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Expressing the Experience: An Analysis of Airbnb Customer Sentiments

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Abstract: There is a growing interest in research related to Airbnb, and one theme that has stood out is the analysis of the consumer experience. This study aimed to analyse the feelings expressed in the online evaluation of users on the Airbnb platform in Fortaleza, capital of Ceará, Brazil. The methodology was developed through quali-quantitative research, a documentary research procedure, and data collection regarding the accommodation offers available on the platform. A total of 2353 reviews in 2019 and 2020 related to 506 accommodation offers were analysed through manual coding with the aid of NVivo software. The results evidenced the positivity of the evaluations, and that positive comments presented fewer characters while negative evaluations presented more details. It was identified that there were differences in the percentages of positive and negative evaluations when differentiated by other factors such as gender of the user (women evaluated more positively and intensely), type of host (*superhost* evaluations were more positive), type of offer (for entire places, the positive polarity was lower than the private room and shared room types), and location (the positive polarity was higher in residential neighbourhoods than in tourist neighbourhoods). Methodologically, this study contributes by illustrating how a set of evaluations can be analysed and interpreted in studies on the accommodation service.

Keywords: sentiment analysis; user experience; online reviews; Airbnb

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1. Introduction

Exacerbated consumption, from the 20th century, reverberated in the exploitation of natural resources, bringing to the fore the concern with the rational and appropriate use of these resources and the need to develop sustainable business models [1]. The sharing economy comes into view in this context and represents collaborative activities to obtain, provide, or share access to goods and services coordinated through community-based online services [2].

Tourism is one of the key sectors for the global economy, which promotes economic and social development, positively impacts the GDP, and increases the number of direct and indirect jobs. The increase in the number of tourists and the sector's turnover before the pandemic highlight the importance of the sector [3].

In this context, tourism finds in the Internet an ideal partner, since it impacts the announcement, sale, distribution, and delivery of products and services, due to the speed and ease with which information can be accessed. Moreover, the evolution of the Internet makes it possible to originate new business models, import foreign capital by offering options to tourists, and reinvent traditional models [4].

Tourism businesses are affected by these new models and platforms [5], while the sharing economy is having a disruptive influence on the travel industry as a whole and, according to Zhu et al. [6], significantly impacting the hospitality and tourism services. The hospitality sector is an essential revenue base [7], and, among the new tourist business models representing the sharing economy, Airbnb stands out.

Airbnb is a digital platform for renting accommodation, which connects individuals who need accommodation as guests with hosts, without owning any property [8]. The platform enables a new way of staying, as it allows tourists the possibility of personalised experiences and accommodation, interaction with locals, and access to housing [9].

On collaborative networks, users are urged to express their opinions about the service used, making reviews an essential resource as they help to establish trust requirements between guest and host. Individuals who have more reputation are generally considered more trustworthy than others with less reputation [10]. On the Internet, trust between strangers occurs primarily through reputation, which is responsible for determining reliability on the basis of the participant's behaviour [11].

Online reviews greatly benefit the accommodation sector, and, while ratings carried out in a quantitative manner—usually grades from 1 to 5—reflect the extent of guest satisfaction with the accommodation, comments reveal guests' feelings, attitudes, and evaluations [12]. This user-generated information has been considered by academics and practitioners as valuable as it can indicate new trends, impacting the reputation of companies and destinations, consumer behaviour, decision making, and satisfaction with services and products.

Tourist behaviour, influenced by sociocultural and technological changes, has surpassed what is traditionally conceived as a tourist concept. Considering the "information technology revolution and the restructuring of capitalism" [13] (p. 17), one can think of the tourist increasingly closer and interconnected with their destination, with the receiving community, and especially with the process of organising their trip. Therefore, it is critical to use appropriate analytical approaches to extract useful data on customer satisfaction from the online reviews [14]. Sentiment analysis allows an Airbnb host to gain insight into the business and identify specific issues that help manage it proactively. Since a bad review can affect the decision of other users, active management of hosts helps to maintain the reputation of the offer. In this way, sentiment analysis allows Airbnb hosts to see what matters to the user and identify frequent issues to help manage the offer proactively.

Airbnb does not offer a platform to query your data. Data and information are sparse in diverse sources, mainly news. Access to data is found through secondary sources, on private websites, such as Inside Airbnb (available online: http://insideairbnb.com/about.html (accessed on 12 January 2021)) and the Tom Slee (available online: http://tomslee.net/category/airbnb-data (accessed on 12 January 2021)), and professional sites, such as the company AirDna (available online: https://www.airdna.co/top/br/fortaleza (accessed on 12 January 2021)).

Several studies, by analysing online reviews, investigated the experience and performed sentiment analysis of tourists [7,15,16] and Airbnb users [17–24]. In Brazil, with respect to user experience [25,26] and sentiment analysis [27], there are still research gaps, such as the importance of the dimensions of user experience in the destinations studied, as well as the order of precedence and the polarity of sentiment associated with these dimensions. Thus, users' diverse backgrounds, such as cultural differences or surrounding environments, should be considered when researching a global phenomenon such as Airbnb. Airbnb research publications began in 2015 [28]. Most were published recently [29], conducted mainly by researchers in the USA, Canada, and Europe [9]. Regarding the geography of the study sites, most studies (40.2%) collected their data in the USA/Canada, in contrast to 29.5% in Europe and only 1.8% in the Caribbean/Latin America [9].

In Brazil, there are still research gaps on the subject, and Fortaleza, capital of Ceará, a state in Brazil's northeast, a tourist destination predominantly of sun and sea, stands out for its growing tourist demand, receiving in 2019 just over 3.7 million tourists [30] (increase of 37.79% compared to 2010). The hotel supply in Fortaleza between 2019 and 2019 also grew, with the number of hotel establishments expanded by 27.09%, increasing from 203 to 258, and about 55.97% of tourists who passed through Fortaleza in 2019 used the hotel network (hotels, inns, flats, and hostels), while 44.03% used the extra-hotel network [30].

In Ceará, according to information from the Institute for Research and Economic Strategy of Ceará, the tourism segment, as part of the services sector, was responsible for 19.5% growth in the post-pandemic period in the state of Ceará [31]. In Fortaleza, the services sector was responsible for a 5.96% growth of the state capital's GDP [32].

In this context, it is important to know the user experience in tourist destinations in northeaster Brazil and understand what affects the user experience in this type of destination, so as to provide insight into how customers see the hosts and Airbnb services. Thus, this research addresses the following question: What sentiment is expressed by users who use Airbnb accommodation services in Fortaleza CE—Brazil?

Thus, this study aimed to analyse the feelings expressed in the online reviews of users on the Airbnb platform in Fortaleza, capital of Ceará, Brazil, and, to do so, it sought to (1) identify the predominance of positive or negative evaluation, content of evaluations, and size pattern of comments, (2) identify the influence of demand characteristics (gender of the guest, type of the host (*superhost*), type of offer, and location of the offer) in the assessment of sentiment, and (3) investigate the attributes that influence the experience, in the context of the growth in the use of the platform and the changes occurring in the hosting market.

