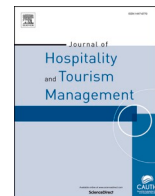




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Does hotel customer satisfaction change during the COVID-19? A perspective from online reviews

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ABSTRACT

The coronavirus disease (COVID-19) has impacted the hotel industry in all aspects. However, the changes in hotel customer satisfaction deserve additional attention. Using online hotel reviews, this study explores the difference between the influencing factors of customer satisfaction before and after the COVID-19 outbreak. By use of Latent Dirichlet Allocation and sentiment analysis, factors that affect customer satisfaction and their emotional strength before and after the COVID-19 outbreak are extracted. Then, multiple regression models are established to compare the differences of the impact of each factor on hotel customer satisfaction in different periods. According to the aforesaid study, hotel customer satisfaction and its influencing factors have changed significantly during the pandemic; hotel customer satisfaction during the pandemic is mainly influenced by service quality. Accordingly, strategies are proposed for hotel managers to improve their customer satisfaction during the COVID-19.

1. Introduction

As a mega public health crisis, COVID-19 has impacted almost every aspect of the hotel business (Gössling et al., 2020). Hotel managers have summarized effective crisis response strategies from past calamities (Israëli et al., 2011; Pappas, 2015, 2018). However, those short-term strategies only aimed at the rapid recovery of the financial performance and operation of the hotel industry (Ritchie & Jiang, 2019), thus little attention was paid to customer satisfaction. Owing to the unique features of the pandemic, such as long duration, large externalities, and broad impacts, COVID-19 has affected the confidence, behavior, and decision-making of customers more significantly than other crises of the same nature. Gössling et al. (2020) stated that COVID-19 would profoundly influence human society in a way similar to the climate change.

Along with the evolution of the Internet, user-generated content (UGC) has become a primary source of information for consumers and businesses to evaluate product satisfaction. Being a typical kind of UGC data, online reviews not only helps potential consumers make purchase decisions but also assists relevant managers in identifying factors that influence satisfaction (Guo et al., 2017). Consequently, such content facilitates customer satisfaction (Wang et al., 2017). The public,

and accessible text data has an abundant sample size and contains a substantial amount of reliable information that cannot be reflected by hotel ratings (Banerjee & Chua, 2016). Hence, this study conducts an empirical analysis to identify the factors that truly affect customer satisfaction on the basis of hotel online reviews.

This study aims to answer the following questions: (1) Do significant differences exist in customer satisfaction before and after the COVID-19 outbreak? and (2) What are the primary factors that contribute to the differences in hotel customer satisfaction? To address these questions, the paper is organized as follows: Literature Review explains the motivations of the study by reviewing related literature; Methodology introduces research design, data preparation and research approach; the Results section analyzes the results of LDA, sentiment analysis and multiple regression. And in the end, Findings and Conclusion are presented to discuss theoretical and managerial implications.

2. Literature review

2.1. Tourism crisis and customer satisfaction

Usually, tourism is considered as an industry vulnerable to crises or

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disasters (Cro & Martins, 2017). The hotel industry is susceptible and prone to suffer from different types of crises, including natural disasters (Möller et al., 2018), terrorist attacks (Kosova & Enz, 2012; Kubickova et al., 2019), political turmoil (Ivanov & Stavrinoudis, 2018) and public health pandemic, such as the severe acute respiratory syndrome (SARS) (Fung et al., 2020), ebola (Novelli et al., 2018) and COVID-19 (Guo et al., 2021).

Crisis management is critical to handling calamities, and the priority of such management varies according to different crises. The hotel industry used to adopt a risk management perspective, focusing more on safety and security (Wang & Ritchie, 2010). For effective management, both academia (Sharma et al., 2021) and industry continue to provide crisis management guidelines and policy framework for industry professionals. Such policies are dedicated to hotel financial performance and operational recovery (Ritchie & Jiang, 2019) and the resilience of hotels to changes (Melian-Alzola et al., 2020), but have not taken customer satisfaction into consideration. Furthermore, even if the current threat dissipates in the near future, people's perceptions of risk in travel or accommodation will change (Bae & Chang, 2020), and preventive measure will affect the attitude of tourists during the pandemic (Gupta et al., 2021). On the premise of meeting basic safety requirements after the COVID-19 outbreak, hotel managers must start thinking about the change in customer satisfaction to improve hotel guest experience.

2.2. Online reviews and customer satisfaction

Online hotel reviews contain a wealth of information, including various attributes of a hotel (Duan et al., 2016), such as cleanliness, location, room, service, sleep quality, and facilities (Liu et al., 2013). Customer satisfaction reveals the gap between the perceived and expected service quality (Padma & Ahn, 2020). Service quality is the critical factor that leads to different customer satisfaction (Yang & Lau, 2015) and customers are satisfied when their perceived service quality outperforms the expected service quality. Service quality can be assessed by hotel attributes extracted from online reviews (Guo et al., 2017). Hence, the overall satisfaction can be studied as the dependent variable, while the individual hotel attributes are studied as independent variables (Hu et al., 2019).

