International Journal of Hospitality Management 91 (2020) 102676

Contents lists available at ScienceDirect

International Journal of Hospitality Management

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

Employing structural topic modelling to explore perceived service quality attributes in Airbnb accommodation

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ARTICLE INFO

Keywords:
Airbnb
Service quality
Online reviews
Structural topic model
Text mining

ABSTRACT

This study employs the structural topic model to extract service quality attributes from 242,020 Airbnb reviews in Malaysia. 22 service related topics were extracted from the corpus and four topics have not appeared in previous Airbnb studies. A widely used modified SERVQUAL questionnaire (MSQ) is cross-validated in this study by comparing its service quality attributes with the results of the topic modelling, which indicates that this MSQ can cover general Airbnb service quality attributes. This study also examines the different preferences of Malaysian and international Airbnb users and the changing patterns of the top six service quality attributes during a five-year period. The findings reveal that Malaysian Airbnb users care more about the appearance and location of the property, and international Airbnb users pay more attention to whether the property can accommodate a group of people. In addition, communication with the host is found to play an increasingly important role in Airbnb users' lodging experiences.

1. Introduction

Service quality is regarded as a major factor for the success of an organization, as it is strongly associated with customer satisfaction, particularly in the service-based industry. As for hospitality industry, service quality is one of the key factors for hoteliers to sustain their competitive advantage and gain customers' confidence in the marketplace with fierce competition (Chen and Chen, 2014). Due to the significant importance of service quality to organizational performance, measuring service quality has aroused the interest of many scholars since 1980s (Grönroos, 1982; Zeithaml et al., 1993). However, in academic research, there is no consensus on the definition of service quality, and most studies conceptualized service quality as the extent to which a provided service meets customer expectation (Lewis et al., 1983). Based on this concept, a generic instrument SERVQUAL was unfolded by Parasuraman et al. (1988) to measure the gap between customers' expectations and perceptions of a service. SERVQUAL and also its variations have been widely used in the hospitality service quality research, and most of these studies have heavily relied on traditional survey methods.

In recent years, customer reviews have been shown as a valuable data source for service quality studies (e.g., Chakrabarti et al., 2018; Brochado et al., 2019; Ju et al., 2019), and Cronin et al. (2000) highlight that customer reviews that reflect customers' past experience can serve as a valid reference to analyze service quality. Comparing with traditional survey methods, one significant advantage of using online customer reviews is that researchers can monitor customers' changing perceptions of service quality by analyzing up-to-date online review data (Korfiatis et al., 2019), which can help companies to consistently meet customers' expectation and maintain a competitive position (Reeves and Bednar, 1994). In addition, customer reviews with unstructured nature can reflect customers' perceptions of service quality more comprehensively, thus these reviews could capture customers' concerns previously overlooked (Li et al., 2013). Lee and Yu (2018) also suggest that service quality attributes extracted from customer reviews can be used to re-examine and expand existing service quality instrument, which can contribute to improvement of survey instrument.

Given the benefits of using customer reviews to assess service quality, this study intends to explore the service quality attributes of Airbnb. Airbnb is an online peer-to-peer (P2P) platform where the host can rent out their properties or spare rooms to potential guests and it is regarded as the most successful sharing economy business model in the lodging sector (Liu and Mattila, 2017). Researchers have shown increasing interest in investigating the phenomenon of Airbnb from various

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https://doi.org/10.1016/j.ijhm.2020.102676
Received 10 March 2020; Received in revised form 11 July 2020; Accepted 26 August 2020
Available online 28 September 2020

perspectives, for example, Airbnb user experience (Cheng and Jin, 2019; Luo and Tang, 2019; Zhang, 2019), the impact of Airbnb on traditional hotels (Blal et al., 2018), Airbnb price determinants (Wang and Nicolau, 2017; Lawani et al., 2019), and Airbnb service quality (Priporas et al., 2017; Ju et al., 2019). Although Airbnb has been widely examined by many researchers, these studies looked mainly at some developed countries, such as the U.S., Australia, and some European countries, few studies have examined the Airbnb phenomenon in developing countries. Hence, this study focuses on Airbnb in a developing country, in particular Malaysia, which responds to the call of Cheng and Jin (2019) and Zhang (2019) on examining Airbnb user experience in different regions. The findings of this study can contribute to generating cross-regional insights into lodging experiences of Airbnb users and serve as the foundation for future comparative studies. The reason for choosing Malaysia is that it is the fastest growing Airbnb market in South East Asia (SEA), with a 73 % year-on-year growth from 2018 to 2019, and there are over 53,000 listings in Malaysia (Inn, 2019).

As for data analysis, we chose a topic model approach, in particular the structural topic model (STM) (Roberts et al., 2014). The effectiveness of applying STM for extracting service quality attributes from customer reviews has been confirmed in the previous study (Korfiatis et al., 2019). We chose SERVQUAL to categorize the extracted service quality attributes by STM, as service quality dimensions of SERVQUAL are generic (Parasuraman et al., 1988), and also we are able to select a SERVQUAL-based instrument that fits the current research context, which can increase the likelihood of finding matching attributes. The present study employed STM to extract service quality related topics from Airbnb reviews and these topics then were used to cross-validate the effectiveness of applying the modified SERVQUAL questionnaire (MSQ) developed by Akbaba (2006) in the context of a P2P accommodation. Furthermore, we utilized the methodological advantage of STM by incorporating two covariates in the topic model, namely, review date, and the nationality of Airbnb users (i.e., Malaysian and international), which can enable us to monitor the chaining preferences of Airbnb users over time and compare preferences of Malaysian and international Airbnb users. The reason for examining the impact of nationality is that customers' expectations in the hospitality industry have been found to differ among different national groups (Armstrong et al., 1997; Ariffin and Maghzi, 2012), and revealing expectations of different customers can help to develop corresponding strategies to satisfy customers with different needs.

The objectives of the present study were: (1) to identify service quality attributes of Airbnb in Malaysia, (2) to cross-validate generalizability of the MSQ, (3) to identify the emphasis of Malaysian and international Airbnb users on different service quality attributes, (4) to identify the seasonal changing patterns of Airbnb service quality attributes. In relation to the above-mentioned research objectives, the study contributes to the sharing economy and hospitality literature by providing new insights into Airbnb users' perceptions of service quality in a developing country through a systematic analysis of customer reviews. This study also contributes to the methodology by proposing a novel method to support the analysis of UGC, so as to promote the analysis and visualization of insights from customer reviews regarding service quality in the hospitality industry.

The remainder of this study is structured as follows. Existing literatures related to customer reviews, service quality research, and text analytics are reviewed in Section 2. In Section 3, detailed STM procedures are explained. Section 4 provides the visualization and description of research results. Section 5 concludes this study by presenting implications, limitations, and suggestions for future studies.

2. Literature review

2.1. Customer reviews and service quality research

With the development of Web 2.0, large volumes of user-generated contents can be found in various media platforms, such as social networks, e-commence platforms, and accommodation booking platforms. Online customer reviews as one of the most important types of UGC are regarded as a significantly influential factor to customers' purchase decision of travel products (Gao et al., 2018), and about 95 % of travelers read the previous customers' reviews online before they book the hotel (Ady, 2015). In the research community of hospitality industry, online customer reviews have gained increasing popularity as a new source of customer voice to explore customer experience, for example, comparing customers' lodging experiences between Airbnb and traditional hotels (Cheng and Jin, 2019; Zhang, 2019), predicting hotel customers' overall satisfaction (Zhao et al., 2019), determining customers' emerging preferences of hotel (Li et al., 2015). However, there has been little research done in the hospitality industry that harness online customer reviews to evaluate service quality, most studies still rely on SERVQUAL-based survey methods.

