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Quality Attributes of Hotel Services in Brazil and the Impacts of COVID-19 on Users' Perception

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Abstract: The unprecedented crisis faced by the hotel industry due to the COVID-19 pandemic has brought about changes in guests' perceptions of service quality attributes. In view of the need to monitor this environment, this study is dedicated to identifying the main negative topics related to the quality of hotel services in Brazil and the impacts of the COVID-19 pandemic on guests' perception of these topics. For this purpose, a set of 866,048 online hotel reviews were collected from the Booking.com platform. Initially, data were analyzed through topic modeling to identify the attributes addressed by guests in their evaluations. Subsequently, an average comparison method was used to evaluate the impact of the pandemic on the evaluation scores of each attribute. A total of 13 topics related to five attributes of hotel service quality were identified. The topics related to room cleaning and check-in were the most negatively impacted by the COVID-19 pandemic, with the largest drops in average evaluation scores.

Keywords: hotels; quality service; COVID-19

Citation: Peres, C.K.; Paladini, E.P. Quality Attributes of Hotel Services in Brazil and the Impacts of COVID-19 on Users' Perception. *Sustainability* **2022**, *14*, 3454. https://doi.org/10.3390/su14063454

Academic Editor: Dimitrios Buhalis

Received: 20 January 2022
Accepted: 11 March 2022
Published: 15 March 2022

1. Introduction

Recent technological advances in the tourism industry have transformed the way individuals consume tourism products. This transformation process is driven by the development of information technologies, which encompass recommendation systems, online reservations, dynamic prices, and interactive service review platforms [1].

Online platforms for the sale of tourist products have become the main customer relationship channels nowadays. As a by-product of this interaction, a growing volume of data related to the service experience are generated by users and made available on these platforms.

User-generated content (UGC) has a direct influence on users' purchasing decisions. Around 35% of travelers change their hotel decisions after browsing social media, 53% say they will not reserve a hotel that does not have reviews, and 87% say reviews help with confidence when making a lodging purchase decision [2].

Thus, the sustainability of hotel businesses depends on online reputation, since this content directly affects the billing of these organizations, with the aggravating factor that these businesses do not have control over what is published on online platforms.

In this context, the quality of services, more than ever, is a key factor in maintaining a business, since customers with a high level of satisfaction regarding the lodging experience, besides expressing their positive perceptions online, are more likely to make recommendations, pay more for the lodging, and make new reservations [3].

Maintaining the quality of services requires the correct identification of attributes that lead to customer satisfaction and loyalty. Nevertheless, reliably identifying the main determinants of satisfaction is a challenge due to the inherent heterogeneity of the demand for lodging according to the traveler's profile and the environmental and cultural aspects involved.

The literature shows that the importance given to quality attributes varies under different environmental and cultural conditions, and new attributes may emerge or change rapidly according to specific conditions. For example, in a study of five-star hotels in Spain, using TripAdvisor's UGC, several elements of service quality in hotels were identified, being classified into the following attributes: staff, services, room, and location [4].

A study conducted in New York, NY, USA, analyzed TripAdvisor's UGC and identified nine topics related to service quality attributes that were classified as sensory experience, brand, hotel class, sleep, location, room, service, value, and cleanliness [5].

In Malaysia, a study analyzed TripAdvisor content for luxury hotels. The study revealed that the major topics on the quality of luxury hotel services were related to the attributes of the hotel (restaurant and breakfast), the room, the staff, the trip (walking, taxi, and business) and possible consequences of the experience (recommendation) [6].

The main attributes identified in a study conducted in Portugal with data from TripAdvisor's UGC were: experience, hotel, learning, lodging, camping, nature, food, ingredients, eco (related to ecology), and yoga [7].

The results of these studies show the variation in importance given by customers to service quality attributes and reinforce the need to identify them correctly in each environment. Nevertheless, several changes have been imposed on the hospitality industry due to the health crisis generated by the COVID-19 pandemic. Even though several surveys have been conducted to try to understand guests' perceptions in different environments, this topic is still poorly investigated in the context of the COVID-19 pandemic [8] (Nilashi, Mehrbakhsh).

Factors such as decisions to reduce occupancy rates and the adoption of safety protocols have changed the service environment of hotels and the relationship with guests. Guests, in turn, also change their behavior toward services due to greater concerns about health risks [9].

After perceiving significant pandemic threats, consumers have shifted their preferences to higher-quality and higher-priced options [10]. Guests are willing to pay more for, recommend, and return to a hotel when they perceive more security benefits than risks [11].

The reduction in hotel revenue [12] and the environment of uncertainty make the direction of resources even more difficult for managers. Identifying the main aspects of customer dissatisfaction in an agile manner is an important point for the proper corrections to be effective and resources to be optimized, thus avoiding further negative comments on the platforms.

The unprecedented challenges generated by the COVID-19 pandemic in the hospitality industry create a research gap. Although the use of previous conceptual and theoretical frameworks can benefit future research, it is critical to generate new knowledge that can provide information to the industry on how to transform their operations according to customer needs and desires due to the COVID-19 pandemic [12].

Considering the research gap related to the effects of the COVID-19 pandemic on the quality of hotel services, this study is dedicated to answering the following research question: what are the main negative topics related to the quality of hotel services in Brazil and the impacts of the COVID-19 pandemic on guests' perceptions of these topics?

Brazil was selected for this study because it has the greatest tourism potential on the planet due to the richness of its natural heritage and biodiversity; however, on the other hand, it loses competitiveness due to a series of structural problems that include labor force and customer servisse [13].

In addition to the already known problems, such as social inequality, corruption, violence, wealth distribution, policy and planning, infrastructure, and environmental conservation, which negatively affect tourism, Brazil has received negative attention from the global media due to its inability to propose effective strategies for virus control. This could make the effects of the pandemic last longer and advance through the 2020s [14].