Substantive empirical studies have shown that customer satisfaction is evolving rather than remaining the same (Hu et al., 2019). Load of factors, such as service quality (Yang & Lau, 2015), facilities (Nunkoo et al., 2020), food (Mohsin & Lockyer, 2010), and hotel rating (Bi et al., 2020), etc. may be the reason for different customer satisfaction towards hotels. In other words, different service contexts and encounters will result in different customer satisfaction (Wu & Liang, 2009). However, COVID-19 has altered not only previous service process as exemplified in the offering of safe products and services (Foroudi et al., 2021), but also the expectations of consumers (Mehta et al., 2021). By taking advantage of this imbalance, it is possible for this paper to identify the key factors that affect customer satisfaction from online reviews of hotels before and after the outbreak of COVID-19.

3. Methodology

3.1. Research design

To answer the research questions, this study employed a mixed analytical method. For the first research question, a paired sample *t*-test was conducted to reveal whether customer satisfaction of each hotel has changed. To answer the second research question, this study has firstly applied Latent Dirichlet Allocation and sentiment analysis, followed by the review analytics procedure from An et al. (2020) study, and then developed review characteristics, which included review topics and review sentiment; then a multiple linear regression analysis was carried out to test the relationship between rating and review characteristics in

order to examine the key influencing factors of customer satisfaction before and after the outbreak of COVID-19.

3.2. Data preparation

Given the different severity of the pandemic in each city, this study selected Chengdu as its research object to avoid deviations on the study results. Having a well-developed hotel industry, Chengdu is among the top ten tourist destinations in China (Wang et al., 2019). As with many cities, it was affected by COVID-19. Ctrip (Nasdaq: TCOM) occupies an OTA market share of 55.7% (CTN, 2019), and provides a multifunctional online review system for consumers to post and read reviews. Kosova and Enz (2012) observed that the hotel industry can rebound within four months during a crisis, as reflected by the data from hotels in New York after 9/11 and the 2008 financial crisis. Hence, this study selected the representative data period from February to May 2020 while using the same period in 2019 as the control.

Using the Houyi (<http://www.houyicaiji.com>) crawler program, a total of 5,361 hotels were collected from the basic dataset in Chengdu. The data contained information on hotels, such as hotel name, star rating, and open time, as shown in Image 1. It also contained information on reviews, including review rating, review text, and check-in time of each review, as shown in Image 2. This study obtained 52,449 valid reviews from February to May 2020 and 104,613 valid reviews from the same period in 2019. A total of 4,942 hotels in Chengdu were finally identified as the study sample with a sampling efficiency of 92.2%.

3.3. Methods of analysis

3.3.1. Paired-samples *T* test

Paired sample *t*-test is one of the widely-used statistical procedures to compare the equality of the means of the two paired populations (Park et al., 2020), therefore, it can be used to reveal whether significant differences exist in hotel customer satisfaction before and after the COVID-19 outbreak.

3.3.2. LDA and sentiment analysis

Latent Dirichlet Allocation is a classic unsupervised machine learning technology which can effectively capture context-specific dimensions (Maier et al., 2018) and process vast unstructured online reviews with little manual intervention (Aggarwal & Gour, 2020; Vu et al., 2019). Naturally, LDA is frequently used to extract important attributes of a product or service; moreover, it is widely used in hotel customer satisfaction research (Guo et al., 2017). The LDA model assumes that whole text corpus can be represented with a set of topics. Mathematically, it adopts the method of “bag of words”, which treats each text as a word frequency vector, thus transforming text information into digital information that is easy to calculate. The key to LDA is the choice of the number of topics, which will largely affect the classification effect.

By processing unstructured textual data, sentiment analysis can extract attitudes and affective tendencies from the text as part of natural language processing (García et al., 2012). The sentiment intensity of a customer toward a specific hotel attribute reflects the actual performance of this element (Bi, Liu, Fan, & Zhang, 2019), and has a positive impact on satisfaction after consumption as well (Kim & Park, 2017). In this study, a third-party module of Python, SnowNLP (<https://pypi.org/project/snownlp>) which is a classical sentiment analysis method is used to conduct sentiment analysis.

3.3.3. Multiple linear regression

Multiple linear regression is selected to analyze the variables and to divide the categories into dependent, control, and independent variables, which resulted in effectively controlling variables.

To assess customer satisfaction toward a hotel in the study time interval, a dependent variable, customers' rating of the hotel was taken as a measure of satisfaction at a given time (Hu et al., 2019). Then, each

customer’s satisfaction (rating) was transformed into hotel-caliber satisfaction by using the rating of an individual hotel in each year as the average of all reviews of the hotel during the period. By introducing hotel rating and operating years, two control variables, the hotel’s characteristics were examined to see whether they were sufficient to test the rating of the hotel.

To examine the relationship between test scores and review characteristics, review topics and review sentiment were taken as independent variables. Review characteristics could be measured by the topic score and review sentiment value of the review LDA model (Xiang et al., 2017). The topic score and the sentiment value of the reviews were transformed into hotel-caliber topic scores and sentiment values, which meant that the score or sentiment value of an individual hotel was the average of all reviews scored or sentiment value on a given topic for each period. Following the suggestion of Hayes (2013), the independent variables were centralized and the moderating effect term lead was calculated to explain the coefficients of the regression equation further.

4. Results

4.1. Results of paired-Samples T test

The analysis shows a significant difference ($t = 6.352, \text{Sig.} = 0.003$) between the scores of 2019 and 2020, where the score for 2019 was 4.45, and the score for 2020 was 4.51. These values indicated that customers were more satisfied with hotels in 2020.

