International Journal of Hospitality Management 80 (2019) 144–154

Contents lists available at ScienceDirect

International Journal of Hospitality Management

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

Research Paper

Understanding hidden dimensions in textual reviews on Airbnb: An application of modified latent aspect rating analysis (LARA)

Yi Luo[a], Rebecca (Liang) Tang[b,*]

[a] Department of Marketing, College of Business Administration, Capital University of Economics and Business, Beijing, 100070, China
[b] Department of Apparel, Events, and Hospitality Management, College of Human Sciences, Iowa State University, Ames, IA, 50010, USA

ARTICLE INFO

Keywords:
Airbnb
Customer reviews
Aspect rating
Aspect weight
Emotions

ABSTRACT

Many customers feel overwhelmed by excessive information provided on peer-review websites (e.g., Yelp). Thus, it is important to generate an effective mechanism to assist customers in identifying the dominant aspects and emotions embedded in textual reviews, and understand the contributions of these aspects and emotions to reviewers' inclusive satisfaction (i.e. overall numerical rating). In the present study the Latent Aspect Rating Analysis (LARA) is modified to achieve this research objective. We identify five aspects; communication, experience, location, product/service, and value. Joy and surprise are the primary emotions shown in textual reviews. This study provides an innovative research venue for incorporating both textual reviews and numerical ratings into assessment. The results also can assist industry practitioners in identifying review patterns and enhancing user experience.

1. Introduction

Since the emergence of the internet in the mid-nineties, it has become a common practice for hospitality and tourism businesses to present themselves on online review platforms, either operated by their own or by third-party organizations (Fang et al., 2016). These review websites provide customers with channels to communicate their opinions, ideas, and experiences about products, services, and brands (Kozinets, 2016). BrightLocal (2017) reports that 97% of customers check online reviews and read an average of seven reviews before generating trust toward a business. Customer reviews are found to have a significant impact on the sales and pricing practices of a business (Lu et al., 2014; Ye et al., 2011). Liu et al. (2017) also suggest that the customer review platforms are reliable information sources to comprehend what drive customer satisfaction, and accordingly assist businesses to improve offerings to meet future demands.

Customer reviews play an even more imperative role for peer-to-peer (P2P) lodging options (e.g., Airbnb listings) than for conventional hotels (Dredge and Gyimothy, 2017). The hosts of P2P accommodations are micro-entrepreneurs (Sundararajan, 2014). Due to a lack of resources, most hosts don't present themselves on other promotional outlets (e.g., TV, radio) as do conventional hotels. User-generated reviews on P2P lodging websites (e.g., Airbnb) are often the dominant or sole channel for customers to learn about these micro-businesses (Edelman and Luca, 2014). Moreover, considering intangibility in the hospitality industry, customers are inclined to rely on peer reviews to decrease potential risks and enhance purchase confidence (La and Choi, 2012). Therefore, extracting and identifying the most meaningful and useful information from customer reviews is critical for both hosts and prospective guests.

Customer reviews are in the form of both numerical scores and plain-text feedback (Yang et al., 2016). The numerical rating of overall performance (e.g., on a scale of 1–5 or 1–10) shows the generic and comprehensive assessment of a business, which is widely used as an indicator of reviewers' inclusive satisfaction (e.g., Ganu et al., 2009; Long et al., 2014). In order to model how and why reviewers decide on their overall ratings of the business, it is crucial to discover their opinions from so-called hidden perspectives. Specifically, in the case of P2P accommodations, reviewers may emphasize or care about certain aspects (e.g., location, service) of a listing to varying extents. For example, the average overall rating for two lodging listings are both 4 out of 5. However, for the first listing, its low price is the dominant reason for the positive rating, while its location far from downtown lowers customer satisfaction. In contrast, the second listing earns its overall rating due to the leverage between superior service and higher price. Therefore, to identify these subtle differences, it is crucial to assess the relative weights among individual attributes (i.e. weight reflects the importance) and valence ratings on these attributes which contribute to

* Corresponding author.
E-mail addresses: luoyi@cueb.edu.cn (Y. Luo), rebeccat@iastate.edu (R.L. Tang).

https://doi.org/10.1016/j.ijhm.2019.02.008
Received 31 July 2018; Received in revised form 23 January 2019; Accepted 14 February 2019
Available online 23 February 2019

Table 1
Analysis of Review Websites in the Hospitality and Tourism Field: Numerical Ratings and Textual Feedback.

Themes	Literature	Platform	Methodology	Sample size
Investigate the product/service attributes and customers' sentiment expressed in textual reviews	Berezina et al. (2015), Bi et al. (2019), Boo and Busser (2018), Dickinger et al. (2017), Duan et al. (2016), Gao et al. (2018), Guo et al. (2017), Li et al. (2015), Liu et al. (2013), Nakayama and Wan (2018), Tontini et al. (2017), Total et al. (2017), Vu et al. (2019), Xiang et al. (2015), Xu (2019), Xu and Li (2016) and Zhou et al. (2014)	Tripadvisor (9); Booking (2); Expedia (1); Agoda (1); Yelp (1); Ciao (1); Dianping (1); an anonymous meeting plan website (1).	Topic modeling; sentiment analysis; text-link analysis; importance-performance analysis (IPA); support vector machine (SVM); ensemble neural network (ENN); machine learning; competitive analysis; pattern mining technique; contrast detection model; correspondence analysis; factor analysis	1–5000 reviews (8); 5001–10,000 reviews (1); 10,001–50,000 reviews (3); 50,000–100,000 reviews (2); 100,001 and above (3)
Examine the relationship between overall numerical rating and numerical ratings of individual aspects provided by the website	Radojevic et al. (2017), Schuckert et al. (2015) and Stamolampros et al. (2019)	Tripadvisor (3)	Topic modeling; *t*-test; multilevel analysis	10,001–50,000 reviews (1); 50,001–100,000 reviews (2)
Assess the relationship between overall numerical rating and some features of textual reviews	Zhang et al. (2016) and Zhao et al. (2019)	Tripadvisor (1); Qunar (1)	Ordered logit and probit models; regression analysis	50,001–100,000 reviews (2)

the overall rating (i.e. rating reflects satisfaction).

However, most customer review websites (e.g., Airbnb, VRBO) don't request numerical ratings of pre-defined attributes of a business from reviewers. And for those websites that do collect feature ratings (e.g., Tripadvisor collects the feature ratings of value, location, sleep quality, rooms, cleanliness, and service with a scale of 1–5), a significant percentage of reviewers do not provide this information (Long et al., 2014). Furthermore, due to lack of details for reviewers to justify their rating decisions, the numerical rating of individual perspectives may be more biased and deficient in identifying the relative weights of latent aspects compared to textual cues (Information Resources Management Association, 2018). Taking this idea further, Ganu et al. (2009) indicate that textual reviews show the capability for more precisely demonstrating reviewers' attitudes, compared to the coarse star ratings of pre-defined attributes on customer review websites. Bassig (2016) also indicates that natural language reviews provide more enriched information than numerical ratings from topics and sentiments.

To gain a deeper and more precise comprehension of the reviews for P2P lodging listings, the Latent Aspect Rating Analysis (LARA) is modified and applied in the present study (Wang et al., 2010). The LARA model explains the overall rating of an entity (i.e. a P2P lodging listing in this case) with the combination of latent ratings and aspect weights in textual reviews and makes two assumptions. First, the overall rating is formed from a combination of all the weighted latent aspect-based ratings, where weights describe the relative importance placed on each aspect for the entity when the overall rating is given. Second, the latent rating on each aspect is formed by another weighted sum of words with emotional dimensions, where weights show the extent of corresponding sentiments. The LARA developers Wang et al. (2010) examine sentiments as one-dimensional scale (positive vs. negative). To more accurately and comprehensively assess customers' valence, in the present study Plutchik's (1994) emotion wheel with four pairs of opposites (sadness-joy, fear-anger, disgust-trust, and surprise-anticipation) is used to replace the sentiment dichotomy.

