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Exploring Simultaneous Presentation in Online Restaurant Reviews: An Analysis of Textual and Visual Content

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ABSTRACT

The purpose of this study is to explore the effect of different types of simultaneous presentation (i.e., reviewer information, textual and visual content, and similarity between textual-visual contents) on review usefulness and review enjoyment in online restaurant reviews (ORRs), as they are interrelated yet have rarely been examined together in previous research. By using Latent Dirichlet Allocation (LDA) topic modeling and state-of-the-art machine learning (ML) methodologies, we found that review readability in textual content and salient objects in images in visual content have a significant impact on both review usefulness and review enjoyment. Moreover, similarity between textual-visual contents was found to be a major factor in determining review usefulness but not review enjoyment. As for reviewer information, reputation, expertise, and location of residence, these were found to be significantly related to review enjoyment. This study contributes to the body of knowledge on ORRs and provides valuable implications for general users and managers in the hospitality and tourism industries.

Keywords: Online Restaurant Review, Simultaneous Presentation, Image Mining, Topic Modeling, Machine Learning

Ⅰ. Introduction

With the boom of the hospitality and tourism industries, online reviews have become an essential, objective, and reliable way to evaluate intangible products and services before consumption (Korfiatis et al., 2012; Lee and Lee, 2016). Review content is considered to be the essence of online reviews, and how review content is presented could change an individual's perception of the product and the usefulness of the review (Xu et al., 2015). In particular, with the rise of 'smart tourism,' as individuals are

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becoming more dependent on the newest developments in information and communications technology (ICT), using features provided by online review platforms and posting visual content have become influential trends (Gretzel et al., 2015; Lin et al., 2012). Along with these trends, online restaurant review (ORR) platforms such as Yelp.com have recently gained popularity as an experience exchange platform, allowing consumers to share information and knowledge in various forms, such as through textual (i.e., review text) and visual contents (i.e., images), and make their own decisions based on these contents as well as on reviewer information. These textual and visual contents and reviewer information are all presented simultaneously to readers online as stimuli to attract attention and gain more votes for review usefulness and enjoyment.

The purpose of our research is therefore to find out which type(s) of presentation forms of ORRs matter when aiming to increase the numbers of usefulness and enjoyment votes among all the simultaneous presentation forms, including the similarity between textual and visual contents. Academically, previous studies have found that various forms of simultaneous presentation partially influence review usefulness and enjoyment in online reviews. For example, Vu et al. (2019) investigated text contents related to dining preference for cuisine popularity; Jabr et al. (2018) examined reviewer information, such as gender, age, and residence of the reviewer; and Lin et al. (2012) focused on the images of reviews. However, a comprehensive examination of all the forms of simultaneous presentation has not yet been conducted, especially not with a focus on visual content in spite of the fact that image mining techniques have become a tool to automatically extract meaning and explore the implicit knowledge hidden within image data (Hsu et al., 2002). Moreover, although we did find a few attempts by previous research to measure content similarity (e.g., Shin et al., 2016), the similarity between textual-visual contents in the context of ORRs using both text mining and image mining techniques has not yet been examined.

The adage that we eat with our eyes first describes vividly the value of images in ORRs. Visual content can therefore be considered 'a feast for the eyes' as they pique consumer interests and make a strong impact on consumer choices. It has been shown that with only textual information, individuals are inclined to remember only 10 percent of the content they see; however, if a relevant image is paired with a textual description, 65 percent or more of the information is processed and retained (Mawhinney, 2019). We therefore argue that while textual content is a necessity in ORRs, the combination of textual and visual contents makes reviews more engaging. Additionally, readers of online review have developed a pattern of information processing in which they do not read every detail of a review; instead, they focus only on details that they assume are interesting and useful. Similarity between textual-visual contents can thus be considered a powerful tool for content evaluation, as it makes the process of determining the content of reviews more efficient.

An all-inclusive examination of all the forms of simultaneous presentation as well as the similarity between textual-visual contents using both text mining (i.e., topic modeling) and image mining (i.e., Google Vision Application Programming Interface (API)) techniques to extract semantic meanings from textual and visual contents has not been conducted in the context of ORRs. Therefore, the results of analyzing simultaneous presentation forms in ORRs will provide significant theoretical implications for topic modeling, image mining, and content similarity of ORRs and will provide practical implications for reviewers and general users of online review platforms as well as managers of restaurants and online review platforms in the hospitality and tourism industries.

Ⅱ. Literature Review

2.1. Online Restaurant Reviews and Simultaneous Presentation Forms

The content of online reviews is presented simultaneously to readers, and all forms of presentations can affect their decisions regarding whether review content is useful or enjoyable. We therefore believe that considering a single presentation form may lead to a biased conclusion on how online reviews are perceived by readers. Although previous studies have examined parts of presentation forms in the context of ORRs, the majority of them are limited to one or two types of forms, and a comprehensive overview and examination have not yet been conducted (see <Appendix>).

In particular, many studies have focused on one of the most obvious simultaneous presentation forms, i.e., *textual content* (referred to as *Type 1* in this study), as the fundamental function of ORRs is to help gather related information about restaurant experiences from other customers (Jeong and Jang, 2011). To name a few, De Pelsmacker et al. (2018) examined text valence, Li et al. (2018a) focused on text with temporal, explanatory, and sensory cues, and Vu et al. (2019) investigated text contents related to dining preference.

On the other hand, a small number of researchers have focused solely on the other simultaneous presentation form, *reviewer information* (referred to as *Type 2* in this study) such as the gender, age, and residence of the reviewer (Jabr et al., 2018), as this information provides 'source effects' in conducting persuasive communication (Janis and Hovland, 1959).

Recently, more researchers have paid attention to identifying *both textual content and reviewer information* (referred to as *Type 3* in this study), as the combination of these two contents is believed to be the key form of simultaneous presentation. For instance, Filieri et al. (2018) found that two-sided review contents and reviewer expertise are considered helpful in service evaluation; Hwang et al. (2018) investigated the impact of dialecticism (contradictory information) and reviewer expertise on decision discomfort; and Zhang and Lin (2018) used review content, reviewer engagement, and reviewer reputation to predict review helpfulness in multilingual textual contents.

These studies found that both textual content and reviewer information are two forms of simultaneous presentation that are significantly related to how ORRs are processed and evaluated. However, the fact that many restaurant experiences are shared not only through related text descriptions but also through images of the food, drinks, or the restaurant environment cannot be neglected (Yang et al., 2017b). Therefore, this study focuses not only on textual content and reviewer information but also on visual content, which has been studied relatively less in the context of ORRs.

2.2. Online Restaurant Reviews and Image Mining

Visual content (e.g., photos and images) can be defined as the pictorial presentation of certain products or services (Kim and Lennon, 2008). Visual content is presented simultaneously to the readers in the form of pictures associated with review texts in ORRs. More recently, image mining techniques have recently been employed in the study of ORRs, and several studies have investigated the effects of visual content. We believe that visual content is as persuasive as textual content, as pictures can be used to support review trustworthiness and reveal real restaurant experiences that are gathered from knowledge and/or observation from the dining experiences (Filieri, 2016; Jeong and Jang, 2011). For example, Lin et al. (2012) initiated by focusing on only *visual content* (referred to as *Type 4* in this study), arguing that the presence of images itself improves ratings of message quality, credibility, consumer interest, and purchase intention.