4.2. Development of key metric

4.2.1. Recognition of review topics

After repeated attempts, it is determined that the number of topics is five, and the number of iterations is 1,500. These values signified that the model had optimal perplexity, and the clear distinction between key topics achieved effective text clustering. Table 1 shows the results of the extracted LDA topics, including Service (T1), Room (T2), Cleanliness (T3), Location (T4), and Value (T5), which had all been presented in previous studies (Guo et al., 2017; Hu et al., 2019) Moro et al., 2018; Zhao & Xu, 2018). Thus, the extracted scores of the topics for each review were retained to prepare for the next step of the study.

4.2.2. Review sentiment Identification

Fig. 1 shows the sentiment distribution of reviews in 2019 and 2020 (the X-axis represents the sentiment value, and the Y-axis represents the percentage of reviews in a specific period). Accordingly, the points toward the X-axis are reviews with a positive sentiment value (the highest being 1), whereas negative reviews are arranged toward the left side, with the lowest being 0. Interestingly, the plot shows a nearly identical graphical distribution in 2019 and 2020, in which the distribution leans to the positive spectrum with a “saddle-shaped” distribution feature.

Table 1
Key topics extracted from online reviews by LDA.

T1: Service		T2: Room		T3: Cleanliness		T4: Location		T5: Value	
Reception	0.063	Room	0.051	Cleanliness	0.113	Travel	0.081	Great	0.114
Breakfast	0.052	Night	0.02	Room	0.077	Location	0.06	Like	0.031
Service	0.044	Great	0.012	Service	0.056	Around	0.039	Patronage	0.027
Room	0.022	Not bad	0.011	Comfortable	0.034	Parking	0.039	Feel	0.024
Staff	0.021	Bad	0.011	Nice	0.032	Subway	0.035	Choice	0.022
Check	0.021	Soundproof	0.01	Environment	0.028	Convenience	0.031	Check	0.019
Free	0.017	Price	0.01	Location	0.026	Breakfast	0.026	Friend	0.018
Pandemic	0.013	Shower	0.01	Facility	0.025	Near	0.017	Environment	0.017
Lovely	0.008	AC	0.01	Reception	0.021	Downstairs	0.016	Business trip	0.017
Attitude	0.008	Restroom	0.009	Service attitude	0.02	Transportation	0.014	Recommendation	0.017

4.3. Results of regression analysis

Table 2 shows the results of the multiple linear regression analysis which is carried out to test the relationship between rating and review characteristics, including review topic and sentiment.

Model 1 indicates whether the hotel’s own characteristics are sufficient to test the rating of the establishment. According to the analysis, hotel grade had a positive effect on hotel rating, and operating years had a negative effect on hotel rating.

Model 2 tests the contribution of review topics to ratings (a measure of the likelihood that a particular topic is included in a review). The adjusted R-squared increased significantly. All topics had significant changes before and after the outbreak of COVID-19, with T1 (Service), T3 (Cleanness), T4 (Location), and T5 (Value) contributing positively to the score and T2 (Rooms) contributing negatively.

Model 3 proves that the sentiment was a strong predictor of scores, as its introduction substantially increased the adjusted R-squared across the model. Upon the inclusion of this variable, the service topic became insignificant in the model of the year 2020, where the word “pandemic” emerged as a topic.

Model 4 investigates the moderating effect of sentiment on each topic. Among the interaction terms, “sentiment * T1 (Service)” was not significant in 2020 ($p = 0.063$) or 2019. T2 (Room) * sentiment, T3 (Cleanness) * sentiment, T4 (Location) * sentiment, and T5 (Value) * sentiment all showed the conversion of coefficient signs, which entailed the non-neutral nature of the words associated with T2 (Room), T3 (Cleanness), T4 (Location), and T5 (Value). Moreover, sentiment had a negative moderating effect on each topic.

Unsurprisingly, these review topics explained the large difference of scores (adjusted R-squared of 0.469 in 2019 and adjusted R-squared of 0.407 in 2020). In addition, different performances were observed in the two years. In terms of explanatory power, the model was significantly stronger in 2019 than in 2020, and this model was stronger for the period before the pandemic.

5. Discussion and conclusion

5.1. Discussion

A significant difference was observed in hotel customer satisfaction before and after the pandemic, with customers being more satisfied with hotels after the COVID-19 outbreak. Although this trend may be counterintuitive, it was found that even in a crisis, customers indeed would be satisfied with hotels. This finding is also supported by the research of Mehta et al. (2021) in North America and Europe. In accordance with the finding, it can be assumed that hotels in China may be able to maintain customer satisfaction by providing expected and desired service to customers. In addition to traditional service expectation, new expectations and service delivery arise due to the preventive measures required to be taken by COVID-19, such as social distancing and sanitization (Das & Tiwari, 2020). Hotels can satisfy new expectations by providing safe services, for instance, take-way food rather than eat-in