The purpose of the present study is to evaluate reviewers' inclusive satisfaction by the aspects and sentiments presented in plain-text reviews. The specific objectives are to: 1) identify the dominant feature aspects presented in review texts; 2) evaluate the pattern of eight emotional dimensions for each feature aspect; and 3) explain the overall rating of a P2P lodging listing with latent ratings for emotions and the relative importance weights on individual aspects. This research is a pioneer in explaining customer satisfaction by modeling the hidden aspects embedded in textual reviews. It "decrypts" reviews of P2P lodging listings through the combination of numerical scores and plain-text reviews. This innovative approach could improve the preciseness of estimating feature ratings of products, services, and experience, which is critical to gain state-of-the-art performance of online review recommendation systems.

The customer review website examined in the present study is Airbnb, which is a dominant player in the P2P lodging marketplace across the world. One reason for choosing Airbnb is the significance of customer reviews on a P2P accommodation website to the individual hosts on the site. The other consideration is that Airbnb only presents the average numerical overall rating for a listing and textual content from individual reviews. No pre-defined aspects or corresponding ratings are provided on the website. Therefore, it is urgently necessary to justify reviewers' general satisfaction from the textual content related to different aspects of Airbnb.

2. Literature review

2.1. Aspect weights for overall customer satisfaction

Relevant research for online reviews in the hospitality and tourism domain have been prolific since the emergence of the internet (Schuckert et al., 2015). As a common practice, online review platforms present customer assessments via a combination of numerical ratings and textual feedback. The research work which explores numerical ratings and textual reviews in the hospitality and tourism field are summarized in Table 1. Tripadvisor is used as the data source for most of these studies. These studies can be classified into three streams. The first stream, reflecting the majority of the collected studies, aims to investigate business attributes and customer sentiments (positive/negative) expressed in textual reviews. Sentiment analysis and topic modeling are the most widely-used techniques in these studies. For example, Zhou et al. (2014) analyze over one thousand reviews of 4- and 5- star hotels on www.agoda.com. The evaluations of hotel attributes are categorized into four groups: satisfied (solely positive in reviews), dissatisfied (solely negative in reviews), bidirectional forces (either positive or negative results), and neutral (no marked influence). Dickinger et al. (2017) investigate sentiment differences of textual reviews in three sectors: tourism, hotels, and food service. Other examples of the first stream include Berezina et al. (2015), Boo and Busser (2018), and Gao et al. (2018). The second stream examines relationships between overall numerical rating and numerical ratings of individual aspects provided by a website. For example, Radojevic et al. (2017) apply multilevel analysis to examine the influential factors on customers' general satisfaction (i.e. overall numerical rating). One of these influential factors is numerical ratings of subcategories provided by Tripadvisor. Similarly, Schuckert et al. (2015) examine the differences in rating behavior (overall rating and ratings of subcategories provided by Tripadvisor) of two customer groups (English vs. non-English). The third stream assess the relationships between overall numerical rating and specific features of textual reviews. For example, Zhao et al. (2019) examine the impact of textual review features (e.g., subjectivity, diversity, readability) on overall rating. Zhang et al. (2016) identify the influence of website-recognized expert reviews on customer rating behavior.

From a summary of previous studies in the hospitality and tourism field, numeric ratings and textual reviews are treated almost as two parallel activities not well-incorporated with respect to understanding customer satisfaction. Although the third stream aims to connect the overall numerical rating with some features of textual reviews, we argue that such linkage is superficial. Customer perceptions and attitudes related to dominant lodging attributes, the essences of written reviews, are not linked to the overall numerical rating. This study is aimed at filling that research gap.

The customer review platforms demonstrate numerical ratings in one of four forms, including the overall rating of a business unit (e.g., Airbnb listing) or a reviewer, and the rating on a pre-defined factor (e.g., cleaning, price) for a business unit or a reviewer. The forms of numerical ratings on 16 popular hospitality and tourism websites are demonstrated in Table 2.

The overall rating for an individual unit or reviewer with a scale of 1–5 or 1–10 is common for these platforms and has widely been used as a predictor for customers' inclusive satisfaction (e.g., Ganu et al., 2009; Long et al., 2014). However, there is some controversy regarding the ratings for pre-defined factors on online review websites for several reasons. First, the ratings on pre-defined factors for a business unit or reviewer is available for only a small proportion of online review platforms. Second, the pre-defined themes vary on different customer review websites. For example, the themes on www.tripadvisor.com are composed of value, location, sleep quality, rooms, cleanliness, and service. The topics on www.hotels.com include location, service, comfort, and cleanliness. The categories on www.trivago.com cover location, rooms, service, cleanliness, value for money, comfort, facilities, and building. Even for the same platform, the pre-defined lodging factors may change over time, with some eliminated or supplemented. This makes the assessment inconsistent either across different platforms or on the same platform over time (McAuley and Leskovec, 2013).

A third area of controversy is that the pre-defined factors on customer review websites are not clear or comprehensive. For example, "accuracy" is one of the pre-defined lodging factors on www.lovehomeswap.com, a P2P accommodation website. Reviewers may be unsure whether this term means the accuracy of service, website description, or another factor. Moreover, the pre-defined lodging factors provided on online review platforms are inconsistent with the critical attributes identified in academic studies. As shown in Table 2, customer review websites usually provide ratings of four to eight pre-defined attributes. However, Dolnicar and Otter (2003) identify 173 key attributes which contribute to customer satisfaction by summarizing the studies relevant to hotel attributes published in academic journals between 1984 and 2000. They further suggest that the attributes may play distinct roles in different types of lodging options (e.g., conventional hotels vs. P2P accommodations). Therefore, the present authors argue that these pre-defined categories on review websites can't effectively present the key lodging factors for customer satisfaction (i.e. overall star rating).

Ganu et al. (2009) suggest that textual content could generate more comprehensive or customized findings about reviewers' experience and attitudes than those derived from pre-defined factor ratings. Koh et al. (2010) suggest that it is more time-consuming for a reviewer to provide textual reviews than numeric ratings, which may suggest that more effort is needed to give an accurate assessment. Therefore, some scholars in the field of computer science have made efforts to explain customers' inclusive satisfaction (i.e. overall star rating) with the regression-based aspect weights extracted from textual reviews rather than pre-defined factor ratings. For example, McAuley and Leskovec (2013) indicate that textual reviews could be used to discover a customer's implicit feelings about business dimensions, which are highly interpretable for his/her overall satisfaction rated with a Likert scale. Ganu et al. (2009) improve the prediction of user experience by taking into account the structure and sentiments conveyed in textual reviews. Long et al. (2014) estimate feature ratings of a business based on the numerical overall rating and textual reviews. Based on the discussions above, we propose our first research question: how do the aspects (e.g., location, experience) identified from textual reviews of an Airbnb listing contribute to customers' overall satisfaction?

2.2. Aspect-based sentiment analysis and Plutchik's emotion wheel

Sentiment analysis has been the focus of recent research endeavors in the business administration domain (e.g., Waller and Fawcett, 2013; Yu et al., 2013). Sentiment analysis can be performed at one of three levels; document-level, sentence-level, and aspect level (Vinodhini and Chandrasekaran, 2012). The three levels assess an entire document, an individual sentence, and the entity aspect, respectively (Liu, 2012). Aspect-level sentiments have been mostly adopted in hospitality studies, since they address user opinions, experience, or concerns on different perspectives of a business, providing insight into customers' attitudinal and behavioral patterns (Pan et al., 2007). For example, Guo et al. (2017) extract the dimensions that contribute to guest satisfaction/dissatisfaction from online hotel reviews and identify heterogeneity among demographic segments. Nakayama and Wan (2018) evaluate cultural distinctions between Western countries and Japan on restaurant customers' preference for entrée items and the corresponding sentiment expressions. Boo and Busser (2018) identify valence on individual themes in meeting planners' reviews.

