Geospatial Intelligence for Reviews of Businesses

by

Dini Irdina Ahmad Ubaidah (31279279)

Thesis

Submitted by Dini Irdina Ahmad Ubaidah (31279279)

in fulfillment of the Requirements for the Degree of

Bachelor of Computer Science with Honours (C3702)

Supervisor: Professor Lim Wern Han

Faculty of Information Technology
Monash University

May, 2024

(Word Count: 6656)

Contents

List of Tables

List of Figures

Geospatial Intelligence for Reviews of Businesses

Dini Irdina Ahmad Ubaidah (31279279)
dahm0004@monash.edu
Monash University, 2024

Supervisor: Professor Lim Wern Han

Abstract

The COVID-19 pandemic has significantly impacted the global hospitality industry, reshaping customer expectations and preferences. This thesis explores the evolving sentiments in hotel reviews across Europe, the Americas, and Asia before, during, and after the pandemic. Using aspect-based sentiment analysis (ABSA) with the PyABSA framework, this study identifies and analyses sentiments towards specific aspects such as Staff & Service, Comfort & Amenities, and Cleanliness & COVID. The findings reveal regional variations in guest priorities, with Staff & Service consistently being the most critical aspect across all regions. The analysis also highlights the increased importance of hygiene during the pandemic and the ongoing challenges in maintaining high service standards post-pandemic. The study concludes with recommendations for future research, emphasising the need for multi-language support, improved aspect detection, and a broader geographical scope to provide more comprehensive insights into global hotel guest experiences.

Geospatial Intelligence for Reviews of Businesses

Declaration

I declare that this thesis is my own work and has not been submitted in any form for another degree or diploma at any university or other institute of tertiary education. Information derived from the published and unpublished work of others has been acknowledged in the text and a list of references is given.

Dini Irdina Ahmad Ubaidah (31279279)
May 29, 2024

Acknowledgments

I would like to express my sincere gratitude to my supervisor, Dr Lim Wern Han, for his invaluable support and guidance throughout this project. His knowledge and advice were crucial to the successful completion of this thesis. I am also deeply thankful to Adrian Lai, who dedicated significant time and effort to help annotate the datasets. Furthermore, to the unit coordinators and teaching team, I'd like to thank you for providing support in the forums. Finally, I am grateful to my family and friends for their constant support and encouragement throughout my academic journey.

Dini Irdina Ahmad Ubaidah (31279279)

Monash University
May 2024

Chapter 1

Previous Literature Review

1.1 Introduction

The hospitality industry, characterised by its elaborate structure of services and experiences, has long been a fascinating area of study. It grows on customer feedback, growing and changing its offerings based on the sentiments and preferences of its clientele. In today's society, within the context of the digital era, online reviews have grown as a crucial platform through which customers share their sentiments, criticisms, and recommendations. The development of websites such as TripAdvisor, Booking.com, and Yelp has enabled individuals ranging from experienced travellers to occasional restaurant-goers to freely share their opinions. However, the outbreak of the COVID-19 pandemic has significantly impacted this industry, leading to unprecedented experiences and sentiments.

As the world struggled with new challenges, the hospitality industry faced its own set of hardships. The implementation of lockdown measures, travel restrictions, and heightened health concerns had a profound impact on the way in which people engaged with hotels and restaurants (Alonso et al., 2020). The events that transpired during the COVID-19 epidemic in January 2020 resulted in a significant reduction of around 90% in China's hotel occupancy (Nicola et al., 2020). According to Nicola et al. (2020), there was an 11.6% decrease in revenue per available room in the United States. Additionally, Baker et al. (2020) observed a one-third reduction in restaurant expenditure specifically during the month of March 2020. The impact of COVID-19 on tourism income in Europe has been observed to have a similar effect, with estimates indicating a monthly decline of one billion euros (Niestadt, 2020).

While numerous research projects have delved into sentiment analysis and aspect detection in the context of online reviews, the existing research offers a limited view of the changes brought about by the pandemic. Most studies tend to focus on specific time periods, often overlooking the wider temporal progression of the pandemic. Moreover, most studies provide insights that are limited by regional constraints, thus ignoring the more general global perspective.

Based on the aforementioned observations, this research proposes two important questions:

1. How have the key aspects mentioned in customer reviews for restaurants and hotels changed during the COVID-19 pandemic, and which specific features were most frequently associated with positive or negative sentiments?

2. Are there observable regional differences in the volume and sentiment of reviews for restaurants and hotels during the COVID-19 pandemic, reflecting the varying impacts on each country's hospitality sector?

The overarching aim of this study is to provide a comprehensive analysis of online customer reviews in the hospitality sector, spanning a wide time frame as well as diverse geographical regions, specifically focusing on the COVID-19 pandemic. Through the combined use of conventional lexicon-based methodology and proven aspect detection techniques, our aim is to interpret the complexities of customer sentiments during these challenging times. Furthermore, by employing temporal and geospatial analysis techniques, our objective is to observe the changing trends and geographical differences in customer reviews. This will offer valuable information that could benefit hotels and restaurants in effectively navigating the uncertainties of the post-pandemic era.

The following sections of this study provide an extensive literature overview, focusing on the current advancements in sentiment analysis, aspect detection, and geospatial-temporal investigations. Subsequently, a project plan is laid out, presenting a breakdown of the methodologies and tools that will be used in our research project.

1.2 Literature Review

1.2.1 Sentiment Analysis

When used in the hospitality industry, sentiment analysis can provide valuable insights into customers' experiences and emotions. By analysing customer reviews, hotels and restaurants can better understand their strengths and weaknesses, and make decisions to improve their services and offerings and cater to changing customer demands. There has been extensive research conducted on the use of sentiment analysis in the hospitality sector. These studies have presented a range of techniques for data preprocessing, feature-based methods, sentiment classification levels, models, and utilisation of diverse datasets, each with its own pros and cons (Ameur et al., 2023).

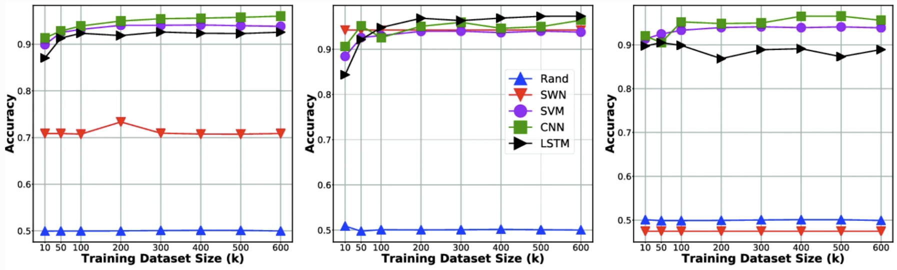
1.2.1.1 Lexicon-based Approach

According to Bagherzadeh et al. (2021), lexicon-based approaches are preferred for sentiment analysis due to their easier implementation and greater performance. An example of a popular lexicon-based approach is the SentiWordNet dictionary. This method was utilised by Asani et al. (2021) to examine the sentiments regarding the names of foods that were retrieved and clustered from reviews posted by users. Another interesting approach done by Nie et al. (2020) is the use of the HowNet sentiment dictionary to develop a customised corpus specifically tailored for hotel sentiment analysis. There is also a more recent dictionary called SentiWords that was created by Gatti et al. (2016). It uses an innovative ensemble approach that reportedly outperforms SentiWordNet. Bagherzadeh et al. (2021) utilized this dictionary to develop their own sentiment analysis technique, producing two hotel-specific word lexicons.

In addition to dictionary-based methods, rule-based approaches like the Valence Aware Dictionary for Sentiment Reasoning (VADER) can also be used for sentiment analysis. According to Al-Natour and Turetken (2020), VADER is highly recommended due to its capability to analyse texts of varying lengths and produce a numeric valence (polarity) score. It has also been widely used as a benchmark lexicon tool in several research studies.

1.2.1.2 Machine Learning Approach

When it comes to machine learning approaches, there are many applicable algorithms. For their research into hotel ratings, Geetha et al. (2017) have used a Naïve Bayes algorithm, which is a supervised learning classification technique. In this study, the algorithm utilises a lexicon of words to compare and identify terms from documents in relation to the lexicon. In the study conducted by Wang et al. (2019) on sentiment analysis methodologies, they evaluated the efficiency of Support Vector Machine (SVM), Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN) models. The findings indicate that all three approaches showed excellent results and yielded high accuracy in sentiment polarity classification. Additionally, the study has demonstrated that the LSTM model exhibits superior performance in classifying positive comments, whereas the CNN model offers higher accuracy for negative comments.



(a) Overall Accuracy (b) Accuracy on Positive Comments (c) Accuracy on Negative Comments

Figure 1.1: Machine learning results from Wang et al. (2019)

As another example, Al-Natour and Turetken (2020) carried out a study that involved the evaluation of different sentiment analysis tools, one of which was Google's Cloud Natural Language API. This tool uses machine learning techniques, specifically Google's deep learning platform, which employs advanced multi-layer artificial neural network (ANN) models to uncover the underlying structure and semantic meaning of texts. Similar to VADER, Google generates a numerical polarity and can analyse reviews of varying lengths. The ANN-based Google stands out as the most robust out of all the techniques that have been tested by Al-Natour and Turetken (2020), as its performance appears to be unaffected by contextual circumstances.

1.2.1.3 Results and Conclusion

While each study has its own specific research objective and contribution, there are certain common findings and conclusions. One notable observation is that different user groups tend to give differing ratings. In their study, Song et al. (2018) examined reviews from from six different countries and written in three separate languages. Their findings indicate that American and British visitors predominantly focused their comments on staff and culture, whereas Australians and Singaporeans tended to engage more with discussions pertaining to food. Similarly, the research conducted by Sun et al. (2022) focused on different categories of travellers, namely family, solo, friend, couple, and business. The study observed that each category showed varying degrees of satisfaction, with solo travellers reporting the lowest scores compared to other traveller patterns.

A number of studies also focused more on the evaluation of sentiment analysis techniques rather than specifically examining review trends for hotels and restaurants. The research project led by Natour and Turetken (2020) found that sentiment analysis scores can accurately represent the sentiment of a review when star ratings are not available. This finding validates the potential of using them as alternatives in cases when star ratings are not obtainable. The study also encourages combining the outputs of several sentiment analysis techniques and merging them with star ratings to greatly improve the precision in identifying the sentiment expressed in a review.

1.2.2 Aspect Detection

For hotels and restaurants, using aspect detection can help identify the specific areas of the business that customers are particularly satisfied or dissatisfied with. This can lead to targeted improvements to the overall customer experience. Although it is still a sub-task of sentiment analysis, aspect detection can help businesses understand which aspects of their offerings are most important to customers and prioritise their efforts accordingly.

1.2.2.1 Unsupervised Learning Algorithms

Unsupervised learning, under the domain of aspect detection, involves the use of algorithms and techniques for the purpose of detecting multiple "aspects" without the presence of predetermined labels or categories.

Topic modelling is a commonly used technique in the field of unsupervised aspect detection. Prominent examples of this method are Latent Dirichlet Allocation (LDA) and Latent Semantic Analysis (LSA). In the study of Guo et al. (2017), they used LDA, a Bayesian learning algorithm, to efficiently capture context-specific topics. The analysis conducted by the LDA model revealed a total of 30 topics, and each topic was characterised by a list of the top 20 words and their corresponding weights. According to the authors, this analysis extracts novel insights from the hotel reviews and uncovers previously unexplored features that have not been considered in previous research. Nevertheless, it is worth mentioning that certain instances reveal that the dimensions put forth by prior research are more detailed compared to the outcomes obtained using LDA and vice versa (Guo et al., 2017).

Another model developed specifically for aspect-based sentiment analysis is Latent Aspect Rating Analysis (LARA) by Wang et al. (2010). Luo and Tang (2019) conducted a study on peer-to-peer (P2P) lodging reviews, for which they made certain modifications and adjustments to the LARA model. These alterations were made in order to enhance the model's effectiveness and to facilitate a more comprehensive and accurate understanding of the reviews. The original model solely assesses sentiments on a one-dimensional scale, distinguishing between positive and negative. In order to improve the accuracy and comprehensiveness of evaluating customers' emotional states, Luo and Tang (2019) employed Plutchik's (1994) emotion

Topic	Relative weight	%	Topic	Relative weight	%
Topic 1: Car Parking			*Topic 2: Bathroom*		
park	30,702.62	14.5%	shower	22,219.07	8.0%
car	9930.66	4.7%	water	13,710.02	4.9%
street	8373.58	3.9%	bathroom	12,487.22	4.5%
free	8115.33	3.8%	hot	8254.09	3.0%
downtown	6510.97	3.1%	air	5988.69	2.1%
lot	5881.83	2.8%	towel	5766.55	2.1%
across	5356.02	2.5%	work	5337.27	1.9%
close	5050.80	2.4%	small	4795.33	1.7%
right	4790.92	2.3%	use	4675.67	1.7%
center	4351.29	2.1%	bath	4662.39	1.7%
drive	4204.18	2.0%	toilet	3914.35	1.4%
block	4124.77	1.9%	cold	3885.34	1.4%
away	3768.79	1.8%	heat	3852.58	1.4%
shop	3134.07	1.5%	light	3316.73	1.2%
access	2978.80	1.4%	sink	2914.07	1.0%
within	2661.61	1.3%	window	2865.75	1.0%
quiet	2566.23	1.2%	open	2647.17	1.0%
next	2269.43	1.1%	need	2596.46	0.9%
road	2261.28	1.1%	two	2481.19	0.9%
side	2013.30	0.9%	con	2325.11	0.8%

Figure 1.2: Example of identifying topics from Guo et al. (2017)

wheel, which consists of four sets of opposing emotions (sadness-joy, fear-anger, disgust-trust, and surprise-anticipation).

1.2.2.2 Deep Learning

There is a diverse range of deep learning models that have the capability to automatically recognise and extract features that are presented inside a given text. These models include CNN, LSTM, and Bidirectional Encoder Representations from Transformers (BERT), and have demonstrated notable improvements when compared to conventional methods. Pezenka and Weismayer (2020) employed the AYLIEN text analysis extension in their study of restaurant reviews, which incorporates a hierarchical bidirectional long short-term memory (H-LSTM) model. This model demonstrates competitive performance when compared to the current leading methods in sentiment analysis. In addition to LSTM, another widely used model in the field is BERT. BERT has demonstrated exceptional performance in aspect identification tasks, positioning it at the forefront of the current state-of-the-art methods. In their study, Ray et al. (2021) employed a methodology that involved the use of a

Figure 1.3: Wordcloud from Geetha et al. (2017)

combination of two BERT models, which were applied in three distinct phases to classify sentiments as positive–negative, neutral–negative, and neutral–positive. These sentiment classifications were then combined using a weight assigning technique.

