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# Dealing with pandemics: An investigation of the effects of COVID-19 on customers' evaluations of hospitality services

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ABSTRACT

The hospitality industry is highly vulnerable to pandemics. However, little is known about how pandemics alter travelers' evaluations of hospitality services. Therefore, this study investigates the changes in travelers' expectations and perceptions of hotel services during different stages of the novel coronavirus 2019 (COVID-19) pandemic. 98,163 Chinese hotel reviews were collected and scrutinized via text mining and sentiment analysis techniques to derive new implications for service optimization. The results reveal shifts in consumers' evaluations well beyond hygienic requirements. Insights obtained from this research can help guide hospitality practice in organizing its priorities during acute pandemic situations and adjusting to possibly longer-lasting shifts in consumer preferences.

## 1. Introduction

Because it features the "spatial movement of people," the tourism industry is arguably among the sectors most vulnerable to the impacts of pandemics (Yu et al., 2020). The outbreak of the novel coronavirus 2019 (COVID-19) has resulted in more than 8.86 million confirmed infections and 465,000 deaths globally, as of June 23, 2020 (WHO, 2020). To contain COVID-19, most countries have issued rigorous restrictions and controls for both international and domestic travel. Accordingly, the World Tourism Organization (UNWTO) stated that COVID-19 would devastate the global business of tourism in 2020, forecasting a 60–80% reduction in international tourist arrivals (UNWTO, 2020). However, not all hotel services are affected equally.

Previous tourism literature has examined whether and how pandemics alter people's travelling decision (e.g., Lee et al., 2012; Wen et al., 2005), as well as the impact of pandemics on travel flows and revenue patterns (e.g., Chen, 2011; Cooper, 2005; Mao et al., 2010). While most of extant studies focused on investigating the effects of pandemics based on a macro and/or meso perspective, there is a paucity of knowledge on how the dynamics of pandemic situations alter individual travelers' perceptions and expectations over time. Through comparing travelers' preferences over hotel attributes before, during and after the COVID-19 pandemic, this study strives to offer new insights toward pandemic-altered consumer behaviors. Such an analysis is expected to offer strategic knowledge for practitioners to better serve customers in their business operation across different stages of public health crisis.

It is reasonable to assume that the changed travel environment also impacts travelers' preference of travel services. The sociological concept of "cocooning" is widely used in social science to explain the human behavior of a person staying in his or her room instead of going out (O'Shea, 2020), which is considered a response intended to insulate the person from perceived danger (Coleman & Ganong, 2014; Kobayashi & Boase, 2014; Snider, 2013), much like self-quarantining during the COVID-19 pandemic. Thus, the current study will adopt the "cocooning" perspective to understand how travelers' expectations of hotel services have changed during the COVID-19 crisis.

With restrictions being imposed on outdoor activities, hotels' exterior settings should become less important to travelers, with experiences provided inside hotels becoming more important. As the rules of social distancing limit the use of shared hotel facilities, it can also be expected that in-room experiences and hygienic considerations will be focal

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points for travelers. Consequently, they will likely exhibit a higher value orientation, and their expectations may shift from hedonic to utilitarian hotel attributes. Therefore, the authors' first research objective is to determine the extent to which consumer expectations regarding hotel attributes (e.g., service, cleanliness, price, and facility) have changed across the COVID-19 pandemic.

A shift in consumers' expectations is also likely to impact their perceptions of hotel performance. Expectancy confirmation theory (Oliver, 1980) assumes that relative satisfaction with hotel attributes shifts alongside alterations in customer expectations. Thus, the authors' second research objective is to determine whether hotels can successfully change their product and service offerings to adjust to fluctuations in consumer expectations.

The COVID-19 pandemic is an external shock, which may alter, not only immediate (re-)actions to the acute situation, but also longer-term consumer behavior. Following the 2008 recession, consumers remained "stay at home shoppers," though the economic need to shop this way disappeared (Slaughter & Grigore, 2015). Building from this precedent, the authors have searched for early indicators of the extent to which customers' changed preferences for the hospitality services may prevail in less acute pandemic phases.

According to these conceptual reflections, three novel research questions were derived to guide this empirical study.

1) What shifts in the importance travelers place on hotel services, across the COVID-19 pandemic, can be identified by conducting text mining on user-generated reviews (UGRs)?
2) What changes in customers' perceptions of service performance, across the COVID-19 pandemic, can be revealed by sentiment analysis on UGRs?
3) What insights can be derived from these changes to direct hospitality practices during the COVID-19 pandemic?

Our study is among the first to investigate and compare travelers' preferences across different stages of a public health crisis. Analyses are based on an especially large amount of customer reviews, which enables broad and statistically validated insights. Specifically, the study is among first to offer a longitudinal analysis toward the ongoing COVID-19 pandemic. While globalization and rapid economic growth have boosted the development of global tourism industry in the past two or three decades, COVID-19 appears to be the first global pandemic in this context and its impacts are profound.

The remainder of the paper is organized as follows. Section 2 reviews the extant studies concerning the effects of pandemics on the tourism industry, while Section 3 introduces the research methodology. The findings are discussed in Section 4, and the implications and contributions of the research for both theory and practice are presented in Section 5. Finally, Section 6 describes the limitations of the study and presents opportunities for future research in this area.

## 2. Literature review

### 2.1. The effects of pandemics on the tourism industry

The tourism industry is both a catalyst for the spread of viruses and a victim of that spread. It is, therefore, among those sectors most seriously influenced by pandemics and crises. The tourism industry has experienced several major pandemics over the last few decades—notably, severe acute respiratory syndrome (SARS) (2002–2004), novel influenza A (H1N1) (2009–2010), avian influenza A (H7N9) (2013–2017), and Ebola Virus Disease (EVD) (2014–2016). Table 1 briefly overviews previous literature investigating the effects of pandemics on tourism.

Since the broad spread of SARS in 2003, the impact of pandemics on tourism has received wide attention from relevant practitioners and researchers, who have examined industry dynamics alongside the epidemics—e.g., perceived risk (Rittichainuwat & Chakraborty, 2009; Wen et al., 2005), travel intentions (Lee et al., 2012), tourist flow (Cooper, 2005), revenue (Chen, 2011), etc. Most studies in this research stream have attempted to extract strategical insights for the tourism industry by studying travel flows and pandemic dynamics. For instance, Gössling et al. (2020) examine the impact of COVID-19 on society, the economy, and the tourism industry. Kuo et al. (2008) compare the impact of SARS and avian influenza on international tourist arrivals. Cooper (2005) chronicles and discusses reactions (tourist flows) to the Japanese tourist industry's response to SARS, and Mao et al. (2010) compare post-SARS tourist arrival recovery patterns between several destinations. A number of studies have also employed qualitative analysis to explore the impact of pandemics on the tourism industry. For instance, Chien and Law (2003) discuss the effects of SARS on hotels in Hong Kong, and Renaud (2020) explores the impact of COVID-19 on the cruise industry.

Most studies have analyzed aggregate travel flows/intention/revenue patterns. Few, however, have investigated the dynamics of individual consumer preferences due to pandemic situations. Exceptions to this rule have generally restricted themselves to considering only travelers' risk assessments (Rittichainuwat & Chakraborty, 2009), revealing that people exhibit an understandable pattern of heightened safety requirements. Notably, Wen et al. (2005), analyze the impacts of pandemics on people's inclination to travel, their preferences during leisure trips, and their concerns about public hygiene. Both Wen et al. (2005)

**Table 1**
Overview of previous literature concerning the effects of pandemics on tourism.

| Authors | Pandemic | Research topic | Level of analysis | Research method |
|---|---|---|---|---|
| Chen (2011) | SARS | Hotel revenue | Macro-level: economics | Quantitative |
| Chien and Law (2003) | SARS | Hotel industry | Macro-level: mixed | Qualitative |
| Cooper (2005) | SARS | Tourist flows | Macro-level: economics | Quantitative |
| Gössling et al. (2020) | COVID-19 | Society, economy, and tourism | Macro-level: mixed | Quantitative |
| Kuo et al. (2008) | SARS & Asian Flu | Travel flows | Macro-level: travel trend | Quantitative |
| Lee and Chen (2011) | SARS | Travel flows | Macro-level: travel trend | Qualitative |
| Lee et al. (2012) | H1N1 | Travel intentions | Micro-level: consumer behavior | Quantitative |
| Mao et al. (2010) | SARS | Tourist flows | Macro-level: travel trend | Quantitative |
| Pine and McKercher (2004) | SARS | Tourism industry | Macro-level: economics | Quantitative |
| Renaud (2020) | COVID-19 | Cruise industry | Macro-level: economics | Qualitative |
| Rittichainuwat and Chakraborty (2009) | SARS, Bird Flu | Perceived travel risks | Micro-level: consumer behavior | Quantitative |
| Tse et al. (2006) | SARS | Crisis management & recovery | Macro-level: mixed | Qualitative |
| Wang (2009) | SARS | Travel flows | Macro-level: economics | Quantitative |
| Wen et al. (2005) | SARS | Consumer behaviour | Micro-level: consumer behavior | Quantitative |
| Wu et al. (2010) | H1N1 | Hotel occupancy | Macro-level: economics | Quantitative |

and Rittichainuwat and Chakraborty (2009) use questionnaires to investigate traveler behavior at the level of intention.