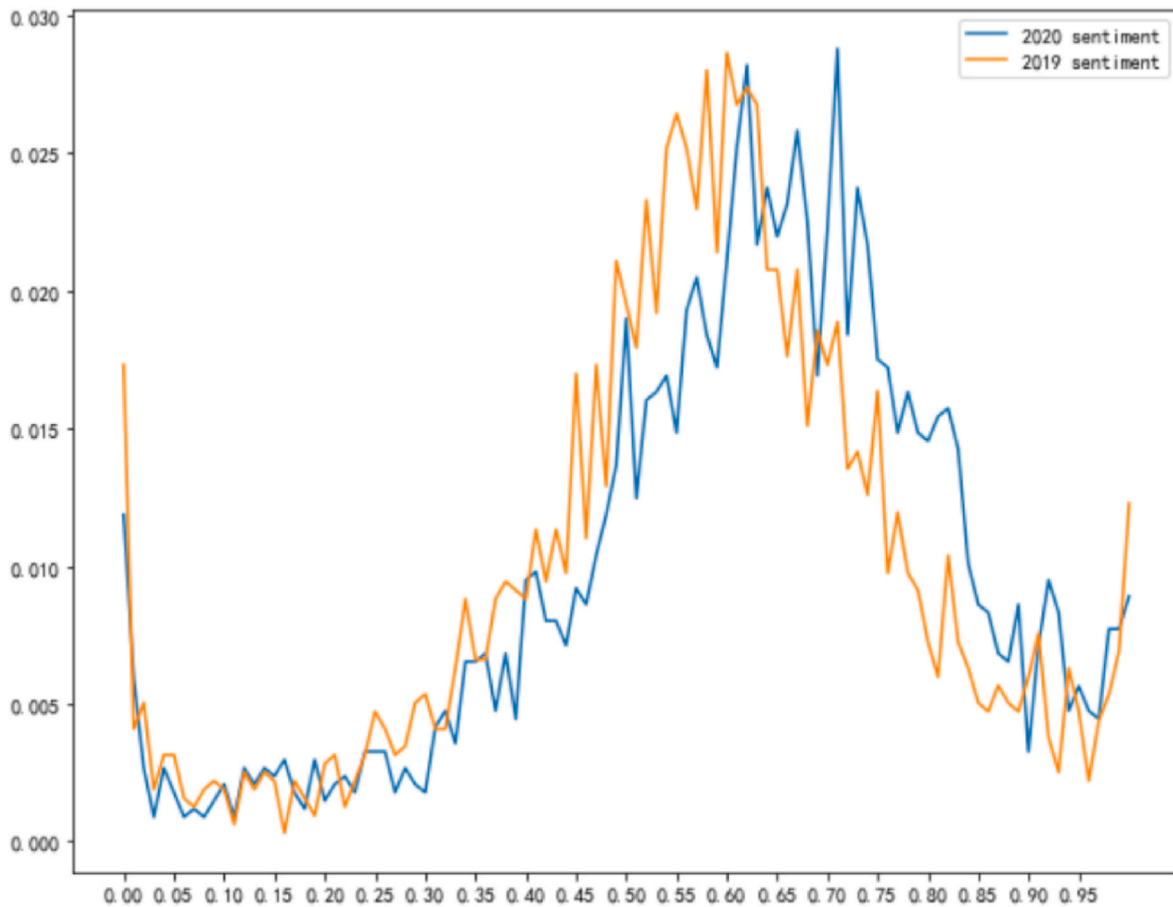


Fig. 1. Sentiment distribution of reviews in 2019 and 2020.

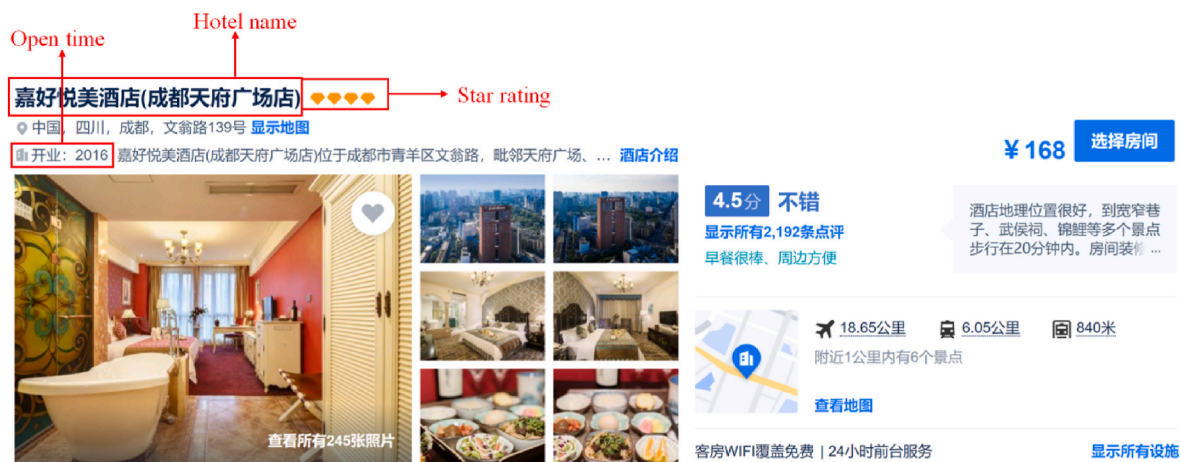


Image 1. Sample of hotels displayed on Ctrip.

(Bhaskara & Filimonau, 2021), which reasonably explains customers’ being more satisfied with hotels after the COVID-19 outbreak.

