefs, or prior knowledge (Padgett & Allen, 1997). While writing an online review, customers elaborate on the specific attributes related to their experiences and engage in cognitive processing to retrieve memory (Malthouse, Calder, Kim, & Vandenbosch, 2016). Customer experiences with the product and service work as a cue to stimulate the customers' responses and share the UGC (Fang, 2014). However, it should be noted that the customers are motivated to recall the attributes that they are more interested in rather than other attributes (Petty et al., 1983). Therefore, UGC showcases the attributes which customers relate themselves with, judgments about the importance and performance of products or services, and emotional responses about their experience (Katz, 2011).

This study aims to uncover images associated with the green restaurant practices, and thus, customers' memory related to the green attributes should be retrieved and analyzed. Customers who left UGC about certified green restaurants had been exposed to the green restaurant practices and attributes, whether or not they consciously recognized such practices or attributes. When writing an online review about a green restaurant, the customer recalls their experiences based on their interests and attributes that are important to them. If they are conscientious about green practices in restaurants, the image relevant to the green attributes would be activated. Therefore, images that customers have about a particular restaurant are context-specific and can be captured by analyzing the UGC.

To recognize the cognitive structure in customers' memory, researchers often seek customers with high involvement because they tend to put more cognitive efforts to establish the in-depth knowledge about products or services than those not as involved (Christensen & Olson, 2002; Petty et al., 1983). Highly involved customers in the products or services tend to share their experiences via UGC (Shao, 2009). By analyzing the customer reviews about their green restaurant experience, the green restaurant images may be identified. However, due to the large volume of UGC, it is difficult to perform traditional content analysis (e.g., manual coding). Thus, this study applied computational analyses to understand the green restaurant customers' freely recalled responses to their dining experiences.

Computational Analyses of Freely Recalled Responses

Most of the knowledge stored in the memory is encoded as a language (Griffiths & Steyvers, 2003). When people engage in linguistic communication, such as reading texts or speaking with others, the features or attributes related to an entity can be retrieved from memory (Fiske, 1984). Given that the freely recalled text data is a “window” to the memory structure, various approaches using probabilistic methods have been proposed to analyze the text data and subsequently to understand the memory (Griffiths & Steyvers, 2003; Shiffrin & Steyvers, 1997).

Although it is beneficial to uncover the semantic structures from the massive amount of unstructured texts, analyzing the unstructured data manually can be time-consuming and has an issue of the human coders’ subjectivity (Rourke et al., 2001). In order to overcome the drawbacks of the manual data analyses of the unstructured data, the machine learning algorithms, such as topic modeling, have been applied to discover the semantic structures in memory (Griffiths & Steyvers, 2002; Griffiths et al., 2007).

The basic premise of extracting the concept with a probabilistic model is that the words related to the same concept appear in the same document (Landauer, 2002). Based on this assumption, the salient concepts can be found by identifying the set of words that often occur together in a document and differentiating the words that do not co-appear (Mimno, Wallach, Talley, Leenders, & McCallum, 2011). In generative probabilistic modeling, the topics are discovered by arranging the semantic relatedness of words given the particular topic (e.g., Griffiths & Steyvers, 2002; Griffiths & Steyvers, 2003; Griffiths et al., 2007). For example, a *food* topic discovered from a probabilistic model consists of a list of semantically coherent words that are relevant to the topic (e.g., food, eat, delicious, taste). Also, these words have a higher probability of occurrence given the *food* topic compared to other topics, such as *sport* or *computer* (Blei, 2012).

A generative probabilistic model has been applied to understand the semantic memory, where the informational nodes are arranged according to semantic similarity (e.g., Griffiths & Steyvers, 2002; Griffiths & Steyvers, 2003; Griffiths et al., 2007). The topics, which consist of a list of words with a different degree of relevance to the particular topic, are considered to be the image categories (Griffiths & Steyvers, 2002). Also, the probability distribution of the words indicates the likelihood of the informational nodes to be activated and recalled (Griffiths & Steyvers, 2002). In summary, the topics discovered in probabilistic topic modeling are considered as image categories in memory, and the words belonging to each topic as the specific attributes relevant to the category (Griffiths & Steyvers, 2003).

Latent Dirichlet allocation (LDA)

Latent Dirichlet allocation (LDA) is the most widely used probabilistic topic model, which allows discovering the latent topic structures by examining the observed words in the documents (Blei, Ng, & Jordan, 2003). The LDA model uses a two-stage approach to uncover latent structures of the corpus. See Figure 2.4 below (Blei, 2012).

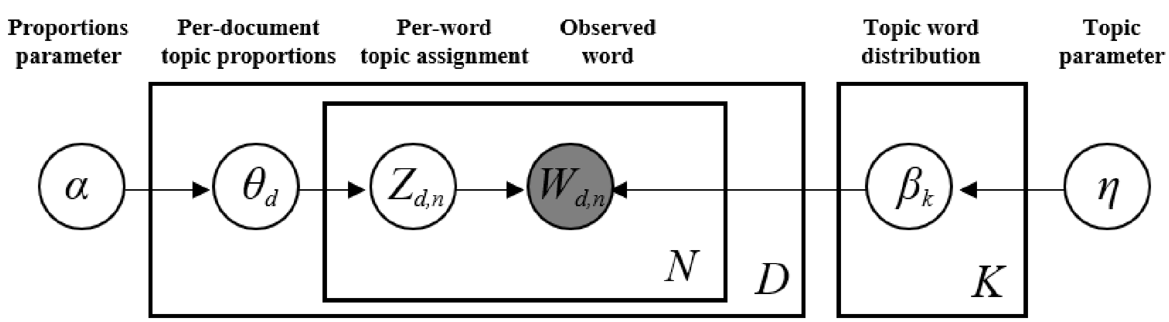

Figure 2.4. Graphical illustration of the generative process of LDA (Blei, 2012)

In the first stage, a mixture of multiple topic proportions (θ) is randomly drawn for each document. LDA assumes that the fixed number of topics for each document is determined prior to actual writing. For example, an author writes about service (60%), food (30%), and price (10%) in a document. According to the decision made in the first phase, the author chooses the vocabulary relevant to each topic. Similarly, in the second stage, (1) a topic (z) is randomly assigned to each term (w) in a document based on the topic proportions found in the first stage, and (2) a word (w) is randomly chosen from the distribution over terms (β). By repeating these procedures, the latent topic structures (i.e., per-document topic proportion [θ] and term distribution [β]) are estimated (Blei, 2012).

LDA is useful for uncovering the cognitive processing and memory structure. The per-document topic proportion (θ) demonstrates the distribution of topics per each document (Blei et al., 2003). For example, the per-document topic proportion could show that an online review document contains two topics, 30% of foods and 70% services. This result is interpreted that two salient image categories existed in the document, recalled at the moment of writing the online review with different importance.

The term distribution (β) demonstrates the degree of relevance of the terms with the topic (Blei et al., 2003). Such relevance is influenced by the likelihood of the person to choose specific words to express a particular topic. Considering the selection of the particular word requires the person to retrieve the word, this concept is compatible with spreading activation in the memory network (Griffiths & Steyvers, 2002); an informational node closely related to a semantic image category is more likely to be recalled given the context (Anderson, 1983). Based on many advantages of using LDA, which include its simplicity and effectiveness in exploring a large corpus, various extensions of LDA have been developed by relaxing its assumptions (Blei, 2012). This study applied one of the extensions of LDA, Structural topic model (STM), and the characteristics of STM are described below.

Structural topic model (STM)

A stream of variant topic models incorporates metadata into a model. Documents generally contain additional information, referred to as *metadata*, such as author, geographical location, and date. It is assumed that understanding the influence of document-specific metadata on latent structures may provide profound insights into the topics. However, it is impossible to vary the latent structures depending on the metadata in LDA, because the topic proportions (θ) of each document and the observed words (w) are drawn from the globally shared priors (α, β) (Blei, 2012). Thus, many extensions of LDA included document-level covariates in the generative process, and studies reported that including metadata is beneficial in improving model fit and topic quality (Mimno & McCallum, 2012; Rosen-Zvi, Griffiths, Steyvers, & Smyth, 2004).

Roberts et al. (2014) introduced a Structural topic model (STM) that includes the metadata in the estimation model to measure systematic differences in topic proportions and topical content depending on observed covariates. STM was developed for social scientists, who are mostly interested in treatment effect estimation or hypothesis testing by comparing relationships between variables. STM attempts to obtain additional strength and enhance predictive power by replacing Dirichlet distribution with a more flexible distribution (Roberts, Stewart, & Airoldi, 2016).

Specifically, STM adds two components into the extant probabilistic topic model, LDA: topic prevalence and topic content (Figure 2.5). Topic prevalence allows covariates (*X*), such as gender and age of reviewers to influence the topic proportion (θ). For example, if reviews of young people contain such topics as atmosphere and delivery, while reviews of older people focus more on staff service and food quality, researchers can postulate that a covariate (age) affects topic prevalence. This means that topic proportion (θ) of a document is influenced by covariate *X*, rather than by a Dirichlet prior.

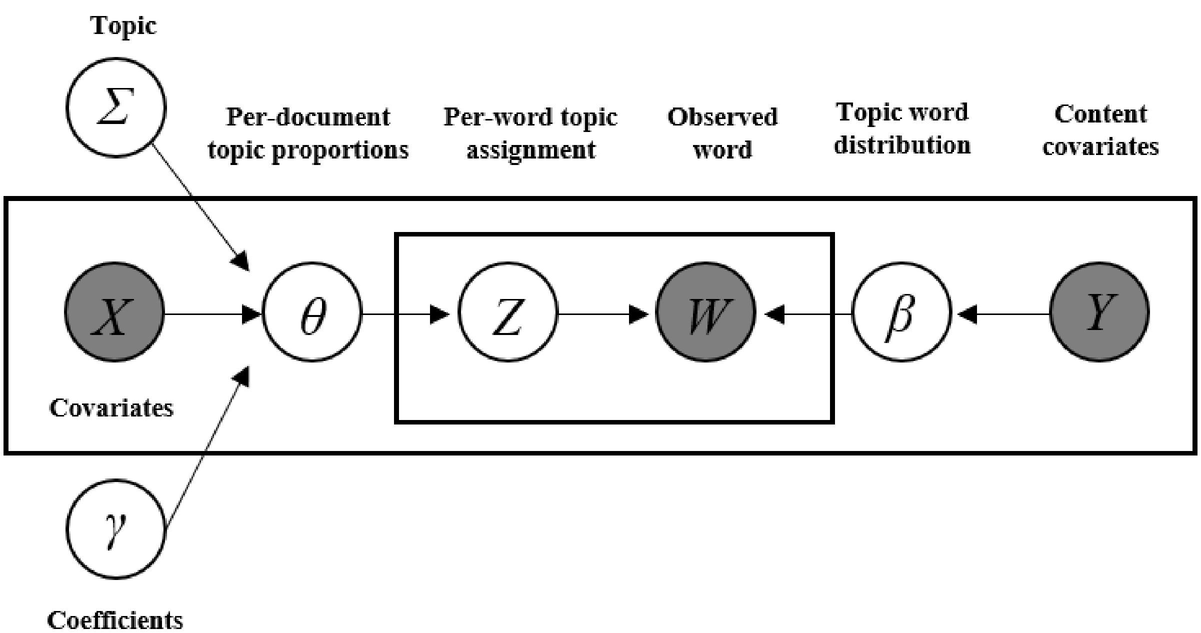

Figure 2.5. Graphical illustration of generative process of STM (Roberts et al., 2016)

Topic content considers that such covariates (*Y*) affect the words representing each topic. According to the previous study, the younger generation tends to perceive green practices more positively than the older generation. If people are asked to write about their perceptions of green practices, these different perceptions may influence a document's tone and term selection. It is possible the younger generation may use more positive terms while the older generation uses more negative terms to describe the same topic. In this situation, “customers’ age” can be included as a covariate (*Y*) and STM compares the vocabulary used to describe a topic depending on the covariate (Roberts et al., 2016). Therefore, among various topic modeling algorithms, STM was applied in the current study due to its ability to estimate the effects of the covariates on the topic proportion and topic content.

Chapter 3 - Methodology

Phase I: Extraction of Green Restaurant Image Categories

Sample

This study examined post-visit reviews of certified green restaurants to capture the green image expressed by patrons in unstructured texts. This study analyzed UGC of green restaurant patrons for data analysis for the following reasons. First, before they submit the UGC, customers dined in a green restaurant, experienced the green attributes, and processed the stimuli consciously or unconsciously to shape a green image (Fang, 2014). Second, customers retrieved the relevant image categories and attributes stored in memory while writing an online review (Malthouse et al., 2016). Finally, the online reviews are written without a predetermined structure, and thus, people can include their general impressions or sentiments derived from green restaurant attributes and their evaluations toward these salient attributes. Therefore, the online reviews can be used to capture various image elements of attributes and holistic impressions. Among various hospitality-related UGC, this study chose TripAdvisor, the largest travel site worldwide, as the source of data as it includes over 760 million reviews for 8.3 million accommodations, restaurants, airlines, and other experiences (TripAdvisor, 2019).

As sustainability has become a major trend in the restaurant industry, many restaurateurs have incorporated green practices into their operations in varying degrees. To access customers' natural responses to green practices in restaurants, customer reviews of certified green restaurants were chosen, because certified green restaurants have implemented a certain degree of green practices to become or remain certified. Among different certification programs available, the Green Restaurant Association (GRA) certification, a nationally recognized certification program, was selected because it has comprehensive certification standards including both food- and environment-focused green practices (Schubert et al., 2010). Moreover, GRA discloses information about their ratings based on seven environmental standards, which include both food-focused green attributes (i.e., sustainable food) and environment-focused green attributes (e.g., water efficiency, waste reduction) and accumulated green score for all green restaurants. Depending on the accumulated green score, each restaurant attained the overall star rating (i.e., 1, 2, 3 or 4 ratings), which can be used as a proxy of green practices that are integrated in each certified green restaurant.

The list of 618 certified green restaurants as of August 22, 2018 was obtained from the GRA website (www.dinegreen.com). Of those, only the certified restaurants which are considered commercial, non-catering foodservice operations with restaurant information available on TripAdvisor were selected as the study sample. A total of 128 restaurants met this study's inclusion criteria, and all UGC written for these restaurants were collected from TripAdvisor in February 2019 using Python-based web crawling. Among 37,052 online reviews, the reviews written before March 2014 (over 5 years old) were removed. To ensure the reviewers experienced the certain degree of green restaurant practices before writing the online reviews, only restsaurant reviews written after the restaurants were certified by GRA were included in the final sample. For example, if a restaurant has participated in a certification program since 2017, online reviews of the restaurant written prior to 2017 were deleted. Also, reviews that were older than 5 years old and written before each restaurant's certification were removed. The restaurants with fewer than 50 reviews were excluded from the sample to examine the effects of the restaurant characteristics on the customers' green perceptions derived from a sufficient number of reviews. Consequently, the final dataset included 25,098 reviews of 70 certified green restaurants, written between March 2014 and February 2019. The process of sampling was visualized in Figure 3.1.

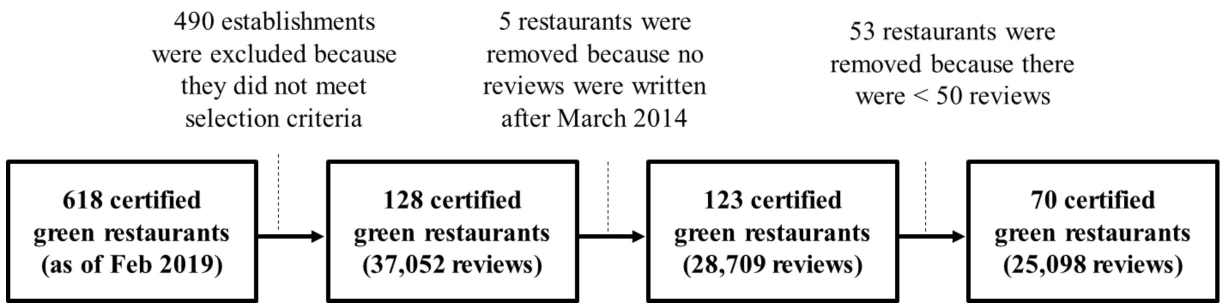

Figure 3.1. The process of sampling

TripAdvisor contains rich metadata at each review-, author-, and operation-level. In addition to writing online reviews and providing overall ratings for each operation they visited, the TripAdvisor reviewers may choose to evaluate specific restaurant attributes (e.g., service, food, and value) on a 5-point scale. Furthermore, some TripAdvisor reviewers publish the reviewer's demographic information, such as their age, gender, and home location (city and state, if disclosed). In addition, TripAdvisor publishes the number of helpful votes that the reviewer received, contributions (i.e., the number of reviews posted), cities that the reviewer visited, and photos posted. The TripAdvisor webpage also discloses information about each operation, such as the number of total reviews, the overall rating score, the rating scores for the specific restaurant attributes, price range, and the location of the restaurant. Therefore, for each review, review-, author-, and restaurant-level metadata were gathered for the further data analysis. Table 3.1 demonstrates the types of metadata for each review that were included in the corpus.