### 2.2. Evolving expectations of travelers

Introduced by Oliver (1980), the expectancy confirmation theory (ECT) has been widely used for understanding customer satisfaction (CS) and service optimizing. According to ECT, CS is a function of customer evaluations, stemming from a comprehensive comparison (confirmation) between customer expectations of and perceptions about product/service attributes (Bhattacherjee, 2001; Kim, 2012; Oliver, 1980). If a service experience matches or exceeds the expectation, customers are satisfied. Conversely, customers will feel dissatisfied. Past studies indicated that consumers' expectations on a service differ in terms of situated service scenarios (e.g., Hu et al., 2019; Lai & Hitchcock, 2017; Rhee & Yang, 2015; Xu, 2018), which affect their evaluation of service attributes as well as satisfaction toward the service.

Hu et al. (2019) and Lai and Hitchcock (2017) found that travelers' evaluations on hotel attributes vary with repeated visits. By comparing first-time visit and re-patronage behaviors of travelers, Li et al. (2008) reported that new visitors were more travel oriented, while repeaters showed more recreation tendency. Xu (2018) found that the antecedents of traveler satisfaction were different with different travel-models (e.g., business, family, couple and solo). Rhee and Yang (2015) reported that the determinants of CS varied when travelers visited different types of hotels (e.g., 5-, 4-, and 3-star). The above studies indicated that travelers' evaluation on a hotel service would differ in accordance to situated service contexts. Likewise, global pandemic may contribute to a contextual factor affecting travelers' evaluation on accommodation service.

Global pandemic may motivate travelers to adopt a "cocooning" behavior. "Cocooning" behavior refers to an act of self-preservation of individuals who stay inside home to insulate from perceived outside danger (Snider, 2013). In the hospitality literature, the view of "cocooning" has been employed to explain the behavior of travelers who seek a quiet atmosphere to escape from daily life. For instance, Dickinson et al. (2017) stated that some travelers trend to "cocoon" themselves at a campsite (e.g., a hotel room or a scenic spot) to escape from social connections. Koh et al. (2010) argued that the "cocooning" travelers aims to relax and rejuvenate, and suggested that sharing the same public areas may lead to dissatisfaction for this type of tourists. In generally, the principal manifestation of "cocooning" travelers is to gain social distance from one another. During the pandemics, travelers may introduce more "cocooning" behaviors, due to the risks of person-to-person infection. As a result, travelers may alter their expectations on a service offering to satisfy the need of 'cocooning' behaviors. For instance, travelers may render higher requirements on service attributes relate to safety and hygiene.

### 2.3. Assessing travelers' evaluations of service attributes

To understand the antecedents of CS, survey-based approaches are often employed to examine customer evaluations pertinent to specific tourism products/services (e.g., Calantone et al., 1989; Kim, 1996; Kim et al., 2005; Lewis, 1985). More recent literature is keen to uncover travelers' open-ended experiences by scrutinizing UGRs via intelligent opinion mining (Table 2). Widespread internet use has stimulated customers to share their travel stories with others via sites like TripAdvisor and Booking (Cheng & Ho, 2015; Filieri, 2015). Travel stories are described as opinions towards a bundle of service attributes (Hu & Trivedi, 2020; Kotler & Armstrong, 2010). Customers self-report their UGRs based on personal experience, recording their critical service encounters (Archak et al., 2011; Chen & Xie, 2008). The prevalence of such sharing has led to the necessity of understanding customers' thinking in online reviews, which has, in turn, driven the development of opinion mining (Ma, Cheng, & Hsiao, 2018). Opinion mining helps researchers extract and interpret customers' experiences with and evaluations of a product/service via textual content.

**Table 2**
Previous studies investigating travelers' evaluations by mining online reviews.

| Authors | Data Sources | Measurement approaches | |
|---|---|---|---|
| | | Expectation/ Importance | Perception/ Performance |
| Hu and Trivedi (2020) | Tripadvisor | Frequency-based | Rating-based |
| Bi et al. (2019) | Tripadvisor | Frequency-based | Rating-based |
| Francesco and Roberta (2019) | Booking | Frequency-based | Rating-based |
| Liu et al. (2019) | Tripadvisor | | Sentiment-based |
| Yadav & Roychoudhury (2019) | Tripadvisor | Frequency-based | Sentiment-based |
| Antonio et al. (2018) | Tripadvisor & Booking | Frequency-based | Sentiment-based |
| Calheiros et al. (2017) | Websites & e-mails | Frequency-based | Sentiment-based |
| Krawczyk & Xiang (2016) | Expedia | Frequency-based | |
| Xu and Li (2016) | Booking | Frequency-based | |
| Chiu et al. (2015) | Wretch and Yahoo Blogs | | Sentiment-based |
| Hananto (2015) | Tripadvisor | Frequency-based | |
| Li et al. (2015) | Tripadvisor | Frequency-based | |
| Xiang et al. (2015) | Expedia | Frequency-based | |
| O'Connor (2010) | Tripadvisor | Frequency-based | |
| Stringam & Gerdes (2010) | Expedia | Frequency-based | |

As demonstrated in Table 2, recent tourism literature has shown increasing interest in employing text mining and sentiment analysis to extract travelers' expectations and perceptions of service attributes from online UGRs (Alaei et al., 2019; Ma et al., 2018). Among such studies, the relative proportions of mentioned attributes is employed to indicate the level of customer preference for the specified attributes (Bi et al., 2019; Hu & Trivedi, 2020; Stringam & Gerdes, 2010), while subjective expressions/emotions toward the mentioned attributes (or direct ratings of specified attributes) imply the performances of those attributes (Antonio et al., 2018; Hu et al., 2020; Yi Liu et al., 2019). UGRs, therefore, serve as an excellent data source for helping researchers and managers understand customers' experiences and improve service quality (Shin et al., 2018).

In our research, we sought to leverage UGRs to identify changing travelers' evaluations of hotel attributes during different stages of the novel coronavirus 2019 (COVID-19) pandemic. 98,163 Chinese hotel reviews, covering three time periods (before-, within- and recovering-stage of COVID-19 pandemic), were selected and scrutinized via content analysis techniques to derive new implications for service optimization along pandemic dynamics.

## 3. Methodology

In line with past studies (e.g., Antonio et al., 2018; Hu et al., 2020; Yadav and Roychoudhury, 2019), the present research investigated customers' preferences and perceptions concerning hotel attributes by exploring customers' online reviews. Fig. 1 describes the structure of data collection and analysis. The single steps will be outlined below.

### 3.1. Data collection

The hotel reviews used in this study were collected on June 3, 2020 from Ctrip.com,[1] which is the largest travel site in China, offering an

[1] In Ctrip.com, only travelers with actual lodging experience are allowed to post comments concerning the booked hotels on Ctrip.com.

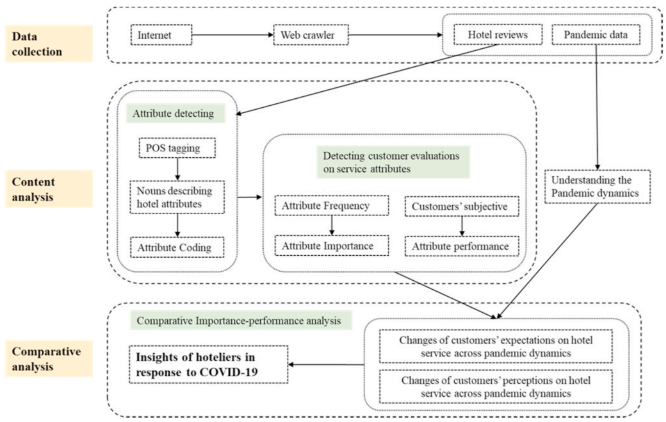


**Fig. 1.** Research framework.

extensive network with more than 1.2 million hotels in 200 countries and regions. Since COVID-19 pandemic was publicly recognized in the beginning of 2020, reviews were collected for the period[2] between January 1, 2020 and June 2, 2020. Previous literature has reported that travel motivation and decision may associate to seasonal patterns (Fernández-Morales et al., 2016; Ferrante et al., 2018; Šegota & Mihalič, 2018). Customer evaluations on hotel attributes may vary along with the change of seasonal variation. Customer reviews from the same period in 2019 therefore were collected as reference period. This enabled comparisons with the before-crisis consumer experience by controlling for possible seasonal changes in travelers' evaluations. A total of 98,163 reviews of all the 183 five-star hotels in Shanghai listed at Ctrip.com were selected as research sample, covering both periods of pre- and in-COVID-19. Table 3 exhibits the distribution of reviews selected from 2019 to 2020, respectively.

### 3.2. Content analysis

#### 3.2.1. Understanding customers' expectations of hotel services based on text mining

A quantitative textual analysis program, KH-Coder, was employed to detect frequently mentioned hotel attributes (customer expectations) in hotel reviews at the sentence level. As Fig. 2 shows, hotel reviews were first divided into sentences. By setting the KH-Coder part-of-speech (POS) option to "nouns" (Archak et al., 2011; Hu & Liu, 2004), the top 100 nouns[3] mentioned in the reviews were detected, which are used to identify the most important hotel attributes that were mentioned by reviewers. Thereafter, three PhD students in the field of tourism research were asked to identify hotel features from those nouns. Note that only term candidates approved by more than or equal to 2/3 of these researchers were selected as hotel attributes in this study. Appendix A shows the top 20 detected attributes, as well as their Chinese codes. The further analysis examines the variations of customers' preference and expectation on these 20 hotel attributes among different time periods.

