Journal of Hospitality and Tourism Technology

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Received 20 August 2016
Revised 23 September 2016
Accepted 25 September 2016

Abstract

Purpose – The purpose of this paper is to use Twitter analysis to explore diner perceptions of four types of Asian restaurants (Chinese, Japanese, Korean and Thai).

Design/methodology/approach – Using 86,015 tweets referring to Asian restaurants, this research used text mining and sentiment analysis to find meaningful patterns, popular words and emotional states in opinions.

Findings – Twitter users held mingled perceptions of different types of Asian restaurants. Sentiment analysis and ANOVA showed that the average sentiment scores for Chinese restaurants was significantly lower than the other three Asian restaurants. While most positive tweets referred to food quality, many negative tweets suggested problems associated with service quality or food culture.

Research limitations/implications – This research provides a methodology that future researchers can use in applying social media analytics to explore major issues and extract sentiment information from text messages.

Originality/value – Limited research has been conducted applying social media analysis in hospitality research. This study fills a gap by using social media analytics with Twitter data to examine the Twitter users' thoughts and emotions for four different types of Asian restaurants.

Keywords Sentiment analysis, Twitter, Text mining, Asian restaurant, Big data analysis

Paper type Research paper

Introduction

Social media marketing has received increasing attention from both academia and practitioners because it can help businesses strengthen their relationships with customers and spread information on products, services and brands (Bilgihan *et al.*, 2014; Xiang *et al.*, 2015). Information diffusion through Web 2.0 platforms like Twitter and Facebook have resulted in raising awareness of brands, helping customers form attitudes and even affecting their decision-making (Kwok and Yu, 2013; Mangold and Faulds, 2009). In particular, the impact of social media in the hospitality industry is significant because customers are more likely to seek personal suggestions on social media and rely on messages posted by other customers on social media (Pantelidis,

Journal of Hospitality and Tourism Technology
Vol. 7 No. 4, 2016
pp. 405-422

1757-9880
DOI 10.1108/JHTT-08-2016-0042

2010). Such social networks are therefore a new form of electronic word-of-mouth (eWOM) (Bruns and Burgess, 2012).

Considering the tremendous increase in social media users and consequent growth in volume of user-generated content, social media analytics has become a new method for investigating trends and patterns (Boyd and Ellison, 2007; Bruns and Burgess, 2011a). Twitter, a popular microblogging service, is used for social media analytics partly because of its popularity and because data collection is feasible (Kwak *et al.*, 2010). Launched in 2006 (Bruns and Burgess, 2011b), Twitter had an estimated 271 million active users in 2014, with 78 per cent of them using Twitter services on their mobile devices (Twitter, 2014a). User-generated content in Twitter, or a tweet, includes diverse attributes like message text, screen name of sender, posting time, language type and so on. Given that customers provide honest opinions on products and service and that information via social media is highly valued by other customers (Burton and Khammash, 2010), social media analysis using Twitter is important to the hospitality industry.

Despite the increasing importance of using social media analytics to predict current trends and matters of common interest (Dodds *et al.*, 2011; Weiss *et al.*, 2010), few empirical studies analyzing tweets in the hospitality management have been conducted (Leung *et al.*, 2013). Kwok and Yu (2013) mentioned that applying social media analytics to restaurant research is still in an early stage. Analyzing customer emotion with user-generated content (i.e. tweet messages) would allow researchers to estimate customer attitudes toward a product, service or brand. Sentiment analysis methods and tools have been tested to verify the accuracy of emotional states; these tools have been developed as user-friendly programs for those unfamiliar with computer programming (Duan *et al.*, 2013; Ghiassi *et al.*, 2013; Thelwall *et al.*, 2011).

This study is designed to apply social media analysis, the emerging research method, to evaluate the perceptions and sentiments toward four different types of Asian restaurants (Chinese, Japanese, Korean and Thai), using Twitter data. Asian restaurants were chosen for this study because of increasing interest in diverse Asian cuisines and the rapid growth of the Asian restaurant sector in the USA (Jang and Ha, 2009; Lee *et al.*, 2012; Ma *et al.*, 2011).

This study makes important theoretical contributions to literature on Asian restaurants in two ways. First, this study is one of the first to use Twitter analysis for exploring the perceptions and sentiments of different types of Asian restaurants. Especially, this study makes important methodological contributions to hospitality research. Prior studies examining perceptions of Asian restaurant have relied heavily on more traditional research methods, particularly surveys with a relatively small number of participants (Sale *et al.*, 2002). This study extends the literature on Asian restaurants by analyzing positive and negative messages and emotions on Twitter. In particular, analyzing emotions in tweets provides insight into how people perceive Asian restaurants.

Second, previous studies have examined perceptions of or attitudes toward Asian restaurants, including Chinese restaurants (Jang *et al.*, 2011; Liu and Jang, 2009), Japanese restaurants, Korean restaurants (Jang *et al.*, 2012) and Thai restaurants (Sukalakamala and Boyce, 2007). Few empirical studies, however, have analyzed and compared customer perceptions of or attitudes toward different types of Asian restaurants in a single study. This study extends previous hospitality literature by exploring and comparing customer perceptions of four different types of Asian restaurants (Chinese, Japanese, Korean and Thai).

The structure of paper is as follows. This paper first reviews the current stream of social media analytics in hospitality and tourism research and previous discussion of customer perceptions of Asian restaurants. Secondly, this study demonstrates social media analysis (e.g. text mining techniques, frequent word analysis and sentiment analysis) to assess customer perceptions of and attitudes toward four types of Asian restaurants. Thirdly, this research applies sentiment analysis to derive sentiment scores from tweet messages, which are then analyzed statistically to confirm mean differences. Lastly, managerial implications driven by research outcomes are offered to researchers and experts in Asian restaurant management and marketing.

Literature review

Previous research has shown consensus on the importance of the social media marketing, with focus on major topics or evaluations of a product or brand popular among social media users (Kaplan and Haenlein, 2010; Luo and Zhong, 2015; Misopoulos *et al.*, 2014; Ryan, 2015). However, most current research in hospitality marketing explores behaviors of social media users. Less research uses social media analysis; even though prior studies stressed the importance of applying social media analytics in the hospitality settings (Leung *et al.*, 2013; Lu and Stepchenkova, 2014; Xiang *et al.*, 2015). To fill the gap in the research, this paper reviewed recent literature on the role of social media in hospitality and on Twitter research applications to lay the groundwork for using social media analytics or big data analysis to reveal perceptions or emotions of social media users. In addition, this research investigated literature on customer perceptions of Asian restaurants to help in interpreting customer opinions found in tweets.

