International Journal of Hospitality Management 94 (2021) 102801

Contents lists available at ScienceDirect

International Journal of Hospitality Management

journal homepage: www.elsevier.com/locate/ijhm

A picture is worth a thousand words: The role of a cover photograph on a travel agency's online identity

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ARTICLE INFO

Keywords:
Cover photograph
Online travel agencies
Information search
Photograph attributes

ABSTRACT

Online travel agencies (OTAs) allow lodging businesses to select one cover photograph to represent itself on the OTA site. The cover photograph plays a crucial role for attracting customers' attention from among alternatives, and lure viewers to view the webpage with detailed information. The present study investigates how the content of a business' cover photograph on OTAs' sites influences customers' behavior when searching for information. The content of a cover photograph may fall within five categories according to attributes: façade, type of place, room amenities, scenery, and property amenities. Only façade and property amenities have positive impacts on customers' viewing times of the webpages with the detailed information of businesses. In contrast, scenery has a negative influence on customers' viewing times. The results of the study contribute, theoretically and methodologically, to OTAs' knowledge base and can assist practitioners' identification of effective cover photographs.

1. Introduction

The lodging industry increasingly relies on electronic marketing intermediaries, also known as online travel agencies (OTAs) (e.g. Expedia, TripAdvisor, Epinions, Airbnb), to increase customer awareness, to create new demand, and to expand distribution channels (Inversini and Masiero, 2014). According to the research by Phocuswright, OTAs in the U.S. occupied 39% of searches within the digital travel market in 2018 and anticipated reaching 41% by 2020, with $81.4 million for gross online bookings (Phocuswright, 2019). Such a finding particularly addresses the importance of OTAs for the lodging industry since the dominant players are small and medium-sized enterprises (SMEs) like accommodation sharing hosts (e.g. Airbnb) (Baek and Lee, 2018; Dell et al., 2017). Due to limited resources, many small and independent lodging providers do not present themselves through distribution and promotional outlets (e.g., official website) other than OTAs. Consequently, OTAs become the primary and even sole channel for customers to learn about and book accommodations from these businesses (Inversini and Masiero, 2014). The popularity of OTAs has boosted the needs of academic research on the topic of customer behavior on these platforms (Talwar et al., 2020a, 2020b).

Since the majority of lodging providers offer availabilities on the platforms of OTAs, customers could enjoy one-stop-shopping by comparing the alternatives (Chatterjee and Wang, 2012). Through setting the screening criteria based on customers' expectations (e.g., location, price range), customers acquire a search list offered by an OTA. The content relevant to a business, shown in the search list, influence customers' initial impressions of the business. This pre-screening stage for customers assists deciding whether or not to click the webpage of the business for detailed information or for selecting alternatives on OTAs' web pages (Li et al., 2009). During the first 2 s-10 s, customers quickly peruse hotel names, cover photographs, star ratings, inclusive review scores, short descriptions, pricing, and other general information (Fig. 1 illustrates a sample search list on an OTA's site), leaving the search list in 10 s-20 s later (Nielsen and Pernice, 2010). Therefore, a crucial consideration is for a business to attract customers' attention from among the alternatives in only several seconds.

Due to the limited content of a business in the search list on the OTA's site, customers must rely on peripheral cues to accelerate decision of whether or not to click the webpage of the business for detailed information (Gigerenzer and Todd, 1999). As an old saying of "a picture is worth a thousand words", the cover photograph of a business in the search list could assist customers' cognitive process and assist formulating reliable perceptions of the venture (Zhang et al., 2003). Quickly

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https://doi.org/10.1016/j.ijhm.2020.102801
Received 22 May 2020; Received in revised form 6 October 2020; Accepted 24 November 2020
Available online 20 January 2021

developing perceptions is especially important for lodging operations since the core feature of the hospitality industry is intangibility. Services cannot be “felt” prior to patronage, making pricing and advertising services a challenge. To address the challenges related to intangible features, marketing materials often adopt tangible indicators such as photographs to assist customers “experiencing” the service prior to patronage (Jeong and Choi, 2005; Koernig, 2003). For the lodging industry, both first-time and experienced customers depend heavily on photographs on websites for choosing among alternatives and booking accommodations (Negri and Vigolo, 2015).

Although the importance of a cover photograph for a business on OTA has acceptance, to the knowledge of the present authors, no previous academic research has focused on this topic. To initiate the discovery of this novel research theme, a crucial question should be answered first. How does a business design an effective cover photograph? One cover photograph cannot present all the attributes of the lodging facility. Identifying what specific interior or exterior features (e.g., inside environment like pool views, scenery surroundings like mountains) in a cover photograph is pivotal for more effectively sparking customers’ interests and luring them to click the “view” button to learn more detailed information of the lodging option. Answering this critical question is the motivation for the current study.

Analysis of photography for general business, and even narrowly in the hospitality and tourism field, shows significantly less progress as compared to that in anthropology, sociology, and interdisciplinary research (Bell and Davison, 2013; Stepchenkova and Zhan, 2013). These existing studies (e.g., Özdemir, 2010; Van der Molen and Van der Voort, 2000) have primarily investigated the features and impacts of photographs through experiments and surveys/interviews, which generally restrict the number of photographs, not exceeding 3,500 (Deng et al., 2019). However, OTAs offer volumes of photographs from businesses and customers, making the analysis of the massive amount of online visual content impossible without automatic photo assessment techniques from computer science. To the knowledge of the present authors, very sporadic studies have adopted big data analytics to analyze the giant photograph warehouse on OTAs or other types of websites in the hospitality and tourism industry (e.g., Deng et al., 2019; Ma et al., 2018a,2018b). Furthermore, to date, no previous studies adopting big data techniques have given attention to cover photographs of businesses in the search list on OTAs’ sites. The present study aims to fill that gap.