SERVQUAL is a multi-dimensional research instrument that aims to capture customer expectations and perceptions of a service through five generic dimensions, namely, tangibles, reliability, responsiveness, assurance, and empathy (Parasuraman et al., 1988). SERVQUAL also can serve as a general framework that can be adapted to fit the attributes of a specific industry (Akbaba, 2006). SERVQUAL has been used in various industries, and it is regarded as the most used instrument to measure service quality in the hospitality industry (Ladhari, 2012). Despite the wide use of SERVQUAL, there are still some limitations when applying SERVQUAL in survey-based research, however, some limitations can be overcome through the analysis of customer reviews. The first limitation is that surveys have limited scope of measurement, as customer's experience is only limited to pre-defined SERVQUAL items, which may make surveys fail to measure customers' true perceptions (Duan et al., 2015) or loss of important information. By contrast, customer reviews that are openly structured can reflect more detailed customer experience and consequently present customer perception more accurately (Berezina et al., 2016). In addition, comparing with survey methods, customer reviews and emerging text analytics provide a more efficient and affordable solution to monitor the dynamic changes of customer preference (Chakrabarti et al., 2018).

Although there are some limitations when applying SERVQUAL in survey-based research, SERVQUAL and some other service quality instruments can serve as useful references to capture service quality attributes for studies that are based on using customer reviews (e.g., Palese and Usai, 2018; Duan et al., 2015; Lee and Yu, 2018). For the present study, the MSQ developed by Akbaba (2006) was selected to group service quality attributes. The reason for choosing a modified version of SERVQUAL is that the original SERVQUAL instrument is too generic and unable to capture specific context elements (Adbholkar et al., 2000), especially in the context of newly developed business. The MSQ developed by Akbaba (2006) is more suitable for the present study, as this instrument has been validated not only in the traditional hospitality industry (e.g., Raza et al., 2012) but also in the context of P2P accommodation (e.g., Priporas et al., 2017), despite that these studies still applied survey methods.

This study aims to use customer reviews to evaluate Airbnb service quality. Conducting research on Airbnb is not only due to its significant position in the P2P lodging sector but also related to that there is no standardized or universal service quality instrument developed specifically for P2P accommodations, and previous Airbnb studies applied instruments developed for traditional hotels (e.g., Priporas et al., 2017; Lalicic and Weismayer, 2018). Guttentag (2013) suggests that Airbnb differentiates traditional hotels by offering unique customer experience through providing authentic experience of living like a local, therefore, instruments developed for traditional hotels may not accurately capture service quality attributes perceived by Airbnb users, as they pursue different living experience than customers who stay in traditional hotels (Tussyadiah, 2016). However, these instruments can serve as the foundation for developing service quality measurements for Airbnb, as both types of accommodations are fundamentally providing the same lodging service. Hence, this study intends to use identified service quality attributes to cross-validate Akbaba's (2006) instrument, and these attributes can also serve as supplementary information for adapting Akbaba's (2006) instrument to the context of Airbnb and specify measures to improve the satisfaction of Airbnb users.

2.2. Techniques for textual data analysis

Due to the unstructured nature and large quantity of online reviews, processing these amounts of written data is far beyond human processing capacity. In order to resolve this problem, various text analysis techniques have been developed to extract novel information from text documents (Delen and Crossland, 2008). As for service quality studies, Chakrabarti et al. (2018) used word frequency analysis and lexicon-based sentiment analysis to assess the service quality of private sector banks in India and the findings of this study show that both responsiveness and tangible dimensions have a significant impact on the user evaluation rating. Another word frequency-based study was conducted by Ju et al. (2019) in the context of Airbnb accommodation, and the results revealed four major topics, namely, "host", "room/house", "location", and "neighborhood". From the methodological perspective, word frequency analysis applied in the previous studies can be a good solution to extract information from corpus, as it simplifies the textual data analysis. However, using word frequency-based approach, each topic is represented by a list of manually selected keywords, which makes this approach difficult to uncover the trend of specific topics, due to the difficulty of identifying the temporal patterns of an individual keyword that indicates a certain concept (Chen et al., 2017), especially an identical word in different documents may indicator different topics.

Another stream of customer reviews-based service quality studies used the topic modelling approach that is based on machine learning, which can automatically extract topics from a corpus without the need of manual summarization, hence reducing subjective biases. The underlying concept of topic modelling is that a document consists of various topics and each topic is a probability distribution over the vocabulary (Blei et al., 2003). The topic modelling results can provide both topic-related keywords and also proportional distributions of different topics over each document, which enables us to monitor changing patterns of customer perceptions to specific topics more effectively by analyzing proportional changes of topics instead of individual word. The topic modelling approach can significantly improve the qualitative interpretability of textual data by revealing the semantic relations of words from a corpus and providing additional insights into the correlations of different topics. Latent Dirichlet Allocation (LDA) (Blei et al., 2003) is a well-known topic model that is designed to automatically organize a large number of documents based on hidden topics, measured as the word co-occurrence patterns (Jacobi et al., 2015). LDA has been widely applied in the academic research. As for service quality studies, Lee and Yu (2018) applied LDA to analyze 42,137 reviews from Google Maps to assess airport service quality. This study revealed the effectiveness of using online reviews to cross-verify standard survey results from traditional industry, hence providing insights for the present study to re-examine Akbaba's (2006) instrument. Palese and Usai (2018) applied LDA to measure service quality of the e-commerce industry based on SERVQUAL model. This study found that customers concern more about topics related to responsiveness (19.13 %) and empathy (20.57 %) than tangibles (14.93 %) and assurance (13.70 %). The authors suggest that it is important for companies to identify service related topics which have significant impacts on customer evaluation to achieve high customer service.

Despite that LDA is able to extract hidden thematic structures from text documents, it lacks additional document-level information, hence it is difficult to use LDA to examine the relationship between document metadata and the content of a document model (Roberts et al., 2016). However, this limitation can be overcome by using STM, an extension of LDA. STM outperforms LDA in terms of that STM allows researchers to incorporate arbitrary document information which appears in the form of covariates to estimate the per-document topic distributions (topic prevalence) and per-topic word distributions (topic content) (Roberts et al., 2016). During the topic modelling process, STM can directly estimate the impacts of document metadata on the prevalence of latent topics. STM has been applied in various studies to analyze different types of reviews, however, only one service quality study has used STM in textual data analysis. Korfiatis et al. (2019) employed STM to measure service quality of Airline industry by analyzing online Airline passengers' reviews. 30 topics were extracted from a corpus consisting of 184, 502 reviews in this research. This study presented the suitability and effectiveness of using STM to map and measure service quality dimensions.

Although various types of text mining techniques have been developed to analyze customer reviews, the selection of appropriate tools should be in line with objectives of the research. Based on the comparisons of techniques that have been widely applied in service quality research, STM is employed to extract service quality related topics, and examine the impact of external factors on changes of topic prevalence.