Social media analytics in hospitality industry

The hospitality industry has actively used social media platforms like Twitter and Facebook as effective marketing tools to improve brand awareness or promote products or services (Bilgihan *et al.*, 2014; Jayawardena *et al.*, 2013; Kwok and Yu, 2013; Nunkoo *et al.*, 2013). In addition, hospitality customers have produced much content (tweets) to share diverse opinions or feelings on their experiences (Park *et al.*, 2015; Zhao *et al.*, 2015).

Previous hospitality research has used different types of user-generated content data. For instance, Kwok and Yu (2013) examined types of messages and communication patterns in the restaurant business and among customers by collecting and analyzing Facebook messages posted on Facebook fan pages of popular restaurants (e.g. McDonald's or Chili's Grill & Bar). The research analyzed types and frequency of social media content and suggested that social media analysis using appropriate methods could help develop effective social media marketing strategies. Recently, Xiang *et al.* (2015) examined hotel guest experience factors and satisfaction using online reviews collected from Expedia.com. The study analyzed experience-related words in the reviews and demonstrated a strong relationship between hotel experiences and ratings in online reviews. Park *et al.* (2015) attempted to use Twitter in social media analytics to investigate cruise travel among Twitter users. This study not only used text mining to identify the major word-themes in tweets, but also attempted network analysis using follower/following relationships to find the most influential players in Twitter networks referring to cruise travel.

Research on twitter analysis

Twitter, launched in 2006, has become one of the most popular social network sites (SNSs) (Java *et al.*, 2007). Social media sites have attracted many people to microblogging services (Stieglitz and Dang-Xuan, 2013) and have allowed customers to connect with other customers, exchanging opinions of products and services (Gräbner *et al.*, 2012). A tweet is a short post with 140-character limit. This means many Twitter users develop unstructured narratives. In spite of the restrictions on tweet length, Twitter produces approximately 500 million tweets every day. The massiveness tweet data has attracted the attention of researchers (Boyd *et al.*, 2010; Williams *et al.*, 2013). In addition, researchers may find the honesty or sincerity of opinion in a Twitter message could be a significant advantage of using Twitter data (Marwick and Boyd, 2011).

Zimmer and Proferes (2014) reviewed 382 research papers on Twitter published between 2007 and 2012, finding the number of papers has grown rapidly, with more disciplines publishing Twitter research, ranging from computer science to communication, information science and business studies. Unfortunately, few papers have been published in hospitality management or marketing. Most papers using Twitter data have analyzed content or network (Zimmer and Proferes, 2014), and researchers analyze tweet messages and user data (Williams *et al.*, 2013). While tweet message data are useful in investigating an opinion or sentiment, user data and relationship data are a valuable part of examining how opinions spread among Twitter users, what is called eWOM (Park *et al.*, 2015). Sentiment analysis is an especially interesting method for assessing the emotional evolution of Twitter users (e.g. customers or employees) on a topic (Aguwa *et al.*, 2012; Kang and Park, 2014; Mattson *et al.*, 2013; Moniz and de Jong, 2014; Ren and Quan, 2012). The development of research methods using Twitter data provides good opportunities to capture significant trends in society and industry, so researchers in diverse disciplines can find meaningful issues or patterns in Twitter communication (Bruns and Burgess, 2012; Luo and Zhong, 2015).

The perception of Asian restaurants

Generally, three factors determine customer perceptions of restaurants: food quality, service quality and atmosphere. Liu and Jang (2009) examined American perceptions of Chinese restaurants in the USA and found that food quality (taste, menu variety or food safety), service reliability (consistency or helpfulness of employees) and environment (cleanliness or design) are crucial in making customers satisfied at Chinese restaurants.

The literature covers the many ways food quality has been measured as a determinant of restaurant customer perception. For instance, Namkung and Jang (2007) used six food attributes (menu variety, healthy options, food taste, food presentation, food freshness and food temperature) to measure food quality in restaurants. Kim *et al.* (2009) considered food quality attributes like freshness, taste and presentation. Along with food quality, service quality is a determinant of consumer experiences at restaurants. SERVQUAL, developed by Parasuraman *et al.* (1988), has been widely used to measure diner expectations and performance evaluations and ultimately improve service quality. Later, Stevens *et al.* (1995) developed DINSERV particularly for restaurants. The final factor that influences customer satisfaction with restaurants and customer revisit intention is atmosphere, which refers to the quality of physical environment using music, color, scent and light (Kotler, 1973). Mehrabian and Russell (1974) recognized the importance of environmental stimuli on individual behavior.

According to M-R model (Mehrabian and Russell, 1974), environmental stimuli influence individual emotional states, which can lead to either approach or avoidance behaviors. That is, physical environment is a critical part of customer emotional responses, leading to both positive and negative behaviors. Baker and Cameron (1996) suggest that consumers are affected by the physical environment because of the lack of the physical contact during the service encounter. Donovan and Rossiter (1982) indicated that positive feelings among customers derived from the physical environment relate to behavioral outcomes like revisit intention. A review of the servicescape literature shows the importance of physical environment; physical evidence (i.e. ethnic art, music and decorations that reflect genuine culture) would be especially important in Asian restaurants (Bitner, 1992). In fact, Jang *et al.* (2011) investigated the impact of authentic atmosphere in Chinese restaurants and found it had a significant, indirect influence on customer behavioral intention through two types of customer emotions. That is, when customers enjoy an authentic atmosphere in ethnic restaurants, they are likely to experience positive emotions, which in turn lead to positive behavior intentions.

Research methodology

Data collection

Twitter offers the tweet data-streaming tool, Application Programming Interface (API), for researchers and developers (Twitter, 2014b). The interface provides users with access keys and tokens to access approximately 1 per cent of all tweet data. For data collection and archiving, ScraperWiki, an online website for data collection (https://scraperwiki.com), was used. As a web-based platform, ScraperWiki is a tool for collecting, analyzing and managing data. Five search words ("Asian restaurant", "Chinese restaurant", "Japanese restaurant", "Korean restaurant" and "Thai restaurant") were used to extract tweets posted in English and collect data. Data were collected from April 29 to July 2, 2014. The total number of tweets was initially 86,015; however, each data set used slightly different terms for collecting data. Table I presents the data collection periods of each date set and shows the grand total of tweet messages used for this research.