Among the major economies, Brazil is the most dependent on domestic tourism, constituting 94% of the sector's total revenue. Among the elements that make up tourism in Brazil, hotels and similar endeavors contribute 5.2% of the sector's GDP [15].

Directing public policy through research in the sector can contribute to coping with the pandemic and enabling postpandemic growth.

2. Materials and Methods

In order to evaluate the effects of the COVID-19 pandemic on customer perception of the quality of hotel services, the methodological approach of this study describes the steps of data acquisition from online reviews by customers, data preparation, and analysis, with the implementation of the Latent Dirichlet Allocation (LDA) algorithm to identify the most relevant topics in the text corpus of the reviews, as well as application of the bootstrap resampling method to make a comparison between averages of the reviews by customers before the pandemic period and during the pandemic period. The steps of data processing are introduced in Figure 1.

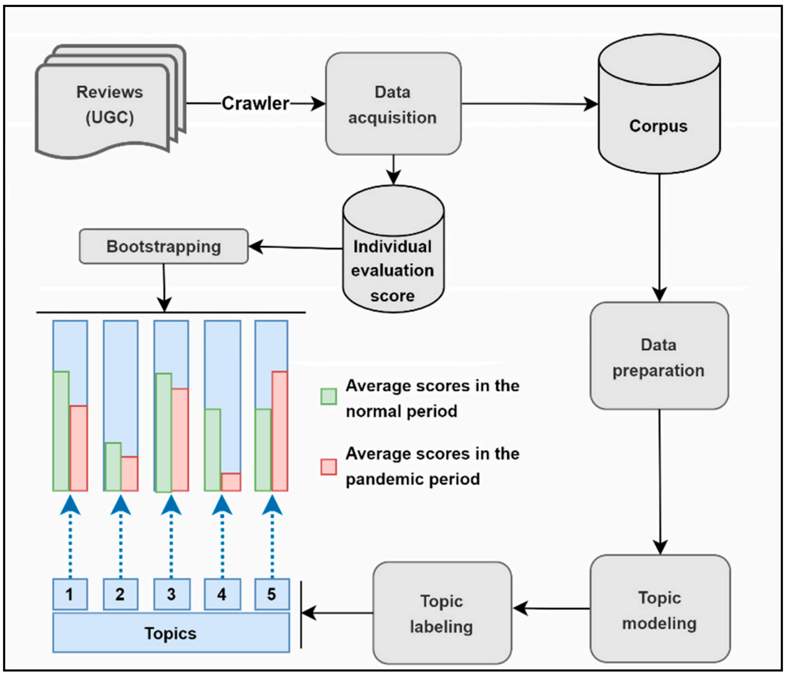

Figure 1. Overview of the steps of data processing.

LDA is an algorithm for automatic detection of topics in texts that belongs to the class of unsupervised methods (where the data set is not previously labeled). Thus, the application of LDA allows the identification of the aspects in the reviews that users have focused on, without the need for prior knowledge [16].

The LDA algorithm is based on the idea that documents are composed of a mixture of topics and seeks to discover latent (hidden) patterns to understand the relationships between documents and words, so that the words that occur in related documents are grouped into topics [17].

The bootstrap method consists of taking consecutive samples from the data set itself by randomly choosing the actual observations one at a time, with replacement [18]. Accordingly, each observation has an equal chance of being chosen each time. Therefore, some observations will be chosen more than once, and some will not be selected. From resampling, the bootstrap method allows reducing the uncertainties about the standard error estimates and confidence intervals of the data [18].

2.1. Data Acquisition

Evaluations were collected from hotels in 62 cities classified in category "A" of the Brazilian Tourism Map. The map is an instrument instituted by the Tourism Regionalization Program, which guides the actions of the Ministry of Tourism in the development of public policies. The municipalities that compose it were indicated by the state tourism agencies in conjunction with the regional governance instances, considering criteria built with the Ministry of Tourism. They are categorized as A, B, C, D, and E according to the best performance of their tourism economy, respectively [19].

The Booking and Tripadvisor platforms were initially considered for data collection, for being platforms frequently used in other studies, according to Chart 5, and more widespread in Brazil, where platforms mentioned in previous studies such as Yelp, Ctrip, HolidayCheck.de, Trustyou, and Agoda are little used. Nevertheless, after initial collection tests, the Booking.com platform was selected for presenting some advantages.

Regarding data security, the Booking platform has a system that guarantees the authenticity of reviews. The platform only allows reviews to be sent to people who have made a reservation and completed their stay. When a review is received, it is checked for inappropriate words, and its authenticity is verified before publication [20].

Another important factor is that, on the Booking platform, travelers must post their positive and negative reviews separately. This facilitates the identification of customer satisfaction and dissatisfaction regarding hotel quality attributes. In addition, initial tests have indicated that, in Brazil, the Booking.com platform has more than 13 times as many reviews as the Tripadvisor platform, considering the last three years.

Data collection on the Booking.com platform took place in an automated way. For this purpose, a crawler was developed and implemented in Python programming language. Negative review data were collected from January 2018 to May 2021. The start date is due to the fact that, at the time of collection, the Booking.com platform provided data from 2018. The end date was the month in which the data were collected.

In this study, January 2020 was defined as the start of the pandemic, since the media was already reporting hundreds of COVID-19 cases in several countries, and the news was already causing great concern in the hospitality industry.

Considering that the importance given by customers to service quality attributes may vary according to social and environmental factors in each context, as presented in the introductory item, the set of attributes used to evaluate service quality by the Booking.com platform was not used in this study. Therefore, the identification of the most important attributes for customers was coducted through the texts of the reviews, which are spontaneously filled in on the platform.