Hotel review characteristics (both topics and sentiments) had a strong explanatory power for hotel satisfaction, and the impact of the pandemic on hotel satisfaction was mainly reflected in terms of service. In other words, service is of particular importance to hotel satisfaction during the pandemic (Albayrak, 2015). Although the COVID-19 pandemic will eventually subside, the negative environment surrounding the service experience will linger (Barnes et al., 2020).

Sentiment has strong explanatory power for hotel satisfaction (Xiang

et al., 2017). With a significantly negative moderating effect, sentiment contributes to 52% of customer satisfaction (Barnes et al., 2020). Stronger sentiment usually represents higher expectations, as factors that may cause customers to be more easily frustrated can reduce their satisfaction toward a hotel. The moderating effect of the cleanliness attribute on satisfaction is significantly stronger in 2020 than in 2019 possibly because customers have higher expectations for this aspect in 2020. Unless a hotel meets customer expectations, the customers will be dissatisfied more easily.



Image 2. Sample of online reviews on Ctrip.

Table 2
Regression analyses of the relationship between ratings and review characteristics.

	Model 1		Model 2		Model 3		Model 4	
	Year 2019 N = 3142	Year 2020 N = 3308	Year 2019 N = 3142	Year 2020 N = 3308	Year 2019 N = 3142	Year 2020 N = 3308	Year 2019 N = 3142	Year 2020 N = 3108
(constant)	4.421	4.592	4.383	4.552	4.395	4.551	4.446	4.623
Rating	.277	.147	.219	.128	.172	.106	.146	.079
Opening time	-.022	-.016	-.014	-.008	-.013	-.006	-.013	-.007
Service			.091	.044	.049	0.025 (<i>p</i> =0.063)	.045	0.014 (<i>p</i> =0.277)
Room			-.418	-.352	-.239	-.230	-.214	-.183
Cleaness			.124	.142	.054	.067	.078	.118
Location			.107	.053	.119	.076	.099	.052
Value			.182	.151	.050	.045	.093	.072
Sentiment					.295	.262	.315	.233
Service * Sentiment							0.015 (<i>p</i> =0.1)	0.014 (<i>p</i> =0.063)
Room * Sentiment							.035	.034
Cleanness* Sentiment							-.064	-.083
Location * Sentiment							-.064	-.051
Value * Sentiment							-.048	-.055
R-square	.051	.022	.319	.283	.419	.368	.472	.409
Adjusted R-squared	.051	.021	.318	.281	.417	.367	.469	.407

Note: Unlabeled *p*-value is *p* < 0.001.

5.2. Conclusion

Almost all hotels were impacted by COVID-19, however, whether hotel customer satisfaction and its influencing factors have changed or not has not been studied so far. To fill this gap, 4,942 hotels in Chengdu displayed in Ctrip were selected to obtain 52,449 valid reviews from February to May 2020 and 104,613 valid reviews from the same period in 2019. LDA and sentiment analysis were applied to extract the factors affecting customer satisfaction and their emotional strength before and after the pandemic. Then, multiple regression models were established to compare the differences of the impact of each factor on hotel customer satisfaction in different periods.

This finding shows that hotel customer satisfaction before and after the COVID-19 outbreak has a significant difference. To be more specific, hotel customer satisfaction becomes higher after the pandemic. Service, Room, Cleaness, Location, Value and Sentiment all impact customer satisfaction significantly before the pandemic, however, Service no longer has significant impact on hotel customer satisfaction after the pandemic, hence one of the main factors significantly affecting the shift in customer satisfaction is Service. Such a finding is in conformity with that of Yang and Lau (2016) who suggested that service quality is the key to customer satisfaction.

5.3. Theoretical implication

The findings of this study can provide a series of important enlightenment for the research on the effects of UGC on customer satisfaction during a crisis by extracting information from online reviews. First, the

study confirms that a hotel can have satisfied customers even in the unprecedented and highly unpredictable COVID-19 crisis. The COVID-19 pandemic will be a new normal like climate change, with long-lasting effects on society (Gössling et al., 2020). This study has introduced a long-term goal—customer satisfaction—into the field of hotel crisis management and compares the satisfaction of hotels before and after the outbreak of COVID-19 crisis. Indeed, hotel satisfaction has changed after the COVID-19 outbreak.

Second, this study provides new explanatory variables for the influencing factors of satisfaction—review topics and sentiments. Both review topics and sentiments have strong explanatory power for satisfaction (ratings) in the study. In the product evaluation context, the non-sentimental words represented by a review topic may convey emotional connotations similar to the effect of emotional words. This characteristic is consistent with the study of Xiang et al. (2015) wherein topical “factors” generated from review texts are highly correlated with the rating.

Finally, this study sheds light on the link between the topics of customer experience and their satisfaction displayed in online reviews, which turns out to be in consistency with the findings of Crotts et al. (2009) and Zhang and Cole (2016), suggesting that UGC (e.g., online reviews) can be used to identify meaningful structures between aspects and attributes related to hotels and tourism products. Moreover, this conclusion is applicable before and after the outbreak of COVID-19.