Data analysis and tools

Text mining and sentiment analysis are both representative and convenient; they can provide insights from text-based content like electronic documents or messages

Searching words	Collection period (no. of days)	No. of tweets in English
Asian restaurant	4/29-7/2 (65 days)	10,398
Chinese restaurant	4/29-7/2 (65 days)	47,931
Japanese restaurant	5/5-5/12 and 6/9-7/2 (32 days)	11,437
Korean restaurant	5/5-6/3 and 6/9-7/2 (54 days)	8,720
Thai restaurant	5/5-5/12 and 6/9-7/2 (32 days)	7,529
(Grand total)		86,015

Table I.
Tweet data set

(Gruzd *et al.*, 2011). Text mining transforms an unstructured data set (natural language messages) into structured data or measureable values (Weiss *et al.*, 2010). For text mining and word frequency analysis, RapidMiner 5.3, a well-known software for data mining and analytics, was used to break tweet messages into single words (tokenization) and then to count frequencies of each word. In particular, the word frequency test ranks the most frequently mentioned words in the tweet data (Weiss *et al.*, 2010).

Sentiment analysis, known as opinion mining or subjectivity analysis, is a method for extracting information to analyze its subjectivity (positive, neutral, or negative) or its strength in texts referring to a certain subject or issue (Boiy *et al.*, 2007; Gräbner *et al.*, 2012; Pang and Lee, 2008; Thelwall *et al.*, 2011). This technique uses automatic computations to measure subjective polarity like positivity or negativity in texts (Gruzd *et al.*, 2011). Sentiment analysis has two stages. It first extracts word(s) with certain connotations and then determines the polarity of the connotation or its strength (Duan *et al.*, 2013). SentiStrength 2.2, developed by a project team in University of Wolverhampton in the UK (http://sentistrength.wlv.ac.uk), has been widely used by researchers as a tool to evaluate the positive (1 to 5) and negative (–1 to –5) strength of a tweet (Gruzd *et al.*, 2011; Stieglitz and Dang-Xuan, 2013; Thelwall *et al.*, 2010). The following example demonstrates how to measure a sentiment score with a tweet. Example of sentiment analysis:

- Example: *"Today's lunch was soba noodles at Japanese neighborhood restaurant. Though little bit expensive, Always yummy. Loving eating it here"*;
- Sentiment measurement: *"Expensive"* – negative word of –2; *"Loving"* – positive word of +4; and
- Sentiment score: (+2) = (–2) + (+4).

Other analytic processes (data screening, filtering and sorting) used Microsoft Excel 2013. Using sentiment scores from sentiment analysis, this study analyzed tweets statistically to show differences among the four restaurant types. One-way analysis of variance (ANOVA) and post hoc test with Scheffé's method were conducted using SPSS 20.0.

Results

Entire data set analysis: all types of Asian restaurants

In the first analysis, this study examined perceptions of Asian restaurants in general. The five sub-data sets were compiled into a single data set to rank frequent words. The text mining and word frequency analysis showed words appearing most frequently in the data set. To better understand major perceptions, certain unnecessary words were deleted: *restaurant*, *http* and *rt* (Table II).

The first finding was that Chinese restaurants (25,703) were the most popular among Asian restaurant types, followed by Japanese (12,221), Thai (9,148) and Korean (6,178). This research found several themes in the overall data: food-related themes like *food* (5,579) and *sushi* (2,300) occurred, as did emotion-related themes like *good* (1,546), *love* (1,374) and *want* (1,289). In addition, *yelp* (1,300), a popular online review website, was among the top words. For food items, sushi was most frequently mentioned.

Rank	Word	Frequency	Rank	Word	Frequency
1	*Chinese*	25,703	11	*dinner*	2,277
2	*Japanese*	12,221	12	*good*	1,546
3	*Thai*	9,148	13	*lunch*	1,543
4	*Korean*	6,178	14	*day*	1,496
5	*Asian*	5,763	15	*call*	1,451
6	*food*	5,579	16	*love*	1,374
7	*go/went*	5,099	17	*order*	1,354
8	*eat*	3,714	18	*time*	1,335
9	*get/got*	3,067	19	*yelp*	1,300
10	*sushi*	2,300	20	*want*	1,289

Notes: n = 53,003 (Asian restaurant = 5,132; Chinese restaurant = 23,602, Japanese restaurant = 11,436, Korean restaurant = 5,308, Thai restaurant = 7,525); The data period: 5/5-5/12 and 6/9-7/2 in 2014; Deleted words: *restaurant*, *http*, and *rt*

Table II. Frequency analysis with top 20 popular words in the entire data

Sub-data sets' analysis: each type of Asian restaurant

To compare the frequency of words among the four types of Asian restaurants, this paper used text mining and word frequency analysis. The top ten popular words in each data set were quite different. This research looked more for distinctive words, not the search words themselves (e.g. *Chinese* and *restaurant*) or common words like *http*, *food*, *dinner*, *lunch* and others. The lists of top words reflected authentic characteristics of foods (e.g. *sushi*) and destinations (e.g. *tokyo* and *seoul*). In data on Chinese restaurants, *chicken* (first) and *bread* (ninth) were frequently mentioned food items (Table IV shows an example of a tweet containing a popular word, *T-4-1*). In data on Japanese restaurants, the top food-related word was *sushi*. Among Korean restaurants, popular food words were *kimchi* (eight) and *barbeque* (tenth). However, the Thai restaurant data included no food-item words. Other noticeable words contain positive emotion: *good* and *delicious*. Many tweets in all the restaurant data sets contained these words. The online review website, *yelp*, was mentioned frequently, especially in the Japanese and Thai restaurant data sets.

Interestingly, word(s) for different restaurant types occurred in each data set. For example, the word, *Thai* (sixth), was found in the Chinese restaurant data set and the word, *Japanese* (first), was found in the Korean restaurant data set. The Thai restaurant data set included *Chinese* (first) and *Japanese* (eight). These results indicate the possibility that the perceptions or identities of Asian restaurants are co-mingled (Table III).

Table IV presents tweet examples that include popular words from Table III to further explain of how the words were used. The example of *T-4-2* containing the hashtag *#yelp* was posted to express appreciation of the food quality of one Japanese restaurant. Examples from tweets on Chinese and Korean restaurants also show an appreciation of the taste of the food.

