Executive Summary

The tourism industry has been booming in an unprecedented manner, and with the advent of the sharing economy, the travel industry has had an exponential growth. Short-term renting has opened a new concept of travelling for people around the world and Airbnb has been the leading platform to facilitate such a trend.

The onset of COVID-19 posed an unforeseen threat to the unprecedented growth of Airbnb, being met with major disruptions in form of travel restrictions, government restrictions and social-distancing protocols. Both business and personal travel plans had to be put on hold globally and the sharing economy faced a drop in revenues. This transpired into plummeting occupancy rates on Airbnb from the levels in 2019 (AirDNA, 2020). The existence of two-way association between rental and property prices and Airbnb activity, defined by occupancy rates and number of listings, means that the response had to be made by cutting down on costs, leading to laying off work force and cutting marketing budgets. Overall, guest experience and preferences are anticipated to be different from what it had been before.

A new frontier in understanding customer satisfaction is the recent rise of online reviews and ratings, which can be used to reveal guests' feelings, attitudes and evaluations. Text mining tools and NLP techniques have been frequently studied in such contexts and have been proven to capture consumption emotions of customers. In the current scenario, such approaches can be administered to explore and contrast the inherent emotions in comments to decode any changes in attitude, and elucidate the impact that the pandemic has had on the overall sentiment and behaviour of the guests. These measures can be furthered through the application of statistical methods, feature extraction, topic identification and visualisation to verify the links with ratings and customer satisfaction.

Thus, this study aims to provide such detailed insights into the effect of COVID-19 on customer behaviours, which Airbnb can utilise to make necessary modifications to its services to meet customer needs based on their perception coming out of the pandemic. Ultimately, the significant textual predictors will connect changes in customer attitudes and preferences and provide predictive recommendations.

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1. Introduction

The sharing economy (SE) has shown to be more than a fragile and transient phenomenon and is capable of reversing global competition (De las Heras. et al. 2021). A tremendous impact was caused by the COVID-19 (coronavirus) pandemic, which emerged at the end of 2019, on practically all facets of social and economic life (Boros. et al. 2020). Due to the decreased flows of domestic and international tourists all over the globe, every sector experienced unprecedented downturn of activity. Airbnb, as part of the tourism industry, experienced the same as guests cancelled their bookings and reservations were on hold until the pandemic restrictions were waived. However, Airbnb had an exceptional position, where it could continue its operations with added regulations and strategic curtailing of costs. The impact of this change on customers' view of the services is yet to be determined.

In tourism industry, online services have changed the way tourists interact with travel agents, through ease of booking, quality of service description, and immediate feedback through online reviews opening up opportunities to collect immense data to gain insight into customer perceptions. As the sheer size of unstructured text data keeps increasing, there is a need to understand and extract information from large scale texts or the world wide web (Hurtado, Agarwal and Zhu, 2016). According to Kaemingk (2020), 97% of consumers conduct internet research before making a purchase choice, 93% of consumers read product evaluations, and the majority of consumers are willing to pay 31% more for the identical products if they are persuaded by positive reviews. Online reviews have a significant indirect impact on sales through review feelings, even though they do not directly affect a product's sales (M. Guha Majumder et al. 2022). The sentiments behind the reviews reflect customer perception and can also be used to gauge service performance. Text mining on such comments can help determine how effectively or poorly Airbnb fared throughout the pandemic and how their strategic choices have affected consumer preference.

The two major pillars of the sharing economy are trust and reputation (Hamari, 2016). Both the customer and the service provider need to keep these two time-bound elements in the back of their minds (Vinod and Sharma, 2021). According to Tussyadiah (2016) and So et al. (2018), economic benefits, environmental benefits, locational benefits, home benefits, and authenticity contend to be the platform-based characteristics that may influence the confidence in Airbnb. During the COVID-19 outbreak, trust was a major concern for all parties participating in Airbnb's peer-to-peer accommodation model (Yu et al., 2021), as hosts had to ensure certain cleaning protocols to prevent transmission of the disease (Farmaki et al., 2020).