To be more specific, the present study is novel in methodology. This research is a pioneer to adopt a supervised deep-learning approach to identify the content and categorize the themes of pictures in a giant photograph warehouse in the hospitality and tourism field. Specifically, to the knowledge of the present authors, we are the first in this field to combine the pictorial analysis techniques of convolutional neural networking and one hot encoding. We further creatively incorporate “quantitated” picture themes into regression models, which is expected to gain more insights from photography analysis.

The purpose of the present study is to investigate how the content of a business’ cover photograph on the searching list of an OTA influences customers’ searching behavior for information. The specific objectives of the research include: 1) to classify the content of a business’ cover photograph by a facility and environmental features on OTAs’ sites; 2) to examine the influence of a business’ cover photographic content on customers’ viewing times of the webpage of businesses on OTAs webpages. Expectedly, the present study paves a new venue of exploring the enormous photography warehouse theoretically and methodologically in the hospitality and tourism field. “Virtual curation” may advance the knowledge body of third-party websites, and even internet, which is crucial for this field considering the nature of “intangibility”. The results is also expected to assist industry practitioners to select the optimum

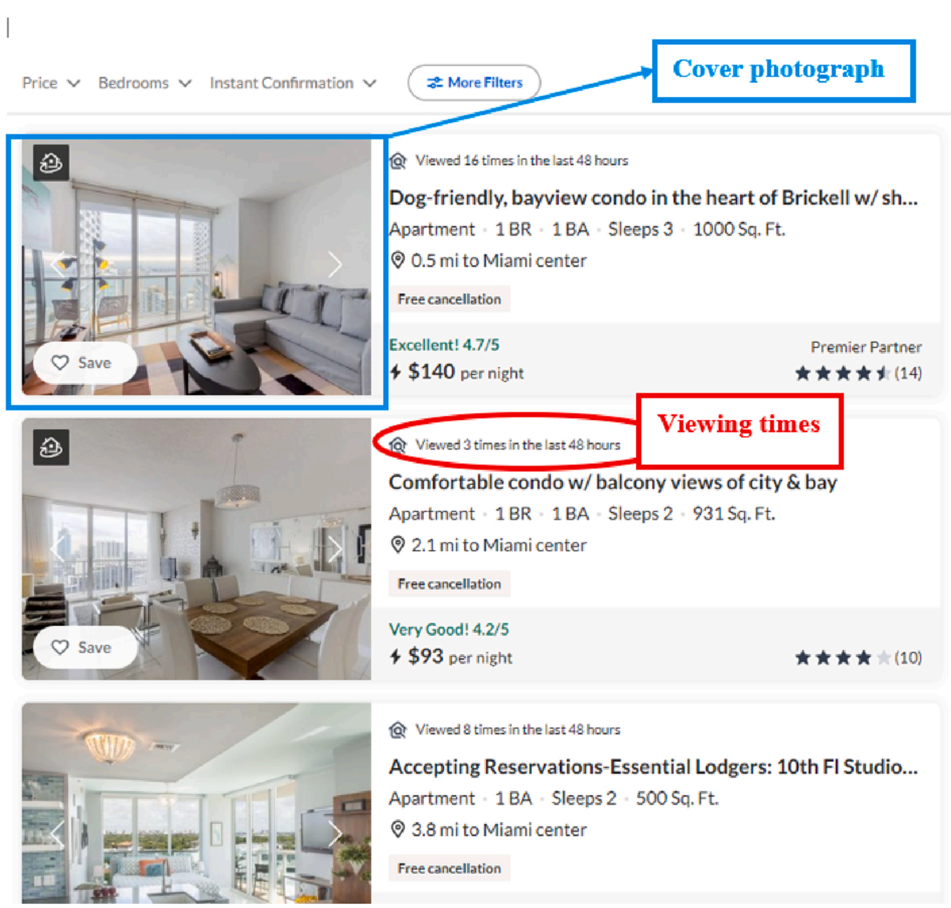


Fig. 1. Sample cover photographs on the search list of OTAs.

cover photograph on the searching list of OTAs, which could further persuade customers to read marketing messages and increase intention to patronize. More broadly, the findings may offer some insights on the identification of cover photographs on brochures, flyers, and other marketing materials.

2. Literature review

2.1. Definition of photographs and its importance

Photographs are one of primary visual stimuli examined in social science (Emmison and Smith, 2000). Visual research originated from the viewpoints of landscape aesthetics as the subdisciplines of visual sociology (e.g., Emmison and Smith, 2000; Harper, 1994) and visual anthropology (Albers and James, 1988; Banks, 1998). Photographs "contain metaphors that may be visual, verbal, mathematical or even musical" (Zaltman, 1997; p. 1039). Textual information (Pink, 2013) and embodied experiences (Bell and Davison, 2013) often accompany photographs. Although photographs cannot directly show the "felt" features of the embodiment (Simpson, 2011), its "descriptive and aesthetic dimensions…together form an equal music of rationality and emotion in their making" (Spencer, 2010; p.202). Therefore, photographs demonstrate multisensory prospects, delivering complicated meanings, and visualizing perceptions. Especially, the importance of photographs has been well documented in the context of social media (e.g., Dhir et al., 2017, 2018; Dhir and Torsheim, 2016).