Comparisons of sentiment scores

The sentiment analysis tool, SentiStrenth 2.2, assessed positive and negative emotions of tweets (Stieglitz and Dang-Xuan, 2013). The range of positivity scores is 1 to 5 and negativity is –1 to –5. As the absolute value gets higher, the indicated strength of

Word	Frequency
Chinese restaurant	
chicken	1,452
good	1,249
order	1,242
local	1,233
people	1,191
Thai	1,078
buffet	1,048
time	980
bread	888
menu	883
Japanese restaurant	
sushi	1,574
Chinese	441
yelp	435
Tokyo	361
Japan	354
want	312
good	298
customers	293
time	272
menu	238
Korean restaurant	
Japanese	314
good	304
photo	262
friend	250
time	231
Korean food	219
delicious	213
kimchi	204
Seoul	201
barbecue	198
Thai restaurant	
Chinese	511
yelp	400
menu	280
cuisine	271
Indian	269
good	267
buffet	238
Japanese	230
time	218
review	204

Notes: n = 75,617 (Chinese restaurant = 47,931, Japanese restaurant = 11,437, Korean restaurant = 8,720, Thai restaurant = 7,529); Deleted words: search words (e.g. "*Chinese*" and "*restaurant*"), *dinner*, *lunch*, *dining*, *food*, *http*, *go*, *others*, *eat*, and *know*

Table III.
Frequency analysis with top 10 popular words in each type of restaurants

sentiment becomes stronger. A positivity score of 1 is neutral as is a negativity score of –1. This study uses a sentiment score derived by adding the positivity and negativity scores:

$$\textit{Sentiment score} = \textit{Positivity score} + \textit{Negativity score}$$

where *Sentiment score* means the emotional direction and strength: positive (1 to 4), neutral (0), or negative (−1 to −4).

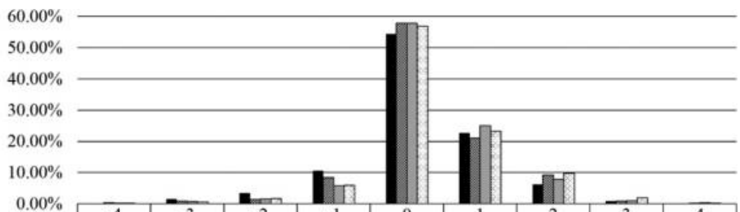
This study conducted individual sentiment analysis to compute and compare sentiment scores for the four types of Asian restaurants. The sentiment score distributions for each restaurant have similar patterns (Figure 1). All groups have many neutral tweets (more than 50 per cent), and the distribution was slightly negatively skewed. Unlike other Asian restaurant types, the scores for Chinese restaurants had relatively high negativity. For example, on the polarity score of –1, tweets referring to Chinese restaurants (10.64 per cent) are more negative than Korean restaurants (5.76 per cent) and Thai restaurants (5.94 per cent).

ANOVA and post-hoc

The sentiment scores for the four types of Asian restaurants were tested to verify significant statistical differences with one-way ANOVA and post hoc test using the Scheffé's method. For the group test, the ratio between the two groups with the largest

No.	Data set	Example tweet
T-4-1	Chinese restaurant	*Orange Chicken: This is my take on the orange chicken that you get at your favorite Chinese restaurant. Crispy.. http://t.co/jQwXToIMhR*
T-4-2	Japanese restaurant	*Amaya Japanese Restaurant And Ultra Lounge on #Yelp: This place is amazing. The sashimi salad is the best I've ever … http://t.co/4pPfM8H6MX*
T-4-3	Korean restaurant	*Went to a Korean restaurant for my birthday. It was absolutely delicious!!! @KoreanFood http://t.co/wgs9eDVubr*
T-4-4	Thai restaurant	*YAYYYY I found a good Thai restaurant that delivers to my house*

Table IV. Example tweets containing popular words of each data set



	−4	−3	−2	−1	0	1	2	3	4
Chinese_Percentage	0.05%	1.60%	3.47%	10.64%	54.47%	22.70%	6.18%	0.80%	0.10%
Japanese_Percentage	0.24%	0.89%	1.43%	8.35%	57.83%	21.06%	9.25%	0.87%	0.07%
Korean_Percentage	0.05%	0.73%	1.51%	5.76%	57.79%	25.00%	7.87%	1.03%	0.26%
Thai_Percentage	0.05%	0.57%	1.61%	5.94%	56.87%	23.22%	9.80%	1.90%	0.04%

Notes: n = 75,617; *Sentiment score = Positive score + Negative score*

Figure 1. Sentiment score distribution of each type of restaurants

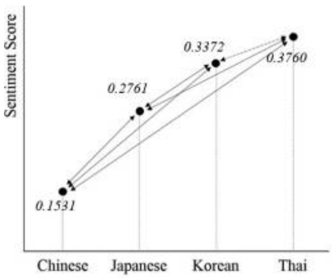
and smallest variance, the Chinese (0.9351) and Korean (0.7777) restaurant groups, was examined to check the assumption of homogeneity of variance among groups. According to Hartley's F_{max} test, if the F-ratio is less than 1, there is no problem with the assumption of homogeneity of variance. The results of ANOVA showed significant differences in sentiment scores among types of Asian restaurants (F = 205.432, p-value $<$ 0.001). The mean of sentiment score of Chinese restaurants was the lowest (0.1532) compared to Japanese (0.2761), Korean (0.3372) and Thai (0.3760) restaurants. Results of the post hoc test showed significant differences (p-value $<$ 0.001) in sentiment scores between each combination of restaurant types, except the combination of Korean and Thai restaurants (Figure 2).

Discussion and implications

Social media bring new opportunities for researching customer opinions (Bruns and Burgess, 2012; Kwok and Yu, 2013; Lu and Stepchenkova, 2014; Xiang *et al.*, 2015). By examining Twitter messages, this study provides some indications of major perceptions and emotional states for four different types of Asian restaurants frequented by Twitter users.

First, this study found that customers had difficulty distinguishing among Chinese, Japanese, Korean and Thai cuisines. For example, the word *Japanese* appeared most frequently in the Korean restaurant data, and *Chinese* in the Thai restaurant data. Tian (2001) argued that some customers could not recognize specific cultural differences among foods, although customers at Chinese restaurants were aware of differences between Chinese foods and American foods. Asian restaurant management and marketing might take note of the idea that people may not distinguish among types of Asian cuisines clearly.

