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Hotel attributes and overall customer satisfaction: What did COVID-19 change?

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ABSTRACT

The effect of hotel attributes on customer satisfaction has been well studied in hospitality literature. However, the importance of hotel attributes for customer satisfaction may change due to the prevailing global pandemic given (1) the negative health consequences of the disease, (2) the guidelines and advisories issued by health agencies, and (3) wide media coverage of the pandemic. These factors can affect the importance that customers attach to different attributes. To date, there have been no studies analyzing these changes, and this study fills the gap by conducting a structural topic modeling-based analysis of hotel reviews before and during the pandemic. The results contribute to the literature by identifying new attributes and providing concrete evidence that attribute prevalence has changed in response to the pandemic. The results also lead to practical recommendations for increasing customer satisfaction in the hospitality industry during the prevailing disaster.

1. Introduction

The coronavirus disease 2019 (COVID-19) pandemic has dealt a deadly blow to the hospitality industry by “affecting the DNA of hospitality at its core” (Rivera, 2020, p. 1). The disease spreads primarily through droplets of saliva or nasal discharge released by the coughing and sneezing of an infected person. Practicing physical distancing, avoiding travel, staying away from large groups, and staying at home are some of the measures recommended to reduce the spread of the disease (World Health Organization [WHO], 2020). These recommendations are antithetical to “coming together,” “host and guest,” and “providing security, psychological, and physiological comfort”—the characteristics of the hospitality industry (King, 1995, p. 220; Rivera, 2020, p. 1). The hospitality industry is especially susceptible to diseases that spread from person to person due to the high volume of customers, labor-intensive operations, and multiple avenues for cross-contamination (Hu, Yan, Casey, & Wu, 2020).

Efforts to stem the spread of the disease through the imposition of travel restrictions brought the world to a standstill. In May 2020, the United Nations' World Tourism Organization (UNWTO) reported that tourism had come to a halt, with 100% of tourist destinations having imposed travel restrictions (UNWTO, 2020a). It estimated a 98% year-on-year decrease in international tourists for the month of May, which translated to a loss of US$320 billion in revenues—a number three times the loss attributed to the global financial crisis. A cumulative revenue loss of US$1 trillion was estimated by the end of May 2020. The situation subsequently improved, and by the middle of July, 40% of the destinations had eased travel restrictions. However, as of the end of July 2020, the tourism confidence index for the January–April evaluation and May–August prospects had fallen to record lows (UNWTO, 2020b).

The reduction in tourism has hit the hospitality industry hard. A report released by the American Hotels and Lodging Association in August 2020 painted a grim picture of the hotel industry. It stated that two-thirds of the hotels are running below 50% occupancy levels, which is insufficient for breaking even. Urban hotels, which employ a large chunk of the industry's workforce, are facing even worse occupancy levels at 38%. Moreover, only 38% Americans say they are likely to travel before the end of the year (American Hotel and Lodging Association, 2020).

This study seeks to answer the calls for “a positive cycle of research to help us recover” (Rivera, 2020, p. 1). Since a successful tourism and hospitality business requires knowledge of what invokes pleasure (King, 1995), we address this question in the context of the pandemic. Specifically, we study hotel reviews of satisfied and dissatisfied customers before and during the pandemic. Arguing that the importance of hotel attributes may have changed due to the current health crisis, we answer

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the question: Which hotel attributes have changed in their prevalence in reviews of satisfied and dissatisfied customers? Additionally, we identify two new hotel attributes.

This knowledge may help hotels tailor their service offerings and marketing campaigns to stimulate demand. Satisfied customers may not only help a particular hotel remain financially viable in these trying times, but they may also help the recovery of the industry as a whole.

In the rest of the paper, we first review the literature on hotel attributes and customer satisfaction, and position our research in terms of three related questions. Next, we describe the methodology, followed by a presentation and discussion of the results. The final section concludes the paper.

2. Literature review

Hospitality is “the provision of food, drink, sleeping accommodation, and entertainment designed to please the guest” (King, 1995, p. 226). Customer satisfaction—defined as the assessment of product or service attributes by the customer (Davras & Caber, 2019)—is, thus, of paramount importance to the hospitality industry. Customer satisfaction is reflected in enhanced financial outcomes for companies in the hospitality industry, as satisfied customers do not switch to competitors, and loyal customers become less price sensitive, leading to an increase in sales revenue (Sun & Kim, 2013; Xu & Li, 2016). Conversely, dissatisfied customers tend to indulge in complaining behavior and negative word-of-mouth publicity (Cheng, Lam, & Hsu, 2005).

The importance–performance model of customer satisfaction suggests that overall satisfaction and dissatisfaction of the customers results from the importance of specific attributes and the performance of the service on those attributes (Albayrak & Caber, 2015; Oh, 2001). Thus, it becomes imperative to identify hotel attributes that significantly impact customer satisfaction. Unsurprisingly, numerous research articles have studied this phenomenon. For example, Dolnicar and Otter (2003) reviewed over two decades of related literature and identified 173 attributes. The fact that customers today have several avenues (e.g., TripAdvisor, Expedia.com, and Booking.com) to express their satisfaction and dissatisfaction has helped to further research on hotel attributes using customer reviews. Using customers' star ratings as a proxy (Radojevic, Stanisic, & Stanic, 2015; Xiang, Schwartz, Gerdes, & Uysal, 2015; Zhao, Xu, & Wang, 2019), several studies have analyzed online reviews to extract attributes that influence overall customer satisfaction. For example, Berezina, Bilgihan, Cobanoglu, and Okumus (2016) studied reviews of hotel guests in Florida to find out what separates satisfied customers from dissatisfied customers. Xiang et al. (2015) analyzed reviews on Expedia.com to study the relationship between hotel attributes and satisfaction ratings. Hu, Zhang, Gao, and Bose (2019) used structural topic modeling to identify hotel attributes that generate customer complaints. Cheng and Jin (2019) analyzed reviews of Airbnb properties to extract attributes that were important to customers. Guo, Barnes, and Jia (2017) extracted 19 important attributes of hotels by applying Latent Dirichlet Allocation algorithm of topic modeling to TripAdvisor reviews.