Evaluations of foreign tourists were not considered in this study. Brazil receives only 0.47% of international tourists. This represents about 6% of national tourism, which is divided among tourists from several countries, the main ones being: Argentina, United States, Chile, Paraguay, Uruguay, France, Germany, Italy, United Kingdom, Spain, and Portugal [21]. Therefore, the low volume of UGC and its distribution in different languages made it impossible to apply tools to analyze the topics of foreign tourists.

Due to the low number of reviews per hotel and high variability, hotels with 1 and 2 stars were excluded from the collection. Hotels with 3, 4, and 5 stars were then considered, resulting in 834,235 reviews referring to 3033 hotels. Considering previous studies, such as [22,23], only hotels with more than 200 reviews were selected to ensure the credibility of each hotel's sample, resulting in 866,048 negative reviews.

In the year of the evaluation, the star rating of the hotel and the individual evaluation score were also collected. The hotels' ratings can vary from 1 to 5, according to the level of service offered, and are fed into the Booking.com platform under the responsibility of each hotel's managers. In Brazil, the star rating of hotels must follow the metrics established by the Brazilian System of Accommodation Classification (SBClass, as per its Portuguese acronym).

The individual score is attributed by the guests at the end of the evaluation to express their satisfaction or dissatisfaction with the quality of the hotel services. The score can vary on a scale of 1 to 10, where 1 corresponds to a terrible evaluation, and 10 corresponds to a very good evaluation of the experience.

2.2. Data Preparation

Text preprocessing was employed to organize, clean, and standardize the textual data and prepare them for insertion into the LDA model. The intent of this procedure is to remove unnecessary content to reduce processing time and increase model performance, and to put the data into a format suitable for processing [24].

The techniques used for preprocessing the data set were: case conversions, punctuation removal, stop words removal, tokenization, and stemming. These tasks were performed by means of Python language with support from the Natural Language Toolkit library (NLTK).

The case conversions technique was used to put all text in lowercase. This is a simple but necessary technique. Since the Python programming language is case-sensitive and treats lowercase and uppercase as different elements, its standardization avoids misinterpretation of the processing algorithms [24].

Punctuation removal was used to remove punctuation and accentuation from the text. Punctuation does not add extra information or values. Therefore, removing all these instances helps to reduce the data size and increase the computational efficiency [25].

Stop words removal was applied to remove words that are more common and/or have no semantic value. By removing these words, the processing algorithms can focus on important keywords and improve context understanding. Similarly, rare words were removed [25].

The text was broken into words by the process of tokenization. Tokenization can be defined as the process of breaking down or dividing textual data into smaller, more meaningful components, sentences or words, called tokens [24].

Subsequently, the affixes (prefixes and suffixes) of the words were removed using the stemming technique, thus returning the word to its basic form [25].

This study considered the application of the lemmatization technique, which, like stemming, seeks to return words to their basic form. However, lemmatization seeks to identify words with the same meaning (synonym). Accordingly, it can reduce the size of the word dictionary and increase the accuracy of analysis models [24]. Nonetheless, this technique was excluded after testing, as it did not show contributions to the model.

2.3. Topic Modeling

After the application of the data cleaning techniques, some data transformation procedures were required to suit the insertion formatting into the LDA algorithm. The data were then transformed into vectors for further insertion into the algorithm using the Bag of Words (BoW) N-grams attribute engineering method.

The BoW model represents each text document as a numerical vector where each dimension is a specific word in the corpus, and the value is its frequency in the document. When adding N-grams, a fusion of previous and following words occurs at the position of each word, according to the value of N [24]. This procedure was performed using the Gemsin package [26].

In this study, the value 2 was used for the BoW N-grams parameter N, i.e., bi-gram. The model was also adjusted to remove terms with fewer than 10 occurrences in all documents and terms that occur in more than 90% of the documents, reducing the terms in the data set from 81,899 to 10,614.

This practice increases model accuracy and reduces computational effort, since single or rare terms have low semantic contribution to the model, and recurring terms interfere with context interpretation [24].

Topic modeling was employed in order to discover the quality attributes of hotel services, that is, aspects that influence customer satisfaction. For this purpose, the Latent

Dirichlet Allocation (LDA) method was used. The LDA method was implemented using the Machine Learning for Language Toolkit (MALLET).

The optimal number of topics was defined based on the coherence score, which is a measure of model quality used in other studies, such as [27,28]. For this purpose, models were generated with a number of topics ranging from 2 to 50.

The quality of the LDA results depends on the optimization of the hyperparameters Alpha, which represents the topic density of the document; and beta, which represents the topic density of the word. With higher values of alpha, the documents will be composed of more topics. On the other hand, with higher values of beta, the topics will be composed of a larger number of words in the corpus.

In this study, the optimization of the LDA hyperparameters took place automatically, since the model was implemented using the Mallet package, which has alpha and beta optimization mechanisms in its structure. The model was adjusted to perform the optimization of these hyperparameters every 10 interactions.

Some tests were performed to identify the best adjustment to the total number of iterations, ranging from 50 to 1000. The value adopted was 500 interations, which presented the highest value of coherence of the model.

The topics revealed by LDA were then analyzed by the researchers and grouped into quality attributes of hotel services. This step was carried out by means of the main words contained in each topic and by reading evaluations. As a basis, it used the attributes treated in previous studies and the most current literature on the subject. This step depends on human perception of the topics, as treated in [29].

2.4. Comparison of Averages

After the topics were identified, the effect of the COVID-19 pandemic on the average scores for each topic was tested. Initial tests were performed with the ANOVA method and Tukey's post hoc test for comparison of averages. However, after analyzing the standardized residuals using the Shapiro–Wilk test and visually analyzing the graphs of the standardized residuals, it was found that the assumption of normality of the residuals was not met.

As an alternative to the ANOVA method, the bootstrap resampling method was adopted to compare the average scores. A total of 1000 rounds of resampling with replacement were performed to obtain the average value of the evaluation grades in each subgroup evaluated, where the condition of normality of the sample was checked.