5.4. Managerial implications

This study is quite pragmatic for management practice. Firstly, by

revealing that customers can be more satisfied with hotels after the COVID-19 outbreak, hotel managers can become more confident in managing customer satisfaction. Secondly, the study offers a new approach to listen to the voice of customers through which hotel managers can ascertain the important dimensions of consumer satisfaction. For example, T2 (Room) affects hotel customer satisfaction negatively before and after the COVID-19 outbreak, thus it can be presumed that T2 (Room) might be the source of complaints and dissatisfaction.

Hotel managers can also monitor the trends of customer satisfaction through the voice of customers so as to make corresponding adjustments strategically. For example, after the outbreak of the pandemic, service becomes critical for hotel customer satisfaction. Hotel managers should make sure that guests are aware of the special situation brought about by COVID-19 and convince their customers that safe service is guaranteed. Specifically, hotels can introduce artificial intelligence (AI), service robots and other new technologies to effectively improve the service quality and reduce the perceived risk of customers.

5.5. Limitations and Prospects

This study has two main limitations in choosing Chengdu as a case study location. Each city issues different public health emergency response measures for the COVID-19 pandemic. As such, the effect of these circumstances on customer satisfaction is not consistent. Therefore, follow-up studies should cover more cities to reinforce the findings of the current research. The conclusions of this study may not be applicable to all situations, as the pandemic has not been subdued at the time of writing. Further studies can make more sufficient arguments based on the development of the pandemic by following up the research using multiple crawling data. According to the current results, additional research may also include offline customers by combining questionnaires or further considering qualitative research methods in the future.

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Declaration of Competing interest

No potential conflict of interest was reported by the author(s).