In response to the trend of more visual information being uploaded on ORRs to share experiences and emotions (Lin and Huang, 2006), several researchers have tried to *combine both textual and visual content* (referred to as *Type 5* in this study). To name a few, Karimi and Wang (2017) examined the impact of both review depth, rating valence, and equivocality together with reviewer profile image on review helpfulness; Nazlan et al. (2018) found that text and star ratings produce higher visit intentions as a whole and that consumers are prone to choose a menu item with images if ratings are presented in numerical instead of star rating format. Yang et al. (2017a) combined review length and review readability with images of the physical environment, food, and beverages, confirming that the imagery format has a positive relationship with review enjoyment.

Moreover, one step further has been taken to explore the similarity between textual and visual contents by considering the meaning of the visual content. Shin et al. (2016) studied text/tags, images, and the similarity between textual and visual contents on Tumblr. Therefore, we categorize this kind of hybrid study that includes *Type 5* (i.e., *Type 1* and *Type 4*) and *Type 1 * Type 4* (i.e., similarity between textual-visual contents) as *Type 6* in our study.

Facilitated by image mining techniques, these studies have expanded from the study of *Type 1* (i.e., *textual content only*), *Type 2* (i.e., *reviewer information only*), and *Type 3* (i.e., *Type 1* + *Type 2*), to the study of *visual content*, which are referred to as *Type 4* (i.e., *visual content only*), *Type 5* (i.e., *Type 1* + *Type 4*), and *Type 6* (i.e., *Type 5* + *Type 1 * Type 4*) (see Appendix). As a comprehensive study of all the types above have not been done, we intend to explore not only textual content and reviewer information, but also visual content using an image mining technique in order to further expand our examination by including the meaning of pictures and the degree of similarity between the visual content and the textual content. It is especially worth studying in the context of ORRs, where readers rely on both the textual and visual contents, along with reviewer information for their restaurant evaluation.

2.3. Topic Modeling and LDA

Topic modeling is a salient tool to investigate user opinions as well as identify and follow topical trends (Nikolenko et al., 2017). It has been used in various fields of study including online reviews, product sales performance analyses (Li et al., 2019), sentiment classifications (Hu et al., 2019), recommendation systems construction (Cho et al., 2015), movie revenue prediction (Cho et al., 2014), and customer complaint analyses for online tourist reviews (Ren and Hong, 2017). As for the context of ORRs in particular, Park et al. (2018) used topic modeling to discover the pattern of word appearances among various topics, and Gan et al. (2017) used it to study sentiments about food and service.

Latent Dirichlet Allocation (LDA) modeling, one of the most common and popular methods of topic modeling, follows a probabilistic procedure that links parameters in documents by a hierarchical generative model (Bagheri et al., 2014). Chen et al. (2015) employed LDA modeling to visualize sentiments in online hotel reviews, Guo et al. (2017) used it to extract meaning from online reviews, and Xiang et al. (2017) used it to extract topics from three platforms of online hotel reviews. Although such studies highlighted the vital role of topic modeling, especially LDA modeling, we found that the majority of them used LDA in topic modeling for textual analysis but did not use it to extract keywords and compare them with the visual content. Additionally, most of the extant research has focused on online tourist reviews, especially online hotel reviews, while online restaurant reviews have received relatively little attention, which underscores the importance of this study.

2.4. Review Usefulness and Review Enjoyment

Perceived usefulness is considered to be a kind of extrinsic motivation, while enjoyment is considered to be a kind of intrinsic motivation, and both usefulness and enjoyment are used in the process of review information (Davis et al., 1992; Park and Nicolau, 2015). Usefulness can be defined as the instrumental value of information that can directly influence behavioral intention (Davis et al., 1992), while enjoyment can be defined as the intrinsic motivation that can affect post-behavioral intentions (Yoo and Gretzel, 2008). Extant research has consistently examined review usefulness and enjoyment since Davis et al. (1992) found out that both usefulness and enjoyment are influential factors for behavioral intention. To name a few, Venkatesh (2000) proved that enjoyment can have an effect on usefulness through ease of use, and Wang et al. (2012) examined the antecedents of enjoyment when using blogging websites.

In the context of ORRs, Liu and Park (2015) found that review enjoyment serves as a determinant of review usefulness, and Yang et al. (2017a) investigated the effect of both textual and imagery cues on review usefulness and review enjoyment. However, to the best of our knowledge, the question of how all the types of simultaneous presentation (i.e., reviewer information, textual content, visual content, and similarity between textual-visual contents) influence review usefulness and enjoyment has not yet been examined. Additionally, how similarity between textual-visual contents influences review usefulness and enjoyment is an open empirical question for the specific context of ORRs. We therefore do not propose formal hypotheses for testing; instead, we allow the propositions resulting from this exploratory study to provide some guidance for future empirical studies on the impact of textual and visual content and the similarity between them on ORRs (Lee et al., 2017).

Ⅲ. Research Methodology

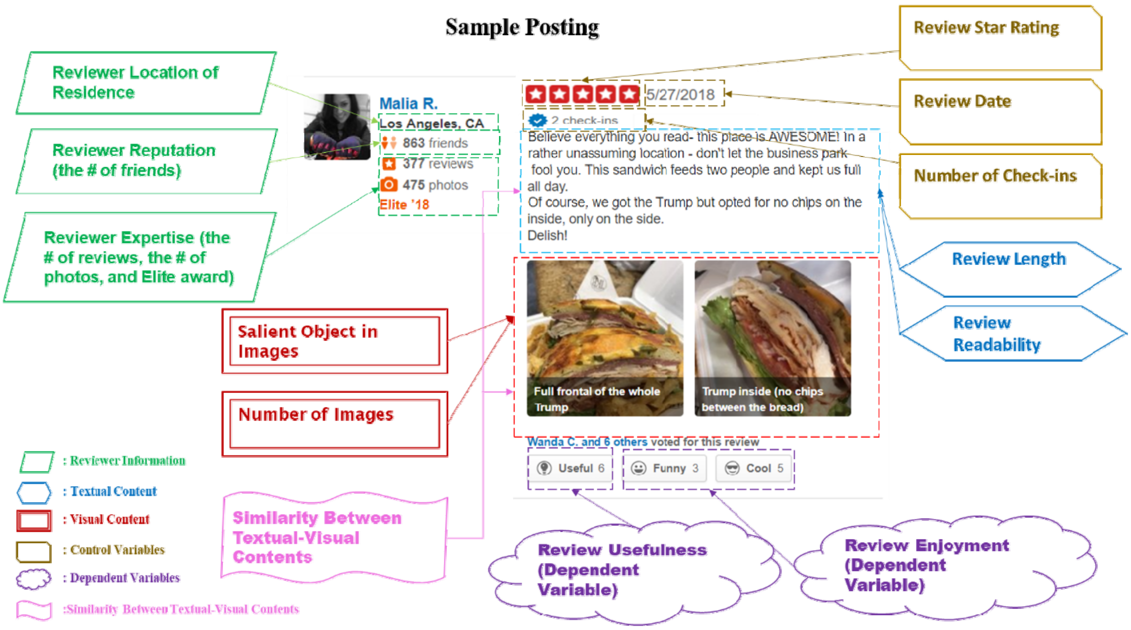
3.1. Data Source and Data Sampling

Our data were collected from the list of Yelp's 'Top 100 Places to Eat for 2018 in the U.S.'. Yelp.com was chosen as the data source as it is a dominant source of ORRs (Luca, 2016). Yelp provides more than 171 million cumulative reviews in almost every type of business, such as restaurants, dentists, and beauty salons as of Quarter 3, 2018, among which 30 million reviews are ORRs, providing a sufficient and representative data pool (Singh and Woo, 2019; Yelp, 2018). Moreover, Yelp has a spam filtering system that is capable of blocking advertisements and unrelated content, resulting in a relatively reliable target population (Li et al., 2018b). In addition, a larger number of user-generated images and photos are also found on Yelp compared to other popular review websites, which provides a large amount of visual content for the process of image mining (Reiley, 2015).