Different perspectives classify photographic content. Specifically, photographs could be classified by the sources or providers, including those generated by customers (e.g., travelers take photos at attractions), businesses (e.g. a cover photography on the OTAs' sites discussed in the present study), or a mix of business- and customer-generated photographs (e.g., photos on www.pinterest.com) (Shin et al., 2020). Photographs could be either product-based or experience-based. Product-based photographs address tangible components of a service setting, including the physical facilities and touchable offerings. Experience-based photographs feature interactions between customers and providers, which highlight intangible components of service experience (Pullman and Robson, 2007). Customers perceive product-emphasized photographs richer in content than experience-emphasized images (Steinbrück et al., 2002). Cover photographs of lodging businesses on OTAs' webpages are mostly those emphasizing products.

Similar to the classification of product-based and experience-based photographs, analysis of content of visual images could employ two approaches: manifest or latent. Manifest content refers to explicit and observable features in a photograph, recorded with a high level of reliability (Berg, 2004). Manifest content consists denotative meaning explicitly and literally agreed among the majority of people (Riffee et al., 2005). In contrast, latent content describes implicit information embedded in the message (Holsti, 1969). However, the comprehension of meaning embedded in a message may vary from one person to another. The extent of such discrepancy also relies on the nature of the content (Kim and Stepchenkova, 2015). Therefore, the focus of most hospitality-related photographic studies is manifest content (Stepchenkova and Zhan, 2013). Accordingly, the present study examines the manifest content of cover photographs, instead of latent content.

Content analysis evaluate manifest content, allowing a verifiable and replicable approach that decodes the picture into multiple categories, which explicitly reflects and quantitatively summarizes incidences, co-occurrences, and gatherings (Riffee et al., 2005). For example, Garrod (2008) compared postcards of cities and photos taken by visitors in several manifest categories, including attractions, locations, panoramic/close-up, and others. MacKay and Couldwell (2004) contrasted promotional images with photos taken by visitor-employed photos using seven manifest groups (i.e., exterior buildings, interiors of the main house, demonstration of the past way of life, farming equipment, animals, grounds, and people). Jenkins (2003) compared the photos on travel brochures for of backpackers and regular tourists by investigating such manifest aspects as iconic landmarks, landscapes, people, animals, active sports, passive activities, and group fun.

2.2. Studies of photography for hospitality and tourism

The research relevant to photographs has been a niche topic for the hospitality and tourism (Kim and Stepchenkova, 2015; Shin et al., 2020; Stepchenkova and Zhan, 2013). Three streams of inquiry classify four studies as shown in Table 1. The first stream investigates the impact of photographic features in distinct contexts (e.g., OTAs, menus, advertisement, tourism brochures) on customers' attitudes and behaviors. The photographic traits consist of source, content, credibility, aesthetics, number, and others. The methods used were experimental designs and structural equation modeling. Examples of the studies in the first stream are Marder et al. (2019); Shin et al. (2020), and Zhang et al. (2019a, 2019b). Aligning with the first stream, the second stream examines the relationship between photographic design, and customers' attention and preferences (Li et al., 2016; Sivaji et al., 2014; Wang and Sparks, 2016). However, these studies examined the effectiveness of photographic design via "microscope" by measuring eye positions and eye movement. The method used was eye-tracking tests and surveys.

The third stream assesses themes, sentiment, or technical features of photographs (e.g., Garrod, 2008; Nikjoo and Bakhshi, 2019; Jenkins, 2003). The research contexts include Facebook, Flickr, user-generated photos, travel articles, and others. The method employee descriptive analysis, market basket analysis, and content analysis, which limit the number of photos analyzed to less than 2,000. The fourth stream had similar purposes and research contexts to the third stream. However, the research targeted harvesting large-scale data with a big data technique, machine learning, deep learning (e.g., artificial intelligence), and other high-tech tools (e.g., Deng et al., 2019; Ma et al., 2018a,2018b; Zhang et al., 2019a,2019b). User-generated content (e.g., OTAs) includes millions of photos, which renders manual decoding infeasible. Thus, automatic analysis techniques adopted in the fourth stream are crucial for such photographic metadata examined in the present study.

2.3. Impact of photographs

According to the visual rhetoric theory, Scott (1994) indicated that photographs as virtual cues are representative of reality, and thus simplify people's cognitive processing and enable them to imagine the enjoyment of an object. Therefore, an attractive photograph which demonstrates the functional and aesthetic designs of products and services could induce customers' positive attitudes and motivate behaviors (Baek and Ok, 2017). Some studies of hospitality and tourism confirmed the significance of photographs in marketing programs. For example, Walters et al. (2007) indicated that inclusion of photographs that present tourism products and services in travel agencies' advertising could generate more favorable images of a destination and of the prospective travel experience than abstract ones encompassing limited information. Consequently the former is more likely to evoke patronage intention. Jun and Holland (2012) suggested that photographs on hotel's websites, showing favorable room features could induce customers' more positive attitudes toward a brand and motivate booking a room. Kirillova and Chan (2018) also indicated that customers assess hotels with a higher aesthetic value to have better physical facilities, offer optimal service, and show greater conviction. To date, a customer's visual attention to photographs in a variety of marketing channels closely links to strengthening self-identity and recall (Garlick, 2002), building connections (Larsen, 2005), brand choice (Atalay et al., 2012), persuasive capability (Hem et al., 2003), trust and credibility (Tractinsky et al., 2000), and likelihood of patronage (Krajbich et al., 2010). In the same vein, the present study aims to test customers' behavior when searching for information (i.e., "click" the webpage with the detailed information

Table 1
Studies of photography for hospitality and tourism.