3. Methodology

3.1. Data collection

The Malaysian Airbnb data for this study were acquired from AirDNA, a data company that has provided Airbnb data for articles published in several high-ranking journals (e.g., Horn and Merante, 2017; Blal et al., 2018). The Airbnb dataset includes 620,487 customer reviews generated from November 2010 to January 2019. Fig. 1 shows the review frequency in different periods, and it is found that the number of reviews is significantly lower between 2010 and 2013. Table 1 shows top ten countries of origin of Airbnb users who left comments in Malaysia. Almost half of Airbnb users were from Malaysia, and Singapore made up the highest proportion with 12.7 % among the non-Malaysian group. There are total 48,517 listings, with average 12.79 reviews per listing. The proportions of listings received less than 10 reviews and over 100 reviews in total listings are 5 % and 0.1 % respectively. This dataset includes four variables, namely, property ID (listing ID), review date, review text, and country (countries of origin of Airbnb users).

3.2. Text preparation

Text pre-processing is conducted to extract desired corpus for the analysis. TM package and NLP package from R programming were mainly used for the text preparation. The first step of text pre-processing is to remove non-English reviews by using the textcat package (Hornik et al., 2013). The detailed processes include: (1) Text tokenization (a key

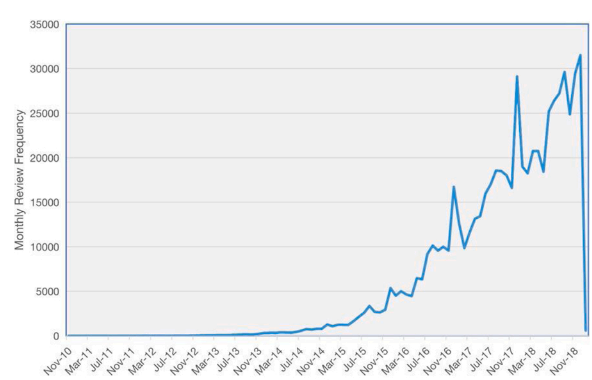

Fig. 1. Monthly review frequency.

Table 1
Summary statistics of top ten country of origin of Airbnb user reviews in Malaysia.

Country of Origin	Frequency	Proportion
Malaysia	305324	49.20 %
Singapore	78910	12.70 %
United States	23504	3.80 %
Australia	21746	3.50 %
China	21248	3.40 %
United Kingdom	19871	3.20 %
Indonesia	15474	2.50 %
Germany	9448	1.50 %
Philippines	8788	1.40 %
India	7485	1.20 %

prerequisite for extracting topics from corpus by splitting sentences into words) (2) Text normalization (converting capital letters into lower case) (3) Excluding reviews with less than 50 words (Palee and Piccoli, 2016), (3) Removing numbers, punctuation marks, and extra white space, (4) Removing default stop words (e.g., "is", "the"), (5) Removing customized stop words (e.g., city names, duplicated words), (6) N-gram analysis was conducted to identify frequent compound words and transform them into unigrams (e.g., "twin towers" to "twintowers"), (7) Removing words which appear in less than 20 documents to filter some insignificant words.

Since this study intends to compare the changing topic prevalence across different periods, the reviews generated from 2010 to 2013 were omitted due to the lower frequency of reviews generated during these periods. Schmiedel et al. (2018) suggest that it is important to ensure the subgroups sufficiently large to make a meaningful comparison. In addition, the rows where reviewer's nationality is not identified were also removed. The final corpus includes 242,020 reviews, and these reviews were used to conduct the following topic modelling analysis.

3.3. Covariates setup

In order to examine the expectations of Malaysian and international Airbnb users and the impact of time on the changes of Airbnb users' service quality perception, nationalities of Airbnb users and review date were included as document-level metadata variables. Based on the country of origin information provided in the dataset, Airbnb users were classified as "Malaysian" and "international" group, which is in light of Ariffin and Maghzi (2012). In addition, review date was converted to a numeric variable (e.g., "2014-01-01" to "1") for the purpose of examining the time effect on the change of the topic prevalence. Covariate analysis is conducted by using the estimateEffect function and a regression analysis is performed where the topic proportions are indicated as the outcome variable shown below:

$$Proportions_{d,k} = \beta_0 + \beta_1 * review.time_d + \beta_2 * nationality_d + \beta_3 * review.time_d * nationality_d + \varepsilon_d.$$

Adopted from Schmiedel et al. (2018)

In this model, d is the d-th document, k is the k-th topic, and β_0 is the intercept. β_1 is the coefficient of $review.time_d$ which is a numerical variable, indicating when this review was generated. β_2 is the coefficient of $nationality_d$ which is a categorical variable, indicating Airbnb users' countries of origin (e.g., Malaysian and international). β_3 is the estimated coefficient which can monitor the moderated effects of "review time" and "nationality" on topic proportions, but the moderated effects are not the scope of the present study. ε_d indicates the standard errors of the model.

3.4. Topic number estimation

Even though there is no single correct method to identify the number of topics when applying STM, examining the trade-off between semantic consistency and exclusivity can be one possible solution (Kuhn, 2018). Following Kuhn (2018) and Hu et al. (2019), the topic number estimation of the present study is mainly based on the evaluation of semantic coherence and exclusivity of the topic model. Semantic coherence is used to validate the internal coherence of a specific topic by measuring the frequency of co-occurrence of the most probable words to each other in the original corpus, a higher semantic coherence score means that the most frequently used words within a topic may frequently appear together. Exclusivity is to measure how well a topic can differentiate itself from other topics by making a comparison between the similarity of word distribution, and a higher exclusivity score means that high-probability words in this topic are less likely to be found in other topics (Schmiedel et al., 2018). Roberts et al. (2017) suggest measuring topic quality by using both semantic coherence and exclusivity of words to topics at the same time. However, models with well-performed statistic results are found to have poor interpretability (Chang et al., 2009). Hence, in addition to using the statistical metrics, the selected topic models were also being validated qualitatively by examining the interpretability of corresponding top words in each topic. In line with Korfiatis et al. (2019), the study commenced with a stepwise estimation for an initial number of eight topics to a maximum of 40 topics. Fig. 2 shows the semantic coherence and exclusivity results of different topic solutions.

As illustrated in Fig. 2, there is no topic model which has a dominant position. As topics in a model increase, the semantic coherence will generally decrease, but the exclusivity score will increase (Kuhn, 2018). Hence, this study followed Schmiedel et al. (2018), selecting the model which can generate comparatively decent results in both semantic coherence and exclusivity. After comparing the mean score of exclusivity (9.695) and semantic coherence (−108.99) and examining the relevance of topic contents, a 22-topic model solution was selected for this study. This model solution is similar to previous studies (Korfiatis et al., 2019; Hu et al., 2019).

4. Findings

4.1. Topic summary and labeling

Table 2 shows the results of topic modeling and labels assigned to

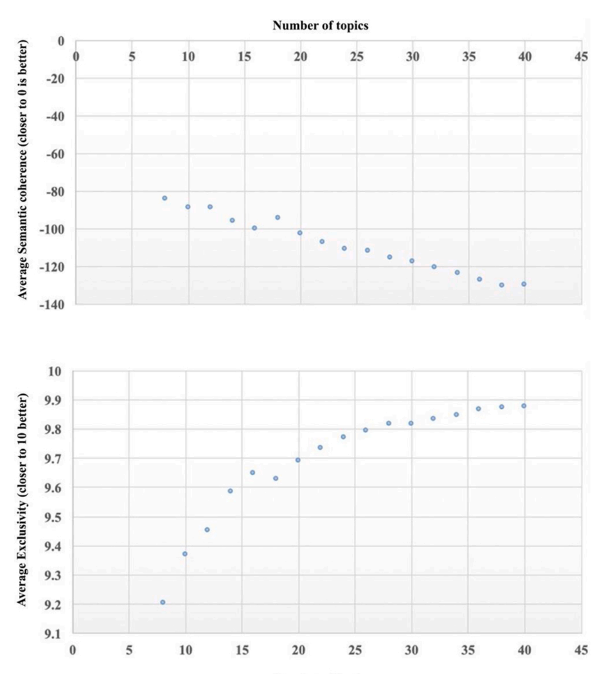

Fig. 2. Semantic coherence and exclusivity of selective topic model solutions.