Yelp's 'Top 100 Places to Eat in the U.S.' list is published every year by selecting the most popular and highly-rated restaurants across the U.S., and both quality and popularity are taken into consideration (Leary, 2018). Data were collected from the top-ranking restaurant from the list for the following two reasons. First, the top-ranking restaurant can be regarded as a representation of restaurants with high levels of popularity, credibility, and quality (Huang et al., 2015). Second, the top-ranking restaurant is likely to generate more reviews, as it can be considered one of the most popular search items on Yelp (Chevalier and Mayzlin, 2006). Therefore, the top-ranking restaurant obviously signals a large quantity of reviews, which guarantees a representative and appropriate sample with reliability and validity (Yang et al., 2017a). Ultimately, we selected a total of 2,121 ORRs from the top-ranking restaurant on Yelp's 'Top 100 Places to Eat for 2018 in the U.S.' list on January, 2019, among which 185 have images in the review content.

3.2. Measurement and Operationalization of Variables

A sample ORR posted on Yelp, which includes reviewer information, textual content, visual content, similarity between textual-visual contents, review usefulness, review enjoyment, and control variables, is shown in <Figure 1>. The operational definitions and measurement methods of the variables are shown in <Table 1>, and two examples of the measurement of similarity between textual-visual contents are



<Figure 1> The Illustration of Variables in an ORR

<Table 1> Operational Definitions and Measurements of Variables

	Variable	Operational Definition	Measurement	Reference(s)
Reviewer Information	Reviewer Reputation	The extent of how socially identified and validated a reviewer is on Yelp.com	The number of friends a reviewer has	Cialdini (2001); Racherla and Friske (2012)
	Reviewer Expertise	The extent of competence and knowledge that a reviewer holds regarding restaurants	The total number of reviews, photos, and Elite awards a reviewer has	Forman et al. (2008); Racherla and Friske (2012); Weiss et al. (2008)
	Reviewer Location of Residence	The extent of how close a reviewer lives to the city where the restaurant is located	0: local 1: non-local	Liu and Park (2015)
Textual Content	Review Length	The degree of how long a review is	The number of total words in a review	Korfiatis et al. (2012)
	Review Readability	The extent of how well a review is understood by readers	The Dale-Chall readability score calculated in a review	Korfiatis et al. (2012)
Visual Content	Salient Objects in Images	The extent of how many objects are noticeable enough to pop up from the surroundings in the pictures	The average number of salient objects from all the images in a review	Shin et al. (2016)
	Number of Images	The extent of how many pictures are included in each review	The total number of pictures in a review	Cheng and Ho (2015)
Similarity Between Textual-visual Contents		The extent of how consistent and similar the textual and visual content is to each other	Cosine similarity score between Google Vision API predicted image labels and topic words extracted from the review texts using LDA	Shin et al. (2016)
Dependent Variables	Review Usefulness	The degree of how beneficial a review is perceived to be	The number of total useful votes in a review	Ghose and Ipeirotis (2011)
	Review Enjoyment	The degree of how appealing a review is perceived to be	The summated numeric total of both funny and cool votes for a review	Liu and Park (2015)
Control Variables	Review Star Rating	The degree to which a review is evaluated numerically by a reviewer	The star rating (1-5) given by a reviewer for a review	Mudambi and Schuff (2010)
	Review Date	The degree of the day of the month and year when a review is written	The date associated with a review	Gu and Ye (2014)
	Number of Check-ins	The degree of how often a reviewer has visited the restaurant that he/she reviews	The number of check-ins provided by a reviewer for a review	Banerjee et al. (2017)

shown in detail in <Table 2>.

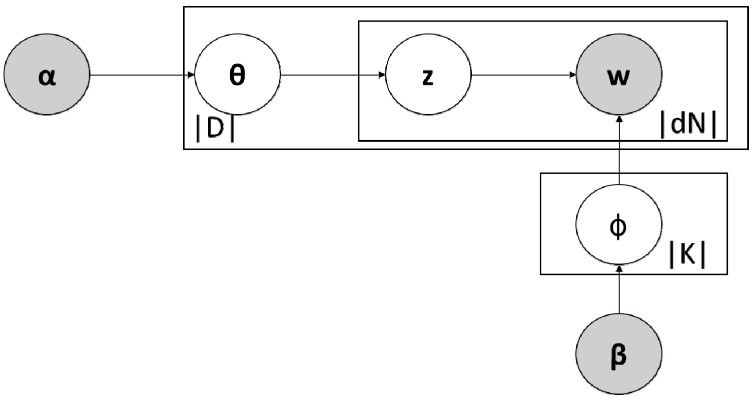
Two dependent variables (i.e., review usefulness and enjoyment) were measured by the number of votes on 'useful' and 'funny and cool' (Ghose and Ipeirotis, 2011; Liu and Park, 2015). For reviewer information, reviewer expertise was measured by the total number of reviews, photos, and Elite awards a reviewer has. Reviewer location of residence, for which 0 is local and 1 is non-local, was measured using Liu and Park (2015)'s two levels of distance between the reviewer and the destination.

For textual content, review length was measured by the number of total words in each review, and review readability was measured by Dale-Chall's readability score calculated in each review (Korfiatis et al., 2012). As for visual content, salient objects in images were measured by the average number of salient objects from the images in each review, and the number of images was measured by the total number of pictures in each review (Cheng and Ho, 2015; Shin et al., 2016). Additionally, similarity between textual-visual contents was measured by the cosine similarity score between image labels predicted by Google Vision API and the topic words extracted from the review texts using LDA (Latent Dirichlet Allocation) topic modeling method (Shin et al., 2016). We also use review star rating, review date, and number of check-ins as our control variables.

3.3. LDA Topic Modeling

To measure the similarity between textual-visual contents, we adopted three steps: (1) use unsupervised learning (LDA topic modeling) to collect keywords from review texts, (2) collect predicted labels in the images using machine learning (ML) models provided by Google Vision API, and (3) calculate the cosine similarity score between the extracted keywords and the predicted image labels.

In the first step, we employed the Latent Dirichlet Allocation (LDA) topic modeling approach proposed by Blei et al. (2003). LDA model topic modeling is a generative probabilistic model used to collect discrete text data and discover topics through posterior inference (Blei et al., 2003). <Figure 2> shows the graphical model representation of LDA, which is a three-level (document-topic-word) hierarchical Bayesian model that belongs to unsupervised learning (Louvigné et al., 2018). This approach has been widely applied to extract latent topics from large amounts of documents (e.g., Singh et al., 2014; Tirunillai and Tellis, 2014), and in our research, LDA provides the best estimation of similarity in the text topics and is therefore used for the purpose of topic divergence maximization (Louvigné et al., 2018). By using the LDA topic modeling approach, keyword



Where α and β: the parameters of the Dirichlet prior distributions, K: the number of topics, D: the number of documents, N: the vocabulary size in the documents, W_{dn}: the nth word in the dth document, Z_{dn}: the topic allocation for W_{dn}, the topic distribution $\theta_d = [\theta_{d1}, \cdots, \theta_{dK}]$: a multinomial distribution over the K topics for the dth document, the word distribution $\phi k = [\phi k1, \cdots, \phi kN]$: a multinomial distribution over N vocabulary words for the kth topic (Louvigné et al., 2018)

<Figure 2> A Graphical Model Representation of LDA (Blei et al., 2003)

sets from review texts are automatically constructed as output for analysis (Shin et al., 2016).