According to the preceding discussions, the mentioning frequencies of service attributes indicate the importance customers' give to these attributes. The study, therefore, used mentioned proportion, within a specified period, to denote an attribute's importance for travelers within that period.

#### 3.2.2. Uncovering attribute performance (customer perceptions) via sentiment analysis

Fig. 2 also presents the sentiment analysis process used in this study. A sentiment analysis program, LIWC2015, was employed to evaluate customers' sentiments at the sentence level. An "attribute dictionary" (Appendix A) was used to link hotel attributes to customers' subjective performance evaluations of these attributes in the sampled sentences. A three-point scale was applied to record customers' subjective performance evaluations. The subjective value of a sentence was recorded as "1" if the sentence captured a positive emotion, as "-1" if the emotion was negative, or as "0" for any other condition. Finally, the average score of customers' subjective evaluations of a specific hotel attribute was calculated to indicate the performance of that attribute.

### 3.3. Comparative analysis

Importance–performance analysis (IPA), also known as "action grid analysis," was first introduced by Martilla and James (1977), and it has since been widely applied in previous literature to examine the importance and performance of service attributes for improving CS (e.g., Jang et al., 2009; Koh et al., 2010; Kuo, 2009; Liu & Jang, 2009). Because it considers service quality as a function of how consumers evaluate a service attribute's importance and performance, IPA develops insights about optimizing service attributes for CS improvement (Qu & Sit, 2007). To implement efficient service improvement strategies in a competitive environment, Taplin (2012) has introduced a revised IPA approach: competitive importance–performance analysis. Taplin (2012) argues that service attributes should be improved by referencing their respective importance and performance in terms of competitors.

Similar to Taplin's (2012) competitive analysis, this study conducts a comparative analysis to examine changes in customer evaluations of service attributes across time series. A revised model, comparative importance–performance analysis (CIPA), has, therefore, been developed to uncover the effects of the COVID-19 pandemic on customer evaluations of hospitality services across the pandemic's dynamics. In CIPA, the weight (importance/performance) difference of an attribute between selected and reference categories is calculated (see following formula). According to the comparison result, CIPA identifies the attribute's relative priority ("increased-importance" or "decreased-importance") and performance level ("strength" or "weakness") between the selected and reference categories.

$$WD = \frac{W^S - W^T}{W^T}$$

WD: Weight (importance/performance) difference.

$W^S$ : Weight (importance/performance) of an attribute in selected time period.

$W^T$: Weight (importance/performance) of an attribute in total dataset overall mean).

Fig. 3 illustrates the rationale behind using CIPA to uncover changes in customer evaluations of hotel attributes between the periods before the COVID-19 pandemic (reference period) and during/after the crisis (experimental group). Changes in attribute importance are noted on the X-axis, and changes in performance evaluation are noted on the Y-axis. The resulting two-dimensional "CIPA Grid" classifies hotel attributes into four quadrants according to differences in importance and performance.

I) The "Unneeded Luxury" quadrant contains hotel attributes, which have become less important but which were rated more highly during the pandemics. Here, hotels were able to improve their respective offerings during the crisis (a strength), while consumers considered the underlying attributes less important.

II) The "Hot-Spots" (increased importance, increased performance) quadrant is an area of strength. Customers assessed the attributes as both more important and better performed during the crisis.

[2] In this study, published dates of reviews given by Ctrip.com are adopted for data categorizing.

[3] Term frequency was calculated at the sentence level. That is, the number of sentences including a specified term was selected as the importance weight of this term in customers' mind.

**Table 3**
Distribution of hotel reviews (five-star in Shanghai) to time series.

| Year/Month | Jan (01/01-01/15) | Jan (01/16-01/31) | Feb (02/01-02/15) | Feb (02/16-02/29) | Mar (03/01-03/15) | Mar (03/16-03/31) | Apr (04/01-04/15) | Apr (04/16-04/30) | May (05/01-05/15) | May (05/16-05/31) | Jun (06/01–06/02) | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2020 | 7317 | 5141 | 1458 | 985 | 1073 | 1633 | 1824 | 2428 | 3549 | 4422 | 544 | 30,374 |
| 2019 | 6777 | 6683 | 10,279 | 5695 | 5725 | 6309 | 5675 | 6008 | 7689 | 6176 | 773 | 67,789 |
| Total | 14,094 | 11,824 | 11,737 | 6680 | 6798 | 7942 | 7499 | 8436 | 11,238 | 10,598 | 1317 | 98,163 |

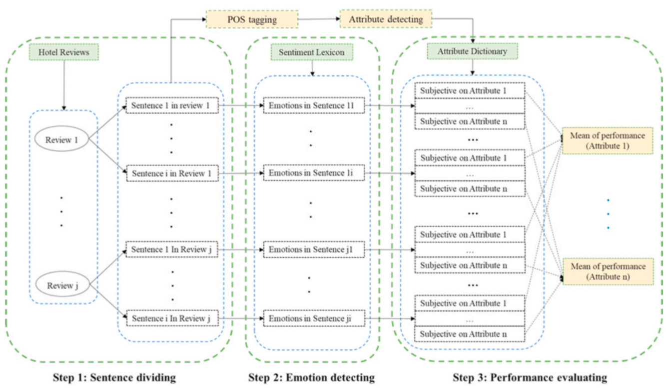


**Fig. 2.** Examining customer evaluations of service attributes via content analysis.

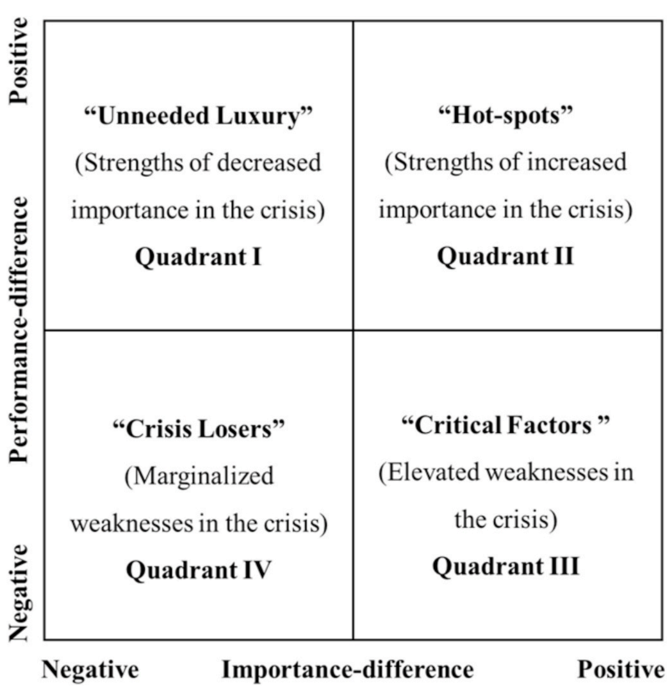


**Fig. 3.** CIPA

III) In the "Critical Factors" quadrant (increased importance, decreased performance), attributes became more important, but the hotels did not successfully address them during the crisis.

IV) Finally, the "Crisis Losers" quadrant (decreased importance, decreased performance) contains hotel attributes characterized by marginalized weaknesses. Thus, their deficiencies need not be addressed with high priority.

## 4. Findings and discussion

### 4.1. Description of pandemic dynamics

Fig. 4 provides a detailed account of how the COVID-19 pandemic has impacted the occupancy of the investigated hotels in Shanghai.[4] The information pertaining to COVID-19—including the number of cumulative infections and critical COVID-19 incidents—was collected from the National Health Commission of the People's Republic of China (PRC) and from the Shanghai Municipal Health Commission. The red line (right scale) is the reported number of cumulative COVID-19 cases in Shanghai (2020), while the blue/black line shows the number of hotel reviews (indicator of hotel occupancy) during the same periods in 2019/2020. The marked *Numbers* and *Letters* with corresponding notes highlight key incidents according to time series. For example, Wuhan announced that all public transportation in the city was temporarily closed on January 23, 2020, (node of *Number 2*). By comparing the trends in the COVID-19 pandemic and hotel occupancy in 2019 and 2020, novel insights into the effects of the pandemic on hotel occupancy have been uncovered.

A drastic decline in hotel occupancy can be observed after the Number 1 node (January 21, 2020). At this point of time, the Chinese government released its first announcement about COVID-19. The comparison of hotel occupancy between 2020 (black line) and 2019 (grew line) confirms that the Chinese hospitality industry began to be sharply influenced by COVID-19 after this first-time node. The slope of the red line (cumulative cases of COVID-19) becomes smoother after node Number 5 (April 14, 2020). On this day, the Chinese government released its announcement concerning the control of COVID-19 and the planned safe and orderly opening of tourist attractions. This indicates that China began reopening the travel market based on controlled risk. The longitudinal comparison of hotel occupancy between 2020 (black line) and 2019 (blue line) also confirms that the Chinese hospitality industry began to recover from the COVID-19 pandemic after node Number 5.