each topic and the source of the label. In the topic labeling process, high probabilities (Highest Prob) words, frequency-exclusivity (FREX) words, and top 10 representative reviews of each topic were used. Words generated from the FREX statistic were mainly used to label the topic, as this measurement weights words by their overall frequency and the degree of exclusivity of those words to the topic which can provide more semantically intuitive representations of topics (Roberts et al., 2014). However, FREX statistic sometimes ranks some uncommon words high (Korfiatis et al., 2019), therefore Highest Prob words will be referred to if FREX terms fail to differentiate a topic. The name for each topic was selected by referring to the pre-identified service attributes from previous Airbnb studies. However, if no matching attributes could be found from previous Airbnb literature, these topics would be labeled manually through group discussion and analysis. Finally, the representative reviews of each topic were examined to validate the appropriateness of selected topic names.

4.2. Topic mapping and content analysis

Based on the description of service quality attributes in MSQ, the topics extracted from STM were assigned to five different dimensions, namely, tangibles, assurance, adequacy in service supply, understanding and caring and convenience (See Table 3).

4.2.1. Tangibles

Under the dimension of tangibles, topic 13 is most related to attribute 1. From the distinctive words of this topic, some general descriptions about property buildings were found, such as "great", "amazing", and "fantastic". By checking the representative reviews of topic 13, it is found that Airbnb users who recommended the property to others often gave positive comments to the location of the property. Topic 12 and 17 match to attribute 2, and the service unit in this topic 12 mainly refers to the pool, in particular, the pool located in the rooftop (e.g., Infinity Pool) was often highlighted by Airbnb users. Some other service units were found in the topic 17, including service units for daily use, such as laundry, washing machines, and kitchen, and also for the purpose of recreation, such as sauna, jacuzzi, and gym. Topic 1 and 16 were found to be related to attribute 3. Topic 1 is mainly about communication devices (e.g., Wi-Fi router). Topic 16 is about property equipment, such as water heaters and air conditioners. From the representative reviews of topic 16, Airbnb users were found often commenting on the air conditioner quality and shower experience, and many of these comments tended to be relatively negative.

Topic 4, 5, 14, 15, 18, and 22 are classified into attribute 4 at the same time. Topic 4 is about the suitability for group accommodation, related top words of this topic include "gather", "group", and "suitabl". The findings of this topic provides further evidence that group traveling has been found to be one of the reasons why people prefer Airbnb instead of traditional hotels (Sthapit and Jiménez-Barreto, 2018). Topic 5 is related to sleeping conditions. Topic 14, 15, and 18 are about living atmosphere. Representative reviews of topic 14 reveal Airbnb users' dissatisfaction with noises that came from the main street or nearby mosques. Topic 15 is about specific scenery Airbnb users can enjoy. Topic 18 is about the internal appearance of the room, as Airbnb users were found to often compliment the decoration and design of the room in this topic. Topic 22 is associated with the cleanness of the rooms, as "clean" appeared in both sections of the top words. Both topic 1 and topic 16 are associated with attribute 5; topic 1 refers to the issues related to Wi-Fi devices, such as the router and modem, and topic 16 is about the water heater and air conditioner. Topic 19 matches to attributes 6 and 7; the related keywords in topic 19 include "toiletry", "iron", "toothbrush" and "towel", and Airbnb users often used the word "extra" to show sufficiency of provided items by Airbnb hosts.

4.2.2. Adequacy in service supply

In this dimension, topic 7 that matches to attribute 8, 9, and 10 is

Table 2
Topic summary and labeling.

Topic #	Topic Label	Top Words	Topic Prop. (%)	Reference
1.	Internet connection	Highest Prob: good, wifi, locat, problem, host, clean, servic FREX: wifi, good, internet, connect, minor, solv, condit	4.3 %	Cheng and Jin (2019)
2.	Booking experience	Highest Prob: day, book, room, didn, host, call, time FREX: told, refund, review, cancel, deposit, final, wrong	4.7 %	Lee and Yu (2018)
3.	Transportation	Highest Prob: station, airport, grab, taxi, uber, minut, bus FREX: sentral, train, station, bus, taxi, monorail, klia (airport)	3.1 %	Zhang (2019)
4.	Group stay	Highest Prob: hous, stay, friend, place, clean, famili, recommend FREX: homestay, gather, group, suitabl, environ, hous, satisfi	10.9 %	Named by authors
5.	Sleep condition/ Bed	Highest Prob: bed, comfort, space, comfi, equip, kitchen, furnish FREX: comfi, bed, queen, size, qualiti, singl, furnish	3.1 %	Zhang (2019)
6.	Car parking	Highest Prob: park, car, secur, access, guard, card, lift FREX: park, lift, guard, carpark, visitor, card, entranc	2.8 %	Zhang (2019)
7.	Hosts' response	Highest Prob: host, place, stay, respon, easi, clean, great FREX: checkin, checkout, respond, prompt, queri, quick, process	9.6 %	Cheng and Jin (2019)
8.	Tourist attraction	Highest Prob: walk, food, locat, distanc, place, minut, street FREX: distanc, attract, gurney, famous, plaza, georgetown, walkabl	5.5 %	Priporas et al. (2017)
9.	Hospitality hosting behavior	Highest Prob: host, home, feel, stay, experi, time, wonder FREX: home, welcom, feel, sweet, husband, warm, memor	7.8 %	Lalicic and Weismayer (2018)
10.	Water activities	Highest Prob: beach, place, relax, quiet, staff, peac, stay FREX: island, scooter, beach, snorkel, villa, hustl, bustl	3.2 %	Named by authors
11.	Shopping	Highest Prob: conveni, shop, mall, restaur, locat, nearbi, place FREX: mall, store, shop, groceri, conveni, tesco, eleven	4.6 %	Luo and Tang (2019)

(continued on next page)

Table 2 (*continued*)

Topic #	Topic Label	Top Words	Topic Prop. (%)	Reference
12.	Swimming pool	Highest Prob: nice, pool, room, view, swim, floor, clean FREX: flat, roof, confort, infin, nice, recommand, swim	5.3 %	Cheng and Jin (2019)
13.	Property attributes	Highest Prob: apart, great, stay, locat, recommend, amaz, host FREX: apart, rocki, fantast, peggi, edna, victoria, amaz	8.4 %	Wang and Nicolau (2017)
14.	The feature of neighborhood	Highest Prob: night, noi, road, breakfast, morn, light, room FREX: sleeper, nasi, noi, hear, mosquito, prayer, earplug	2.5 %	Lawani et al. (2019);
15.	Seaview	Highest Prob: unit, view, balconi, sea, watch, face, enjoy FREX: unit, seaview, movi, balconi, eve, watch, penthous	2.4 %	Named by authors
16.	Room equipment	Highest Prob: room, water, bathroom, aircond, shower, toilet, hot FREX: heater, toilet, pressur, condition, shower, filter, aircond	4.8 %	Zhang (2019)
17.	Amenities and service	Highest Prob: build, pool, cook, gym, kitchen, includ, facil FREX: complex, laundri, sauna, machin, washer, stock, includ	2.4 %	Wang and Nicolau (2017)
18.	Room characteristics/ Pets	Highest Prob: love, room, place, live, hous, decor, beauti FREX: cute, guesthous, cat, concept, chill, style, pet	3.8 %	Lawani et al. (2019)
19.	Daily necessities/ Free food and drink	Highest Prob: provid, min, drive, towel, basic, drink, coff FREX: toiletri, iron, necess, snack, toothbrush, gent, complimentari	2.5 %	Zhang (2019)
20.	Rental rules	Highest Prob: check, arriv, person, time, host, late, meet FREX: late, allow, meet, flight, patient, delay, wait	4 %	Wang and Nicolau (2017)
21.	Child friendly	Highest Prob: kid, condo, place, love, famili, enjoy, stay FREX: legoland, kid, toy, kitti, medina (mall), puteri (harbor), louis	2.5 %	Named by authors
22.	General experience/ Cleanness	Highest Prob: stay, place, clean, host, locat, great, area FREX: pleasant, area, clean, thing, stay, expect, place	1.8 %	Lawani et al. (2019)