While early research attempted to extract attributes with the tacit assumption that the importance of different attributes is uniform across demographic and other variables, more recent research has accepted that attribute importance does vary based on several factors. For instance, none of the 173 attributes identified by Dolnicar and Otter (2003) are related to sustainable practices in hotels; hospitality research now accepts that green attributes contribute to customer satisfaction (Han, Lee, Trang, & Kim, 2018; Millar & Baloglu, 2011; Robinot & Giannelloni, 2010). Similarly, Francesco and Roberta (2019) studied American, Chinese, and Italian hotel customers and found that they emphasize different attributes. Bodet, Anaba, and Bouchet (2017) found that the country of residence has an impact on hotel attributes' contribution to customer satisfaction. The importance of attributes might also change over time. Jang, Liu, Kang, and Yang (2018) analyzed TripAdvisor reviews over six years and found changes in the importance of hotel attributes over time.

Despite the advances in understanding the major attributes valued by hotel customers, there remains a significant gap. We do not know how customer preferences change in the face of pandemics or epidemics. Before the current pandemic, hospitality and tourism had been hit by several outbreaks, including severe acute respiratory syndrome in 2003 (Johnson Tew, Lu, Tolomiczenko, & Gellatly, 2008), swine influenza in 2009 (Page, Song, & Wu, 2011), Middle East Respiratory Syndrome in 2012 (Shi & Li, 2017), and Ebola in 2014 (Novelli, Gussing Burgess, Jones, & Ritchie, 2018). These diseases, with the exception of Ebola, are respiratory illnesses similar to COVID-19. However, our review of the literature did not yield any study that examined hotel attributes' importance in the wake of these diseases.

Customer satisfaction theories suggest that epidemics and pandemics might have an impact on customers' evaluation of hospitality services. First, following the value-percept theory that suggests that what is valued in a product or service determines satisfaction (Westbrook & Reilly, 1983), the advisories issued by health agencies such as the Food and Drug Administration, Centers for Disease Control and Prevention (CDC), and WHO might increase the importance of businesses' hygiene practices for customers due to their level of trust in these organizations (Kowitt, Schmidt, Hannan, & Goldstein, 2017). Second, following the comparison level theory that argues for more than one determinant of comparison level—such as prior experiences with similar products, expectations produced by marketing, and experiences of other customers who have used the product or service (LaTour & Peat, 1979)—media coverage of best practices implemented in certain hospitality businesses might lead customers to expect the same practices in the businesses they patronize. Customer preferences for hotel attributes might change in some unexpected ways too, given the unprecedented nature of the phenomenon. Instead of hypothesizing the changes, we propose an exploratory method of detecting the changes.

The Director-General of the WHO, Dr. Tedros Adhanom Ghebreyesus, expressed, in August 2020, the hope that the pandemic would be controlled within two years (British Broadcasting Corporation, 2020). However, two years is a long time for hospitality businesses, where the unsold inventory of hotel rooms expires at the end of each day. Therefore, we propose to study the changes in customer preferences for hotel attributes by analyzing user reviews of hotels before and during the pandemic. A prospective traveler's decision to stay in a hotel is greatly influenced by the online reviews written by other travelers (Guo et al., 2017; Hu et al., 2019). Travelers rely on these reviews to shortlist those hotels that have better ratings (Gavilan, Avello, & Martinez-Navarro, 2018); this makes it important for the hotel industry to identify the attributes that generate good ratings and positive reviews that lead to their consideration by prospective customers. Thus, we seek to answer the following three questions:

1. Which hotel attributes have become more prevalent in reviews of (dis-) satisfied customers as the pandemic has progressed?
2. Which hotel attributes have become less prevalent in reviews of (dis-) satisfied customers as the pandemic has progressed?
3. Which hotel attributes have remained unchanged in reviews of (dis-) satisfied customers as the pandemic has progressed?

3. Method

To find the changes in hotel attribute prevalence with the progression of the pandemic, we analyzed TripAdvisor reviews of hotels using structural topic modeling (STM), which is one of the newer members in the suite of topic modeling algorithms developed in the past two decades, instead of the more popular Latent Direchelt Allocation (LDA). These algorithms analyze observed words in a body of text to identify latent topics or themes in that text. Similar to the more popular LDA, STM is a Bayesian generative topic model that assumes each topic to be a distribution over words and each document to be a mixture of topics

(Blei, 2012; Blei, Ng, Jordan, & Lafferty, 2003). Fig. 1 shows STM split into three components: core language model, topical prevalence parameters, and topical content parameters. Each node is a variable labeled with its role in the data generation process. The shaded nodes denote observable variables. The rectangles denote replication over 1-N words, 1-K topics, and 1-D documents. The core language model is the same as that in the more widely used model, LDA, consisting of two steps. First, randomly choose a distribution over topics for a document. Second, for each word in a document, randomly choose a topic from the distribution over topics in first step, and randomly choose a word from the corresponding distribution over the vocabulary (Blei, 2012; Blei et al., 2003).

The novelty of STM comes in the other two components. Unlike LDA, the parameters in STM are prior structures specified in the form of generalized linear models parameterized by document specific covariates as depicted by shaded nodes at both ends of the plate diagram. Thus, topic proportions in a document and topic-word distributions are affected by the document level covariates (Roberts et al., 2014). For a brief comparison of LDA and STM, see Hu et al. (2019).

STM was useful for this research because of two reasons. First, STM, like LDA, is a mixed membership model—wherein a document is assumed to include several topics. This is true for hotel reviews. A review typically covers more than one hotel attribute. Second, and more importantly, STM, unlike LDA, allows for the inclusion of document level covariates in the analysis. Since the purpose of this study was to identify changes in the prevalence of attributes with the progression of the pandemic, the date of the reviewer's stay in a hotel needed to be included in the analysis. Topic prevalence may also vary due to review extremity—positive versus negative—which can be included in STM as a covariate. Roberts, Stewart, and Airoldi (2016) have rigorously demonstrated the efficacy of STM over LDA in such instances.

3.1. Data collection

The empirical setting of this study is online reviews provided by hotel customers. Specifically, we analyzed the reviews on TripAdvisor, which is the largest platform for reviews of hotels, restaurants, and tourist attractions. O'Connor (2008) provided a comprehensive description of the website, which has been a subject of analysis in several studies in hospitality (Berezina et al., 2016; Hu et al., 2019; Jang et al., 2018; Zhao et al., 2019).