3. Results

The result of the evaluation of the optimal number of LDA topics is shown in Figure 2. As can be observed, the greatest coherence of the model took place in 19 topics. Therefore, this was the value adopted for the model.

After analysis, two topics were excluded for not being related to quality attributes of hotel services. In addition, two topics related to room facilities, two topics related to hotel infrastructure and two topics related to reservation were merged.

The topics were then labeled, as described in the methodology. The total number of ratings on each topic revealed by LDA is shown in the graph in Figure 3.

With the analysis of the topics, as described above, they were grouped into six quality attributes of hotel services, since they deal with different aspects of these attributes. The topics related to each attribute and the main terms of each topic are presented below.

Table 1 presents the six attributes classified in the attribute "room". The attribute "room" stands out in relation to the others, since 37.67% of the evaluations were classified in this attribute.

The topic related to the bathroom in the room deals with aspects related to accessory items of the bathroom (shower, box, faucet, douche, door, toilet seat) and their working conditions (dirty, old, broken, weak, etc.). Some examples of negative evaluations of this topic: "the toilet seat was defective, hurting whoever sat on it"; "clogged sink, poorly lit bathroom"; "the water in the shower was not at a stable temperature, it kept changing between hot and cold".

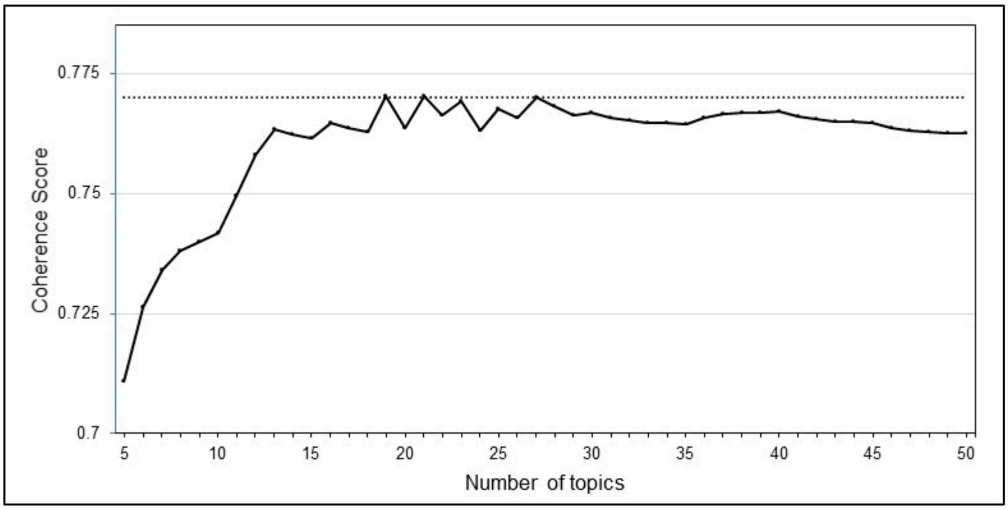

Figure 2. Coherence of the model according to the number of evaluation topics.

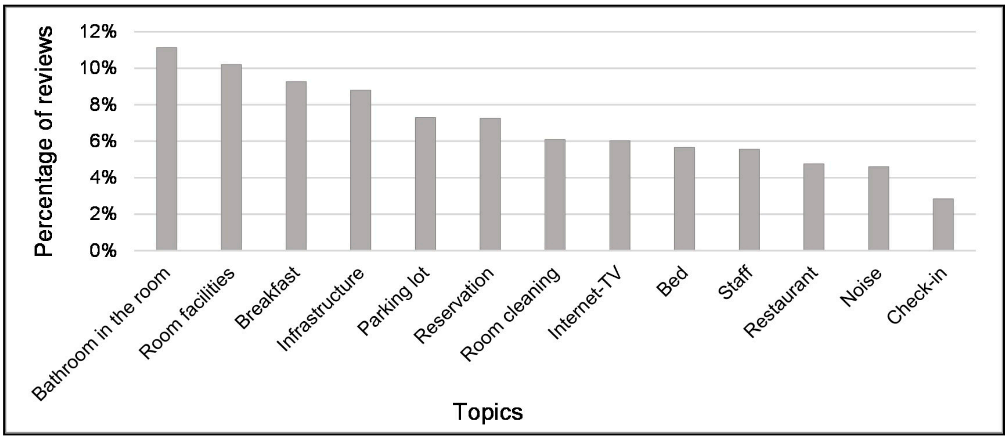

Figure 3. Number of reviews per topic.

The topic about the room facilities is related to aspects of the accommodation environment (size, state of conservation, decoration, etc.) and to lacking or unusable items (furniture, air conditioning, lighting, etc.). Some examples of negative evaluations of this topic include: "I think the room deserves a paint job"; "the air conditioner was poorly positioned in the room I stayed in, close to the floor"; "the wardrobe door was stuck".

The topic about noise deals with issues related to the quality of sleep, such as noise from other accommodations, coming from the outside environment or originating from the equipment in the room itself, such as air conditioning and windows. Some examples of negative evaluations related to noise include: "The air conditioner is very noisy"; "The room I stayed in, the noise from the ducts of the kitchen hood passing by the window was unbearable"; "Noise from the rooms at bedtime, you can even hear something falling on the other room".

The topic related to room cleaning deals with several aspects of hygiene (dirt, stains, mold, smell, etc.) of the items in the accommodation, such as: bedding and bathing clothes, bathroom, walls, floors, and carpet, among others. Some examples of negative evaluations of this topic include: "the floor and the furniture are very dusty, I don't like it"; "they don't change bed linen and towels daily"; "bathroom very dirty, strong smell of sewage, minibar with fungi".

Table 1. Topics related to the attribute "room".