This study will investigate whether the significant factors influencing customer purchase behaviour, derived from review texts, remained the same or changed after the pandemic.

For the relevance of analysis, the study will use the timeframe between January 2019 and December 2021. The period of study is shortened to restrict outputs of analysis relevant only to the accomplishment of concentrated comparison between the pre- and post- pandemic era based on recency. The mentionable differences in metrices are investigated through exploratory analysis, and then taken into deeper mining techniques to understand the sentiments that were resultant of those policies undertaken by Airbnb. All data are read from AirDNA repository, cleaned and loaded in database to analyse accordingly. The analysis is performed on various aggregation levels to maximise perspectives utilised in extracting the outputs. The comparison of the outcomes of the pre- and post- pandemic period is performed through building regression models and contrasting through estimation approach and significance testing. Textual outputs are also juxtaposed and observed through judgemental evaluation. Besides, topics are modelled and projected on temporal graphs to visualise the change in prevalence. Overall outcomes are analysed and linked with underlying behaviour of customers to get an idea of the general change in attitudes with respect to the ratings and prices provided in the data.

The novelty of this study is the integration of different text mining approaches with statistical methods and predictive analysis while utilizing temporal projections and considering each output into two separate periods. The outcomes of the analysis will aim to identify changes in customer attitudes, described through usage of particular words, emotions and topics. All these are accomplished through appropriate data preparation from large text and selective metadata inclusion. The tools utilized for analysis in this research are R and R Studio, leveraging the relevant text mining packages available. SQLite is used as preferred method for faster data ingestion and dataset extraction of large datasets.

2. Literature Review

Airbnb has been the pioneer for the emerging tourism trend that resembles the nomadic style of living. The disruptive power of Airbnb's unique nature was not just due to its ability to provide options at reasonable prices; it also fundamentally altered how travellers view, choose, and experience lodging while travelling (Guttentag, 2013; Mody et al., 2017). In regards to buying decisions, customers are highly dependent on reviews and how the service is rated at any particular time (Chen et al., 2020). This provides the basis for using publicly available Airbnb customer reviews to understand any change in customer perception during the pandemic.

In any sector, customer satisfaction plays a crucial role in the success of the business which is largely influenced by the quality of the product or the service the customers are paying for. On one hand, a satisfactory experience can increase the loyalty of the customer to the business (Ruiz-Molina and Gil-Saura, 2008) which would contribute to creating a brand equity (Bhattacharya and Sen, 2003). For instance, Yang et al. (2019) claims that the customers are more inclined to use Airbnb consistently if their trust-attachments are established on cognitive trust. Depending on the customer loyalty, the business will have a trusted and stable customer base, and the satisfied customers would inadvertently be promoting the brand through word-of-mouth, which could happen through reviews (Engel et al. 1969; Villanueva et al., 2008). On the other hand, according to Yang et al. (2019), a satisfied customer is less likely to perceive the shortcomings of the Airbnb host if their overall experience was of good quality. Thus, as the attributes that the customers value transpire into good experience, the lacking of some services may not affect overall ratings. However, with the information sharing through leaving review becoming widespread and requiring very little effort, the smallest details attained provide the possibility of leaving a big impact on the course of success of a business.

It is expected for the customers' valuation of hygiene to change in the post-pandemic era. As Airbnb hosts had to conform to the new expectations of their guests, it is reported that there was a significant increase in the amount of time and money the hosts put into cleaning and managing their properties (Fairley et al., 2021). While Airbnb has rolled out newer service models, by taking the Airbnb experiences service virtual or introducing "Enhanced Cleaning" procedures and recommended hosts to increase the time between guest stays (Pareja, 2015), uncertainty still remained regarding the rejuvenation of the pre-pandemic trends and whether the concept of tourism has changed permanently. For laying out a path forward, customer behaviours and the unique attributes of Airbnb that they value are researched. In contrast to hotels where service interactions are often faceless, Airbnb guests usually develop a much closer relationship with the hosts (Kiatkawsin et al., 2020). However, during the pandemic, such interaction had to be restricted to online correspondence, which is a change that customers had to bear. This study is conducted to evaluate whether such conventions are still important for customers after the pandemic.