Note: "Topic Prop." represents the estimated proportion of each topic; "Reference" indicates the source of the topic name.

Table 3
Mapping of identified topics to MSQ.

Dimension	Attribute	Topic
Tangibles	1. The property has visually appealing buildings and facilities	Topic 13
	2. The service units of the property have adequate capacity (dining rooms, meeting rooms, swimming pools, business center facilities, etc.)	Topic 12, Topic 17
	3. The property has modern-looking equipment (air conditioner, furniture, elevator, communication devices, etc.)	Topic 1, Topic 16
	4. The atmosphere and equipment are comfortable and appropriate for purpose of stay (beds, chairs, rooms, etc. comfortable, clean, and tranquil)	Topic 4, Topic 5, Topic 14, Topic 15, Topic 18, Topic 22
	5. The equipment of the property works properly without causing breakdowns	Topic 1, Topic 16
	6. Materials associated with the services are adequate and sufficient (soap, shampoo, towel, etc.)	Topic 19
	7. Food and beverages served are hygienic, adequate, and sufficient	Topic 19
Adequacy in Service supply	8. The Airbnb host provides prompt service	Topic 7
	9. The Airbnb host provides the services at the time it promises to do so	Topic 7
	10. The Airbnb host is always available when needed	Topic 7
	11. The Airbnb host keeps accurate records (reservations, guest records, bills, orders, etc.)	Topic 2
	12. The Airbnb host resolves guest complaints and compensate for the inconveniences guests go through	Topic 2
Understanding and caring	13. The Airbnb host provides flexibility in services according to guest demands	Topic 20
	14. The Airbnb host always treat guests in a friendly manner	Topic 9
	15. The Airbnb host understands the specific needs of guests	Topic 21
Assurance	16. The property and its facilities have operating hours convenient to all their guests.	Topic 20
Convenience	17. It is easy to access to the property (transportation, car parking area, etc.)	Topic 3, Topic 6
	18. Getting information about the facilities and services of the property is easy (reaching information via phone, internet, etc., direction signs, etc.)	Topic 7

Note: Adopted from Akbaba (2006). In order to make the description of the service quality attributes more suitable to Airbnb context, some words in the original questionnaire were modified, and we only present the matching attributes.

about hosts' reliability and efficiency of service. Topic 2 is both associated with attribute 11 and 12. From the representative reviews of topic 2, it is found that Airbnb users like to complain about incorrect refund amount or delayed refund after cancellation, and Sthapit and Björk (2019) also found that issue with refunds is one of factors that led to Airbnb's poor customer service.

4.2.3. *Understanding and caring*

Under the dimension of understanding and caring, topic 20 matches to attribute 13. Topic 20 is about flexibility of check in and out, and from the representative reviews of topic 20, we discovered that many Airbnb users were allowed to check in/out flexibly in certain circumstances, such as flight delay or traffic jam. Topic 9 is more related to attribute 14, as Airbnb users frequently commented on the warm welcome from the Airbnb host in the representative reviews of this topic, and also highlighted the home-like experience. Topic 21 shows that Airbnb host paid attention to specific needs of children, which matches to attribute 15.

4.2.4. Assurance

Only topic 20 is categorized into the dimension of assurance. This topic represents the convenience provided by Airbnb hosts, particularly at check in/out times, hence matching to attribute 16.

4.2.5. Convenience

Topic 3, and 6 match to attribute 17 at the same time. Topic 3 is related to transportation, both private (e.g., Grab, Uber, taxi) and public transportation (e.g., KTM, Monorail, MRT) were mentioned in topic 3, and Airbnb users tend to emphasize the distance from the property to public transportation. Topic 6 is more linked to the accessibility to car park. Topic 7 is related to attribute 18. From the representative reviews of this topic, we found that Airbnb users often contacted Airbnb host via mobile phone regarding check in and out information and they often complimented hosts' prompt response. In addition, some Airbnb users also commented on the usefulness of instruction provided by the Airbnb host.

Topic 8, 10, and 11 were not mentioned in the MSQ. However, these topics could still be grouped into the dimension of convenience, which confirms the wide generalizability of the MSQ. Topic 8 is about convenience to reach surrounding tourist attractions, and topic 10 and 11 are about easy access to places where they can participate in some water activities and go shopping. The emergence of these three topics supports that Airbnb users tend to prefer locations where they can easily reach the point of interest (Gutierrez et al., 2017; Sthapit and Jiménez-Barreto, 2018).

4.3. Topic correlation analysis (topic network)

One of the differences between the STM and many other membership models is that it specifically estimates the correlation between topics (Lucas et al., 2015). Fig. 3 shows topics which are likely to co-occur within the same documents. The different width of the connecting edge indicates the strength of correlation between topics, and two topics with a correlation coefficient greater than 0.05 are connected together. The size of each label signifies the topic proportion, the larger the label, the more words in the corpus are allocated to the corresponding topic. According to Fig. 3, "hosts' response" is associated with both "rental rules" and "internet connection". After examining relevant reviews, it is found that communications between Airbnb host and users are often related to the rental regulations (e.g., late or early check in/out) and internet related issues. This result can bring constructive suggestions for improving the service quality. For example, hosts can prepare the information most concerned by Airbnb users in advance, which can reduce the frequency of customers contacting hosts to inquire relevant information. Especially when hosts are busy, they may not be available immediately. In addition, the connections of some topics also reveal Airbnb users' preferences. For instance, "property attributes", "shopping", and "tourist attraction" are closely linked to "transportation", which may indicate that Airbnb users tend to care about whether the accommodation is with convenient transportation to their desired destinations.