Topics	Number of Occurrences of the Main Terms
Bathroom in the room	Bathroom (43,752), water (24,161), shower (23,846), room (18,124), box (11,624), small (7332), outlet (7201), hot (7179), bowl (6351), cold (5776), sink (4985), lacking (4338), hot (3840), wet (3666), working (3427), faucet (3188), tight (3064), cleanliness (3015), door (2728), problem (2680), clogged (2579), douche (2167), drain (2097), ancient (2068), dirty (1956), heating (1925), broken (1821), weak (1766), towel (1758), toilet seat (1642), temperature (1623), old (1604)
Room facilities	Room (20,757), ancient (16,113), required (12,789), bathroom (9090), renovation (8236), old (6673), facilities (5989), maintenance (5877), small (4223), lacking (3578), cleanliness (3542), furniture (3249), structure (2774), air conditioning (2736), improving (2220), elevator (2137), building (2127), bad (2031), bed (1978), musty smell (1908), lighting (1749), swimming pool (1711), accomodation (1685), needing (1651), caution (1635), dirtiness (1441), unsatisfactory (1401), dark (1381), general (1379), door (1280), towel (1272), modernizing (1270), painting (1232), shower (1160), urgent (1132), appearance (1125), decoration (1091), changing (1079), repair (1064)
Noise	Room (29,295), noise (25,899), night (8141), does (7000), hallway (6473), guests (6432), side (6332), air-conditioning (4507), bothers (3848), bathroom (3679), loud (3664), acoustics (3421), sleeping (3264), other (3171), heard (3094), breakfast (2844), door (2807), footsteps (2761) conversation (2693), people (2665), everyone (2517), acoustic isolation (2492), dawn (2465), bad (2341), waking up (2322), street (2220), cleanliness (2214), bed (2196), window (2077), sound (2023), work (1877), noisy (1837), pool (1789), staff (1733), elevator (1726)
Room cleaning	Room (29,131), cleanliness (27,252), bathroom (23,932), dirty (16,669), towels (12,650), smell (10,001), old (5974), mold (5713), bed (4714), floor (4670), wall (3927), unsatisfactory (3892), stains (3782), bad (3782), lacking (3592), bedding (3497), sheets (3304), change (3253), air conditioning (2908), guests (2603), box (2577), hair (2351), finding (2217), grimy (2110), full (2082), ancient (1935), carpet (1896), water (1843), required (1809), door (1789), hallway (1786), used (1759), horrible (1754), hygiene (1718)
Bed	Bed (43,382), room (22,240), couple (11,926), mattress (9877), single (9179), pillow (8352), small (7609), uncomfortable (5630), two (5507), comfort (4288), springs (4220), bad (3801), putting together (3301), clothes (3183), breakfast (3017), hard (2993), sleep (2653), air conditioning (2477), size (2426), cleanliness (2341), old (2338), changing (1906), guest (1807), mattresses (1804), lacking (1721), sheets (1720), low (1705), towels (1641), blankets (1634), ancient (1513), horrible (1475), dirty (1349), extra (1346)

The topic related to bed deals with issues related to the conditions of use and comfort of the bed. In this topic, aspects such as mattress density, pillow height, bedding conditions, and bed size, among others, are addressed. Some examples of negative evaluations related to the bed include: "the mattress was spliced with two single beds, so it was not comfortable"; "mattress a little hard"; "double bed too small and uncomfortable mattress and pillows".

The topics related to the attribute "infrastructure" are presented in Table 2. This attribute has three topics, where 22.14% of the evaluations were classified. The topics in this attribute deal with various aspects of infrastructure; however, there is greater emphasis on issues related to parking and internet, since specific topics on these issues were revealed.

The topic about Internet–TV is related to the availability and speed of internet services, audio and video equipment, TV channels, availability of power outlets, and appropriate environment for the use of personal electronics. Some examples of negative evaluations of this topic include: "the Wi-Fi signal was bad"; "lack of cable channels, with movies and sports channels"; "internet very unstable".

In the topic related to parking lot, the customers report problems with the space, vehicle incidents, distance from the parking lot to the hotel, time restrictions, abusive prices or those not disclosed at the time of reservation, and the lack of parking lot in certain establishments. Some examples of negative reviews related to parking lot include: "paid parking is a negative point"; "they don't have their own parking and we have to pay, without being told in advance"; "private parking nearby, but at night it is a little dangerous to walk alone on the sidewalk".

Table 2. Topics related to the attribute "infrastructure".

Topics	Number of Occurrences of the Main Terms
Internet-TV	TV (17,516), room (17,259), Wi-Fi (13,368), operation (13,312), bad (10,624), internet (9511), channels (8621), signal (5938), works (4562), weak (3638), TV (3401), tune (3171), cable (2715), image (2524), few (2477), lacking (2295), right (2088), control (2003), slow (1903), quality (1854), ancient (1844), problem (1488), horrible (1461), service (1348), outlet (1260)
Parking lot	Parking lot (31,869), car (15,038), location (9753), street (8101), garage (6373), place (6075), vacancy (4997), guest (4373), paying (4366), having (4328), near (4275), front (4058), night (3997), access (3986), can (3655), arrival (3645), far (3589), small (3346), leaving (3319), lacking (3233), stay (3151), valet (3135), tight (2782), bad (2668), day (2546), required (2445), near (2432), entrance (2414), parking (2285), danger (2172), noise (2150), vehicle (2147), getting off (2129), reception (2123), attendance (2058), service (2004), staff (1826), region (1822), difficult (1812)
Infrastructure	Could (30,116), swimming pool (19,329), improving (16,527), having (15,801), room (8678), bathroom (3753), bigger (3344), small (3200), gym (2911), area (2659), heating (2645), lacking (2418), guests (2218), space (2152), coffee (2113), time (1802), children (1755), beds (1615), water (1518), dirty (1455), parking lot (1436), bar (1357), required (1321), options (1318), sauna (1259), roof (1235), restaurant (1194), shower (1074), air conditioning (1053), reception (1052), bad (1028)

The topic related to hotel infrastructure deals with issues such as pool, elevator, collective spaces for eating and leisure, accessibility, gym, sauna, etc. Some examples of negative evaluations of this topic include: "elevators were not working well, took too long"; "crowded, crowded elevator, swimming pools full and out of order, not enough chairs", "the whirlpool and sauna were not working".