According to the study of Salon et al. (2021), it has been found in perspective of US citizens that they are expecting COVID-19 to have an effect on their daily lives. Along with a growth in telecommuting, respondents anticipate that their behaviours around air travel and commute will change. Two-thirds of the participants in Salon et al.'s (2021) study showed their inclination towards commuting less often. This brings up the possibility of people considering the restaurants being around the location of the Airbnb while evaluating them, even though the overall estimation of dining in restaurants are expected to decrease. In parallel to the reducing commute demand, transit demands are also expected to decrease (Salon et al., 2021), hence if the customer is supposed to go to the Airbnb location through transit commute, they may change their minds. After the emergence of COVID-19 pandemic, communication gap also became apparent for the customers. According to Vargo and Lusch (2004), communication makes it possible for both parties to exchange resources in a way that allows for cooperative value generation. Sthapit (2019) remarks that for Airbnb, quick responses to customer queries and good communication, as well as attentive hosts are some of the core pillars for customer satisfaction. Numerous evaluations on Airbnb at the start of the pandemic suggest that several customers thought the company's customer service was insufficient and ineffective due to service failure and miscommunication, which was a significant problem given that customers typically tried to resolve their issues by contacting their hosts first (Sthapit, 2022). This realisation during the pandemic may be a result of consumers modifying their evaluation standards as the questions they were asking turned out to be essential pieces of the information they required before their stays. In this situation, poor service in the guise of inadequate communication can quickly result in undesirable client experiences (Pine & Gilmore, 1998).

Due to the strong association prevalent between online reviews and sales for e-commerce businesses, methods of text mining have been taken up in this study to address this business problem. There are predominantly three approaches used for automating text analysis tasks today (Kiatkawsin, Sutherland and Kim, 2020). One is to reconcile predefined words with sentiments from dictionaries with collected text to analyse customer emotions. The second approach is to train machine learning techniques to detect pre-determined features from a text corpus to understand the predictability of a target variable. And the third is to use Latent Dirchlet Allocation (LDA) approach, based on word co-occurrences, to extract topics that shed light on the dominant issues to customers. The evolution of topics in text has a low resolution yet high sensitivity property, which means that a topic's popularity does not change much in days or months (i.e., low resolution), but for several consecutive years they may change dramatically and fade quickly (i.e., high sensitivity) (Hurtado, Agarwal and Zhu, 2016). The analysis backing this study will utilize the three approaches to achieve various insights from reviews. Consumption emotions are key elements of guests' responses that affect customer satisfaction, especially in the lodging industry (Han and Back, 2006, 2007). Thus, combining findings, such as textual features, sentiments, and topics, from the text mining approaches with target variables, such as ratings, can help identify the causes behind the numbers. In tourism and hospitality, sentiment analysis helps businesses not only to measure tourists' or guests' attitudes toward their products and services but also to position themselves in the market with competitors (Ma et al., 2018). To understand change in attitude due to pandemic, if any, the hypothesis of Ma et al. (2018) is used to contrast sentiments of Airbnb guests before and after pandemic to achieve the objective of this study.

Ratings from visitors may reflect more than just hosts providing high quality service (Zhu, Lin and Cheng, 2020), which is why the extraction of textual features and exploratory analysis is important to this study in addition to sentiment analysis. A common step in the data mining pre-processing stage is feature selection, and there are numerous alternative methods that can be considered for the selection of textual features (Khadjeh Nassirtoussi et al., 2014). A popular method is known as "bag-of-words", which entails splitting the text into its words and evaluating each one as a feature.