Second, this study attempted to measure sentiment scores from texts, examining statistical differences by type of Asians restaurant. Recently, researchers have discussed applying sentiment analysis of user-generated content like online reviews or social media messages for investigating satisfaction with brands or products. For instance, Kang and Park (2014) measured sentiment scores from online reviews to measure customer satisfaction with mobile services, and Moniz and de Jong (2014) used sentiment analysis to examine employee satisfaction with their work. Luong and Houston (2015) collected Twitter data and assessed satisfaction of the public with rail service using sentiment analysis. Sentiment analysis is thus a useful approach for



(I)	(J)	Mean difference (I-J)
Chinese	Japanese	–0.12307***
	Korean	–0.18410***
	Thai	–0.22296***
Japanese	Korean	–0.06103***
	Thai	–0.09989***
Korean	Thai	–0.03886 (NS, p-value. = 0.78)

Notes: One-way ANOVA: F = 205.432, p-value $<$ 0.000; Post hoc: Scheffe's method; *** $<$ 0.001

Figure 2.
Results of sentiment score mean comparison

investigating satisfaction among customers. In this study, sentiment analysis showed a number of sentiment states for Asian restaurants. Overall, tweets contained more positive than negative emotions toward Asian restaurants (Figure 1). With sentiment scores of each sub-data set, ANOVA and post hoc tests confirmed significant differences. During data collection, Thai restaurants showed the highest positive level in tweets of all the Asian restaurant types. Twitter users, however, posted tweets referring to Chinese restaurants with relatively negative sentiment. This finding is consistent with Jang *et al.*'s (2009) study of Asian restaurant performance, where reported performance rates (e.g. taste, edibility and quality), as evaluated by customers of Chinese, Japanese and Thai restaurants, showed that Japanese and Thai restaurants received more positive evaluations than Chinese restaurants.

To better understand the attributes related to emotional polarity (i.e. positivity or negativity) of opinions expressed on Twitter, this paper randomly reviewed both highly positive and highly negative tweets. Interestingly, most positive sentiment tweets related to food quality attributes (e.g. "*enjoying excellent Chinese food at Country Sky restaurant in Marina District, San Francisco. (iPhone photo by Paul) http://t.co/KQwYBxh12t*"). It is clear that food quality and taste are important in making Twitter users express positive emotional words like *good* and *delicious*. Such findings support the claim as well as the results of previous studies that focused on the importance of authentic food quality in ethnic restaurants (Jang *et al.*, 2009; Ma *et al.*, 2011). On the other hand, many negative tweets expressed unfamiliarity with the food culture or criticized poor service (e.g. "This guy in a Thai restaurant I'm at is being a total fu**ing ass-hat to the waiter, and he's really pissing me. #iwanttogovomitonhim" or "I'm shit at using metal chopsticks"). In addition, some tweets were positive about food quality but negative about price (e.g. "Today's lunch was soba noodles at Japanese neighborhood restaurant. Though little bit expensive, Always yummy. Loving eating it there"). Future research could focus on more detailed interpretation and investigation of factors associated with emotions, expanding the sentiment analysis approach by reviewing/coding more tweets.

This study contributes to the existing body of research on Asian restaurants. First, this paper applied social media analytics using Twitter data. Although a number of research articles have examined data from online reviews (Xiang *et al.*, 2015; Ye *et al.*, 2009), analyzing tweets from restaurant settings has not been previously attempted. Understanding tweets is significant in the restaurant industry; it provides information on timely issues and what customers are saying, both positive and negative. Furthermore, this study used several approaches and research methods (data mining, frequency analysis, sentiment analysis, ANOVA and reviewing tweet messages) to examine differences in perceptions of Asian restaurants. Unlike prior studies using survey methods to measure perceptions of Asian restaurants, this study attempted to rank comparisons using popular words and sentiment score distributions, reviewing positive and negative tweets on Asian restaurants. Although a single tweet is limited to 140 characters, the size of tweet data itself (i.e. the number of individual opinions) is much larger than sample sizes of typical research methods like surveys or interviews. This approach could, thus, be helpful in investigating more general perceptions or opinions (Lu and Stepchenkova, 2014).

In particular, sentiment analysis presented with user-generated content is an interesting method for researchers who want to assess customer attitudes or evaluations (satisfaction) of products, services or brands. Researchers can indeed quantify and extract subjective information from text messages, which is a notable contribution to the methodology of the hospitality and tourism field. Many researchers have recently discussed how to link sentiment scores to satisfaction (Aguwa *et al.*, 2012; Kang and Park, 2014; Mattson *et al.*, 2013; Moniz and de Jong, 2014; Ren and Quan, 2012) and have shown a significant relationship between sentiment scores and satisfaction. Restaurant management and marketing can use diverse sentiment analyses to capture varying opinions of social media users, information that could be useful in the industry.

Restaurant managers who recognize the advantages of social media marketing for business will develop a competitive edge (Chau and Xu, 2012). First, social media marketing, as suggested by the results, allows managers to monitor the popularity of different types of Asian restaurants or cuisines (Fan and Gordon, 2014). Collecting tweets or other user-generated content in social media means stakeholder popularity or trends in the market can be identified, allowing observations of how trends change in the industry by continuously collecting and analyzing Twitter data about Asian restaurants. Asian restaurant associations could fund, on behalf of individual Asian restaurants, a research project to monitor trends and issues using longitudinal data from Twitter or other social media platforms. The research could detect emerging words related to each cuisine or ethnic type, and thus follow particular trends or issues. Also, restaurant managers themselves may be able to use one of the several convenient web applications or websites to investigate popular words, sentiment distribution, or random examples containing a keyword of each restaurant type. Sentiment Viz (www.csc.ncsu.edu/faculty/healey/tweet_viz/tweet_app/) is one of these free web applications that visualize tweet sentiments. Users can randomly search tweets with a search word and sentiment scores of collected tweets are automatically visualized for users.

Second, once sentiment trends associated with positive or negative expressions are identified, Asian restaurant managers should consider how to respond to those trends. This study showed that Twitter users are generally positive about Asian restaurants. However, reviewing negative tweets in the data can provide practitioners with information they need to improve the perceptions of each type of restaurant (Jang *et al.*, 2009; Ma *et al.*, 2011; Sloan, 2001). Owners or managers of Chinese restaurants may consider that cleanliness and noise in a restaurant led to negative emotions. Japanese restaurants should consider value, service and environment and how they are associated with higher prices. Korean restaurants could consider food quality and better service for customers who are not familiar with their food culture (using chopsticks, for example). Thai restaurants may need to improve food quality, perhaps by making food less spicy, and service quality.