Table 3.1. Types of metadata for each review

Type of metadata	For all online reviews	If available
Review information	Online review title Online review text Overall rating	Ratings for the specific restaurant attributes (i.e., service, food, and value)
Author information	The number of helpful votes The number of contributions The number of cities visited The number of photos posted Duration of the TripAdvisor membership	Home location Age Gender
Restaurant information	Average overall rating Ratings for the restaurant attributes (i.e., service, food, and value) Location	

Text preprocessing and data analysis

In order to uncover the major categories in the massive amount of UGC, a topic modeling technique, structural topic model (STM) was employed (Roberts et al., 2014). Using STM, researchers efficiently analyzed the content and developed the coding scheme and categories. Before conducting STM, text preprocessing was conducted to clean and transform the text corpus for further text mining. This process involved (1) converting all words into lower case, (2) removing numbers and non-alphabetic characters including punctuations, (3) removing stop words (e.g., he, she, the, a), (4) finding stemming words, (5) removing words having fewer than three characters, and finally, (6) creating a document-term matrix.

Creating the context-specific stop words was necessary to improve the topic quality of the dataset to remove words that appear frequently but are not meaningful (Wallach, Mimno, & McCallum, 2009). After running multiple topic models with a different number of topics, the researchers reviewed the top words to identify the stop words. Specifically, proper nouns (e.g., Poland, Kevin), preposition (e.g., on, in), adverb/conjunction (e.g., actually, though), and some verbs with less significant meanings (e.g., become, exist) were included in the stop words. In addition, names of dishes (e.g., pasta, taco) and ingredients (e.g., avocado, celery) were included in the stop words. Many reviewers described menu items, and topics related to types of dishes are likely to appear with a large number of reviews. Despite the high proportion of such content, the types of dishes are often irrelevant to the common restaurant attributes and green attributes that this study aims to discover. The list of stop words built by the researcher was reviewed by another researcher, who has an expertise in restaurant studies and big data, to ensure that meaningful words were not included in the stop words. For the ambiguous ones, the two researchers discussed until a consensus was reached.

STM requires researchers to provide the number of topics (*k*) prior to building a topic model. This stage is called model selection, which can be accomplished by a number of different methods (Griffiths & Steyvers, 2004). To determine the best *k* value, this study used the multiple approaches by comparing the quality of structural topic models built with different *k* values for every five topic models (e.g., 10, 15, 20, … 100). If the number of topics (*k*) is too small, topics tend to be aggregated, and thus, top words in a single topic will represent multiple concepts (Mimno et al., 2011). Moreover, important topics may not be isolated if *k* is too small.

The four quantitative indices (i.e., held-out likelihood, residuals, semantic coherence, and lower bound), which indicate the performance of topic modeling, were compared to determine the optimal *k* value. The topic models were considered performing well when the number of topics was between 50 and 70. Based on the rough approximation, the performances of topic models with a number of *k* were compared, and eventually, 51 was determined as the optimal *k* for this study (Figure 3.2).

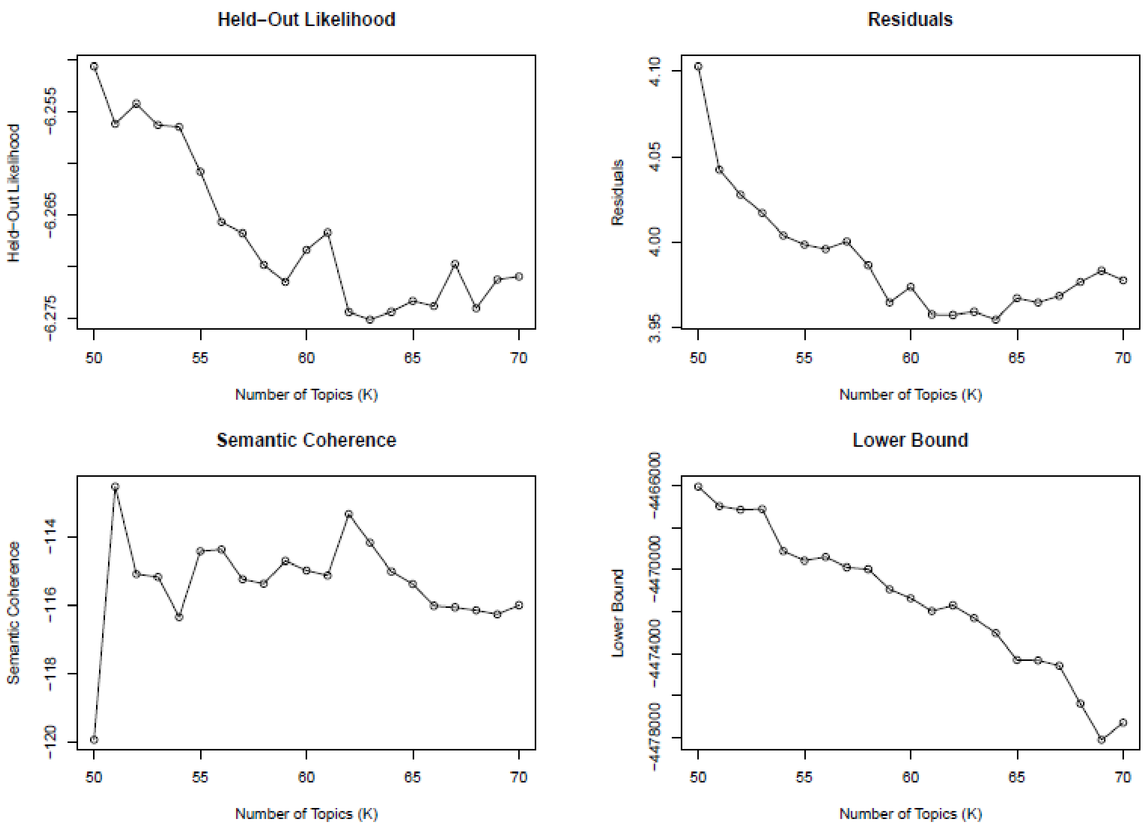

Figure 3.2. The performances of topic models with different number of topics

Model cohesiveness and exclusivity were also evaluated for the validity of the models using a diagram (Figure 3.3). Semantic coherence measures the extent to which each topic has a consistent meaning, and exclusivity assesses whether each topic is uncorrelated with others that contain different content or meanings (Quinn, Monroe, Colaresi, Crespin, & Radev, 2010). Although the exclusivity score of the topic 35 was lower than other topics, the model with 51 topics appeared to be the best in terms of both quantitative index and qualitative evaluations.

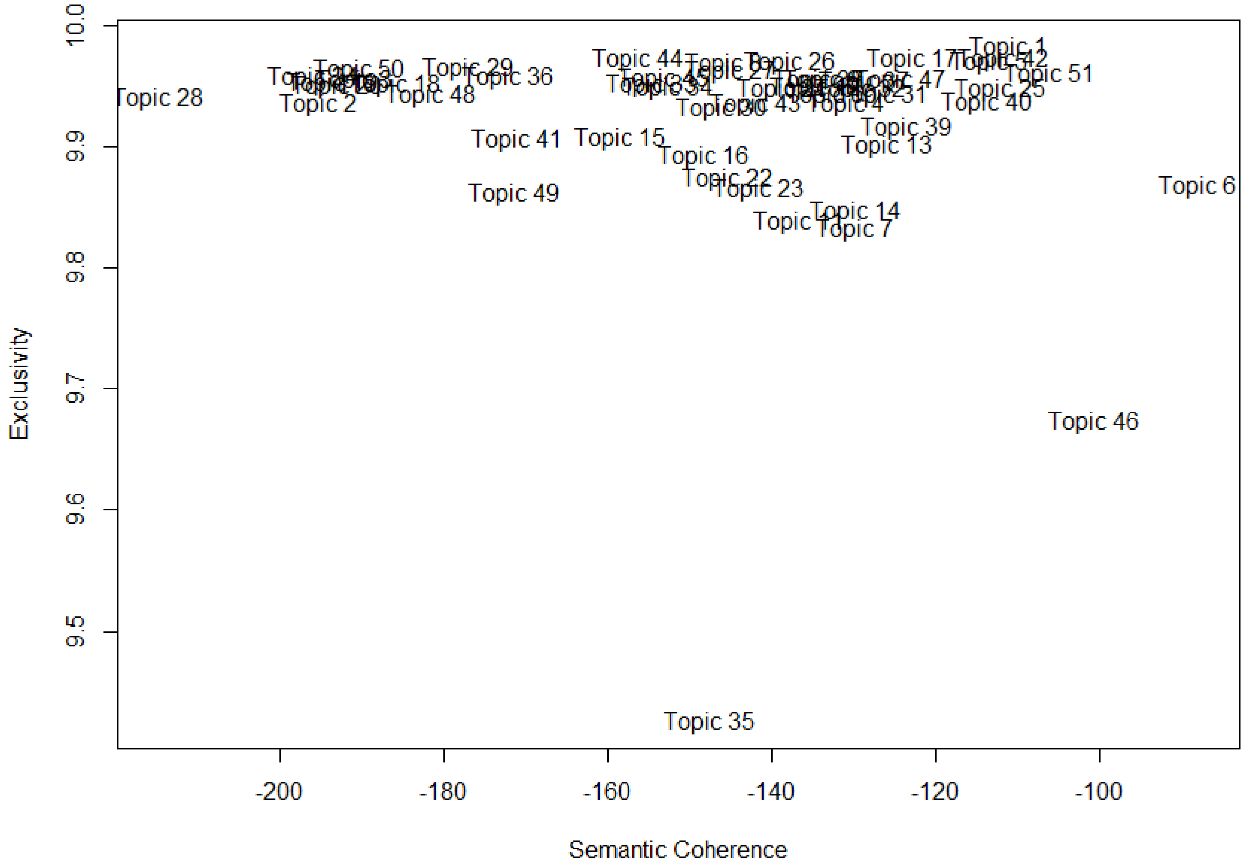

Figure 3.3. Semantic coherence and exclusivity of topic models (*k* = 51)

Content analyses

Content analyses were conducted to (1) label the topics derived from the topic modeling, (2) evaluate the topic interpretability, and (3) comprehend customers' perceptions toward green practices expressed in UGC. STM automatically extracts a mixture of words with different probabilistic contributions to the topic and a mixture of topics in different proportion for each document. However, the topics generated by the topic modeling need to be manually labeled. Therefore, two researchers conducted the manual content analyses by independently reviewing 20 top words and 20 documents closely related to each topic (i.e., 20 reviews with the highest topic proportion in each topic) to determine the preliminary labels. After the researchers separately named the preliminary labels for topics, the appropriateness of the initial labeling was compared. As for the topics that two researchers had different labels or considered to have low interpretability, the researchers discussed them until reaching the consensus on the labels.

Another purpose of the manual content analyses of the topics was to evaluate the interpretability of the topics. Although STM generates the useful indices of the topic modeling performance (e.g., held-out likelihood, semantic coherence), the topic models with good performance of quantitative evaluation may not guarantee to produce the most interpretable topics (Chang, Gerrish, Wang, Boyd-Graber, & Blei, 2009). To evaluate the topic interpretability, the researchers manually evaluated top words for each topic. In addition, 20 documents highly relevant to each topic were reviewed to assess whether each topic contains a single theme. After conducting the content analyses, the researchers agreed that interpretability of both topic 49 and topic 51 was low, and thus, they were excluded in further analyses.

Finally, the online reviews that were highly associated with the green attributes were reviewed to understand the customers' perceptions toward green practices shared in UGC. It is a time-consuming process to identify the documents containing the particular concept from the massive dataset. However, by combining the computer-assisted text analysis (i.e., topic modeling) with the manual content analysis, documents containing customers' green perceptions were efficiently identified.

Statistical analyses

Descriptive statistics, including frequencies, means, and standard deviations were calculated to summarize the data using SPSS v.22.0 (IBM Corp., 2013). A factorial MANCOVA test with LSD post hoc comparison was applied. The dependent variables were the weights of the two green topics: Local/organic ingredients (T10) and vegetarian/healthy option (T37). Two independent variables were GRA certification ratings (i.e., 1, 2, and 3 or 4 ratings) and the length of time that each restaurant was GRA certified (i.e., less than one year, 1-3 years, 4-6 years, and 7 years). There were only six restaurants that attained GRA's four star rating and 927 online reviews for these restaurants. Thus, the restaurants that attained GRA's three or four star ratings were grouped together for data analysis. Furthermore, the year that an online review was written was included as a covariate to control for the changes in customers' interests in green practices over time. Box's M tests were conducted to test the assumption of homogeneity of covariance matrices. Two green topics found in the study were mostly related to food-related green attributes. Therefore, the green points that the restaurant attained from "sustainable food" standard may have a more close association with the weights of the two green topics than GRA rating scores. Therefore, the effects of sustainable food ratings and the duration of the certification participation on the weights of the two green topics were examined.

Another factorial MANCOVA was used to examine the effects of sustainable food ratings and the duration of certification participation. The mean differences on two green topic weights were assessed by the sustainable food ratings and the duration of GRA certification participation while controlling for the year an online review was written as a covariate.

In addition, to test the differences in the customers' green perceptions among customers with different demographics, the third factorial MANCOVA was conducted with age groups and gender as independent variables and the year when each review was written as a covariate. A baseline *p*-value of 0.05 was used as the cutoff for statistical significance (Kline, 2001).

Phase II: Exploration of a Green Restaurant Image Network Structure

Samples

The same dataset that was used for Phase I was used for Phase II. A total of 25,098 reviews written by patrons of 70 certified green restaurants listed on TripAdvisor between March 2015 and February 2019 were collected. This dataset was used when examining the higher-level image network from 70 certified green restaurants listed on TripAdvisor. To examine the lower-level green image network, 246 reviews with the highest topic proportion for green practices from the entire sample were selected to explore the image associations within the UGC with green practices only. The main reason for selecting this small number of reviews for further analyses was because of the cost of analytical software. The version used in this study (Lite) was able to analyze only 15,000 characters. Therefore, a smaller subsample was selected for further analyses.

Extraction of image categories: Topic modeling

The current study applied the structural topic model (STM) to discover latent themes in the large corpus as an alternative of human evaluation (Muller, Guha, Baumer, Mimno, & Shami, 2016). Prior to STM, the common procedures for text preprocessing (e.g., converting to lower case, removing non-alphabetic words, stop words, and short words) were followed to clean data (Park, Chae, & Kwon, 2018). The optimal number of topics was determined as 51 based on both quantitative indices (e.g., held-out likelihood and semantic coherence scores) and manual content analysis. The topics generated from STM were manually labeled by reviewing the top words and the online reviews closely related to each topic.

Among 51 topics, there were two topics related to green attributes: local/organic ingredients (T10) and vegetarian/healthy option (T37). To identify the online reviews that contained customers' perceptions toward green restaurant practices, the online reviews that had high document-topic proportions on two green topics were selected. A cutoff value was set at 15% because the green topics were clearly discernable among the documents that had the topic proportions of at least 15% on two green topics. There were 151 online reviews that had over 15% of document-topic proportions on the local/organic ingredient topic (T10), 96 online reviews on the vegetarian/healthy option topic (T37), and 246 online reviews on both topic 10 and 37. The green image network was established by using 246 online reviews.

Network analysis

Two types of network structures were estimated. First, topic-level networks were examined to understand how higher-level image categories are connected and how the retrieval of one category may spread to the other image categories (N = 25,098 reviews). Second, the green image networks corresponding to the green topics were explored based on the co-occurrence of the unique words found in green restaurant reviews (N = 246 reviews).

Topic-level image network

A topic-level image network was created based on the topic proportion correlation matrix. The *igraph* software package in R was used to visualize and obtain the following network statistics: average degree, network diameter, graph density, modularity, average clustering coefficients, and average path length. The overview and definitions of the network metrics were illustrated in Table 3.2 (Cherven, 2013; Kardes, Sevincer, Gunes, & Yuksel, 2014).

Table 3.2. The overview and definitions of the network metrics

Metrics	Definitions
Degree	The average number of edges connected to a node
Graph density	The actual number of edges in a graph divided by the maximum number of edges a graph can have with the number of nodes
Network diameter	The longest distance of all shortest distance between all pairs of nodes
Path length	The average of the distance between all pairs of nodes
Modularity	The strength of dividing a network into multiple groups

Network visualization

The threshold for the topic correlation was set at 0.1 and the edges below the threshold were dropped for the network visualization (Roberts, Stewart, & Airoldi, 2016). Based on the topic proportion correlation matrix, a community detection algorithm, *Louvain* was applied to identify the common features of the complex topic networks (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008). The colors of the nodes were determined by the groups identified by the community detection.