Through sentiment analysis, it is possible to use the measured sentiment to support and drive improvements for hosts and hotels to better compete with the growing use of the platform; this study contributes to the literature by understanding Airbnb users' experiences in a Brazilian tourist destination.

2. Literature Review

2.1. Airbnb

Sharing economy practices have impacted traditional business models, providing a new source of income, promoting community building, and addressing environmental issues such as over-consumption and pollution by offering a more sustainable way of consuming [33,34]. Considered the representative of home-sharing companies, Airbnb offers a peer-to-peer (P2P) online platform that matches guests looking for accommodation with hosts willing to rent out their free space, where both parties pay a transaction fee [35]. In this way, ordinary individuals can rent out their space as tourist accommodation, either the "entire place" (house, condominium, etc.) or a "private room" in a residence where the host is present [9]. Since its founding in 2007, Airbnb has expanded from offering an air mattress on the founders' flat floor to 5.6 million private accommodation offerings in more than 220 regions and countries around the world [36].

Airbnb has revolutionised the tourism and hospitality sector, posing a huge threat to traditional accommodation providers, especially budget and midscale hotels [37]. Factors driving the growth of Airbnb include the price, diversity of accommodation available, alternative to mass commoditisation of large hotel chains, desire for an authentic local experience, unique character and homely feel offered by the accommodation, and direct interactions with hosts and local communities [38–41].

The Airbnb guest is motivated by practicalities such as cost and location [9,42], but guests' desire for authentic and innovative experiences is also important. Therefore, authentic experiences are related to three main aspects: hosting, interaction with the host, and local culture. In addition, points related to economics, home benefits, sustainability and sharing ethos, local authenticity, and novelty of experience are considered [43].

Furthermore, user (re)purchase motivation relates to price value, enjoyment, and home benefits, significantly explaining the overall attitude toward Airbnb [41]. There is also a relationship among satisfaction, trust, and purchase intention in the context of Airbnb. Trust is a mediating variable between transaction-based satisfaction and repurchase intention [44]. Likewise, socioenvironmental responsibility is also a determining factor in consumers' evaluations of the platform, followed by environmental, economic, and ethical aspects [34].

In 2019, 54 million active bookers worldwide booked 327 million nights and experiences on the platform, and, since its founding, there have been more than 825 million visitors on Airbnb, and around 69% of revenue that year was generated by stays from repeat guests. More than 68% of guests left reviews about their stays, and hosts and guests have collectively written more than 430 million reviews (as of September 2020) [45].

2.2. Airbnb User Reviews

In the tourism context, people use the Internet to search for diverse information, making opinions and sentiments expressed in a review an important tool for the tourist decision-making process [46]. Thus, tourism user-generated content has become an instrument for comprehending consumer behaviour and developing new services based on previous experiences.

User reviews for sentiment analysis have been used in several publications in the tourism sector, such as air services [47], cruise ships [15], hospitality [16], and particularly, Airbnb [17–24,27,48].

Other studies [49] looked at reviews on Airbnb sites. About 72% of users wrote at least one review of the place, and 94% of the star ratings ranged from four to five (scale of one to five), demonstrating that considering only stars for decision making may not be the best strategy. To better understand the possible reasons for this phenomenon, another study [50] investigated whether guests faithfully convey their experiences on Airbnb and found that a significant proportion of guests do not tell the whole truth or avoid comments when the experience is not positive. Some of the most important reasons for these behaviours include avoiding harming the host.

In the context of research related to user experience dimensions, a study [19] analysed Airbnb reviews in Sydney and found they were overwhelmingly positive and focused primarily on the convenience of location, accommodation amenities, availability, flexibility, and communication of hosts. Another study [51] analysed Airbnb reviews in Portland, USA and found that experience ratings focused on service, facilities, location and visual features, feeling at home, and comfort of staying in a home. One study [52] compared reviews of Airbnb offerings in the US, India, and Portugal, and, contrary to the authors' expectation that different cultural norms around individualism would lead to divergent review patterns, they detected homogeneity among reviews, which led the authors to conclude that Airbnb experiences were similar in different countries.

Still on user experience, a study with Airbnb users in the US supported the hypothesis that the Airbnb customer experience encompasses four dimensions (home benefits, personalised services, authenticity, and social iteration), and it was demonstrated that these dimensions significantly influence customers' behavioural intentions [53]. Furthermore, he authors of [54] identified that social interaction influences the overall consumer experience in the sharing economy, and they surveyed Airbnb's service quality attributes in the dimensions of facilities, host, web efficiency, and web responsiveness.

Through the prism of value cocreation, analysis of Airbnb reviews in Malta highlighted the value derived from the various experiential facets of Airbnb by focusing on six common themes related to value cocreation: arriving and being welcomed, expressing positive/negative feelings, evaluating the accommodation and location, interacting with and receiving help from hosts, recommending the accommodation to others, and thanking each other [55]. In a similar way, analysis of Airbnb reviews in Jamaica found that value came from a combination of the house, the surrounding community, and the hosts, while guests also found value in travelling like a local, cooking and cleaning with the host, cultural learning, and relaxing [56].

2.3. Sentiment Analysis

Sentiment analysis aims to extract opinions, feelings, and emotions in different communication channels, mainly in textual format [57]. Using these techniques, it is possible to extract opinions, feelings, and emotions in different communication channels. With the growth of social media use around the world, identifying sentiment in texts has become an important tool for social media data analysis, enabling several new services [58]. Tourism researchers have been using sentiment analysis to understand the activity from new perspectives, in the context of hospitality and Airbnb specifically. A sentiment analysis toolkit was applied in Airbnb reviews, and the most mentioned positive aspects were *apartment*, *host, place, location, room, neighbourhood, stay, time, restaurant,* and *bed*. The most negative aspects mentioned in the reviews were *bars, walk, block, stay, apartment, thing, problem, neighbourhood, minute,* and *place.* Around 75.11% positive aspects were found, in contrast to 8.55% negative and 16.33% neutral aspects [18].

In one study using a sentiment classifier to quantify the percentage of positive and negative reviews and sentences from 15 cities in the United States, the results indicated that 98.1% of reviews and 76.4% of sentences were positive while only 1.06% of reviews and 4.7% of sentences were negative [59]. Another study, by analysing Airbnb reviews, identified that the themes that appeared most in evaluations (*recommend*, *host*, *location,* and *feel at home*) were associated with positive feelings, while topics about *smell*, *cleanliness*, *amenities,* and *in-room facilities* tended to be negative [24].

In turn, some authors explored linguistic patterns and found that text reviews presented a strong asymmetry regarding positive sentiment, where 93% of the analysed reviews were classified as positive [48]. Of the 7% not entirely positive reviews, three out of four came from guests, typically referring to issues with comfort (48%), communication (21%), or cleanliness (15%). The authors suggested that negative experiences are communicated by means of subtle or "lukewarm" cues, for instance, by explicitly not writing or emphasising something.

Lastly, evaluations through sentiment analysis from two sharing economy platforms (Airbnb and Couchsurfing) and a platform that works mainly with hotels (Booking.com) found that the evaluations of the sharing economy tend to be considerably more positive than those of the traditional economy [27]. Furthermore, it was identified that the ratio of positive to negative words in 14 million Airbnb reviews was more than twice as high as the benchmark of Yelp reviews [60].