Third, ethnic restaurants need to maintain high food quality, but focus on strengthening cultural authenticity to attract customers (Sloan, 2001). Existing literature agrees that food quality and/or authenticity has the most influence of the major perception dimensions for improving revisit intention as well as satisfaction (Jang *et al.*, 2012; Liu and Jang, 2009). The results revealed that Thai restaurants had no specific food item associated with their cuisine. In addition to that, some tweets in the Thai restaurant data set contained the ethnic words *Chinese* and *Japanese*. This may indicate a problem in differentiating their cultural identity in the Asian restaurant industry. As Tian (2001) also suggested, Thai restaurants, in particular, need to establish their authenticity, not just in food, but atmosphere. Music and interior design are important for ethnic restaurants. Considering the results of this study, Thai restaurants need to promote the authenticity of their food as well as improve food quality (Jang *et al.*, 2009).

Fourth, data collection involves an amazing number of tweets. Millions of tweets are disseminated through the Twitter network. Moreover, the internet and social media networks are still growing rapidly (Litvin *et al.*, 2008). Asian restaurant operators may capitalize effectively on the popularity of social media and especially Twitter. The results included no brand names among Asian cuisines or restaurants in the popular word list, possibly because many Asian restaurants are small businesses, not members of chains. Recent research indicates that marketers should use the information diffusion patterns (eWOM) and sentiment states in the Twitter network (Jansen *et al.*, 2009; Misopoulos *et al.*, 2014; Stieglitz and Dang-Xuan, 2013). Furthermore, social media platforms can be useful marketing tools; they are both low cost and high speed. For small businesses like Asian restaurants, marketing that uses social media networks can effectively and efficiently increase the profile of a restaurant, allow managers to provide promotions to customers or build relationships with customers. To effectively spread information via Twitter, retweets are necessary. Previous research suggests marketers compose a tweet with an image or a link for further information to encourage retweets.

Limitations and recommendations

Although this study is exploratory, intended to reveal an emerging research method in hospitality, this study has several limitations. First, although the amount of data was quite large, the data collection period was relatively short. To observe broader perceptions of Asian restaurants, future studies could collect data over several seasons or years. Second, the data include many tweets from commercial organizations, not just individuals, which may have skewed the results. Different groups, like commercial groups, use Twitter for different reasons, among them advertising, which may affect the quality of the analysis (Park *et al.*, 2015). Discussion and interpretation of findings would be more meaningful if future studies could divide tweets into groups with different characteristics. Third, this study limited search words. However, other tweets may refer to Chinese restaurants, for instance, without actually using that particular term. Future research may need to more accurately identify search terms that elicit more tweets. Fourth, this study provided descriptive results through social media analytics, especially text mining, word frequency analysis and sentiment analysis. To investigate other meaningful patterns in the social media communication (Bruns, 2012; Pang and Lee, 2008), future studies could apply different analysis techniques like network mapping analysis to find the most influential Twitter accounts; regression analysis might also reveal antecedent factors facilitating information dissemination (sharing or retweeting a message).

References

Aguwa, C.C., Leslie, M. and Turgut, O. (2012), “Voice of the customer: customer satisfaction ratio based analysis”, *Expert Systems with Applications*, Vol. 39 No. 11, pp. 10112-10119.

Baker, J. and Cameron, M. (1996), “The effects of the service environment on affect and consumer perception of waiting time: an integrative review and research propositions”, *Journal of the Academy of Marketing Science*, Vol. 24 No. 4, pp. 338-349.

Bilgihan, A., Peng, C. and Kandampully, J. (2014), "Generation Y's dining information seeking and sharing behavior on social networking sites", *International Journal of Contemporary Hospitality Management*, Vol. 26 No. 3, pp. 349-366.

Bitner, M. (1992), "Servicescapes: the impact of physical surroundings on customers and employees", *Journal of Marketing*, Vol. 56 No. 2, pp. 57-71.

Boiy, E., Hens, P., Deschacht, K. and Moens, M. (2007), "Automatic sentiment analysis in on-line text", paper presented at the International Conference on Electronic Publishing 2007 Conference, Vienna, 13-15 May, available at: www.cs.kuleuven.be/groups/liir/publication_files/892138_elpub2007.content.pdf (accessed 10 May 2014).

Boyd, D., Golder, S. and Lotan, G. (2010), "Tweet, tweet, retweet: conversational aspects of retweeting on twitter", paper presented at the 43th Hawaii International Conference on System Sciences, Honolulu, HI, 5-8 January, available at: www.danah.org/papers/TweetTweetRetweet.pdf (accessed 13 May 2015).

Boyd, D.M. and Ellison, N.B. (2007), "Social network sites: definition, history, and scholarship", *Journal of Computer-Mediated Communication*, Vol. 13 No. 1, pp. 210-230.

Bruns, A. (2012), "How long is a tweet? Mapping dynamic conversation networks on Twitter using Gawk and Gephi", *Information, Communication & Society*, Vol. 15 No. 9, pp. 1323-1351.

Bruns, A. and Burgess, J.E. (2011a), "New methodologies for researching news discussion on Twitter", paper presented at the Future of Journalism 2011 Conference, Cardiff, 8-9 September, available at: http://eprints.qut.edu.au/46330/1/New_Methodologies_for_Researching_News_Discussion_on_Twitter_(final).pdf (accessed 10 May 2014).

Bruns, A. and Burgess, J.E. (2011b), "The use of Twitter hashtags in the formation of ad hoc publics", paper presented at the 6th European Consortium for Political Research General Conference, Reykjavik, 25-27 August, available at: http://eprints.qut.edu.au/46515/1/The_Use_of_Twitter_Hashtags_in_the_Formation_of_Ad_Hoc_Publics_(final).pdf (accessed 10 May 2014).

Bruns, A. and Burgess, J.E. (2012), "Researching news discussion on Twitter: new methodologies", *Journalism Studies*, Vol. 13 Nos 5/6, pp. 801-814.

Burton, J. and Khammash, M. (2010), "Why do people read reviews posted on consumer-opinion portals?", *Journal of Marketing Management*, Vol. 26 Nos 3/4, pp. 230-255.

Chau, M. and Xu, J. (2012), "Business intelligence in blogs: understanding consumer interactions and communities", *MIS Quarterly: Management Information Systems*, Vol. 36 No. 4, pp. 1189-1216.

Dodds, P.S., Harris, K.D., Kloumann, I.M., Bliss, C.A. and Danforth, C.M. (2011), "Temporal patterns of happiness and information in a global social network: hedonometrics and Twitter", *PloS One*, Vol. 6 No. 12, p. e26752.