1.2.2.3 Results and Conclusion

Aspect detection and sentiment analysis have yielded many interesting results in the study of reviews within the hospitality industry. In the field of hotel research, Geetha et al. (2017) constructed a wordcloud as a visual representation of their findings. Notably, their analysis reveals a higher frequency of references to the terms "staff" and "service" in the context of premium hotels. Furthermore, Luo and Tang (2019) conducted a study on Airbnb ratings and found that the most important factor in selecting accommodations is location. Following the factor of location, the sentiment aspect of the product or service received a significantly high rating in terms of overall satisfaction. For managerial functions, hosts should provide the amenities or services that visitors like in order to provide them a lodging experience that feels like home (Luo and Tang, 2019).

For restaurants, Li et al. (2023) initiated a study to determine the significance of several aspect-based sentiments in predicting the survival of these establishments. After dividing the sample into independent and chain businesses and low and high price levels, they also carried out feature importance analyses individually. The researchers discovered that the tastiness of the food played a significant role in predicting the survival of chain restaurants. In contrast, sentiment towards service, location, and price was found to have a more significant impact on independent restaurants. Additionally, a study carried out by Yu et al. (2017) also explored a similar research topic, albeit with a specific focus on the different cuisines offered by restaurants and the variations in aspects and sentiments towards them. The researchers noted that a key issue faced by Italian, French, and eastern Asian restaurants is the problem of high prices. On the other hand, Chinese and Vietnamese restaurants tend to receive worse ratings due to the rude behaviour shown by their waiters.

1.2.3 Temporal Analysis

When analysing online reviews of hotels and restaurants, using temporal analysis can offer insights into how customer opinions and sentiments change over a specific period of time. This can help businesses spot patterns and trends in customer feedback and make adjustments accordingly. Additionally, temporal analysis can help businesses track the effectiveness of changes made to address customer concerns.

1.2.3.1 Trend Analysis

Trend analysis is the identification and interpretation of patterns and trends over time. In the context of hotel and restaurant reviews, this analysis has the ability to offer valuable findings regarding the changing preferences of customers and any arising issues. The research presented by Ye et al. (2018) aimed to gain insights into the temporal trends linked to tourists' preferences for accommodations. Seasonal analysis was conducted to determine the specific months during which travellers are most inclined to choose a certain hotel or area for their stay. The counting of reviews was performed based on a certain time unit, such as monthly intervals, in order to provide time-series data that accurately depicted temporal patterns. While it is acknowledged that not all tourists included comments regarding the duration of their visit, the variations in review numbers across different months could potentially reveal temporal trends.

Another relevant example is how Huang et al. (2022) used reviews from certain time periods to continuously monitor changes in the volume of restaurant complaints involving COVID-19 over time. The line chart presented below depicts the seven-day moving average of consumer complaints and COVID-19 instances throughout the period of May to June in the year 2020. Using this approach, researchers are able to analyse the data pattern indicating a correlation between the amount of daily complaints regarding restaurants' violations and the occurrence of COVID-19 cases.

1.2.3.2 Time-series Cross-correlation

Cao et al. (2021) used the time-series cross-correlation methodology to assess the potential connection between the temporal patterns of restaurant reviews and the

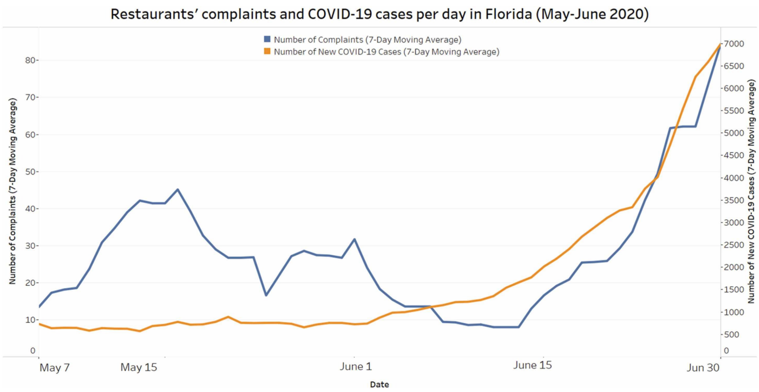


Figure 1.4: Line chart from Huang et al. (2022)

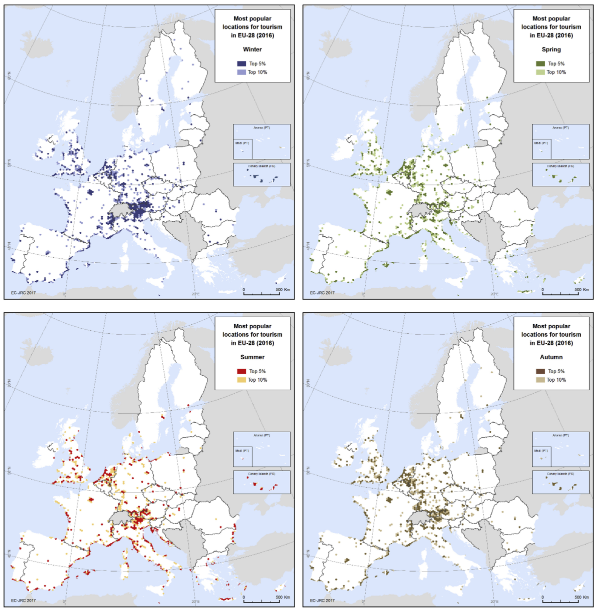


Figure 1.5: Most popular locations for tourism per season from Batista e Silva et al. (2018)

rise of the COVID-19 pandemic. The time series data is first extracted from both Yelp reviews and the COVID-19 statistics time series. Two correlation approaches were used in the study: Spearman's Correlation, which assumes a monotonic but potentially non-linear relationship between the two time series, and Pearson's Correlation metric, which served as a means of verifying the robustness of the results (Cao et al., 2021).

1.2.3.3 Results and Conclusion

By conducting temporal analyses of reviews, valuable tourist trends for hotels and restaurants can be observed, which are also closely linked to geospatial analysis. Batista e Silva et al.'s (2018) research on tourism in Europe shows that many destinations in Europe see the highest concentration of tourists during the month of August. Furthermore, large cities exhibit consistently high levels of tourism throughout the year, while specific regions, such as coastal areas in certain countries, have peak popularity exclusively during the summer season.

1.2.4 Geospatial Analysis

The utilisation of geospatial analysis in the study of hotel and restaurant reviews is a useful way for businesses to gain insight regarding variations in customer sentiment and preferences across different regions. Through the process of mapping the geographical locations of reviewers and their corresponding comments, businesses can identify distinct patterns and trends within consumer feedback. This information allows businesses to make appropriate adjustments to their strategies in order to better cater to customer demands.

1.2.4.1 Spatial Clustering

In their study, Hasnat and Hasan (2018) utilised three clustering techniques, namely K-Means (Kanungo et al., 2002), density-based spatial clustering of applications with noise (DBSCAN) developed by Ester et al. (1995), and Mean-Shift introduced by Comaniciu and Meer (2002), to analyse the spatial patterns of destination choices made by both tourists and residents. The primary objective of the clustering analysis was to identify the regions or areas in the state of Florida that were frequented by tourists and locals. The centres of each cluster have been identified in all three methods based on the output clusters. Furthermore, they also determined the number of unique users and the number of sample coordinates that composed each cluster. The reason for trying three separate approaches was to identify the most effective method for efficiently organising the coordinates into discernible clusters in real-time.

1.2.4.2 Hotspot Analysis

The study conducted by Beneki and Spiggos (2021) uses the Getis-Ord Gi* statistic as a means to detect shot spots and cold spots in terms of the quantity of reviews received by restaurants. Hotspots and coldspots were used as measures to identify geographical locations where restaurants exhibit a significant difference in the number of reviews received based on their surrounding area. To be more specific, the study applied the Getis-Ord Gi* and the Anselin Local Moran's I techniques to examine spatial patterns by placing restaurants within a specified area and comparing their statistical outcomes with the previously defined global results. In Huang et al.'s (2022) study, the authors used a similar approach to examine the variations in

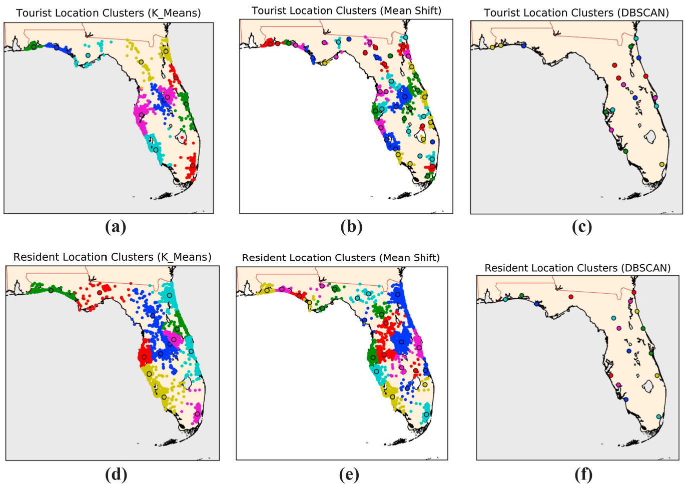


Figure 1.6: Centres of clusters in all the three different methods from Hasnat and Hasan (2018)

restaurant violations and COVID-19 cases at the county level. They conducted a hotspot analysis by using the ArcGIS tool to calculate the Getis Ord Gi* statistics.

Another example of this is where Jing et al. (2020)) adopted the Kernel Density estimation (KDE) technique to identify and analyse the spatial density and hotspots within the city of Beijing, China. The KDE technique is a robust spatial analysis method used for converting a group of points spread across a geographic area into a smooth surface. This process also estimates the density values for the given points (Nakaya and Yano, 2010). The KDE methodology focuses mostly on the study of spatial patterns within data. Conversely, clustering techniques prioritise the classification of data and the exploration of the spatial clusters presented by geographical phenomena (Kalinic and Krisp, 2018). As a result, the researchers chose KDE as a method of choice to examine the spatial distribution of tourists and identify tourist hotspots.

1.2.4.3 Results and Conclusion

Batista e Silva et al. (2018) have demonstrated in their study how different areas in Europe fluctuate in popularity, which connects back to the findings in the temporal analysis section. One of their findings is that the centre and western regions of Europe, particularly nations such as the Netherlands, Germany, and Britain, exhibit consistently high levels of tourist activity throughout the year. A possible reason for this trend could be attributed to the high population density and the specific kind of tourism, such as business or cultural, which may not be as susceptible to changing seasons. By using spatial analysis, Huang et al. (2022) were also able to identify notable clusters of customer complaints regarding restaurant violations and COVID-19 cases in Florida counties. The popular tourist destinations in the state of Florida, such as Orlando and Miami, revealed a considerably higher number of complaints related to restaurant violations and COVID-19 cases in comparison to other counties.

1.2.5 Datasets

Since most of the research papers analysed are in the context of hotels and restaurants, the datasets that are most widely used are from TripAdvisor and Yelp. A majority of the papers surrounding hotels use TripAdvisor, and this is no surprise as it is one of the largest travel guidance platforms with more than a billion reviews, and it is also available in 22 languages (TripAdvisor, 2023). Additionally, for Zhang et al. (2022)'s study, the platform's user profiles hold crucial information pertaining to the user's identity, including self-reported locations. These details can be used to determine the spatial and cultural distance to hotel locations. TripAdvisor also offers users the ability to rate four key aspects: location, cleanliness, service, and value. This feature proves to be particularly useful for research focused on aspect detection.

Another popular platform for hotels is Booking.com, one of the leading third-party hotel reservation websites with a massive number of consumer reviews. One notable characteristic that distinguishes this platform is the implementation of a customer review verification system. Specifically, the platform restricts the ability to post comments and ratings to customers who have made room bookings through the website. This measure helps authenticate the reviews and minimise the possibility of fraudulent or fake reviews (Xu et al., 2017).

When considering restaurants, Yelp stands as a highly favoured platform for extracting and analysing review data. One helpful aspect of Yelp is that it allows for researchers to examine users' past review behaviours. This can be accomplished by looking at the quantity of reviews they have posted and their previous rating patterns, which are measured by the average number of stars assigned to all their Yelp reviews (Gan et al., 2017).

1.3 Summary of the State of the Art

1.3.1 Sentiment Analysis and Aspect Detection

For both sentiment analysis and aspect detection, the state of the art methodologies typically involve transformer-based deep learning models, with particular emphasis on BERT (Bidirectional Encoder Representations from Transformers). These models are popular due to their greater understanding of context supported by attention mechanisms (Devlin et al., 2018). Apart from that, it is important to note that the Cloud Natural Language Processing API developed by Google is also widely regarded as being state of the art. This is mainly due to its use of advanced multi-layer ANN models, which can effectively uncover the underlying structure and semantic meaning of textual data (Al-Natour and Turetken, 2020).

1.3.2 Spatio-Temporal Analysis

According to Wang et al. (2020), modern techniques for temporal analysis primarily involve deep learning models, including recurrent neural networks (RNN) and variations such as Long Short-Term Memory (LSTM). These models have become the accepted standard for analysing sequential data. In the field of geospatial analysis, state of the art methodologies again mostly involve the use of advanced deep learning models, which possess the capability to capture spatial dependencies. Additionally, spatial auto-correlation and clustering algorithms are also often used to identify spatial clusters and patterns within large datasets.

1.3.3 Gap in Literature

A common subject for future investigation in research papers involves looking at reviews over varying time intervals. According to Luo and Xu (2021), their investigation on restaurant reviews focused on data collected during the first six months of 2020, a period marked by the COVID-19 pandemic. However, Luo and Xu (2021) suggest that future research endeavours could benefit from investigating datasets spanning longer timeframes, covering the periods preceding, during, and after the pandemic. This approach could lead to a better understanding of the changing trends in online restaurant reviews.

Another prevalent limitation found in many studies is the narrow geographical scope, often limited to a single city or country. Therefore, the applicability of their findings to other regions may be limited. An example of this can be found in the study conducted by Nie et al. (2023), which focused on the classification of several aspects of hospitality quality in the context of the COVID-19 pandemic. However, the study focused mainly on a particular region within China. Therefore, the authors expressed an intention to expand the scope of their future research into a national level analysis and investigate more regions.

Our proposed research aims to address the above gaps in the following manner:

- **Temporal Analysis**: In accordance with the recommendations from Luo and Xu (2021), our study will conduct an extensive temporal analysis of reviews. By grouping reviews into distinct temporal intervals spanning the periods before, during, and after the pandemic, we aim to analyse the change of sentiments and key aspects throughout the pandemic. This approach will enable us to gain a better grasp of the changing dynamics in customer reviews over time.

- **Geographical Scope**: Extending beyond the limitations of a singular geographical region, our study will adopt a broader perspective by including reviews from various countries. The overall goal of this broader perspective is to properly capture the wide spectrum of global sentiments, highlighting both common patterns and distinct regional variations. By including reviews from diverse geographical regions and analysing them, we aim to provide insights that are more universally applicable.