The researchers further defined two COVID-19 time phases: "*Within COVID-19 pandemic*" and "*Recovering from COVID-19 pandemic*." The first phase lasted from January 21, 2020, to April 13, 2020 (between the events of nodes *Number 1* and *5*; see Fig. 4), and the second lasted from April 14, 2020, to June 2, 2020 (between node *Number 5* and the day of data collection). In the remainder of this paper, the authors use "*Within*" and "*Recovering*" to indicate above two phases; they also use "R1," "R2," and "R (R1+R2)" to refer to the reference periods in 2019. Table 4 shows the definitions of the above phases.

### 4.2. Changes in hotel attribute importance

Appendix B shows the detected attribute importance (proportion) according time series. Then, to visually compare attribute distributions between different stages of the pandemic, the proportion of mentioned attributes was further standardized as "importance difference"

[4] Shanghai adopted a conditional shutdown for travelers during the COVID-19 pandemic, which was based on dynamic evaluations of travelers' risk levels (departure and health quick response (QR) code).

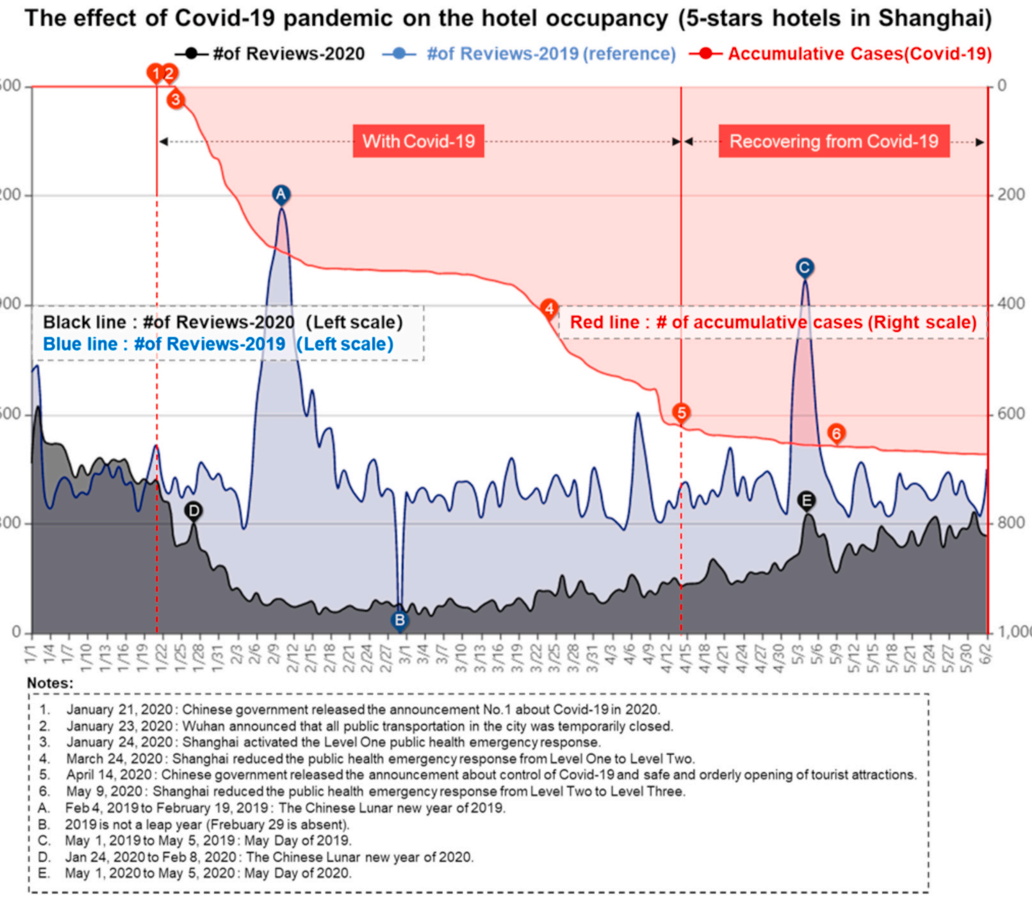


**Fig. 4.** Effects of the COVID-19 pandemic on hotel occupancy (# of hotel reviews).

**Table 4**
Classifications and definitions of time series based on pandemic dynamics.

| Year/ Month | Jan 21–Apr 13 | Apr 14–Jun 2 |
|---|---|---|
| 2020 | *Within*: The period within the COVID-19 pandemic | *Recovering*: The period of recovering from the COVID-19 pandemic |
| 2019 | Reference 1 (R1): The reference period of "*Within*" in the previous year | Reference 2 (R2): The reference period of "*Recovering*" in the previous year |
| | Reference (R): The full reference period in the previous year (R1 + R2) | |

(Appendix C) according to the formula introduced in Section 3.3.3. Values were displayed as differences from the average importance weight, which was derived from the entire dataset.

Fig. 5 visualizes the significant changes (see the last four columns in Appendix B) in attribute importance weights over time, comparing the *Within* and *Recovering* periods with R1 and R2. To improve the readability of the figure, we sorted the attribute sequence by the descending order of absolute differences "R1 VS Within". In Fig. 5, positive (negative) values represent the higher (lower) importance of a single hotel attribute in a specific time period, indicating an increase (decrease) in the attribute's importance weight. The comparison between pre-COVID-19 (dotted lines) and the two pandemic periods (solid lines) reveals large shifts in importance weights for single hotel attributes. In contrast, only minor differences exist between the two reference periods in 2019 (dotted lines). Binomial proportion tests in Appendix B show that only 3 out of 20 observations in "R2 VS R1" are significant different. While 11 out of 20 and 12 out of 20 observations are significant different in the "Within VS R1" and "Recovering VS R2" comparisons. This lets us to conclude that changes in hotel attribute importance are mostly

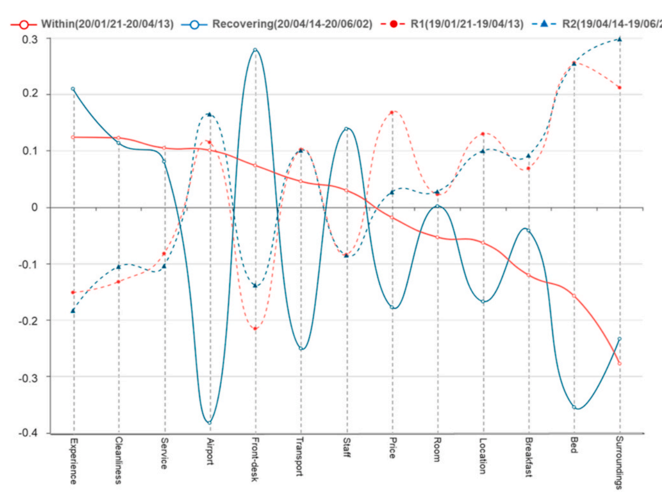


**Fig. 5.** Changes in hotel attribute importance across pandemic dynamics.

attributable to the impact of pandemic and not to seasonal difference.

A few attributes (e.g., *breakfast, location* and *surrounding*) lost importance in both pandemic periods. Consumers' deteriorated interest in these attributes hints towards limited experiential opportunities in the pandemics, e.g. for crowding or exposing outside the hotels. Conversely, some attributes (e.g., *experience, cleanliness, service,* and *front-desk*) gained importance in the pandemic phases because of increasing demand of inside experiences and security/hygiene. Transportation issues (e.g., *transport* and *airport*) became less important in the later *Recovering* period, indicating a shift away from public transportation means.

Unexpectedly, core hotel attributes, especially *bed* comfort, as well as *price* considerations continually decreased in importance during the pandemic, while *room* attributes were only in the rigorous period of pandemic (*Within*) of less concern.

### 4.3. Changes in customers' performance assessments

By setting the entire dataset's performance mean as a reference, the authors standardized the achieved attribute performance in a specific period for comparison analysis. Appendix D presents attribute performance (based on customers' subjective evaluations) according to time series, and Appendix E displays the changes in customer perceptions across the pandemic's dynamics. Fig. 6 visualizes the significant variations (see Appendix B) of customers' performance assessments over time, again comparing the *Within* and the *Recovering* periods with R1 and R2. Positive (negative) values represent a more positive (negative) assessment of a single hotel attribute in a specific time period, indicating an improved (decreased) performance.

In Fig. 6, both pre-COVID-19 periods (dotted lines) exhibit only marginal differences, which indicates that customers' performance assessments of hotel services were stable in normal, non-pandemic times. Statistical comparisons also found no significant differences in the assessment of hotel attributes' performances when comparing both reference periods R1 and R2 (see Appendix D). This let us conclude that seasonal effects did not impact customers' performance assessments of hotel attributes. In contrast, there were major differences in customers' performance assessments of hotel attributes between the *Within*, *Recovering and pre-COVID-19 periods*.