4.4. Topic trend analysis

Due to the space limitations, this study selected the top six topics based on estimated topic proportion for trend analysis. Fig. 4 shows the changing estimated mean proportions of selected topics. Only "group stay" exhibits a comparatively clear seasonal increase in topic proportion starting from around January 2017. This may be explained by that January is during one of the peak tourist seasons in Malaysia (Chen and Pearce, 2012). As Airbnb is regarded as a popular choice of tourism accommodation (Guttentag et al., 2017), and many tourists who chose Airbnb were found to prefer group travel (Volgger et al., 2018), which may lead to the high demand of Airbnb properties that can accommodate multiple people and the increase of "group stay" related discussions

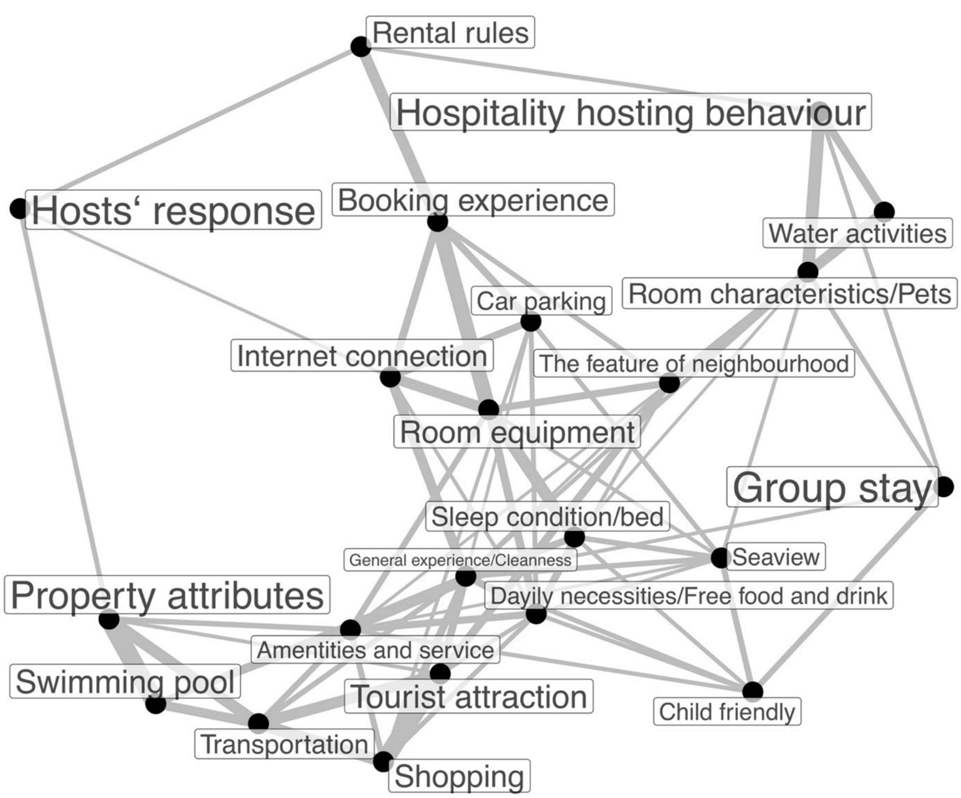

Fig. 3. Estimated topics correlation map.

in this period. Among the remaining topics, “hosts’ response” experienced a substantial and continuous increase throughout the whole period and became the dominated topic after 2017, which indicates that communications with Airbnb hosts become increasingly important. However, we cannot conclude that topics with downward trends are no longer important, as Airbnb users, especially those experienced Airbnb users may start to take certain service attributes as granted and ignore them in reviews, nevertheless, this still needs to be verified in future research.

4.5. Customer preference analysis

Fig. 5 shows the topics which are more likely to appear in reviews written by Malaysian or international Airbnb users, which reveals the differences in their preferences when commenting on Airbnb accommodation experience. The analysis is conducted by comparing the mean proportion of same topics in these two groups, and results have been statistically tested.

Fig. 5 illustrates that Malaysian and international Airbnb users have distinct preferences, which supports that customers’ expectations of service quality are influenced by the nationality (Ariffin and Maghzi, 2012; Pantouvakis and Renzi, 2016; Zgolli and Zaiem, 2017). It is notable that “property attributes” is significantly more prevalent in reviews written by Malaysian Airbnb users, which shows that Malaysian Airbnb users were more likely to concern about the characteristics of the property (e.g., location, appearance). International Airbnb users put more emphasis on whether the property is suitable for the family or group stay. As for the remaining 20 topics, the proportional differences between international and Malaysian Airbnb users are less significant, within 0.05 %. Among these topics, Malaysian Airbnb users cared more about “transportation”, “hospitality hosting behavior”, “water activities”, “swimming pool”, and “amenities and service”, whereas international Airbnb users paid more attention on “car parking”, “seaview”, and “room characteristics/pets”. “Shopping” and “the feature of neighborhood” have similar proportions in both groups.

5. Discussion and conclusion

This study employed a novel technique to identify service quality attributes of Airbnb in Malaysia. More specifically, 22 service quality attributes associated with Airbnb users’ lodging experience were discovered. Comparing with existing Airbnb research, Airbnb host related topics are the most prevalent in previous studies (e.g., Luo and Tang, 2019; Cheng and Jin, 2019; Lawani et al., 2019), and two Airbnb host related topics were extracted from the present study. This common ground confirms the important role of hosts in Airbnb users’ lodging experience (Ju et al., 2019), especially to establish good communication with Airbnb users, which can contribute to fostering an initial trusting

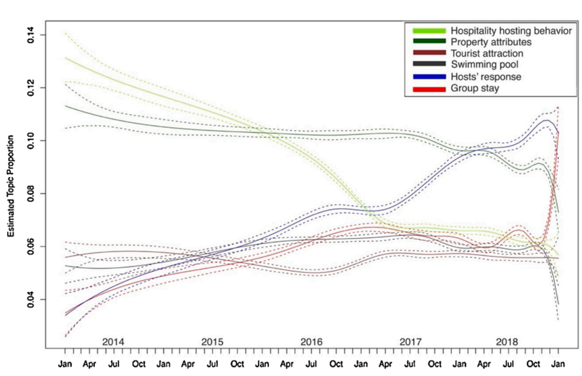

Fig. 4. Changing estimated topic proportion over time (January 2014 to January 2019).

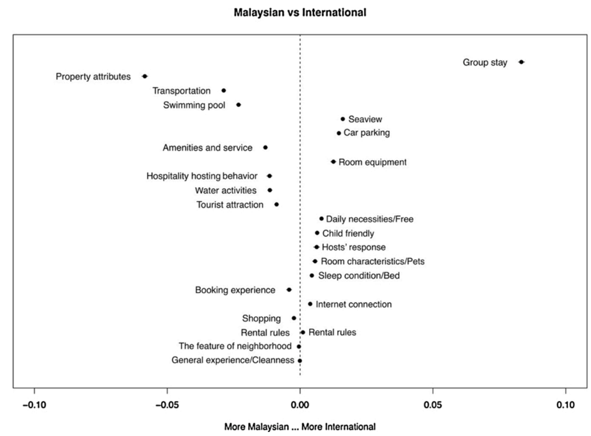

Fig. 5. Topic proportion comparison (Malaysian vs. International).

relationship (Cheng and Jin, 2019). It is also interesting to notice that extracted attributes under the dimension of convenience are irrelevant to accommodation experience, but more linked to the local experience, such as visiting surrounding tourist attractions and participating in water activities. As pursuing more authentic local experience is regarded as one of major motivations for travelers to choose Airbnb (Guttentag, 2013), it is worthwhile for future research to investigate in what degree the conveniences provided to explore local experience affect the Airbnb users’ perception of service quality. Four attributes that have not appeared in previous Airbnb research were also identified, namely, “group stay”, “water activities”, “seaview”, and “child friendly”, which reflects service quality attributes that Airbnb users cared more about in Malaysia than in other countries.