1.4 Research Project Plan

1.4.1 Data Collection and Preprocessing

The first step involves acquiring the necessary datasets for the analysis. Currently, numerous online review platforms are readily available on the internet. In particular, TripAdvisor and Booking.com are prominent platforms for hotel reviews. For restaurants, Yelp serves as a great source of data. However, it is important to acknowledge that Yelp does not have universal popularity. In Malaysia, the use of Yelp is not commonplace, resulting in a lack of reviews for most restaurants. In contrast, in the United States and other European countries, Yelp is widely used, leading to a substantial number of ratings for each restaurant. TripAdvisor can also serve as another platform for extracting restaurant reviews. While one dataset each for hotels and restaurants is sufficient for the analysis, it is preferable to employ two distinct datasets for each category in order to increase the robustness of the analysis. Besides that, we are also going to use another dataset containing worldwide COVID-19 case statistics from each country to address the second research question.

Following the methodology implemented by Ye et al. (2018), our proposed approach involves the creation of a web crawler with the goal of extracting various types of data from the travel platforms. This data includes the hotel's name and address, the date of the stay, the review text, and the country of origin of the reviewer. For most of the platforms, there are already certain aspects included in the reviews (e.g. cleanliness, service, location, value for money) that can be useful for further analysis.

Regarding temporal travel patterns, the calculation of reviews will be conducted based on a certain temporal unit, such as monthly or quarterly intervals.

We will also be following Chang et al.'s 2019 data preprocessing steps for the review data and we will be using Python's Natural Language Toolkit (NLTK):

1. The sentiment of reviews can be determined by assigning a rating of 1-3 stars for negative sentiment and 4-5 stars for positive sentiment.

2. Reviews that do not have any aspect label should be excluded from the analysis.

3. All words in the reviews should be converted to lowercase.

4. Punctuations, stop words, and words that appear less than 5 times in the corpus should be eliminated from the dataset.

5. Each word in the reviews should be stemmed to its root using the Porter Stemmer algorithm.

1.4.2 Research Hypotheses

Considering the research questions of this study, it is important that we formulate clear hypotheses that will serve as a framework for the following analysis. The hypotheses are:

1. Q1. How have the key aspects mentioned in customer reviews for restaurants and hotels changed during the COVID-19 pandemic, and which specific features were most frequently associated with positive or negative sentiments?

    - H1.1: During the COVID-19 pandemic, the importance of aspects such as hygiene, service, and safety measures have increased significantly, and reviews with positive sentiment are more likely to mention these.
    - H1.2: Negative sentiments in reviews are more strongly linked with aspects related to poor establishment maintenance and bad quality of service during the COVID-19 pandemic.

2. Q2. Are there observable regional differences in the volume and sentiment of reviews for restaurants and hotels during the COVID-19 pandemic, reflecting the varying impacts on each country's hospitality sector?

    - H2.1: Countries with higher COVID-19 case numbers and stricter restrictions will show a decline in the volume of positive reviews for restaurants and hotels

- H2.2: Countries that stabilised and controlled the spread of COVID-19 earlier will have a faster recovery in positive sentiment in reviews for their hospitality sector.

Having established these hypotheses, the following sections will discuss the specific approaches that will be employed to verify these assumptions and extract useful insights.

1.4.3 Lexicon-based Methodology for Sentiment Analysis

While deep learning models are currently considered the state of the art for sentiment analysis and spatio-temporal analysis, we have decided that the extensive development and training required for such models may be too time-consuming and resource-intensive. Furthermore, our research objectives do not necessitate extremely advanced sentiment analysis techniques to achieve the intended results. Therefore, to begin with, this study will implement a lexicon-based methodology, specifically utilising the SentiWords dictionary. This dictionary is well-known for its ensemble method, which is said to outperform standard lexicons such as SentiWordNet. Hence, it will provide the fundamental foundation for sentiment categorisation. However, the main challenge will be effectively capturing the various sentiments of this unusual period (COVID-19 pandemic), so we will likely be modifying and refining the lexicon.

For greater precision and to adjust for nuances that may be overlooked by the lexicon, we will use VADER (Valence Aware Dictionary and Sentiment Reasoner). VADER possesses unique features which include not only an extensive set of words, but also the inclusion of punctuation marks, capitalisation, degree modifiers, the presence of the conjunction such as "but," and negations (Mathayomchan and Taecharungroj, 2020). Therefore, sentiment scores will be calculated for each review using both SentiWords and VADER. By employing a combination of these two techniques, we can reduce the limitations or biases associated with a singular approach, and the aggregate score will demonstrate greater robustness. Furthermore, both SentiWords and VADER will be implemented in Python, with VADER even having its own 'vaderSentiment' library.

1.4.4 Topic Modelling with LDA

To begin the process of aspect detection, we will be using the previously defined lexicon-based approach. This strategy entails using predetermined lists of keywords or phrases that are commonly linked with the aspects of restaurants and hotels. For example, the notion of cleanliness can be implied by words or expressions like "clean," "tidy," or "well-maintained."

To complement the lexicon-based method and to pick up unexpected aspects, we'll use Latent Dirichlet Allocation (LDA). The use of the LDA technique allows for the detection of common themes or aspects within reviews by considering each review as an individual document (Guo et al., 2017). For example, in the case where many reviews contain terms such as "bed," "comfortable," and "sleep," the LDA algorithm can likely detect a topic relating to the level of comfort provided by hotel rooms. One notable benefit of LDA is its ability to identify hidden aspects that may not be clearly captured within a predefined lexicon (Guo et al., 2017).

Following Tirunillai and Tellis's (2014) explanation, the term "dimension" is defined as a core concept that is spread across a collection of words used by consumers to express their experiences with hotels. In the literature on LDA, these dimensions are also referred to as "topics." The literature refers to a review as a "document" which is comprised of a series of N words, denoted as $w = (w_1, w_2, \ldots, w_N)$. A corpus, denoted as $D = w_1, w_2, \ldots, w_M$, consists of M reviews. Additionally, it is assumed that the corpus consists of K dimensions, which include all M reviews within a specified time period (Tirunillai and Tellis, 2014). In terms of implementation, there are Python libraries such as 'gensim' that give implementations for various topic modelling techniques, including LDA and Latent Semantic Analysis (LSA). In addition, the 'scikit-learn' library also offers an implementation specifically for LDA.

1.4.5 Temporal Analysis and Visualisation

The main method used for temporal analysis will be the segmentation of the reviews into discrete time intervals. The time frame of performing this task can vary, either on a monthly or quarterly basis, contingent upon the quantity and level of detail of the data at hand. The sentiment scores obtained from the combined lexicon method (SentiWords and VADER) will be averaged at each interval to determine the leading sentiment during that specific time frame. Moreover, in order to determine the changing preferences of customers during the course of the pandemic, the number of references to significant factors such as hygiene, service, and safety will be measured for each time period. The trends, covering both sentiment and aspect detection, will then be visually represented through the use of line graphs or bar charts. This visual representation will serve to offer a clear and temporal summary of the changes in customer reviews.

The 'pandas' library in Python will be used for the handling and analysing of time-series data. Following that, the 'matplotlib' library offers a wide range of functions for visualising and analysing time-based trends. Apart from that, Tableau could also be used as a tool for visualising time-series data and identifying temporal patterns.

1.4.6 Geospatial Analysis and Map Visualisation

In the context of geospatial analysis, we will assign each review to their geographic location, determined by the country or city where the reviewed hotel or restaurant is located. The average sentiment scores will be determined for each of the geographic areas, using the combined lexicon approach. This analysis will identify specific areas that have received notably positive or negative comments. Furthermore, a frequency analysis will be conducted for each geographical area in order to detect the occurrences of certain key aspects (e.g. hygiene, service, etc.). This study will help reveal any regional sensitivities or preferences that have developed throughout the pandemic.

In order to visually represent the new insights, we will generate visualisations such as heat maps or choropleth maps. These maps will be color-coded to represent sentiment (e.g. blue for positive and red for negative), which will give a comprehensive view of regional sentiment trends. To enhance the depth of this analysis, we will use bar charts to visually show the distribution of key aspect mentions throughout different regions. Finally, an additional layer of COVID-19 statistics will be placed over the sentiment data in order to carry out a more comprehensive analysis of the relationship between the number of COVID-19 cases and the volume and sentiment of reviews in each respective country. Through the comparison of regional sentiments and the severity of the pandemic, we can get a deeper understanding of the the pandemic's impact on the hospitality sector across many locations.

In order to carry out these tasks, the Python libraries 'geopandas' and 'bokeh' will be used for the purpose of handling and visualising geospatial data. Additionally, Tableau might be used again due to its ability to generate interactive map visualisations and bar charts.

1.4.7 Concluding the Research

Following the end of the analysis, the study will conclude with an interpretation of the results within the context of the research questions and hypotheses. The study will highlight key findings, such as the aspects that were most frequently mentioned during the pandemic and the variations in sentiments across different regions. Based on the latest insights, this study aims to offer recommendations to the hospitality industry in order to improve their ability to respond to the changing tastes and concerns of their customers throughout both the current and post-pandemic periods.

1.5 Conclusion

The COVID-19 epidemic has had a major impact on various industries, and the hospitality sector finds itself at a major turning point amidst these significant changes. This study aims to break down the dynamic structure of customer reviews on platforms such as TripAdvisor and Yelp in the context of the recent pandemic. The primary approaches employed in this study will be the SentiWords and VADER techniques, which will facilitate the analysis of the overall sentiment expressed in the reviews. On top of that, the LDA technique will be used to identify particular topics or aspects that are currently receiving more attention in comments compared to previous times.

By looking into these reviews, our objective is to provide the hospitality industry with valuable insights regarding the changing preferences and concerns of customers. Recognising these changes is crucial for businesses in the hospitality sector, as it can guide them in making informed decisions and adjustments. Ultimately, this study aims to offer a guide for businesses to better cater to their customers, ensuring that even in the midst of a pandemic, the industry can continue to thrive and meet the needs of its clientele.

Chapter 2

Introduction

The COVID-19 pandemic has profoundly transformed the global hospitality industry, disrupting travel patterns and reshaping customer expectations. With global lockdowns, travel restrictions, and health protocols, hotels faced unprecedented challenges, necessitating rapid adaptation. This thesis explores the evolving sentiments in customer reviews of hotels before, during, and after the pandemic, providing insights into the aspects that customers valued or criticized the most.

Aspect-based sentiment analysis (ABSA) has emerged as a vital tool for understanding consumer opinions at a granular level. Unlike traditional sentiment analysis that classifies entire reviews as positive or negative, ABSA identifies specific aspects (e.g., cleanliness, staff, location) and assigns sentiment to each aspect. This granular understanding is crucial for hotels aiming to align their services with customer expectations.

2.1 Scope Adjustment from Initial Proposal

In the initial project proposal, the research scope included analyzing customer reviews for both hotels and restaurants. However, during the course of the study, we decided to focus exclusively on hotels. This decision was driven by several factors:

- Data Availability: There were significantly more reviews and complete data available for hotels compared to restaurants, especially in terms of keywords and aspects.

- Focused Analysis: Concentrating on one sector allowed for a more detailed and focused analysis, enhancing the quality and depth of the insights.

- Practical Considerations: Given the time and resource constraints, narrowing the scope to hotels made the research more manageable and achievable.

By refining the scope of the study, this research aims to provide a more comprehensive and in-depth understanding of the impacts of the COVID-19 pandemic on hotel reviews, offering valuable insights to stakeholders in the hospitality industry.

2.2 Research Questions

This research aims to address two primary questions:

1. How have the key aspects mentioned in customer reviews for hotels changed during the COVID-19 pandemic, and which specific features were most frequently associated with positive or negative sentiments?

2. Are there observable regional differences in the volume and sentiment of reviews for hotels during the COVID-19 pandemic, reflecting varying impacts on each country's hospitality sector?

2.3 Objectives and Contributions

To answer these questions, we combined multiple analytical approaches, leveraging PyABSA and simpler analyses like review length and star rating comparisons. The specific objectives of this study include:

- Creating and annotating a comprehensive dataset of hotel reviews, which includes pre-pandemic, pandemic, and post-pandemic periods.

- Training and fine-tuning a PyABSA model specifically for the hotel review dataset to improve the accuracy and relevance of aspect-based sentiment analysis.

- Exploring review length and star rating trends across different regions and timeframes.

- Identifying the most frequently mentioned aspects and their associated sentiments before and after the pandemic.

- Providing actionable insights for the hospitality sector to improve service quality and customer satisfaction.

Chapter 3

Background

3.1 Hotel Industry

The hotel industry plays a crucial role in the global economy, contributing significantly to employment, tourism, and overall economic growth. The industry encompasses a wide range of establishments, from luxury resorts to budget accommodations, and it is continuously evolving to meet the needs of travellers (Ivanov and Zhechev, 2012). In this context, customer reviews have emerged as a vital component of the hotel industry, influencing consumer behaviour and business performance.

3.1.1 Importance of Reviews in the Hotel Industry

Customer reviews serve as a source of information for potential guests, providing insights into the experiences of previous visitors. Reviews can cover a wide range of aspects, including room quality, cleanliness, staff behaviour, amenities, location, and overall value for money (Stringam and Gerdes Jr, 2010). Positive reviews can enhance a hotel's reputation, attract more customers, and increase revenue, while negative reviews can have the opposite effect, deterring potential guests and impacting the hotel's bottom line (Gursoy, 2019).

Moreover, reviews are not only beneficial for consumers but also for hotel management. They offer valuable feedback that can be used to improve services, address any issues, and raise guest satisfaction. The sentiment expressed in reviews provides direct insights into what customers appreciate or dislike, helping hotels to prioritise improvements and investments (Levy et al., 2013).

3.1.2 Impact of COVID-19 on the Hotel Industry

The COVID-19 pandemic has had a profound and unprecedented impact on the hotel industry, exacerbating the need for hotels to understand customer sentiment through online reviews. The implementation of travel restrictions, lockdowns, and social distancing measures led to a sharp decline in travel demand, resulting in significant financial losses for hotels worldwide (Gössling et al., 2020). Many establishments were forced to temporarily or permanently close their doors as a result of the sharp decline in occupancy rates and the loss of revenue streams (Baum and Hai, 2020).

The pandemic also reshaped customer expectations, with increased emphasis on hygiene, safety protocols, and contactless services (Nicola et al., 2020). Hotels had to adapt quickly to these new demands, implementing enhanced cleaning procedures, contactless check-in and check-out processes, and modified dining options to ensure the safety and well-being of their guests. During the pandemic, the nature and focus of customer reviews shifted. Hygiene and cleanliness became paramount concerns, with guests prioritising safety measures such as sanitisation, social distancing protocols, and contactless services (Foroudi et al., 2021).