Previous hospitality and tourism studies have primarily assessed the sentiments of individual attributes with polarities, including positive vs. negative (e.g., Liu et al., 2013; Yan et al., 2018), or positive vs. neutral vs. negative (e.g., Geetha et al., 2017; Gitto and Mancuso, 2017; Kirilenko et al., 2018). The assumption of these studies is that all emotional states can be classified into a one-dimensional scale of valence. However, this postulation is unconvincing since human preferences don't always conform to simple scalability (Lichtenstein and Slovic, 2006; Tversky and Thaler, 1990). Pfister and Böhm (2008) further indicate that it is dogmatic to map many emotional dimensions

Table 2
Numerical Ratings of Customer Reviews on Hospitality and Tourism Websites.

website	Overall rating for one unit	Overall rating for an individual reviewer	Rating for each category in one unit	Rating for each category for an individual reviewer	Sample secondary data source	Overall rating scale	Rating scale for categories
www.airbnb.com	x				http://insideairbnb.com/get-the-data.html	1–5	
www.booking.com	x		x			1–10	Location, staff, value for money, cleanliness, comfort, facilities, free wifi
www.tripadvisor.com	x			x	https://www.kaggle.com/crawford/las-vegas-tripadvisor-reviews	1–5	Value, location, sleep quality, rooms, cleanliness, service
www.hotels.com	x		x			1–10	Location, service, comfort, cleanliness
www.travelocity.com	x	x	x			1–5	Room cleanliness, service & staff, room comfort, hotel condition
www.orbitz.com	x	x	x			1–5	Cleanliness, service & staff, comfort, property condition
www.hostelworld.com	x	x	x	x	https://www.kaggle.com/koki25ando/hostel-world-dataset/version/4	1–10	Value for money, staff, security, atmosphere, location, cleanliness, facilities
www.agoda.com	x	x	x			1–10	Cleanliness, location, service, facilities, room comfort and quality, value for money
www.priceline.com	x	x	x			1–10	Hotel cleanliness, hotel staff, location of hotel
www.trivago.com	x		x		https://www.kaggle.com/rohitanil/trivago-data	1–10	Location, rooms, service, cleanliness, value for money, comfort, facilities, building
www.vrbo.com	x	x				1–5	
www.homeaway.com	x	x				1–5	
www.flipkey.com	x	x				1–5	
www.wimdu.com		x				1–10	
www.9flats.com	x	x	x			1–5	Cleanliness, location, accuracy of description, facilities, value for money
www.lovehomeswap.com		x	x				Location, listing accuracy, comfort, cleanliness, communication
Total	14	11	10	2	4		

(e.g., trust, surprise) into a dichotomy or trichotomy. Each of the underlying emotional dimensions is composed of distinct origins, meanings, and appraisals (Solomon and Stone, 2002). Therefore, Esmin et al. (2012) and Ghazi et al. (2010) suggest that multi-dimensional emotions could be an alternative to the dichotomy or trichotomy in sentiment analysis.

Several psychological theories present fundamental human emotions from manifold facets (e.g., Ekman, 1992; Parrot, 2001; Plutchik, 1994). For instance, Francisco and Gervás (2006) suggest a framework with three emotion perspectives (pleasantness, activation, and dominance) and use it to label sentences in fairy tales. Ekman (1992) propose six fundamental emotion aspects, including anger, fear, sadness, disgust, joy, and surprise. Plutchik (1994) further expands Ekmanös (1992) framework by supplementing two additional emotion dimensions (anticipation and trust). Plutchik (1994) shows the eight emotional dimensions with a wheel, comprised of four opposing pairs of emotional states: sadness-joy, fear-anger, disgust-trust, and surprise-anticipation. We adopt Plutchik's framework for three reasons. First, the use of the emotion wheel is well-founded in psychological studies. Second, in contrast to some other optional models [e.g., Ekman (1992)] in which negative emotions are dominant, Plutchik's framework balances positive and negative emotional perspectives. Third, the wheel is the superset of the emotional dimensions of other researchers [e.g., Ekman (1992)]. Accordingly, we propose our second research question: what is the distribution of eight emotional dimensions for each of the aspects shown in textual reviews?

Based on the first and second research questions, the third research question is proposed: how is the overall rating for an Airbnb listing explained with the combination of relative importance weights (research question one) and latent valence ratings (research question two) on individual aspects reflected in textual reviews?

3. Methodology

3.1. Data collection

The Airbnb listings in Los Angeles were chosen because Los Angeles is among the top 10 cities internationally with the most Airbnb listings (Statista, 2017) and one of the top travel cities in the U.S. (Escapehere, 2018). An automated web crawler was used to conduct data collection during the time period of December 18 to 29, 2017. The indicators extracted from each Airbnb listing included listing ID, overall rating, listing price, geographic location (longitude & latitude), and review content. A total of 7537 Airbnb listings with 250,439 customer reviews were collected. After deleting 591 listings without overall ratings (i.e. a listing with less than three reviews has no overall rating), 6946 listings with 248,693 reviews were retained for data analysis.

3.2. Modified latent aspect rating analysis (LARA)

The present study adopted a modified Latent Aspect Rating Analysis (LARA) approach to achieve the research goals. Wang et al. (2010) developed the innovative text mining technique LARA for two purposes: 1) to assess the relative importance weight of each aspect of an entity (i.e. an Airbnb listing) that contributes to the overall rating; 2) to identify the latent sentiment rating of each aspect which contributes to the overall rating. The key concepts in LARA are defined as follows for the Airbnb context in the present study:

Overall rating: It is an average of numerical overall ratings provided by all reviewers for a specific Airbnb listing.

Aspect: It is one of the primary themes (e.g., price) extracted from a review document (i.e. the congregation of all written reviews for an Airbnb listing). Each aspect (e.g., price) is presented with a small set of words (e.g., cheap, expensive).

Sentiment: It is composed of eight dimensions: sadness, anger, joy, trust, anticipation, disgust, surprise, and fear.

Aspect rating: It demonstrates the extent of sentiment toward an aspect in a review document. For example, a higher rating of joy means a greater inclination to the joy dimension toward the corresponding aspect.

Aspect weight: It explains the extent of emphasis placed on an aspect in a review document. For example, a higher weight on the aspect of price shows more focus on the aspect of price in the review document.

Two sample textual reviews of an Airbnb listing with an overall rating of 4.5 are provided below.

Review #1: "The host is untrustworthy! He said he would provide free breakfast, but actually he didn't."

Review #2: "Even though the communication before arrival was inefficient, I still love this beautiful neighborhood."

In review #1, the aspect focuses on communication, and the sentiment for the communication aspect is angry, as demonstrated by use of the word "untrustworthy". In review #2, the two aspects of focus are communication and location. The sentiment for the communication aspect is sadness, demonstrated by use of the word "inefficient". The sentiment for the location aspect is joy, as shown by use of the words "love" and "beautiful".

The aspect rating and aspect weight were calculated with the modified LARA, as illustrated in Fig. 1. The modified version advanced the precision and effectiveness of the original LARA, with aspect identification (Step 2) and sentiment detection (Step 3) significantly improved (explained below).

3.2.1. Step 1. Data pre-processing

We pre-processed the textual data by eliminating both non-textual and irrelevant content, which followed two steps. First, all of the posts

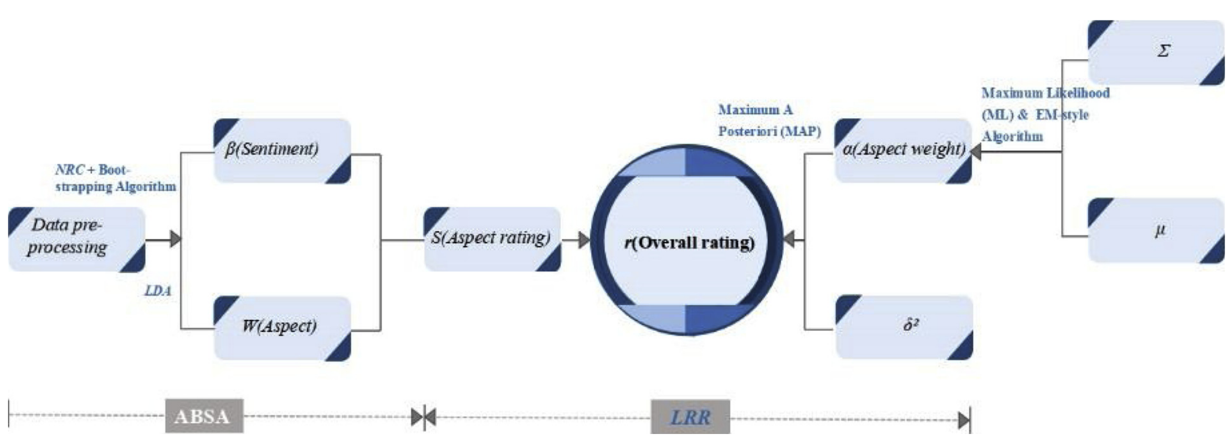

Fig. 1. Modified LARA graphical representation.

were converted into "bags" of words, by separating sentences into individual words using the tokenization function. Second, the words (e.g., "I", "am", and "is") that didn't contribute to further analysis were removed from the dataset (e.g., "stop words").