The first decision point was choosing the geographical setting of the study. While previous studies using TripAdvisor used both multi- and single-country data, this study used single-country data due to the vast differences in the prevalence and progression of COVID-19 across different countries. Studying hotel reviews in a single country ensured that these differences do not impact the results of the study. We chose to study hotels located in the United States for three reasons: (1) it had the highest number of COVID-19 cases in the world at the time of data collection in July 2020; (2) it is the world's largest economy, and therefore, has numerous hotels—ensuring availability of data despite reduced economic activity; and (3) the hotels did not shut down for a long time period.

First, we manually searched TripAdvisor hotels for mentions of "coronavirus" or "covid"; this search was case insensitive. This avoided searching for reviews of hotels that might have shut down in response to the pandemic. The website displays a maximum of only 1000 results split into 34 pages at a time. Therefore, we varied the search location sequentially to all 50 states. This ensured that we did not miss any results. From the search results, we extracted 7018 unique hotel names. Thereafter, we programmatically extracted the 20 most recent reviews from each hotel using the rvest package (Wickham, 2020) in R (R Core Team, 2020), yielding 132,313 reviews.

3.2. Data pre-processing

For each review, we extracted the title of the review, the review text, the reviewer's rating on a 1-to-5 scale, and the date of stay in the hotel. Any review that did not have any one of these details was removed. Reviews earlier than December 2019 or in languages other than English were also removed, leaving 88,271 reviews to be used for further analysis.

We transformed the review data in two ways. First, following the previous literature, we defined reviews with ratings of four or five stars as positive reviews representing satisfied customers, and reviews with ratings of one, two, or three stars as negative reviews representing dissatisfied customers (Taecharungroj, 2019; Taecharungroj & Mathayomchan, 2019). As expected, the number of positive reviews was greater than the number of negative reviews. We created a balanced sample by randomly selecting a matching number of positive reviews for the number of negative reviews in each month from December 2019 to June 2020. This yielded a total of 40,724 reviews to be analyzed in this study.

Second, we split the span of December 2019–June 2020 into three phases: pre-pandemic, early, and middle. The pre-pandemic phase encompasses December 2019 and January 2020. January is included in the

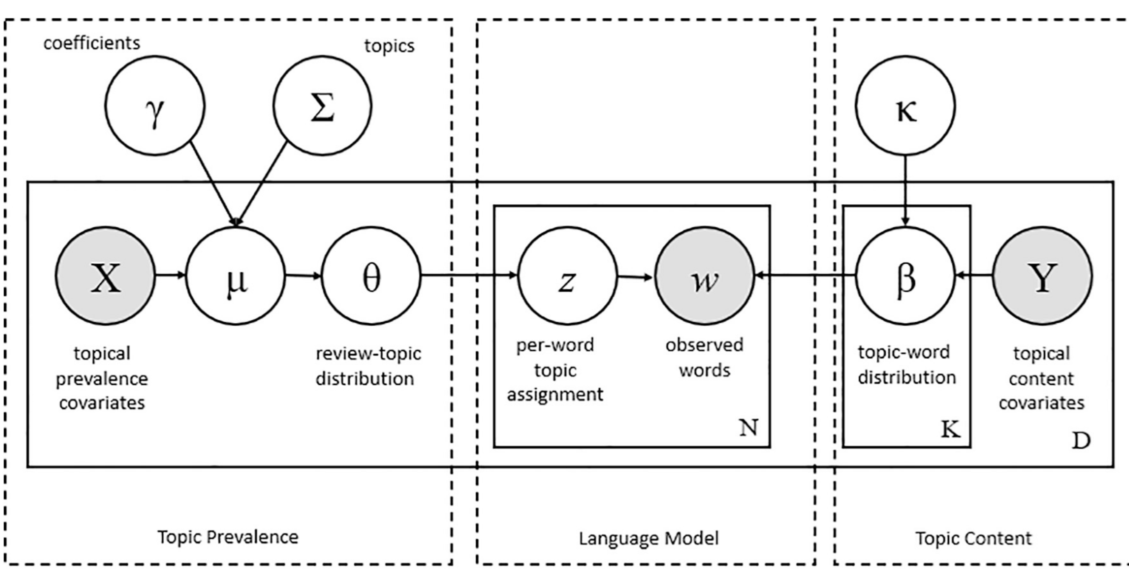

Fig. 1. Plate diagram of the structural topic model.

pre-pandemic phase as the first case of COVID-19 infection in the United States was reported only in the last week of January, and the whole month reported only seven cases compared to 2.5 million cases at the end of June 2020. It is not possible to split a month across different phases as the date of travel in TripAdvisor is reported as month and year only (e.g., January 2020 or February 2020). The early phase covers February and March 2020. The end of March saw 200,000 cases of COVID-19. The middle phase comprises April, May, and June 2020. The three phases are depicted by vertical lines in Fig. 2, which plots the number of COVID-19 cases on a logarithmic scale versus the date (CDC, 2020; Ritchie, 2020).

3.3. STM setup

The purpose of the study was to identify the changes in hotel attributes mentioned by customers in their reviews as the pandemic progressed. In addition, the study aimed to identify the differences in the changes in satisfied versus dissatisfied reviews. Thus, we needed to model the prevalence of topics as a function of the phase of the pandemic, the review extremity, and an interaction of the two. STM was determined as the perfect fit for such analyses, as it allowed us to model how document-level covariates affect the prevalence of topics. The two covariates modeled in this study were the phase of the pandemic when the reviewer stayed in the hotel, and the extremity of the review. Review extremity was taken as a binary variable with “Positive” =1 denoting positive reviews and “Positive” = 0 denoting negative reviews. Eq. (1) shows the relationship between the two covariates and topic prevalence. Function g(.) is a generalized linear function.

$$Prevalence = g(Phase, Positive, Phase*Positive) \quad (1)$$

Although STM is an unsupervised text mining tool, it requires the specification of the number of latent topics to be identified. To choose the number of topics, we computed semantic coherence and exclusivity scores by varying the number of topics from 20 to 40. Semantic coherence denotes that the identified topics are likely to be similar to human judgment. Exclusivity denotes the probability of words appearing in more than one topic. High semantic coherence scores may be obtained by a small number of generic topics. Therefore, both semantic coherence and exclusivity need to be considered. Based on prior literature (e.g., Hu et al., 2019) and the two criteria, we specified 30 topics in the model.