3. Materials and Methods

This study was applied, exploratory, and descriptive, and it adopted mixed methods framed by qualitative and quantitative analysis techniques (see Figure 1).

In the first stage, the research was grounded in a literature and documentary research of the concepts of Airbnb, sentiment analysis, and user experience, present in existing materials such as scientific articles, books, and websites.

3.1. Data Collection

Airbnb does not provide public access to its data, and, on the private websites, for Brazil, only data for Rio de Janeiro are available. Therefore, for this research, the data were extracted directly from the Airbnb website. The data were collected from the Airbnb website using the Web Scraping technique, which extracts different, unstructured information from websites automatically and represents the data in a coherent structure such as a spreadsheet [61]. The tool used in this research was Parse Hub (available online: https://parsehub.com/ (accessed on 1 July 2020)), and the data were achieved between 24 and 28 October 2020.

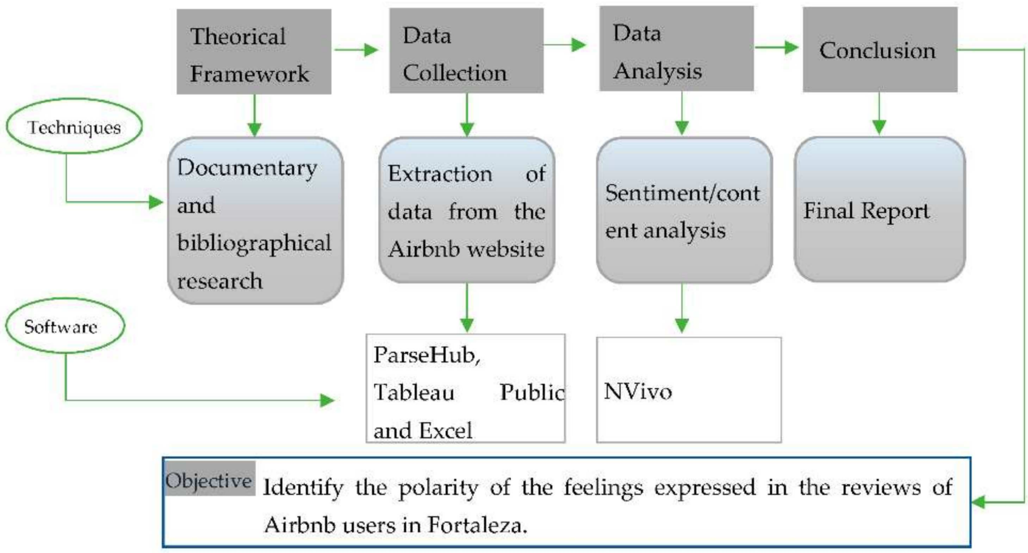

Figure 1. Sentiment analysis steps.

The data collected during this phase were description, location, host, *superhost*, daily rate, type, guests, rooms, beds, bathroom, ratings, overall average ratings, rating criteria (location, accuracy, value, cleanliness, communication, and check-in), and a list of reviews (maximum of six) including guest name, date, and description. All result files were imported into Tableau Public (available online: https://public.tableau.com/pt-br/s/ (accessed on 25 September 2020)), a free software designed for analysing and creating web-based interactive data visualisations. Dashboards with the collected information were created. The data (available online: https://public.tableau.com/views/AvaliaesdoAirbnbemFortaleza24-28out/AvaliaesdoAirbnbemFortaleza?:language=pt&:display_count=y&publish=yes&:origin=viz_share_link (accessed on 28 October 2020)) were analysed and validated.

A total of 2537 user reviews associated with 682 listings were extracted. From this set, the listings that had no reviews, the invalid or incomplete reviews, and those posted between 2013 and 2018 were removed from the sample. At the end of the process, 2338 reviews of 503 listings remained and were exported into a CSV file.

This file was then imported into Microsoft Excel to create four columns in the spreadsheet, namely, "location (group)", "listing type (group)", "guest gender", and "host gender". After consulting the website, the researcher filled in this information. It was either incomplete at the origin (location and type of listing) or did not exist and had to be suggested (gender information). Following the manual intervention, the XLSX file was imported into NVivo Plus version 12, which was used to assist in coding, categorising, and interpreting the data by applying content and sentiment analysis.

3.2. Data Analysis

Sentiment analysis is defined as "a special type of text mining focused on identifying subjective statements and opinions and sentiments contained, particularly in consumer-generated content on the internet" [62] (p. 121). With sentiment analysis, it is possible to "define automatic techniques capable of extracting subjective information from natural language texts, such as opinions and feelings, in order to create structured knowledge that can be used by a support system or decision maker" [63].

Using these techniques, it is possible to extract opinions, feelings, and emotions in different communication channels. With the growth of social media use around the world, the identification of sentiment in texts has become an important tool for the analysis of social media data, enabling several new services [58].

Currently, sentence sentiment detection methods can be divided into two classes: those based on machine learning and lexical methods [58]. Methods based on machine learning usually rely on labelled databases to train the classifiers, whereas lexical methods use lists, dictionaries of associated words, and specific sentiments; thus, their efficiency is directly linked to the vocabulary used, for the various existing contexts [63].

There are several tools available for sentiment analysis. In this work, we initially used NVivo's automatic coding, whose process uses the scoring system presented in Figure 2. Each word that contains sentiment has a predefined score. The content is coded for a set of sentiment nodes, ranging from very positive to very negative [64].

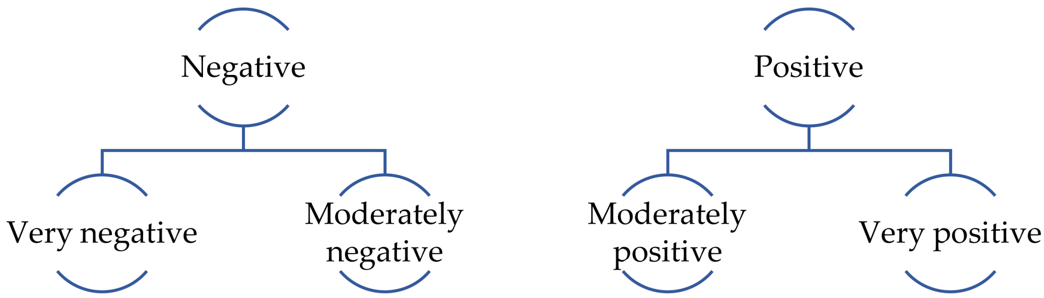

Figure 2. System for sentiment coding.

However, when running this tool in an automatic way, the result is not compatible with the expected return. One of the factors may be the use of off-the-shelf dictionaries developed for, and typically validated on, a specific task and domain, which often do not perform well on other tasks [65].