Themes	Literature	Context	Methodology	Sample size
1. Investigate the relationship between photographic features, attitudes, and behavior	Shin et al. (2020); Hou et al. (2017); Ma et al. (2018a,2018b); Zhang et al. (2019a,2019b); Smith and Mackay (2001); Marder et al. (2019); Ert et al. (2016); Bufquin et al. (2019); Kuo et al. (2015); Hinton et al. (2013)	online travel agency website (1); menus (2); Advertisement (1); Microcelebrity endorsements (1); Tourism brochures (1); Tripadvisor (1); Airbnb (1); hotel websites (2);	Experiment design (9); Structure equation modeling (1);	100–250 participants (5); 251–400 participants (2); 400–1282 participants (3)
2. Examine the relationship between photographic design, attention, and preference	Wang and Sparks (2016); Li et al. (2020), 2016; Espigares-Jurado et al. (2020); Sivaji et al. (2014)	Tourism Australia's collection of photographic images (1); Tourism photos from unknown sources (1); Advertisement (1); hotel websites (1); hotel website and tripadvisor (1)	Eye-tracking experiment & surveys (5)	14–51 participants (4); 372 participants (1)
3. Assess the themes, sentiment, or technique features of photographs (1)	Deng et al. (2019); Zhang et al. (2019); Kim and Stepchenkova (2015); Ma et al. (2018); Deng and Li (2018); Trpkovski et al. (2018); Trpkovski (2018)	YFCC-100 M, a Flickr metadata set of Yahoo! (2); Flickr profile (1); Yelp and Tripadvisor (1); Individual users (1); Tripadvisor(1)	Big data technique; machine learning, deep learning; AR; regression analysis; sentiment analysis; visual photo content assessment and visual photo quality assessment	4000–10000 photos (2); 20000–40000 photos (4); 1.2 million photos (1);
4. Assess the themes, sentiment, or technique features of photographs (2)	Garrod (2008); Ghaderi and Béal (2020); Matteucci (2013); Mackay and Couldwell (2004); Pullman and Robson (2007), 2006; Nikjoo and Bakhshi (2019); Donaire et al. (2014); Pan et al. (2014); Jenkins (2003); Hsu and Song (2013); Jeong and Choi (2005); Lo (2012)	Tourists provided photos (6) Facebook (1); Flickr (1); "Why we travel" section of The New York Times (1); Tourism brochures (1); Travel articles (1); hotel websites (1);	descriptive analysis; market basket analysis; content analysis;	13–65 respondents (6); 120–203 participants (2); 145–1786 photos (3); 88 travel articles (1); 203 hotel websites (1)

of a business) after checking the cover photograph of a business in the search list on an OTA.

As a follow-up to the discussions in Section 3.1, the distinct features of the manifest content of photographs apparently give customers different perceptions. For example, Saleh and Ryan (1992) suggested that the general appearance of the hotel is more important than the diverse facilities for perceptions of guests at a hotel, especially for those with limited experience. Alfakhri et al. (2018) focused on the importance of hotels' interior designs (e.g., color, lighting, and layout) for creating value for both hoteliers and guests. Accordingly, the present study tests how the distinct features of the manifest content of cover photographs impact the number of "clicks" per webpage with the detailed information of a specific business on the OTA.

3. Method

3.1. Data collection

This research selected www.homeaway.com as the investigation site for two reasons. First, this site is among the top five lodging sharing platforms across the world. Considering that the lodging sharing hosts more rely on OTAs than brand chain hotels for doing businesses, it is urgent to test an OTA which primarily serves for these hosts. Second, this site offers real-time viewing times of any individual listing in the past 48h (see Fig. 1), which is the dependent variable of the present study. Viewing times during a specific period of 48h for any individual business was obtained to measure customers' further information search behavior.

Data were collected during November 10–16, 2018. We selected the lodging businesses from the top five travel destinations in the U.S.: Chicago, New York City, Las Vegas, Los Angeles, and Orlando (Schmalburch, 2017). Initially we collected the cover image, viewing times during in the past 48h, and some other relevant information (i.e., distance to the center of the city, price, grading, and review count) of each listing in the five travel destinations. All the contents of a listing aforementioned were collected synchronously, since any of them was dynamically changing. Excluding sporadic listings which didn't offer viewing times during the past 48h, a total of 18,071 cover photographs (one cover photograph corresponds to one business) were retrieved.

3.2. Data analysis

3.2.1. Step 1. Image feature extraction

Xception is a tool that applies a convolutional neural network (CNN) for image analysis. Xception follows traditional CNN algorithms to investigate the internal structure of image data through convolution layers. Each image inputted was first converted as typical combinations of pixels that represent a range of cognitive features. Subsequently, all these combinations were converted into matrixes, termed as *feature maps*. In the process of running Xception, *feature maps* passed unique separable convolution layers (i.e., process 1×1 convolution first, and then channel-wise spatial convolution), so that the image data was decoded. The parameters of these layers were deep learned during the training process. Next step, the function of maximum pooling was used to filter image data through multiple layers, which calculated the maximum value for each patch of the *feature maps* and then ran rectified linear calculation (i.e., involve nonlinear factors in the CNN since in actual life most of the data in the neural network are nonlinear). The multiple layers were further connected and any object (i.e., identification of an item in a photograph, such as a table, a person, or others) was further converted as multiple computed features represented in the form of the respective scores through the Softmax function. By comparing the probability of each object in different identified features, the one with the highest probability was retained (Fig. 2).

The algorisms, used in the image feature extraction process of Xception discussed above, are demonstrated below by adapting Yang et al. (2019). *Feature maps* were input, and each can be combined to convolve multiple values:

$$x_j^l = f\left(u_j^l\right) \tag{1}$$

$$u_j^l = \sum_{i \epsilon M_j} x_i^{i-1} * k_{ij}^l + b_j^l \tag{2}$$

As shown in Eq. (1), x_j^l denotes the output of the l convolution channel of the j convolutional layer, and u_j^l in Eq. (2) represents the net activation of the l convolutional channel of the j convolutional layer, as convolved and offset by the gradation difference value of the previous layer.