Eigenvector centrality: A centrality measurement and classifications

Among various centrality measures, eigenvector centrality was selected to measure the strength of the image association. Based on the understanding of how nodes flow in the network, the appropriate centrality metric should be chosen to measure the strength of the image association (Wasserman & Faust, 1994). According to Collins and Loftus (1975), the relational links tend to go in both directions between two nodes. Eigenvector centrality counts the circuitous trajectories and the paths that nodes visit multiple times, and thus, they can measure the influences of long-term and indirect links (Borgatti, 2005). Thus, the eigenvector was selected for this study to measure the strength of image association.

Based on the eigenvector centrality score, the nodes were classified into the following three groups: core, semi-periphery, and periphery (Wang et al., 2018). Specifically, the nodes that had higher than 0.8 eigenvector centrality score were classified as the core. The nodes with higher eigenvector centrality scores than the average score were classified as semi-periphery, and the ones with lower than the average score were classified as periphery.

Lower-level green image network

The lower-level green image networks were examined by creating the green image network with the online reviews closely related to two green topics (T10 and T37). To create a green image network, the co-occurrence of the unique words found in green restaurant reviews was evaluated. In the green image network, the nodes are the unique words that represent the lower-level image associations, and the ties connecting the nodes represent the associations among these unique words.

Network visualization

A software tool, *InfraNodus* (www.inforanodus.com), was used to convert the texts in the online reviews into the network structure. Preprocessed texts of 246 reviews closely relevant to two green topics were used as an input for network visualization. To build the green image network with the visible image nodes, the maximum number of the nodes was set to 300 and 300 unique words with high frequency were chosen. In addition to bigram occurrences, which model the associations for two words appearing next to each other within a sentence, and 3-gram and 4-gram sequences were included to build the network. For example, for the sentence “I visited a green restaurant”, the associations between “visited” and “green” (3-gram) and “visited” and “restaurant” (4-gram) were identified by adding an edge between these words.

InfraNodus creates a network data, a GEXF (Graph Exchange XML Format) file, which can be read in other applications, such as *Gephi*. The GEXF file generated by InfraNodux was further processed in Gephi to visualize the network and calculate the network statistics. In order to customize the network visualization, *Yifan Hu* layout algorithm was used (Hu, 2005). The colors of nodes were determined by modularity class, which represents the communities of the network. The community detection algorithm (Blondel et al., 2008) used in the topic-level network was applied in the green image network. The node and label sizes corresponded to the eigenvector centrality.

Consistent with the topic-level network, the centrality scores were used to classify the image nodes into core, semi-periphery, and periphery. With the green image network, types and favorability of image associations were examined. To determine the types of the nodes (i.e., cognitive vs affective), the researcher manually reviewed the image nodes. Favorability of image associations was evaluated by sentiment and emotion analysis belonging to IBM Natural Language Understanding (NLU, Lite). NLU is one of Artificial Intelligent (AI) technologies that IBM offers via its Cloud Platform. NLU extracts sentiment (-1: very negative to +1: very positive) and emotion scores for five emotion categories (i.e., sadness, joy, fear, disgust, and anger) by analyzing the texts. With the input of preprocessed online reviews relevant to two green topics, IBM NLU's application programming interface (API) was used in Python. The key terms found in the network analyses were used as keywords to extract the sentiment and emotion scores.

Chapter 4 - Results

Data Profile

Descriptive characteristics of certified green restaurants (*N* = 70) and customer reviews (*N* = 25,098) are illustrated in Tables 4.1 and Table 4.2, respectively. The majority of certified green restaurants (*N* = 58) had an average 4.0 or 4.5 TripAdvisor star ratings. The restaurants were certified for six years on average (*M* = 6.2, *SE* = 3.1), with the longest period of certification being 12 years. In order to be a certified green restaurant, the restaurant must earn green points by meeting environmental standards. Depending on the total green points, the certified green restaurants attained GRA's star ratings. The majority of the certified restaurants (*N* = 35) attained GRA's three-star ratings.

Table 4.1. Descriptive characteristics of certified green restaurants (*N* = 70)

		N	%
Average star rating	3.0	3	4.2
	3.5	9	12.9
	4.0	28	40.0
	4.5	30	42.9
	Average: 4.1 (SD: 0.4, Min: 3.0, Max: 4.5)		
The number of TripAdvisor reviews	50-100	19	27.1
	100-199	11	15.7
	200-499	18	25.7
	500-999	14	20.0
	1000 or greater	8	11.5
	Average: 525.9 (SD: 765.7, Min: 50, Max: 4,202)		
Duration of GRA certification participation	1-3 years	17	24.3
	4-6 years	20	28.6
	7-9 years	17	24.3
	10-12 years	16	22.9
	Average: 7.2 (SD: 3.1, Min: 2, Max: 13)		
GRA ratings	1 Star (62 green points)*	14	20.0
	2 Star (100 green points)*	15	21.4
	3 Star (175 green points)*	35	50.0
	4 Star (300 green points)*	6	8.6

Note. * Minimum green points required to attain GRA's star ratings

The majority of TripAdvisor reviewers had the four- or five-star ratings (*N* = 20,994, 83.6%). Approximately 30% of TripAdvisor reviewers revealed the age group to which they belong, and 40% of reviewers disclosed their gender. Among the customers who revealed the demographic information, the majority of customers (*N* = 2,953, 39.7%) belonged to the 50 – 64 age group, and more female customers (*N* = 5,007, 52.2%) left online reviews than males.

Table 4.2. Descriptive characteristics of TripAdvisor reviews and reviewers (*N* = 25,098)

		N	*% (Valid %)*
Star ratings	1	591	2.4
	2	939	3.7
	3	2,574	10.3
	4	6,436	25.6
	5	14,558	58.0
Year when the review was written	2014	3,072	12.2
	2015	5,130	20.4
	2016	6,540	26.1
	2017	5,344	21.3
	2018	4,541	18.1
	2019	471	1.9
Reviewers' age groups	13-24	68	.3 (.9)
	25-34	914	3.6 (12.3)
	35-49	2,341	9.3 (31.4)
	50-64	2,953	11.8 (39.7)
	65+	1,170	4.7 (15.7)
	Missing	17,652	70.3 (n.a.)
Reviewers' gender	Woman	5,007	19.9 (52.2)
	Man	4,585	18.3 (47.8)
	Missing	15,506	61.8 (n.a.)

Note. Valid percentages are percentages of reviews, of which reviewers revealed corresponding information. n.a. = not applicable.

Phase I: Extraction of Green Restaurant Image Categories

Topic modeling: Discovery of image categories

Topic modeling was implemented with the UGC shared by certified green restaurant customers to discover the salient and frequently noted image categories mentioned by green restaurant customers (research questions [RQ] 1 and 2). With STM, 49 salient and interpretable topics (i.e., customers' image categories) were discovered. Based on the document-topic proportion (θ), the expected topic proportion and the top three words for each topic are illustrated in Figure 4.1. The topic proportion is a proxy of the popularity and importance of the topic (Guo, Barnes, & Jia, 2017). Topic 1, which was titled *Good food, service, & atmosphere*, appeared to be the most frequently appeared topic, followed by topic 17.

With multiple topics regarding the similar attributes or concepts emerging, the topics were categorized into the following higher-level dimensions, including four general restaurant attributes (i.e., food, service, atmosphere, and value), green attributes, overall restaurant experience evaluation, and behavioral intention (Table 4.3). In addition to topic weights (the expected topic proportion), the number of reviews with greater than 0.1 weights were listed in Table 4.3 to demonstrate the number of reviews containing customers' perceptions about the corresponding topic. It should also be noted that stemming is conducted to identify the words having the same root form, and therefore, the words listed on Table 4.3. may not be complete.

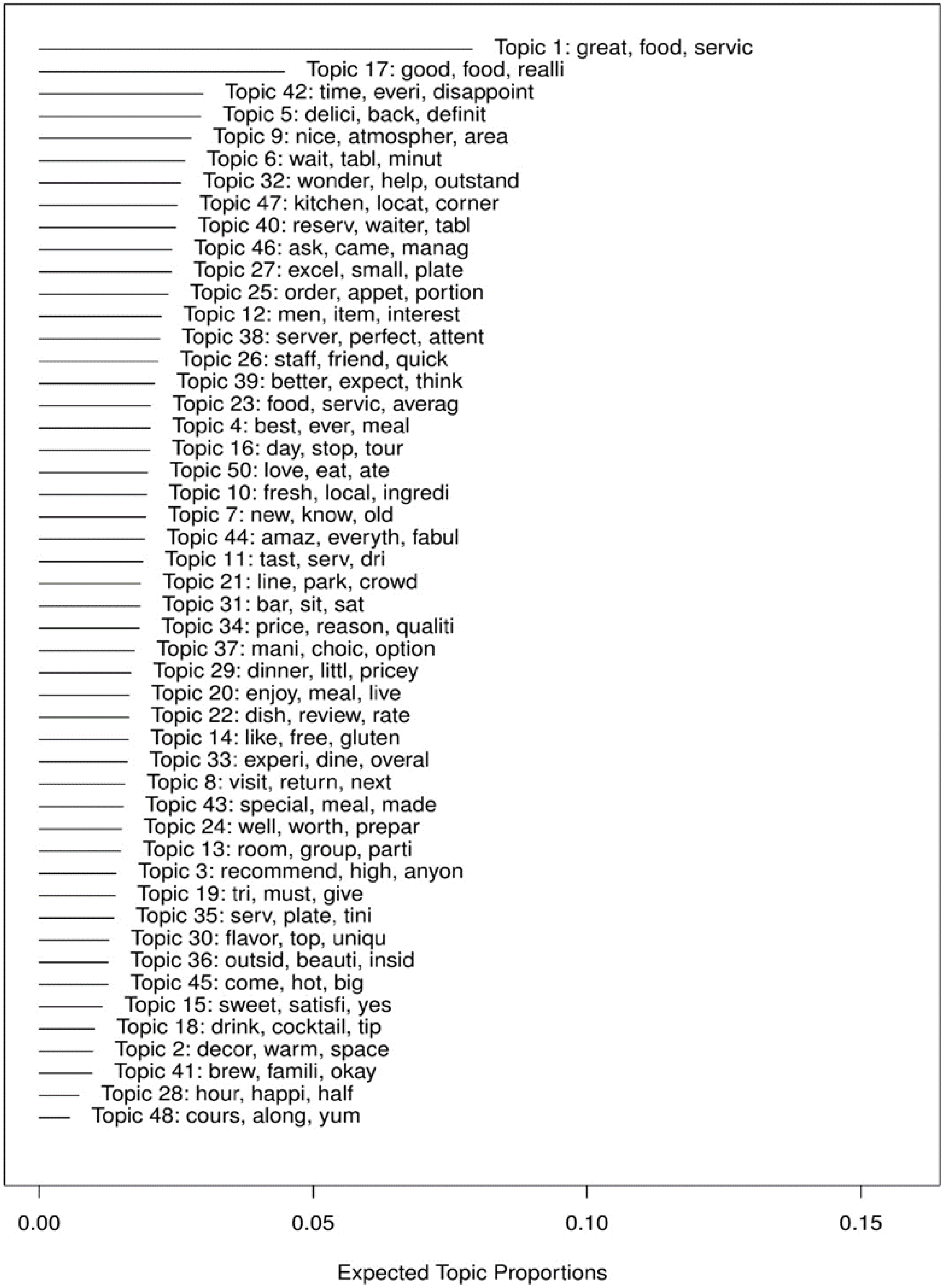

Figure 4.1. The expected topic proportions and top three words

Table 4.3. Overview of the topics: Top words and topic weights

Dimension	Topic number and labels	Top words (highest probability)	Topic weight	The number of reviews greater than 0.1 weights
Food	T5: Good flavor	delici, back, definit, went, stop	0.029	196
	T25: Excessive portion size	order, appet, portion, entre, larg	0.024	256
	T27: Small plates	excel, small, plate, share, favorit	0.024	137
	T12: Menu variety	men, item, interest, differ, select	0.022	219
	T50: Overall good flavor	love, eat, ate, yummi, place	0.020	47
	T11: Bad flavor	tast, serv, dri, season, light	0.019	525
	T14: Accommodation for diet restrictions	like, free, gluten, felt, normal	0.016	334
	T30: Unique flavor	flavor, top, uniqu, mix, combin	0.013	85
	T45: Disappointing food characteristics (flavor, portion size, temperature)	come, hot, big, cold, spici	0.013	110
	T15: Good flavor	sweet, satisfi, yes, rich, creami	0.011	317
	Sub-total		0.191	2,226
Service	T6: Bad service (slow service)	wait, tabl, minut, arriv, seat	0.027	1,044
	T32: Good service (knowledgeable employees)	wonder, help, outstand, select, list	0.026	296
	T40: Good service (prompt seating)	reserv, waiter, tabl, made, busi	0.025	501
	T46: Bad service (inattentive service)	ask, came, manag, waitress, order	0.024	1,174
	T26: Good service (quick, friendly service)	staff, friend, quick, super, fast	0.022	130
	T38: Good service (attentive staffs)	server, perfect, attent, cook, start	0.022	150
	T21: Bad service (long wait)	line, park, crowd, long, open	0.018	407
	Sub-total		0.164	3,702

Table 4.3. Overview of the topics: Top words and topic weights (Continued)

Dimension	Topic number and labels	Top words (highest probability)	Topic weight	The number of reviews greater than 0.1 weights
Atmosphere	T 9: Atmosphere (seating area)	nice, atmospher, area, view, pleasant	0.028	550
	T47: Convenient location	kitchen, locat, corner, villag, stay	0.025	786
	T20: Background music	enjoy, meal, live, music, charm	0.016	97
	T13: Excessive noise	room, group, parti, tabl, loud	0.015	325
	T36: Building exterior	outsid, beauti, insid, patio, head	0.013	143
	T 2: Décor	decor, warm, space, vibe, brown	0.010	63
	Sub-total		0.107	1,964
Value	T23: Overprice with poor quality	food, servic, averag, expens, disappoint	0.020	1,258
	T34: Fair value	price, reason, qualiti, food, fair	0.018	257
	T29: Pricey choices (good value)	dinner, littl, pricey, expens, romant	0.017	13
	T24: Good value (time and money)	well, worth, prepar, wait, drive	0.015	38
	Sub-total		0.070	1,566
Mixed	T 1: Good food, service, & atmosphere	great, food, servic, place, atmospher	0.079	6,652
	T17: Good food mixed with dissatisfying factors	good, food, realli, servic, pretti	0.045	1,652
	T35: Disappointing performance (food, service, value)	serv, plate, tini, small, tabl	0.014	624
	Sub-total		0.138	8,928
Green attributes	T10: Local/organic ingredients (sustainable sourcing)	fresh, local, ingredi, farm, creativ	0.020	441
	T37: Vegetarian/healthy option	mani, choic, option, green, vegetarian	0.017	266
	Sub-total		0.037	707
Overall restaurant experience evaluation	T42: Repeat customer experience (consistency)	time, everi, disappoint, never, last	0.030	196
	T39: Not meeting expectation	better, expect, think, noth, bad	0.021	376
	T 4: Overall satisfaction	best, ever, meal, eaten, far	0.020	509
	T44: Exceptional experience	amaz, everyth, fabul, absolut, incred	0.019	193
	Sub-total		0.090	1,274

Table 4.3. Overview of the topics: Top words and topic weights (Continued)

Dimension	Topic number and labels	Top words (highest probability)	Topic weight	The number of reviews greater than 0.1 weights
Behavioral intention	T 8: Revisit intention	visit, return, next, trip, recent	0.016	50
	T 3: Restaurant recommendation	recommend, high, anyon, end, highlight	0.014	38
	T19: Menu recommendation	tri, must, give, won, foodi	0.014	56
	Sub-total		0.044	144
Other	T16: Proximity to attractions	day, stop, tour, decid, spot	0.020	493
	T 7: Unique place	new, know, old, real, diner	0.019	352
	T22: High online review ranking	dish, review, rate, read, differ	0.016	267
	T43: Special occasions	special, meal, made, thank, treat	0.015	228
	T28: Negative incidents (foodborne illness)	hour, happi, half, seem, close	0.007	71
	Sub-total		0.077	1,411
Type of operations	T31: Bar service	bar, sit, sat, watch, fun	0.018	429
	T33: Fine dining experience	experi, dine, overal, fine, extrem	0.016	93
	T18: Bar menu options	drink, cocktail, tip, specialti, round	0.010	44
	T41: Brewery experience	brew, famili, okay, decent, flight	0.010	196
	T48: Specialty food experience	cours, along, yum, follow, gourmet	0.006	26
	Sub-total		0.060	788

Among the topics found in this study, there were multiple topics representing the same attribute, such as food flavor, but containing different emotional states. For example, both topic 15 and topic 11 were regarding food flavor. Although topic 15 contained the top words that described good flavors of foods and customers' satisfaction through them, such as rich, cream(y), and satisf(ying), the topic 11 included top words related to poor-quality foods, such as dr(i), burnt, and overdone. Similarly, there were several topics regarding service quality, containing the positive sentiment (e.g., knowledgeable employees [T32], attentive staffs [T38]) and the negative sentiment (e.g., slow service [T6], inattentive service [T46]). The topic model also extracted the topics regarding the atmosphere, such as location (T47) and background music (T20). The value-related topics demonstrated that customers' evaluation of value can be situation-specific. The same word *expens(ive)* was used in both topic 23 and topic 29. In topic 23, the term *expens(ive)* co-appeared with food, service, and disappoint. Content analysis of the top words and online reviews closely related topic 23 showed that the customers were dissatisfied with the high prices for the unsatisfactory quality food or service. In topic 29, the same word *expens(ive)* co-appeared with the terms indicating the pricey choices (e.g., upscale, splurge, worthwhile), indicating that the customers were willing to pay more for good quality meals.