This study extends extant service and hospitality research by exploring Airbnb service quality attributes in a developing country, and the results can serve as a useful reference for future comparative studies. This study demonstrated an effective solution to cross-validate a conventional service quality instrument. Specifically, we compared extracted service quality attributes with items from Akbaba’s (2006) instrument, and those attributes that are not included in Akbaba’s (2006) instrument can serve as useful guidelines for researchers to develop survey instruments to measure Airbnb users’ perception of service quality in the similar context as the present study. By taking advantage of the methodological strength of STM, the present study also goes beyond previous Airbnb studies by analyzing changing patterns of Airbnb users’ perceptions to service quality attributes, and examining different weights placed by Airbnb users from different national groups (Malaysian and international) instead of only identifying overall Airbnb users’ perceptions of service quality. These additional insights provide fresh perspectives on understanding the preferences of Airbnb users in Malaysia, which can enlighten future studies to evaluate Airbnb users’ voices from different angles.

From the perspective of methodology, this study demonstrated the suitability of using STM to extract insightful information from enormous quantity of unstructured textual data. STM provides an effective solution to conduct service quality related research in the hospitality industry. In particular, with the incorporation of covariates in STM, researchers can directly examine the influence of different factors to customers’ perception of service quality.

The findings of this study provide Airbnb management deeper insights into how customers perceive Airbnb service quality and also serve as a foundation to develop relevant strategies to improve service quality. For instance, in order to help Airbnb users to find accommodations which better suit their needs, Airbnb can optimize the online recommendation system by referring to identified attributes that are associated with the specific needs of users, such as shopping and visiting tourist attractions. Two host-related attributes were identified in this study, namely, "hosts' response" and "hospitality hosting behavior", which suggests Airbnb hosts to maintain timely communication with Airbnb users and create a home-like lodging experience to meet Airbnb users' expectations. In addition, the discovery of some attributes that reveal specific needs of Airbnb users also can help Airbnb hosts develop more effective promoting strategies. For instance, apart from providing information about some general accommodation related attributes (e.g., room equipment, amentias, and service) in the listing homepage, Airbnb hosts also can highlight other convenience related benefits, such as easy access to specific local tourist attractions or public transportations. The attribute of "the feature of neighborhood" reminds Airbnb hosts to ensure sound insulation of the room if their properties are near the main street, construction site, or mosque, as many Airbnb users complained about the noise from these places in reviews. From "room equipment", we frequently found complaints related to the functionality of air conditioners and poor shower experience. One of unique attributes extracted in this study is "child friendly", which suggests Airbnb hosts to offer personalized services to meet the needs of specific groups of people. In addition, the trend analysis of selective attributes in this study indicates the dynamic nature of Airbnb users' preference, therefore Airbnb management should develop a system to monitor the changing perception and emphasis of Airbnb user by analyzing up-to-date customer reviews. Lastly, the comparison analysis reveals the different emphasis of Malaysian and international Airbnb users on service quality attributes, and the results can provide Airbnb company and hosts useful information regarding priority setting when developing strategies to enhance lodging experiences for Malaysian and international Airbnb users.

However, there are still some limitations in this study. The first limitation is that this study only employed data from one sharing economy based accommodation platform, and the results may not be able to generalize some other sharing economy based accommodation platforms (e.g., HomeAway, Flipkey). Future studies should collect data from different sharing economy based accommodation platforms to verify whether customers' perceptions of service quality differ across different platforms. Another limitation is that this study only demonstrated the changing trends of selective service attributes perceived by Airbnb users. Future study should be conducted to investigate factors that trigger the changing perception of Airbnb users, which can contribute to predicting the variation of the customer preference and making corresponding adjustments to improve customers' satisfaction. Moreover, this study only divides the Airbnb users into Malaysian and international group, and the findings about the preference of international group may not be able to generalize all the non-Malaysians, as the international group consists of Airbnb users from countries with diverse cultural environments. Future studies should divide Airbnb users into more segmented groups based on the cultural norms to determine the impact of cultural factors on Airbnb users' perception of service quality.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author Wei Chong Choo. The data are not publicly available due to restrictions of the third-party data provider (AirDNA, LLC.).

Funding

The authors received no specific finding for this work.

Declaration of Competing Interest

The authors report no declarations of interest.

Acknowledgement

The authors would like to thank Mrs. Zhao Zhengni for her language assistance, and the constructive comments from anonymous reviewers.

References

Ady, M., 2015. How To Present Travel Review Content For Optimal Bookings [online] Trust You. Available at: https://www.trustyou.com/resources/consumer-research-identifies-how-to-present-travel-review-content-for-optimal-bookings [Accessed 1 Feb. 2020].
Akbaba, A., 2006. Measuring service quality in the hotel industry: a study in a business hotel in Turkey. Int. Hosp. Manag. 25 (2), 170–192.
Ariffin, A., Maghzi, A., 2012. A preliminary study on customer expectations of hotel hospitality: influences of personal and hotel factors. Int. J. Hosp. Manag. 31 (1), 191–198.
Armstrong, R., Mok, C., Go, F., Chan, A., 1997. The importance of cross-cultural expectations in the measurement of service quality perceptions in the hotel industry. Int. J. Hosp. Manag. 16 (2), 181–190.
Berezina, K., Bilgihan, A., Cobanoglu, C., Okumus, F., 2016. Understanding satisfied and dissatisfied hotel customers: text mining of online hotel reviews. Int. J. Hosp. Manag. 25 (1), 1–24.
Blal, I., Singal, M., Templin, J., 2018. Airbnb's effect on hotel sales growth. Int. J. Hosp. Manag. 73, 85–92.
Blei, D.M., Ng, A.Y., Jordan, M.I., 2003. Latent dirichlet allocation. J. Machine Learn. Res. 3 (Jan), 993–1022.
Brochado, A., Rita, P., Oliveira, C., Oliveira, F., 2019. Airline passengers' perceptions of service quality: themes in online reviews. Int. J. Hosp. Manag. 31 (2), 855–873.
Chakrabarti, S., Trehan, D., Makhija, M., 2018. Assessment of service quality using text mining – evidence from private sector banks in India. Int. J. Bank Market. 36 (4), 594–615.
Chang, J., Gerrish, S., Wang, C., Boyd-Graber, J.L., Blei, D.M., 2009. Reading tea leaves: how humans interpret topic models. Adv. Neural Inf. Processing Syst. 288–296.
Chen, W.-J., Chen, Mi-L., 2014. Factors affecting the hotel's service quality: relationship marketing and corporate image. J. Hosp. Market. Manag. 23 (1), 77–96.
Chen, T., Pearce, P., 2012. Research note: seasonality patterns in Asian tourism. Tourism Econ. 18 (5), 1105–1115.
Chen, H., Zhang, G., Zhu, D., Lu, J., 2017. Topic-based technological forecasting based on patent data: a case study of Australian patents from 2000 to 2014. Technol. Forecast. Social Change 119, 39–52.
Cheng, M., Jin, X., 2019. What do airbnb users care about? An analysis of online review comments. Int. J. Hosp. Manag. 76, 58–70.
Cronin, J.J., Brady, M.K., Hult, G.T.M., 2000. Assessing the effect of quality, value and customer satisfaction on behavioral intensions in service environments. J. Retail. 76 (2), 193–218.
Delen, D., Crossland, M.D., 2008. Seeding the survey and analysis of research literature with text mining. Expert Syst. Appl. 34 (3), 1707–1720.
Duan, W., Yu, Y., Cao, Q., Levy, S., 2015. Exploring the impact of social media on hotel service performance. Cornell Hosp. Q. 57 (3), 282–296.
Gao, B., Li, X., Liu, S., Fang, D., 2018. How power distance affects online hotel ratings: the positive moderating roles of hotel chain and reviewers' travel experience. Tourism Manag. 65, 176–186.
Grönroos, C., 1982. An applied service marketing theory. Eur. J. Market. 16 (7), 30–41.
Gutierrez, J., Garcia-Palomares, J.C., Romanillos, G., Salas-Olmedo, M.H., 2017. The eruption of Airbnb in tourist cities: comparing spatial patterns of hotels and peer-to-peer accommodation in Barcelona. Tourism Manag. 62, 278–291.
Guttentag, D., 2013. Airbnb: disruptive innovation and the rise of an informal tourism accommodation Sector. Curr. Issues Tourism 1–26.
Guttentag, D., Smith, S., Potwarka, L., Havitz, M., 2017. Why tourists choose Airbnb: a motivation-based segmentation study. J. Travel Res. 57 (3), 342–359.
Horn, K., Merante, M., 2017. Is home sharing driving up rents? Evidence from Airbnb in Boston. J. Housing Econ. 38, 14–24.
Hornik, K., Mair, P., Rauch, J., Geiger, W., Buchta, C., Feinerer, I., 2013. The textcat package for n-gram based text categorization in R. J. Statist. Software 52 (6), 1–17.
Hu, N., Zhang, T., Gao, B., Bose, I., 2019. What do hotel customers complain about? Text analysis using structural topic model. Tourism Manag. 72, 417–426.
Inn, T., 2019. Airbnb Generates Rm3bil In Direct Economic Impact In Malaysia Last Year. [Online] The Star Online. Available at: <https://www.thestar.com.my/business/business-news/2019/07/02/airbnb-generates-rm3bil-in-direct-economic-impact-in-malaysia-last-year> [Accessed 20 June 2020].
Jacobi, C., van Atteveldt, W., Welbers, K., 2015. Quantitative analysis of large amounts of journalistic texts using topic modelling. Digital J. 4 (1), 89–106.
Ju, Y., Back, K., Choi, Y., Lee, J., 2019. Exploring Airbnb service quality attributes and their asymmetric effects on customer satisfaction. Int. J. Hosp. Manag. 77, 342–352.
Korfiatis, N., Stamolampros, P., Kourouthanassis, P., Sagiadinos, V., 2019. Measuring service quality from unstructured data: a topic modeling application on airline passengers' online reviews. Expert Syst. Appl. 116, 472–486.
Kuhn, K., 2018. Using structural topic modeling to identify latent topics and trends in aviation incident reports. Transp. Res. Part C: Emerg. Technol. 87, 105–122.
Ladhari, R., 2012. The lodging quality index: an independent assessment of validity and dimensions. Int. J. Contemp. Hospitality Manag. 24 (4), 628–652.
Lalicic, L., Weismayer, C., 2018. A model of tourists' loyalty: the case of Airbnb. J. Hosp. Tour. Technol. 9 (1), 78–90.
Lawani, A., Reed, M., Mark, T., Zheng, Y., 2019. Reviews and price on online platforms: evidence from sentiment analysis of Airbnb reviews in Boston. Reg. Sci. Urb. Econ. 75, 22–34.