The analysis was performed in R (R Core Team, 2020) using the “stm” package (Roberts, Stewart, & Tingley, 2019).

4. Results and discussion

4.1. Identification of topics in reviews

The first inferential task from the STM output was the identification

Table 1
Topic summary.

Topic Type: COVID	
COVID precautions	mask, sanit, precaut, covid, wear, social, pandem
Topic Type: Facilities	
Room dirtiness	carpet, stain, sheet, hair, vacuum, dirti, filthi
Room equipment	maker, cold, pressur, water, hot, juic, microwave
Parking	park, garag, vehicl, lot, campground, road, valet
Noise	nois, loud, sleep, hear, window, stair, air
Equipment functioning	didnt, dont, turn, bother, that, okay, guess
Smell	smoke, cigarett, smell, roach, marijuana, complain, empty
Recreation facilities	play, golf, game, lake, pit, fun, fish
Topic Type: Service	
Service quality	western, team, appreci, best, sure, kind, beyond
Food and beverages	menu, food, casino, drink, salad, druri, chicken
Breakfast	breakfast, continent, buffet, varieti, comfort, complimentari, sausag
Booking and cancellation	cancel, refund, credit, email, deposit, card, account
Service failure	told, said, phone, call, final, later, apology
Room size	king, queen, size, sofa, bed, suit, slept
Staff attitude	courteous, smile, profession, definit, knowledg, recommend, outstand
Celebration	birthday, celebr, anniversari, rememb, special, met, wow
Front desk	desk, front, ladi, man, guy, woman, attitude
Check-in/Check-out	earli, readi, wait, shuttl, morn, hour, pick
Topic Type: Location	
Outdoor location	amp, cabin, ski, mountain, fireplac, river, lodg
Blue space	ocean, beach, balconi, pool, indoor, swim, umbrella
Convenient location	shop, downtown, conveni, easi, locat, mall, attract
Topic Type: Value	
Value for money	rate, per, cost, upgrad, worth, reason, pay
Topic Type: General Experience	
Property impression	updat, decent, overal, bit, older, pretti, adequ
Trip type	far, overnight, new, recent, surpris, stop, colleg
Brand image	hilton, marriott, member, brand, diamond, hyatt, elit
Concern elimination	request, situat, issu, note, address, mention, review
Repeat visit	year, famili, last, time, weve, will, forward
Experience comparison	hampton, facil, quick, inn, confer, compar, courtyard
Pet	dog, pet, thing, peopl, done, isnt, normal
Good feeling	perfect, cozi, histori, love, fabul, delici, immacul

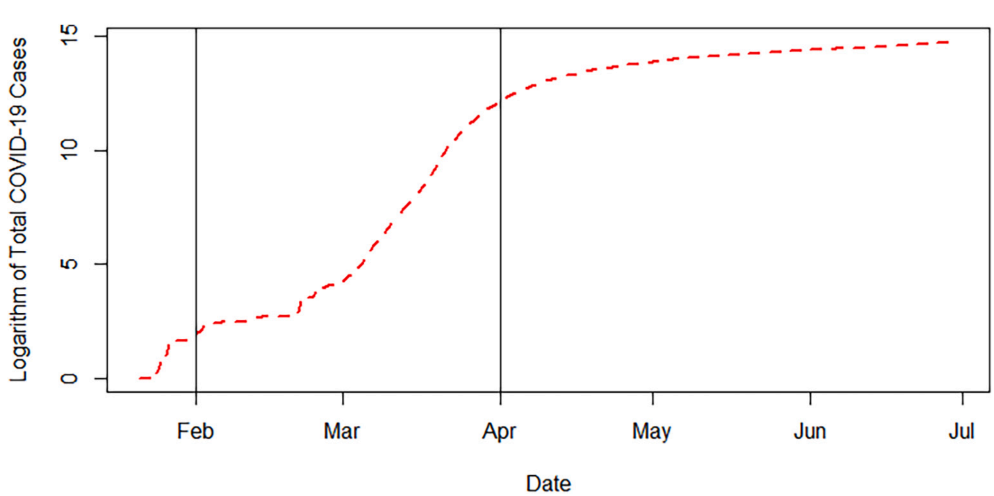

Fig. 2. Total number of COVID-19 cases in the United States over time; vertical lines separate the three phases.

of topics, which are presented in Table 1. The right column presents the STM output and shows the constituent words of each topic. The first column presents the topic labels. Based on the words and reviews representative of a topic, the labels were assigned by the first author and confirmed by the second author. The identified themes were consolidated into six groups based on the existing literature (Hu et al., 2019). While the first group, "COVID," which contains just one topic ("COVID precautions"), is new, the other five groups are in line with the existing literature. There are also two new topics identified in this study: "blue spaces" and "smell." These topics are most likely related to the prevailing pandemic and are discussed in further detail in Section 4.2.1.

4.2. Changes in topic prevalence

We consider the changes in topic prevalence in three categories: topics whose prevalence increased as COVID-19 progressed, topics whose prevalence decreased as COVID-19 progressed, and topics whose prevalence remained unchanged as COVID-19 progressed. Due to space constraints, we present and discuss the 16 most highlighted themes based on their change in prevalence. The complete results are available in Appendix A.

4.2.1. Increased prevalence

Two topics saw a significant increase in topic prevalence over the three phases in both satisfied and dissatisfied reviews. The first topic, COVID precautions, consists of the terms *covid, precaut(ion), sanit(izer), mask, social(distancing), and pandem(ic)*, implying that the topic is related to hotels adhering to COVID-19 precautions and guidelines. As expected, the prevalence of this topic has increased over time in both positive and negative reviews. From zero prevalence in the pre-