In addition to the customer perceptions of specific restaurant attributes, many people expressed their overall impression of the restaurant experiences and behavioral intention in UGC. Therefore, topics related to the overall evaluation (e.g., overall satisfaction [T4], exceptional experience [T44]) and behavioral intention (e.g., restaurant recommendation [T3], revisit intention [T8]) also appeared. These topics were differentiated from the topics about the specific restaurant attributes because they had the top words describing the customers' emotional states, such as amaz(ing) or an intent to engage in the certain behavior, such as recommend.

As the topic modeling algorithm is grounded on discovering patterns of words that co-appear in the same context, some topics contained multiple aspects that may make them incompatible with the previous studies. For example, there were many customers who mentioned the multiple restaurant aspects (e.g., food, service, and atmosphere) simultaneously in the review. Thus, the topics regarding customers' evaluation of several key restaurant attributes emerged, and they were classified into "mixed." Due to the nature of the UGC, there appeared to be the topics that did not directly relate to the green restaurant attributes covered in the previous literature. For example, topic 43, special occasions, emerged because many customers mentioned that the purpose of their visit was to celebrate a special day. For the topics that were not related to restaurant attributes and green restaurant practices, they were classified into "other" or "type of operation."

Among the four general restaurant attributes, the number of topics assigned to food quality dimension was the highest, accounting for 19.1% of the total topic weight, followed by service quality dimension, accounting for 16.4% of the total topic weight. Two topics related to green practices emerged: local/organic ingredients (T10) and vegetarian/healthy option (T37). GRA denoted that serving vegan or vegetarian dishes may reduce harmful environmental impacts (GRA, 2019). Based on the GRA green standards, the current study considered vegetarian/healthy option (T37) as a green topic. A more detailed discussion about the green topics based on content analysis is presented in the next section.

To identify the similarities and differences between the image categories discovered from UGC and findings of the previous research using the traditional research methods (RQ 3), the topics extracted from STM were compared with the restaurant attributes identified from the previous studies (Table 4.4).

Table 4.4. A comparison of the topics derived from STM and measurement items found in the previous studies

Dimensions	Specific aspects	Topic number and labels	References
Food	Flavor	T 5: Good flavor T11: Bad flavor T15: Good flavor T30: Unique flavor T50: Overall good flavor	(Han & Hyun, 2017; Jang & Namkung, 2009; Jang, Kim, & Bonn, 2011; Jin et al., 2012; Ryu et al., 2012; Ryu & Lee, 2017)
	Portion size	T25: Excessive portion size T27: Small plates	(DiPietro & Gregory, 2012)
	Menu variety	T12: Menu variety	(Jin et al., 2012; Ryu, Han, & Kim, 2008; Ryu et al., 2012; Wu & Mohi, 2015)
	Healthy (nutritious) options	T37: Vegetarian/healthy option*	(Jang & Namkung, 2009; Jang et al., 2011; Ryu et al., 2012)
	Fresh foods	T10: Local/organic ingredients (Sustainable sourcing)*	(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; Ryu & Lee, 2017)
	Food smell	Not found	(Ryu et al., 2012)
Service	Willingness to help	T32: Good service (knowledgeable employees)	(Jang & Namkung, 2009; Jang et al., 2011; Ryu et al., 2012; Ryu & Lee, 2017)
	Speed of service	T 6: Bad service (slow service) T21: Bad service (long wait) T26: Good service (quick, friendly service) T40: Good service (prompt seating)	(Ryu et al., 2008; Ryu et al., 2012)
	Comfortable/ friendly staffs	T38: Good service (attentive staffs) T46: Bad service (inattentive service)	(Ryu et al., 2012; Ryu & Lee, 2017)
	Instill confidence	Not found	(Jang & Namkung, 2009; Jang et al., 2011)
	Best (specific) interests	Not found	(Jang & Namkung, 2009; Ryu & Lee, 2017)
	Accurate service	Not found	(Jang et al., 2011; Ryu et al., 2012)

Note. * Topics related to green attributes

Table 4.4. A comparison of the topics derived from STM and measurement items found in the previous studies (Continued)

Dimensions	Specific aspects	Topic number and labels	References
Atmosphere	Interior design	T 2: Décor	(DiPietro & Gregory, 2012; Han & Hyun, 2017; Jang & Namkung, 2009; Jang et al., 2011; Ryu et al., 2008; Ryu et al., 2012; Ryu & Lee, 2017; Wu & Mohi, 2015)
	Background music	T20: Background music	(Jang & Namkung, 2009; Ryu et al., 2012; Ryu & Lee, 2017)
	Location	T47: Convenient location	(DiPietro & Gregory, 2012; Jang et al., 2011; Ryu et al., 2008)
	Building exterior	T 9: Atmosphere (seating area) T36: Building exterior	(Ryu & Lee, 2017)
	Comfort for socializing	T13: Excessive noise	(Jang et al., 2011)
	Cleanness	Not found	(Ryu et al., 2008; Ryu et al., 2012; Ryu & Lee, 2017; Wu & Mohi, 2015)
	Employees' attire (appearance)	Not found	(Jin et al., 2012; Ryu et al., 2008; Ryu et al., 2012)
	Colors	Not found	(Jang & Namkung, 2009)
	Facility layout	Not found	(Jang & Namkung, 2009; Wu & Mohi, 2015)
	Lighting	Not found	(Jang & Namkung, 2009)
Value	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; Ryu et al., 2012; Ryu & Lee, 2017)
Green attributes	Food	T10: Local/organic ingredients (Sustainable sourcing)* T37: Vegetarian/healthy option*	(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*	(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)*	(Choi & Parsa, 2006)
	Administrative (Organizational)	Not found	(Ham & Lee, 2011; Kwok et al., 2016)

Note. * Topics related to green attributes

Table 4.4. A comparison of the topics derived from STM and measurement items found in the previous studies (Continued)

Dimensions	Specific aspects	Topic number and labels	References
Overall restaurant experience evaluation		T 4: Overall satisfaction T39: Not meeting expectation T42: Repeat customer experience (consistency) T44: Exceptional experience T51: Positive experience	(Echtner & Ritchie, 1993; Stylos, Vassiliadis, Bellou, & Andronikidis, 2016)
Behavioral intention	Revisit intention	T 8: Revisit intention	(Babin, Lee, Kim, & Griffin, 2005; Blodgett, Hill, & Tax, 1997; Hellier, Geursen, Carr, & Rickard, 2003; Heung & Gu, 2012; Jeong & Jang, 2011; Kim & Ok, 2009; Ladhari, Brun, & Morales, 2008; Ryu et al., 2008)
	Intention to recommend	T 3: Restaurant recommendation T19: Menu recommendation	
	Intention to do word-of-mouth	N/A	

Note. * Topics related to green attributes

With two topics (T10 and T37) related to green practices, content analysis was conducted to understand the customers' green perceptions in-depth, and the exemplary reviews that had high weights for both green topics are demonstrated in Table 4.5 below. The findings from the content analysis indicated that the customers, who recognized the restaurants served organic or locally sourced ingredients, evaluated them as fresh or high quality (ID: 15655, 15493). Some customers who recognized the locally sourced ingredients considered the health benefits of having sustainable food (ID: 15493). In addition, both top words and the online reviews (ID: 4910, 15493) demonstrated that many customers valued locally sourced ingredients because such practices can support the local community.

Similar to local/organic ingredient (T10), customers who recognized that the restaurant served vegetarian options (T37) also mentioned the health benefits (ID: 15599). For many of the customers who mentioned this topic, the focus of green practices was on the ecological environment issues (ID: 4158, 15648, 15599). Also, the customers who advocated the vegan/vegetarian lifestyles appreciated a variety menu options for the customers with different needs (ID: 4158, 15599).

Table 4.5. Exemplary online reviews highly related with the green topics

	Verbalization of the aspect	Identified themes
T10: Local/organic ingredients	(ID: 15655; T10: 31.%; 5-star) Pleasant surprise! Our breakfast was hearty and I appreciated **the natural ingredients** and the **farm to table approach** for the **freshest** food	Recognition of local/organic ingredient sourcing Appraisal of local/organic ingredients
	(ID: 4910; T10: 28.3%; 5-star) This restaurant has fabulous food, reasonable prices and **supports the area** by using everything possible that is **locally sourced**	Recognition of local/organic ingredient sourcing Awareness of local community support
	(ID: 15493; T10: 24.7%; 5-star) You are getting **local grown, organic ingredients**. Because the ingredients are so carefully sourced and of such **a high quality**, expect to find prices that reflect that. He (*The owner*) really cares about what he serves and **about our health**. I also love how they **support the local artist community** by displaying pieces for sale around the restaurant on a monthly basis.	Recognition of local/organic ingredient sourcing Appraisal of local/organic ingredients Awareness of health benefits Awareness of local community support
T37: Vegetarian/healthy option	(ID: 15648; T37: 51.8%; 5-star) They are **environmentally conscious** (recycling sort bins in house) and cater to both **vegetarian and vegan lifestyles**	Recognition of vegetarian options Awareness of environment friendly practices
	(ID: 4158; T37: 32.2%; 5-star) Excellent for **vegans, vegetarians and meat eaters!** (…) It's often hard finding vegan food in small towns but this place offered a **variety of options** and all were delicious! **Very ethical and eco minded menu**. Will go again!	Awareness of environment friendly practices A variety options
	(ID: 15599, T37: 27.0%, 4-star) There are many delicious options, with strong emphasis on **healthy** **sustainable** food and **lots of vegan/GF choices**. (…) Bus your own table, with the opportunity to separate **recyclables, trash, etc**. A good solid breakfast place for the **health conscious**.	Awareness of environment friendly practices A variety options Awareness of health benefits

The effects of restaurant characteristics on the customers' green perceptions

To understand the effects of green restaurant certification on the weights of customers' green image (RQ 4), A factorial MANCOVA was conducted to test the effects of the green certification on the customers' green perceptions with two independent variables (i.e., GRA certification ratings and the duration of the green restaurants' participation in the GRA certification). Box's Test of Equality was significant (Box's M = 4250.66, $p < .001$), indicating the assumption of homogeneity of covariance matrices was violated. Thus, this study used Pillai's trace (V), which is more robust than other statistics with violations of statistical assumptions (IBM, 2019). There were positive effects of both GRA certification ratings, $V = .012$, $F(4, 50{,}170) = 75.359$, $p < .001$, and the periods of certification participation, $V = .004$, $F(6, 50{,}170) = 16.932$, $p < .001$. An interaction of the GRA certification rating and the period of certification participation was also positive, $V = .007$, $F(12, 50{,}170) = 14.659$, $p < .001$ (Table 4.6).

The results from the univariate ANOVAs demonstrated that the significant effects of GRA certification ratings on weights of both local/organic ingredient topic (T10), $F(2, 25{,}085) = 120.138$, $p < .001$, and vegetarian/healthy menu topic (T37), $F(2, 25{,}085) = 53.428$, $p < .001$. Specifically, the average topic weight of the local/organic ingredient topic (T10) was significantly higher among the customers who visited green restaurants that attained GRA's three or four star ratings (Adj $M = .022$, $SE = .000$) than the customers who visited restaurants with one star rating (Adj $M = .016$, $SE = .001$) or two star rating (Adj $M = .016$, $SE = .000$). Similarly, the average topic weight of the vegetarian/healthy option (T37) was significantly higher among the customers of the green restaurants with three or four star ratings (Adj $M = .019$, $SE = .000$) than those with one star rating (Adj $M = .018$, $SE = .001$) or two (Adj $M = .015$, $SE = .000$).

Table 4.6. The effects of GRA certification: GRA ratings and duration of certification participation

	Local/organic ingredient (T10)	Vegetarian/healthy option (T37)
	Adj Mean (SE)	Adj Mean (SE)
GRA certification rating		
(Pillai's trace = .012***, η^2 = .006)	F= 120.138***	F = 53.428***
1 rating (N = 1,382)	.016$_a$ (.001)	.018$_b$ (.001)
2 rating (N = 4,875)	.016$_a$ (.000)	.015$_a$ (.000)
3 or 4 ratings (N = 18,841)	.022$_b$ (.000)	.019$_b$ (.000)
Duration of the certification participation		
(Pillai's trace = .004***, η^2 = .002)	F= 5.936***	F = 31.057***
Less than one year (N = 2,419)	.018$_a$ (.001)	.015$_a$ (.001)
1-3 years (N = 10,033)	.017$_a$ (.000)	.016$_a$ (.000)
4-6 years (N = 9,089)	.018$_a$ (.000)	.017$_b$ (.000)
7 years or longer (N = 3,557)	.020$_b$ (.000)	.021$_c$ (.000)
Interaction: GRA certification rating × Duration of the certification participation (Pillai's trace = .007***, η^2 = .003)	F= 15.553***	F = 15.592***
Covariate: Year of the online review was written (Pillai's trace = .004***, η^2 = .004)	F= 88.532***	F = 25.196***

Note. $^{***}p$ < .001. Means sharing the different subscript differ at p < 0.05 in the LSD comparison, two-tailed.

After controlling the time (i.e., year) that the reviews were written, the effects of the duration of a green certification program participation were significant on the weights of both local/organic ingredient topic (T10), $F(3, 25{,}085) = 5.936$, $p < .001$, and vegetarian/healthy option (T37), $F(3, 25{,}085) = 31.057$, $p < .001$. The average weight of local/organic ingredient topic (T10) was significantly higher among the customers of recently GRA-certified green restaurants, which participated in the program for less than one year (Adj M = .018, SE = .001) than those participated in one to three years (Adj M = .017, SE = .001). As the duration of the green certification participation reached up to four to six years, the average topic weight for local/organic ingredients (T10) revived and became similar to the first year of the certification program (Adj *M* = .018, *SE* = .000). The average topic weight was highest among the certified green restaurants that participated in the certification for seven years or longer (*M* = .020, *SE* = .000). For the vegetarian/healthy option topic (T37), there was a gradual increase in topic weights with the increase in the duration of participation in GRA certification. The average topic weight for vegetarian/healthy option (T37) was lowest (*M* = .015, *SE* = .001) for the green restaurants that had participated in the certification for less than a year and highest for the restaurants that participated in the certification for seven years or longer (*M* = .017, *SE* = .000).

The univariate ANOVA revealed the significant interaction effect of the GRA ratings and the duration of the certification participation in local/organic ingredient topic weight, $F(6, 25{,}085) = 15.553$, $p < .001$ and vegetarian/healthy option topic weight, $F(6, 25{,}085) = 15.592$, $p < .001$. The interaction between the GRA certification rating and the duration of the certification participation is visualized in Figure 4.2.

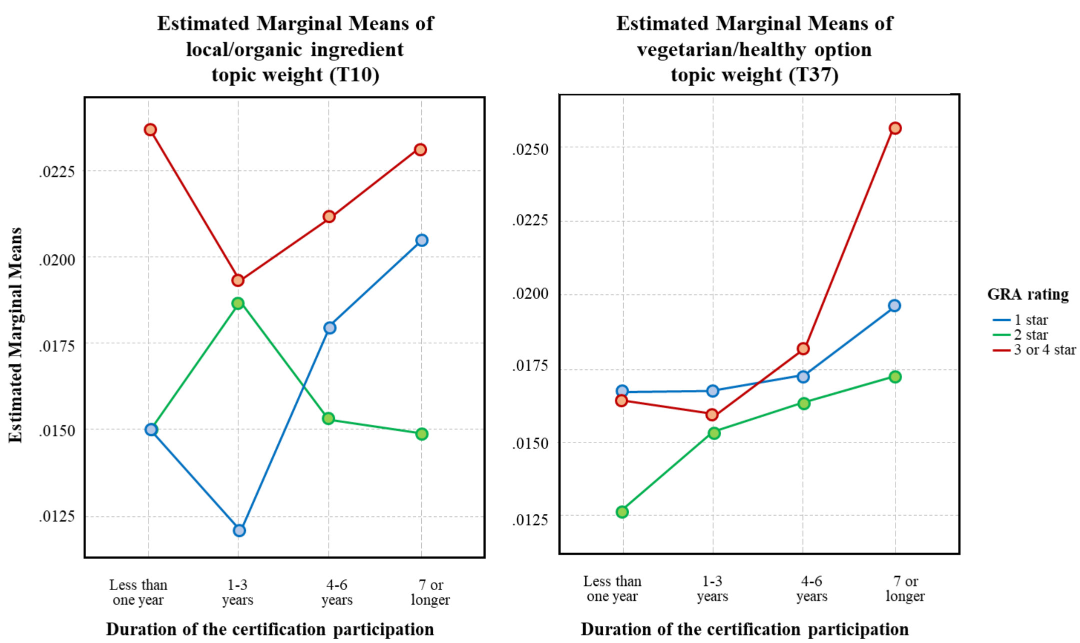

Figure 4.2. An interaction of GRA certification rating and the duration of the certification participation

As Box's Test of Equality was significant (Box's M = 5215.64, $p < .001$), Pillai's trace (V) was used to determine the significant effects of independent variables on the weights of the two green topics. There were significant main effects of both sustainable food ratings, $V = .010$, $F(4, 50{,}170) = 64.728$, $p < .001$, and the periods of certification participation, $V = .008$, $F(6, 50{,}170) = 33.587$, $p < .001$. An interaction of the GRA certification rating and the period of certification participation was also significant, $V = .009$, $F(12, 50{,}170) = 18.341$, $p < .001$ (Table 4.7).