Higher performance assessments in both COVID-19 periods may indicate that travelers exhibited a greater level of forgiveness on some attributes (e.g., *surroundings*) during the pandemic, while other attributes (e.g., *cleanliness* and *front-desk*) may have been significantly improved in the pandemics by hotel management. Attributes (e.g., *breakfast, experience* and *decor*) exhibiting a declining performance in the *recovering* phase indicate that hotels were initially unable to fulfill customers' expectations regarding these attributes. However, their performance assessments increased along with the eliminating of pandemic. Only *facility* was rated more negatively in both pandemic phases, since the implementation of hotel facilities were mostly outside the control of the hotels' management.

### 4.4. Service optimization for pandemic crises

To derive practical implications for service optimization during pandemic crises, the researchers employed CIPA as introduced in Section 3.3.3. In it, customers' evaluations (standardized weight) of hotel attributes during two stages of the COVID-19 pandemic were compared with those from the same periods of 2019 (as a baseline of comparison). Fig. 7 depicts the empirical findings of these comparisons (see Appendix F for numerical details). Three time periods are compared within Fig. 7; the origin in the coordinate system served as the reference point (pre-COVID-19 pandemic), i.e., the importance/performance weights of each service attribute in 2019. *Within* is represented by red dots, and *Recovering* is represented by blue cubes. The horizontal distance between both points indicates changes in importance, and the vertical distance implies performance differences between different periods.

A visual inspection of Fig. 7 reveals only a few attributes in the lower right quadrant—those with decreased performance and increased importance (see Section 3.3.3). All other quadrants are approximately equally populated by hotel attributes. This indicates that, overall, hotels have successfully addressed travelers' changing demands. Only one attribute was located in the "Critical Factors" quadrant during the acute stage of COVID-19 pandemic: *restaurant* services. This highlights travelers' acute need for food services, which the hotels could not successfully address. Hotels, however, have adjusted their food offerings in the *Recovering* period; the perceived performance of restaurant services increased, turning this attribute into a "Hot-Spot." This exemplifies hotels successfully adapting to changing consumer needs. In contrast, increased demand for *experience* was successfully addressed in the acute *Within* period, probably due to low expectation levels, while increased expectations in the *Recovering* period were not as well fulfilled.

Focusing on the acute *Within* period (red dots), it is evident that *cleanliness*, *front desk*, *service*, and *staff* were pandemic "Hot-Spots" of increased importance and strengthened performance. In this regard, hotels seemed to have quickly and successfully adjusted to the changed requirements caused by the pandemic. Exterior attributes and amenity-related are widely dispersed in the left half of the figure, indicating decreased attribute importance but divergent performance valuations. The upper left quadrant of "Unneeded Luxury" includes attributes such as *surroundings*, *airport*, *décor* and *bed*. Here, travelers gave hotels more positive feedback, although they also articulated less attribute importance. Other exterior attributes (*location, transport*) and core attributes (*breakfast, room, and price*) were rated more critically, but were also considered less important, making them appear to be "Crisis Losers." Travelers might have recognized the limitations of hotel management for changing these attribute settings according to the novel travel needs caused by the pandemic.

Focusing on the *Recovering* period (blue cubes), larger differences are evident, both in terms of attribute importance and performance

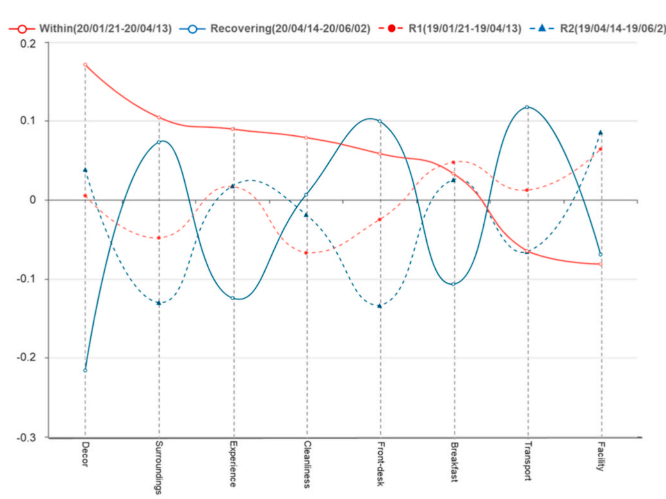


**Fig. 6.** Changes in customers' performance assessments of hotel attributes across pandemic dynamics.

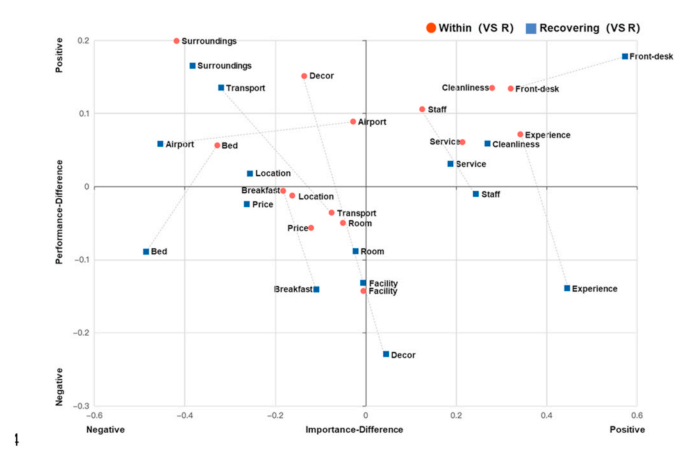


**Fig. 7.** Comparative importance-performance analysis (comparisons between both pandemic stages (Within and Recovering) with the entire reference period R.

evaluation. Several attributes are located farther from the origin, signaling a larger shift from previous customer evaluations. These changes were not limited to performance assessments but included importance evaluations as well. Thus, contrary to prima-facie expectations, the situation has not gone "back to normal"; instead, the changed positioning hints at more sustainable shifts in consumer preferences. Regarding performance evaluations, hotel attributes were assessed more critically in the *recovering* period. The high consumer forgivingness during the acute stage of the pandemic seems to have diminished as travelers valued many hotel attributes more negatively (lower quadrants). Furthermore, major changes in attribute importance weights are evident in Fig. 7. These changes occurred, not unidirectionally, but in both directions of decreased and increased importance. The *Recovering* period is, thus, characterized by a wider spread of attribute importance weights, indicating major shifts in consumer expectations.

Further insights into the pandemic dynamics can be gained from a comparison of attribute positions during the *Within* (red circles) and *Recovering* (blue cubes) periods. Major differences between both positions are highlighted by dotted lines in Fig. 7. Here, the three attributes *décor*, *staff* and *experience* stand out. They changed from being an "Unneeded Luxury" or "Hot-Spot" during the *Within* period to being a "critical factor" in the *Recovering* period. The underlying reason for this might be the cocooning effect; that is, travelers, who have adapted to the ongoing restrictions for outside activities, have begun placing more emphasis on experiences inside their semiprivate settings.

## 5. Implications

### 5.1. Theoretical implications

Most prior research investigated the impact of pandemics on travel flows from a macro or meso perspective and provided suggestions for policy-makers. This study, examined the changes in travelers' service evaluations across the COVID-19 pandemic to gain actionable insights for hospitality managers. A large number of customer reviews offered detailed insights at a micro-operational perspective. Insights obtained from this research can assist guide hospitality managers in organizing their priorities during acute pandemic situations and adjusting to possibly longer-lasting shifts in consumer preferences.

One of the novel insights in the theoretical realm relates to the identification of evolving travelers' expectations. This study is among the first to investigate the impact of COVID-19 by dividing the pandemic into two stages: *Within* and *Recovering*. Such granular analyses offer deeper insights into the evolution of travelers' evaluations on service attributes as a pandemic evolves. Past studies demonstrated that an individual would have different expectations toward hotel services when travelling on different travel-models or when staying at different types of hotels. Our study offers concrete evidences that the emergence of major pandemics, like COVID-19, also alters travelers' expectations. A wide range of variations in traveler preferences, such as *experience*, *cleanliness*, *service*, and *breakfast*, are revealed in the stage of acute COVID-19 situation. Interestingly, the effect of COVID-19 on travelers' expectations (e.g., *front-desk*, *transport*, *location*, and *bed*) even continues in the recovering phase—travelers seem get used to the regular pandemic situation, thus, there is a possibly enduring shift in expectations.

Furthermore, our study contributes to tourism literature by introducing cocooning theory to explain how travelers' expectations can be altered as a result of cocooning themselves against potential dangers during pandemics. We found that travelers alter their expectations on hotel service by highlighting the requirements related to social distance and hygiene in the stage of pandemics. In addition, in the acute phase of pandemic, travelers expected cuts in hotel attributes less relate to safety, thereby becoming more forgiving. As a result, some nuclear hotel attributes (e.g., *room*, *bed* and *price*) that were conventionally stressed by travelers are perceived as less important during the pandemic. Taken together, we contend that cocooning theory offers a useful theoretical lens to understand travelers' behavior during pandemics.