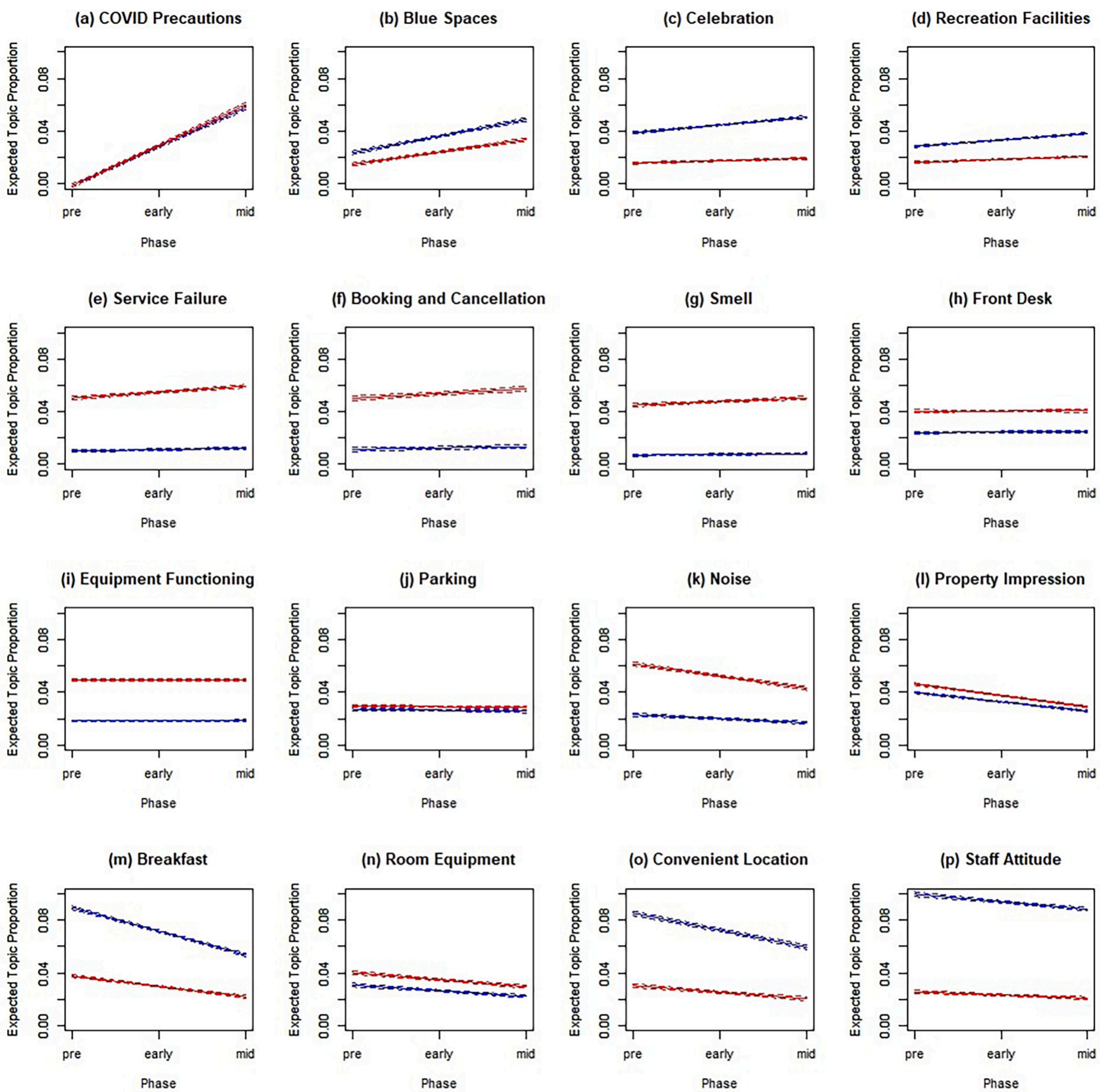

Fig. 3. Topic prevalence and COVID-19; red lines depict negative reviews, and blue lines depict positive reviews.

pandemic reviews, it increased to more than 6% in the last phase. This topic witnessed the maximum increase over time as compared to other topics (coefficient of phase = 0.03, $p < 0.0001$). This is true for both positive and negative reviews; Fig. 3(a) shows the overlap of the two plots. In fact, as Table 2 shows, there is no statistical difference in topic prevalence between positive and negative reviews (coefficient of interaction term = −0.001, ns). This might mean that implementing COVID-19 best practices is appreciated by hotel customers, and not implementing the guidelines is perceived adversely by hotel customers.

Related reviews confirm this inference. For instance, reviewers who gave a one-star rating wrote: "This hotel is NOT enforcing the use of masks in common areas. THEY ARE PUTTING HIGH RISK PATRONS AT RISK AND BREAKING THE LAW!!!" (emphasis in original); "No face coverings on any of the staff. This is an unacceptable practice during these times and in violation of New York covid laws"; and "I was extremely disappointed with the LACK OF (emphasis in original) social distancing!! I didn't observe ANY (emphasis in original) precautions being taken."

Conversely, reviewers who gave five-star ratings wrote: "We witnessed all staff being diligent about cleaning and mask wearing…we do appreciate [hotel name] being courageous and taking care of their guests and employees"; "Very clean and takes customer safety seriously. Hand sanitizers everywhere and signs that indicate what the hotel has been doing so far in order to keep customers healthy"; and "We felt comfortable staying here as the motel appeared to be following the CDC and Oregon Health Authority guidelines for infection control…the room was without magazines, pens, and other items that could be sources of cross contamination." The reviews suggest that there is a definitive preference for adherence to COVID-19 guidelines in hotels among consumers.

The topic "blue spaces" is related to hotels near water and consists of the words *ocean, beach, umbrella, pool, swim, and balcony*. The increase in prevalence of this topic over time is second only to "COVID precautions" (coefficient of phase: 0.009, $p < 0.0001$). The increase in this topic's prevalence among positive reviews is greater than its increase in prevalence among negative reviews (coefficient of interaction term: 0.003, $p < 0.0001$). The presence of this topic, albeit unexpected, is easy to understand with the benefit of hindsight. The prevailing pandemic has disrupted lives around the world, and the disruptions and risks to health are stressful for many (Tan et al., 2020; Taylor et al., 2020). Exposure to blue spaces, such as oceans, rivers, lakes, and swimming pools, is known to have a calming effect on the mind and improve physical and mental health (Wheeler, White, Stahl-Timmins, & Depledge, 2012; White, Alcock, Wheeler, & Depledge, 2013). Thus, with the benefit of hindsight, it may be inferred that hotel customers are likely to seek rooms with a view of, or proximity to, water.