References

- Aggarwal, S., & Gour, A. (2020). Peeking inside the minds of tourists using a novel web analytics approach. *Journal of Hospitality and Tourism Management*, 45, 580–591. <https://doi.org/10.1016/j.jhtm.2020.10.009>
- Albayrak, T. (2015). Importance performance Competitor analysis (IPCA): A study of hospitality companies. *International Journal of Hospitality Management*, 48, 135–142. <https://doi.org/10.1016/j.ijhm.2015.04.013>
- An, Q., Ma, Y., Du, Q., Xiang, Z., & Fan, W. (2020). Role of user-generated photos in online hotel reviews: An analytical approach. *Journal of Hospitality and Tourism Management*, 45, 633–640. <https://doi.org/10.1016/j.jhtm.2020.11.002>
- Bae, S. Y., & Chang, P.-J. (2020). The effect of coronavirus disease-19 (COVID-19) risk perception on behavioural intention towards 'untact' tourism in South Korea during the first wave of the pandemic (March 2020). *Current Issues in Tourism*, 24(7), 1017–1035. <https://doi.org/10.1080/13683500.2020.1798895>
- Banerjee, S., & Chua, A. Y. K. (2016). In search of patterns among travellers' hotel ratings in TripAdvisor. *Tourism Management*, 53, 125–131. <https://doi.org/10.1016/j.tourman.2015.09.020>
- Barnes, D. C., Mesmer-Magnus, J., Scribner, L. L., Krallman, A., & Guidice, R. M. (2020). Customer delight during a crisis: Understanding delight through the lens of transformative service research. *Journal of Service Management*, 32(1), 129–141. <https://doi.org/10.1108/josm-05-2020-0146>
- Bhaskara, G. I., & Filimonau, V. (2021). The COVID-19 pandemic and organisational learning for disaster planning and management: A perspective of tourism businesses from a destination prone to consecutive disasters. *Journal of Hospitality and Tourism Management*, 46, 364–375. <https://doi.org/10.1016/j.jhtm.2021.01.011>
- Bi, J.-W., Liu, Y., Fan, Z.-P., & Zhang, J. (2020). Exploring asymmetric effects of attribute performance on customer satisfaction in the hotel industry. *Tourism Management*, 77. <https://doi.org/10.1016/j.tourman.2019.104006>. Article 104006.
- Cro, S., & Martins, A. M. (2017). Structural breaks in international tourism demand: Are they caused by crises or disasters? *Tourism Management*, 63, 3–9. <https://doi.org/10.1016/j.tourman.2017.05.009>
- Crotts, J. C., Mason, P. R., & Davis, B. (2009). Measuring guest satisfaction and Competitive position in the hospitality and tourism industry: an application of Stance-shift analysis to travel blog Narratives. *Journal of Travel Research*, 48(2), 139–151. <https://doi.org/10.1177/0047287508328795>
- CTN. (2019). *China OTAs turn over 700 billion yuan in H1 2019, Ctrip accounts for 55.7%*. Retrieved from <https://www.chinatravelnews.com/article/131335>. (Accessed 16 February 2022).
- Das, S. S., & Tiwari, A. K. (2020). Understanding international and domestic travel intention of Indian travellers during COVID-19 using a Bayesian approach. *Tourism Recreation Research*, 46(2), 228–244. <https://doi.org/10.1080/02508281.2020.1830341>
- Duan, W., Yu, Y., Cao, Q., & Levy, S. (2016). Exploring the impact of social media on hotel service performance: A sentiment analysis approach. *Cornell Hospitality Quarterly*, 57(3), 282–296. <https://doi.org/10.1177/1938965515620483>
- Foroudi, P., Tabaghdhi, S. A. H., & Marvi, R. (2021). The gloom of the COVID-19 shock in the hospitality industry: A study of consumer risk perception and adaptive belief in the dark cloud of a pandemic. *International Journal of Hospitality Management*, 92. <https://doi.org/10.1016/j.ijhm.2020.102717>. Article 102717.
- Fung, C., Tsui, B., & Hon, A. H. Y. (2020). Crisis management: A case study of disease outbreak in the Metropark hotel group. *Asia Pacific Journal of Tourism Research*, 25(10), 1062–1070. <https://doi.org/10.1080/10941665.2020.1784245>
- García, A., Gaines, S., & Linaza, M. T. (2012). A Lexicon based sentiment analysis retrieval system for tourism domain. *e-Review of Tourism Research*, 10(2), 35–38.
- Gössling, S., Scott, D., & Hall, C. M. (2020). Pandemics, tourism and global change: A rapid assessment of COVID-19. *Journal of Sustainable Tourism*, 29(1), 1–20. <https://doi.org/10.1080/09669582.2020.1758708>
- Guo, Y., Barnes, S. J., & Jia, Q. (2017). Mining meaning from online ratings and reviews: Tourist satisfaction analysis using latent dirichlet allocation. *Tourism Management*, 59, 467–483. <https://doi.org/10.1016/j.tourman.2016.09.009>
- Guo, L., Liu, K., Song, Y., & Yang, Z. (2021). Recovering hotel room sales during the COVID-19 pandemic: Lessons from OTA information using the quantile regression approach. *Current Issues in Tourism*, 25(1), 94–114. <https://doi.org/10.1080/13683500.2021.1900079>
- Gupta, S., Aggarwal, A., Gupta, S., & Anchal. (2021). Corona's Spillover effects on tourism industry - Scale development and Validation. *Tourism Analysis*, 26(2–3), 2–3. <https://doi.org/10.3727/108354221x16187814403155>
- Hayes, A. F. (2013). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Guilford Press.
- Hu, F., Teichert, T., Liu, Y., Li, H., & Gundyrevva, E. (2019). Evolving customer expectations of hospitality services: Differences in attribute effects on satisfaction and Re-Patronage. *Tourism Management*, 74(OCT), 345–357. <https://doi.org/10.1016/j.tourman.2019.04.010>
- Hu, N., Zhang, T., Gao, B., & Bose, I. (2019). What do hotel customers complain about? Text analysis using structural topic model. *Tourism Management*, 72, 417–426. <https://doi.org/10.1016/j.tourman.2019.01.002>
- Israeli, A., Mohsin, A., & Kumar, B. (2011). Hospitality crisis management practices: The case of Indian luxury hotels. *International Journal of Hospitality Management*, 30, 367–374. <https://doi.org/10.1016/j.ijhm.2010.06.009>
- Ivanov, S., & Stavrinoudis, T. A. (2018). Impacts of the refugee crisis on the hotel industry: Evidence from four Greek islands. *Tourism Management*, 67, 214–223. <https://doi.org/10.1016/j.tourman.2018.02.004>
- Kim, W., & Park, S. (2017). Social media review rating versus traditional customer satisfaction: Which one has more incremental predictive power in explaining hotel performance? *International Journal of Contemporary Hospitality Management*, 29, 784–802. <https://doi.org/10.1108/IJCHM-11-2015-0627>
- Kosova, R., & Enz, C. (2012). The terrorist attacks of 9/11 and the financial crisis of 2008: The impact of external Shocks on U.S. Hotel performance. *Cornell Hospitality Quarterly*, 53, 308–325. <https://doi.org/10.1177/1938965512457021>
- Kubickova, M., Kirimhan, D., & Li, H. (2019). The impact of crises on hotel rooms' demand in developing economies: The case of terrorist attacks of 9/11 and the global financial crisis of 2008. *Journal of Hospitality and Tourism Management*, 38, 27–38. <https://doi.org/10.1016/j.jhtm.2018.10.002>
- Liu, S., Law, R., Rong, J., Li, G., & Hall, J. (2013). Analyzing changes in hotel customers' expectations by trip mode. *International Journal of Hospitality Management*, 34, 359–371. <https://doi.org/10.1016/j.ijhm.2012.11.011>
- Maier, D., Waldherr, A., Miltner, P., Wiedemann, G., Niekle, A., Keinert, A., ... Adam, S. (2018). Applying LDA topic modeling in communication research: Toward a valid and reliable methodology. *Communication Methods and Measures*, 12(2–3), 93–118. <https://doi.org/10.1080/19312458.2018.1430754>
- Mehta, M. P., Kumar, G., & Ramkumar, M. (2021). Customer expectations in the hotel industry during the COVID-19 pandemic: A global perspective using sentiment analysis. *Tourism Recreation Research*, 1–18. <https://doi.org/10.1080/02508281.2021.1894692>
- Melían-Alzola, L., Fernández-Monroy, M., & Hidalgo-Penate, M. (2020). Hotels in contexts of uncertainty: Measuring organisational resilience. *Tourism Management Perspectives*, 36. <https://doi.org/10.1016/j.tmp.2020.100747>. Article 100747.
- Mohsin, A., & Lockyer, T. (2010). Customer perceptions of service quality in luxury hotels in New Delhi, India: An exploratory study. *International Journal of Contemporary Hospitality Management*, 22(2), 160–173. <https://doi.org/10.1108/09596111011018160>
- Möller, C., Wang, J., & Nguyen, H. T. (2018). #Strongerthanwinston: Tourism and crisis communication through Facebook following tropical cyclones in Fiji. *Tourism Management*, 69, 272–284. <https://doi.org/10.1016/j.tourman.2018.05.014>