### 5.2. Practical implications

While each dimension (importance or performance) of travelers' assessments provides useful insights for optimizing hotel offerings, a full picture is found by jointly considering relative changes via CIPA. This can help guide hospitality practice to prioritize its measures in acute pandemic situations (*Within*) and to adjust to possibly longer-lasting shifts (*Recovering*) in consumer preferences. For instance, the effects of cocooning can be observed consistently in travelers, who are necessarily outside of their own home but, nonetheless, are searching for a safe haven (e.g., *cleanliness*). These shifts extend to more quality-related hotel attributes, such as *experience* and *front-desk* support; however, these changes did not occur immediately in the acute *Within* period of the COVID-19 pandemic. Instead, major changes in these areas were only observed in the *Recovering* phase. This suggests the possibility of some longer-lasting shifts in customer expectations.

Specifically, service-related attributes—such as *staff* and *experience*—were measured as being "good work" during the acute *Within* period of the COVID-19 pandemic, but they experienced a shift toward increased importance and decreased performance evaluations in the *Recovering* stage. Hoteliers, therefore, should enhance relevant offerings to match dynamic customer requirements. Some core supplies, like *breakfast* and *room*, also showed a similar shift; however, they only showed a potential transformation from "Crisis Losers" to "Critical Factors," indicating that the requirements on some core offerings are recovering as the pandemic eased, and hoteliers may increasingly improve core supplies over time. Exterior attributes—including *surroundings*, and *location*, *transport*—exhibited no significant effects according to time series, up to the date of data collection. Thus, exterior attributes are still considered "Unneeded Luxury".

In general, improvement strategies should be based on the evolving priority of attributes in different pandemic periods to efficiently allocate the limited resources of an organization. Hygiene and relevant inside service (e.g., *service* and *front-desk*) show to gain higher priority during both pandemic periods. Some tangible supplies (e.g., *room*, *facility* and *breakfast*) have reversed their shifts during the *Recovering* period, implying that customers' requirements concerning these issues are returning to normal patterns. Hoteliers should, therefore, emphasize different attributes over pandemic dynamics.

## 6. Limitations and future research

This paper presents several limitations, but also provides directions for future research. The dataset used in the current study was collected from single website. The number of reviews in 2020 was inherently lower than in the pre-COVID-19 reference period of 2019. Nothing shows that COVID-19 has been completely eliminated in China up to the submission date of the current manuscript. Therefore, the *Recovering* period might continue for some more time. A repeated analysis could uncover further differences among "Before COVID-19," "With COVID-19," and "After COVID-19" (pre/in/post) periods based on an updated and enlarged dataset, possibly extending the databased to other websites.

The empirical bases of analysis is restricted to five-star hotels in a major city in China. Pandemic situations may vary from country to country, and there also may be significant cultural differences (e.g., Liu et al., 2017; Zhang et al., 2015) between countries' handling of the pandemics. The current methodology can be repeated to uncover practical implications for distinct regions based on different datasets. Customers' expectations on service attributes is also expected to vary between different hotel-types (e.g., Hu & Trivedi, 2020; Xu & Li, 2016).

## Declaration of competing interest

None of the authors have received research grants from any Company towards the submitted manuscript or have any conflict of interest. This article does not contain any studies with animals performed by any of the authors.

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## Appendices.

*Appendix A. The detected top 20 hotel attributes (codes)*

| N | Attributes | Attributes (Chinese) | Code in Chinese | Frequency (Sentence level) |
|---|---|---|---|---|
| 1 | Service | 服务 | 服务 | 20,372 (15.99%) |
| 2 | Room | 房间 | 房间｜房 | 18,833 (14.78%) |
| 3 | Breakfast | 早餐 | 早餐 | 14,848 (11.65%) |
| 4 | Location | 位置 | 位置｜地理 | 11,925 (9.36%) |
| 5 | Environment | 环境 | 环境 | 9543 (7.49%) |
| 6 | Facility | 设施 | 设施 | 6722 (5.28%) |
| 7 | Front desk | 前台 | 前台 | 6807 (5.34%) |
| 8 | Staff | 服务员 | 服务员｜人员｜态度 | 7943 (6.23%) |
| 9 | Value | 性价比 | 性价比 | 3984 (3.13%) |
| 10 | Transport | 交通 | 交通 | 3508 (2.75%) |
| 11 | Cleanliness | 卫生 | 卫生 | 3026 (2.37%) |
| 12 | Bed | 床 | 床 | 2817 (2.21%) |
| 13 | Surroundings | 周边 | 周边 | 2786 (2.19%) |
| 14 | Experience | 体验 | 体验 | 3217 (2.52%) |
| 15 | Price | 价格 | 价格 | 2677 (2.10%) |
| 16 | Airport | 机场 | 机场 | 2071 (1.23%) |
| 17 | Parking | 停车场 | 停车场 | 1821 (1.43%) |
| 18 | Lobby | 大堂 | 大堂 | 1754 (1.38%) |
| 19 | Restaurant | 餐厅 | 餐厅 | 1641 (1.29%) |
| 20 | Décor | 装修 | 装修 | 1937 (1.45%) |

*Appendix B. Attribute importance (frequency) across pandemic dynamics*

| N | Attributes | Attribute distribution | | | | Binomial proportion test | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | R 1 (2019: 01/21–04/13) | R 2 (2019: 04/14–06/02) | Within (2020: 01/21–04/13) | Recovering (2020: 04/14–06/02) | R2 VS R1 | Within VS R1 | Recovering VS R2 | Recovering VS Within |
| 1 | Service | 9357 (15.26%) | 5146 (14.89%) | 2458 (18.36%) | 3411 (17.96%) | *−1.525 n.s.* | *8.910 *** | *9.273 *** | *−0.920 n.s.* |
| 2 | Room | 9091 (14.83%) | 5147 (14.90%) | 1838 (13.73%) | 2757 (14.52%) | *0.289 n.s.* | *−3.252 *** | *−1.178 n.s.* | *2.000 n.s* |
| 3 | Breakfast | 7302 (11.91%) | 4203 (12.16%) | 1313 (9.81%) | 2030 (10.69%) | *1.166 n.s.* | *−6.893 *** | *−5.087 *** | *2.567 n.s* |
| 4 | Location | 6091 (9.93%) | 3341 (9.67%) | 1103 (8.24%) | 1390 (7.32%) | *−1.322 n.s.* | *−6.020 *** | *−9.164 *** | *−3.058 *** |
| 5 | Environment | 4477 (7.30%) | 2644 (7.65%) | 1029 (7.69%) | 1393 (7.34%) | *1.986 n.s* | *1.546 n.s.* | *−1.327 n.s.* | *−1.184 n.s.* |
| 6 | Facility | 3272 (5.34%) | 1760 (5.09%) | 699 (5.22%) | 991 (5.22%) | *−1.619 n.s.* | *−0.536 n.s.* | *0.627 n.s.* | *−0.013 n.s.* |
| 7 | Front-desk | 2811 (4.58%) | 1739 (5.03%) | 839 (6.27%) | 1418 (7.47%) | *3.134 *** | *8.184 *** | *11.441 *** | *4.174 *** |
| 8 | Staff | 3622 (5.91%) | 2038 (5.90%) | 889 (6.64%) | 1394 (7.34%) | *−0.057 n.s.* | *3.230 *** | *6.520 *** | *2.422 n.s* |
| 9 | Value | 1965 (3.21%) | 1009 (2.92%) | 417 (3.12%) | 593 (3.12%) | *−2.441 n.s* | *−0.535 n.s.* | *1.316 n.s.* | *0.039 n.s.* |
| 10 | Transport | 1771 (2.89%) | 997 (2.89%) | 367 (2.74%) | 373 (1.96%) | *−0.026 n.s.* | *−0.923 n.s.* | *−6.458 *** | *−4.609 *** |
| 11 | Cleanliness | 1338 (2.18%) | 778 (2.25%) | 378 (2.82%) | 532 (2.80%) | *0.702 n.s.* | *4.489 *** | *3.940 *** | *−0.119 n.s.* |
| 12 | Bed | 1507 (2.46%) | 849 (2.46%) | 221 (1.65%) | 240 (1.26%) | *−0.007 n.s.* | *−5.626 *** | *−9.358 *** | *−2.895 *** |
| 13 | Surroundings | 1444 (2.36%) | 871 (2.52%) | 188 (1.40%) | 283 (1.49%) | *1.605 n.s.* | *−6.817 *** | *−7.855 *** | *0.635 n.s.* |
| 14 | Experience | 1415 (2.31%) | 768 (2.22%) | 409 (3.06%) | 625 (3.29%) | *−0.848 n.s.* | *5.077 *** | *7.431 *** | *1.189 n.s.* |
| 15 | Price | 1411 (2.30%) | 699 (2.02%) | 259 (1.94%) | 308 (1.62%) | *−2.820 *** | *−2.598 *** | *−3.268 *** | *−2.114 n.s* |
| 16 | Airport | 1048 (1.71%) | 617 (1.79%) | 226 (1.69%) | 180 (0.95%) | *0.870 n.s.* | *−0.169 n.s.* | *−7.659 *** | *−5.896 *** |
| 17 | Parking | 927 (1.51%) | 471 (1.36%) | 191 (1.43%) | 232 (1.22%) | *−1.845 n.s.* | *−0.734 n.s.* | *−1.375 n.s.* | *−1.601 n.s.* |
| 18 | Lobby | 775 (1.26%) | 512 (1.48%) | 198 (1.48%) | 269 (1.42%) | *2.813 *** | *1.989 n.s* | *−0.602 n.s.* | *−0.465 n.s.* |
| 19 | Restaurant | 764 (1.25%) | 423 (1.22%) | 187 (1.40%) | 267 (1.41%) | *−0.293 n.s.* | *1.411 n.s.* | *1.785 n.s.* | *0.068 n.s.* |
| 20 | Decor | 921 (1.50%) | 538 (1.56%) | 176 (1.31%) | 302 (1.59%) | *0.667 n.s.* | | *0.297 n.s.* | *2.024 n.s* |