Table 4.7. The effects of GRA certification: Sustainable food rating and duration of certification participation

	Local/organic ingredient (T10)	Vegetarian/healthy option (T37)
	Adj Mean (SE)	Adj Mean (SE)
Sustainable food rating		
(Pillai's trace = .010***, $\eta^2 = .005$)	$F = 71.316^{***}$	$F = 77.888^{***}$
Less than 20 points (N = 6,264)	$.017_a$ (.000)	$.016_a$ (.000)
20 - 40 points (N = 12,944)	$.019_b$ (.000)	$.016_a$ (.000)
40 or greater (N = 5,890)	$.024_c$ (.000)	$.022_b$ (.000)
Duration of the certification participation		
(Pillai's trace = .008***, $\eta^2 = .005$)	$F = 4.811^{**}$	$F = 61.124^{***}$
Less than one year (N = 2,419)	$.022_c$ (.001)	$.016_a$ (.001)
1-3 years (N = 10,033)	$.019_a$ (.000)	$.016_a$ (.000)
4-6 years (N = 9,089)	$.020_b$ (.000)	$.018_b$ (.000)
7 years (N = 3,557)	$.020_c$ (.000)	$.023_c$ (.000)
Interaction: Sustainable food rating × Duration of the certification participation (Pillai's trace = .009***, $\eta^2 = .004$)	$F = 12.714^{***}$	$F = 28.715^{***}$
Covariate: Year of the online review was written (Pillai's trace = .002***, $\eta^2 = .002$)	$F = 35.908^{***}$	$F = 13.823^{***}$

Note. $^{**}p < .01$, $^{***}p < .001$, Means sharing the different subscript differ at $p < 0.05$ in the LSD comparison, two-tailed.

The results from the univariate ANOVAs demonstrated that the significant effects of sustainable food ratings on topic weights of both local/organic ingredient topic (T10), $F(2, 25{,}058) = 71.316$, $p < .001$, and vegetarian/healthy menu topic (T37), $F(2, 25{,}058) = 77.888$, $p < .001$. Specifically, the average topic weight of the local/organic ingredient topic (T10) was significantly higher among the customers of the green restaurants with sustainable food ratings greater than 40 points (Adj $M = .024$, $SE = .000$) than less than 20 points (Adj $M = .017$, $SE = .000$) and between 20 and 40 points (Adj $M = .019$, $SE = .000$). Similarly, the average topic weight of the vegetarian/healthy option (T37) was significantly higher among the customers of the green restaurants with sustainable food ratings greater than 40 points (Adj $M = .022$, $SE = .000$) than those with less than 20 points (Adj $M = .016$, $SE = .000$) or between 20 and 40 points (Adj $M = .016$, $SE = .000$).

The univariate ANOVAs revealed the significant interaction effect of the GRA ratings and the duration of the certification participation on local/ organic ingredient topic weight, $F(6, 25{,}085) = 15.553$, $p < .001$, and vegetarian/healthy option topic weight, $F(6, 25{,}085) = 15.592$, $p < .001$. The interaction between the GRA certification rating and the duration of the certification participation was plotted in Figure 4.3.

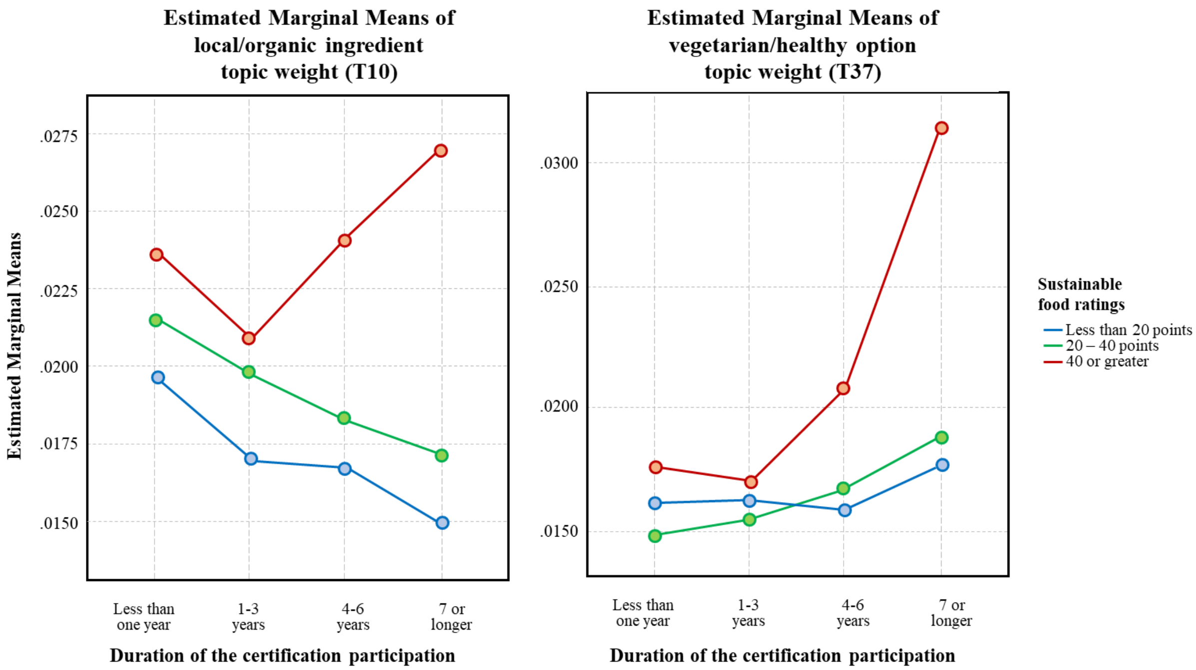

Figure 4.3. An interaction of sustainable food rating and duration of certification participation

The effects of customer demographics on the green perceptions

To examine the effects of the customers' demographic backgrounds on the weights of green image topics (RQ 5), a factorial MANCOVA was conducted with the customers' age and gender as independent variables, the weights of two green topics (T10 and T37) as dependent variables, and the year of a review was written as a covariate (Table 4.8). Box's Test of Equality was significant (Box's M = 664.109, $p < 0.001$), and thus, Pillai's trace (V) was used. Females mentioned significantly more about the vegetarian/healthy option topic than males ($V = .002$, $F(2, 7{,}157) = 6.985$). However, the main effect of age, $V = .002$, $F(6, 14{,}316) = 6.985$, $p > .05$, and the interaction of the age and gender, $V = .001$, $F(6, 14{,}316) = .864$, $p > .05$, were not significant.

Table 4.8. The effects of demographics: Age and gender

	Local/organic ingredient (T10)	Vegetarian/healthy option (T37)
	Adj Mean (SD)	Adj Mean (SD)
Age		
(Pillai's trace = .002, η^2 = .001)	F= 3.162*	F = .292
25-34 years (N = 873)	$.019_a$ (.001)	.018 (.001)
35-49 years (N = 2,276)	$.019_a$ (.000)	.018 (.000)
50-64 years (N = 2,878)	$.020_a$ (.000)	.018 (.000)
65+ years (N = 1,140)	$.021_b$ (.001)	.018 (.001)
Gender		
(Pillai's trace = .002***, η^2 = .002)	F= 2.740	F = 12.773***
Male (N = 3,602)	.019 (.000)	$.017_a$ (.000)
Female (N = 3,565)	.020 (.001)	$.019_b$ (.001)
Interaction: Age × gender		
(Pillai's trace = .001, η^2 = .000)	F= 1.045	F = .841
Covariate: Year of the online review was written		
(Pillai's trace = .004***, η^2 = .004)	F= 25.423***	F = .684

Note. *$p < .05$, ***$p < .001$, Means sharing the same subscript differ at $p < 0.05$ in the LSD comparison, two-tailed.

For the gender, the factorial MANOVA model was followed up by calculating between-subjects ANOVAs. The difference between male and female was significant for vegetarian/healthy option topic weight, $F(1, 7{,}158) = 12.773$, $p < .001$, but not for local/organic ingredient topic weight, $F(1, 7{,}158) = 2.740$, $p > .05$. For the vegetarian/healthy option topic, the adjusted average topic weight was significantly higher among female customers (Adj M = .019, SE = .000) than male customers (Adj M = .017, SE = .000).

Phase II: Exploration of a Green Restaurant Image Network Structure

Topic-level image network

Topic-level image network statistics

In order to estimate the structure of higher-level image categories, 51 topics were constructed as a network. The overview of the topic network was illustrated in Table 4.9. There were 173 edges that connected 51 nodes. The average degree was 6.8, indicating that each topic node was connected to about seven other nodes. The density of topic network was 0.13, which means that about 13% of nodes were connected. The average path length was 2.74, indicating that on average, the nodes were separated by three degrees from each other. The network diameter was 7.0, which means that all nodes can be connected within seven degrees. There were 12 communities, and the modularity score was 0.45, which indicates the nodes within the same groups were tightly connected but sparsely connected between nodes in different groups.

Table 4.9. Network statistics of topic network (*N* = 25,098 reviews)

Network overview	Statistics
The number of nodes	51.00
The number of edges	173.00
Average degree	6.78
Graph density	0.13
Average path length	2.74
Network diameter	7.00
Modularity	0.45

Core-periphery structures in subgroups

Figure 4.4 below illustrates the topic-level image network based on the topic proportion correlation matrix. As a result of STM, 51 topics that may represent the higher-level image categories were identified (Table 4.10). The eigenvector centrality scores for these 51 topics were calculated to identify the influential image categories that may be retrieved easily and readily spread to other image categories. Based on the eigenvector centrality scores, the topics were clustered into core, semi-periphery, and periphery. Two topics were clustered into core: topic 44 (customer satisfaction) and topic 5 (good flavor), meaning that the customers were more likely to recall these two positive image categories. There were 17 semi-periphery topics with eigenvector centrality scores between 0.24 and 0.80. The majority of semi-periphery topics were pertain to customers' evaluation toward the general restaurant attributes (e.g., good service [T32 and T38], good flavor [T50]) or overall evaluation toward the restaurant (e.g., positive experience [T51], satisfaction [T4]). Finally, 32 periphery topics, which outnumbered the core and semi-periphery topics, were identified. Many periphery topics were related to objective descriptions of the specific restaurant attributes (e.g., T36: building, T47: location) or unique restaurant attributes that may be specialized in the green restaurants (e.g., T10: local/organic ingredients, T37: vegetarian/healthy options).

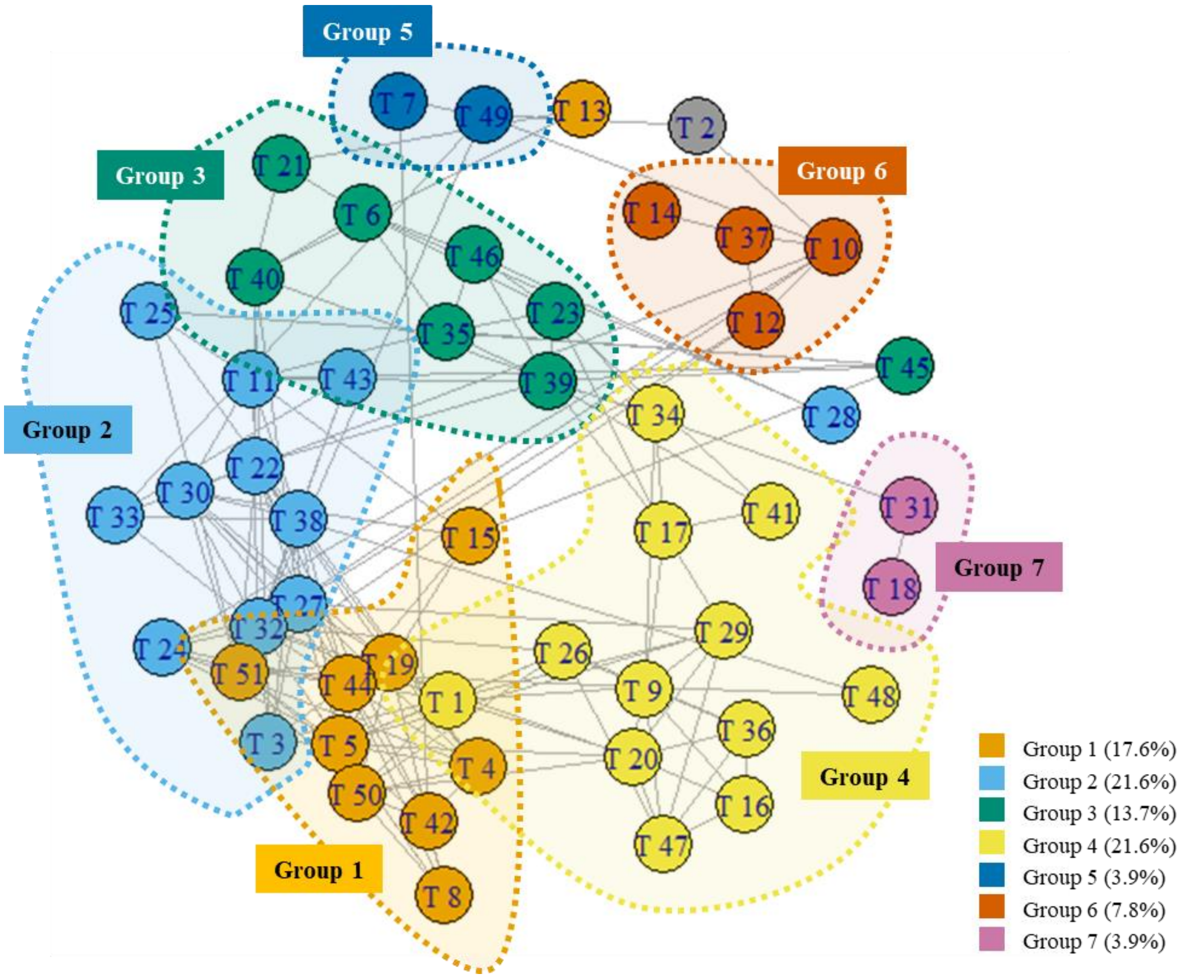

Figure 4.4. The topic-level image network

The characteristics of subgroups

As the results of Louvain community detection algorithm, 12 groups were found containing two or more topics (Figure 4.4). Group 1, which accounted for 17.6% of the topic nodes, contained both core topics (i.e., satisfaction [T44] and good flavor [T5]), and all the topics in this group had positive emotions. For example, the topics belonging to group 1 consisted of the positive evaluation toward the food quality (i.e., flavor; T5: Good flavor) and overall restaurant performance (e.g., T4: satisfaction). Also, group 1 contained the topics regarding customers' behavioral intention (e.g., T8: revisit intention) or indicating actual visiting revisits or recommendation behaviors (e.g., T19: menu recommendation, T42: repeat customers). On the other hand, the topics containing the negative emotions were clustered into group 3. Except for topic 40, which was about providing prompt and efficient service to customers, all the other topics in group 3 contained negative sentiment. Although most of these topics had high topic weights greater than the average (0.019), their centrality scores were low and thus clustered into the periphery. Two green topics (i.e., local/organic ingredient [T10] and vegetarian/healthy option [T37]) were clustered together into group 6 along with two other topics (i.e., T12: menu selections, T14: dietary restriction). This finding suggests that the customers often mentioned these two green topics together or the other topics in group 6.