As the industry begins to recover, understanding these shifts in customer sentiment is crucial for hotels to adapt and meet the evolving expectations of travellers. Analysing reviews from the pre-pandemic, pandemic, and post-pandemic periods provides valuable information into how guest priorities have changed and what aspects are now most critical.

3.2 Sentiment Analysis

Sentiment analysis (SA) is an area of research focused on analysing people's opinions, sentiments, evaluations, attitudes, and emotions on various topics, including products, services, organisations, individuals, issues, events, subjects, and their specific characteristics (Liu, 2022). In addition to the hospitality industry, sentiment analysis has proven to be advantageous in virtually every other sector, including commerce, finance and investment, product research and development, media, and so on. By investigating, evaluating, and organising this data, subsequent users are able to make more informed decisions (Ndoni et al., 2021). Researchers are now investigating many fields, such as sentiment classification, subjectivity classification, aspect-based sentiment analysis, and cross-domain sentiment analysis, in order to accomplish this goal. Sentiment analysis can be conducted at three distinct levels: document level, sentence level, and aspect level.

3.3 Aspect Extraction

Aspect extraction is an extensively studied area of natural language processing that involves identifying aspects from text in order to obtain insights (Mai and Zhang, 2020). Aspect extraction can be performed using many methods such as frequency-based, syntax-based, supervised or unsupervised machine learning, deep learning, and hybrid approaches (Ndoni et al., 2021). The most direct approach for aspect detection is through frequency-based approaches, which involve finding the nouns and noun phrases that are cited most frequently in a dataset of reviews (Hu and Liu, 2004). Another approach is syntax-based, which identifies aspects by analysing their syntactic relationship with other words in a sentence, and the key benefit of this approach is its ability to identify low-frequency aspects.

3.4 Aspect-Based Sentiment Analysis (ABSA)

The objective of aspect-based sentiment analysis (ABSA) is to determine the polarity of sentiment for each predefined aspect presented in a document (Ilmania et al., 2018). Both content and aspect influence a sentence's sentiment polarity.

Attention Mechanisms

In the realm of deep learning, attention mechanisms empower models to selectively focus on specific parts of the input text during prediction (Ilmania et al., 2018). This is particularly valuable in ABSA, where attention mechanisms can pinpoint the words or phrases most pertinent to a specific aspect. For example, in the sentence "The room was spacious and clean, but the breakfast was disappointing," an attention mechanism might emphasise "spacious," "clean," and "disappointing" when evaluating the sentiment associated with the aspects "room" and "breakfast," respectively. Notably, PyABSA incorporates attention mechanisms in several of its models, including the influential Transformer-based models like BERT and RoBERTa (Devlin et al., 2019).

Deep Learning Models

Deep learning models have revolutionised natural language processing (NLP) tasks, including ABSA, due to their capacity to discern intricate patterns within data.

- LSTM-based models (Hochreiter and Schmidhuber, 1997): These models excel at capturing sequential information in text, crucial for comprehending the context surrounding aspects and sentiments.

- GCN-based models (Zhang et al., 2019): By utilising graph structures to depict relationships between aspects and words, GCN-based models have the potential to enhance aspect extraction and sentiment classification.

- Transformer-based models (BERT, RoBERTa) (Devlin et al., 2019): Renowned for their ability to grasp contextual relationships in text, these models have achieved state-of-the-art performance across numerous ABSA tasks.

There are many advantages of employing deep learning models in ABSA. They can effectively process large datasets, learn complex representations, and generalise well to unseen data.

3.5 PyABSA

(Yang et al., 2023), is a modularised framework built on PyTorch, designed to facilitate reproducible ABSA research. Its modular design empowers users to easily customise and extend the framework, tailoring it to specific research requirements. PyABSA boasts an impressive collection of 29 models and 26 datasets, showcasing its adaptability to diverse research scenarios. The framework prioritises ease of use and reproducibility, enabling both novice and seasoned researchers to conduct ABSA experiments effectively.

3.5.1 Features

Model Training and Evaluation: PyABSA provides a user-friendly interface for training and evaluating ABSA models. Its configuration manager allows for easy customisation of hyperparameters and experimental settings. The metric visualiser automatically records, manages, and visualises various performance metrics, aiding in model selection and comparison. In our research, we utilised these features to systematically train and evaluate different PyABSA models on our hotel review dataset, identifying the most effective models for our specific tasks.

3.5.2 Aspect Term Extraction (ATE) and Aspect Sentiment Triplet Extraction (ASTE)

PyABSA provides comprehensive support for many fundamental ABSA subtasks, but these are the ones we have used: Aspect Term Extraction (ATE) and Aspect Sentiment Triplet Extraction (ASTE). ATE involves identifying the specific terms or entities in text that are being discussed or evaluated, while ASTE goes a step further by extracting triplets of aspect terms, their associated sentiment, and the opinion terms expressing that sentiment. In our research, we tested PyABSA's ATE and ASTE models for extracting relevant information from hotel reviews. This included identifying aspects like "room," "service," "location," and "cleanliness," as well as determining the sentiment (positive, negative, or neutral) associated with each aspect.

Chapter 4

Methodology

4.1 Data Collection

The data for this research was exclusively collected from TripAdvisor, a prominent online travel platform known for its huge repository of user-generated reviews on hotels, restaurants, and other travel-related services.

To collect the data, we utilised a web scraping approach using existing code from Scrapfly. It uses Python scripts to extract relevant information and stores it in a structured format for further analysis. The scraper extracted key information from each review such as: star rating, review text, review date, and also the metadata about the hotel being reviewed.

Volume and Scope of Collected Data

The web scraping process resulted in the collection of thousands of hotel reviews from various regions and time periods. The data spans multiple years, allowing for a detailed analysis of trends over time. Specifically, the dataset includes:

- Review Volume: Thousands of reviews, providing a robust sample size for statistical analysis.
- Temporal Range: Reviews from 2017 to 2023, covering pre-pandemic (2017-2019), pandemic (2020-2021), and post-pandemic (2022-2023) periods. This temporal span allows for a detailed analysis of changes over time.
- Geographical Diversity: Reviews from 18 major cities across three continents, enabling a comprehensive comparison of regional differences in customer sentiments. The cities included in the dataset are:

- Europe: London, Berlin, Rome, Paris, Copenhagen, Amsterdam, Madrid
- North America: New York, Toronto, Las Vegas, Mexico City
- Asia: Mumbai, Beijing, Bangkok, Kuala Lumpur, Singapore, Shanghai, Tokyo

While the data collection process was comprehensive, there were certain limitations. Firstly, the data is restricted to reviews published on TripAdvisor, which may not accurately reflect the opinions of all hotel guests. Although there are other platforms available, such as Google Reviews and Booking.com, we have chosen to only include reviews from TripAdvisor owing to limitations in time and resources.

4.2 Data Annotation

Table 3.1 lists the aspect categories and the associated words used to identify them during the annotation process.

The data annotation process was a critical step in ensuring the accuracy of the aspect-based sentiment analysis (ABSA). Given the complexity of customer reviews, a robust annotation framework was essential for capturing the nuances of sentiments towards various aspects of hotel services.

Annotation Guidelines

To maintain consistency and quality, a set of annotation guidelines was established. The key included:

1. Aspect Identification: Annotators were instructed to identify specific aspects mentioned in each review. These aspects included Staff & Service, Location, Comfort & Amenities, Food & Drink, Design & Maintenance, Cleanliness & COVID, Facilities, Value for Money, and Sustainability.

2. Sentiment Classification: Each identified aspect was classified based on the sentiment expressed by the reviewer. The sentiments were categorised as positive, negative, or neutral.

3. Handling Ambiguity: In cases where the sentiment was ambiguous, annotators were encouraged to use their judgement to determine the predominant sentiment. When in doubt, such cases were marked for review by a second annotator to ensure accuracy.

Aspect Category	Relevant Words
Staff & Service	staff, service, concierge, friendly, people, reception, front desk, waiter, bartender, helpful, kind, lady, gentleman, personnel, welcoming, hospitality, wait, accommodating, understaffed, request
Location	location, situated, located, position, near, walking distance, central, city centre, in the heart of, base, tram, metro, station, placement, outside, public transportation, bus, center
Value for Money	price, value, free, complimentary, voucher, worth, pay, refund, charge, discount, limited, waste
Food & Drink	delicious, tasty, breakfast, dinner, lunch, drinks, food, wine, coffee, cocktail, buffet, dessert, meal, dining, menu
Hotel Facilities	gym, spa, pool, sauna, garden, courtyard, lounge, bar, internet, restaurant, bistro, cafe, parking, terrace, gift store/shop, communal spaces, casino, fitness room
Cleanliness & COVID	mask, hygiene, clean, dirty, stain, smell, hoovering, dust, hand sanitiser, sanitation, disinfect, hair, smear, measures, COVID measures, protection screen, social distancing, safety
Comfort & Amenities	bed, room, suite, view, A/C, heating, dark, noise, temperature, hot, cold, noisy, quiet, bathroom, light, shower, water pressure, small, large, TV, kitchenette, toiletries, insulation, sound-proof, coffee machine, window, accommodation
Design & Maintenance	hotel, design, decor, interior, atmosphere, ambiance, leakage, maintenance, well-kept, beautiful, broken, faulty, lovely, gorgeous, decorated, elegant, luxury, damaged, modern, theme, setting
Sustainability	contribute, donate, green, eco, eco-conscious, sustainable, environmental, natural resources, climate, carbon neutrality, CO2, go green

Table 4.1: Aspect Categories and Relevant Words

To facilitate the annotation process, we used the customised annotation tool developed within the PyABSA framework as well as manual annotation through Visual Studio Code.

4.3 PyABSA

In our research, we leveraged PyABSA's capabilities to efficiently implement and experiment with different ABSA techniques. The choice of specific PyABSA models was guided by their suitability for our hotel review data and research questions, with reference to the model evaluation results in Appendix B of Yang et al. (2023).

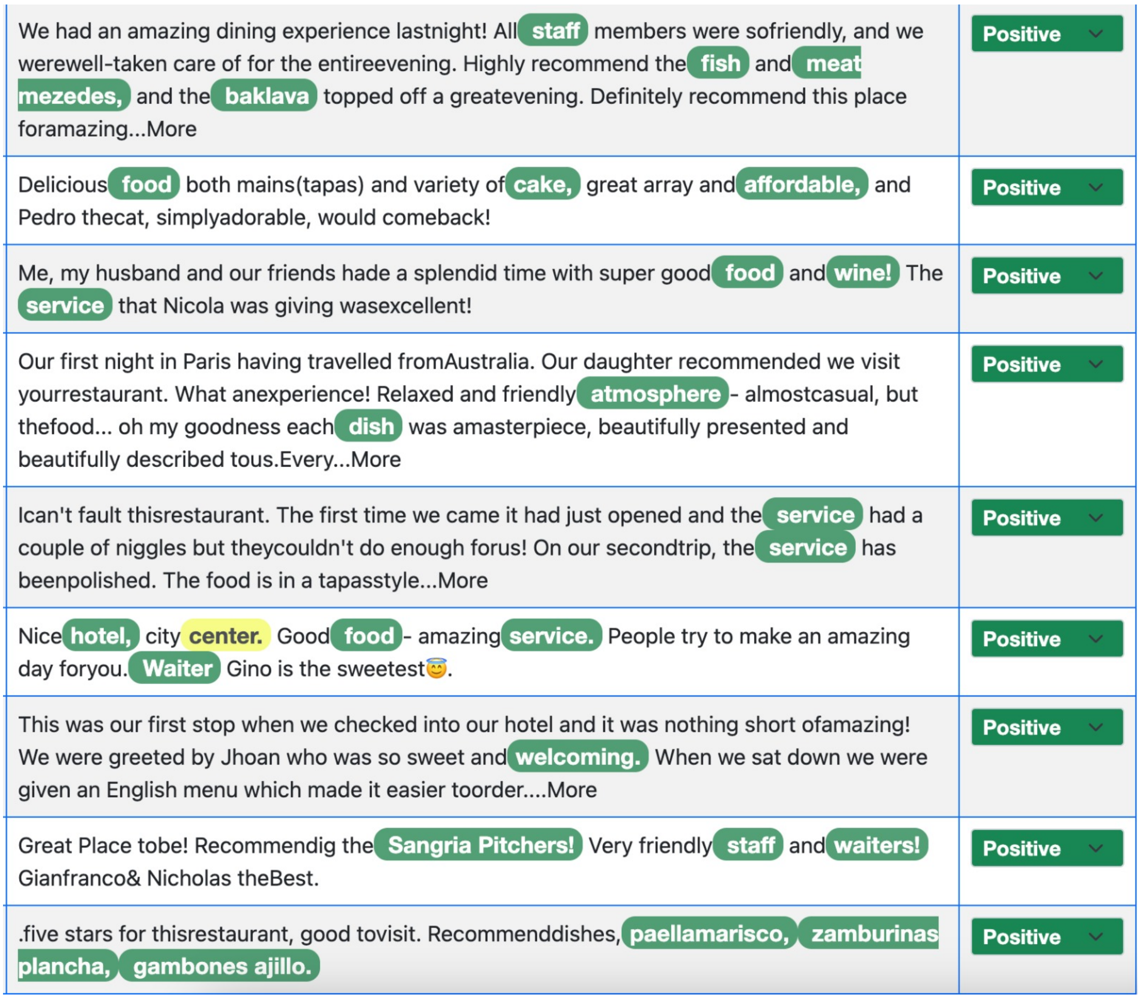


Figure 4.1: Snapshot of the Annotation Tool

The annotated dataset was used to train PyABSA models for aspect-based sentiment analysis. Two specific subtasks were selected:

1. Aspect Term Extraction Polarity Classification (ATEPC): This subtask focuses on identifying aspect terms and their sentiments within the review text.

2. Aspect Sentiment Triplet Extraction (ASTE): This subtask involves extracting triplets that include the aspect, the sentiment, and the opinion term related to the aspect.

4.3.1 Model Selection

In this study, three different pre-trained BERT models were tested to determine their effectiveness. The training process was carried out using the PyABSA library, and model performance was evaluated to select the best-performing model for each subtask.

Pre-trained BERT Models	
microsoft/deberta-v3-base	Known for its robust performance in various natural language processing tasks, DeBERTa (Decoding-enhanced BERT with disentangled attention) incorporates enhancements over the standard BERT architecture (He et al., 2020).
bert-base-cased	A standard BERT model with cased text, which helps in preserving the case information, potentially improving the handling of proper nouns and acronyms in reviews (Devlin et al., 2019).
yangheng/deberta-v3-base-absa	A model specifically fine-tuned for ABSA tasks, which was expected to perform well in extracting and classifying aspects and sentiments.

Table 4.2: Pre-trained BERT Models Tested

Table 3.2 details the configurations used for training these models. These configurations were selected based on prior research from (Yang et al., 2023) to ensure optimal performance for both ASTE and ATEPC tasks.