Donovan, R.J. and Rossiter, J.R. (1982), "Store atmosphere: an environmental psychology approach", *Journal of Retailing*, Vol. 58 No. 1, pp. 34-57.

Duan, W., Cao, Q., Yu, Y. and Levy, S. (2013), "Mining online user-generated content: using sentiment analysis technique to study hotel service quality", paper presented at the 46th Hawaii International Conference on System Sciences, Maui, HI, 7-10 January, available at: www.computer.org/csdl/proceedings/hicss/2013/4892/00/4892d119.pdf (accessed 10 April 2015).

Fan, W. and Gordon, M.D. (2014), "The power of social media analytics", *Communications of the ACM*, Vol. 57 No. 6, pp. 74-81.

Ghiassi, M., Skinner, J. and Zimbra, D. (2013), "Twitter brand sentiment analysis: a hybrid system using n-gram analysis and dynamic artificial neural network", *Expert Systems with Applications*, Vol. 40 No. 16, pp. 6266-6282.

Gräbner, D., Zanker, M., Fliedl, G. and Fuchs, M. (2012), "Classification of customer reviews based on sentiment analysis", *Proceedings of the 19th Conference on Information and Communication Technologies in Tourism (ENTER) in Helsingborg, Sweden, 2012*, Springer Link, Vienna, pp. 460-470.

Gruzd, A., Doiron, S. and Mai, P. (2011), "Is happiness contagious online? A case of Twitter and the 2010 Winter Olympics", Paper Presented at the 44th Hawaii International Conference on System Sciences, Manoa, HI, 4-7 January, available at: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=5718715 (accessed 3 June 2014).

Jang, S.S. and Ha, A. (2009), "Asian foods in the US: developments, customer profiles, and experiences", *Journal of Foodservice Business Research*, Vol. 12 No. 4, pp. 403-412.

Jang, S.S., Ha, A. and Silkes, C.A. (2009), "Perceived attributes of Asian foods: from the perspective of the American customers". *International Journal of Hospitality Management*, Vol. 28 No. 1, pp. 63-70.

Jang, S.S., Liu, Y. and Namkung, Y. (2011), "Effects of authentic atmospherics in ethnic restaurants: investigating Chinese restaurants", *International Journal of Contemporary Hospitality Management*, Vol. 23 No. 5, pp. 662-680.

Jang, S.S., Ha, J. and Park, K. (2012), "Effects of ethnic authenticity: investigating Korean restaurant customers in the US", *International Journal of Hospitality Management*, Vol. 31 No. 3, pp. 990-1003.

Jansen, B.J., Zhang, M., Sobel, K. and Chowdury, A. (2009), "Twitter power: Tweets as electronic word of mouth", *Journal of the American Society for Information Science and Technology*, Vol. 60 No. 11, pp. 2169-2188.

Java, A., Song, X., Finin, T. and Tseng, B. (2007), "Why we Twitter: understanding microblogging usage and communities", paper presented at the 9th WebKDD and 1st SNA-KDD 2007 Workshop on Web Mining and Social Network Analysis, New York, *NY, 12-15 August*, available at: http://ebiquity.umbc.edu/_file_directory_/papers/369.pdf (accessed 4 April 2015).

Jayawardena, C.C., McMillan, D., Pantin, D., Taller, M. and Willie, P. (2013), "Trends in the international hotel industry", *Worldwide Hospitality and Tourism Themes*, Vol. 5 No. 2, pp. 151-163.

Kang, D. and Park, Y. (2014), "Review-based measurement of customer satisfaction in mobile service: sentiment analysis and VIKOR approach", *Expert Systems with Applications*, Vol. 41 No. 4, pp. 1041-1050.

Kaplan, A.M. and Haenlein, M. (2010), "Users of the world, unite! The challenges and opportunities of social media", *Business Horizons*, Vol. 53 No. 1, pp. 59-68.

Kim, W.G., Ng, C.Y.N. and Kim, Y. (2009), "Influence of institutional DINESERV on customer satisfaction, return intention, and word-of-mouth", *International Journal of Hospitality Management*, Vol. 28 No. 1, pp. 10-17.

Kotler, P. (1973), "Atmospherics as a marketing tool", *Journal of Retailing*, Vol. 49 No. 4, pp. 48-64.

Kwak, H., Lee, C., Park, H. and Moon, Su. (2010), "What is Twitter, a social network or a news media?", paper presented at the 19th International Conference on World Wide Web, Raleigh, NC, 26-30 April, available at: http://dl.acm.org/citation.cfm?id=1772751 (accessed 25 May 2014).

Kwok, L. and Yu, B. (2013), "Spreading social media messages on Facebook: an analysis of restaurant business-to-consumer communications", *Cornell Hospitality Quarterly*, Vol. 54 No. 1, pp. 84-94.

Lee, L.E., Niode, O., Simonne, A.H. and Bruhn, C.M. (2012), "Consumer perceptions on food safety in Asian and Mexican restaurants", *Food Control*, Vol. 26 No. 2, pp. 531-538.

Leung, D., Law, R., van Hoof, H. and Buhalis, D. (2013), "Social media in tourism and hospitality: a literature review", *Journal of Travel & Tourism Marketing*, Vol. 30 Nos 1/2, pp. 3-22.

Litvin, S.W., Goldsmith, R.E. and Pan, B. (2008), "Electronic word-of-mouth in hospitality and tourism management", *Tourism Management*, Vol. 29 No. 3, pp. 458-468.

Liu, Y. and Jang, S.S. (2009), "Perceptions of Chinese restaurants in the US: what affects customer satisfaction and behavioral intentions?", *International Journal of Hospitality Management*, Vol. 28 No. 3, pp. 338-348.

Lu, W. and Stepchenkova, S. (2014), "User-generated content as a research mode in Tourism and Hospitality applications: topics, methods, and software", *Journal of Hospitality Marketing & Management*, Vol. 24, pp. 119-154.

Luo, Q. and Zhong, D. (2015), "Using social network analysis to explain communication characteristics of travel-related electronic word-of-mouth on social networking sites", *Tourism Management*, Vol. 46, pp. 274-282.

Luong, T.T. and Houston, D. (2015), "Public opinions of light rail service in Los Angeles: an analysis using Twitter data", Paper Presented at the iConference 2015, Newport Beach, CA, 24-27 March, available at: www.ideals.illinois.edu/bitstream/handle/2142/73771/480_ready.pdf?sequence=2 (accessed 10 August 2015).