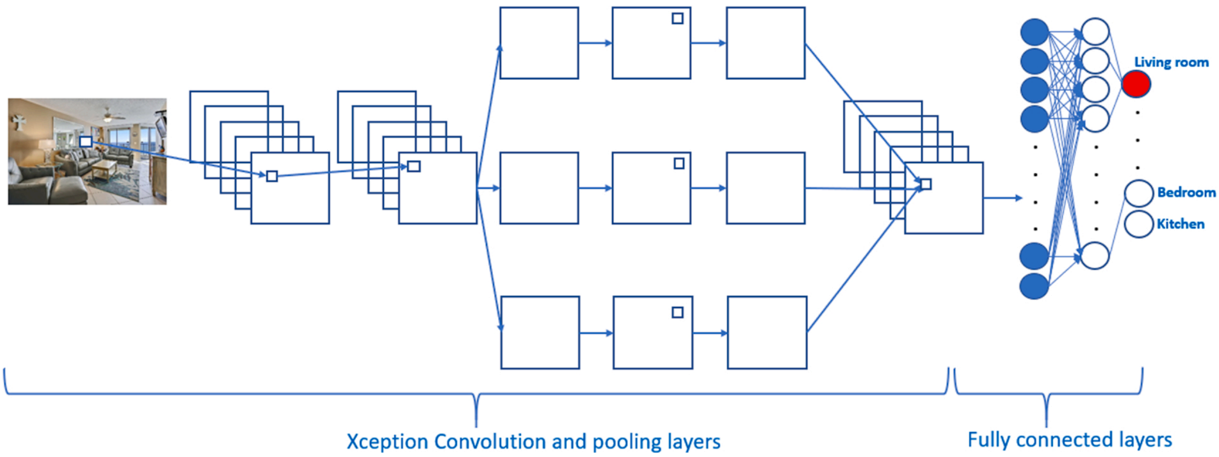


Fig. 2. Flow of Xception analysis.

Subsequently, use the above results as the input of the connection layer in Eqs. (3) and (4).

$$x^l = f(u^l) \tag{3}$$

$$u^l = w^l x^{l-1} + b^l \tag{4}$$

where w^l denotes the weight coefficient of the fully connected layer of layer l, and b^l refers to the threshold offset term.

In the process of image feature extraction described above, the proposed model was trained end-to-end instead of piecewise pre-training of each object (i.e., identification of an item in a photograph, such as a table, a person, or others). The training, test, and validation set were divided into 6:2:2 as advised by previous studies (e.g., Gao et al., 2019; Kim et al., 2019), which are especially applicable for the datasets of 100,000 and lower. The gradient descent approach was employed to adjust the parameters of the training error in the training process suggested by Yang et al. (2019) as shown in Eq. (5):

$$\delta^l = \frac{\partial E}{\partial u^l} \tag{5}$$

where δ^l denotes the squared error function displaying a variation in u^l, and E denotes the diversification square between the expected and practical output.

3.2.2. Step 2. Feature classification

After running the Xception model, we got multiple objects (i.e., identification of an item in a photograph, such as a table, a person, or others) of each cover photograph. One hot algorithm was applied to identify the main content of a photograph using the objects and classify all the photographs into different features using the method of one hot encoding. One hot encoding is a widely used Machine Learning (ML) algorithm which shows satisfactory performance in feature categorization of photography (Potdar et al., 2017).

The proposed models in one hot encoding received a series of encoded objects as input. They were encoded by regulating an alphabet of size m as the input language, and then quantizing respective objects based on the 1-of-m encode process. Subsequently, the series of objects were converted to a range of such m sized vectors. In the current study, the maximum number of objects in each photograph was set as 10. The object quantizing order was backward, so the latest reading on objects was constantly arranged close to the start of the output, which allowed the linked layers to easily correlate weights with the latest reading. The classification of the photographs mentioned above was generated by Uriarte-Arcia et al. (2014) with the following steps:

1. Let $\{x^\mu \mu = 1,\ 2,\ \ldots,\ p\}$ be one group of n-dimension basic inputted patterns achieving practical data inside the relevant parts, classified as m categories.
2. Let $\left\{\hat{y}^1, \hat{y}^2, \ldots, \hat{y}^\mu\right\}$ as one group of translated basic outputted patterns for size p. And respectively translated basic outputted pattern's ith part to receive the coding process in accordance with the expression below:

$$\hat{y}_i^\mu = \begin{cases} 1 & if\ \ i = \mu \\ 0 & otherwise \end{cases} \tag{6}$$

3. Calculating the mean vector $\bar{x}$ as shown in Eq. (7).

$$\bar{x} = \frac{1}{p}\sum_{\mu=1}^{p} x^\mu \tag{7}$$

4. Taking the mean vector as the new origin of the coordinate axes.
5. Converting into novel translated patterns, where a new set of translated patterns were generated using Eq. (8).

$$\hat{x}^\mu = x^\mu - \bar{x} \forall x^\mu \varepsilon \{1, 2, \ldots, p\} \tag{8}$$

3.2.3. Step 3. Negative binomial regression

Viewing times during a period of 48h served as the dependent variable in the data analysis. Similar to many other OTAs, most of the listings received no viewing or booking in a short period of time. Thus, the dataset in the present study was left-skewed distribution (Fig. 3). The negative binomial regression, one model under the extension of the poisson regression, turned out to be proper for our dataset for two reasons (Fang et al., 2016; Wang et al., 2019). First, the negative binomial regression conducts the measuring process more precisely as compared with the poisson regression on the count data under over-dispersion with the inconsistent mean and variance. Second, the negative binomial regression, unlike the multiple regression, is capable of being introduced into the model of count, in which an individual variable receives the counting to be integers that are not negative (Hilbe, 2011).