Model Configurations	
Batch Size	16
Dropout	0.5
Optimizer	AdamW
Max Sequence Length	128
Learning Rate	2e-5
Number of Epochs	30

Table 4.3: Model Configurations for ASTE and ATEPC

Model Training Results

The YangHeng Deberta and Microsoft Deberta models consistently outperformed the BERT-cased model across most metrics, indicating their superior capability in handling both aspect term extraction and sentiment classification.

However, there are some limitations to note. Despite being high, the ATE_F1 scores show that aspect term extraction can still be improved. Additionally, the low F1 scores in the ASTE task highlight the challenges in accurately extracting complete aspect-sentiment-opinion triplets, indicating the need for further refinement and training of the models.

Due to its strong performance in both accuracy and F1 metrics, we chose to use ATEPC as our PyABSA model and YangHeng's pre-trained Deberta model to carry out the sentiment analysis on our dataset.

Model	Metric	Value
ATEPC YangHeng Deberta	Accuracy	98.87%
	APC_F1	97.97%
	ATE_F1	84.94%
ATEPC BERT-cased	Accuracy	96.99%
	APC_F1	94.31%
	ATE_F1	82.01%
ATEPC Microsoft Deberta	Accuracy	98.50%
	APC_F1	97.16%
	ATE_F1	85.67%
ASTE YangHeng Deberta	F1	69.63%
ASTE BERT-cased	F1	64.85%
ASTE Microsoft Deberta	F1	70.00%

Table 4.4: Comparison of ATEPC and ASTE Models

4.4 Sentiment Analysis

Methodology for Calculating Aspect Sentiment Percentages

The analysis of hotel reviews involves evaluating the sentiment associated with various aspects of the hotels, such as Staff & Service, Location, Comfort & Amenities, etc. Each review can mention multiple aspects, and each aspect can be mentioned more than once within the same review. To derive meaningful insights, we performed the following steps:

1. **Aspect Identification and Sentiment Analysis:** Each review passed in was processed to identify mentions of specific aspects and the sentiment associated with each mention. This was done using a combination of natural language processing techniques and a pre-trained model.

2. **Counting Aspect Mentions:** For each review, every occurrence of an aspect was counted along with its associated sentiment. This means that if an aspect was mentioned multiple times within a single review, each mention was included in the count.

3. **Aggregating Counts:** The counts of each aspect's mentions (positive, negative, and neutral) were aggregated across all reviews. This provided the total number of times each aspect was mentioned with a specific sentiment across the entire dataset.

4. **Calculating Percentages:** The percentage of reviews mentioning each aspect with a particular sentiment was calculated by dividing the total count of that

sentiment for the aspect by the total number of reviews. This can be expressed with the following formula:

$$\text{Percentage} = \left(\frac{\text{Count of Sentiment for Aspect}}{\text{Total Number of Reviews}} \right) \times 100$$

For example, if the Staff & Service aspect was mentioned positively 5,000 times in a dataset of 25,000 reviews, the percentage of positive sentiment for Staff & Service would be calculated as:

$$\text{Percentage of Positive Sentiment} = \left(\frac{5000}{25000} \right) \times 100 = 20\%$$

This calculation assumes each aspect mention contributes independently to the sentiment analysis. However, in cases where an aspect is mentioned multiple times in a single review, the percentages may sum to more than 100%. This is a limitation of the current methodology, which will be addressed in future iterations by ensuring each aspect is only counted once per review.

Despite potential over-counting of aspects within single reviews, the percentages offer valuable insights into which aspects are most frequently discussed and how they are generally perceived by guests.

Dataset Sample Size

Due to time limitations and computational resource constraints, only 25,000 samples from each region were used for the analysis, instead of utilising the full dataset of over 300,000 reviews. This approach allowed for a more manageable analysis while still providing a representative overview of the sentiment trends in each region.

4.5 Additional Analyses

In addition to aspect-based sentiment analysis, several other analyses were conducted to gain insights into review patterns and trends:

1. Volume of Reviews: Reviews were categorised into three time periods, to analyse changes in the volume of reviews and identify patterns across different regions.

2. Length of Reviews Comparison by Region and Time: This analysis examined the average length of reviews over different regions and time periods to understand how review length might vary.

3. Star Rating of Reviews Comparison by Region and Time: This analysis compared the distribution of star ratings across different regions and time periods to identify any patterns or changes in customer satisfaction.

4. Correlation Between Review Length and Star Rating: This analysis explored the relationship between the length of reviews and their star ratings to determine if more detailed reviews correspond to higher or lower ratings.

To conduct these additional analyses, we utilised Python along with several other libraries. The data manipulation and aggregation were handled using Pandas, a data analysis library. Visualisation tasks, including generating bar charts and examining trends, were carried out using Seaborn and Matplotlib, which provide a wide range of plotting capabilities to represent data insights effectively. These tools enabled a comprehensive analysis of the review data, highlighting key patterns and trends across different regions and time periods.

Chapter 5

Results & Analysis

5.1 Analysis of Results

5.1.1 European Hotel Reviews

The sentiment analysis conducted on the Europe hotel reviews from 2017 to 2023 reveals significant insights into customer perceptions across various aspect categories. The analysis highlights the distribution of sentiments—positive, negative, and neutral—across different aspects.

Table 5.1: Sentiment Analysis of Hotel Reviews in Europe (2017-2023)

Aspect Category	**Positive (%)**	**Negative (%)**	**Neutral (%)**
Overall (2017-2023)			
Staff & Service	69.524	6.685	0.032
Location	65.088	2.924	0.020
Comfort & Amenities	59.655	17.926	0.232
Food & Drink	41.081	5.505	0.096
Design & Maintenance	24.275	3.316	0.044
Cleanliness & COVID	23.111	4.040	0.028
Facilities	18.354	3.224	0.024
Value for Money	12.970	3.988	0.008
Sustainability	0.760	0.088	0.000
2017			
Staff & Service	59.795	7.221	0.062
Location	67.897	3.282	0.041
Comfort & Amenities	59.200	17.231	0.246

Aspect Category	Positive (%)	Negative (%)	Neutral (%)
Food & Drink	38.769	6.379	0.082
Design & Maintenance	25.374	4.308	0.021
Cleanliness & COVID	20.636	2.995	0.041
Facilities	20.287	3.467	0.041
Value for Money	13.559	4.677	0.000
Sustainability	0.369	0.021	0.000
2018			
Staff & Service	60.577	7.350	0.043
Location	64.765	3.568	0.064
Comfort & Amenities	58.397	18.504	0.256
Food & Drink	39.167	5.321	0.107
Design & Maintenance	26.410	3.504	0.085
Cleanliness & COVID	20.385	3.248	0.021
Facilities	19.252	3.739	0.021
Value for Money	12.735	4.957	0.000
Sustainability	0.556	0.107	0.000
2019			
Staff & Service	65.265	7.137	0.022
Location	66.408	3.816	0.000
Comfort & Amenities	57.934	20.073	0.172
Food & Drink	41.462	6.468	0.172
Design & Maintenance	23.264	3.364	0.065
Cleanliness & COVID	22.208	4.463	0.022
Facilities	17.486	3.342	0.022
Value for Money	12.398	3.838	0.000
Sustainability	0.647	0.065	0.000
2020			
Staff & Service	62.879	6.926	0.000
Location	56.277	2.489	0.000
Comfort & Amenities	53.680	18.615	0.216
Food & Drink	37.446	6.818	0.000
Design & Maintenance	25.325	2.706	0.000
Cleanliness & COVID	23.810	4.004	0.000
Facilities	14.502	3.355	0.000
Value for Money	13.853	3.896	0.000
Sustainability	1.623	0.108	0.000

Aspect Category	Positive (%)	Negative (%)	Neutral (%)
2021			
Staff & Service	78.874	5.220	0.000
Location	63.214	2.121	0.000
Comfort & Amenities	66.150	17.292	0.489
Food & Drink	40.620	4.568	0.000
Design & Maintenance	26.672	2.365	0.000
Cleanliness & COVID	26.917	4.486	0.000
Facilities	16.721	2.284	0.000
Value for Money	11.093	3.589	0.082
Sustainability	1.060	0.082	0.000
2022			
Staff & Service	79.263	5.917	0.052
Location	65.819	2.284	0.000
Comfort & Amenities	61.069	17.571	0.208
Food & Drink	43.654	4.983	0.078
Design & Maintenance	23.462	3.063	0.052
Cleanliness & COVID	25.539	5.191	0.000
Facilities	16.818	2.310	0.026
Value for Money	12.640	3.063	0.000
Sustainability	0.831	0.078	0.000
2023			
Staff & Service	83.316	5.999	0.000
Location	62.862	1.875	0.000
Comfort & Amenities	61.362	16.309	0.208
Food & Drink	43.678	4.270	0.083
Design & Maintenance	21.891	2.645	0.021
Cleanliness & COVID	26.099	4.437	0.062
Facilities	18.746	3.312	0.021
Value for Money	13.726	3.353	0.021
Sustainability	1.166	0.167	0.000

Patterns and Trends

Pre-Pandemic Trends (2017-2019)

Before the pandemic, Staff & Service showed consistent improvement in positive sentiment, rising from 59.80% in 2017 to 65.27% in 2019. This indicates a steady increase in guest satisfaction with hotel services. Location maintained high positive sentiment throughout this period, with slight fluctuations, reflecting consistent approval of hotel locations. Comfort & Amenities also received positive feedback, though the negative sentiment remained high, peaking at 20.07% in 2019, indicating persistent issues in this area.

Pandemic Period (2020-2021)
During the pandemic, sentiment dynamics changed notably. The positive sentiment for Staff & Service dropped slightly to 62.88% in 2020 but then increased significantly to 78.87% in 2021, reflecting efforts to maintain service quality despite challenges. Comfort & Amenities saw a decrease in positive sentiment to 53.68% in 2020, likely due to restrictions and reduced services. Additionally, Cleanliness & COVID emerged as a critical category during this period, with positive sentiments increasing to 26.92% in 2021, indicating guests' appreciation for improved hygiene measures. However, the negative sentiment for cleanliness also increased, reflecting complications with sanitation standards.

Post-Pandemic Trends (2022-2023)
Post-pandemic, Staff & Service continued to show strong positive feedback, increasing to 79.26% in 2022 and 83.32% in 2023, indicating a recovery and improvement in service quality. Comfort & Amenities showed improvement in positive sentiment, reaching 61.36% in 2023, though the negative sentiment remained high, indicating ongoing mixed experiences. The Cleanliness & COVID category maintained its importance, with positive sentiments around 25-26%. 'Facilities' also saw positive feedback recovering to 18.75% in 2023, suggesting that guests were regaining access to hotel amenities and were largely satisfied with them.

Certain aspects like Design & Maintenance, Value for Money, and Sustainability showed relatively stable trends over the years with no significant fluctuations. These aspects maintained consistent feedback, which is why they were not discussed in detail. For instance, Design & Maintenance and Value for Money had stable positive and negative sentiments, indicating that guest perceptions in these areas remained largely unchanged. Sustainability was infrequently mentioned, suggesting it was not a major concern for guests.

5.1.2 American Hotel Reviews

The sentiment analysis of American hotel reviews from 2017 to 2023 is covered in this section.

Table 5.2: Sentiment Analysis of Hotel Reviews in North America (2017-2023)

Aspect Category	Positive (%)	Negative (%)	Neutral (%)
Overall (2017-2023)			
Staff & Service	53.916	11.316	0.004
Location	22.472	1.604	0.008
Comfort & Amenities	52.088	16.276	0.088
Food & Drink	26.264	4.384	0.040
Design & Maintenance	19.120	4.504	0.040
Cleanliness & COVID	19.484	5.964	0.008
Facilities	26.320	6.220	0.028
Value for Money	9.924	8.872	0.000
Sustainability	0.464	0.076	0.000
2017			
Staff & Service	50.858	8.576	0.000
Location	26.819	1.845	0.000
Comfort & Amenities	61.331	16.138	0.156
Food & Drink	25.234	3.612	0.026
Design & Maintenance	20.478	4.938	0.026
Cleanliness & COVID	17.568	3.768	0.000
Facilities	26.767	6.003	0.052
Value for Money	13.591	7.069	0.000
Sustainability	0.260	0.104	0.000
2018			
Staff & Service	49.590	8.882	0.000
Location	24.205	1.558	0.042
Comfort & Amenities	53.315	14.018	0.084
Food & Drink	26.921	3.957	0.084
Design & Maintenance	19.638	3.662	0.105
Cleanliness & COVID	15.513	3.220	0.021
Facilities	25.363	5.304	0.084
Value for Money	11.177	8.546	0.000
Sustainability	0.526	0.042	0.000
2019			
Staff & Service	54.367	10.426	0.000
Location	23.736	1.546	0.000
Comfort & Amenities	57.125	15.420	0.146

Aspect Category	Positive (%)	Negative (%)	Neutral (%)
Food & Drink	29.315	4.471	0.021
Design & Maintenance	20.623	4.806	0.021
Cleanliness & COVID	20.184	4.012	0.000
Facilities	29.127	5.725	0.000
Value for Money	11.158	9.110	0.000
Sustainability	0.543	0.042	0.000
2020			
Staff & Service	53.804	12.314	0.078
Location	15.843	1.569	0.000
Comfort & Amenities	50.431	12.000	0.078
Food & Drink	25.255	4.941	0.000
Design & Maintenance	17.804	3.373	0.000
Cleanliness & COVID	25.647	6.745	0.078
Facilities	18.039	5.961	0.000
Value for Money	9.255	7.765	0.000
Sustainability	0.784	0.078	0.000
2021			
Staff & Service	51.971	15.851	0.000
Location	15.721	1.776	0.000
Comfort & Amenities	42.832	16.501	0.000
Food & Drink	22.477	4.807	0.000
Design & Maintenance	15.894	4.764	0.000
Cleanliness & COVID	22.044	10.091	0.000
Facilities	23.647	8.229	0.000
Value for Money	7.579	10.394	0.000
Sustainability	0.346	0.043	0.000
2022			
Staff & Service	58.061	14.013	0.000
Location	20.568	1.607	0.000
Comfort & Amenities	47.338	19.463	0.000
Food & Drink	26.770	5.575	0.100
Design & Maintenance	18.734	4.771	0.025
Cleanliness & COVID	20.768	8.589	0.000
Facilities	28.478	7.057	0.025
Value for Money	7.383	10.673	0.000
Sustainability	0.502	0.025	0.000

Aspect Category	Positive (%)	Negative (%)	Neutral (%)
2023			
Staff & Service	58.434	12.275	0.000
Location	22.623	1.408	0.000
Comfort & Amenities	46.382	18.153	0.099
Food & Drink	24.846	3.927	0.000
Design & Maintenance	18.079	4.668	0.049
Cleanliness & COVID	20.474	8.397	0.000
Facilities	25.710	6.199	0.000
Value for Money	7.557	8.397	0.000
Sustainability	0.420	0.198	0.000

Patterns and Trends

Pre-Pandemic Trends (2017-2019)

Before the pandemic, Staff & Service consistently showed strong positive sentiments, peaking at 54.37% in 2019. The Location category maintained a positive sentiment of around 23-27%, reflecting consistent guest satisfaction with hotel locations. Comfort & Amenities showed positive feedback ranging from 53.31% to 61.33%, indicating a general appreciation for these aspects. However, this category also had one of the higher negative sentiments, peaking at 16.14% in 2017, reflecting areas where guests felt improvements were needed.