The principle of LDA modeling is to allocate words from separate and multiple reviews into a single new document by assigning a probability to words, and a new topic consisting of highly related co-occurring topic words is generated as a result (Mou et al., 2019). The process of generating a new document is described below:

(1) For each review, choose the topic distribution θ_r ~ Dirichlet (∂)
(2) For each word W_{Nd} in the review r
  (a) Choose a topic Z_{Nr} ~ Multinomial (θ_r)
  (b) Choose a word W_{Nr} from p ($W_{Nr}|Z_{Nr}$, β) (i.e., $\Phi_{r,N}$)

LDA modeling has a document collection layer, document layer, and word layer (Fu et al., 2013). Two Dirichlet priors α and β are used to determine the document-topic distribution θ and the topic-word distribution Φ under the assumption that both θ and Φ follow multinomial distribution (Mou et al., 2019). In order to estimate parameters for θ and Φ, the most commonly used approaches for approximate inference are Gibbs Sampling and Variational Inference (Blei et al., 2003; Griffiths and Steyvers, 2004). After determining the model parameters, the posterior probability of a given document d regarding the latent topic θ can be defined as the followings (see Equations (1) and (2)) (Fu et al., 2013):

$$p(\theta, \mathbf{z}|\mathbf{w}, \alpha, \beta) = \frac{p(\theta, \mathbf{z}, \mathbf{w}|\alpha, \beta)}{p(\mathbf{w}|\alpha, \beta)} \tag{1}$$

where

$$p(\theta, \mathbf{z}|\mathbf{w}, \alpha, \beta) = p(\theta|\alpha) \prod_{i=1}^{N_d} p(z_i|\theta) p(w_i\,|z_i, \beta) \text{ and}$$
$$p(\mathbf{w}|\alpha, \beta) = \int p(\theta|\alpha) (\prod_{i=1}^{N_d} \sum_{z_i} p(z_i\,|\theta) p(w_i|z_i, \beta) d_\theta \tag{2}$$

P ($w|\alpha$, β) in Eq. (1) represents the probability of the extracted word, and the probability indicates the relative importance of each word in a single topic. The higher the probability is, the more relevant the word is to the topic (Mou et al., 2019).

3.4. Similarity Between Textual-Visual Contents

For the second step in measuring the similarity between textual-visual contents, we collected predicted labels in images using ML models provided by Google Vision API, which has been recently used for image detection and classification (e.g., Hyam, 2017; Vossen et al., 2018). Google Vision API is an image classification service that was launched by Google in 2016, and AutoML Vision Beta in Google Vision API is an image classification algorithm that has been developed by large training sets (Cloud Vision API, 2019; Hyam, 2017). It classifies pictures into thousands of categories, detects objects in pictures, and generates lists of labels, such as 'sandwich,' 'burger,' and 'appetizer' (Cloud Vision API, 2019). Despite the fact that the size of the total label pool is not published, it is estimated to be dynamic, and we encountered thousands of labels in Google Vision API in the course of this study (Hyam, 2017).

In the last step, we measured the similarity between the two contents. Measuring the similarity between the two different kinds of contents was not a simple task, as a consistent representation needed to be employed in the process, but was made possible by ML technique for both textual and visual contents in the first and second steps (Shin et al., 2016). Specifically, we calculated the cosine similarity score between textual content (i.e., extracted keywords) and visual content (i.e., predicted image labels). We measured the similarity of post i as the cosine similarity between c_i and c_i^{avg} (see Equation (3)).

<Table 2> Examples of Similarity between Textual-visual Contents

Image		
Google Vision API predicted image labels	drink, wine glass, stemware, alcoholic beverage, tableware, red wine, cocktail, bar, glass	crowd, communication, event, conversation, fun
Keywords extracted from the review texts using LDA	mussels, wine, staff, place, energy, décor, red, glass, bartenders	service, food, line, trip
Similarity score	0.512	0.032

Similarity between textual-visual content

$$= \frac{c_i^T * c_i^{avg}}{||c_i^T|| * ||c_i^{avg}||} \quad (3)$$

As a detailed demonstration, we compare two example pictures from our sample data in <Table 2>. The first example (left) has a higher similarity score as there are several overlapping words between the Google Vision API predicted image labels and the keywords extracted from the review texts, such as 'glass' and 'wine,' while the second example (right) has a lower similarity score for the Google Vision API predicted image labels and does not contain the words from the texts (Shin et al., 2016).

Ⅳ. Data Analysis and Results

4.1. Data Analysis Procedure

The data were collected using a web crawling technique of Python, and the collected data were analyzed using negative binomial regression analysis. The reasons for using negative binominal regression analysis were twofold. First, a large quantity of reviews received 0 usefulness and/or enjoyment votes, and the distribution therefore did not follow normal distribution, making linear regression unfit for this study. Second, a count data model was used, as both usefulness and enjoyment are count variables and as the Poisson regression model is a reliable count data model, it was assumed that both review usefulness and enjoyment would follow a Poisson distribution (Fang et al., 2016). Poisson regression, however, requires that the mean be equal to the variance (Fang et al., 2016), while the mean of our dependent variables was smaller than the variance ($Mean_{usefulness} = 0.77$, $Variance_{usefulness} = 1.970$; $Mean_{enjoyment} = 2.85$, $Variance_{enjoyment} = 102.086$). The extended model of Poisson regression, i.e., negative binomial regression, was therefore applied in this study (see Equation (4)).

$$P(Y = y_i|x) = \frac{\Gamma(\theta+y_i)}{\Gamma(1+y_i)\Gamma(\theta)} r_i^{y_i}(1-r_i)^{\theta}$$
$$\lambda_i = \exp(x_i'\beta), r_i = \lambda_i/(\theta+\lambda_i) \quad (4)$$

Where x_i represents a vector of independent variables, and β represents a vector of parameters to be estimated.

4.2. Results

A correlation analysis and multi-collinearity test were taken before the empirical test, and the results are shown in <Table 3>. The results of the correlation analysis are acceptable as all the correlations are lower than 0.90 (Tabachnick and Fidell, 2007). The variance inflation factor (VIF) values were calculated to check multi-collinearity, and based on the threshold suggested by Schroeder et al. (1990), the multi-collinearity problem did not exist in this study as the VIF values were all smaller than 5.