The features of cover photographs generated in step 1 and step 2 of Section 3.2 were used as the independent variables. Four control variables were used in data analysis, including distance to the center of the city, price, grading, and review counts. Distance to the center of the city shows the business's value of location. Price indicates the money value of the temporal living space. The grading was offered by the OTA measured with 1–5. Review counts measure how many reviews had been left by the reviewers for one listing.

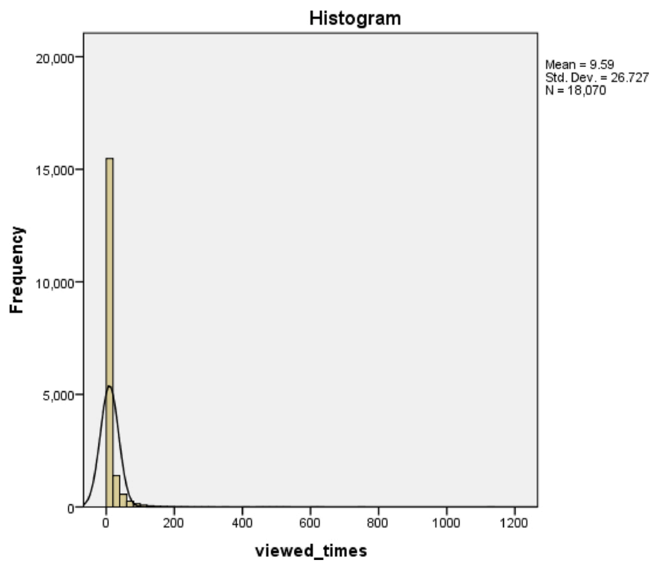


Fig. 3. Histogram of viewing times in the last 48h.

4. Results

4.1. Descriptive analysis

A descriptive summary of all the dependent variable, independent variables, and control variables is presented in Table 2.

4.2. Feature classification

Five features of cover photographs content were generated by following steps 1 and 2 in section 3.2. A total of 101,457 objects in 18,071 photographs were extracted and further five features of these photographs were generated, which are demonstrated in Table 3. After carefully reviewing the photographs classified into each feature group, the five features were labeled as façade, type of place, room amenities, scenery, and property amenities. Specifically, the façade describes the outside appearance of the lodging facility, including the face of a building or the frontage that looks onto a street. The type of place indicates configurations of the dwellings. Examples are composed of single-family houses, townhouses, and apartments. Room amenities are items placed in bedrooms, bathrooms, kitchens, and other inside spaces for the convenience and comfort of guests. Scenery depicts the surrounding natural environment or views from the stand of the lodging space. Property amenities describe items or facilities outside of the rooms that the lodging business provides for the usefulness and ease of guests.

Table 2
Descriptive statistics results of variables.

	Minimum	Maximum	Mean	Std. Deviation
Distance to the center of the city (mile)	.1	31.0	9.21	6.440
Pricing (US$)	0	17,555	456.42	815.493
Grading (1–5 star rating)	0	5	1.94	2.111
Review counts (Number of reviews)	0	275	7.48	17.801
Viewing times (Number of views)	0	1,131	9.59	26.727
Facade	0	1	.19	.389
Type of place	0	1	.18	.381
Room amenities	0	1	.20	.403
Scenery	0	1	.15	.355
Property amenities	0	1	.11	.309

4.3. Negative binomial regression

The multicollinearity test indicated that all the variables were correlated with each other except three pairs (room amenities - price, scenery - room types, room amenities, and viewing times (Table 4). However, the respective variable's variance inflation factor (VIF) had a range from 1.864 to 3.154, lower than the cutoff point of 5 (Hair et al., 1998). Thus, the multicollinearity effect was insignificant. This study then performed the negative binomial regression based on the McFadden's pseudo resulted a r-squared value at 0.138 with the likelihood ratio p-value reached .000. The regression results are presented in Table 5.

In the negative binomial regression model, the control variables were overall indicated to impact viewing times significantly. Distance to center of city ($\beta = -1.008$, p value = .000***), and price ($\beta = -.506$, p value = .000***) had negatively effects on viewing times, while with positive coefficients, grading ($\beta = .424$, p value = .000***) and review counts ($\beta = .367$, p value = .000***) both positively influenced viewing times in the present study. Among the five photograph features as the independent variables, the three of them showed significant impacts on viewing times at the significance level of 0.01. Specifically, façade ($\beta = .015$, p value = .009*), and property amenities ($\beta = .085$, p value = .001**) showed positive impacts on the viewing times, while scenery ($\beta = -.234$, p value = .004**) had negative effect on viewing times. However, room amenities ($\beta = -.035$, p value = .062) and type of places ($\beta = .215$, p value = .038) did not show significant influence on viewing times at .01 significant level.

In the meantime, the robustness check was performed with the linear regression. Since viewing times in 48h did not distribute normally and the minimal data reached "0", the log value (viewing times + 1) was the dependent variable regarding the linear regression in the robustness check. The result was consistent with that generated from the negative binomial regression.

5. Conclusion

The present research pioneers categorizing cover photographic content and examines the relationship between attributes of cover photographic content of a business and further information search behavior on the OTA (i.e., viewing times of the webpage with the detailed information of the business). Specifically, categorizing cover photographic content encompasses façade, type of place, room amenities, scenery, and property amenities. Among the five categories, only the photographs representing façade and property amenities have significantly positive impacts on customers' behavior when searching for information on OTAs.