Hotel guests that gave five-star reviews clearly appreciated blue spaces, giving reviews such as: "The pools and beach are amazing!"; "We were fortunate to get a resort view room with a good view of the ocean"; and "Great Accommodations with Amazing views of the Gulf." Conversely, negative reviews lamented unmet expectations of blue spaces. For example, reviewers wrote: "We booked a room thinking it was a beachfront hotel room…If we only knew from how they advertise the unit we wouldn't have stayed at the bayside and instead booked another condo in front of the beach"; "Makes no sense that the pool that is full of chlorine is closed LOL. However, everything else is open, which takes more interaction then jumping in a swimming pool full of chlorine. Like please open the pool people"; and "Pool is too crowded and there is no chairs to sit. The complex is too large for the pool area. They need to add a pool or make the current pool bigger."

This suggests that hotels need to pay attention to the maintenance of swimming pools. Hotels might also take advantage of access to beaches and lakes, and allocate rooms with water views during periods of low occupancy.

The topic "celebration" consists of the words *celebration*, *birthday*, *anniversary*, and *special*, implying that the topic relates to celebrations of birthdays, anniversaries, and other special events. Although the prevalence of the topic has increased in both negative and positive reviews over the course of the pandemic, the increase in its prevalence among positive reviews is much higher (coefficient of interaction term = 0.004, $p < 0.0001$) than its slight increase in prevalence among negative reviews (coefficient of phase = 0.002, $p < 0.0001$). Fig. 3(c) plots the two trends. The vast majority of the reviews mentioning this topic express gratitude to the hotel and staff for enabling customers to celebrate a special occasion. For instance, reviewers said: "From the bottom of my heart, I want to thank the employees for making this day magical. My siblings and I had a surprise party for our mom"; "The [hotel] will forever be an important part of our wedding week! The entire staff was simply amazing!"; and "There are not enough words to explain the experience you get here, you can feel all the heart and soul that was put into… making our birthday weekend as special as you made it!!!"

The topic and reviews suggest that a greater percentage of customers are coming to hotels to celebrate special occasions. While business-as-usual trips are on hold, hotels can promote celebratory visits to reduce revenue losses. Marketing campaigns directed specifically toward celebrations may be helpful.

The topic "recreation facilities" consists of the words *play, golf, lake, fish, pit, and fun*, implying that the reviewers in this topic focus on the

Table 2
Topic prevalence as a function of phase and customer rating.

Topic	Intercept	Positive	Phase	PhasePositive
COVID precautions	−0.0321****	0.000976 ns	0.030593****	−0.00099 ns
Blue spaces	0.005408****	0.005483***	0.009347****	0.003296****
Service failure	0.045806****	−0.0368****	0.004496****	−0.00341****
Booking and cancellation	0.046589****	−0.03622****	0.003582****	−0.00255*
Smell	0.042158****	−0.03564****	0.002776****	−0.00225***
Celebration	0.014002****	0.01867****	0.001739****	0.004253****
Recreation facilities	0.013958****	0.009292****	0.002265****	0.002736****
Front desk	0.040314****	−0.01681****	0.000119 ns	0.000431 ns
Equipment functioning	0.049146****	−0.03072****	0.000127 ns	0 ns
Parking	0.030327****	−0.0022 ns	−0.00065 ns	−0.00025 ns
Noise	0.070605****	−0.04471****	−0.00914****	0.006151****
Property impression	0.055041****	−0.00796****	−0.00865****	0.001489***
Breakfast	0.045536****	0.062094****	−0.00787****	−0.01008****
Room equipment	0.045494****	−0.01046****	−0.00532****	0.001017 ns
Convenient location	0.035185****	0.063099****	−0.00494****	−0.00798****
Staff attitude	0.027984****	0.077597****	−0.0024****	−0.00335****

* $p < 0.05$.
*** $p < 0.001$.
**** $p < 0.0001$.

recreational activities available to them at the hotel. Fig. 3(d) shows that although there has been some increase in the prevalence of this topic over the course of the pandemic in negative reviews (coefficient = 0.002, $p < 0.0001$), the increase in its prevalence among positive reviews is significantly higher (coefficient of interaction term = 0.003, $p < 0.0001$). Reviewers who have given five-star ratings mentioning this topic have appreciated the recreational activities available at the hotel. For example, reviewers wrote: “The pool is beautiful, mini golf, fire pit! We went to the activities center and my kids decorated a flower pot to keep; it was so cute!”; “We stayed right on the lake, and there are floating piers you can fish off of…”; and “If you're looking for a family-friendly, relaxing location for kids to ride bikes and enjoy being outside, this is the place for your crew.”

This topic also reveals some actionable insights for hotel managers. Recreational facilities should be increased or better utilized during the pandemic for better customer service. Low-cost recreational facilities may help balance cost considerations with customer satisfaction.

Three topics saw an increase in prevalence mainly in negative reviews over the course of the pandemic: “service failure” (*told, said, phone, call, final, later, apology)*, “booking and cancellation” (*cancel, refund, credit, email, deposit, card, account*), and “smell” (*smoke, cigarette, smell, marijuana, complain*). The trends in their prevalence are depicted in Fig. 3(e, f, and g, respectively).

Hotels might have had to change their standard operating procedures due to COVID-19, and the new processes would need time to mature. This might have led to an increase in instances of service failure. Although the cause of increased service failure is not certain, the implication for the hotel is clear: service delivery must be reassessed to reduce instances of service failure.

Similarly, disruption caused by COVID-19 is probably forcing changes in travel plans requiring cancellation or rescheduling of visits. This might explain the increased prevalence of the topic of booking and cancellation. Hotels might reduce such complaints by stating their reservation and cancellation policies more clearly at the time of booking. Flexibility toward cancellations might also be explored.

The third topic with increased prevalence in negative reviews, “smell,” is also probably linked to the pandemic. Customers might be more attuned to hygiene in general. Moreover, as the disease spreads via droplets suspended in air, customers might be more concerned about air quality in particular. The evident implication is that hotels need to pay greater attention to maintaining hygiene to reduce foul odors in hotel premises.