Lee, K., Yu, C., 2018. Assessment of airport service quality: a complementary approach to measure perceived service quality based on google reviews. J. Air Trans. Manag. 71, 28–44.
Lewis, R.C., Booms, B.H., Berry, L., Shostack, L., Upah, G., 1983. The Marketing Aspects of Service Quality. Emerging Perspectives on Services Marketing. American Marketing Association, Chicago, pp. 99–107.
Li, H., Ye, Q., Law, R., 2013. Determinants of customer satisfaction in the hotel industry: an application of online review analysis. Asia Pacif. J. Tourism Res. 18 (7), 784–802.
Li, G., Law, R., Vu, H., Rong, J., Zhao, X., 2015. Identifying emerging hotel preferences using emerging pattern mining technique. Tourism Manag. 46, 311–321.
Liu, S.Q., Mattila, A.S., 2017. Airbnb: online targeted advertising, sense of power, and consumer decisions. Int. J. Hosp. Manag. 60, 33–41.
Lucas, C., Nielsen, R., Roberts, M., Stewart, B., Storer, A., Tingley, D., 2015. Computer-assisted text analysis for comparative politics. Political Anal. 23 (2), 254–277.
Luo, Y., Tang, R., 2019. Understanding hidden dimensions in textual reviews on Airbnb: an application of modified latent aspect rating analysis (LARA). Int. J. Hosp. Manag. 80, 144–154.
Palese, B., Usai, A., 2018. The relative importance of service quality dimensions in E-commerce experiences. Int. J. Inf. Manage. 40, 132–140.
Pantouvakis, A., Renzi, M., 2016. Exploring different nationality perceptions of airport service quality. J. Air Transp. Manag. 52, 90–98.
Parasuraman, A., Zeithaml, V.A., Berry, L.L., 1988. SERVQUAL: a multiple item scale for measuring consumer perception of service quality. J. Retail. 64 (1), 12–37.
Priporas, C., Stylos, N., Rahimi, R., Vedanthachari, L., 2017. Unraveling the diverse nature of service quality in a sharing economy: a social exchange theory perspective of Airbnb accommodation. Int. J. Hosp. Manag. 29 (9), 2279–2301.
Raza, M.A., Siddiquei, A.N., Awan, H.M., Bukhari, K., 2012. "Relationship between service quality, perceived value, satisfaction and revisit intention in hotel industry". Interdisc. J. Contemp. Res. Bus. 4 (8), 788–805.
Reeves, C., Bednar, D., 1994. Defining quality: alternatives and implications. Acad. Manag. Rev. 19 (3), 419.
Roberts, M.E., Stewart, B.M., Tingley, D., Lucas, C., Leder-Luis, J., Gadarian, S.K., Rand, D.G., 2014. Structural topic models for open-ended survey responses. Am. J. Polit. Sci. 58 (4), 1064–1082.
Roberts, M.E., Stewart, B.M., Airoldi, E.M., 2016. A model of text for experimentation in the social sciences. J. Am. Stat. Assoc. 111, 988–1003.
Roberts, M.E., Stewart, B.M., Tingley, D., 2017. stm: R package for structural topic models. J. Statist.Software.
Schmiedel, T., Müller, O., vom Brocke, J., 2018. Topic modeling as a strategy of inquiry in organizational research: a tutorial with an application example on organizational culture. Org. Res. Methods 22 (4), 941–968.
Sthapit, E., Björk, P., 2019. Sources of distrust: Airbnb guests' perspectives. Tourism Manag. Perspect. 31, 245–253.
Sthapit, E., Jiménez-Barreto, J., 2018. Exploring tourists' memorable hospitality experiences: an Airbnb perspective. Tourism Manag. Perspect. 28, 83–92.
Volgger, M., Pforr, C., Stawinoga, A., Taplin, R., Matthews, S., 2018. Who adopts the Airbnb innovation? An analysis of international visitors to Western Australia. Tourism Recreat. Res. 43 (3), 305–320.
Wang, D., Nicolau, J.L., 2017. Price determinants of sharing economy based accommodation rental: a study of listings from 33 cities on airbnb.com. Int. J. Hosp. Manag. 62, 120–131.
Zeithaml, V.A., Berry, L.L., Parasuraman, A., 1993. The nature and determinants of customer expectations of service. J. Acad. Market. Sci. 21 (1), 1–12.
Zgolli, S., Zaiem, I., 2017. Customer-to-customer interaction in tourism experience: moderating role of nationality. Arab Econ.Bus. J. 12 (1), 44–56.
Zhang, J., 2019. What's yours is mine: exploring customer voice on Airbnb using text-mining approaches. J. Consumer Market. 36 (5), 655–665.