6. Implications

The present study offers important theoretical contributions from three primary perspectives. First, this research takes a creative supervised deep-learning approach by combining convolutional neural networking (CNN) and one hot encoding to harness the wealthy information in photographs on OTAs. Since the emergence of the Internet, an explosion of researchers' interests of pictorial content for the hospitality and tourism has arisen because cameras can capture significant aspect of travel experiences and encounters. However, due to the deficiency of methodologies, large-scale pictorial content on the Internet cannot be effectively and efficiently analyzed. Despite researchers in computer science having made progress for the methodologies, limited ones have adjusted for the nature features of offerings for the hospitality and tourism. The strategic combination of CNN and one hot encoding in analysis of photography are akin to the mixture of exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) in textual mining analysis (Fabrigar and Wegener, 2011; Reyment and Jvreskog, 1996). The methods we adopted are comprehensible and applicable in analysis

Table 3
Summary of image categories, sample features and random selected photographs for each category.

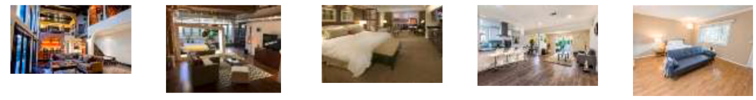
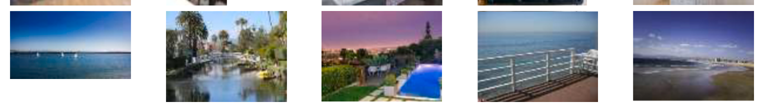
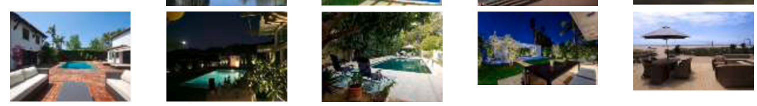
Category	Sample features	
Façade	Townhouse, apartment building, single family house	
Type of Place	Studio, suite, loft apartment	
Room Amenities	Dishwasher; microwave; sofa, dining table	
Scenery	Mountain, lake, dock,	
Property Amenities	Outdoor pool, balcony, outside tennis court	

Table 4
Correlation matrix of variables.

Correlations	1	2	3	4	5	6	7	8	9	10
Distance	1									
Pricing	−.046**	1								
Grading	−.100**	−.071**	1							
Review counts	.400**	.349**	−.097**	1						
Viewing times	−.122**	−.014	.016*	−.028**	1					
Façade	−.008*	.031**	.053**	.020**	−.018*	1				
Type of place	.080**	−.003	.065**	.099**	.011*	−.220**	1			
Room amenities	.107**	−.021**	−.011	.045**	−.006	−.241**	−.233**	1		
Scenery	−.055**	.071**	−.053**	−.003	.035**	−.199**	−.192**	−.211**	1	
Property amenities	−.057**	−.032**	.471**	−.068**	−.019*	−.165**	−.159**	−.175**	−.144**	1

***$p < .001$, ** $p < .005$, *$p < .01$.

Table 5
Results of the negative binomial regression.

	Variables	Estimate	Std. Error	z value	Pr(>|z|)
	(Intercept)	2.444	.895	21.002	.000***
Control variables	Distance	−1.008	.767	6.823	.000***
	Pricing	−.506	.561	4.772	.000***
	Grading	.424	.713	7.592	.000***
	Review counts	.367	.234	2.142	.000***
Independent variables	Façade	.015	.144	6.148	.009*
	Type of place	.215	.027	2.660	.038
	Room amenities	−.035	.144	−1.448	.062
	Scenery	−.234	.051	2.314	.004**
	Property amenities	.085	.131	2.492	.001**

Note: DV = Viewing Times; McFadden's pseudo r-squared value is 0. 138; n = 18,071; p-value of likelihood ratio is .000.
***$p < .001$, ** $p < .005$, *$p < .01$.

of photography in the hospitality and tourism field.

Second, apparently, the present study is the first to employ big data techniques to investigate the relationship between photographic content and customers' behavior. As shown in Table 1, previous studies for hospitality and tourism have dominantly applied surveys/interviews or experimental design to test a limited amount of feedback from customers who reacted to specific photographs. These methods sometimes cause respondents to offer, intuitively, socially sought-after and over-rationalized answers (Decker and Trusov, 2010). However, people's decisions in daily life are the result of limited cognitive effort (Kahneman, 2003). The investigation of massive amounts of real customers' behaviors towards the extensive number of cover photographs in the present study authentically demonstrates the public's decision-making based on experiential, emotional, and instinctive processes. This technique is a closer representation of reality.

Third, the result of the present study adds to the knowledge based involving OTAs. Although OTAs have gained significant attention from the researchers of hospitality and tourism, previous studies have focused on textual reviews (e.g., Cheng and Jin, 2019; Ma et al., 2018a,2018b), pricing mechanism (Cai et al., 2019), and customers' numerical ratings and review helpfulness (Luo and Tang, 2019; Wang et al., 2019). However, photography has generally remained under-explored in the context of OTAs. Especially cover photography of businesses on OTAs' sites as peripheral cues plays a crucial role at the stage of pre-purchase evaluation of alternatives during a customer's decision-making process. The pre-purchase evaluation of alternatives has received only sporadic attention in previous studies that investigate a customer's decision-making process. The present study contributes to this deficit.