Table 4.10. Topic weights and centrality of image categories in the topic-level network

Label	Weights	Centrality	C/P	Label	Weights	Centrality	C/P
Group 1				**Group 4**			
T44: Satisfaction	0.019	1.000	C	T1: Good food & service & atmosphere	0.079	0.706	S
T5: Good flavor	0.029	0.995	C	T26: Good service (Professional employees)	0.022	0.321	S
T50: Good flavor	0.020	0.697	S	T20: Background music	0.016	0.296	S
T19: Menu recommendation	0.014	0.571	S	T9: Outdoor, indoor seating	0.028	0.248	S
T51: Positive experience	0.010	0.523	S	T29: Overprice	0.017	0.203	P
T4: Satisfaction	0.020	0.494	S	T36: Building	0.013	0.092	P
T42: Repeat customers	0.030	0.393	S	T47: Location	0.025	0.084	P
T8: Revisit intention	0.016	0.364	S	T17: Good food + dissatisfying factor	0.045	0.081	P
T15: Good flavor	0.011	0.204	P	T16: Touristic place	0.020	0.060	P
Group 2				T34: Reasonable value	0.018	0.036	P
T32: Good service (Knowledgeable staffs)	0.026	0.740	S	T41: Brewing company	0.010	0.015	P
T27: Small plates	0.024	0.669	S	**Group 5**			
T38: Good service (Attentive staffs)	0.022	0.546	S	T49: Good service	0.012	0.047	P
T3: Recommendation	0.014	0.483	S	T7: Iconic place	0.019	0.024	P
T22: Online review	0.016	0.452	S	**Group 6**			
T30: Unique flavor	0.013	0.391	S	T10: *Local/organic ingredients*	0.020	0.103	P
T24: Good value	0.015	0.366	S	T12: Menu selections	0.022	0.092	P
T11: Bad flavor	0.019	0.178	P	T37: *Vegetarian/healthy option*	0.017	0.020	P
T33: Fine dining	0.016	0.150	P	T14: Dietary restriction	0.016	0.002	P
T43: Special occasions	0.015	0.109	P	**Group 7**			
T25: Big portion size	0.024	0.085	P	T31: Bar	0.018	0.007	P
Group 3				T18: Bar	0.010	0.001	P
T40: Good service (Reservation)	0.025	0.103	P	**Group 8-12**			
T39: Disappointment	0.021	0.065	P	T2: Décor/ambiance	0.010	0.009	P
T35: Mixed dissatisfying factors	0.014	0.039	P	T13: Noise	0.015	0.006	P
T23: Overprice	0.020	0.035	P	T28: Happy hour	0.007	0.003	P
T46: Bad service (Employees' attitude)	0.024	0.021	P	T45: Portion size	0.013	0.033	P
T6: Bad service (Slow service)	0.027	0.018	P	T48: Course meal/gourmet	0.006	0.062	P
T21: Crowded, popularity	0.018	0.010	P				

Note. Italic indicates the image associations related to green restaurant attributes. C: core; S: semi-periphery; P: periphery (Wang et al., 2018)

Green image network

Green image network statistics

In order to comprehend the green restaurant image, the online reviews closely related to two green topics (N = 247) were selected to construct the green image network using the word co-occurrence matrix. In the image network with 300 image nodes, there were more than 6,000 edges (See Table 4.11). The average degree was 40.6, which means there were about 41 nodes connected to each node. Graph density was 0.14, indicating approximately 14% of the nodes were interconnected with each other, and thus the network is sparse. The average path length was 1.89 and network diameter was 3.0. The results demonstrated that the nodes are typically separated by two degrees from any other node, and the longest path between the two pairs of the nodes was three degrees. There were five communities present in a network with the modularity score of 0.14.

Table 4.11. Network statistics of the green image network (*N* = 247)

Network overview	Statistics
The number of nodes	300.00
The number of edges	6,088.00
Average degree	40.59
Graph density	0.14
Average path length	1.89
Network diameter	3.00
Modularity	0.14

Types, strength, and favorability of green image associations

The green image network was visualized in Figure 4.5. The size of nodes and labels of the image network were proportional to the eigenvector centrality scores, and the same color of the nodes represented the subgroup. The detailed features of the green image network were illustrated in Table 4.12. Similar to the topic-level network analysis, the image associations were classified into core, semi-periphery, and periphery depending on the eigenvector centrality (Wang et al., 2018). Also, the image associations describing the objective and descriptive features were labeled as "cognitive" and the subjective evaluations as "affective" (Echtner & Ritchie, 1993).

The core image nodes with the high eigenvector centrality, identified in green image network analysis, were *food*, *fresh*, *good*, *great*, and *local*. There were 94 semi-periphery image nodes and 201 periphery image nodes. In the green image network, the terms regarding ingredient sourcing and vegetarian/healthy options appeared frequently across core-periphery classifications. For example, the image associations relevant to local/organic ingredients and their retrieval classifications were *local* (core), *organic* (semi-periphery), *farm* (semi-periphery), *farmer* (semi-periphery), and *homegrown* (periphery). The image associations relevant to vegetarian/healthy options and their retrieval classifications were *healthy* (semi-periphery), *vegetarian* (semi-periphery), *vegetarian* (semi-periphery), *veggie* (semi-periphery), *vegetable* (semi-periphery), and *health* (periphery). The image nodes describing the environment-focused green attributes (e.g., *environment*, *eco*, *recycled*) were also found among the periphery image associations.

In group 1 (Table 4.12), the key image nodes that had high eigenvector centrality were mostly related to vegetarian/healthy options. Within the same group, there appeared to be positive affective image nodes, such as *good*, *interesting*, and *freshly*. The terms describing the vegetarian/healthy options and positive adjectives were grouped together partly because the customers often used the positive adjectives to describe the attributes appeared in group 1. In group 5, the cognitive image nodes describing ingredient sourcing (e.g., local, ingredient, farm) appeared as key image nodes along with positive affective image nodes (e.g., fresh, delicious).

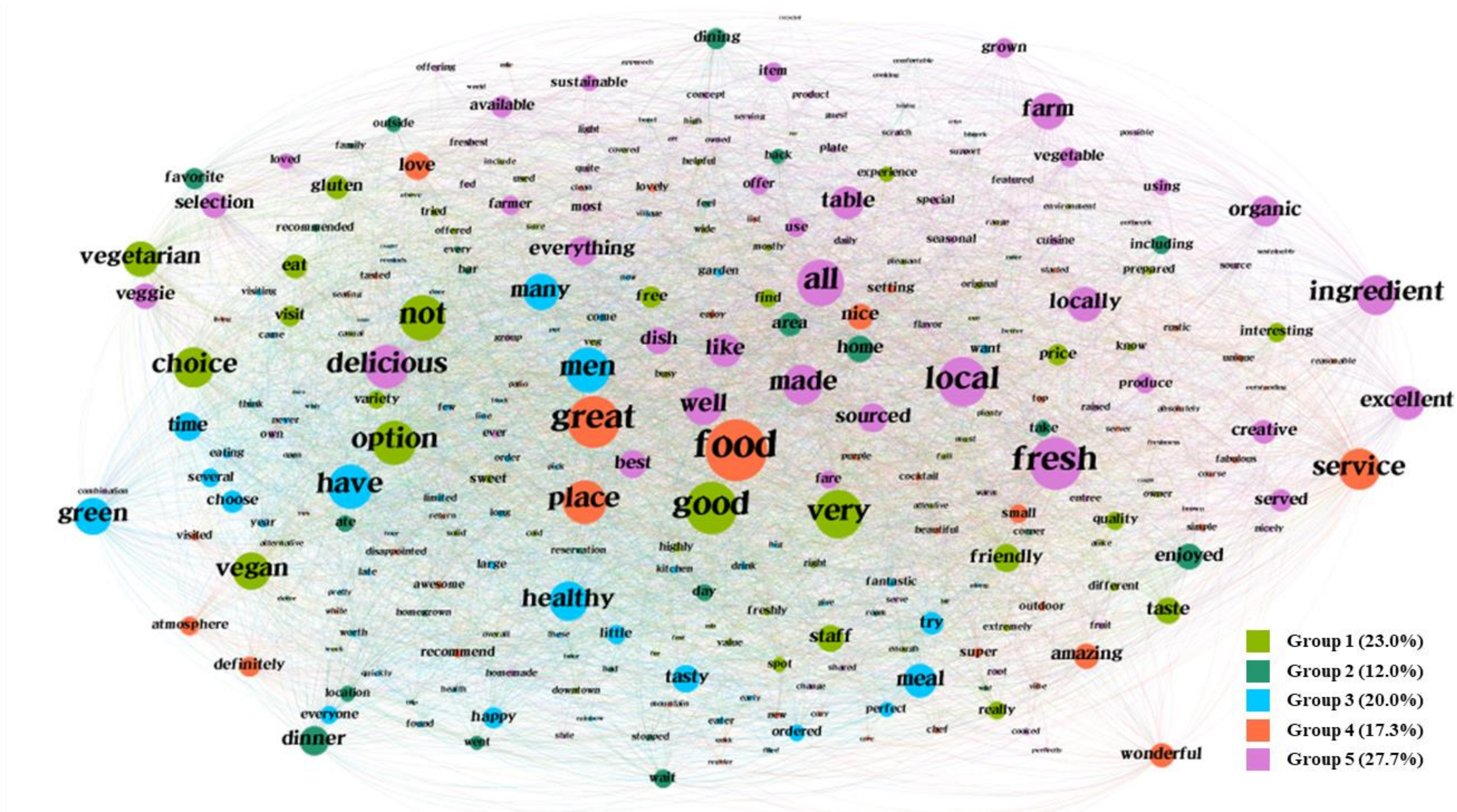

Figure 4.5. The green image network

Table 4.12. Strength and types of green image associations in subgroups

Label	Centrality	C/P	Type	Label	Centrality	C/P	Type	Label	Centrality	C/P	Type
Group1				extremely	0.198	P		week	0.082	P	
good	0.844	C	Affective	helpful	0.197	P	Affective	pay	0.061	P	
very	0.780	S	Cognitive	busy	0.195	P	Affective	**Group 2**			
not	0.741	S		offered	0.190	P	Cognitive	dinner	0.470	S	Cognitive
option	0.712	S	Cognitive	wide	0.186	P	Affective	home	0.430	S	Cognitive
choice	0.654	S	Cognitive	value	0.183	P	Cognitive	enjoyed	0.423	S	Affective
vegan	0.606	S	Cognitive	used	0.177	P		area	0.380	S	Cognitive
vegetarian	0.573	S	Cognitive	owner	0.176	P		favorite	0.347	S	Affective
friendly	0.449	S		downtown	0.165	P		dining	0.341	S	Cognitive
staff	0.438	S	Cognitive	pleasant	0.151	P	Affective	wait	0.306	S	Cognitive
taste	0.423	S	Cognitive	enough	0.148	P	Affective	including	0.305	S	
eat	0.388	S		cold	0.147	P		day	0.280	S	
gluten	0.379	S	Cognitive	sure	0.145	P		ate	0.271	S	
free	0.353	S		must	0.140	P		take	0.263	S	
price	0.344	S	Cognitive	include	0.138	P		outside	0.259	S	Cognitive
visit	0.335	S		full	0.136	P		location	0.257	S	Cognitive
interesting	0.308	S	Affective	solid	0.136	P		back	0.246	P	Affective
find	0.300	S		alike	0.134	P		went	0.236	P	
quality	0.297	S	Cognitive	covered	0.130	P		bar	0.223	P	
variety	0.294	S	Cognitive	casual	0.130	P		recommended	0.221	P	Affective
really	0.293	S		*environment*	0.126	P	Cognitive	feel	0.210	P	
sweet	0.268	S	Affective	attentive	0.125	P	Affective	every	0.203	P	
prepared	0.251	P		overall	0.124	P		family	0.187	P	
know	0.247	P		plenty	0.123	P	Affective	reservation	0.186	P	Cognitive
different	0.247	P	Affective	high	0.123	P	Affective	stopped	0.182	P	
experience	0.246	P		alternative	0.121	P	Cognitive	*homegrown*	0.166	P	Cognitive
spot	0.243	P		range	0.120	P		corner	0.161	P	
highly	0.240	P		for	0.113	P		room	0.145	P	Cognitive
tried	0.222	P		above	0.112	P		had	0.137	P	
freshly	0.220	P	Affective	mix	0.111	P	Cognitive	open	0.119	P	
original	0.218	P		fast	0.111	P	Affective	trip	0.118	P	
mostly	0.215	P		better	0.101	P	Affective	wild	0.114	P	Affective
right	0.203	P	Affective	*eco*	0.097	P	Cognitive	decor	0.109	P	Cognitive
veg	0.199	P	Cognitive	hit	0.092	P		near	0.103	P	

Note. Italic indicates the image associations related to green restaurant attributes. C: core; S: semi-periphery; P: periphery (Wang et al., 2018)

Table 4.12. Strength and types of green image associations in subgroups (Continued)

Label	Centrality	C/P	Type	Label	Centrality	C/P	Type	Label	Centrality	C/P	Type
hour	0.102	P		eater	0.199	P		**Group 4**			
hotel	0.092	P		kitchen	0.199	P		food	1.000	C	Cognitive
comfortable	0.085	P	Affective	never	0.194	P		great	0.841	C	Affective
historic	0.084	P	Affective	few	0.189	P	Affective	place	0.703	S	Cognitive
building	0.069	P	Cognitive	came	0.184	P		service	0.665	S	Cognitive
Group 3				visiting	0.183	P		love	0.438	S	Affective
men	0.721	S		think	0.180	P		nice	0.417	S	Affective
have	0.717	S		late	0.177	P	Affective	amazing	0.411	S	Affective
healthy	0.632	S	Affective	found	0.163	P		wonderful	0.398	S	Affective
green	0.601	S	Cognitive	now	0.155	P		definitely	0.330	S	
many	0.585	S		big	0.153	P	Affective	small	0.305	S	Affective
meal	0.543	S	Cognitive	these	0.146	P		atmosphere	0.302	S	Cognitive
time	0.462	S		early	0.140	P	Affective	super	0.297	S	Affective
tasty	0.450	S	Affective	give	0.138	P		recommend	0.273	S	Affective
try	0.365	S		village	0.137	P		setting	0.271	S	Cognitive
choose	0.359	S		line	0.136	P		visited	0.249	P	
happy	0.343	S	Affective	pick	0.134	P		lovely	0.230	P	Affective
several	0.309	S		health	0.127	P	Cognitive	outdoor	0.223	P	Cognitive
little	0.307	S	Affective	pretty	0.124	P		awesome	0.220	P	Affective
everyone	0.293	S		quickly	0.121	P	Affective	enjoy	0.214	P	Affective
want	0.289	S		rainbow	0.118	P		unique	0.213	P	Affective
ordered	0.270	S		put	0.100	P		simple	0.211	P	Affective
come	0.257	S		filled	0.099	P		cocktail	0.199	P	Cognitive
garden	0.247	P	Cognitive	block	0.099	P		top	0.198	P	
perfect	0.245	P	Affective	reminds	0.099	P		purple	0.188	P	
fantastic	0.245	P	Affective	along	0.094	P		new	0.187	P	
year	0.238	P		wish	0.094	P		rustic	0.183	P	Affective
large	0.237	P	Affective	door	0.083	P		beautiful	0.183	P	Affective
eating	0.224	P	Cognitive	tour	0.081	P		fabulous	0.182	P	Affective
drink	0.217	P	Cognitive	counter	0.075	P		disappointed	0.180	P	Affective
long	0.216	P		down	0.064	P		chef	0.177	P	Cognitive
order	0.206	P	Cognitive	same	0.059	P		tasted	0.160	P	
worth	0.205	P	Affective					list	0.159	P	
limited	0.202	P	Affective					absolutely	0.155	P	

Note. Italic indicates the image associations related to green restaurant attributes. C: core; S: semi-periphery; P: periphery (Wang et al., 2018)

Table 4.12. Strength and types of green image associations in subgroups (Continued)

Label	Centrality	C/P	Type	Label	Centrality	C/P	Type	Label	Centrality	C/P	Type
reasonable	0.155	P	Affective	everything	0.470	S		offering	0.183	P	Cognitive
return	0.142	P		best	0.450	S	Affective	fruit	0.180	P	
clean	0.141	P	Affective	dish	0.434	S	Cognitive	quite	0.179	P	
server	0.141	P	Cognitive	veggie	0.417	S	Cognitive	freshest	0.174	P	Affective
started	0.141	P		selection	0.413	S	Cognitive	entree	0.169	P	Cognitive
course	0.135	P	Cognitive	creative	0.384	S	Affective	*source*	0.166	P	Cognitive
seating	0.134	P	Cognitive	served	0.362	S		fed	0.163	P	
vibe	0.134	P	Cognitive	available	0.352	S		root	0.162	P	
mountain	0.129	P		*vegetable*	0.323	S	Cognitive	featured	0.161	P	
cozy	0.125	P	Affective	*grown*	0.323	S	Cognitive	nicely	0.160	P	Affective
white	0.123	P		offer	0.318	S		scratch	0.158	P	Cognitive
patio	0.123	P	Cognitive	produce	0.318	S	Cognitive	cooked	0.154	P	
quick	0.118	P	Affective	use	0.315	S		shared	0.153	P	
living	0.114	P		item	0.314	S	Cognitive	change	0.152	P	
care	0.109	P		*farmer*	0.310	S	Cognitive	serving	0.150	P	Cognitive
outstanding	0.108	P	Affective	fare	0.295	S		owned	0.147	P	
regular	0.096	P		*sustainable*	0.275	S	Cognitive	combination	0.145	P	
yes	0.091	P		most	0.268	S		warm	0.144	P	Affective
mile	0.087	P		using	0.265	S		support	0.144	P	Cognitive
Group 5				loved	0.256	S	Affective	style	0.141	P	Cognitive
fresh	0.849	C	Affective	special	0.242	P	Affective	possible	0.137	P	
local	0.803	C	Cognitive	ever	0.238	P		serve	0.133	P	Cognitive
all	0.755	S		cuisine	0.229	P	Cognitive	guest	0.120	P	
delicious	0.705	S	Affective	own	0.223	P		authentic	0.116	P	Affective
made	0.648	S		plate	0.223	P	Cognitive	approach	0.114	P	
ingredient	0.642	S	Cognitive	seasonal	0.220	P	Cognitive	perfectly	0.107	P	Affective
well	0.614	S		group	0.216	P		art	0.102	P	
farm	0.591	S	Cognitive	concept	0.211	P	Cognitive	brown	0.096	P	
locally	0.560	S	Cognitive	product	0.206	P	Cognitive	freshness	0.090	P	Affective
excellent	0.550	S	Affective	light	0.205	P		sustainably	0.086	P	Cognitive
table	0.535	S	Cognitive	raised	0.200	P	Cognitive	world	0.085	P	
like	0.533	S		*homemade*	0.199	P	Cognitive	cooking	0.084	P	
organic	0.497	S	Cognitive	flavor	0.193	P	Cognitive	artist	0.073	P	
sourced	0.473	S	Cognitive	daily	0.186	P		*recycled*	0.049	P	Cognitive

Note. Italic indicates the image associations related to green restaurant attributes. C: core; S: semi-periphery; P: periphery (Wang et al., 2018)

In both group 1 and group 5, the image associations related to food-focused green practices had the high eigenvector centrality (i.e., core or semi-periphery), but the image nodes relevant to environment-focused green practices only appeared in the periphery classification. The majority of image nodes assigned to group 4 were relevant to general restaurant attributes, such as food, service, and atmosphere. Compared to other groups relevant to green attributes, group 4 consisted of more various adjectives depicting the customers' subjective evaluations toward the general restaurant attributes.