Pandemic Period (2020-2021)

During the pandemic years, the sentiment dynamics shifted. The positive sentiment for Comfort & Amenities dropped to 50.43% in 2020 and further to 42.83% in 2021, reflecting the impact of COVID-19 on guest experiences. Cleanliness & COVID became a more prominent category during this period, with positive mentions rising to 25.65% in 2020 and 22.04% in 2021, indicating guests appreciated heightened hygiene measures. However, the negative sentiment for cleanliness also increased, suggesting concerns about sanitation. The 'Facilities' aspect was notably impacted, with positive sentiment dropping to 18.04% in 2020 from 29.13% in 2019, reflecting possible closures or limited access to hotel amenities due to pandemic restrictions.

Post-Pandemic Trends (2022-2023)

Post-pandemic, there were noticeable improvements in several aspects. Staff & Service saw an increase in positive mentions to 58.06% in 2022 and 58.43% in 2023, indicating a recovery in service quality. The negative sentiment for this category decreased compared to 2021. Comfort & Amenities remained a mixed category with positive feedback at 47.34% in 2022 and 46.38% in 2023, but with a high negative sentiment around 18-19%, suggesting ongoing issues in these areas. The focus on Cleanliness & COVID persisted, with consistent positive and negative sentiments.

5.1.3 Asia Hotel Reviews

This section discusses the sentiment analysis of hotel reviews from Asia from 2017 to 2023.

Table 5.3: Sentiment Analysis of Hotel Reviews in Asia (2017-2023)

Aspect Category	**Positive (%)**	**Negative (%)**	**Neutral (%)**
Overall (2017-2023)			
Staff & Service	94.845	5.836	0.004
Location	27.073	1.385	0.004
Comfort & Amenities	51.929	7.609	0.084
Food & Drink	49.360	4.807	0.068
Design & Maintenance	17.651	2.293	0.008
Cleanliness & COVID	16.783	2.057	0.012
Facilities	24.928	2.910	0.024
Value for Money	9.926	2.826	0.012
Sustainability	1.097	0.048	0.000
2017			
Staff & Service	67.142	7.586	0.000
Location	35.981	3.039	0.000
Comfort & Amenities	59.116	11.735	0.063
Food & Drink	40.675	6.811	0.147
Design & Maintenance	17.938	3.332	0.000
Cleanliness & COVID	14.229	3.311	0.021
Facilities	31.769	4.065	0.063
Value for Money	12.343	5.448	0.042
Sustainability	0.587	0.021	0.000
2018			
Staff & Service	74.173	7.415	0.023
Location	33.151	1.574	0.000
Comfort & Amenities	57.426	9.537	0.205
Food & Drink	42.505	5.248	0.023
Design & Maintenance	19.325	2.898	0.000

Aspect Category	Positive (%)	Negative (%)	Neutral (%)
Cleanliness & COVID	14.944	2.441	0.046
Facilities	29.204	3.536	0.000
Value for Money	12.001	3.605	0.023
Sustainability	0.913	0.068	0.000
2019			
Staff & Service	90.610	5.863	0.000
Location	30.420	1.277	0.000
Comfort & Amenities	51.558	7.897	0.087
Food & Drink	50.974	4.587	0.065
Design & Maintenance	18.672	2.640	0.022
Cleanliness & COVID	15.058	1.947	0.000
Facilities	26.612	3.354	0.043
Value for Money	10.710	2.834	0.000
Sustainability	0.844	0.043	0.000
2020			
Staff & Service	106.479	4.379	0.000
Location	19.796	0.840	0.000
Comfort & Amenities	49.310	6.119	0.060
Food & Drink	52.669	4.379	0.060
Design & Maintenance	19.196	2.100	0.060
Cleanliness & COVID	21.236	1.620	0.000
Facilities	19.616	2.040	0.060
Value for Money	10.438	2.340	0.000
Sustainability	1.560	0.060	0.000
2021			
Staff & Service	115.342	5.559	0.000
Location	10.117	0.111	0.000
Comfort & Amenities	45.081	4.558	0.000
Food & Drink	55.753	4.447	0.056
Design & Maintenance	12.563	1.001	0.000
Cleanliness & COVID	20.289	1.334	0.000
Facilities	12.285	2.223	0.000
Value for Money	7.337	0.889	0.000
Sustainability	1.501	0.000	0.000
2022			
Staff & Service	116.765	4.939	0.000

Aspect Category	**Positive (%)**	**Negative (%)**	**Neutral (%)**
Location	19.861	0.591	0.000
Comfort & Amenities	44.626	5.183	0.000
Food & Drink	50.957	4.487	0.070
Design & Maintenance	14.400	1.217	0.000
Cleanliness & COVID	19.165	1.670	0.000
Facilities	20.904	2.052	0.000
Value for Money	7.061	1.635	0.000
Sustainability	1.565	0.000	0.000
2023			
Staff & Service	120.140	3.802	0.000
Location	22.623	1.408	0.000
Comfort & Amenities	48.027	4.624	0.082
Food & Drink	24.846	3.927	0.000
Design & Maintenance	18.167	1.582	0.000
Cleanliness & COVID	20.474	8.397	0.000
Facilities	25.710	6.199	0.000
Value for Money	7.557	8.397	0.000
Sustainability	0.420	0.198	0.000

Patterns and Trends

Pre-Pandemic (2017-2019)
Before the pandemic, the positive sentiment for Staff & Service steadily increased from 67.14% in 2017 to 90.61% in 2019, showing a marked improvement in service quality. Comfort & Amenities also saw positive feedback, though the negative sentiment remained noticeable. Food & Drink experienced an upward trend in positive sentiment, reaching 50.97% in 2019. Location maintained moderate positive feedback, and 'Facilities' showed strong positive sentiments around 30% in 2017 and 26.61% in 2019.

Pandemic (2020-2021)
During the pandemic, several changes were observed. The Staff & Service category saw an extreme increase in positive sentiment, peaking at 106.48% in 2020 and 115.34% in 2021, indicating extraordinary efforts by the staff to maintain service standards and to provide excellent care for quarantined guests. The Cleanliness & COVID category gained importance, with positive sentiment increasing to 21.24% in 2020 and maintaining a similar level in 2021, reflecting the increased focus on

hygiene. Positive sentiment for Location dropped considerably during the pandemic (reaching a low of 10.1% in 2021), demonstrating the impact of COVID-19 on this aspect's importance. This could be that due to the regulations, the majority of guests were unable to leave the hotel premises regardless.

Post-Pandemic (2022-2023)
Post-pandemic, Staff & Service continued to receive exceptionally high positive feedback, with 116.77% in 2022 and 120.14% in 2023, indicating continued excellence in service quality. Positive mentions for Location experienced a significant surge post-pandemic, reaching 22.6% in 2023. However, in this case, negative sentiment also saw an increase. Besides that, Cleanliness & COVID continued to be a concern, maintaining positive sentiment around 20-21%, indicating ongoing importance of hygiene measures for guests.

5.2 Comparison Between Regions

Table 5.4: Sentiment Analysis of Hotel Reviews Across Regions in 2023

Aspect Category	Europe (%)	Americas (%)	Asia (%)
Staff & Service			
Positive	69.524	53.916	94.845
Negative	6.685	11.316	5.836
Neutral	0.032	0.004	0.004
Location			
Positive	65.088	22.472	27.073
Negative	2.924	1.604	1.385
Neutral	0.02	0.008	0.004
Comfort & Amenities			
Positive	59.655	52.088	51.929
Negative	17.926	16.276	7.609
Neutral	0.232	0.088	0.084
Food & Drink			
Positive	41.081	26.264	49.36
Negative	5.505	4.384	4.807
Neutral	0.096	0.04	0.068
Cleanliness & COVID			
Positive	23.111	19.484	16.783

Aspect Category	Europe (%)	Americas (%)	Asia (%)
Negative	4.04	5.964	2.057
Neutral	0.028	0.008	0.012
Facilities			
Positive	18.354	26.32	24.928
Negative	3.224	6.22	2.91
Neutral	0.024	0.028	0.024
Value for Money			
Positive	12.97	9.924	9.926
Negative	3.988	8.872	2.826
Neutral	0.008	0	0.012
Sustainability			
Positive	0.76	0.464	1.097
Negative	0.088	0.076	0.048
Neutral	0	0	0

Patterns in General

Europe In Europe, Staff Service is the most important aspect, with a high positive sentiment of 69.52%, indicating that guests greatly value the quality of service provided by hotel staff. Following closely is the Location aspect, which also receives high positive feedback at 65.09%, showing that the convenience and strategic positioning of hotels are crucial for European guests. Notably, Europe prioritises Location far more than North America and Asia, surpassing them by nearly 40%. Besides that, Comfort & Amenities was another significant aspect, with 59.65% of the reviews mentioning it positively. This reflects guests' appreciation for comfortable rooms, good air conditioning, and other in-room amenities. However, this category also had a notable negative sentiment, with 17.93% of reviews expressing dissatisfaction, indicating areas like room size, noise levels, or temperature control might need improvement. Sustainability is the least important aspect, with only 0.76% positive sentiment, indicating that environmental concerns are not a primary focus for guests in this region.

North America In North America, Staff & Service is again the most critical aspect, with a significant positive sentiment of 53.92%. However, there is a noticeable emphasis on Facilities, with a positive sentiment of 26.32%, showing that amenities like pools and gyms are particularly valued. An interesting thing to note is that the

Value for Money aspect has the smallest disparity between positive and negative sentiment compared to the other regions. This could indicate that for some guests, the cost may have been justified by the quality of service, amenities, and overall experience, while others may have felt that the price did not match the quality of the hotel. Additionally, Food & Drink is significantly less valued in North America compared to Europe and Asia. On the other hand, Sustainability remains the least important aspect, similar to Europe, with a very low positive sentiment of 0.46%.

Asia In Asia, Staff Service stands out as the overwhelmingly most important aspect, with an exceptionally high positive sentiment of 94.85%, highlighting the emphasis placed on hospitality and service quality. Comfort & Amenities also has the lowest negative sentiment compared to the other regions, suggesting that guests are largely satisfied with the comfort and quality of their rooms. Additionally, Food Drink is highly valued, with 49.36% positive sentiment, indicating the significance of dining options for guests. Sustainability, though slightly higher than in other regions, remains the least important aspect with 1.10% positive sentiment.

Patterns According to Time Period

Pre-Pandemic (2017-2019)

In Europe, Staff Service improved steadily, while Comfort Amenities had a mix of positive and negative sentiments. North America showed stable positive sentiment for Staff Service and notable positive feedback for Comfort Amenities, although this aspect also had significant negative sentiment. In Asia, there was a steady improvement in Staff Service, with high positive sentiment for Comfort Amenities and Food Drink.

Pandemic (2020-2021)

During the pandemic, Europe saw an increase in positive sentiment for Staff Service, with continued importance placed on Cleanliness COVID. In North America, there was a noticeable decline in positive sentiment for Comfort Amenities, accompanied by an increase in negative sentiment for Cleanliness COVID. Asia experienced a sharp increase in positive sentiment for Staff Service, highlighting the high importance of Cleanliness COVID during this period.

Post-Pandemic (2022-2023)

Post-pandemic, Europe maintained a high positive sentiment for Staff Service, along with a slight recovery in Comfort Amenities. North America displayed a gradual recovery in Staff Service, but feedback for Comfort Amenities remained mixed. Asia continued to have exceptionally high positive sentiment for Staff Service, with consistent positive feedback for Comfort Amenities and Food Drink.

5.3 Secondary Analyses

The following section presents a secondary analysis of the hotel reviews. The data is divided into four analyses: the volume of reviews by region and time period, the average review rating by region and year, the average review length by region and year, and the correlation between review length and rating. Each analysis is discussed in detail to uncover trends, patterns, and insights.

5.3.1 Volume of Reviews by Region and Time Period

This graph displays the number of reviews categorised by region and time period. This analysis shows how the volume of reviews fluctuate according to different factors.

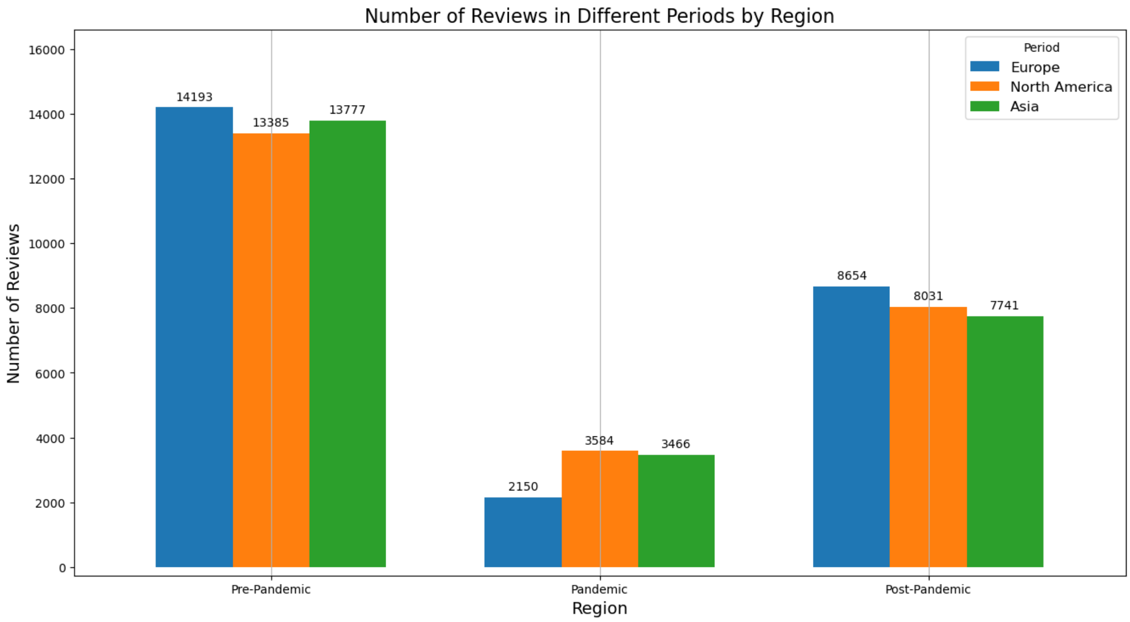


Figure 5.1: Volume of Reviews Across the Regions from 2017 to 2023

By analysing the volume of reviews during these periods, we observed that all regions experienced a significant decrease in the number of reviews during the pandemic period (2020-2021) compared to the pre-pandemic period (2017-2019). For instance, Europe had 2,150 reviews during the pandemic, down from 14,193 pre-pandemic, while North America saw a decline from 13,385 to 3,584 reviews, and Asia from 13,777 to 3,466 reviews. Post-pandemic, the review volumes increased, indicating a recovery in guest activity, although not uniformly back to pre-pandemic levels. Europe recorded 8,654 reviews post-pandemic, North America had 8,031, and Asia had 7,741. These patterns highlight the significant impact of the COVID-19 pandemic on the hospitality sector, with a sharp decline in guest reviews during the pandemic period across all regions. The post-pandemic increase in review volume suggests a gradual recovery, and shows the different recovery trajectories of the hospitality sector globally.