(*continued on next page*)

(*continued*)

| N | Attributes | Attribute distribution | | | | Binomial proportion test | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | R 1 (2019: 01/21–04/13) | R 2 (2019: 04/14–06/02) | Within (2020: 01/21–04/13) | Recovering (2020: 04/14–06/02) | R2 VS R1 | Within VS R1 | Recovering VS R2 | Recovering VS Within |
| | | | | | | | *−1.632 n.s.* | | |
| | Total | 61,309 (100.00%) | 34,550 (100.00%) | 13,385 (100.00%) | 18,988 (100.00%) | | | | |

R1: Reference dataset 1 (January 21, 2019–April 13, 2019).
R2: Reference dataset 2 (April 14, 2019–June 2, 2019).
Within: Duration of COVID-19 (January 21, 2020–April 13, 2020).
Recovering: Duration of recovering from COVID-19 (April 14, 2020–June 2, 2020).
Note: "**" denotes significant at the 99% confidence level, and "n.s." denotes insignificant.

## *Appendix C. Changes in customer expectations (attribute importance) across pandemic dynamics*

| N | Attributes | Attribute distribution | | | | | Importance difference (Mean as reference) | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | R 1 | R 2 | Within | Recovering | Mean | R1 | R2 | *Within* | Recovering |
| 1 | Service | 15.26% | 14.89% | 18.36% | 17.96% | 16.62% | −0.082 | −0.104 | 0.105 | 0.081 |
| 2 | Room | 14.83% | 14.90% | 13.73% | 14.52% | 14.49% | 0.023 | 0.028 | −0.053 | 0.002 |
| 3 | Breakfast | 11.91% | 12.16% | 9.81% | 10.69% | 11.14% | 0.069 | 0.092 | −0.120 | −0.041 |
| 4 | Location | 9.93% | 9.67% | 8.24% | 7.32% | 8.79% | 0.130 | 0.100 | −0.063 | −0.167 |
| 5 | Environment | 7.30% | 7.65% | 7.69% | 7.34% | 7.49% | −0.026 | 0.021 | 0.026 | −0.021 |
| 6 | Facility | 5.34% | 5.09% | 5.22% | 5.22% | 5.22% | 0.023 | −0.024 | 0.001 | 0.000 |
| 7 | Front-desk | 4.58% | 5.03% | 6.27% | 7.47% | 5.84% | −0.215 | −0.138 | 0.074 | 0.279 |
| 8 | Staff | 5.91% | 5.90% | 6.64% | 7.34% | 6.45% | −0.084 | −0.085 | 0.030 | 0.139 |
| 9 | Value | 3.21% | 2.92% | 3.12% | 3.12% | 3.09% | 0.037 | −0.055 | 0.008 | 0.010 |
| 10 | Transport | 2.89% | 2.89% | 2.74% | 1.96% | 2.62% | 0.102 | 0.101 | 0.046 | −0.250 |
| 11 | Cleanliness | 2.18% | 2.25% | 2.82% | 2.80% | 2.52% | −0.132 | −0.105 | 0.123 | 0.114 |
| 12 | Bed | 2.46% | 2.46% | 1.65% | 1.26% | 1.96% | 0.256 | 0.255 | −0.157 | −0.354 |
| 13 | Surroundings | 2.36% | 2.52% | 1.40% | 1.49% | 1.94% | 0.212 | 0.298 | −0.277 | −0.233 |
| 14 | Experience | 2.31% | 2.22% | 3.06% | 3.29% | 2.72% | −0.151 | −0.183 | 0.124 | 0.210 |
| 15 | Price | 2.30% | 2.02% | 1.94% | 1.62% | 1.97% | 0.168 | 0.027 | −0.018 | −0.177 |
| 16 | Airport | 1.71% | 1.79% | 1.69% | 0.95% | 1.53% | 0.115 | 0.165 | 0.101 | −0.382 |
| 17 | Parking | 1.51% | 1.36% | 1.43% | 1.22% | 1.38% | 0.095 | −0.013 | 0.033 | −0.115 |
| 18 | Lobby | 1.26% | 1.48% | 1.48% | 1.42% | 1.41% | −0.104 | 0.051 | 0.049 | 0.004 |
| 19 | Restaurant | 1.25% | 1.22% | 1.40% | 1.41% | 1.32% | −0.055 | −0.071 | 0.060 | 0.067 |
| 20 | Decor | 1.50% | 1.56% | 1.31% | 1.59% | 1.49% | 0.007 | 0.044 | −0.118 | 0.067 |

Mean: average importance of an attribute across the entire dataset.
R1: importance of an attribute in Reference dataset 1 (January 21, 2019–April 13, 2019).
R2: importance of an attribute in Reference dataset 2 (April 14, 2019–June 2, 2019).
Within: importance of an attribute during COVID-19 (January 21, 2020–April 13, 2020).
Recovering: importance of an attribute in the period of recovering from COVID-19 (April 14, 2020–June 2, 2020).
Difference weight was calculated according to the formula in Section 3.3.3.

## *Appendix D. Attribute performance (subjective customer evaluation) across pandemic dynamics*

| N | Attributes | Attribute performance (Mean, lower limit and upper limit at 99% confidence level) | | | | Performance difference | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | R 1 (2019: 01/21–04/13) | R 2 (2019: 04/14–06/02) | Within (2020: 01/21–04/13) | Recovering (2020: 04/14–06/02) | R2 VS R1 | Within VS R1 | Recovering VS R2 | Recovering VS Within |
| 1 | Service | 0.718 [0.704,0.732] | 0.702 [0.683,0.720] | 0.755 [0.729,0.782] | 0.734 [0.711,0.758] | n.s. | n.s. | n.s. | n.s. |
| 2 | Room | 0.608 [0.594,0.621] | 0.611 [0.593,0.629] | 0.587 [0.557,0.617] | 0.555 [0.529,0.581] | n.s. | n.s. | n.s. | n.s. |
| 3 | Breakfast | 0.682 [0.666,0.697] | 0.667 [0.647,0.688] | 0.673 [0.637,0.708] | 0.581 [0.551,0.612] | n.s. | n.s. | ** | ** |
| 4 | Location | 0.755 [0.738,0.772] | 0.733 [0.710,0.756] | 0.738 [0.699,0.777] | 0.760 [0.723,0.797] | n.s. | n.s. | n.s. | n.s. |
| 5 | Environment | 0.889 [0.869,0.909] | 0.895 [0.869,0.921] | 0.917 [0.877,0.958] | 0.871 [0.834,0.908] | n.s. | n.s. | n.s. | n.s. |
| 6 | Facility | 0.623 [0.600,0.646] | 0.636 [0.604,0.667] | 0.538 [0.489,0.587] | 0.545 [0.502,0.588] | n.s. | ** | ** | n.s. |
| 7 | Front-desk | 0.535 [0.510,0.559] | 0.475 [0.444,0.506] | 0.580 [0.536,0.625] | 0.603 [0.567,0.639] | n.s. | n.s. | ** | n.s. |
| 8 | Staff | 0.545 [0.523,0.566] | 0.515 [0.486,0.544] | 0.591 [0.548,0.633] | 0.529 [0.493,0.565] | n.s. | n.s. | n.s. | n.s. |
| 9 | Value | 0.769 [0.739,0.799] | 0.760 [0.719,0.802] | 0.799 [0.735,0.862] | 0.769 [0.713,0.825] | n.s. | n.s. | n.s. | n.s. |
| 10 | Transport | 0.661 [0.629,0.692] | 0.610 [0.568,0.652] | 0.610 [0.543,0.678] | 0.729 [0.658,0.800] | n.s. | n.s. | ** | n.s. |
| 11 | Cleanliness | 0.716 [0.680,0.752] | 0.753 [0.706,0.800] | 0.828 [0.761,0.895] | 0.773 [0.713,0.832] | n.s. | n.s. | ** | n.s. |
| 12 | Bed | 0.729 [0.695,0.763] | 0.763 [0.718,0.809] | 0.783 [0.696,0.870] | 0.675 [0.587,0.763] | n.s. | n.s. | n.s. | n.s. |
| 13 | Surroundings | 0.614 [0.580,0.649] | 0.561 [0.517,0.606] | 0.713 [0.618,0.807] | 0.693 [0.611,0.774] | n.s. | n.s. | ** | n.s. |
| 14 | Experience | 0.620 [0.586,0.655] | 0.621 [0.574,0.668] | 0.665 [0.601,0.729] | 0.534 [0.480,0.589] | n.s. | n.s. | n.s. | ** |
| 15 | Price | 0.516 [0.481,0.551] | 0.515 [0.465,0.565] | 0.486 [0.406,0.567] | 0.503 [0.426,0.581] | n.s. | n.s. | n.s. | n.s. |
| 16 | Airport | 0.502 [0.461,0.543] | 0.507 [0.454,0.560] | 0.549 [0.463,0.635] | 0.533 [0.432,0.635] | n.s. | n.s. | n.s. | n.s. |
| 17 | Parking | 0.507 [0.464,0.550] | 0.556 [0.496,0.617] | 0.534 [0.441,0.627] | 0.457 [0.368,0.546] | n.s. | n.s. | n.s. | n.s. |
| 18 | Lobby | 0.493 [0.446,0.540] | 0.502 [0.444,0.560] | 0.500 [0.408,0.592] | 0.572 [0.489,0.656] | n.s. | n.s. | n.s. | n.s. |
| 19 | Restaurant | 0.510 [0.463,0.558] | 0.499 [0.435,0.563] | 0.481 [0.387,0.576] | 0.536 [0.452,0.619] | n.s. | n.s. | n.s. | n.s. |
| 20 | Decor | 0.556 [0.513,0.599] | 0.574 [0.518,0.631] | 0.648 [0.550,0.745] | 0.434 [0.355,0.512] | n.s. | n.s. | ** | ** |