The topics related to the attribute "reservation" are presented in Table 3. This attribute has two topics, where 10.1% of the evaluations were classified. This attribute includes the relationship before the trip, check-in and reception in general at the hotel, and check-out.

Table 3. Topics related to the attribute "reservation".

Topics	Number of Occurrences of the Main Terms
Check-in	Room (21,667), arrival (10,590), reception (10,191), request (9021), attendance (7382), daily rate (5941), guest (5919), calling (5702), talking (5661), time (4835), employee (4724), coming back (4539), can (4503), there was (4471), stay (4094), information (3811), breakfast (3692), employee (3518), entering (3472), leaving (3310), passing (3244), payment (3029), night (2959), still (2900), reception (2900), reservation (2892), question (2851), knew (2690), service (2672), nobody (2574), waiting time (2513), problem (2457), required (2337), morning (2319), towel (2292), getting (2273), swimming pool (2272), changing (2220), notice (2139)
Reservation	Room (38,091), payment (18,555), day (18,446), reservation (16,698), price (15,005), charge (12,570), problem (9680), lodging (9632), parking lot (9315), breakfast (8333), arrival (8032), attendance (6869), information (6747), stay (6715), there was (6512), changing (6306), reception (6183), request (5363), time (5204), first (5128), time (4780), service (4262), request (4250), resolving (4190), fee (4126), staff (4075), price (3760), situation (3691), part (3651)

Regarding the topics about check-in and reservation, customers reported problems such as scheduling errors, incompatibility of room specifications with those displayed on the online platforms, waiting times, inflexibility of schedules (early check-in and late check-out), and lack of receptivity from front-line staff. Some examples of reviews during the pandemic include: "I bought an apartment facing the sea, as told on the website, but they wanted to put me in a room facing the parking lot"; "Charging system was not transparente"; "Upon arrival at the accommodation, I was required to charge an additional amount for a child's bed".

In the topic related to the attribute "staff", 5.56% of the evaluations were rated. According to Table 4, this topic is associated with aspects such as service, attention, reception, promptness, friendliness, politeness, availability, receptivity, kindness, and friendliness. Some examples of evaluations of this topic include: "the service at the reception desk is horrible, rude people"; "very monosyllabic employees"; "room service is slow and employees are grumpy".

Table 4. Topic related to the attribute "staff".

Topics	Number of Occurrences of the Main Terms
Staff	Attendance (29,725), staff (17,354), reception (15,464), room (11,096), check-in (10,928), breakfast (5491), delay (5454), accommodation (5126), reception (4575), arrival (4511), people (3839), check-out (3835), cleanliness (3535), delay (3457), lacking (3367), time (3310), staff (3222), education (3189), waiting time (2941), service (2660), time (2643), queue (2597), request (2546), friendliness (2282), bad (2112), helpful (2067), only (1941), stay (1926), restaurant (1900), there was (1896), few (1842), coffee (1784), customers (1769), staff (1719), promptness (1705), entrance (1653)

The topics related to the attribute "food" are presented in Table 5. This attribute has two topics, where 14.03% of the evaluations were rated. This attribute deals with general issues of food for guests in the hotel, but there is more emphasis on breakfast.

Table 5. Topics related to the attribute "food".

Topics	Number of Occurrences of the Main Terms
Restaurant	Restaurant (10,712), service (9433), price (8752), lacking (6512), order (5541), minibar (5300), food (4687), expensive (4425), breakfast (4006), drink (3482), dinner (3449), offers (3379), attendance (3375), dishes (2988), water (2861), menu (2770), could (2665), guests (2571), having (2321), glass (2114), value (2107), bar (2051), bad (2015), cleanliness (1982), swimming pool (1873), options (1757), daily rate (1746), small (1746), reception (1746), meals (1717), lunch (1686), night (1672), coffee (1670), option (1639), quality (1603), staff (1492), unsatisfactory (1491), charge (1410)
Breakfast	Breakfast (87,193), morning (75,483), options (17,545), few (13,089), room (12,688), variety (9569), could (7380), weak (6753), breads (6130), lacking (6092), served (5266), better (5148), fruits (5062), bad (4848), cleanliness (4464), daily rate (4219), cake (3981), unsatisfactory (3944), could have (3910), attendance (3778), juice (3680), small (3651), guests (3635), simple (3508), eating (3118), drinking (2587), staff (2547), quality (2505), replacement (2465), cold (2463), food (2307), taste (2292)

The topic about breakfast is mainly associated with the morning meal and the variety, availability, and taste of products such as coffee, fruits, and cakes, in addition to the quality of customer service. The topic about food and restaurant deals with similar issues; however, it is related to the other meals that guests have in the hotel. Some examples of evaluations on this topic include: "Breakfast could include local gastronomy items"; "Breakfast cakes could be fresher"; "Breakfast was unsatisfactory. Not enough variety of food. The breads and cakes were not fresh".

After identifying the topics and grouping them into the quality attributes of hotel services, this study went on to analyze the impact of the COVID-19 pandemic on guests' perception of service quality in each identified attribute.

Impact of the Pandemic on Average Scores for Quality Attributes

In the analysis performed to check the difference in the average scores of the attributes considering the pandemic period, the results confirmed that the period significantly affected the topic scores. The interaction graph in Figure 4 shows the differences in the average individual topic scores, comparing the pandemic period with the previous one in each star class of the evaluated hotels.