The present study also offers important practical implications. First, OTAs could incorporate the findings of the study into guidance on designing photographs for individual lodging businesses. Theories of first impression formation in psychology (e.g., Aronson et al., 2007; Lorenzo et al., 2010) could be used to support our findings and proposed strategies. A first impression is the occurrence or happening when an individual initially encounters a subject (e.g., another person, an item, or a picture of a lodging business) and forms a mental image of the subject (Mackie and Smith, 2007). Impression accuracy may differ significantly upon the observer and the subject being observed (Flora, 2011). The first impression of a subject given to the observer could greatly impact how it is perceived and treated in many settings of everyday life (Aronson et al., 2007). In the case of cover photography, a viewer's first impression generated in several seconds help him/her make the decision whether or not to click the webpage of the business to learn more. Humans form first impressions from general physical beauty of a subject despite warning not to do so (University of Pennsylvania, 2006). General appearance of a subject matters since some visible qualities are useful in guiding adaptive actions that even a trace of those qualities could generate an impression (Lorenzo et al., 2010). The theories of first impression have also been applied in previous studies on the design of hotels, restaurants, and tourism attractions (e.g., Hao, 2019; Huang, 2019; Xu, 1989). It is consistent with the findings of the present study. In the case of cover photographs, the façade and property amenities represent the generative appearance of a lodging business, which give customers clues whether it is trustworthy and competitive in offering accommodations. Therefore, a lodging business is encouraged to use a cover photograph that addresses the facility's strengths: uniqueness of façade and property's amenities, which create exceptional differentiation among alternatives in the searching list. Using a themed hotel as an example, the front of Walt Disney World's Swan and Dolphin Hotel could employ a cover photograph in the searching list on OTAs because the image demonstrates the exclusive fairy tale world, which differentiates from other lodging options.

In contrast, a lodging business should be aware that cover photography featuring scenery suppresses customers' interest in clicking the webpage with detailed information of the facility. This phenomenon could be explained with theories of semantic priming effects in psychology (Neely, 1991). Priming refers to exposure to a stimulus impacts an individual's feedback to a subsequent stimulus, without consciousness or cognitive intentions (McNamara, 2005). The effects of semantic priming on photography processing are evaluated under circumstances in which a subject is asked to recognize as rapidly and simply as possible (Sperber et al., 1979). Semantic relatedness is crucial to facilitate the identification of the photography (Franek and Rezny, 2017). The semantic priming effects of photography have been widely proven at distinct settings in the hospitality and tourism field, such as menu design (Hou et al., 2017), lodging business websites (Jeong and Choi, 2005), and tourist photographs (Garrod, 2008). In the setting of cover photographs in the search list of OTAs, a photograph which gives viewers the straightforward clue of a lodging business's image (e.g., façade and property amenities) is more likely to be cognitively accepted than the one which is lack of direct relatedness (e.g., scenery around). Furthermore, when searching accommodations at a specific location (e.g., close to a beach), all the options in the list share the scenery, regarding all options similar in this regard. Accordingly, the cover photograph of scenery cannot highlight the advantage of the business; therefore, such images should be avoided as a cover photograph.

To take the idea further, the photographic examples, selected from the categories this study identifies, could represent guidance from OTAs to help the lodging businesses better recognize those photographs to be encouraged or discourage for designing covers. Moreover, OTAs should regularly examine cover photographs of lodging businesses with a specific screening criterion (e.g., lodging type, price range). The critique can allow individual lodging businesses to learn whether its cover photograph enjoys better review times as compared to peers. The lodging business could become aware of whether its cover photograph effectively induces customers' feelings of "having a desire to be there" and "see if it's worth what you pay for" (Kirillova and Chan, 2018). Furthermore, the selection of a cover photograph also provides the lodging business an opportunity to review its offering, identify the strengths, and differentiate itself from competitors.

Although this study only testes cover photographs on the OTAs, the results may applicable to other similar settings, such as the cover page of a promotional brochure, the lending webpage of a hotel's official website, and even the background image of a membership card. Often, these settings use very limited images, only one in most cases. Thus, the photograph should be "sharp" enough to spark customers' interests, attract their attention for marketing messages, and lure them in to further informational search. From an even broader point of view, the results decode the puzzle of how to apply effectively one photograph as a peripheral cue to initiate marketing communications with customers in the lodging industry.

7. Limitations and future research

This study has several limitations. First, the present study adopted a sharing lodging platform as the investigative site. Considering, the facilities of the sharing lodging spaces are different from those of hotels that reflected in the photographs, future studies might examine cover photographs on OTAs with the focus of hotels (e.g., www.tripadvisor.com, www.travelocity.com). Second, the viewing behavior tested in the present study only demonstrates motives for customers to do further search for information, but does not provide sufficient information to generate patronage behavior. Future studies may expand the research model by including booking times. The expansive research model could tested either in an experimental setting or on the OTAs which offer the timely data of booking times (e.g., www.booking.com). Third, the study does not classify lodging offerings according to property types, price categories, and other criteria. Future studies may reexamine the model for different classes of the offerings, which could provide more fine-grained suggestions for industry practitioners. Fourth, in the search list of OTAs, a lodging business offers one cover photograph, star rating or grading, inclusive review score, short description, price, and other general information. Based on the results of the present research, future studies may improve design machine learning algorithms to analyze the combinative impacts of pictorial, textual (e.g., short description), and numerical (e.g., review score, price, star rating) content on viewing times of the webpage with the detailed information of the business. Last but not the least, regression analysis with the supplement of big-data technique and machine learning tools used in the present study is effective to identify general customer behavior trends. However, it is deficient to capture customers' subtle attitude change and fails to precisely identify customer preference. Thus, eye-tracking experiments are highly recommended in future studies to investigate the relationship between the themes of cover photographs and further information search behavior on OTAs.

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