4.2.2. Decreasing prevalence

Three topics—“breakfast,” “property impression,” and “convenient location”—decreased in prevalence over the three phases in both negative and positive reviews, as shown in Fig. 3(m, l, and o respectively). Breakfast, consisting of the words *breakfast*, *continental*, *buffet*, *variety*, *complimentary*, and *sausage*, has seen a reduction in prevalence, most likely due to the reduction or cessation of the breakfast service in response to the COVID-19 pandemic. This abundance of precaution has been received well by the customers as the prevalence has decreased in reviews of either valence. This is consistent with the trend seen in the topic COVID precautions. The important implication for hotels is that taking precautions to avoid the spread of COVID-19 is likely to be met with positive responses from customers, even for major decisions such as ending breakfast service.

Similarly, the decrease in the prevalence of “convenient location” might be due to the fact that customers might be avoiding public transport and arriving via personal vehicles. The decrease in the prevalence of “property impression” might be, again, due to the customers being more likely to avoid common areas or other characteristics such as blue spaces and recreational facilities becoming more important.

“Noise” and “room equipment” (Fig. 3(*k*,n)) have seen a significant decrease in prevalence in negative reviews. Again, this is most likely due to COVID-19. Less traffic, reduced construction activities, and lower occupancy in hotels directly implies reduced noise. Similarly, due to the risk of contracting COVID-19 from room equipment, the availability of certain components may be of lesser importance to customers.

Finally, “staff attitude” (Fig. 3(p)) has seen a decrease in prevalence in positive reviews. This might be due to reduced interaction with hotel staff due to the pandemic.

4.2.3. Topics with no change in prevalence

“Front desk,” “equipment functioning,” and “parking” (Fig. 3(h, i, and j, respectively)) are three topics that did not experience any change in prevalence over the three phases. The coefficient of phase is statistically insignificant for all three attributes, as shown in Table 2. Front desk (*desk, front, ladi, man, guy, woman, attitude*), and equipment functioning (*didnt, dont, turn, bother, that, okay, guess*) are consistently more prevalent in negative reviews. Parking (*park, garag, vehicl, lot, campground, road, valet*), in contrast, is equally prevalent across negative and positive reviews. Thus, customer experiences with the front desk staff and functioning of equipment are as important now as they were prior to the start of the pandemic.

5. Conclusion

This study aimed to analyze changes in hotel customer preferences due to the ongoing COVID-19 pandemic. Using STM to analyze TripAdvisor reviews before and during the pandemic, we identified attributes and their changing prevalence as the pandemic worsened. The results provide actionable insights to reduce the adverse effects of an unprecedented and prevailing pandemic on the hotel industry.

5.1. Practical implications

The study results have several implications for managers in the hospitality industry. They also have implications for hospitality consultants, policy makers, and the research community.

First, hotels, and hospitality businesses in general, must pay particular attention to implementing COVID-19 precautions and following guidelines issued by various health and medical agencies. The implementation of the relevant precautionary measures has been appreciated in positive reviews, while lack of implementation has been criticized in negative reviews. The detailed recommendations from Hu et al. (2020) on COVID-19 safety compliance in the hospitality industry could be a useful resource for managers focused on this area.

Second, we suggest better utilization of blue spaces—views of oceans, rivers, lakes, or swimming pools. An increasing proportion of customers have appreciated such spaces as they are known to have a soothing effect on the mind (Wheeler et al., 2012; White et al., 2013) in stressful times (Tan et al., 2020; Taylor et al., 2020). Complaints about misleading descriptions of access or water views indicate that businesses need to be very clear in their descriptions. Unmet expectations lead to poor review ratings.

Third, we recommend cultivating spaces for celebratory events and general recreation. The results show that an increasing proportion of customers are visiting hotels to celebrate special events. There is also an increasing appreciation of recreational facilities. Marketing managers may run campaigns to attract more customers for special celebrations. Furthermore, increasing recreational facilities while maintaining COVID-19 safety measures would help in obtaining better ratings.

Fourth, COVID-19 might cause disruptions in services. An increasing proportion of negative reviews complain about service failure and issues with bookings and cancellations. Businesses face high financial risk if these issues are not managed in times of reduced economic activity. Offering vouchers in lieu of refunds is one approach to be explored. In addition, business owners and managers may benefit from the recommendations made by Duarte Alonso et al. (2020) for being resilient during the pandemic.

Fifth, managers will need to pay attention to facility odors. As

COVID-19 spreads via airborne droplets containing the virus (WHO, 2020), customers are paying acute attention to air hygiene, in addition to surface hygiene.

Sixth, the research findings may help hospitality industry consultants in advising their clients. The study may also be replicated for other businesses in the industry to better understand the shift in customer preferences due to the pandemic.

Finally, the findings of the study have practical implications for policy makers and the research community. Policy makers may fund research to identify shifts in customer preferences due to the pandemic. The research community, meanwhile, must take up more such projects to deliver actionable evidence-based insights to businesses affected by the pandemic.

5.2. Theoretical implications

This study contributes to the literature in three ways. First, by conducting a topic modeling analysis of user reviews during a pandemic, it reveals the hotel attributes that matter the most to customers. We add three attributes—safety measures, blue spaces, and smell—to enrich the understanding of important hotel attributes in the hospitality literature. These new attributes are possibly linked to the prevailing pandemic. This study is the first to analyze customer reviews during the pandemic for the purpose of extracting important hotel attributes. In addition to the new attributes, this study also confirms several attributes identified in earlier studies (Berezina et al., 2016; Bodet et al., 2017; Cheng & Jin, 2019; Francesco & Roberta, 2019; Hu et al., 2019; Radojevic et al., 2015). The replication of results, in addition to new findings, enriches scientific literature as it indicates that the results are generalizable across contexts.

Second, by conducting STM analyses of user reviews from December 2019 to June 2020, we were able to identify the attributes whose importance increased, decreased, or remained constant as the pandemic progressively worsened. This analysis adds to a broader understanding of the pandemic and its implications, thereby adding to the growing body of literature attempting to make sense of these unprecedented times (Duarte Alonso et al., 2020; Hu et al., 2020; Huang, Makridis, Baker, Medeiros, & Guo, 2020).This is the first study to explore which hotel attributes are important in the face of a respiratory disease. Outside of the context of the pandemic, this is the second study after Jang et al.'s (2018) study to take a dynamic view of the importance of hotel attributes.

Third, this study makes an important methodological contribution to the literature by being the first study to use review metadata to identify temporal trends in hotel attribute prevalence in customer reviews.