Research suggests that using manual or group coding produces better performance when using sentiment analysis methods [65,66]. Thus, it was decided to perform a nonautomated analysis of perceived polarity according to the interpretation of the discourse in each of the evaluations with the support of the software for the coding operation

Each comment was analysed individually, and the dominant sentiment was defined. As a criterion, the totality of the context of each evaluation was considered, and the auto coding sequence implemented by NVIVO was used as a reference: (a) the score for each word determines the node of feeling to which it is encoded; (b) the word score may change if preceded by a modifier (for example, more or slightly) that intensifies the feeling; (c) words with a score that fit the neutral range are not encoded. Figure 3 presents the steps used for this manual analysis and the drivers for the selection of polarity and intensity of feeling.

Sentiment analysis, in particular, can be reduced relatively easily to simple questions suitable for individual or group hand coding [65]. Two aspects were primarily evaluated: the orientation of feeling and the intensity of feeling. The orientation of feeling, or polarity, indicates the opinions and subjective feelings of people as positive, negative, or neutral, generally meaning the absence of feeling [67]. Consumers can express a variety of positive and negative feelings that reflect emotions such as disappointment, satisfaction, anger, surprise, and gratification [67].

Sentiment intensity, on the other hand, shows that the orientation of the sentiment has different levels of strength, which can be identified by varying the strength or by intensifying and diminishing words [68]. For example, "good" is clearly weaker than "excellent"; thus, the use of intensifier increases the degree of positivity or negativity.

After the categorisation of polarity and intensity, it was possible to identify the terms with more occurrences, performing a word frequency analysis of the text units from each of the four levels of polarity of the sentiments analysed, using the 100 terms with greater incidence and with at least four characters as parameters.

Some examples of the analysis performed, using the criteria presented in Figure 3, are presented in Figure 4.

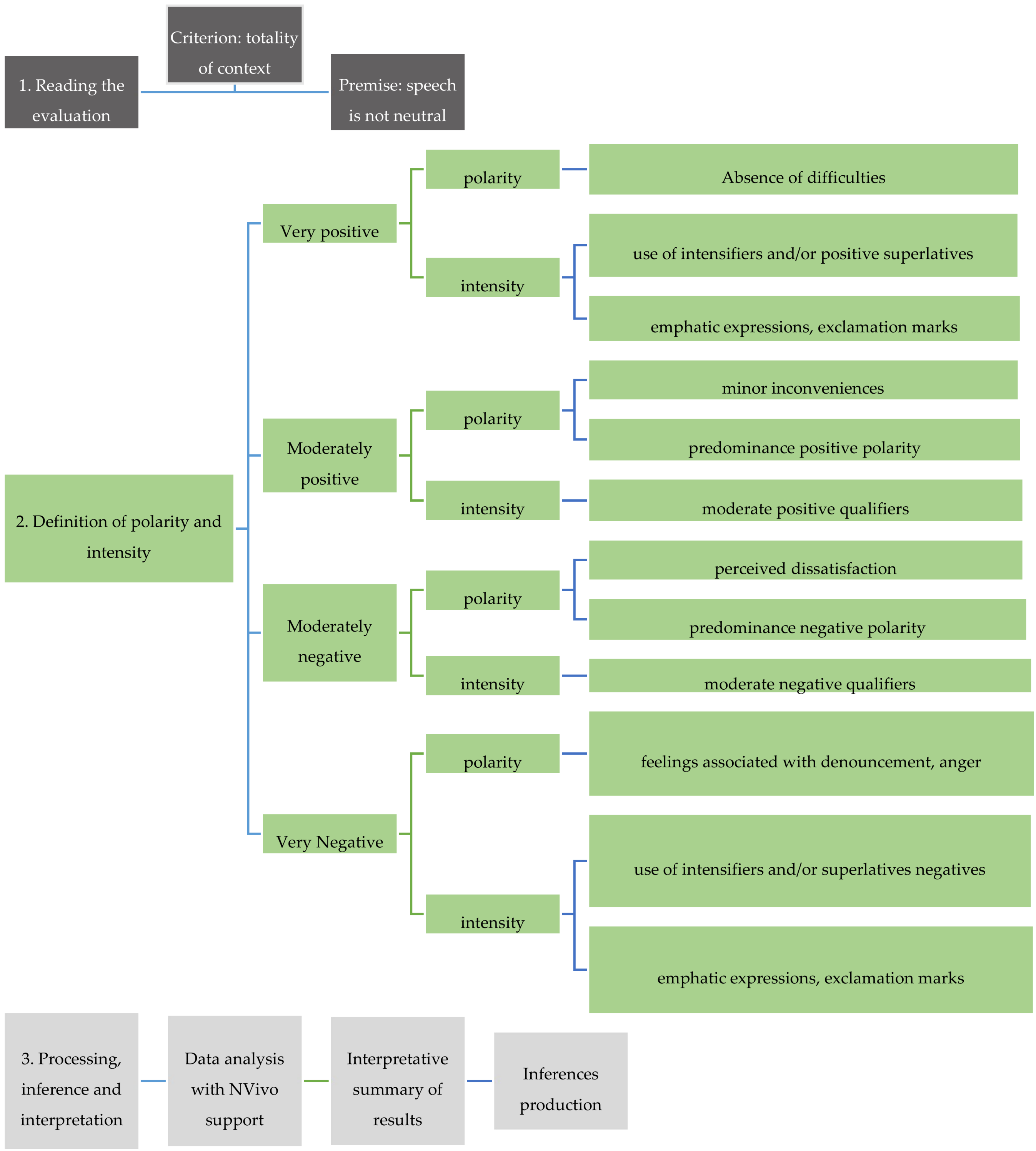

Figure 3. Sentiment analysis steps.

Very Positive

- "What an amazing experience we had, the reception was super attentive, Marcella is a love, the location is perfect, everything was impeccable, very organised and clean, not to mention the view that is a show apart, it will definitely be our corner in Fortaleza the next times."

Moderately Positive

- "The location is great, the flat is beautiful, functional and matches the photos. One or another detail of cleanliness was not so good, but nothing impossible or inadequate. The host is very accessible and responds quickly. It's worth renting."

Moderately Negative

- "Older flat. The furniture is quite old, but nothing to detract from the stay. The mattress is not very good and there were not enough sheets for all guests. There were some details but the host was informed and said he would take the necessary measures. The host was very attentive and helpful during the whole stay! As we only arrived at night in the flat to sleep, it was ok..."

Very Negative

- "The flat does not match the photos, terrible ventilation, poor structure of cozy, the ad says it is cozy, noisy air conditioning, small TV and had no TV in the rooms, I spent a week repeating clothes for no place to hang clothes and had no washing machine..."

Figure 4. Examples of the identification of sentiment in Airbnb user reviews in Fortaleza.

4. Results and Discussion

The evaluations posted on the platform after using the service were used to analyse the emotional dimension of the tourist experience. The focus was the analysis of the polarity of feelings perceived according to the interpretation of the discourse in each of the evaluations. The analysis was performed in a nonautomated way using NVivo software as a support to the categorisation process. All user evaluations were analysed individually, and the predominant feeling was defined, to the detriment of the use of a dictionary or lexicon, aimed at identifying feelings from isolated words. Four gradations were used: very positive, moderately positive, moderately negative, and very negative.