3.2.2. Step 2. Aspect identification

The purpose of this step was to identify the primary aspects from reviews and extract the seed words for each aspect. Wang et al. (2010) used pre-defined aspects provided by a customer review website and manually selected some seed words for each pre-defined aspect. However, as aforementioned, pre-defined aspects are not always available on customer review websites and the seed words manually selected can lack credibility. We therefore updated the method in this step with Latent Dirichlet Allocation (LDA), a widely used technique for identifying underlying topics with limited human intervention from a large volume of reviews (Guo et al., 2017). Since LDA provides only a small number of seed words corresponding to each aspect, a boot-strapping algorithm was further used to maximize the extraction of words relevant to seed words corresponding to each aspect. The boot-strapping algorithm treats the words of each aspect as input and allocates every sentence to the aspect that shares the maximum term coinciding with the sentence. Specifically, the dependences between aspects and words are computed using the Chi-Square (χ^2) statistic (Wang et al., 2010), and the words with a high dependence are contained in the corresponding keyword list of the aspect (as shown in Eq. (1)). C_1 consists of the frequency with which *w*occurs in sentences pertaining to aspect A_i; C_2 represents the frequency at which w occurs in sentences that do not pertain to A_i; C_3 means the number of sentences pertaining to aspect A_i containing w; C_4 represents the number of sentences that do not belong to aspect A_i and do not contain word w; and C consists of the total number of word occurrences. The procedure was reiterated until the keyword list for each aspect was unchanged or the iteration amount exceeded the threshold.

$$\chi^2(w, A_i) = \frac{C \times (C_1C_4 - C_2C_3)^2}{(C_1 + C_3) \times (C_2 + C_4) \times (C_1 + C_2) \times (C_3 + C_4)} \tag{1}$$

3.2.3. Step 3. Sentiment detection

The purpose of Step 3 was to detect the sentiments that customers expressed in their reviews. The original LARA model optimized the sentiment polarities as free parameters when generating aspect ratings with a word frequency matrix in a linear combination. However, each discrete emotion has its own unique characteristics that can have a different impact on each aspect embedded in customer reviews (Ahmad and Laroche, 2015), which contributes to the overall experience judgment. Therefore, the present authors tested the emotional dimensions (anger, anticipation, fear, disgust, joy, sadness, surprise, and trust) in Plutchik's emotion wheel. Specifically, sentiment polarities were calculated as the sum of the emotional word values for each aspect using the National Research Council (NRC)'s emotional lexicon (Mohammad and Turney, 2013).

3.2.4. Step 4. Latent regression rating (LRR)

The assumption of LARA was that an overall rating is generated through the weighted combination of latent ratings across all aspects. The purpose of Step 4 was to create aspect ratings and aspect weights based solely on review content, referred to as Latent Regression Rating (LRR) (Wang et al., 2010). The procedure adapted from Wang et al. (2010) is presented as follows. The Eq. (2) shows the calculation of aspect ratings.

$$s_d \sim \sum\nolimits_{j=1}^{n} \beta_{dij} W_{dij} \tag{2}$$

The aspects ratings s_d per listing are a linear combination of W_{di} and β, where $\beta \in \mathfrak{R}$ indicates the word sentiment polarities on aspect A_i obtained from the sentiment detection [as shown in Eq. (2)]. A word frequency matrix W_d is created with boot-strapping for each listing d, which offers the normalized frequency of the words in each aspect.

The weighted sum of the aspect rating vector s_d and the aspect weight vector α_d determine the γ_d overall rating as shown in Eq. (3). Specifically, it is assumed that the overall rating is a sample obtained from a Gaussian distribution (with mean and variance δ^2).

$$\gamma_d \,\tilde{}\, N(\sum_{i=1}^{\kappa} \alpha_{di} \sum_{j=1}^{n} \beta_{dij} W_{dij,} \delta^2) \tag{3}$$

To take the diversity of reviewers' preference into consideration, the aspect weight (α_d) is treated as a set of random variables drawn from an underlying prior distribution. The Multivariate Gaussian distribution is applied as the prior distribution for aspect weights in order to capture the dependencies among different aspects so that Eq. (4) could be applied.

$$\alpha_d \sim N(\mu, \Sigma) \tag{4}$$

By combining Eqs. (3) and (4), a Bayesian regression is generated:

$$P(\overline{)r}d) = \int p(\overline{)a_d} \quad \mu, \Sigma)p(\overline{)r_d} \sum_{i=1}^{k} \alpha_{di} \sum_{j=1}^{n} \beta_{dij} W_{dij}, \ \delta^2)d\alpha_d \tag{5}$$

The maximum a posteriori (MAP) estimation method is applied to retrieve the most probable value of α_d in a given review. The MAP estimation object function of listing d is defined as:

$$\mathscr{L}(d) = \log p(\alpha_d|\mu,\Sigma) p\left(r_d, \sum_{i=1}^{\kappa} \alpha_{di} \sum_{j=1}^{n} \beta_{dij} W_{dij,} \delta^2\right) \tag{6}$$

An expansion is developed by associating all of the terms with respect to α_d in each review [denoted as $\mathscr{L}(\alpha_d)$] as follows:

$$\begin{aligned} \hat{\alpha_d} &= \arg\max \mathcal{L}(\alpha_d) \\ \hat{\alpha_d} &= \arg max\left[-\frac{(\gamma - \alpha_d^T s_d)^2}{2\delta^2} - \frac{1}{2}(\alpha_d - \mu)^T \Sigma^{-1}(\alpha_d - \mu)\right] \end{aligned} \tag{7}$$

To address the issue of constraint non-linear optimization above, the conjugate-gradient-interior-point method is used via the derivatives Eq. (8) with respect to α_d:

$$\frac{\partial \mathscr{L}(\alpha_d)}{\partial \alpha_d} = -\frac{(\alpha_d^T S_d - r_d)S_d}{\delta^2} - \Sigma^{-1}(\alpha_d - \mu) \tag{8}$$

The model parameters are estimated with the maximum likelihood (ML) estimator. In other words, the ML estimator is employed to find the optimal $\Theta = (\mu, \Sigma, \delta^2)$ to maximize the likelihood of observing all overall ratings. The log-likelihood function on the entire set of reviews is generated:

$$\mathscr{L}(D) = \sum_{d \in D} \log p(r_d|\mu, \Sigma, \delta^2, \mathrm{W_d}) \tag{9}$$

Thus, the ML estimate is:

$$\hat{\Theta} = \underset{\theta}{argmax} \sum_{d \in D} \log p(r_d| \mu, \Sigma, \delta^2, \mathbf{W}_d) \tag{10}$$

To compute the ML estimation, all of the parameter values are first randomly initialized to obtain $\Theta(0)$ and then the following EM-style algorithm is used to update the parameters iteratively by alternately executing the E-step and then the M-step in each iteration as follows:

1 E-Step: For each listing d in the corpus, the aspect rating s_d and aspect weight α_d are inferred based on the current parameter $\Theta(t)$ (the subscript t indicates the iteration) as aforementioned.
2 M-Step: With the inferred aspect rating s_d and aspect weight α_d based on the existing parameters $\Theta(t)$, the updated parameters are employed and $\Theta(t+1)$ is obtained through the maximization of the "complete likelihood" (the probability of observing all the variables), including the overall ratings r_d, the inferred aspect ratings s_d,

and the aspect weights α_d for all the listings. The goal of this process is to maximize probability of observing all α_d computed in the M-Step. Thus, for all of the reviews, the present study follows the updating formula based on the ML estimation for a Gaussian distribution:

$$\Sigma_{(t+1)} = \frac{1}{|D|}\sum_{d\in D}(\alpha_d - \mu_{(t+1)})(\alpha_d - \mu_{(t+1)})^T \tag{11}$$

$$\mu_{(t+1)} = \frac{1}{\lceil D\rceil}\sum_{d\in D}\alpha_d \tag{12}$$

Next, a method is determined to update δ^2. Since α_d is assumed to be known, the updated δ^2 could be maximized. To solve this optimization problem, the following updated formula is applied:

$$\delta^2_{(t+1)} = \frac{1}{\lceil D\rceil}\sum_{d\in D}(r_d - \alpha_d^T S_d)^2 \tag{13}$$

4. Results and discussion

4.1. Review descriptive analysis

A summary of all usable 6946 listings is presented in Table 3. The overall ratings of the Airbnb listings in Los Angeles were dominantly 5 stars (57.745%), followed by 4.5 stars (34.797%), and 4 stars (6.335%). The listings with lower than 4-star ratings only accounted for approximately 2% of the total Airbnb accommodations in this area. The reviewers provided

145774 (58.616%), 89 325 (35.918%), and 12 701 (5.107%) textual reviews for the 5-star, 4.5-star, and 4-star listings, respectively. Less than 1% of textual reviews were created for the listings at 3.5-star or lower ratings.