5.3. Limitations and future research

Despite the practical and actionable insights revealed, this study is not without its limitations. The first limitation is that the TripAdvisor reviews included in this study are limited to those given prior to June 2020. Whether the attributes identified in this study continue to be relevant beyond the study period needs to be verified by future studies. Another hindrance to generalizability might be the geographic setting of the study. The geographical setting was limited to the United States to avoid any effect of inter-country variation in the progression of the pandemic on the results. As more data become available, future studies might extend the findings of this research by incorporating a greater number of countries in their analysis. It is also possible that the reviewers during and before the pandemic may be different. For example, those choosing to travel during the pandemic may be more risk-taking, which, in turn, might influence their reviews. Another possibility, although quite low due to the disruption caused by the pandemic, is that the trends identified reflect seasonal variations.

An unexpected discovery in this study was the increased prevalence of blue spaces. This indicates increased presence of stress in hotel customers due to the pandemic. Future studies might explore the relationship between stress and consumption behavior in the hospitality industry. While several studies have focused on stress from the employees' perspective, the role of stress in determining customer satisfaction has not been studied. A better understanding of this relationship might help businesses adapt their offerings in times of stressful events such as epidemics, pandemics, natural disasters, and terror attacks.

Finally, the changing prevalence of hotel attributes in reviews suggests that more research is needed to understand this phenomenon. Attribute importance might change due to regular events such as seasons or one-off events like major sports events. Future research can help identify more contexts in which attribute importance changes.

Author contributions

Arpita Srivastava was involved in conceptualization, analysis, and editing.

Vivek Kumar was involved in conceptualization, data collection, analysis, writing, and editing the manuscript drafts.

Declarations of interest

No competing interests.

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Appendix A

Prevalence of all topics as a function of phase of the pandemic (phase) and customer satisfaction (Positive). Standard errors are in parentheses.

Topic	Intercept	Positive	Phase	Phase*Positive
COIVD precautions	−0.0321	0.000976	0.030593	−0.0009872
	(0.001235)	(0.001745)	(0.000665)	(0.00093669)
Blue spaces	0.005408	0.005483	0.009347	0.00329594
	(0.001026)	(0.001578)	(0.000498)	(0.00074968)
Service failure	0.045806	−0.0368	0.004496	−0.0034145
	(0.0011)	(0.001448)	(0.000519)	(0.0006873)
Booking and cancellation	0.046589	−0.03622	0.003582	−0.0025507
	(0.001593)	(0.00219)	(0.000759)	(0.00103218)

(*continued on next page*)

(*continued*)

Topic	Intercept	Positive	Phase	Phase*Positive
Smell	0.042158	−0.03564	0.002776	−0.0022525
	(0.001122)	(0.001342)	(0.00053)	(0.00063994)
Good feeling	0.006704	0.039417	0.000546	0.00619265
	(0.000793)	(0.001265)	(0.000366)	(0.00060532)
Celebration	0.014002	0.01867	0.001739	0.0042528
	(0.00072)	(0.00115)	(0.000335)	(0.00053959)
Recreational facilities	0.013958	0.009292	0.002265	0.00273602
	(0.00059)	(0.00089)	(0.000271)	(0.00040591)
Front desk	0.040314	−0.01681	0.000119	0.00043091
	(0.000977)	(0.001218)	(0.000457)	(0.00058709)
Equipment functioning	0.049146	−0.03072	0.000127	−8.40E-05
	(0.000726)	(0.000897)	(0.000326)	(0.0004032)
Parking	0.030327	−0.0022	−0.00065	−0.0002499
	(0.000934)	(0.001299)	(0.000438)	(0.00059824)
Noise	0.070605	−0.04471	−0.00914	0.00615129
	(0.001243)	(0.0017)	(0.000588)	(0.00077908)
Property impression	0.055041	−0.00796	−0.00865	0.00148907
	(0.000783)	(0.00102)	(0.000332)	(0.00044907)
Breakfast	0.045536	0.062094	−0.00787	−0.010081
	(0.000951)	(0.001468)	(0.00044)	(0.00066553)
Room size	0.046604	0.000348	−0.00536	0.00011071
	(0.000932)	(0.001367)	(0.000431)	(0.00060445)
Room equipment	0.045494	−0.01046	−0.00532	0.00101699
	(0.001128)	(0.001601)	(0.000501)	(0.00070203)
Convenient location	0.035185	0.063099	−0.00494	−0.007982
	(0.001246)	(0.001871)	(0.000576)	(0.00084772)
Staff attitude	0.027984	0.077597	−0.0024	−0.003348
	(0.001004)	(0.001789)	(0.000463)	(0.00079767)
Trip type	0.029747	0.011381	−0.00275	−0.0011675
	(0.000443)	(0.000684)	(0.000204)	(0.00031249)
Brand image	0.050392	−0.01455	−0.00344	0.00071672
	(0.000807)	(0.001168)	(0.000369)	(0.00053213)
Check-in/Check-out	0.045285	−0.00901	−0.00234	5.41E-05
	(0.000896)	(0.001246)	(0.000427)	(0.00060091)
Experience comparison	0.016464	0.014486	−0.00117	−0.0010011
	(0.000356)	(0.000532)	(0.000167)	(0.00023461)
Food and beverages	0.028714	0.008098	−0.00202	−0.000254
	(0.000747)	(0.001091)	(0.000337)	(0.00050299)
Value for money	0.041093	−0.01464	−0.00129	−0.000177
	(0.000723)	(0.000948)	(0.000333)	(0.00043426)
Room dirtiness	0.079255	−0.06961	−0.00247	0.00230664
	(0.001848)	(0.002432)	(0.00086)	(0.00111648)
Concern elimination	0.032454	−0.01789	0.001024	−0.0004546
	(0.000602)	(0.000767)	(0.000259)	(0.00033558)
Pet	0.024783	−0.00615	0.001218	−0.000145
	(0.000499)	(0.000631)	(0.000225)	(0.00030042)
Service quality	0.020633	0.017078	7.99E-05	0.00159815
	(0.000492)	(0.000757)	(0.000226)	(0.00034903)
Outdoor location	0.013597	0.01287	0.000188	0.00199152
	(0.000731)	(0.001348)	(0.000337)	(0.00060745)
Repeat visit	0.028815	0.012506	0.001716	0.00180164
	(0.000801)	(0.001138)	(0.000377)	(0.00055224)

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