4.1. Dataset Information

We collected 2353 reviews of Airbnb offers in Fortaleza conducted between January 2019 and October 2020. The gender of users was predominantly male, with 1348 reviews (about 57.66% of the sample), in contrast to 982 (42.00%) reviews of the feminine gender and eight reviews (0.34%) where it was not possible to identify the gender on the basis of names, totalling 2338 reviews. As for the hosts identified in the offers, the majority were female, with 254 hosts (about 50.50%), in contrast 233 (46.32%) male hosts. Some offers named companies that managed the property (1.39%), as well as other hostels, hotels, and inns (1.39%), while some identified a couple or mother and son (0.60%).

Regarding the neighbourhoods where the Airbnb offers were collected, the most common were Meireles (37.97%), Praia de Iracema (14.71%), Mucuripe (7.55%), Centro (7.55%), Aldeota (5.17%), and Praia do Futuro I and II (2.58%), here called tourist neighbourhoods, in line with the distribution of means of accommodation in Fortaleza. However, in addition to these seven neighbourhoods representing 75.53% of the offers, Airbnb offers were identified in 48 other neighbourhoods, here called residential.

In relation to the number of reviews per type of offer, 1516 reviews (64.84%) were related to lodgings of the entire place type, in contrast to 793 (33.92%) of private rooms and 29 (1.24%) of shared rooms. In relation to the number of evaluations by tourist areas and predominantly residential areas, it was verified that 1846 evaluations were from tourist areas and 492 were from residential areas.

4.2. Feeling in the Evaluations

As can be seen in Table 1, the results show the predominance of the categorisation of the feeling "very positive", with 1137 evaluations (48.63%), followed by "moderately positive", with 1043 evaluations (44.61%), and a much smaller categorisation for "moderately negative" and "very negative" with only 99 (4.24% of the sample) and 59 evaluations (2.52%), respectively. Overall, 93.24% of the evaluations were positive and 6.76% were negative.

Table 1. Sentiment analysis results.

Polarity	References	Coverage	Coverage by Polarity
Very positive	1.137	48.63%	93.24%
Moderately positive	1.043	44.61%	
Negative	99	4.24%	6.76%
Very negative	59	2.52%	
Total	2.338	100%	100%

This trend is consistent with the results from [59], which indicated that 98.1% of Airbnb reviews were positive while 1.06% were negative, and from [48], where the majority of evaluations (93%) were categorically positive. It should be noted that not all users post reviews, because, when a consumer is not satisfied with their Airbnb experience, they tend not to write a review, rather than negatively evaluate the site [49].

Prior research has shown that the large proportion of positive reviews on Airbnb may be due to sociological effects influencing people to be more tactful in their complaints when reviewing another human [69], especially after a feeling of mutual trust and familiarity has been established through the experience on sharing economy platforms [27]. Furthermore, even when a guest-and-host interaction has taken place mostly, or entirely, online, the person-to-person nature of this type of collaborative consumption seems to play a very strong role in the positive evaluation found in these reviews.

The categorisation "very positive" was associated with experiences reported from discursive constructions with emphatic expressions of satisfaction, featuring the use of exclamation marks, positive superlatives, and a lexicon composed of terms such as "great", "excellent", "incredible", and other qualifiers that indicate optimism and absence of difficulties or dissatisfaction during the experience [25]. It is also known that, topics such as recommended, host, location, and feel at home can be associated with the positive feelings expressed in Airbnb reviews [24]. Examples of accommodation experiences rated "very positive" were the following:

> "Un **great host, the place is very cosy with a super clean environment**. The site has a **great location**, Nelo was **super helpful and very flexible with check-in and check-out**, so far it has been one of the best **experiences I've had as a guest. Highly recommend**."

> "It is too difficult to find other positive adjectives different to those already said by other users! **The best Airbnb that me and my family have ever stayed in** and Clarke's attention then? **No equal! Excellent place, more than approved, super indico and will surely return soon**!!!!" (original review in capital letter)

The classification "moderately positive" was attributed to experiences that presented moderate or not very intense qualifiers, such as "very good", "good", "beautiful", "pleasant", or "correct", in a descriptive context of the experience, and which may have presented slight inconveniences, negative details or reservations in the narration, but in which the predominance of a positive polarity was perceivable [25]. In this sense, characteristics such as pleasant communication with the hosts, convenient location, and reliable amenities could also be considered [24]. Illustrative examples of moderately positive accommodation experiences were the following:

> **"Very good, nice environment very clean**, Silvio and Samia are a very **friendly and made us feel comfortable, the flat and the building** are **very good** and with a **good location**."

> **"Very well-equipped space** and comfortably holds 5 people, as it has a single box in the living room. **Television** with numerous closed channels available. **clean bathroom and shower** with hot water option working perfectly, as well as **air conditioning** and **cooktop**. **Has a** small side view to the waterfront very nice. Close to everything and has several tour companies for Ceará's beaches right next to the reception entrance. **Overall, all very satisfactory. My only suggestion would be to buy a microwave oven**."

The classification "moderately negative" was used to classify evaluations with inconveniences during the narration of the experience, even if they did not present themselves as serious for the subject. Slight positive elements may have been presented, but a pessimistic discourse predominated [25]. Illustrative examples of moderately negative accommodation experiences were the following:

> "The **space is very well located**, and Flavia is an **excellent person, super high spirits. The only thing that caught us a little bit was the cleaning**, because our room had some very visible **cobwebs, and the floor was also dusty**. But otherwise, we were very well received in Flavia's apartment".

> "A **good cost benefit**. The room has what is necessary, but **the conservation of the room did not please me. The room has what is necessary, but the conservation** of the room did not please me."

The classification "very negative" was associated with dissatisfaction in the report of the experience, characterised by the lexicon and emphatic and intense exclamations with the use of negative superlatives or feelings associated with denunciation, disappointment, anger, and deceit [25]. Similarly, commonly topics related to smell, cleanliness, amenities, and facilities in the room tended to be negative [24]. The difficulties imposed by local and tourist habits could also be listed, such as entry and exit times and compliance with local rules [70]. For this reason, it is essential that tourists acquire knowledge related to the culture of the place for a better adaptation to the local context [71]. Illustrative example on accommodation experiences rated "very negative" were the following:

> "The location is great, **but we would not stay again. I needed to check in a few hours earlier and they were not very accommodating**, they charged **me for the full day**. The front door is jammed and it's a sacrifice to open it, the blind in the bathroom doesn't work very well **and every time you shower you have to wash the bathroom, the house doesn't have a filter, so you spend a lot on water**."

> **"Poorly maintained flat and bringing risks to guests, because some pieces of the lining of the balcony came down, breaking a plastic chair**, just after I left the same. **Heavy pieces that were attached to the ceiling with already rusty wire, showing that they had no maintenance. Old towels and utensils. The bed was also old and made a lot of noise**. The owner was informed of what had happened on the balcony and **sent a person to do the repair without my knowledge** and when I came back in the afternoon, this person was doing the

repair. I thought that was strange, **the fact that all my belongings were exposed and there was no one accompanying the service and without my knowledge**."

4.3. Content of the Evaluations

The terms most used by users can help hosts to understand which words they can use in the information of the offers, in order to improve their ad on the platform and the rating of their property. Figure 5 shows the 20 most frequent words in the positive and negative comments, including derived words, with a minimum length of three characters.