4.2. Aspect-based sentiment analysis

Five aspects were extracted by following the procedure of LDA as described in Section 3.2. Among the word groups for each aspect, only ten meaningful seed words are listed in Table 4 as examples. After carefully reviewing all the seed words of each aspect, these five aspects were labeled as communication, value, product/service, location, and experience. Specifically, communication described the host-guest interactions throughout the pre-purchase, actual stay, and post-purchase stages. Experience was defined as customers' internal responses to any direct/indirect contact with a firm along a multiplicity of touchpoints. Accordingly, the experience aspect described information search, purchase, consumption, and after-sale processes involved in the Airbnb guest experience. The location aspect depicted the geographical convenience of Airbnb accommodations. The product/service aspect referred to tangible products (e.g., room facilities, kitchen appliances) and intangible services (e.g., meeting customers' special needs, offering greetings, or giving guidance for using room facilities). The value aspect explained the worth of economic outcomes, and the payoff between cost paid and benefit received.

Table 3
Descriptive summary of Airbnb listings with different overall ratings.

Overall rating	Total numbers of listing ID (N = 6946)	Percentage of Listings (%)	Total numbers of reviews (N = 248,693)	Percentage of Reviews (%)
1.5	1	0.014	3	0.001
2	1	0.014	3	0.001
2.5	5	0.072	25	0.010
3	10	0.144	52	0.021
3.5	61	0.878	810	0.326
4	440	6.335	12,701	5.107
4.5	2417	34.797	89,325	35.918
5	4011	57.745	145,774	58.616

Besides the seed words described above, more relevant words were further extracted with the boot-strapping technique in each of the five aspects. A total of 101,457 key words for the five aspects were identified. A random selection of 30 key words for each aspect extracted via boot-strapping are presented in Table 4.

The NRC Emotion Lexicon was adopted to test the sentiment polarities and extents of eight emotion dimensions from the boot-strapped words for each aspect. These words consisted of nouns, verbs, adjectives, and adverbs. Since the NRC only provides sentiment levels for adjectives, the adjectives approximated to the verbs, nouns, and adverbs of the key words were extracted and used in the calculation of the sentiment polarities. If the words were adjectives, they were directly counted into the sentiment polarities. The top 1000 words related to each aspect were selected. Fig. 2 shows the result of the aspect-based sentiment analysis (ABSA) aforementioned. Specifically, customers often experienced the mixed sentiments of "joy" and "surprise" (nearly 50/50) with the communication aspect, whereas the experience aspect was highly associated with "surprise". The aspects of product/service, value, and location generally were associated with the feelings of "joy", although the extents were different.

4.3. Latent rating regression

Latent Rating Regression (LRR) was used to generate the rating of each aspect for each Airbnb listing. Due to space limitations, Table 5 only shows the average aspect ratings for sentiments with the overall 6946 listings. The results indicated that the aspect ratings may differ significantly for some listings that had the same overall ratings. Specifically, Airbnb customers on average gave the highest ratings on the aspect of experience, followed by location and product/service. The value aspect had the least average rating.

Most Airbnb guests are new to the rising room-sharing economy, and thus their sentiments toward the novel lodging experience contribute most to their overall satisfaction. Compared with staying in a conventional hotel, guests who choose shared accommodations seek to experience local lifestyles at their rentals. Therefore, it is understandable that the sentiment rating for the novel experience contributed most to overall satisfaction in the findings. No matter what Airbnb guests' travel purposes are (e.g., business, leisure, etc.), location is the fundamental factor in lodging choices. Thus, the findings indicated that a customer's valence toward location weighed heavily in overall satisfaction. After location, the sentiment aspect of product/service was highly rated in inclusive satisfaction. In order to provide Airbnb guests with home-like accommodations, the facilities or services that they need or prefer must be offered by hosts. Guests' emotional feelings toward the products or services contributed significantly to overall satisfaction. The valence toward value as the payoff between cost and benefit played the least important role in overall satisfaction. The mean-square error ($\Delta^2_{overall}$) indicated the accuracy of the results by measuring the difference between the overall rating generated by the model γ_{di} and the ground-truth overall rating provided by the Airbnb website $\gamma^*_{di.}$ $\Delta^2_{overall}$ shown in Eq. (14). The resulting value of $\Delta^2_{overall}$ was 0.4, reflecting an improved solution to the optimization problem that was acceptable in the textual mining algorithms used in previous studies (Miner et al., 2012; Theodoridis, 2015). The result therefore supported the usability of this model.

$$\Delta^2_{overall} = \sum_{d=1}^{\lceil D\rceil}\sum_{i=1}^{\kappa}(\gamma_{di} - \gamma^*_{di})^2/(\kappa \times \lceil D\rceil) \tag{14}$$

Table 5 also displays the average weight of each aspect that contributed to customers' overall satisfaction. The results showed that Airbnb customers weighed location highest and weighed communication least in overall satisfaction. Location is widely discussed and addressed in textual reviews, whereas customers show considerably little

Table 4
Summary of LDA seed words and boot-strapping key words for each aspect.

Aspect	Seed words obtained from LDA	Boot-strapping key words
Communication	host, communicate, talk, idea, guide, friends, problem, neighbor, recommendations, suggestions	guidance, guy, guests, questions, people, guest, friendship, opinion, quick, interaction, helpful, suggestions, messages, neighbors, advice, fun, contact, response, email, problems, phone, details, help, text, trouble, attention, meet, complaints, info, concern
Experience	stay, experience, neighbor, service, view, hospitality, future, overall, environment, care	pleasure, nice, thoughtful, kind, check, anything, time, trip, plenty, welcoming, local, fun, cozy, safe, stayed, perfect, amazing, fantastic, enjoyed, day, feel, kids, quality, cool, style, travel, joy, hope, appreciation, tradition
Location	location, downtown, distance, place, area, Hollywood, west, station, convenience, walking	lake, noise, downtown, convenient, walk, street, spot, sights, city, highway, beach, building, blocks, center, areas, shopping, metrolink, Universal, market, drive, bus, store, corner, road, minutes, Beverly, uptown, restaurant, easy, find
Product/Service	bathroom, bedroom, kitchen, room, space, parking, towel, internet, breakfast, pool	bed, coffee, view, pictures, TV, privacy, book, shower, instructions, wifi, Uber, garage, snacks, loft, fridge, arrival, check-in, dryer, drinks, facilities, tidy, balcony, sheets, shampoo, laundry, towel, food, dinner, spa, exercise
Value	money, price, worth, value, quality, truth, recommend, reason, accepted, charge	promote, reservation, described, chance, hotel, couple, sale, living, comfy, times, honeymoon, good, super, family, expectation, absolutely, right, waste, economy, excellent, reasonable, better, posting, coupon, accommodations, choice, deal, option, save, rate

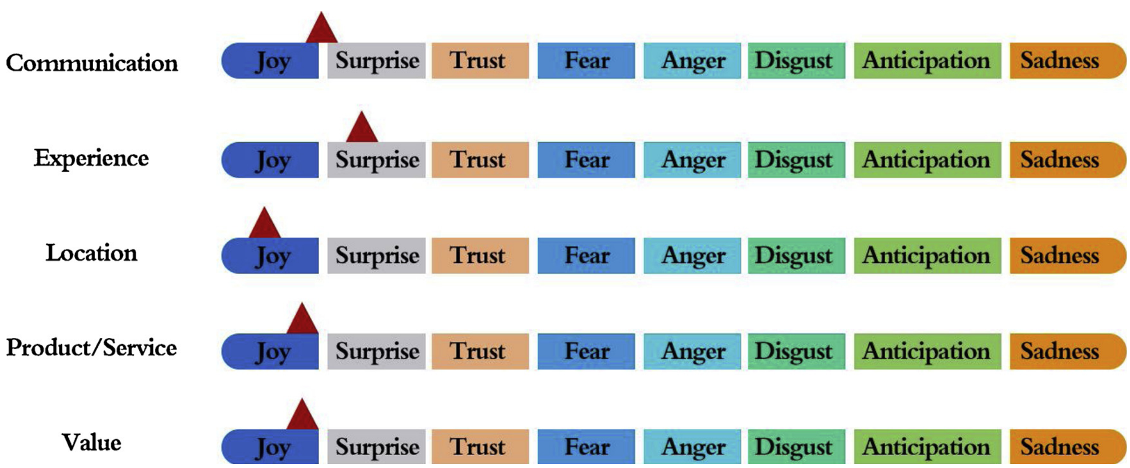

Fig. 2. Results of aspect-based sentiment analysis of each aspect.

interest in communications and interactions with the hosts.