As can be seen in the graph, the average score for all topics is lower during the pandemic period regardless of hotel class. The topics related to check-in and room cleanliness stand out the most, since they have the lowest average scores in the normal period and had the biggest average drops in the pandemic period.

Based on the results of the comparisons of averages of individual scores, it is possible to state that guests give lower scores in the evaluations carried out during the pandemic period in relation to the quality attributes of hotel services identified in the evaluations.

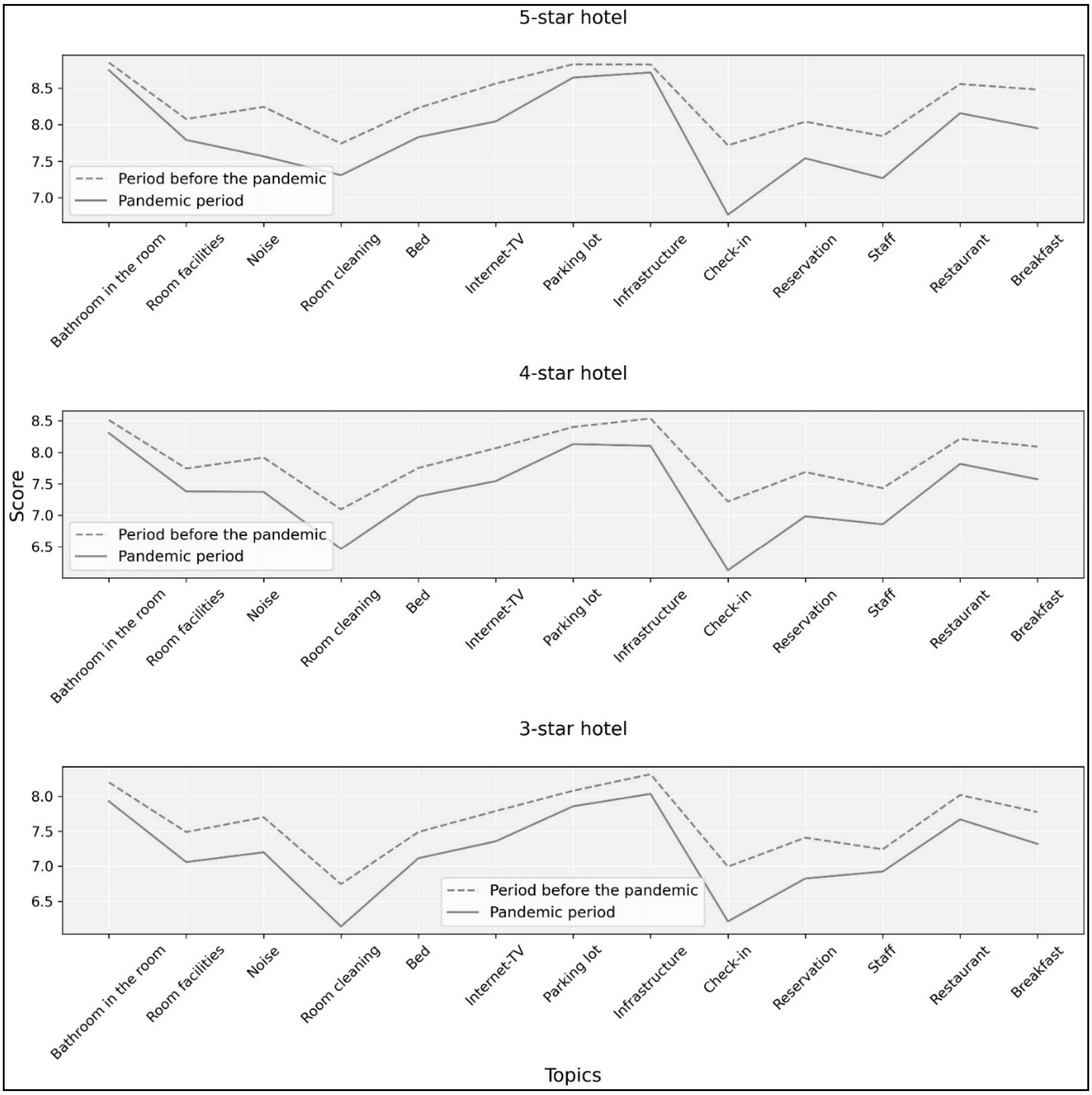

Figure 4. Pandemic effects on topic average scores in each hotel class.

4. Discussion and Conclusions

This study identified a series of topics related to service quality attributes in Brazilian hotels. Comparing the average score of the evaluations made by the customers, it was possible to conclude that the pandemic period had a negative impact on the average scores of all the identified attributes. It was also possible to conclude that there is a significant difference in average scores when comparing the topics of each attribute.

These findings contradict the results of previous studies, such as [30], which reported a greater willingness of customers to assign higher ratings to the service experience. This can be explained by Brazil's inability to manage the pandemic, as [14] points out.

Besides the obvious issue of risk, such as crowding and lack of compliance with health protocols, some issues may have contributed to a considerable worsening in the evaluation scores. A possible explanation for the worse evaluation in pandemic times may be related to the fact that guests became more judicious and attentive to items not valued in the period before the pandemic.

Another point to be considered is that due to the reduction in occupancy rates, hotels have promoted a drastic reduction in service levels, suspending equipment maintenance, restricting food services, and promoting the closing of social and recreational areas. In many cases, there has been a reduction in the number of employees due to COVID-19 leaves, difficulties with outsourced services, lack of transportation for employees, and delays in the delivery of cleaning materials and raw materials for food preparation.