Polarity	Word (original language)	Similar words (original language)	Word (translated)	Frequency
Positive	localização	localização, localizações, localizada, localizado, localizados, localizar	location	984 3.1%
	bem	bem	well	823 2.59%
	excelência	excelência, excelente	excellence	662 2.08%
	apartamentos	apart, apartamento, apartamentos	apartments	600 1.89%
	super	#super, super	super	561 1.76%
	recomendo	recomendo	recommend	451 1.42%
	ótima	ótima	great	449 1.41%
	limpos	limpa, limpar, limpas, limpo, limpos	clean	449 1.41%
	atencioso	atenciosa, atenciosas, atencioso, atenciosos	atencioso	354 1.11%
	volto	volta, voltando, voltar, voltarei, voltarem, voltaremos, voltaria, voltaríamos, voltarmos, voltei, volto	come back	333 1.05%
	local	local, localidade	local	322 1.01%
	espaço	espaço	space	275 0.87%
	confortável	confortáveis, confortável, confortavelmente, conforto, confortos	comfortable	262 0.82%
	maravilhosos	maravilhas, maravilhos, maravilhos@, maravilhosa, maravilhosamente, maravilhosas, maravilhoso, maravilhosos	wonderful	260 0.82%
	ótimo	ótimo	great	255 0.80%
	lugar	lugar, lugares	place	253 0.80%
	estadia	estadia	stay	243 0.76%
	bom	bom	good	233 0.73%
	vista	vista, vistas, visto	view	232 0.73%
	aconchegante	aconchegante	cozy	221 0.70%
Negative	localização	localização, localizado	location	82 1.8%
	bem	bem	well	63 1.38%
	quartos	quarta, quarto, quartos	bedrooms	54 1.19%
	apartamento	apartamento, apartamentos	apartment	54 1.19%
	limpeza	limpeza	cleanliness	36 0.79%
	melhorar	melhor, melhorado, melhorar, melhorará, melhores, melhoria, melhorias	improve	33 0.72%
	anfitrião	anfitrião	host	33 0.72%
	excelente	excelente	excellent	32 0.70%
	bom	bom	good	32 0.70%
	problemas	problema, problemas	problems	31 0.68%
	boa	boa	good	30 0.66%
	estadia	estadia	stay	29 0.64%
	camas	cama, camarão, camas	beds	29 0.64%
	local	local	local	25 0.55%
	espaço	espaço	space	25 0.55%
	flat	flat	flat	23 0.51%
	condicionado	condicionado, condicionados	conditioning	23 0.51%
	hóspedes	hóspede, hóspedes	guests	21 0.46%
	banheiro	banheiro, banheiros	bathroom	21 0.46%
	falta	falta, faltam, faltar, faltaram, faltou	missing	20 0.44%

Figure 5. Most frequent words in positive and negative comments (top 20).

For the positive comments (left graph), the words “location”, “good”, “excellence”, “flats”, “super”, “recommend”, “clean”, “great”, “attentive”, and “return” were the first ten words, indicating access to stays with good location, clean, attentive hosts, and intention to recommend and return. In [18], the most mentioned positive aspects were “apartment”, “host”, “place”, “location”, “room”, “neighbourhood”, “stay”, “time”, “restaurant”, and “bed”. The authors of [24] identified that the themes with positive feelings that appeared most in evaluations were associated with “recommend”, “host”, “location”, and “feel at home”. In the case of negative words, it can be seen in the graph on the right that the 10 most frequent words were “location”, “well”, “flats”, “rooms”, “cleanliness”, “host”, “improve”, “good”, “excellent”, and “problems”. In [24], the topics about “smell”, “cleanliness”, “amenities”, and “in-room facilities” tended to be negative. In turn, “bars”, “walk”, “block”, “stay”, “apartment”, “thing”, “problem”, “neighbourhood”, “minute”, and “place” stood out as topics related to negative reviews in [18].

Compared to the positive words, words such as “rooms”, “cleanliness”, “host”, “improve”, and “problems” were associated with negative comments indicating the need for an improvement in cleanliness, rooms, and host reports related to the need for improvement and problem solving.

All the items listed in the sentiment analysis provide an overall understanding such that it is possible to identify points for improvement, shortcomings, and the needs of users expressed in the comments.

The evaluation of the sentiment of Airbnb users in Fortaleza corroborates other research identifying that the vast majority of the reviews published by users are positive. There is greater positivity regarding the polarity of comments on sharing economy platforms when compared to formal economy platforms [58]. Analysis of comments on Airbnb in Sydney identified that they were mostly positive [19]. In turn, analysis of reviews on Airbnb found that around 72% of users wrote at least one review about the place they stayed, with 94% of the reviews ranging between four and five stars [49].

4.4. Size of Assessments

Table 2 presents the size distribution of the positive and negative polarity comments.

Table 2. Size distribution of the evaluations.

Number of Characters	Positive Polarity		Negative Polarity	
	Quantity	Percentage	Quantity	Percentage
<100	986	45.23%	31	19.62%
101–200	678	31.10%	33	20.89%
201–300	285	13.07%	26	16.46%
301–400	121	5.55%	31	19.62%
401–500	48	2.20%	10	6.33%
501–600	30	1.38%	8	5.06%
601–700	12	0.55%	11	6.96%
701–800	8	0.37%	2	1.27%
801–900	5	0.23%	2	1.27%
901–1000	2	0.09%	1	0.63%
>1000	5	0.23%	3	1.90%
Full	2.180	100%	158	100%

Through this information, it was possible to analyse that, on average, the positive comments tended to be smaller. While 76.33% of the positive comments had a length up to 200 characters, among the negative comments, this percentage fell to 40.51%. The percentage of long comments, over 500 characters, was 4.72% among the positive comments and 23.42% among the negative ones.

The objectivity in the evaluation was noticeable in many comments, especially when the evaluation was positive. Examples of positive comments shorter than 200 characters were the following:

> "I will summarise, if it were possible, I would put a thousand stars." (Size 54)

> "I liked Lea's space, very good location, on the seafront of Fortaleza, clean flat!!! All great!!" (Size 116)

> "Flat very well located, with easy access and great sea view. Comfortable bed and wonderful shower. It made my trip to Fortaleza much more enjoyable and welcoming." (Size 178)

However, when the evaluation had explicit negative points, the user tended to inform in more detail the reason for dissatisfaction, the discontentment, while also including positive points, alternating the negative information with positive information, sometimes trying to minimise negativity. An example of a negative comment longer than 500 characters is the following:

> "Space of the flat ok, excellent location. The flat lacks maintenance, and they are small things, but they are things that bother … I didn't use the kitchen but the exhaust fan was very dirty with grease; the air conditioner was noisy and extremely dirty, it was scary to breathe that air but there was no other way, the external filter was cleaned by the hotel maintenance guy, it was very … but very dirty; the toilet flush, if you use it at night it wakes up the person who is accompanying you so loud; there was no hygienic paper reserve, I had to buy it; the intimate shower falling and that shower hose, no comments. Would not rent again." (Size 688)

4.5. User Sentiment by Gender

Regarding the assessment per gender of the users, it was found that, of the 1348 users identified as male, 613 (45.48%) assessed the experience as "very positive", in contrast to 639 (47.40%) as "moderately positive", 64 (4.75%) as "moderately negative", and 32 (2.37%) as "very negative". As to the people identified by the female gender (982), 520 (52.96%) assessed the experience as "very positive", in contrast to 400 (40.73%) as "moderately positive", 35 (3.56%) as "moderately negative", and 27 (2.75%) as "very negative", as shown in Figure 6.