Favorability of key image associations relevant to green practices was examined by sentiment and emotion analysis (Table 4.13). Sentiment scores for the green image associations extracted from the text were greater than 0.99, indicating positive sentiments. Furthermore, among five emotion categories, scores assigned for joy were the highest, confirming positive sentiments related to green images.

Table 4.13. Sentiment and emotion scores for key green image associations

	Sentiment score	Sentiment label	Emotion				
			Anger	Joy	Sadness	Fear	Disgust
Overall	0.995	Positive	0.001	0.985	0.014	0.000	0.000
Local	0.995	Positive	0.001	0.985	0.014	0.000	0.000
Locally	0.994	Positive	0.001	0.984	0.015	0.000	0.000
Farm	0.994	Positive	0.001	0.985	0.014	0.000	0.000
Organic	0.995	Positive	0.001	0.984	0.015	0.000	0.000
Sustainable	0.995	Positive	0.001	0.985	0.014	0.000	0.000
Vegan	0.997	Positive	0.001	0.983	0.016	0.000	0.000
Vegetarian	0.997	Positive	0.001	0.983	0.016	0.000	0.000

Chapter 5 - Discussion

With the increasing interests in sustainability in the hospitality industry, the effects of green practices on customers' perceptions and behavior intention have become an important research topic (Gao, Mattila, & Lee, 2016; Nisa, Varum, & Botelho, 2017). The majority of previous literature on green practices used attribute-based measurement items to assess customers' green images (Jeong, Jang, Day, & Ha, 2014; Kwok, Huang, & Hu, 2016; Lee, Hsu, Han, & Kim, 2010; Wu, Ai, & Cheng, 2016). However, some green practices, such as the use of energy- or water-saving kitchen equipment, are often not observable or discernable to customers without proper advertisement. Thus, green restaurant customers may not be able to process these practices to shape green images (Namkung & Jang, 2013). Therefore, it is important to understand the customers' actual experiences about the green practices in restaurants so that the accurate green image can be captured (Wang & Horng, 2016; Yu, Li, & Jai, 2017). In Phase I, the current study attempted to identify the green restaurant-specific attributes and image categories stored in the certified green restaurant customers' memory. In Phase II, the green image network structures and image dimensions were explored based on the associative network model (Anderson, 1983).

Phase I: Extraction of Green Restaurant Image Categories

Topic modeling: Discovery of image categories

Based on the previous studies (Griffiths & Steyvers, 2002; Griffiths et al., 2007), this study hypothesized that the topics discovered from the topic modeling may represent the image categories stored in people's long-term memory. The top words for each topic demonstrated the cognitive evaluation (knowledge or belief) and affective evaluation (emotional appraisals or feelings) towards the specific restaurant attributes or towards the overall experience in the restaurant they visited (Baloglu & McCleary, 1999). The topics regarding customers' cognitive and affective appraisals of the specific restaurant attributes outnumbered the topics regarding the overall evaluation of the restaurant in terms of both the number of topics and topic weights. The results indicated that the majority of online review content consisted of the customers' appraisals of the specific attributes. The high weight on topic 1 (good food, service, & atmosphere) indicated that there were many customers who recalled these three restaurant attributes together. Among the core restaurant attributes (i.e., food, service, atmosphere, and value), the number of topics related to food quality and the gross weight of these topics was the highest. This finding may indicate that the food quality was the most important antecedent of restaurant image, as suggested by Ryu, Lee, and Kim (2012).

The topics extracted from STM did not cover all the specific restaurant attributes that were found to be important in the previous studies. For example, an employee' attire was considered an important factor in determining a customer's evaluation of atmosphere (Jin, Lee, & Huffman, 2012; Ryu et al., 2012), but no relevant topic was found in the current study. Many certified green restaurant customers mentioned accommodation for diet restrictions (T14), and the amount of content was high enough to appear as a topic. However, such attributes were not considered in the previous studies (e.g., Han & Hyun, 2017; Jang & Namkung, 2009; Ryu & Lee, 2017).

Although the certified green restaurants in the sample implemented both environment- and food-focused green practices, only topics related to food-focused green practices appeared in the current study. This finding may reflect the low visibility of these environment-focused green practices. Moreover, people were less likely to mention the restaurant's participation in the certification program. DiPietro, Cao, and Partlow (2013) found that less than 3% of customers who visited a certified green restaurant accurately identified the certification information, indicating a lack of customer interest in the certification program or lack of visibility of certification participation. They also found that customers perceived implementing green practices into the restaurant operation to be more important than attaining the official green certification (DiPietro, Gregory, & Jackson, 2013).

The low visibility of green practices has emerged as an issue in other hospitality industries. For example, a previous study applying topic modeling to green hotel reviews did not find any topic relevant to green attributes (Calheiros, Moro, & Rita, 2017). Another study which analyzed online reviews of green hotels found only a small percentage of customers who experienced green practices mentioned the green practices in the online reviews (Yu et al., 2017).

Serving organic/locally sourced ingredients (T10) and vegetarian/healthy options (T37) is mainly about food-focused green attribute proposed by Kwok et al. (2016) and health-concern proposed by Choi and Parsa (2006) in the green restaurant framework. The results from content analysis indicated that some customers who mentioned two sustainable food-related topics identified in this study associated these topics with health benefits. Previously, researchers confirmed that serving sustainable foods might appeal to health-conscious customers who care about their health and thus pay close attention to what they eat (Kwok et al., 2016; Namkung & Jang, 2013). Some customers supported locally sourced ingredients to help the local community, which falls under the social concern perspective proposed by Choi and Parsa (2006). Although Kwok et al. (2016) proposed that social concerns were less relevant to the green restaurant practices, this study found that social concern, specifically community support, can be a key driver of consuming locally sourced ingredients. Also, many customers who mentioned the vegetarian/healthy options recognized the restaurants' efforts to incorporate environment-focused green practices, such as recycling.

The effects of restaurant characteristics on the customers' green perceptions

To identify the effects of restaurant characteristics on the customers' green perceptions, the green certification ratings and the duration of the certification participation were used. The green certification ratings were used as a proxy of the degree of the green practices incorporated into their operations. For the vegetarian/healthy option topic, the higher the GRA ratings and the longer the restaurants participated in the certification program, the more reviews included this topic. A similar pattern was found when the sustainable food ratings and the duration of GRA certification participation were used to estimate the difference on the vegetarian/healthy option topic weight. For the local/organic ingredient topic, the higher both the GRA ratings and sustainable food ratings, the more likely their customers mentioned the topic. However, for restaurants with a low sustainable food rating (less than 40 points), the average topic weight peaked in the first year of the restaurant's participation in the certification program, but it dropped significantly over time. For restaurants with a high sustainable food rating (higher than 40 points), the average topic weight decreased significantly after the first year, but it revived and increased over time. When people are confronted with new information or stimuli that do not match existing memories, people tend to make extra efforts to process the information or ignore it (Fiske & Taylor, 1991; Goodstein, 1993; Halkias, 2015). Compared to general restaurant attributes, serving local/organic ingredients may be considered as a relatively atypical attribute, especially at the beginning of implementing the attribute. As a result, people may exert more efforts to process these attributes, which leads them to shape a green image in their memory more easily (Halkias, 2015). Over time, customers who experienced sustainable foods may become accustomed to these attributes and perceive them as normal (Rust & Oliver, 2000). Unless the restaurant keeps improving the performance, the same attributes may not be surprising or memorable to the customers. Although serving sustainable food may not be considered as a new or unique attribute as time goes, those who are highly involved in the green attributes may be motivated to process these attributes (Goodstein, 1993). Thus, the customers with high involvement in sustainable foods are more likely to visit the well-positioned restaurant on sustainable food products, and they may continue to comment on these attributes.

The effects of customer demographics on the green perceptions

The green restaurant customers' demographics were examined in relation to the perceived green image. Results showed that female customers mentioned the vegetarian/healthy options significantly more often than male customers, confirming previous findings that women tend to be care about healthy options (Kwok et al., 2016).

Phase II: Exploration of a Green Restaurant Image Network Structure

Topic-level image network

Based on the image categories discovered in the previous stage, the green image network structure stored in the customers' memory was identified and analyzed. In terms of the recallability of image categories by spreading activation, the positive image categories tended to be retrieved more easily than the negative image categories. There was an inconsistency between the frequency and the eigenvector score because some of the image categories that people mentioned frequently in UGC were not central in terms of spreading activation (Wang, Li, & Lai, 2018). For example, the image categories containing negative sentiment, which had the relatively high topic weights (e.g., bad service [T6 and T46], disappointment [T39]), 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 rather than talk about the objective or positive restaurant attributes. This may be confirmed by the fact that the multiple image categories with negative sentiments were clustered together and created its own subgroup. This may indicate the spillover effects of negative perception on the other relevant attributes (Ahluwalia, Unnava, & Burnkrant, 2001).

Also, the image categories regarding general restaurant attributes were more tightly connected to other image categories than the categories describing more unique or specific attributes related to green practices. Two topics related to green attributes (i.e., local/organic ingredients [T10] and vegetarian/healthy option [T37]) were grouped together along with two other topics (i.e., T12: menu selection and T14: dietary restriction), implying that the customers often stated these topics together. These grouping phenomena may demonstrate the underlying reasoning behind perceiving and recalling green attributes. For example, the customers who have dietary restrictions may be more likely to recognize the vegetarian/healthy options and recall them.

Green image network

By using the online reviews concerning the green attributes, the green image network was visualized to understand a set of perceptions toward green attributes in a consumer's mind (Chen, 2010). The positive affective image associations (e.g., fresh, good, and great) were found to be central nodes to play an important role in spreading activation. These affective image associations demonstrated the customers' feelings and beliefs based on an appraisal of the green attributes (Baloglu & McCleary, 1999). The abstract image associations, such as affective image, were found to be more accessible and durable in memory than more concrete image associations, such as cognitive image (Chattopadhyay & Alba, 1988). Therefore, previous studies emphasized the importance of creating a positive affective image because affective image components are strongly associated with the overall image, loyalty, and decision making (Lin, Morais, Kerstetter, & Hou, 2007; Stylos, Vassiliadis, Bellou, & Andronikidis, 2016; Zhang, Fu, Cai, & Lu, 2014). Findings from this study may indicate that the green restaurant customers built the emotional responses based on the appraisal of green practices.

This study revealed the unique or distinctive image associations relevant to green restaurant attributes (Baloglu & McCleary, 1999). These unique image associations were related to both food-focused (e.g., local, organic, vegan) and environment-focused green attributes (e.g., environment, eco, recycled). Compared to the food-focused green image associations, the environment-focused green image associations were more sparsely connected to other image nodes, and thus they were less likely to be activated (Wang & Horng, 2016). Moreover, the environment-focused image associations did not create their own subgroup but belonged to one of the subgroups where the food-focused green image associations are central. These results may imply that the image associations of environment-focused green attributes were only accessible for those who recalled the salient food-focused green practices. A previous study, which applied topic modeling into the online reviews of certified green restaurants, did not discover the topics relevant to environment-focused green attribute (Park, Chae, & Kwon, 2018). The lack of the environment-focused green topic in the massive UGC may attribute to the limited recallability of these attributes alone.

Finally, this study revealed the existence of positive sentiment and emotions attached to the overall green image network and key green image associations. The favorability of the particular image associations can be influenced by the feeling or beliefs about the relevant higher-level image category (Keller, 1993). The findings of positive sentiment and emotions confirmed the strong connections between positive image associations and the green attribute image associations.

Chapter 6 - Summary and Conclusions

Summary

Although the customers' interests in green practices have increased in the restaurant industry, research related to green practices in the restaurant context remains limited (Kim, Lee, & Fairhurst, 2017). This study examines customers' perceptions of green restaurant practices via user-generated content provided after visiting certified green restaurants. This study applied topic modeling with 25,098 customer reviews of 70 certified green restaurants collected from TripAdvisor.com followed by content analysis, a factorial MANCOVA, and network analysis.

Phase I: Extraction of green restaurant image categories

Phase I of this study aimed to identify salient image categories from user-generated content (UGC) of customers of certified green restaurants using topic modeling to test the category-based processing perspective (Fiske, Neuberg, Beattie, & Milberg, 1987). The specific objectives were to (a) discover the salient image categories stored in the green restaurant customers by analyzing the unstructured text of UGC with the topic modeling algorithm, (b) identify image categories frequently mentioned by the green restaurant customers, (c) compare similarities and differences between the image categories discovered from UGC and findings of the previous research, (d) examine the effects of restaurant characteristics on the customers' green image, and (e) examine the effects of customers' demographic backgrounds on the green image. The findings corresponding to Phase I research questions are summarized below.

Research Question 1 & 2: What are the salient image categories stored in customers' memory who visited green restaurants, and the image categories frequently mentioned by the green restaurant customers?

As a result of implementing Structural topic model to discover the customers' green image categories stored in memory, 49 interpretable topics emerged. In terms of the number of topics and topic weights, the topics related to customers' cognitive and affective evaluation of the specific restaurant attributes outweighed the topics related to the overall evaluation of the restaurant. The results indicated that cognitive and affective images were more prevalent than overall or holistic impressions in the green restaurant customers' memory. Topic 1 (good food, service, & atmosphere) had the highest topic proportion, meaning that many customers recalled multiple restaurant attributes together. The number of topics regarding food quality and the sum of the weight of these topics was the highest among core restaurant attributes (i.e., food, service, atmosphere, and value). Also, two topics related to green practices (i.e., local/organic ingredient [T10] and vegetarian/healthy option [T37]) were discovered. The topic proportions of local/organic ingredient and vegetarian/healthy option were 21st and 28th highest among 49 topics, which accounted for 3.7% of the entire topics.

Research Question 3: What are similarities and differences between the image categories discovered from UGC and findings of the previous research?

The topics relevant to four core restaurant attributes (i.e., food, service, atmosphere, and value) emerged. The number of topics related to food quality and the sum of these topic weights were the highest, which may indicate that the food quality was the most important factor in restaurant image (Ryu, Lee, & Kim, 2012). However, some of the restaurant attributes (e.g., employees’ attire or facility layout) that have been used in the previous research did not appear as a topic, indicating that these attributes were less memorable or accessible at the moment of writing an online review. Also, this study found a topic related to accommodation for diet restrictions (T14), which has not been considered in previous studies.

Research Question 4: What are the effects of green restaurant certification on the customers’ green image?

With a factorial MANCOVA, the effects of the formal green certification participation on the customers’ green perceptions have been explored. The customers of the certified green restaurants, which attained higher GRA certification rating scores and participated in the certification for a longer period, recalled the green topics more than those who visited the restaurants with lower GRA certification scores for a shorter period.