5.3.2 Average Review Rating by Region and Year

This graph presents the average star rating of hotel reviews over the years, categorised by region. This analysis helps understand how customer satisfaction has changed over time and across different regions.

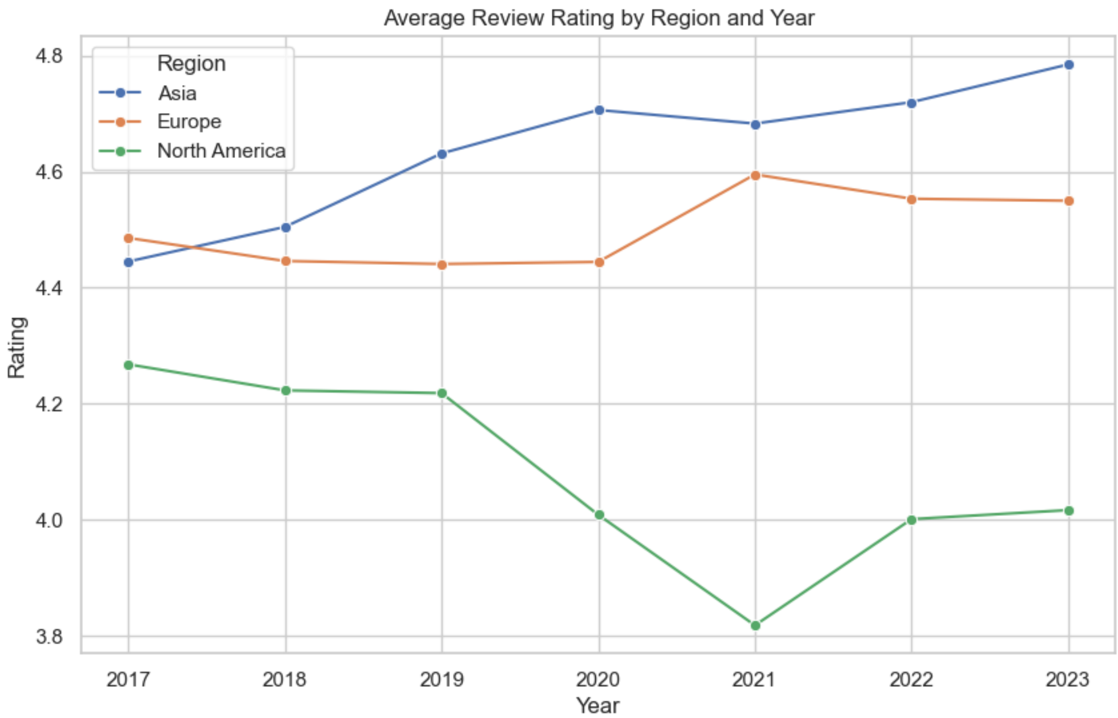


Figure 5.2: Average Rating Across the Regions from 2017 to 2023

In Asia, the average ratings show a consistent increase from 2017 to 2023, rising from around 4.4 to 4.7. This upward trend suggests improving customer satisfaction in the region over the years. Europe maintains relatively stable ratings, barely any changes from 2018 to 2020. North America, on the other hand, displays a more volatile pattern. The ratings declined from 4.2 in 2017 to below 4.0 in 2021, reflecting significant customer dissatisfaction during the peak of the COVID-19 pandemic. However, the ratings gradually recovered to around 4.0 by 2022.

The sharp decline in North American ratings in 2020 coincides with the peak of the pandemic, indicating a period of heightened customer dissatisfaction. This decline could be attributed to various factors, including reduced service quality, operational disruptions, and increased customer expectations for safety and hygiene. In contrast, Asia and Europe did not exhibit such fluctuations, possibly due to better management of customer experiences and quicker adaptation to new COVID safety protocols.

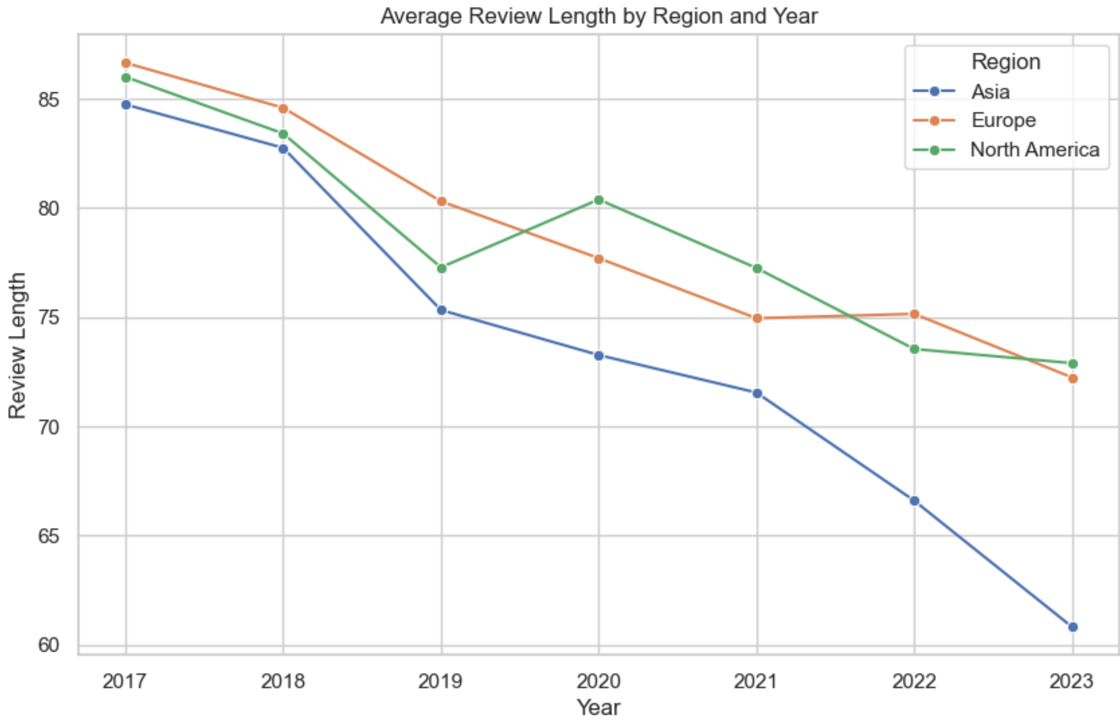


Figure 5.3: Average Review Length of Each Region from 2017 to 2023

The gradual recovery in ratings post-2021 across all regions reflects the industry's efforts to restore service quality and meet current customer expectations. The variations in average ratings highlight the differences in customer satisfaction and expectations across regions, providing valuable insights for hotels to tailor their services accordingly.

5.3.3 Average Review Length by Region and Year

The third graph illustrates the average review length over the years for three regions: Asia, Europe, and North America. The review length is calculated as the number of words in each review.

The overall trend in the average review length across all regions shows a clear downward trajectory from 2017 to 2023. In Asia, this decline is particularly pronounced, with the average review length dropping from around 85 words in 2017 to approximately 60 words in 2023. Europe and North America also experienced reductions in review length, though not as steep as in Asia. In 2017, European reviews were the longest, followed by North America and Asia. However, by 2023, the review lengths had significantly reduced across all regions.

Interestingly, the data shows that the average review length has been decreasing steadily even before the COVID-19 pandemic, suggesting that the pandemic might not have influenced this trend. This trend might be driven by several causes unrelated to the pandemic, such as shifts in digital communication habits and user behaviour.

However, it is noteworthy that North America is the only region that saw an increase in review length in 2020. This exception could suggest a regional difference in how the pandemic impacted customer experiences and review behaviours. One possible explanation is that due to COVID-19, service quality may have declined, and hygiene protocols might not have been well adapted, leading to poorer and more detailed reviews. This notion is backed by the data in the first graph, which shows that hotel ratings in North America dropped drastically during the pandemic.

In summary, while the chart indicates a general decline in review lengths from 2017 to 2023, the steady decrease observed even before the pandemic suggests that the trend might be influenced more by broader factors rather than the pandemic itself. The increase in review length for North America in 2020 highlights a regional difference that should be explored further to understand the unique impacts of COVID-19 on hotel reviews in that region.

5.3.4 Average Review Length by Rating and Region

The last graph examines the relationship between review length and star rating, further broken down by region. This analysis explores whether the length of a review correlates with the rating given by the reviewer.

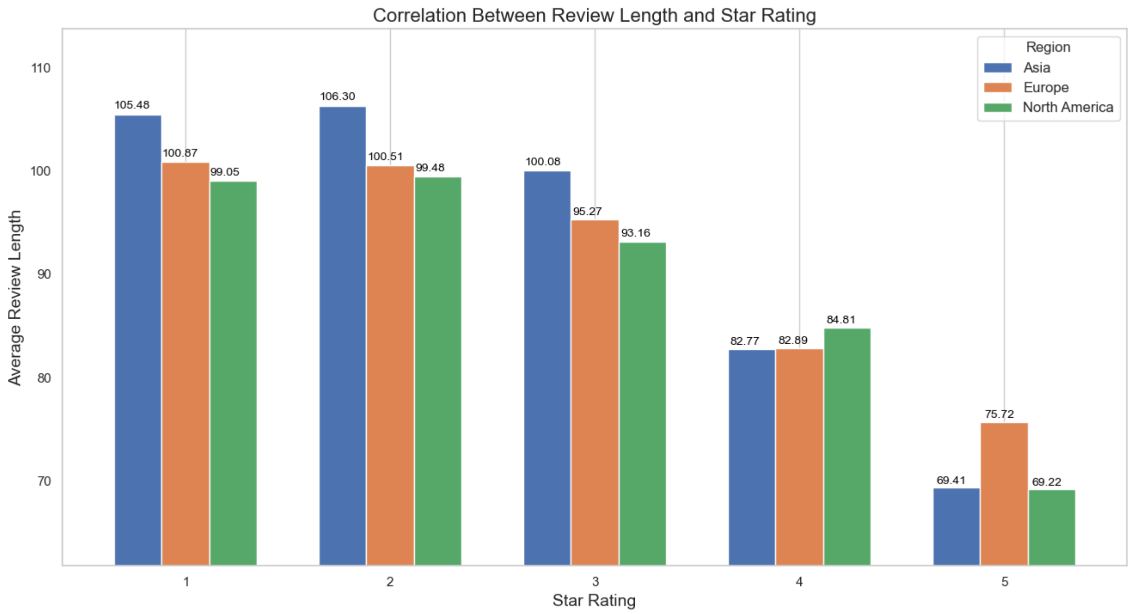


Figure 5.4: Correlation Between Review Length and Star Rating from 2017 to 2023

There is an evident inverse relationship between review length and star rating across all regions. Reviews with lower ratings (1 or 2 stars) tend to be longer, while higher-rated reviews (4 or 5 stars) are generally shorter. For example, in Asia, 1-star reviews average around 105 words, whereas 5-star reviews average about 69 words. This pattern suggests that dissatisfied customers provide more detailed feedback to emphasise their negative experiences and suggest improvements.

The trend is consistent across Asia, Europe, and North America, indicating a common behaviour among reviewers irrespective of regional differences. Europe shows the smallest difference in review lengths across ratings, while Asia exhibits the most significant variation. This consistency in behaviour underscores the importance of detailed negative reviews, which often contain valuable insights for improving service quality.

Understanding the relationship between review length and rating can help hotels identify detailed negative feedback that may require immediate attention. The longer length of lower-rated reviews suggests that these customers are more motivated to provide feedback, highlighting specific issues and areas for improvement.

Chapter 6

Limitations & Future Work

Language Barriers

One significant limitation of this study is the language barrier. A considerable portion of hotel reviews in Japan, Korea, and China were written in the native languages. Since the PyABSA model used in this analysis does not cater to these languages, a substantial amount of potentially valuable data was excluded. This is particularly impactful as these regions experienced significant disruptions during the pandemic, and the missing data could have provided crucial insights.

Proper Nouns and Aspect Detection

The current PyABSA model does not account for proper nouns such as the names of people. This poses a challenge, especially for reviews from North America, where guests often refer to staff members by name. This limitation makes it difficult for the model to detect and categorize mentions of staff as an aspect, potentially skewing the analysis of the Staff & Service category.

Temporal Perspectives in Reviews

Another limitation is the inclusion of both past and present perspectives within individual reviews. Some reviews discuss the hotel's condition or service quality over different time periods, such as stating that the hotel was amazing in the past but is now run-down and dirty. This can lead to ambiguous sentiment analysis results, as the model may not effectively distinguish between temporal references within a single review.

Regional Coverage

The study currently covers hotel reviews from Europe, Asia, and North America. However, expanding the analysis to include additional regions such as Africa, Oceania, and South America would provide a more comprehensive understanding of global hotel guest experiences. Including these regions could offer more diverse perspectives and insights, enhancing the generalisability of the findings.

Categorisation by Hotel Type

Future work could also involve categorising hotels based on their budget, mid-range, and luxury status. This categorisation would enable an analysis of whether guest priorities and sentiments differ across different types of hotels. It would be interesting to explore if aspects like "Comfort & Amenities" or "Value for Money" are perceived differently in budget hotels compared to luxury ones.

By addressing these limitations and expanding the scope of the analysis, future studies can provide more comprehensive and accurate insights into hotel guest sentiments and experiences across different regions and hotel categories.

Chapter 7

Conclusion

This thesis aimed to explore the evolving sentiments in hotel reviews across three major regions: Europe, North America, and Asia, with a particular focus on the periods before, during, and after the COVID-19 pandemic. To achieve this, we employed aspect-based sentiment analysis (ABSA) using the PyABSA framework to identify and analyse sentiments towards specific hotel aspects.

The research process began with extensive data collection from various online platforms. This was followed by rigorous preprocessing and annotation of the data to identify relevant aspects and their associated sentiments. We then implemented the PyABSA framework to perform aspect-based sentiment analysis. The model was trained to recognise and classify sentiments related to various hotel aspects. The results of the sentiment analysis were compared across the three regions and over different time periods, enabling us to identify key trends and differences in guest priorities and experiences.