Model 1 shows the relationship between the controlled variables and the two dependent variables (i.e., review usefulness and review enjoyment). The controlled variables include review star rating, review date, and number of check-ins. The results indicate that without main independent variables, only the review date is significantly related to usefulness (see <Table 4>). Model 2 includes all the variables, and it can be seen that review date, review readability, salient objects in images, and similarity between textual-visual contents have a positive relationship with review usefulness. In addition, review enjoyment, reviewer reputation, reviewer expertise, reviewer location of residence, review readability, and salient objects in images have a positive relationship with review enjoyment. It can be seen that review readability and salient objects in images have a significant positive relationship to both dependent variables and

<Table 3> Correlations, Multi-collinearities, and Descriptive statistics (n = 185)

	1	2	3	4	5	6	7	8	9	10	11	12	13	VIF
RSR	1													1.275
RD	-.189*	1												1.204
NC	.047	-.287**	1											1.346
RRP	-.101	.050	-.054	1										1.751
REP	.119	-.016	-.039	.352**	1									1.006
RLR	.183*	.058	-.077	.083	.160	1								1.585
RL	-.213**	.115	.018	.293**	.131	.084	1							1.440
RRD	.033	.084	-.25**	.136	.178	-.070	.118	1						1.335
SBI	.035	.083	.086	.063	.158	.072	.072	-.070	1					1.714
NI	-.066	.208**	.065	.156*	.385**	-.012	.278**	.046	.581**	1				1.914
SB	.111	-.102	.064	.085	.010	.000	-.032	-.168*	-.104	.033	1			1.393
RU	-.101	.341**	-.090	-.028	-.076	.041	.038	.064	-.098	-.067	-.083	1		1.092
REJ	-.118	.056	-.020	.800**	.356**	.042	.361**	.201**	.151*	.193**	.006	-.039	1	1.887
Mean	4.85	42658	2.04	233.57	1567.3	0.96	121.95	6.74	2.18	1.83	0.089	0.77	2.85	-
SD	0.551	486.54	3.345	493.16	2461.6	0.204	103.34	1.10	2.27	0.880	0.070	1.404	10.104	-

Note: *p < 0.05; **p < 0.01; RSR = Review Star Rating; Review Date = RD; NC = Number of Check-ins; RRP = Reviewer Reputation; REP = Reviewer Expertise; RLR = Reviewer Location of Residence; RL = Review Length; RRD = Review Readability; SBI = Salient Objects in Images; NI = Number of Images; SB = Similarity between Textual-visual Contents; RU = Review Usefulness; REJ = Review Enjoyment

<Table 4> Results of Negative Binomial Regression

	Model 1		Model 2	
	Path Coefficient (Standard Error)		Path Coefficient (Standard Error)	
	Usefulness	Enjoyment	Usefulness	Enjoyment
RSR	0.530 (0.1166)	0.000 (0.0468)	0.278 (0.1533)	0.239 (0.1778)
RD	0.000*** (0.0002)	0.004 (0.001)	0.005** (0.0003)	0.025 (0.0002)
NC	0.557 (0.0563)	0.561 (0.0173)	0.228 (0.1366)	0.377 (.0582)
RRP			0.204 (0.0003)	0.000*** (8.0671E-5)
REP			0.317 (6.5313E-5)	0.000*** (2.2403E-5)
RLR			0.731 (0.0011)	0.000*** (0.0005)
RRD			0.016* (0.1738)	0.001*** (0.1145)
SBI			0.008** (0.0926)	0.000*** (0.0227)
NI			0.425 (0.1981)	0.752 (0.1107)
SB			0.086† (2.0370)	0.894 (1.2600)
Alpha	0.000 (10.0139)	0.032 (4.3610)	0.004 (14.2766)	0.004* (7.2385)
Log Likelihood	-235.914044	-1093.017	-108.909	-213.643
Likelihood-ration test of alpha = 0	62.817 ($p < 0.001$)	69.525 ($p < 0.001$)	36.124 ($p < 0.001$)	404.219 ($p < 0.001$)
Number of Obs.	185	185	185	185

Note: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

that similarity between textual-visual contents was positively related to only review usefulness, not review enjoyment.

Ⅴ. Discussion and Propositions

For textual content, readers of ORRs primarily preferred to use review readability to assess review usefulness, which is consistent with the findings of much research on online reviews. In particular, Korfiatis et al. (2012) found that review readability has a significant impact on review usefulness, Hu et al. (2012) validated the role of review readability by experimental manipulation, and Liu and Park (2015) confirmed it in the context of ORRs.

On the other hand, our results indicated that review length is not used much to estimate review usefulness. This finding is consistent with those of many other studies. For example, Korfiatis et al. (2012) verified that review length has less of an effect on review usefulness than review readability, Yang et al. (2017a) also found that review length holds little importance in comparison with other textual cues, and Xiang et al. (2017) suggested that review length is a weak indicator of review usefulness on Expedia. We thus assume that some readers may shift their attention to other textual content cues, such as review readability, when evaluating online reviews in terms of review usefulness and enjoyment. Thus, based on these results, the following proposition can be assumed:

Proposition 1: Among textual contents, review readability *would play an important role in both review usefulness and review enjoyment.*

Among reviewer information, we found noticeable differences between the factors influencing review usefulness and review enjoyment. Specifically, reviewer reputation, reviewer expertise, and reviewer location of residence are not significantly related to review usefulness, while all of them have a significant positive relationship with review enjoyment. A possible explanation might be that reviewer information disclosure is considered a heuristic cue for message evaluation (Forman et al., 2008), which connects it more closely to review enjoyment, where pleasure and inherent satisfaction are the priority (Park and Nicolau, 2015). On the other hand, for review usefulness, where the utilitarian factor is the main focus, systematic cues, such as review content, are taken into more consideration. Therefore, the following proposition can be assumed:

Proposition 2: Reviewer information would have more of an importance in review enjoyment than review usefulness.

Among visual contents, salient objects in images are significantly related to both review usefulness and review enjoyment. We therefore conclude that salient objects in images would have an important role in both review usefulness and review enjoyment. The reason could be that as salient objects in images encourage eye-fixation on images (Jiang et al., 2013), multiple salient objects can therefore increase the amount of information processed in images while also focusing more attention on the review content (Liu and Han, 2016).

However, our results did not show a significant relationship between the number of images and review usefulness and review enjoyment. A possible explanation might be that due to information overload, readers might not click all the pictures listed in each review; they may click on only the ones that they find useful and/or enjoyable, resulting in whether a review contains one or several images becoming less relevant. Thus, based on these results, the following proposition can be assumed:

Proposition 3: Among visual contents, salient objects in images would have an impact on both review usefulness and review enjoyment.

Similarity between textual-visual contents is only significantly related to review usefulness, not to review enjoyment. We thus argue that similarity between textual-visual contents would have a more important role in review usefulness than review enjoyment. A possible explanation might be that as review enjoyment is related more to hedonic aspects, such as pleasure and inherent satisfaction (Park and Nicolau, 2015), when readers vote for review enjoyment, they focus more on how cool, interesting, and funny the review is; whether the review is consistent and similar between textual and visual contents is not a major consideration. On the contrary, as review usefulness is related more to the instrumental value of the review (Ryan and Deci, 2000), whether the review content has a high similarity between textual-visual contents matters more as they may want to use the provided information for guidance when they actually go to the particular restaurant mentioned in the review. Based on this result, the following proposition can be assumed:

Proposition 4: Similarity between textual-visual contents would have more of an importance in review usefulness than review enjoyment.

Ⅵ. Conclusion and Implications

Theoretically, this study provides implications on topic modeling, image mining, and content similarity of ORRs. To start, topic modeling method has been used to investigate user opinions and to analyze customer complaints, sentiments, and product sales performance based on online reviews. As for the context of ORRs, topic modeling has mostly been used for sentiment and textual analysis, and this is especially the case for LDA modeling, but we furthered the study by using it for the calculation of similarity between textual-visual contents. Despite the fact that topic modeling has been used to extract key words and further compare them to image tags in social media, it has not been employed in the context of ORRs, for which topical trends are vital for restaurant owners and online restaurant review platform managers.

Second, this study contributes to the literature on image mining in ORRs. The reason is that the image labels used in previous research are primarily generated by users themselves through the form of tags on various social media platforms. Consequently, the image mining technique for image label extraction from the semantic content of images has rarely been employed, especially in the context of ORRs. This study extracted image labels from the content of images by employing image mining technique of Google Vision API, a more advanced ML model than self-developed models, which dramatically increased the validity of our findings.