R1: performance of an attribute in Reference dataset 1 (January 21, 2019–April 13, 2019).
R2: performance of an attribute in Reference dataset 2 (April 14, 2019–June 2, 2019).
Within: performance of an attribute during COVID-19 (January 21, 2020–April 13, 2020).
Recovering: performance of an attribute in the period of recovering from COVID-19 (April 14, 2020–June 2, 2020).
Note: "**" denotes significant at the 99% confidence level, and "n.s." denotes insignificant.

*Appendix E. Changes in customer performance evaluation across pandemic dynamics*

| N | Attributes | Attribute performance | | | | | Performance difference (Mean as reference) | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | R 1 | R 2 | Within | Recovering | Mean | R1 | R2 | *Within* | *Recovering* |
| 1 | Service | 0.718 | 0.702 | 0.755 | 0.734 | 0.727 | −0.013 | −0.035 | 0.039 | 0.010 |
| 2 | Room | 0.608 | 0.611 | 0.587 | 0.555 | 0.590 | 0.030 | 0.035 | −0.005 | −0.060 |
| 3 | Breakfast | 0.682 | 0.667 | 0.673 | 0.581 | 0.651 | 0.048 | 0.026 | 0.033 | −0.107 |
| 4 | Location | 0.755 | 0.733 | 0.738 | 0.760 | 0.747 | 0.011 | −0.018 | −0.012 | 0.018 |
| 5 | Environment | 0.889 | 0.895 | 0.917 | 0.871 | 0.893 | −0.004 | 0.002 | 0.027 | −0.025 |
| 6 | Facility | 0.623 | 0.636 | 0.538 | 0.545 | 0.585 | 0.064 | 0.086 | −0.081 | −0.069 |
| 7 | Front-desk | 0.535 | 0.475 | 0.580 | 0.603 | 0.548 | −0.025 | −0.134 | 0.059 | 0.100 |
| 8 | Staff | 0.545 | 0.515 | 0.591 | 0.529 | 0.545 | 0.000 | −0.054 | 0.084 | −0.03 |
| 9 | Value | 0.769 | 0.760 | 0.799 | 0.769 | 0.774 | −0.007 | −0.018 | 0.032 | −0.007 |
| 10 | Transport | 0.661 | 0.610 | 0.610 | 0.729 | 0.653 | 0.012 | −0.065 | −0.065 | 0.118 |
| 11 | Cleanliness | 0.716 | 0.753 | 0.828 | 0.773 | 0.767 | −0.067 | −0.019 | 0.079 | 0.007 |
| 12 | Bed | 0.729 | 0.763 | 0.783 | 0.675 | 0.737 | −0.012 | 0.035 | 0.062 | −0.085 |
| 13 | Surroundings | 0.614 | 0.561 | 0.713 | 0.693 | 0.645 | −0.048 | −0.130 | 0.105 | 0.073 |
| 14 | Experience | 0.620 | 0.621 | 0.665 | 0.534 | 0.610 | 0.017 | 0.018 | 0.090 | −0.124 |
| 15 | Price | 0.516 | 0.515 | 0.486 | 0.503 | 0.505 | 0.021 | 0.019 | −0.037 | −0.004 |
| 16 | Airport | 0.502 | 0.507 | 0.549 | 0.533 | 0.523 | −0.040 | −0.030 | 0.049 | 0.020 |
| 17 | Parking | 0.507 | 0.556 | 0.534 | 0.457 | 0.514 | −0.013 | 0.083 | 0.040 | −0.11 |
| 18 | Lobby | 0.493 | 0.502 | 0.500 | 0.572 | 0.517 | −0.046 | −0.029 | −0.033 | 0.108 |
| 19 | Restaurant | 0.510 | 0.499 | 0.481 | 0.536 | 0.507 | 0.008 | −0.015 | −0.050 | 0.057 |
| 20 | Decor | 0.556 | 0.574 | 0.648 | 0.434 | 0.553 | 0.005 | 0.039 | 0.171 | −0.216 |

Mean: average performance of an attribute across the entire dataset.
R1: performance of an attribute in Reference dataset 1 (January 21, 2019–April 13, 2019).
R2: performance of an attribute in Reference dataset 2 (April 14, 2019–June 2, 2019).
Within: performance of an attribute during COVID-19 (January 21, 2020–April 13, 2020).
Recovering: performance of an attribute in the period of recovering from COVID-19 (April 14, 2020–June 2, 2020).
Difference weight was calculated according to the formula in Section 3.3.3.

*Appendix F. Changes in customers' overall evaluations of hotel attributes across pandemic dynamics*

| N | Attributes | Within (VS R) | | Recovering (VS R) | |
|---|---|---|---|---|---|
| | | Importance-difference | Performance-difference | Importance-difference | Performance-difference |
| 1 | Service | 0.214 | 0.061 | 0.187 | 0.031 |
| 2 | Room | −0.075 | −0.036 | −0.022 | −0.088 |
| 3 | Breakfast | −0.183 | −0.006 | −0.109 | −0.141 |
| 4 | Location | −0.162 | −0.012 | −0.256 | 0.018 |
| 5 | Environment | 0.035 | 0.029 | −0.012 | −0.023 |
| 6 | Facility | −0.005 | −0.143 | −0.006 | −0.132 |
| 7 | Front-desk | 0.321 | 0.134 | 0.573 | 0.178 |
| 8 | Staff | 0.125 | 0.106 | 0.243 | −0.010 |
| 9 | Value | 0.004 | 0.043 | 0.007 | 0.004 |
| 10 | Transport | −0.050 | −0.050 | −0.320 | 0.135 |
| 11 | Cleanliness | 0.279 | 0.135 | 0.269 | 0.059 |
| 12 | Bed | −0.328 | 0.056 | −0.486 | −0.089 |
| 13 | Surroundings | −0.418 | 0.199 | −0.383 | 0.165 |
| 14 | Experience | 0.342 | 0.071 | 0.445 | −0.139 |
| 15 | Price | −0.121 | −0.057 | −0.263 | −0.024 |
| 16 | Airport | −0.028 | 0.089 | −0.454 | 0.058 |
| 17 | Parking | −0.022 | 0.020 | −0.162 | −0.127 |
| 18 | Lobby | 0.102 | 0.007 | 0.055 | 0.153 |
| 19 | Restaurant | 0.128 | −0.049 | 0.136 | 0.058 |
| 20 | Decor | −0.136 | 0.151 | 0.045 | −0.229 |

R: importance/performance of an attribute in reference dataset (January 21, 2019–June 2, 2019).
Within: importance/performance of an attribute during COVID-19 (January 21, 2020–April 13, 2020); Recovering: importance/performance of an attribute in the period of recovering from COVID-19 (April 14, 2020–June 2, 2020).
Difference weight was calculated according to the formula in Section 3.3.3.

## Credit author statement

Feng Hu: Conceptualization, Methodology, Formal analysis, Writing – original draft. Thorsten Teichert: Validation, Writing – original draft preparation, Writing – review & editing. Shengli Deng: Resources, Writing – original draft preparation, Project administration., Yong Liu: Writing –

review & editing. Guotao Zhou: Data curation.

**Impact statement**

The hospitality industry is highly vulnerable to pandemics. However, little is known about how pandemics alter travelers' evaluations of hospitality services. How to deal with pandemics, particularly, how to guide hospitality practice in organizing its priorities during acute pandemic situations and adjusting to possibly longer-lasting shifts in consumer preferences, is still unclear. This study investigates the changes in travelers' expectations and perceptions of hotel services during different stages of the novel coronavirus 2019 (COVID-19) pandemic. 98,163 Chinese hotel reviews were collected and scrutinized via text mining and sentiment analysis techniques to derive new implications for service optimization. The results reveal shifts in consumers' evaluations well beyond hygienic requirements. Novel insights for service optimization can help direct hospitality practice during the COVID-19 pandemic.

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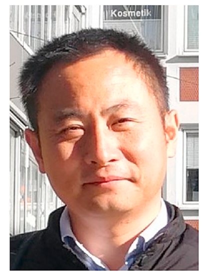


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