- Moro, S., Ramos, P., Esmerado, J., & Jalali, S. M. (2018). Can we trace back hotel online reviews' characteristics using gamification features? *International Journal of Information Management*, 44, 88–95. <https://doi.org/10.1016/j.ijinfomgt.2018.09.015>
- Novelli, M., Gussing Burgess, L., Jones, A., & Ritchie, B. W. (2018). 'No Ebola...still doomed' – the Ebola-induced tourism crisis. *Annals of Tourism Research*, 70, 76–87. <https://doi.org/10.1016/j.annals.2018.03.006>
- Nunkoo, R., Teeroovengadam, V., Ringle, C. M., & Sunnassee, V. (2020). Service quality and customer satisfaction: The moderating effects of hotel star rating. *International Journal of Hospitality Management*, 91. <https://doi.org/10.1016/j.ijhm.2019.102414>. Article 102414.
- Padma, P., & Ahn, J. (2020). Guest satisfaction & dissatisfaction in luxury hotels: An application of big data. *International Journal of Hospitality Management*, 84. <https://doi.org/10.1016/j.ijhm.2019.102318>. Article 102318.
- Pappas, N. (2015). Marketing hospitality industry in an Era of crisis. *Tourism and Hospitality Planning & Development*, 12, 333–349. <https://doi.org/10.1080/21568316.2014.979226>
- Pappas, N. (2018). Hotel decision-making during multiple crises: A Chaordic perspective. *Tourism Management*, 68, 450–464. <https://doi.org/10.1016/j.tourman.2018.04.009>
- Park, C., Wang, M., & Hwang, W. Y. (2020). A study on Robustness of the paired sample tests. *Industrial Engineering and Management Systems*, 19(2), 386–397. <https://doi.org/10.7232/iems.2020.19.2.386>
- Ritchie, B. W., & Jiang, Y. (2019). A review of research on tourism risk, crisis and disaster management: Launching the annals of tourism research curated collection on tourism risk, crisis and disaster management. *Annals of Tourism Research*, 79. <https://doi.org/10.1016/j.annals.2019.102812>. Article 102812.
- Sharma, G. D., Thomas, A., & Paul, J. (2021). Reviving tourism industry post-COVID-19: A resilience-based framework. *Tourism Management Perspectives*, 37. <https://doi.org/10.1016/j.tmp.2020.100786>. Article 100786.
- Vu, H., Li, G., & Law, R. (2019). Discovering implicit activity preferences in travel itineraries by topic modeling. *Tourism Management*, 75, 435–446. <https://doi.org/10.1016/j.tourman.2019.06.011>
- Wang, & Ritchie, B. W. (2010). A theoretical model for strategic crisis planning: Factors influencing crisis planning in the hotel industry. *International Journal of Tourism Policy*, 3(4), 297–317. <https://doi.org/10.1504/IJTP.2010.040390>
- Wang, C., Xiang, Z., & Song, H. (2017). A Preliminary analysis of relationships between Traveller characteristics and hotel review ratings. In *Information and Communication technologies in tourism 2017* (pp. 571–580). https://doi.org/10.1007/978-3-319-51168-9_41
- Wang, W., Ying, S., Lyu, J., & Qi, X. (2019). Perceived image study with online data from social media: The case of boutique hotels in China. *Industrial Management & Data Systems*, 119(5), 950–967. <https://doi.org/10.1108/imsd-11-2018-0483>
- Wu, C., & Liang, A. (2009). Effect of experiential value on customer satisfaction with service encounters in luxury-hotel restaurants. *International Journal of Hospitality Management*, 28, 586–593. <https://doi.org/10.1016/j.ijhm.2009.03.008>
- Xiang, Z., Du, Q., Ma, Y., & Fan, W. (2017). A comparative analysis of major online review platforms: Implications for social media analytics in hospitality and tourism. *Tourism Management*, 58, 51–65. <https://doi.org/10.1016/j.tourman.2016.10.001>
- Xiang, Z., Schwartz, Z., Gerdes, J. H., & Uysal, M. (2015). What can big data and text analytics tell us about hotel guest experience and satisfaction? *International Journal of Hospitality Management*, 44, 120–130. <https://doi.org/10.1016/j.ijhm.2014.10.013>
- Yang, F. X., & Lau, V. M. C. (2015). LuXurY™ hotel loyalty – a comparison of Chinese Gen X and Y tourists to Macau. *International Journal of Contemporary Hospitality Management*, 27(7), 1685–1706. <https://doi.org/10.1108/ijchm-06-2014-0275>
- Zhang, Y., & Cole, S. T. (2016). Dimensions of lodging guest satisfaction among guests with mobility challenges: A mixed-method analysis of web-based texts. *Tourism Management*, 53, 13–27. <https://doi.org/10.1016/j.tourman.2015.09.001>
- Zhao, Y., & Xu, X. (2018). Predicting overall customer satisfaction: Big data evidence from hotel online textual reviews. *International Journal of Hospitality Management*, 76, 111–121. <https://doi.org/10.1016/j.ijhm.2018.03.017>