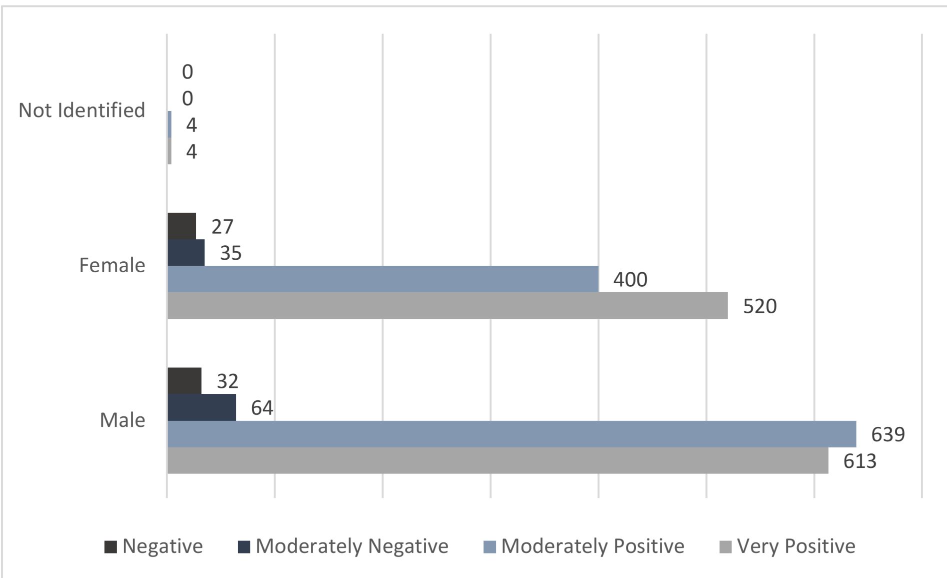

Figure 6. Sentiment analysis results by gender of user.

The data suggest that the female gender evaluated more positively (93.69%) than the male gender (92.88%), and that they were prone to evaluate positively and negatively with greater intensity. Men, on the other hand, tended to evaluate positive and negative comments with greater moderation.

4.6. Feeling for Superhost Offers

In the collected data, there were 77 female hosts categorised as *superhost*, in contrast to 79 male hosts and one company. Table 3 shows the distribution of the number of ratings per polarity of feeling and gender of the *superhost*.

Table 3. Results of sentiment analysis of *superhost* offers.

Polarity	Number of Comments Related to *Superhost* Offers			Total
	Male (79)	Female (77)	Company (1)	
Very positive	231	237	2	470
Moderately positive	201	172	4	377
Negative	4	6	0	10
Very negative	12	11	0	23
Total	448	426	6	880

The number of hosts classified as *superhost* was balanced between genders. About 96.00% of the ratings of female *superhosts* were positive (409 very positive and moderately positive ratings out of 448 ratings) and 96.43% of the ratings of male *superhosts* were positive (431 very positive and moderately positive ratings out of 426 ratings).

Compared to the percentage of positive evaluations of 93.44%, presented in Table 1 (p. 15), it can be seen that both female and male *superhosts* were evaluated more positively than normal hosts.

4.7. Sentiment by Type of Accommodation

The factors that may elucidate greater positivity or a lack of negativity in a review comment made on the Airbnb platform include the bond generated by the personal interaction between host and guest, as well as the fear of receiving a retort from the host or of harming the host with a bad review, which may drive away potential new guests [49]. On Airbnb, when users do not have a satisfactory experience, they tend not to write a review instead of negatively rating the place [49].

Users who use the private room or shared room type offers have greater interaction and communication with the hosts and can be characterised more genuinely today as a sharing economy, given that they share an idle space within their homes. To check if the types of offers could influence the positivity of the evaluations, Table 4 verifies the number of evaluations per polarity and type of offer. The percentage of positive evaluations for the entire place type offers was 92.02%, for the private room type offers was 95.46%, and for the shared room type offers was 96.54%, indicating that there may be a relationship of positivity according to the type of offer.

Table 4. Results of sentiment analysis by type of accommodation.

Polarity	Type of Offer			Total
	Entire Place	Private Room	Shared Room	
Very positive	691 (45.58%)	432 (54.48%)	14 (48.27%)	1.137
Moderately positive	704 (46.48%)	325 (40.98%)	14 (48.27%)	1.043
Negative	74 (4.88%)	24 (3.03%)	1 (3.46%)	99
Very negative	47 (2.70%)	12 (1.51%)	0 (0%)	59
Total	1.516 (100%)	793 (100%)	29 (100%)	2.338

4.8. Sentiment by Type of Neighbourhood

Table 5 presents the results of the evaluation of sentiment by type of neighbourhood, with the "tourist" type being represented by Aldeota, Centro, Meireles, Mucuripe, Praia de Iracema, and Praia do Futuro, and the "residential" type being represented by the others. In predominantly residential neighbourhoods, the positive polarity was proportionally higher (96.34%) than in tourist neighbourhoods (92.42%), indicating that the location can influence the sentiment analysis.

Table 5. Results of sentiment analysis by type of neighbourhood.

Polarity	Type of Neighbourhood		Total
	Residential	Tourism	
Very positive	280 (56.91%)	857 (46.43%)	1.137
Moderately positive	194 (39.43%)	849 (45.99%)	1.043
Negative	10 (2.03%)	89 (4.82%)	99
Very negative	8 (1.63%)	51 (2.76%)	59
Total	492 (100%)	1.846 (100%)	2.338

According to Table 4, 70.73% of the reviews of residential neighbourhoods were of the offer type full room and shared room, while, in tourist neighbourhoods, 74.32% of the reviews were of the type entire place. Thus, the type of offer and the location were directly connected.

4.9. Polarity in User Experience Categories

Content analysis was used to categorise and code the most frequent themes in the users' evaluations, whereas, to associate an evaluation with the theme, "positive", "negative", and "mixed" polarity was identified. The coding and categorisation process was then performed by selecting the entire evaluation and not excerpts. An evaluation could be associated with different themes, but with only one polarity.

Figure 7 presents the percentage distribution of the polarity of the evaluations within each theme.