In this research, we have addressed the two primary questions:

1. **How have the key aspects mentioned in customer reviews for hotels changed during the COVID-19 pandemic, and which specific features were most frequently associated with positive or negative sentiments?**

   The analysis revealed that during the COVID-19 pandemic, the key aspects mentioned in customer reviews underwent significant changes. The importance of Staff & Service increased universally, with positive sentiment notably rising, particularly in Asia where it peaked during the pandemic. Cleanliness & COVID emerged as a critical category across all regions, reflecting guests' increased concerns about hygiene. This aspect saw increased positive mentions due to improved hygiene measures but also faced negativity where standards were perceived as inadequate. 'Facilities' saw a decline in positive feedback during the pandemic, especially in North America, due to reduced services and restrictions.

2. **Are there observable regional differences in the volume and sentiment of reviews for hotels during the COVID-19 pandemic, reflecting varying impacts on each country's hospitality sector?**

   The research identified clear regional differences in the sentiment and volume of reviews during the COVID-19 pandemic. In Europe, Staff & Service saw consistent improvement in positive sentiment, while Comfort & Amenities continued to receive mixed feedback. In North America, Cleanliness & COVID became a significant concern, with both positive and negative sentiments rising. Staff & Service showed recovery post-pandemic. In Asia, there was a drastic increase in positive sentiment towards Staff & Service, demonstrating the region's strong focus on maintaining service quality. Additionally, cleanliness and COVID-related measures remained crucial, with sustained positive feedback post-pandemic. Besides that, the volume of reviews decreased significantly during the pandemic across all regions, reflecting the impact of travel restrictions and reduced hotel occupancy. Post-pandemic, there was a partial recovery in the number of reviews, indicating a gradual return to normalcy.

These findings highlight how different regions responded to the challenges posed by the pandemic and indicate the varying priorities and concerns of hotel guests across Europe, North America, and Asia. The insights gained from this analysis provide valuable guidance for the hospitality industry to focus on key aspects that matter most to guests, particularly in times of crisis.

While this study provided valuable insights, it also faced several limitations. Future research should address these limitations to provide a more comprehensive understanding of global hotel guest experiences and improve the applicability of ABSA in diverse linguistic contexts.

Chapter 8

Appendix

Github Code

Link to Github: https://github.com/DiniIrdina/Hotel_Reviews_SA

Datasets in Google Drive

Link to Google Drive: https://drive.google.com/drive/folders/1eH9vPLhY-6B_PZmfb9e4I2b92LS2tp7T?usp=drive_link

References

Al-Natour, S. and Turetken, O. (2020). A comparative assessment of sentiment analysis and star ratings for consumer reviews. *International Journal of Information Management*, 54:102132.

Alonso, A. D., Kok, S. K., Bressan, A., O'Shea, M., Sakellarios, N., Koresis, A., Solis, M. A. B., and Santoni, L. J. (2020). Covid-19, aftermath, impacts, and hospitality firms: An international perspective. *International journal of hospitality management*, 91:102654.

Ameur, A., Hamdi, S., and Yahia, S. B. (2023). Sentiment analysis for hotel reviews: A systematic literature review. *ACM Computing Surveys*.

Asani, E., Vahdat-Nejad, H., and Sadri, J. (2021). Restaurant recommender system based on sentiment analysis. *Machine Learning with Applications*, 6:100114.

Bagherzadeh, S., Shokouhyar, S., Jahani, H., and Sigala, M. (2021). A generalizable sentiment analysis method for creating a hotel dictionary: using big data on tripadvisor hotel reviews. *Journal of Hospitality and Tourism Technology*, 12(2):210–238.

Baker, S. R., Farrokhnia, R. A., Meyer, S., Pagel, M., and Yannelis, C. (2020). How does household spending respond to an epidemic? consumption during the 2020 covid-19 pandemic. *The Review of Asset Pricing Studies*, 10(4):834–862.

Batista e Silva, F., Herrera, M. M., Rosina, K., Barranco, R. R., Freire, S., Schiavina, M., et al. (2018). Analysing spatiotemporal patterns of tourism in europe at high-resolution with conventional and big data sources. *Tourism Management*, 68:101–115.

Baum, T. and Hai, N. T. T. (2020). Hospitality, tourism, human rights and the impact of covid-19. *International Journal of Contemporary Hospitality Management*, 32(7):2397–2407.

Beneki, C. and Spiggos, T. (2021). Spatial patterns of tourism activity through the lens of tripadvisor's online restaurant reviews: A case study from corfu. In *Culture* *and Tourism in a Smart, Globalized, and Sustainable World: 7th International Conference of IACuDiT, Hydra, Greece, 2020*, pages 559–585. Springer.

Cao, I., Liu, Z., Karamanolakis, G., Hsu, D., and Gravano, L. (2021). Quantifying the effects of covid-19 on restaurant reviews. In *Proceedings of the Ninth International Workshop on Natural Language Processing for Social Media*, pages 36–60.

Chang, Y.-C., Ku, C.-H., and Chen, C.-H. (2019). Social media analytics: Extracting and visualizing hilton hotel ratings and reviews from tripadvisor. *International Journal of Information Management*, 48:263–279.

Comaniciu, D. and Meer, P. (2002). Mean shift: A robust approach toward feature space analysis. *IEEE Transactions on pattern analysis and machine intelligence*, 24(5):603–619.

Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.

Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2019). Bert: Pre-training of deep bidirectional transformers for language understanding.

Ester, M., Kriegel, H.-P., and Xu, X. (1995). *A database interface for clustering in large spatial databases*, volume 2. Inst. für Informatik.

Foroudi, P., Tabaghdehi, S. A. H., and Marvi, R. (2021). The gloom of the covid-19 shock in the hospitality industry: A study of consumer risk perception and adaptive belief in the dark cloud of a pandemic. *International Journal of Hospitality Management*, 92:102717.

Gan, Q., Ferns, B. H., Yu, Y., and Jin, L. (2017). A text mining and multidimensional sentiment analysis of online restaurant reviews. *Journal of Quality Assurance in Hospitality & Tourism*, 18(4):465–492.

Gatti, L., Guerini, M., and Turchi, M. (2016). Sentiwords: Deriving a high precision and high coverage lexicon for sentiment analysis. *IEEE Transactions on Affective Computing*, 7(4):409–421.

Geetha, M., Singha, P., and Sinha, S. (2017). Relationship between customer sentiment and online customer ratings for hotels-an empirical analysis. *Tourism Management*, 61:43–54.

Gössling, S., Scott, D., and Hall, C. M. (2020). Pandemics, tourism and global change: a rapid assessment of covid-19. *Journal of sustainable tourism*, 29(1):1–20.

Guo, Y., Barnes, S. J., and Jia, Q. (2017). Mining meaning from online ratings and reviews: Tourist satisfaction analysis using latent dirichlet allocation. *Tourism Management*, 59:467–483.

Gursoy, D. (2019). A critical review of determinants of information search behavior and utilization of online reviews in decision making process (invited paper for 'luminaries' special issue of international journal of hospitality management). *International Journal of Hospitality Management*, 76:53–60.

Hasnat, M. M. and Hasan, S. (2018). Identifying tourists and analyzing spatial patterns of their destinations from location-based social media data. *Transportation Research Part C: Emerging Technologies*, 96:38–54.

He, P., Liu, X., Gao, J., and Chen, W. (2020). Deberta: Decoding-enhanced bert with disentangled attention. *arXiv preprint arXiv:2006.03654*.

Hochreiter, S. and Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, 9(8):1735–1780.

Hu, M. and Liu, B. (2004). Mining opinion features in customer reviews. In *AAAI*, volume 4, pages 755–760.

Huang, A., de la Mora Velasco, E., Farhangi, A., Bilgihan, A., and Jahromi, M. F. (2022). Leveraging data analytics to understand the relationship between restaurants' safety violations and covid-19 transmission. *International Journal of Hospitality Management*, 104:103241.

Ilmania, A., Abdurrahman, Cahyawijaya, S., and Purwarianti, A. (2018). Aspect detection and sentiment classification using deep neural network for indonesian aspect-based sentiment analysis. In *2018 International Conference on Asian Language Processing (IALP)*, pages 62–67.

Ivanov, S. and Zhechev, V. (2012). Hotel revenue management–a critical literature review. *Tourism: an international interdisciplinary journal*, 60(2):175–197.

Jing, C., Dong, M., Du, M., Zhu, Y., and Fu, J. (2020). Fine-grained spatiotemporal dynamics of inbound tourists based on geotagged photos: A case study in beijing, china. *IEEE Access*, 8:28735–28745.

Kalinic, M. and Krisp, J. M. (2018). Kernel density estimation (kde) vs. hot-spot analysis–detecting criminal hot spots in the city of san francisco. In *Proceeding of the 21 Conference on Geo-Information Science*.

Kanungo, T., Mount, D. M., Netanyahu, N. S., Piatko, C. D., Silverman, R., and Wu, A. Y. (2002). An efficient k-means clustering algorithm: Analysis and implementation. *IEEE transactions on pattern analysis and machine intelligence*, 24(7):881–892.

Levy, S. E., Duan, W., and Boo, S. (2013). An analysis of one-star online reviews and responses in the washington, dc, lodging market. *Cornell Hospitality Quarterly*, 54(1):49–63.

Li, H., Bruce, X., Li, G., and Gao, H. (2023). Restaurant survival prediction using customer-generated content: An aspect-based sentiment analysis of online reviews. *Tourism Management*, 96:104707.

Liu, B. (2022). *Sentiment analysis and opinion mining*. Springer Nature.

Luo, Y. and Tang, R. L. (2019). Understanding hidden dimensions in textual reviews on airbnb: An application of modified latent aspect rating analysis (lara). *International Journal of Hospitality Management*, 80:144–154.

Luo, Y. and Xu, X. (2021). Comparative study of deep learning models for analyzing online restaurant reviews in the era of the covid-19 pandemic. *International Journal of Hospitality Management*, 94:102849.

Mai, D. and Zhang, W. E. (2020). Aspect extraction using coreference resolution and unsupervised filtering. In Shmueli, B. and Huang, Y. J., editors, *Proceedings of the 1st Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 10th International Joint Conference on Natural Language Processing: Student Research Workshop*, pages 124–129, Suzhou, China. Association for Computational Linguistics.

Mathayomchan, B. and Taecharungroj, V. (2020). “how was your meal?” examining customer experience using google maps reviews. *International Journal of Hospitality Management*, 90:102641.

Nakaya, T. and Yano, K. (2010). Visualising crime clusters in a space-time cube: An exploratory data-analysis approach using space-time kernel density estimation and scan statistics. *Transactions in GIS*, 14(3):223–239.

Ndoni, A., Mestric, I. I., and Street, M. (2021). Aspect detection enhancement for aspect based sentiment analysis. In *2021 International Conference on Military Communication and Information Systems (ICMCIS)*, pages 1–6.

Nicola, M., Alsafi, Z., Sohrabi, C., Kerwan, A., Al-Jabir, A., Iosifidis, C., Agha, M., and Agha, R. (2020). The socio-economic implications of the coronavirus pandemic (covid-19): A review. *International journal of surgery*, 78:185–193.

Nie, R.-x., Chin, K.-s., Tian, Z.-p., Wang, J.-q., and Zhang, H.-y. (2023). Exploring dynamic effects on classifying service quality attributes under the impacts of covid-19 with evidence from online reviews. *International Journal of Contemporary Hospitality Management*, 35(1):159–185.

Nie, R.-x., Tian, Z.-p., Wang, J.-q., and Chin, K. S. (2020). Hotel selection driven by online textual reviews: Applying a semantic partitioned sentiment dictionary and evidence theory. *International Journal of Hospitality Management*, 88:102495.

Niestadt, M. (2020). Covid-19 and the tourism sector.

Pezenka, I. and Weismayer, C. (2020). Which factors influence locals' and visitors' overall restaurant evaluations? *International Journal of Contemporary Hospitality Management*, 32(9):2793–2812.

Plutchik, R. (1994). *The psychology and biology of emotion.* HarperCollins College Publishers.

Ray, B., Garain, A., and Sarkar, R. (2021). An ensemble-based hotel recommender system using sentiment analysis and aspect categorization of hotel reviews. *Applied Soft Computing*, 98:106935.

Song, S., Saito, H., and Kawamura, H. (2018). Content analysis of travel reviews: Exploring the needs of tourists from different countries. In *Information and Communication Technologies in Tourism 2018: Proceedings of the International Conference in Jönköping, Sweden, January 24-26, 2018*, pages 93–105. Springer.

Stringam, B. B. and Gerdes Jr, J. (2010). An analysis of word-of-mouse ratings and guest comments of online hotel distribution sites. *Journal of Hospitality Marketing & Management*, 19(7):773–796.

Sun, S., Jiang, F., Feng, G., Wang, S., and Zhang, C. (2022). The impact of covid-19 on hotel customer satisfaction: evidence from beijing and shanghai in china. *International Journal of Contemporary Hospitality Management*, 34(1):382–406.

Tirunillai, S. and Tellis, G. J. (2014). Mining marketing meaning from online chatter: Strategic brand analysis of big data using latent dirichlet allocation. *Journal of marketing research*, 51(4):463–479.

TripAdvisor (2023).

Wang, H., Lu, Y., and Zhai, C. (2010). Latent aspect rating analysis on review text data: a rating regression approach. In *Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 783–792.

Wang, S., Cao, J., and Philip, S. Y. (2020). Deep learning for spatio-temporal data mining: A survey. *IEEE transactions on knowledge and data engineering*, 34(8):3681–3700.

Wang, X., Ounis, I., and Macdonald, C. (2019). Comparison of sentiment analysis and user ratings in venue recommendation. In *Advances in Information Retrieval: 41st European Conference on IR Research, ECIR 2019, Cologne, Germany, April 14–18, 2019, Proceedings, Part I 41*, pages 215–228. Springer.

Xu, X., Wang, X., Li, Y., and Haghighi, M. (2017). Business intelligence in online customer textual reviews: Understanding consumer perceptions and influential factors. *International Journal of Information Management*, 37(6):673–683.

Yang, H., Zhang, C., and Li, K. (2023). Pyabsa: A modularized framework for reproducible aspect-based sentiment analysis.

Ye, B. H., Luo, J. M., and Vu, H. Q. (2018). Spatial and temporal analysis of accommodation preference based on online reviews. *Journal of Destination Marketing & Management*, 9:288–299.

Yu, B., Zhou, J., Zhang, Y., and Cao, Y. (2017). Identifying restaurant features via sentiment analysis on yelp reviews. *arXiv preprint arXiv:1709.08698*.

Zhang, C., Li, Q., and Song, D. (2019). Aspect-based sentiment classification with aspect-specific graph convolutional networks.

Zhang, Z., Qiao, S., Chen, Y., and Zhang, Z. (2022). Effects of spatial distance on consumers' review effort. *Annals of Tourism Research*, 94:103406.