The ratings and weights were further analyzed for extended applications. For example, to obtain a deeper understanding of Airbnb customers' sentiment rating behaviors, the listings were categorized into two price groups (expensive or cheap). The average ratings for individual themes between the two price groups are demonstrated in Table 6. For example, a listing with an asking price of $500 and above was described as expensive, while a listing price of $100 and below was called cheap. This showed that reviewers gave expensive rentals higher ratings primarily due to the appeal of their locations and products/services, and gave lower ratings due to undesirable overpricing and communication. In contrast, reviewers gave cheap accommodations higher ratings considering good pricing/value and fine locations, and gave such rentals lower ratings for their poor products/services.

By inferring the latent aspect weight for individual reviews, the reviewers' relative emphasis on an aspect can be discerned. Location was the most emphasized in customers' overall satisfaction for both expensive and cheap accommodations. For example, expensive accommodations provide private views of the city, or are close to locales for events (such as the LA Convention Center, the Staples Center, and LA Live). Low-paying customers are interested in downtown areas and locations where they could easily access transportation hubs and shopping centers.

5. Conclusions and implications

5.1. Conclusions

The present study innovatively applies the modified LARA to examine how and why reviewers assess Airbnb listings as they do. Specifically, the five primary aspects which contribute to overall satisfaction include communication, experience, location, product/service, and value. All the five aspects fall into either the "joy" or "surprise" dimensions on Plutchik's emotion wheel. "Joy" is a positive valence, while "surprise" is a negative valence. The aspect ratings show that reviewers' overall satisfaction is dominated by the emotions demonstrated in experience, followed by location and product/service. The modified LARA report that reviewers place the most emphasis on location, followed by experience and value, in plain-text reviews based on the results of aspect weights. The methodology and results in this study are expected to improve effectiveness and functionality with respect to analyzing a large-scale online review pool for hospitality and

Table 5
Summary of average aspect ratings & weights.

	Communication	Experience	Location	Product/service	Value
Overall average aspect ratings	3.753	4.210	4.079	3.946	3.570
Overall average aspect weights	0.138	0.183	0.370	0.137	0.172

Table 6
The comparison of aspect weights and ratings between expensive and cheap Airbnb listings.

		Communication	Experience	Location	Product/service	Value
Aspect ratings	Cheap	2.924	3.131	3.216	2.391	3.393
	Expensive	2.985	3.037	3.413	3.179	2.879
Aspect weights	Cheap	0.144	0.195	0.333	0.131	0.196
	Expensive	0.139	0.178	0.377	0.139	0.167

tourism businesses. The details are discussed in the Sections of 5.2 and 5.3 below.

5.2. Theoretical implications

The present study provides significant theoretical contributions from the following perspectives. First, this research modifies LARA to improve the accuracy and effectiveness of analyzing online reviews in the hospitality and tourism domain. It adopts an innovative approach combining regression analysis, natural language processing, and machine learning to harness the wealth of review content. Specifically, this study provides a more comprehensive and effective method for sentiment analysis with the combination of LDA and boot-strapping in online reviews. The LDA method has been increasingly applied in the hospitality and tourism domain in recent years (e.g., De Smet et al., 2011; Guo et al., 2017). The boot-strapping method can assist researchers to acquire a greater number of related keywords per aspect by supplementing LDA, which improves the efficiency of aspect identification.

Second, while big data analytics has been touted as a new research paradigm in many disciplines, very few applications in the hospitality and tourism domain fully explore its capabilities. In particular, previous studies have focused on extracting different lodging topics/aspects from textual reviews, but the inherent connection between the topics/aspects receives little attention. This study modifies LARA to model the relative weights of different lodging aspects in textual reviews. It innovatively creates highly interpretable textual labels for defining and weighing latent aspects, which contribute to the theoretical foundation for understanding customer rating behavior. Third, previous studies on online reviews in the hospitality and tourism field adopt a dichotomy (positive vs. negative) or trichotomy (positive vs. neutral vs. negative) of valence. The present study explores more detailed emotional dimensions with the NRC Emotion Lexicon. The results could more precisely explain customers' rating behaviors and better depict their experiences and attitudes.

5.3. Practical implications

Besides the theoretical significance, the present research offers unique practical contributions. The modified LARA framework assists hospitality and tourism practitioners to efficiently identify review patterns and develop tools for users to better search, comprehend, and assess reviews from three perspectives. First, we provide an innovative technique to summarize customer review content from different perspectives. The modified LARA generates aspect ratings aggregated from all the reviews of a business, which is a concise aspect-based opinion summary for the venture. Through examining the textual content on each of the primary aspects, a business can more precisely understand customers' needs and wants, which is a supplement to traditional data collection techniques (e.g., surveys and experiments). For example, in the case of Airbnb listings, several key words on the aspect of communication are "guidance", "friendship", "advice", "email", "phone", "text", "trouble", "complaints", "attention", "quick", "response". These words suggest that guests need quick responses, guidance, and advice from hosts through emails, phone calls, and text messages, and that guests also hope hosts could pay attention to their complaints and actively solve problems. Furthermore, guests expect to establish friendships with their hosts rather than having "just business" relationships. Several examples of key words in the location dimension include "lake", "downtown", "convenient", "walk", "spot", "sights", "highway", "beach", "shopping", "university", and "restaurant". These words indicate that guests prefer locations for Airbnb accommodations that are convenient to downtown areas, lakes/beaches, sightseeing attractions, shopping centers, university campuses, dining places, and transportation hubs.

Second, the modified LARA can be used to customize the ranking of business listings. The customer review websites in the hospitality and tourism domain mostly provide limited or no ranking options for customer searches. For example, Airbnb does not provide any ranking of the business listings. Yelp sorts the businesses with three options (best match with filter, highest rated, and most reviewed), while Tripadvisor ranks the businesses with four options (traveler ranked, best value, lowest price, and distance). However, none of them offer rankings or filter the businesses based on a specific feature. As discussed in the literature review, only a limited number of customer review websites request that reviewers give star ratings for pre-defined feature aspects, and such ratings are not compulsory for reviewers. Therefore, it is challenging to rank or filter businesses based on pre-defined themes. With the modified LARA, online review platforms could extract and rank the feature dimensions from plain-text reviews. Giving a specific feature's weight preference (i.e. high to low, or low to high) as a query, customers could sort the businesses based on their personalized needs.

Third, the latent aspect weights of written reviews help industry practitioners understand customers' preference. In the case of Airbnb listings, among the five primary aspects extracted from plain-text reviews, location plays a dominant role, followed by experience and value. Airbnb is branded as a provider of experience for cultural and authentic travel, which is distinct from conventional hotels. However, reviewers believe that a convenient location is the dominant reason for them to choose Airbnb listings. It appears that the branding of experience on Airbnb may not yet be successful enough or requires some adjustment. Since the present study investigates only customer reviews for Airbnb listings in Los Angeles, the results may not be generalizable to other places. The bottom line is that convenient locations for accommodations available should be emphasized in marketing programs and activities for Los Angeles.