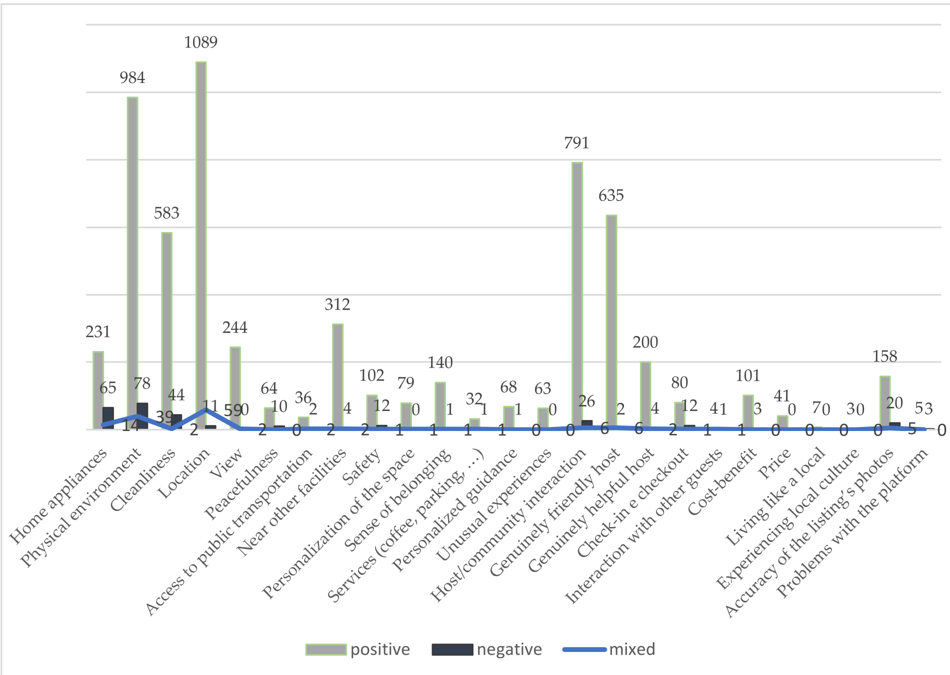

Figure 7. Polarity by themes that identified the user experience in the evaluations.

The most evaluated themes with negative polarity were "website problems", with 37.5% of the evaluations related to the theme categorised with negative polarity, "houseware" with 21%, "interaction with other guests" with 16.7%, and "tranquillity" with 13.5%. The categories without negative references were "view", "personalisation of the environment", "unexpected experience", "live like a local", "experience the local culture", and "price".

Identifying user sentiment in relation to each topic allows monitoring the experience in relation to specific services or products in order to improve customer experiences [72].

5. Conclusions

The present research analysed 2353 reviews from 2019 and 2020 related to 506 Airbnb accommodation offers in Fortaleza, and then used Parse Hub software for data collection and NVivo to employ sentiment analysis to identify the positive and negative opinions of Airbnb users in Fortaleza, Ceará, Brazil, in order to contribute to the debate about Airbnb users' experiences. The study contributes to the literature on tourism and hospitality by providing a coherent and detailed understanding of the Airbnb user experience in light of sentiment analysis, giving viability and broadening the understanding of this phenomenon that is new in the national and local tourism panorama. Moreover, by working the polarities and types of feeling, it delivers to the field of study possibilities of new studies using the constructs and types of feeling investigated here. It also produces the idea of adaptation of the sentiment indicators in a context different from traditional accommodation services, either because it is a specific offer or because it is a specific type of consumer/demand. Thus, the theoretical contributions of the study are not only in the identification and degree of polarity of the sentiment, but in the categorisation of different types, making more in-depth theoretical references possible in the future.

Methodologically, it contributes by illustrating how user-generated content can be captured and treated using sentiment analysis through manual coding in tourism and hospitality studies. Furthermore, the study involves the use of data from the software correlated with the raw data (the evaluations written by the tourists). This confrontation promotes a deepening of the analysis and a methodological maturity to the study.

The study confirmed previous research results about the positivity of comments in Airbnb reviews. It identified that, on average, the positive reviews had more characters than the negative reviews, and that the negative reviews were more detailed. In the positive evaluations, the most frequent words were "location", "well", "excellence", "flats", "super", "recommend", "clean", "great", "attentive", and "I'll come back", whereas, among the negative evaluations, the most frequent words were "location", "well", "flats", "rooms", "clean", "host", "improve", "good", "excellent", and "problems". Compared to positive words, words such as "rooms", "cleanliness", "host", "improve", and "problems" were more associated with negativity.

Another issue identified was the differences in the percentages of positive and negative evaluations when differentiated by other factors such as gender of the user, type of host, type of offer, and location. Female users evaluated more positively than male users, and they were prone to evaluate with greater intensity, while male users tended to evaluate with greater moderation. This is a major discovery of this work, since it can help hosts and the platform itself to offer a better service and achieve greater loyalty from the positive experience.

Hosts classified as *superhost* had more positive evaluations than standard hosts. Offers of the shared room and private room types had proportionally more positive evaluations than entire places, whereas, in predominantly residential neighbourhoods, the positive polarity was proportionally higher than in tourist neighbourhoods. However, most offers of the private room and shared room types were located in residential neighbourhoods; hence, the evaluations by type of offer and location are directly related. Therefore, it is concluded that, even if the lived experience in Airbnb is directly related to tourism, it seems to be more positive when there is a greater relationship with the local community, given that it was in residential neighbourhoods where there was a greater positive polarity in the comments.

The higher positivity can be harmful to users since bad offers may not be evident. Negative experiences that are not shared end up hindering the choice, which may lead users to disregarding a good place due to the friendliness of feelings present in the comments. Therefore, generating a greater dialogue between host and visitor should be a premise of this social network, because then the negative comments would be minimised and the positive ones would be highlighted, thus generating a greater reliability of the reviews.

This study extends existing service and hospitality research by exploring sentiment analysis on Airbnb in the northeast of Brazil, and the results can serve as a useful reference for future comparative studies. Through this type of analysis (sentiment analysis), it is possible to use the measured sentiment to support the Airbnb product and direct improvements to the hosts of the platform. It can be used as a source to measure Airbnb's performance and understand customers' needs and wants, as the use of text analytics can provide a better understanding of the guest's experience. Furthermore, identifying user sentiment by theme allows for monitoring the experience against specific attributes, driving improvements.

In this study, it is managerially suggested that owners, when receiving male guests, should focus on objective issues (the study showed that the segment was more objective) and, when receiving female guests, should focus on hospitality, friendliness, and service (more subjective and profound requirements). The study also provides Airbnb owners with management possibilities. By understanding the behaviour related to post-purchase sentiment, it is possible for owners to have prior knowledge of how to proceed in certain situations. The comments on the platform reflect the quality perception that guests have of their experience.

Lastly, the article contributes to the development and initial identification of the experience evaluation variables. As we researched the polarity and intensity of the variables, we created a set of terms that can, in the future, be tested for the development of measurement scales. Thus, from the point of view of theoretical contributions and this exploratory study, we provide the a set of themes that can become indicators/variables of the experience in this service segment.

Future studies can identify whether there are differences between the sentiment expressed by Airbnb users in different cities, making it possible to reach different cultures and regions. There is still potential to differentiate Airbnb reviews considering different origins and types of offers (entire place, private room, and shared room) since the type of accommodation implies a difference in the sentiment identified in the analysis. Lastly, using the methodological procedure proposed in this research, it is possible to expand the line of research and perform the same type of analysis for other Airbnb products, such as experiences and online experiences.

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