Research Question 5: What are the effects of the customers’ demographic backgrounds on the green image?

A factorial MANCOVA also examined the effects of the customers’ demographic characteristics on the green image. Female customers talked more about the vegetarian/healthy option than male customers. The significant main effect of age and the interaction effect of age and gender were not found.

Phase II: Exploration of a green restaurant image network structure

Phase II of this the current study aimed to understand the green image network structure based on the associative network model (Anderson, 1983) and to explore the image dimensions (Keller, 1993). The specific objectives were to (a) visualize green image network structures that represent the memory structure encoded in customers' memory, (b) identify the characteristics of the higher- and lower-level green image networks, and (3) examine the dimensions of image associations (i.e., types, favorability, and strength). The findings corresponding to Phase II research questions are summarized below.

Research Question 1: How can the green image network structures that represent the memory structure be visualized?

This study explored topic-level image networks to understand how the higher-level image categories are organized and how people retrieve image categories (Figure 6.2). A topic-level network structure was built based on topic proportion correlation matrix generated by STM. A community detection algorithm was applied to group the image categories that are semantically related. Two green topics (i.e., local/organic ingredient [T10], vegetarian/healthy option [T37]) were clustered together into group 6 along with two other topics (i.e., menu selections [T12], dietary restriction [T14]).

In addition, the green image networks were visualized with the online reviews including green attributes based on the co-occurrence of the unique words, and the size of image nodes was determined by the centrality score (Figure 6.3). In the green image network, image nodes relevant to food-focused green attributes (e.g., food, local, and fresh) played an important role in terms of frequency and centrality.

Research Question 2: What are the characteristics of the higher- and lower-level green image networks?

When exploring the topic-level image network and the green image network, the following network statistics were identified: average degree, network diameter, graph density, modularity, average clustering coefficients, and average path length. In the case of the topic-level image network, 51 topic nodes were connected with 173 edges. Each topic node was linked to an average of seven other nodes and approximately 13% of nodes were interconnected. Additionally, the topic nodes were separated by an average of three degrees from each other, and all nodes were connected within seven degrees. In the green image network, 300 image nodes (i.e., image associations) were linked with more than 6,000 edges. On average, one image node was linked with 41 other image nodes. The image network was sparse because only 14% of the image nodes were linked with each other. The image nodes are separated by two degrees from another node, and the longest path between the two pairs of the nodes was three degrees.

Research Question 3: What is the strength of image associations that estimates the likelihood of the specific attributes to be recalled?

Based on the eigenvector centrality scores, this study identified the influential image categories and the image associations that may be retrieved easily and spread to others quickly. Then, the image categories and the image associations were classified into core, semi-periphery, and periphery retrieval classifications. In the topic-level image network, there were two core image categories (i.e., customer satisfaction [T44] and good flavor [T5]), indicating these positive topics may be recalled easily among green restaurant customers. Among 17 semi-periphery image categories, the majority of them addressed customers' appraisal of the common restaurant attributes (e.g., good service [T32 & T38] and good flavor [T50]) or overall evaluation (e.g., positive experience [T51], satisfaction [T4]). Similar to core image categories, semi-periphery image categories were about the positive evaluation of the restaurant attributes or the overall experience. There were 32 periphery image categories, outnumbering the core and semi-periphery categories. Compared to the core and semi-periphery categories, periphery categories tended to be more objective descriptions about the restaurant attributes (e.g., building [T36], location [T47]) or unique attributes that may be specialized in the green restaurants (e.g., local/organic ingredients [T10], vegetarian/healthy options [T37]).

When evaluating a green image network built with UGC which had high green topic proportion, *food*, *fresh*, *good*, *great*, and *local* appeared as core image associations. Additionally, 94 semi-periphery and 201 periphery image associations were revealed. Unlike core image associations, these semi-periphery and periphery mage associations were too diverse to characterize at the network level. Several image associations related to green practices were identified as follows with indication of retrieval classifications: (1) local/organic ingredients (e.g., local [core], organic [semi-periphery], farm [semi-periphery], and farmer [semi-periphery]) and (2) vegetarian/healthy options (i.e., healthy [semi-periphery], vegan [semi-periphery], vegetarian [semi-periphery], veggie [semi-periphery], and vegetable [semi-periphery]). The image associations relevant to food-focused green attributes had relatively high centrality scores. Although there were image associations regarding environment-focused green attributes (e.g., environment, eco, recycled), they had low centrality scores and belonged to the periphery retrieval classification.

Research Question 4: What are the types of image associations (i.e., cognitive and affective) in the green image network?

In the green image network, the image associations describing the objective and descriptive features were labeled as *cognitive* and the subjective evaluations as *affective* (Echtner & Ritchie, 1993). Some cognitive image associations related to food-focused green attributes (e.g., local, organic, and vegetarian) found to be influential in terms of the strength of image associations. The majority of affective image associations contained positive sentiments (e.g., good, interesting, and pleasant), indicating the customers' positive appraisals of the green attributes.

Research Question 5: What is the degree of favorability of image associations that indicate the customers' emotional connections with the specific attributes?

Favorability of image associations was determined by sentiment and emotion analysis under IBM Natural Language Understanding (NLU). NLU extracts sentiment (-1: very negative to +1: very positive) and emotion scores for five emotion categories (i.e., sadness, joy, fear, disgust, and anger). Sentiment analysis indicated the positive sentiment for both the overall image network and the key green image associations with the sentiment score higher than 0.99. According to the emotion analysis result, the scores on joy were the highest among the five emotion categories. The results indicated that customers who recognized the green practices tended to have a positive sentiment and emotion about their overall experiences. Moreover, they evaluated the specific restaurant attributes very positively.

Implications

Theoretical implications

In the phase I of this study, the salient image categories stored in green restaurant customers' memory were discovered. Under the attribute-based perspective, a green image is determined based on customer assessments of green practices distinguished from other restaurant operations (Chen, 2008; Namkung & Jang, 2013). However, the category-based perspective suggests that people engage in implicit processing using the existing categories due to limited cognitive capacity (Fiske, 1984). Based on the category-based perspective, it is required to first identify whether customers perceive the green attributes to be relevant to their general restaurant image (Keaveney & Hunt, 1992).

In addition, the effects of external stimuli (i.e., green restaurant certification information) and the demographics on green image were explored. The green restaurant certification information may represent the degree of administration-focused green practices, which refer to operators' efforts to participate in green certifications and train employees (Kwok, Huang, & Hu, 2016). Considering external (physical) stimuli may contribute to cognitive image formation (Gartner, 1994), it is important to examine the type or extent of specific aspects that facilitate the processing of information by customers to form long-term images. Also, personal factors, such as demographics, may affect their preferences and assessment of the information and experiences that they are exposed to and ultimately influence their cognitive and affective images (Baloglu, 2000).

Based on the associative network theory (Anderson, 1983), Phase II of this study conceptualized the green restaurant image structure stored in people's memory, including both higher-level image categories and lower-level image associations. The configuration of the green image network showed the relationships between the lower-level image associations belonging to the green practice-related image categories. Specifically, this study tested the three features of the green image network (i.e., types, strength, and favorability of image associations) using the multiple approaches (Keller, 1993). The types of image associations were identified by characterizing them as either cognitive or affective image components (Baloglu & McCleary, 1999; Gartner, 1994). The findings of this research contribute to the green image research by identifying cognitive and affective image associations and how these associations play different roles in the image formation process and future behavior (Zhang, Fu, Cai, & Lu, 2014).

Methodological implications

Images formed by individuals tend to be context-specific and be largely influenced by personal traits (Zimmer & Golden, 1988). Therefore, it is ideal to use unstructured measurements to discover the unique and holistic features of an image (Keaveney & Hunt, 1992). However, the majority of the previous studies adopted the attribute-based structured measurements due to its efficiency and reproducibility (Echtner & Ritchie, 1993). As an alternative to an attribute-based perspective, which assumes that people are actively involved in processing specific attributes, this study has adopted a category-based perspective to capture green restaurant images held by green restaurant patrons (Fiske et al., 1987; Halkias, 2015).

Most of the previous studies that aimed to understand the green image adopted cross-sectional surveys using predetermined scales (Chen, 2010; Han, Hsu, & Lee, 2009; Jeong, Jang, Day, & Ha, 2014). This study examined the free-recall responses in forms of UGC written by the green restaurant customers to operationalize the green restaurant image grounded on the category-based perspective. By doing so, customers' natural responses and various image elements, including personal options, feeling, and holistic image, were captured (Echtner &

Ritchie, 1991; Keaveney & Hunt, 1992). When the attribute-based measurement items were given to survey respondents, they simply need to decide and answer questions whether or not they have encountered the particular attributes in the past, rather than retrieving relevant information from their memory (Anderson & Bower, 1972). Moreover, most of the survey measurements did not include “do not know” answers, even if some measurement items may be irrelevant to the respondents or difficult to answer (Shoemaker, Eichholz, & Skewes, 2002). Therefore, the measurements may work as a “mold” to force people to answer the attributes regardless of their actual retrieval of image categories or attributes to process the entity (Keaveney & Hunt, 1992).

Also, a generative probabilistic topic model was applied to understand how the green restaurant customers elaborated the external stimuli (i.e., green restaurant practices) and stored them in memory (Griffiths, Chater, Kemp, Perfors, & Tenenbaum, 2010; Griffiths, Steyvers, & Tenenbaum, 2007). It was proposed that the generative process of discovering the topics and the list of semantically coherent words under the topics may correspond to the spreading activation in the memory network (Anderson, 1983; Griffiths & Steyvers, 2002). This study implemented STM to extract the latent topics from UGC (Roberts et al., 2014).

To understand the effectiveness of a free-recall method to capture the customers’ actual image perception, the topics expressed in UGC were compared with the restaurant attributes identified in previous studies, which used structured measurements. The image categories discovered with STM were compared with the restaurant attributes proposed by the previous studies to identify the restaurant attributes customers recognized and discover new categories that previous studies overlooked (Guo, Barnes, & Jia, 2017). Some restaurant attributes were identified in the previous restaurant-quality measurements but did not appear in UGC of this study. The absence of these topics may imply that people were not consciously aware of the relevant aspects or that they did not remember them at the moment of writing UGC.

Grounded on the understanding of human cognition and the probabilistic model, previous studies proposed that the topics model corresponds with the construction of semantic memory (Griffiths et al., 2007; Sanborn, Griffiths, & Navarro, 2010). This study used the topic modeling algorithm to investigate the green restaurant customers' cognitive process and the image stored in customers' memory. In addition, the topic-level image network was drawn to comprehend the spreading activation phenomena among the higher-level cognitive units (Anderson, 1983).

Regarding the strength of image associations, the core-periphery model was tested to comprehend the likelihood of image retrieval depending on the characteristics of the image associations (Lai & Li, 2012). For this purpose, the eigenvector centrality was used as a proxy to estimate the strength of image associations (Wang, Li, & Lai, 2018). Finally, the favorability of the image associations were identified by extracting the sentiment and emotion of the overall image network and the key image associations.

Practical implications

This research also provides the following practical implications for the restaurant industry through insights learned from the UGC. The findings of this study benefit the practitioners by demonstrating which green attributes are well recognized and memorable to the customers. Also, the results uncover the emotional responses toward the green restaurant attributes, which help the restaurateurs understand their performance compared to the customers' demands. For example, the number of online reviews containing environment-focused green practices was significantly lower than food-focused green practices, suggesting the low visibility of or low interest in environment-focused green practices. Therefore, restaurateurs, who choose to implement environment-focused green practices, should promote their engagement in green practices, such as recycling or composting using various media or through employee training.

Although the restaurateurs implemented green practices (e.g., serving sustainable foods), the effectiveness of green practices on customers' image perceptions or willingness to share their experiences may not last long. The decrease in customers' interests in green practices over time may be attributed to the fact that the customers get used to green practices and no longer perceive them as something new. To remind the customers of the green practices, managers may use new advertising visuals or campaigns that attract the customers' attention.

Also, restaurants may highlight the psychological benefits gained through consuming green foods in their marketing communications. The customers who recognize the local sourcing often advocate for local community support or a healthy lifestyle. In other words, the cognitive image shaped based on experiencing the green restaurant practices may lead to an affective restaurant image formation. To accomplish such an impact, restaurants serving local ingredient may use photos or marketing materials to attract customers who are concerned about their personal health or the welfare of the local community, which in turn may create positive emotions. In addition, green restaurants that serve vegetarian or healthy menu options may target female customers who tend to be more interested in such practices than male customers. Managers may develop marketing plans or menu options that appeal to female customers.

The findings from Phase II of this study may provide implications on how restaurant operations can influence their customers to build a positive company image by understanding the recallable image stored in their customers' mind (Echtner & Ritchie, 1993). The types of cognitive green image associations identified the specific restaurant attributes that the customers recognized, evaluated, and remembered when they recalled their experiences. For the green attribute image associations, food-related green attributes were more recallable than the environment-focused green attributes. Hence, the restaurateurs may promote the highly visible green attributes in their marketing strategy (i.e., food-focused green practices) or improve the visibility of the green attributes less salient to the customers (i.e., environment-focused green practices).

While the food-focused green image associations were clustered to create a subgroup, the environment-focused green image associations were not clustered into a distinctive subgroup. These results imply that the environment-focused green image associations were not independently recalled. Therefore, restaurant managers who engaged green restaurant practices may highlight the multiple aspects of the green attributes together, so that easily recallable green attributes can spread to less visible attributes forming a stronger green image.

The unique image associations relevant to the green attribute were identified mostly as cognitive associations. Emotional responses to the green restaurant attributes serve as antecedents of customer satisfaction, revisit intention, or willingness to pay more (Chen, 2010; Lee, Hsu, Han, & Kim, 2010). Thus, the green restaurant managers may attempt to elicit affective responses when promoting green attributes, rather than highlighting the objective features of green attributes (Zhang et al., 2014). For example, a restaurateur, who promotes the locally sourced ingredients, may highlight the emotional benefits of consuming locally-sourced products by focusing on creating warm feelings of helping the local community.

Limitation and Suggestions for Future Research

This study has several limitations. Even though big data analytics is a powerful tool to gain insights from post-visit UGC, this study relied on TripAdvisor as a single data source. Therefore, customer sentiments that may have been shared offline or in other online platforms were not included in the dataset. Future research may consider analyzing multiple sources, such as online reviews from multiple social media platforms or unstructured texts gathered from the traditional qualitative methods (e.g., open-ended survey or in-depth interview).

Since this study explored only GRA certified green restaurants, which actively engage green practices in their operations, the results may not be directly applicable to restaurants with low engagement in sustainable activities. Including non-green restaurants in future research design may improve the ability to compare customers' green perceptions and their impact on attitudes in certified green and non-certified restaurants.

To examine the effects of customers' demographics on green perceptions, the reviewers' demographics found in TripAdvisor were utilized. However, only about 40% of reviewers disclosed their demographic information, and therefore, the results of the study need to be interpreted with caution.

Another limitation of using online reviews is about the credibility of data. Some operations hire a marketing company to have more positive reviews for them or write the negative online reviews to ruin the reputation of the competitors (Luca & Zervas, 2016). To address this issue, machine learning algorithms to detect fake reviews can be applied in the future study (Mukherjee, Liu, & Glance, 2012).

Finally, the extant studies have focused on customer perspectives toward green practices, but research incorporating the perspectives of restaurant managers or employees is limited. Therefore, future research may evaluate restaurateurs' or employees' engagement in sustainable restaurant practices as antecedent variables of customers' green perceptions in restaurant operation.

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Appendix A - Kansas State University IRB Approval

KANSAS STATE UNIVERSITY | University Research Compliance Office

TO: Dr. Junehee Kwon
Hospitality Management
108 Justin Hall

Proposal Number: 9527

FROM: Rick Scheidt, Chair
Committee on Research Involving Human Subjects

DATE: 11/09/2018

RE: Proposal Entitled, "Exploring customers' perceptions toward green restaurants using user-generated content"

The Committee on Research Involving Human Subjects / Institutional Review Board (IRB) for Kansas State University has reviewed the proposal identified above and has determined that it is EXEMPT from further IRB review. This exemption applies only to the proposal - as written – and currently on file with the IRB. Any change potentially affecting human subjects must be approved by the IRB prior to implementation and may disqualify the proposal from exemption.

Based upon information provided to the IRB, this activity is exempt under the criteria set forth in the Federal Policy for the Protection of Human Subjects, **45 CFR §46.101, paragraph b, category: 4, subsection: .**

Certain research is exempt from the requirements of HHS/OHRP regulations. A determination that research is exempt does not imply that investigators have no ethical responsibilities to subjects in such research; it means only that the regulatory requirements related to IRB review, informed consent, and assurance of compliance do not apply to the research.

Any unanticipated problems involving risk to subjects or to others must be reported immediately to the Chair of the Committee on Research Involving Human Subjects, the University Research Compliance Office, and if the subjects are KSU students, to the Director of the Student Health Center.

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