Furthermore, reviewers stress the importance of value as the difference between cost spent and benefit received. This is consistent with the findings of Zervas et al. (2017) which suggest that Airbnb users are more price-conscious than hotel guests when the benefits are identical. However, based on a report by the worldwide travel company Busbed (2016), among 22 top travel cities across the world, hotel rates in six of them are cheaper than Airbnb rates, while Airbnb rentals are cheaper in the other 16 cities. Specifically, the average prices between hotels and Airbnb are fairly close in Los Angeles (difference of $5.09). Airbnb is thus advised to share with hosts the weight of value among the five key attributes identified in the present study. Given the identical benefits of accommodations, hosts could consider lowering prices to win customers in competition with hotels in the same area.

Moreover, with big data platforms (e.g., Azure by Microsoft), the modified LARA could efficiently provide weights and sentiment ratings on distinct aspects for any Airbnb listing. Airbnb could summarize the aspect weight and rating results for any lodging segment (e.g., Airbnb listings in a specific zip code area; high-end vs. low-end accommodations) and provide suggestions for their hosts accordingly. A good example is the segmentation of expensive and cheap hotels discussed in the result section.

Fourth, the distributions of the eight emotion dimensions for five aspects also suggest strategies for industry practitioners. With ABSA, the exact affective dimensions toward a specific lodging aspect could be identified instead of only general positive/negative attitudes. These specific emotional dimensions allow businesses to immediately identify “whether the customers are happy with, dissatisfied with, losing trust in, or angry with their product or a particular feature of the product” (Mohammad and Turney, 2013, p. 4). Industry practitioners could establish an “emotion-awareness system” with the analysis of emotional information, identify the reasons, and take actions for service failures. For example, in our findings the dominant emotion toward the experience aspect is surprise among the eight emotional dimensions, which leans to negative valence. A potential reason is that the hosts of Airbnb listings are micro-entrepreneurs who lack the resources to provide standardized experiences as conventional hotels do. Although the heterogeneous lodging experience is a shining point of Airbnb, sometimes unanticipated occurrences may make guests feel dissatisfied.

6. Limitations and future research

Although the present study provides significant contributions, several limitations and future research directions need to be addressed. First, the present study focused on the LARA’s explanation function of the overall rating based on topics and sentiments extracted from review text. Future studies could further explore the potential of LARA’s predictability. For example, in some cases, reviewers only provide textual reviews without numerical ratings. The method used in the present study could predict overall ratings by harnessing the useful information presented in review text. In addition, the machine learning algorithms could be trained to predict the ratings that reviewers may give for Airbnb listings with similar internal (facilities, service) and external factors (e.g., location) that they have not yet reviewed.

Second, the aspect-based sentiment analysis used in the present study did not take the semantics of reviews into account. Some complicated expressions (e.g., double negative sentences) were not detected. Future studies could consider applying other techniques (e.g., the *n*-gram) that are capable of discerning semantics. Third, the sample of the present study was Airbnb listings in Los Angeles. The results can’t be generalizable to other cities, especially small towns which may have distinct findings from large cities like Los Angeles. Lastly, this study is a pioneer of analyzing multiple emotional dimensions with Plutchik’s emotion wheel in hospitality and tourism studies. Future studies could take the idea further to examine a distinct or even larger set of emotional dimensions.

References

Ahmad, S.N., Laroche, M., 2015. How do expressed emotions affect the helpfulness of a product review? Evidence from reviews using latent semantic analysis. Int. J. Electron. Commer. 20 (1), 76–111.

Bassig, M., 2016. Online Reviews and Ratings Only Partially Reveal What Customers Really Think. Retrieved on 26 March 2018 from. https://www.reviewtrackers.com/online-reviews-ratings-partially-reveal-customers/.

Berezina, K., Bilgihan, A., Cobanoglu, C., Okumus, F., 2015. Understanding satisfied and dissatisfied hotel customers text mining of online hotel reviews. J. Hosp. Mark. Manage. 25 (1), 1–24.

Bi, J., Liu, Y., Fan, Z., Hang, J., 2019. Wisdom of crowds: conducting importance-performance analysis (IPA) through online reviews. Tour Manag. 70, 460–478.

Boo, S., Busser, J.A., 2018. Tourists’ c approach. J. Travel Tour. Mark. 30 (8), 1–14.

BrightLocal, 2017. Local Consumer Review Survey 2017. Retrieved on 12 November 2017 from. https://www.brightlocal.com/learn/local-consumer-review-survey/.

Busbed, 2016. Comparing Airbnb and Hotel Rates Around the Globe. March 03 Retrieved on 21 December 2017 from. https://www.busbud.com/blog/airbnb-vs-hotel-rates/.

De Smet, W., Tang, J., Moens, M.F., 2011. Knowledge transfer across multilingual corpora via latent topics. May. Pacific-Asia Conference on Knowledge Discovery and Data Mining. Springer, Copenhagen, Denmark, pp. 549–560.

Dickinger, A., Lalicic, L., Mazanec, J., 2017. Exploring the generalizability of discriminant word items and latent topics in online tourist reviews. Int. J. Contemp. Hosp. Manage. 29 (2), 803–816.

Dolnicar, S., Otter, T., 2003. Which hotel attributes matter? A review of previous and a framework for future research. In: Griffin, T., Harris, R. (Eds.), Proceedings of the 9th Annual Conference of the Asia Pacific Tourism Association (APTA). University of Technology Sydney., Australia, pp. 176–188.

Dredge, D., Gyimothy, S., 2017. Collaborative Economy and Tourism: Perspectives, Politics, Policies and Prospects. Springer, Copenhagen, Denmark.

Duan, W., Yu, Y., Cao, Q., Levy, S., 2016. Exploring the impact of social media on hotel service performance: a sentimental analysis approach. Cornell Hosp. Q. 57 (3), 282–296.

Edelman, B.G., Luca, M., 2014. Digital Discrimination: the Case of Airbnb.cOm. Harvard Business School NOM Unit Working Paper No, 14-054, 10 January. Harvard Business School, Cambridge MA.

Ekman, P., 1992. An argument for basic emotions. Cogn. Emot. 6 (3–4), 169–200.

Escapehere, 2018. 10 Best Cities to Visit in the United States!. Retrieved on 11 April 2018 from. https://www.escapehere.com/destination/10-best-cities-to-visit-in-the-united-states/.

Esmin, AhmedA.A., De Oliveira, R.L., Matwin, S., 2012. Hierarchical classification approach to emotion recognition in twitter. December. Machine Learning and Applications (ICMLA), 2012 11th International Conference on, vol. 2. IEEE, Piscataway, NJ, pp. 381–385.

Fang, B., Ye, Q., Kucukusta, D., Law, R., 2016. Analysis of the perceived value of online tourism reviews: influence of readability and reviewer characteristics. Tour. Manag. 52, 498–506.

Francisco, V., Gervás, P., 2006. Automated mark up of affective information in English texts. September. International Conference on Text, Speech and Dialogue. Springer, Berlin, Heidelberg, pp. 375–382.

Ganu, G., Elhadad, N., Marian, A., 2009. Beyond the stars: improving rating predictions using review text content. June. WebDB, vol. 9. pp. 1–6.

Gao, S., Tang, O., Wang, H., Yin, P., 2018. Identifying competitors through comparative relation mining of online reviews in the restaurant industry. Int. J. Hosp. Manag. 71, 19–32.

Geetha, M., Singha, P., Sinha, S., 2017. Relationship between customer sentiment and online customer ratings for hotels—an empirical analysis. Tour. Manag. 61, 43–54.

Ghazi, D., Inkpen, D., Szpakowicz, S., 2010. Hierarchical versus flat classification of emotions in text. Proceedings of the NAACL HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text. Association for Computational Linguistics, Los Angeles, CA, pp. 140–146 June.

Gitto, S., Mancuso, P., 2017. Improving airport services using sentiment analysis of the websites. Tour. Manage. Perspect. 22, 132–136.

Guo, Y., Barnes, S.J., Jia, Q., 2017. Mining meaning from online ratings and reviews: tourist satisfaction analysis using latent dirichlet allocation. Tour. Manag. 59, 467–483.

Information Resources Management Association, 2018. Mobile Commerce: Concepts, Methodologies, Tools, and Applications. IGI Global, Hershey, PA.