Third, the way in which we compared the similarity between textual-visual contents in ORRs was innovative. Even though the concept of content similarity has been examined by extant studies, these were done in the other contexts, such as social media, leaving the context of ORRs uninvestigated. Moreover, this study is the first to use both text mining (i.e., LDA topic modeling) and image mining (i.e., Google Vision API) methods to extract keywords from textual and visual contents, allowing for a more rigorous data collection methodology.

This study also provides several practical implications. First, reviewers can increase the numbers of review usefulness and enjoyment votes with the help of our findings. Based on our findings, review readability in textual content and salient objects in images in visual content are significant elements for both review usefulness and review enjoyment. If reviewers want to increase the numbers of usefulness and enjoyment votes for their reviews, they need to write their reviews in a way that is easy to understand and try to include multiple salient objects in their pictures. Moreover, our findings also imply that for more usefulness votes, reviewers should consider ways to increase the similarity between their textual-visual contents so that people find the content more consistent and relevant. As for increasing the number of enjoyment votes, more reviewer information can be disclosed, such as their location of residence, in order to associate more expertise with one's reputation and gain trust.

Second, general users of online review platforms can search review information more efficiently by referring to the similarity between textual-visual contents investigated in this study. Particularly in the era of information overload, readers may not look through all the text and pictures in every review; instead, they may use the similarity between textual-visual contents as a tool to decide whether or not the review is useful. That is, when online review readers browse one particular review among hundreds of thousands, they may tend to first scan the textual content and then check the images that pique their interests, and if both the contents are interesting and consistent with each other, they would consider the review worth reading and further decide whether the review is useful or enjoyable. A result of this pattern of information processing highlights the importance of the similarity between textual-visual contents, and this is especially the case for ORRs, where the adage that we eat first with our eyes prevails. Thus, the similarity between textual-visual contents highlighted in this study will help general users of online review platforms find useful content more effectively.

Third, managers of restaurants could benefit from our findings by starting to pay more attention to providing an environment that encourages consumers to post high quality pictures of food, as images can give readers a more concrete picture of the food offered and allow for the focal information to be evaluated more effectively (Yang et al., 2017a). Images can also help curb consumers' uncertainties about certain types of cuisine with which they are not familiar as well as the need to guess about the restaurant atmosphere or environment. The reviews will attract more long-term interest, and readers will be able to experience the feelings of being in the restaurant without ever having to leave their home.

Lastly, our findings have important implications for managers of online review platforms, such as Yelp.com. If managers provide incentives to encourage users to develop image-posting behaviors (especially images with multiple salient objects) and increase the consistency and similarity between their texts and images, their platforms would benefit and gain higher web traffic. For instance, 'Yelpers,' who join Yelp activities and leave reviews, can be encouraged to post more images and increase the similarity between their textual-visual contents, awards of 'the most popular posting' can be given using community coins, and votes for 'the most impressively consistent contents' can also be initiated to increase the enthusiastic participation on online review platforms.

Four limitations were identified in this study but leave room for future research. First, our data were collected from ORRs on Yelp.com, but whether our findings can be generalized to other online review platforms, such as TripAdvisor, is not confirmed. Thus, further empirical studies should gather data from various online review websites and aim to provide more diverse implications. Second, only the top-ranking restaurant from Yelp's 'Top 100 Places to Eat in the U.S.' was used for empirical analysis, and even though the internal validity of this study was secured, future studies should use a larger number of restaurants to increase the generalizability of our findings. Third, we employed the concept of cosine similarity to measure the similarity between textual-visual contents, but different measurements of similarity scores should be used in future studies for further validation. Fourth, salient objects in images were manually coded to measure visual content, but more up-to-date ML methods should be used in future studies.

Disclosure statement

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<References>

[1] Bagheri, A., Saraee, M., and De Jong, F. (2014). ADM-LDA: An aspect detection model based on topic modelling using the structure of review sentences. *Journal of Information Science, 40*(5), 621-636.

[2] Banerjee, S., Bhattacharyya, S., and Bose, I. (2017). Whose online reviews to trust? Understanding reviewer trustworthiness and its impact on business. *Decision Support Systems, 96*, 17-26.

[3] Blei, D. M., Ng, A. Y., and Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research, 3*, 993-1022.

[4] Chen, Y. S., Chen, L. H., and Takama, Y. (2015). Proposal of LDA-based sentiment visualization of hotel reviews. *IEEE International Conference on Data Mining Workshop (ICDMW) Proceeding*, 687-693.

[5] Cheng, Y. H., and Ho, H. Y. (2015). Social influence's impact on reader perceptions of online reviews. *Journal of Business Research, 68*(4), 883-887.

[6] Chevalier, J. A., and Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research, 43*(3), 345-354.

[7] Cho, S. Y., Choi, J. E., Lee, K. H., and Kim, H. W. (2015). An online review mining approach to a recommendation system. *Information Systems Review, 17*(3), 95-111.

[8] Cho, S. Y., Kim, H. K., Kim, B. S., and Kim, H. W. (2014). Predicting movie revenue by online review mining: Using the opening week online review. *Information Systems Review, 16*(3), 111-132.

[9] Cialdini, R. B. (2001). Harnessing the science of persuasion. *Harvard Business Review, 79*(9), 72-81.

[10] Cloud Vision API (2019). *Cloud vision.* [1] Retrieved from https://cloud.google.com/vision/Accessed 20 18.1.20.

[11] Davis, F. D., Bagozzi, R. P., and Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology, 22*(14), 1111-1132.

[12] De Pelsmacker, P., Dens, N., and Kolomiiets, A. (2018). The impact of text valence, star rating and rated usefulness in online reviews. *International Journal of Advertising, 37*(3), 340-359.

[13] Fang, B., Ye, Q., Kucukusta, D., and Law, R. (2016). Analysis of the perceived value of online tourism reviews: Influence of readability and reviewer characteristics. *Tourism Management, 52*, 498-506.

[14] Filieri, R. (2016). What makes an online consumer review trustworthy? *Annals of Tourism Research, 58*, 46-64.

[15] Filieri, R., McLeay, F., Tsui, B., and Lin, Z. (2018). Consumer perceptions of information helpfulness and determinants of purchase intention in online consumer reviews of services. *Information & Management, 55*(8), 956-970.

[16] Forman, C., Ghose, A., and Wiesenfeld, B. (2008). Examining the relationship between reviews and sales: The role of reviewer identity disclosure in electronic markets. *Information Systems Research, 19*(3), 291-313.

[17] Fu, X., Guo, L., Yanyan, G., and Zhiqiang, W. (2013). Multi-aspect sentiment analysis for Chinese online social reviews based on topic modeling and HowNet Lexicon. *Knowledge-Based Systems, 37*, 186-195.

[18] Gan, Q., Ferns, B. H., Yu, Y., and Jin, L. (2017). A text mining and multidimensional sentiment analysis of online restaurant reviews. *Journal of Quality Assurance in Hospitality & Tourism, 18*(4), 465-492.

[19] Ghose, A., and Ipeirotis, P. G. (2011). Estimating the helpfulness and economic impact of product reviews: Mining text and reviewer characteristics. *IEEE Transactions on Knowledge and Data Engineering, 23*(10), 1498-1512.

[20] Gretzel, U., Sigala, M., Xiang, Z., and Koo, C. (2015). Smart tourism: Foundations and developments. *Electronic Markets, 25*(3), 179-188.