Ma, J., Qu, H., Njite, D. and Chen, S. (2011), "Western and Asian customers' perception towards Chinese restaurants in the United States", *Journal of Quality Assurance in Hospitality & Tourism*, Vol. 12 No. 2, pp. 121-139.

Mangold, W.G. and Faulds, D.J. (2009), "Social media: the new hybrid element of the promotion mix", *Business Horizons*, Vol. 52 No. 4, pp. 357-365.

Marwick, A. and Boyd, D. (2011), "To see and be seen: celebrity practice on Twitter", *Convergence: The International Journal of Research into New Media Technologies*, Vol. 17 No. 2, pp. 139-158.

Mattson, R.E., Rogge, R.D., Johnson, M.D., Davidson, E.K.B. and Fincham, F.D. (2013), "The positive and negative semantic dimensions of relationship satisfaction", *Personal Relationships*, Vol. 20 No. 2, pp. 328-355.

Mehrabian, A. and Russell, J.A. (1974), *An Approach to Environmental Psychology*, MIT Press, Cambridge, MA.

Misopoulos, F., Mitic, M., Kapoulas, A. and Karapiperis, C. (2014), "Uncovering customer service experiences with Twitter: the case of airline industry", *Management Decision*, Vol. 52 No. 4, pp. 705-723.

Moniz, A. and de Jong, F. (2014), "Sentiment analysis and the impact of employee satisfaction on firm earnings", *Advances in Information Retrieval*, Vol. 8416, pp. 519-527.

Namkung, Y. and Jang, S.S. (2007), "Does food quality really matter in restaurants? Its impact on customer satisfaction and behavioral intentions", *Journal of Hospitality & Tourism Research*, Vol. 31 No. 3, pp. 387-409.

Nunkoo, R., Gursoy, D. and Ramkissoon, H. (2013), "Developments in hospitality marketing and management: social network analysis and research themes", *Journal of Hospitality Marketing & Management*, Vol. 22 No. 3, pp. 269-288.

Pang, B. and Lee, L. (2008), "Opinion mining and sentiment analysis", *Foundations and Trends in Information Retrieval*, Vol. 2 Nos. 1-2, pp. 1-135.

Pantelidis, I.S. (2010), "Electronic meal experience: a content analysis of online restaurant comments", *Cornell Hospitality Quarterly*, Vol. 51 No. 4, pp. 483-491.

Parasuraman, A., Zeithaml, V.A. and Berry, L.L. (1988), "Servqual: a multiple-item scale for measuring consumer perceptions of service quality", *Journal of Retailing*, Vol. 64 No. 1, pp. 12-40.

Park, S.B., Ok, C.M. and Chae, B.K. (2015), "Using Twitter data for cruise tourism marketing and research", *Journal of Travel & Tourism Marketing*, doi: 10.1080/10548408., 2015.1071688.

Ren, F. and Quan, C. (2012), "Linguistic-based emotion analysis and recognition for measuring consumer satisfaction: an application of affective computing", *Information Technology and Management*, Vol. 13 No. 4, pp. 321-332.

Ryan, C. (2015), "Trends in hospitality management research: a personal reflection", *International Journal of Contemporary Hospitality Management*, Vol. 27 No. 3, pp. 340-361.

Sale, J.E.M., Lohfeld, L.H. and Brazil, K. (2002), "Revisiting the quantitative-qualitative debate: implications for mixed-methods research", *Quality and Quantity*, Vol. 36 No. 1, pp. 43-53.

Sloan, A.E. (2001), "Ethnic foods in the decade ahead", *Food Technology*, Vol. 55 No. 10, pp. 18-19.

Stevens, P., Knutson, B. and Patton, M. (1995), "DINESERV: a tool for measuring service quality in restaurants", *The Cornell Hotel and Restaurant Administration Quarterly*, Vol. 36 No. 2, pp. 5-60.

Stieglitz, S. and Dang-Xuan, L. (2013), "Emotions and information diffusion in social media: sentiment of microblogs and sharing behavior", *Journal of Management Information Systems*. Vol. 29 No. 4, pp. 217-248.

Sukalakamala, P. and Boyce, J.B. (2007), "Customer perceptions for expectations and acceptance of an authentic dining experience in Thai restaurants", *Journal of Foodservice*, Vol. 18 No. 2, pp. 69-75.

Thelwall, M., Buckley, K., Paltoglou, G., Cai, D. and Kappas, A. (2010), "Sentiment strength detection in short informal text", *Journal of the American Society for Information Science and Technology*, Vol. 61 No. 12, pp. 2544-2558.

Thelwall, M., Buckley, K. and Paltoglou, G. (2011), "Sentiment in Twitter events", *Journal of the American Society for Information Science and Technology*, Vol. 62 No. 2, pp. 406-418.

Tian, R.G. (2001), "Cultural awareness of the consumers at a Chinese restaurant: an anthropological descriptive analysis", *Journal of Food Products Marketing*, Vol. 7 Nos 1/2, pp. 111-130.

Twitter (2014a), "About Twitter, Inc", available at: https://about.twitter.com/company (accessed 26 September 2014).

Twitter (2014b), "The streaming APIs overview", available at: https://dev.twitter.com/streaming/overview (accessed 10 October 2014).

Weiss, S.M., Indurkhya, N., Zhang, T. and Damerau, F. (2010), *Text Mining: Predictive Methods for Analyzing Unstructured Information*, Springer, New York, NY.

Williams, S.A., Terras, M.M. and Warwick, C. (2013), "What do people study when they study Twitter? Classifying Twitter related academic papers", *Journal of Documentation*, Vol. 69 No. 3, pp. 384-410.

Xiang, Z., Schwartz, Z., Gerdes, J.H. and Uysal, M. (2015), "What can big data and text analytics tell us about hotel guest experience and satisfaction?", *International Journal of Hospitality Management*, Vol. 44, pp. 120-130.

Ye, Q., Law, R. and Gu, B. (2009), "The impact of online user reviews on hotel room sales", *International Journal of Hospitality Management*, Vol. 28 No. 1, pp. 180-182.

Zhao, X., Wang, L., Guo, X. and Law, R. (2015), "The influence of online reviews to online hotel booking intentions", *International Journal of Contemporary Hospitality Management*, Vol. 27 No. 6, pp. 1343-1364.

Zimmer, M. and Proferes, N.J. (2014), "A topology of Twitter research: disciplines, methods, and ethics", *Aslib Journal of Information Management*, Vol. 66 No. 3, pp. 250-261.

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