Kirilenko, A.P., Stepchenkova, S.O., Kim, H., Li, X., 2018. Automated sentiment analysis in tourism: comparison of approaches. J. Travel Res. 57 (8), 1012–1025.

Koh, N.S., Hu, N., Clemons, E.K., 2010. Do online reviews reflect a product’s true perceived quality? An investigation of online movie reviews across cultures. Electron. Commer. Res. Appl. 9 (5), 374–385.

Kozinets, R.V., 2016. Amazonian forests and trees: multiplicity and objectivity in studies of online consumer-generated ratings and reviews, a commentary on de Langhe, Fernbach, and Lichtenstein. J. Consum. Res. 42 (6), 834–839.

La, S., Choi, B., 2012. The role of customer affection and trust in loyalty rebuilding after service failure and recovery. Serv. Ind. J. 32 (1), 105–125.

Li, G., Law, R., Vu, H., Rong, J., Zhao, X., 2015. Identifying emerging hotel preferences using emerging pattern mining technique. Tour. Manag. 46, 311–321.

Lichtenstein, S., Slovic, P. (Eds.), 2006. The Construction of Preference. Cambridge University Press, Cambridge, MA.

Liu, B., 2012. Sentiment analysis and opinion mining. Synth. Lect. Hum. Lang. Technol. 5 (1), 1–167.

Liu, S., Law, R., Rong, J., Li, G., Hall, J., 2013. Analyzing changes in hotel customers’ expectations by trip mode. Int. J. Hosp. Manag. 34, 359–371.

Liu, Y., Teichert, T., Rossi, M., Li, H., Hu, F., 2017. Big data for big insights: investigating language-specific drivers of hotel satisfaction with 412,784 user-generated reviews. Tour. Manag. 59, 554–563.

Long, C., Zhang, J., Huang, M., Zhu, X., Li, M., Ma, B., 2014. Estimating feature ratings through an effective review selection approach. Knowl. Inf. Syst. 38 (2), 419–446.

Lu, Q., Ye, Q., Law, R., 2014. Moderating effects of product heterogeneity between online word-of-mouth and hotel sales. J. Electron. Commer. Res. 15 (1), 1–12.

McAuley, J., Leskovec, J., 2013. Hidden factors and hidden topics: understanding rating dimensions with review text. October. Proceedings of the 7th ACM Conference on Recommender Systems. ACM, New York, NY, pp. 165–172.

Miner, G., Elder, I.V.J., Hill, T., 2012. Practical Text Mining and Statistical Analysis for Non-Structured Text Data Applications. Academic Press, Cambridge, MA.

Mohammad, S.M., Turney, P.D., 2013. NRC Emotion Lexicon. National Research Council, Canada.

Nakayama, M., Wan, Y., 2018. Is culture of origin associated with more expressions? An analysis of Yelp reviews on Japanese restaurants. Tour. Manag. 66, 329–338.

Pan, B., MacLaurin, T., Crotts, J.C., 2007. Travel blogs and the implications for destination marketing. J. Travel Res. 46 (1), 35–45.

Parrot, W., 2001. Emotions in Social Psychology. Psychology Press, Philadelphia, PA.

Pfister, H.R., Böhm, G., 2008. The multiplicity of emotions: a framework of emotional functions in decision making. Judgm. Decis. Mark. 3 (1), 5–17.

Plutchik, R., 1994. The Psychology and Biology of Emotion. Harper-Collins, New York, NY.

Radojevic, T., Stanisic, N., Stanic, N., 2017. Inside the rating scores: a multilevel analysis of the factors influencing customer satisfaction in the hotel industry. Cornell Hosp. Q. 58 (2), 134–164.

Schuckert, M., Liu, X., Law, R., 2015. A segmentation of online reviews by language groups: how English and non-English speakers rate hotels differently. Int. J. Hosp. Manag. 48, 143–149.

Solomon, R.C., Stone, L.D., 2002. On “positive” and “negative” emotions. J. Theory Soc. Behav. 32 (4), 417–435.

Stamolampros, P., Korfiatis, N., Kourouthanassis, P., Symitsi, E., 2019. Flying to quality: cultural influences on online reviews. J. Travel Res. 58 (3), 496–511.

Statista, 2017. Number of Airbnb Listings in Select Major Cities Worldwide as of Sep 2017. Retrieved on 11 April 2018 from. https://www.statista.com/statistics/752498/airbnb-number-of-listings-in-major-cities-worldwide/.

Sundararajan, A., 2014. Peer-to-peer businesses and the sharing (collaborative) economy: overview, economic effects and regulatory issues. Written Testimony for the Hearing Titled The Power of Connection: Peer to Peer Businesses. January. Available at: http://smallbusiness.house.gov/uploadedfiles/1-15-2014_revised_sundararajan_testimony.pdf.

Theodoridis, S., 2015. Machine Learning: a Bayesian and Optimization Perspective. Academic Press, Cambridge, MA.

Tontini, G., Bento, G., Milbratz, T., Volles, B., Ferrari, D., 2017. Exploring the nonlinear impact of critical incidents on customers’ general evaluation of hospitality services. Int. J. Hosp. Manag. 6, 106–116.

Total, S., Martinez-Torres, M., Gonzalez-Rodriguez, M., 2017. Identification of the unique attributes of tourist destinations from online reviews. J. Travel Res. 57 (7), 1–12.

Tversky, A., Thaler, R.H., 1990. Anomalies: preference reversals. J. Econ. Perspect. 4, 201–211.

Vinodhini, G., Chandrasekaran, R.M., 2012. Sentiment analysis and opinion mining: a survey. Int. J. Adv. Res. Comput. Sci. Softw. Eng. 2 (6), 282–292.

Vu, H., Li, G., Law, R., Zhang, Y., 2019. Exploring tourist dining preferences based on restaurant reviews. J. Travel Res. 58 (1), 149–167.

Waller, M.A., Fawcett, S.E., 2013. Data science, predictive analytics, and big data: a revolution that will transform supply chain design and management. J. Bus. Logist. 34 (2), 77–84.

Wang, H., Lu, Y., Zhai, C., 2010. Latent aspect rating analysis on review text data: a rating regression approach. July. Proceedings of the 16th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM, New York, NY, pp. 783–792.

Xiang, Z., Schwartz, Z., Gerdes Jr., J., Uysal, M., 2015. What can big data and text analytics tell us about hotel guest experience and satisfaction? Int. J. Hosp. Manag. 44, 120–130.

Xu, X., 2019. Examining the relevance of online customer textual reviews on hotels’ product and service attributes. J. Hosp. Tour. Res. 43 (1), 141–163.

Xu, X., Li, Y., 2016. The antecedents of customer satisfaction and dissatisfaction toward various types of hotels: a text mining approach. Int. J. Hosp. Manag. 55, 57–69.

Yan, Q., Zhou, S., Wu, S., 2018. The influences of tourists’ emotions on the selection of electronic word of mouth platforms. Tour. Manag. 66, 348–363.

Yang, Y., Mueller, N.J., Croes, R.R., 2016. Market accessibility and hotel prices in the Caribbean: the moderating effect of quality-signaling factors. Tour. Manag. 56, 40–51.

Ye, Q., Law, R., Gu, B., Chen, W., 2011. The influence of user-generated content on traveler behavior: an empirical investigation on the effects of e-word-of-mouth to hotel online bookings. Comput. Hum. Behav. 27 (2), 634–639.

Yu, Y., Duan, W., Cao, Q., 2013. The impact of social and conventional media on firm equity value: a sentiment analysis approach. Decis. Supp. Syst. 55 (4), 919–926.

Zervas, G., Proserpio, D., Byers, J.W., 2017. The rise of the sharing economy: estimating the impact of Airbnb on the hotel industry. J. Mark. Res. 54 (5), 687–705.

Zhang, Z., Zhang, Z., Yang, Y., 2016. The power of expert identity: how website-recognized expert reviews influence travelers’ online rating behavior. Tour. Manag. 55, 15–24.

Zhao, Y., Xu, X., Wang, M., 2019. Predicting overall customer satisfaction big data evidence from hotel online textual reviews. Int. J. Hosp. Manag. 76, 111–121.

Zhou, L., Ye, S., Pearce, P., Wu, M., 2014. Refreshing hotel satisfaction studies by reconfiguring customer review data. Int. J. Hosp. Manag. 38, 1–10.