[21] Griffiths, T. L., and Steyvers, M. (2004). Finding scientific topics. *The National Academy of Sciences of the United States of America Proceedings, 101*(suppl

1), 5228-5235.
[22] Gu, B., and Ye, Q. (2014). First step in social media: Measuring the influence of online management responses on customer satisfaction. *Production and Operations Management, 23*(4), 570-582.
[23] Guo, Y., Barnes, S. J., and Jia, Q. (2017). Mining meaning from online ratings and reviews: Tourist satisfaction analysis using Latent Dirichlet allocation. *Tourism Management, 59*, 467-483.
[24] Hsu, W., Lee, M. L., and Zhang, J. (2002). Image mining: Trends and developments. *Journal of Intelligent Information Systems, 19*(1), 7-23.
[25] Hu, N., Bose, I., Koh, N. S., and Liu, L. (2012). Manipulation of online reviews: An analysis of ratings, readability, and sentiments. *Decision Support Systems, 52*(3), 674-684.
[26] Hu, N., Zhang, T., Gao, B., and Bose, I. (2019). What do hotel customers complain about? Text analysis using structural topic model. *Tourism Management, 72*, 417-426.
[27] Huang, A. H., Chen, K., Yen, D. C., and Tran, T. P. (2015). A study of factors that contribute to online review helpfulness. *Computers in Human Behavior, 48*, 17-27.
[28] Hwang, Y., Choi, S., and Mattila, A. S. (2018). The role of dialecticism and reviewer expertise in consumer responses to mixed reviews. *International Journal of Hospitality Management, 69*, 49-55.
[29] Hyam, R. (2017). Automated image sampling and classification can be used to explore perceived naturalness of urban spaces. *PloS One, 12*(1), e0169357.
[30] Jabr, W., Qi, Z., Lohtia, R., and Guillory, M. D. (2018). The influence of information display and availability on reviewer usefulness status. *The proceedings of Americas Conference on Information Systems (AMCIS)*, 14-24.
[31] Janis, I., and Hovland, C. (1959). *Personality and persuasibility*. New Haven: Yale University Press, CT.
[32] Jeong, E., and Jang, S. S. (2011). Restaurant experiences triggering positive electronic word-of-mouth (eWOM) motivations. *International Journal of Hospitality Management, 30*(2), 356-366.
[33] Jiang, H., Wang, J., Yuan, Z., Wu, Y., Zheng, N., and Li, S. (2013). Salient object detection: A discriminative regional feature integration approach. In *Conference On Computer Vision and Pattern Recognition, IEEE*, 2083-2090.
[34] Karimi, S., and Wang, F. (2017). Online review helpfulness: Impact of reviewer profile image. *Decision Support Systems, 96*, 39-48.
[35] Kim, M., and Lennon, S. (2008). The effects of visual and verbal information on attitudes and purchase intentions in internet shopping. *Psychology & Marketing, 25*(2), 146-178.
[36] Korfiatis, N., GarcíA-Bariocanal, E., and SáNchez-Alonso, S. (2012). Evaluating content quality and helpfulness of online product reviews: The interplay of review helpfulness vs. review content. *Electronic Commerce Research and Applications, 11*(3), 205-217.
[37] Leary, B. (2018). *Yelp's top 100 places to eat for 2018*. Retrieved from https://www.yelpblog.com/2018/02/yelps-top-100-places-to-eat-for-2018/Accessed 2018.1.25.
[38] Lee, D., Gopal, A., and Lee, D. (2017). *Micro-Giving: On the use of mobile devices and monetary subsidies in charitable giving*. Available at SSRN 3280553.
[39] Lee, J., and Lee, H. J. (2016). Your expectation matters when you read online consumer reviews: The review extremity and the escalated confirmation effect. *Asia Pacific Journal of Information Systems, 26*(3), 449-476.
[40] Li, H., Wang, C. R., Meng, F., and Zhang, Z. (2018a). Making restaurant reviews useful and/or enjoyable? The impacts of temporal, explanatory, and sensory cues. *International Journal of Hospitality Management*. Online Publication.
[41] Li, L., Lee, K. Y., and Yang, S.-B. (2018b). Exploring the effect of heuristic factors on the popularity of user-curated 'Best places to visit' recommendations in an online travel community. *Information Processing & Management*. Online Publication.
[42] Li, X., Wu, C., and Mai, F. (2019). The effect of

online reviews on product sales: A joint sentiment-topic analysis. *Information & Management, 56*(2), 172-184.
[43] Lin, T. M., Lu, K. Y., and Wu, J. J. (2012). The effects of visual information in eWOM communication. *Journal of Research in Interactive Marketing, 6*(1), 7-26.
[44] Lin, Y. S., and Huang, J. Y. (2006). Internet blogs as a tourism marketing medium: A case study. *Journal of Business Research, 59*(10-11), 1201-1205.
[45] Liu, N., and Han, J. (2016). Dhsnet: Deep hierarchical saliency network for salient object detection. In *Conference on Computer Vision and Pattern Recognition, IEEE*, 678-686.
[46] Liu, Z., and Park, S. (2015). What makes a useful online review? Implication for travel product websites. *Tourism Management, 47*, 140-151.
[47] Louvigné, S., Uto, M., Kato, Y., and Ishii, T. (2018). Social constructivist approach of motivation: social media messages recommendation system. *Behaviormetrika, 45*(1), 133-155.
[48] Luca, M. (2016). Reviews, reputation, and revenue: The case of Yelp.com.
[49] Mawhinney, J. (2019). 45 Visual content marketing statistics you should know in 2019. Retrieved from https://blog.hubspot.com/marketing/visual-content-marketingstrategy#sm.0001sdcqnoj0qf67xfy1llpmev7v2/Accessed 2019.3.19.
[50] Mou, J., Ren, G., Qin, C., and Kurcz, K. (2019). Understanding the topics of export cross-border e-commerce consumers feedback: an LDA approach. *Electronic Commerce Research*, 1-29.
[51] Mudambi, S. M., and Schuff, D. (2010). Research note: What makes a helpful online review? A study of customer reviews on Amazon. com. *MIS Quarterly, 34*(1), 185-200.
[52] Nazlan, N. H., Tanford, S., and Montgomery, R. (2018). The effect of availability heuristics in online consumer reviews. *Journal of Consumer Behaviour, 17*(5), 449-460.
[53] Nikolenko, S. I., Koltcov, S. and Koltsova, O. (2017). Topic modelling for qualitative studies. *Journal of Information Science, 43*(1), 88-102.
[54] Park, E., Chae, B., and Kwon, J. (2018). The structural topic model for online review analysis: Comparison between green and non-green restaurants. *Journal of Hospitality and Tourism Technology*. Online publication.
[55] Park, S., and Nicolau, J. L. (2015). Asymmetric effects of online consumer reviews. *Annals of Tourism Research, 50*, 67-83.
[56] Racherla, P., and Friske, W. (2012). Perceived 'usefulness' of online consumer reviews: An exploratory investigation across three services categories. *Electronic Commerce Research and Applications, 11*(6), 548-559.
[57] Reiley, L. (2015). *Yelp heavy hitters talk about company's growing clout and struggles*. Retrieved from https://www.tampabay.com/things-to-do/consumer/yelp-heavy-hitters-talk-about-companys-growing-clout-and-struggles/2242766/ Accessed 2018.1.15.
[58] Ren, G., and Hong, T. (2017). Investigating online destination images using a topic-based sentiment analysis approach. *Sustainability, 9*(10), 1765.
[59] Ryan, R. M., and Deci, E. L. (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary Educational Psychology, 25*(1), 54-67.
[60] Schroeder, M. A., Lander, J., and Levine-Silverman, S. (1990). Diagnosing and dealing with multicollinearity. *Western Journal of Nursing Research, 12*(2), 175-187.
[61] Shin, D., He, S., Lee, G. M., Whinston, A. B., Cetintas, S., and Lee, K. C. (2016). Content complexity, similarity, and consistency in social media: A deep learning approach. *SSRN Electronic Journal*.
[62] Singh, P. V., Sahoo, N., and Mukhopadhyay, T. (2014). How to attract and retain readers in enterprise blogging? *Information Systems Research, 25*(1), 35-52.
[63] Singh, R., and Woo, J. (2019). Applications of machine learning models on Yelp data. *Asia Pacific Journal of Information Systems, 29*(1), 117-143.
[64] Tabachnick, B. G., and Fidell, L. S. (2007). Multivariate analysis of variance and covariance.