The attribute "room" was the most mentioned in the evaluations, and therefore, it generates negative reviews for the Brazilian hotel industry. The literature brings several studies that corroborate the results of this research, treating the room as an attribute that generates negative reviews [27,31–33].

On the other hand, several of these studies have identified this attribute as generating positive reviews [5,34,35] and being associated with customer satisfaction [6,36–38].

Previous studies treat the attribute "room" in a generic way. Nevertheless, this study found that there are variations in the average scores of the different topics related to the room setting. Whereas the average scores of evaluations related to the bathrrom in the room remain high, room cleaning has the lowest average customer evaluation scores, which is a critical factor for generating negative evaluations.

Considering the aspects of the pandemic, this study shows that guests became more critical of room cleaning in this period, corroborating with the findings of [9] in the context of large Chinese cities. Nevertheless, it can be noted that five-star hotels had less impact on average review scores.

An important highlight is that, in other studies, hotel cleaning is treated as an attribute related to the hotel as a whole. This study identified that guests at Brazilian hotels are more concerned about this issue when it comes to the room environment.

The topic "noise" was also identified as a generator of negative reviews related to the attribute "room". In other studies, this topic is also addressed in the context of sleep quality. Previous surveys that corroborate the results of this study are [5,22,27,39,40].

The attribute "infrastructure" is identified in the reviews where the topics related to parking lot and internet and television are the main generators of negative reviews. This attribute seems to be more important for guests in the area covered by this study, as it was not found frequently in previous studies, making the large number of reviews related to this attribute a striking finding of the current study.

When addressed in other studies, this attribute was also identified as generating negative evaluations [39,40] in Brazil [32]. Considering the effect of the pandemic, despite the worsening in the average evaluation scores, the scores of the topics related to the attribute "infrastructure" remained relatively high.

The results of this study point out that the attribute "reservation" is valued by the customer. The topic related to check-in is a critical factor for hotels, as it received the lowest average score and had a significant worsening effect in the pandemic period. These results confirm the findings of studies by [9], which identified a considerable worsening in the evaluations of this attribute during the pandemic period.

An important point to be highlighted is that four- and five-star hotels had greater drops in average evaluation scores during the pandemic period. This drop in ratings can be explained by the customers' feelings of insecurity in the check-in environment, as it is a point of contact between/among guests, or changes in this service due to security protocols.

The attribute about staff has been identified frequently in previous studies, being related to negative reviews [6,28,31,35,39,41] or positive reviews [7,34,38,42]. In the pandemic period, the attribute "staff" retained the third worst score of the attributes, with the sharpest drop in five-star hotels.

The attribute regarding food appears prominently in this study. Corroborating with the studies of [31,39], the topic "breakfast" is cited in a high number of reviews. Like this study, previous surveys have also identified service failures in breakfast [22,40]. Despite the drop during the pandemic period, the average breakfast evaluation scores remained relatively high.

4.1. Practical Implications

The main findings of this study allow pointing out the issues with the greatest negative impact from guests' points of view and directing the efforts of decision makers toward more effective strategies to cope with the pandemic. Priority actions should be given to the items related to the topics "check-in", "room cleaning", and "staff", which received the lowest average scores in the guest reviews.

Considering that the topic "check-in" is related to the overall hotel arrival environment, managers should consider implementing self-service technologies to reduce physical contact between guests and between guests and staff, such as check-in and check-out mechanisms through facial recognition [43].

Improving the communication of health-related information between hotels and customers is critical to the control and prevention of infectious diseases and has been shown to be a predictor in terms of hotel selection [11].

Room cleaning was also highlighted negatively. In addition to the basic cleaning routine, hotels should adopt cleaning and sanitizing protocols that are adequate to combat coronavirus. The communication of cleanliness to the customer is also an important factor in reducing negative reviews. In this sense, protecting individual use items with packaging and making visible checklists of the cleaning routine are actions that can contribute to improving customer perception.

Security and cleanliness will be the main criteria affecting travelers' destination selection after the COVID-19 pandemic. Stricter and more systematic hygiene control must be carried out in hotels, given the proportion of the pandemic's impacts. The security image of the hotel has become a valuable asset from the customers' point of view in the COVID-19 era [11].

Regarding the attribute "staff", which has a negative highlight with a drop in average evaluation scores, especially in five-star hotels, the standardization of service processes is also an essential factor, since it allows the defininition of metrics to evaluate results.

Robots can also be used to assist employees in terms of performing tasks such as dispensing face masks, delivering basic cleaning kits to rooms, dispensing hand sanitizers, taking temperatures, and preparing fast food [43].

The application of this type of self-service technology in hotels is particularly beneficial in maintaining social distance and privacy for guests and can help to make the hotel service more secure against infection without compromising the quality of service [11].

Hotels, especially small and medium-sized ones, may face difficulties in promoting adequate responses to customer demands in this new scenario due to a lack of capabilities. Horizontal relationships between hotels of the same size have shown to be beneficial in the Brazilian hotel network at other times [44] and may be an important strategy for overcoming the challenges imposed by the COVID-19 pandemic.

4.2. Limitations and Directions for Future Research

This study only considered reviews by domestic tourists and in Portuguese due to data limitations of the Booking.com platform. Future investigations may expand this scope with other data sources to include content generated by foreign tourists.

The data were obtained from a platform where ratings refer to hotel attributes. Nevertheless, aspects outside the hotels' control can also influence the decision to visit or return to a tourist destination. Thus, future investigations could address this issue using available content and other platforms related to tourism products, as well as reviews on social networks such as Twitter, Instagram, and Facebook, among others.

Author Contributions: Conceptualization, C.K.P. and E.P.P.; methodology, C.K.P. and E.P.P.; investigation, C.K.P.; formal analysis, C.K.P. and E.P.P.; resources, C.K.P.; supervision E.P.P.; writing—original draft, C.K.P.; writing—review and editing, C.K.P. and E.P.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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