Using Multivariate Statistics, 3, 402-407.
[65] Tirunillai, S., and Tellis, G. J. (2014). Mining marketing meaning from online chatter: Strategic brand analysis of big data using latent dirichlet allocation. *Journal of Marketing Research, 51*(4), 463-479.
[66] Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research, 11*(4), 342-365.
[67] Vossen, P., Caselli, T., and Cybulska, A. (2018). How concrete do we get telling stories? *Topics in Cognitive Science, 10*(3), 621-640.
[68] Vu, H. Q., Li, G., Law, R., and Zhang, Y. (2019). Exploring tourist dining preferences based on restaurant reviews. *Journal of Travel Research, 58*(1), 149-167.
[69] Wang, Y. S., Lin, H. H., and Liao, Y. W. (2012). Investigating the individual difference antecedents of perceived enjoyment in students' use of blogging. *British Journal of Educational Technology, 43*(1), 139-152.
[70] Weiss, A. M., Lurie, N. H., and MacInnis, D. J. (2008). Listening to strangers: whose responses are valuable, how valuable are they, and why? *Journal of Marketing Research, 45*(4), 425-436.
[71] Xiang, Z., Du, Q., Ma, Y., and Fan, W. (2017). A comparative analysis of major online review platforms: Implications for social media analytics in hospitality and tourism. *Tourism Management, 58*, 51-65.
[72] Xu, P., Chen, L., and Santhanam, R. (2015). Will video be the next generation of e-commerce product reviews? Presentation format and the role of product type. *Decision Support Systems, 73*, 85-96.
[73] Yang, S.-B., Hlee, S., Lee, J., and Koo, C. (2017a). An empirical examination of online restaurant reviews on Yelp. com: A dual coding theory perspective. *International Journal of Contemporary Hospitality Management, 29*(2), 817-839.
[74] Yang, S.-B., Shin, S., Joun, Y., and Koo, C. (2017b). Exploring the comparative importance of online hotel reviews' heuristic attributes in review helpfulness: A conjoint analysis approach. *Journal of Travel & Tourism Marketing, 34*(7), 963-985.
[75] Yelp (2018). An Introduction to Yelp Metrics as of September 30, 2018. Retrieved from https://www.yelp.com/factsheet/ Accessed 2018.1.27.
[76] Yoo, K. H., and Gretzel, U. (2008). What motivates consumers to write online travel reviews? *Information Technology & Tourism, 10*(4), 283-295.
[77] Zhang, Y., and Lin, Z. (2018). Predicting the helpfulness of online product reviews: A multilingual approach. *Electronic Commerce Research and Applications, 27*, 1-10.

<Appendix> Summary of Literature on Online Restaurant Reviews Regarding 6 Types of Simultaneous Presentation

Type	Independent variables	Dependent variables	Method	Sample source	Findings	Reference
Type 1: textual contents only	Text valence, star rating, and rated usefulness	Review impression, positive word-of-mouth intention	A 2 × 2 full factorial between-subjects experimental design	The panel of a professional market research agency	More involved and more susceptible individuals have stronger evaluative responses to the effect of review text valence.	De Pelsmacker et al. (2018)
	Text with temporal, explanatory, and sensory cues	Review usefulness and review enjoyment	Text mining approach and econometric analysis	Yelp.com	Text with temporal cues affect review usefulness, explanatory cues have an effect on both review usefulness and review enjoyment. Sensory cues are shown to have a stronger impact on review enjoyment.	Li et al. (2018)
	Text contents related to dining preference	Cuisine popularity	Text processing	TripAdvisor	Tourist dining preferences in cuisine, meal, and restaurant features are analyzed.	Vu et al. (2019)
Type 2: reviewer information only	Reviewer information	Review usefulness	Binomial regression	Yelp and TripAdvisor	Reviewer information is a vital predictor of usefulness, it becomes less significant when reviewers get more status on the platform.	Jabr et al. (2018)
Type 3: Type 1 + Type 2	Text included two-side information + Reviewer expert	Purchase intentions	Questionnaire	Online + travelers at HK airport	Two-sided reviews and reviewer expertise are considered helpful when evaluating service performance and quality.	Filieri et al. (2018)
	Dialecticism (contradictory information) + Reviewer expertise	Decision discomfort	A 3 × 2 × 2 experimental design	229 U.S. consumers and recruited through MTurk	When review contents are written by non-experts, highly dialectical thinkers show similar levels of attitude certainty among univalent and mixed conditions of reviews.	Hwang et al. (2018)
	Review content + Reviewer engagement and reviewer reputation	Review helpfulness	Multilingual review helpfulness prediction model	Multilingual textual contents	Better performance on review helpfulness classification and prediction is achieved by including the variables generated by the proposed instantiated multilingual system.	Zhang and Lin (2018)
Type 4: visual contents only	Images	Ratings of the message quality, blog's credibility, consumers' interest, and purchase intention	A 2 × 2 between-subjects design and a 2 × 4 between-subjects design	155 subjects in a laboratory setting	Blogs that have visual information are significantly higher in the four aspects (i.e., ratings of the message quality, blog credibility, consumer interest, and purchase intention) than identical content without visual information.	Lin et al. (2012)

<Appendix> Summary of Literature on Online Restaurant Reviews Regarding 6 Types of Simultaneous Presentation (Cont.)

Type	Independent variables	Dependent variables	Method	Sample source	Findings	Reference
Type 5: Type 1 + Type 4	Depth, rating valence, and equivocality + Reviewer profile image	Review helpfulness	Heteroscedasticity-consistent regression	Online reviews of mobile gaming applications	Reviewer profile image significantly increases review helpfulness, but no differential effect is found among image types.	Karimi and Wang (2017)
	Text and rating format + Visual cues	Dining intentions and menu item choice	Experiments	210 respondents from an online market research company	Consumers are prone to choose a menu item with images if ratings are in numerical rather than star rating format.	Nazlan et al. (2018)
	Review length and review readability + Physical environment images and food and beverage images	Review usefulness and review enjoyment	Tobit regression model	Yelp.com	Attributes of textual format influence review usefulness, and attributes of imagery format have a positive relationship with review enjoyment.	Yang et al. (2017a)
Type 6: Type 5 + Type 1 * Type 4	Text and tags + Images + Cosine similarity	Engagement (likes and reblogs)	Deep learning approaches	Social media: Tumblr	Complementary textual content, proper visual stimuli (e.g., beautiful images, celebrities, adult-content, etc.), and consistent themes are positively related to engagement.	Shin et al. (2016)

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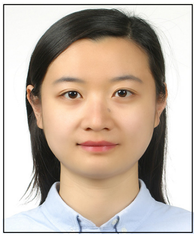

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