Topic modelling, in its simplest form, can be a supervised or an unsupervised model that determines the set of underlying themes for a collection of documents as well as the affinities of each document to these subjects (Nikolenko et al., 2016). Latent Dirichlet Allocation (LDA) is a recently popular approach to find the logic behind word co-occurrence to find the most probable topic structure that is covered in a text corpus, like a database of online guest reviews. It might be feasible to discover what users are discussing, spot underlying subject patterns and follow them over time, as well as pinpoint the most pertinent set of words for a given topic, by evaluating the collection of themes learned from, for example, a dataset of reviews over a period of time (Nikolenko et al., 2016). Using such concept, the comparison of the common themes in pre-pandemic and post-pandemic period could provide substantial idea of the attitudes of customers for achieving the objective of this study.

Thus, the existing literatures have paved the way for the research questions formulated for this work and has been examined for potential gap to be addressed. The technical frameworks utilized in these literatures have also provided the inspirations for building the methodology of this study.

3. Methodology

The aim of the analysis is to implement text analytics to extract insights about customer attitude changes. Therefore, this section will cover the fundamentals of text mining process and venture into the core analysis. The analysis is inspired by the aim of the study as well as relevant literatures. The targeted metrics are selected based on the attained information from reviews.

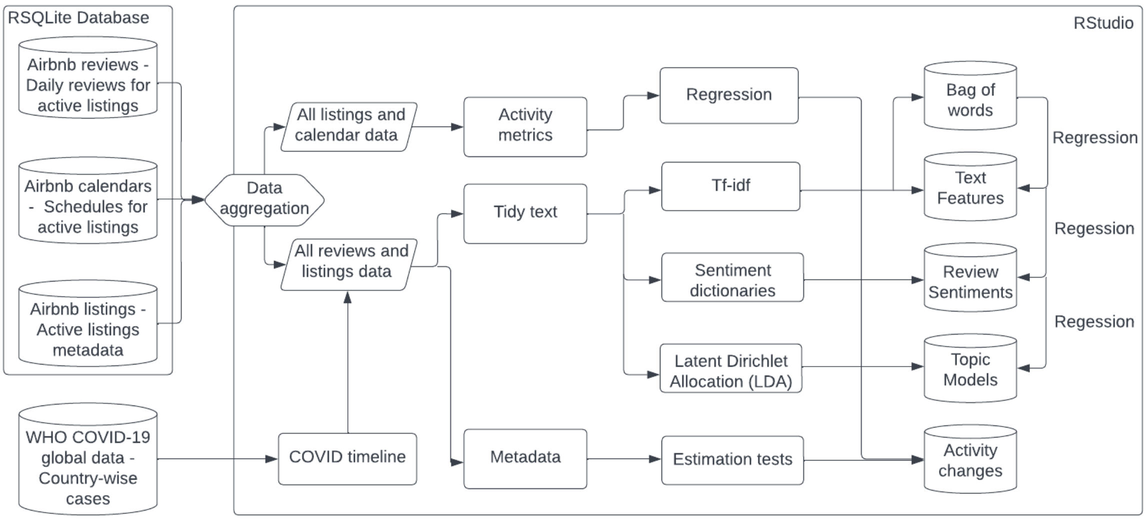

Figure 1: Conceptual Diagram

3.1. Data Collection

This study aims to understand the changes in customer attitudes to Airbnb, hence, online reviews are sourced. Airbnb has a publicly available repository of data on "Inside Airbnb" website, which records monthly snapshots of Airbnb datasets. The data for 16 cities from various parts of the world are collected based on the popularity of the cities for tourism. The rationale is that the effects of pandemic, as seen in the most popular cities, will impact Airbnb the most as well and hence, the change in customer attitudes from these cities will be representative of the expected impact to be seen in other regions where Airbnb has active operations. The selected cities for this study are:

1. Amsterdam 2. Bangkok 3. Barcelona 4. Hong Kong 5. Istanbul 6. London 7. Melbourne 8. New York 9. Paris 10. Porto 11. Rome 12. San Francisco 13. Singapore 14. Sydney 15. Madrid 16. Vienna

For each of the selected cities, the files as stated in table 1 are downloaded to local drive. Due to the size of the files, the 'fread' method is used to reliably and quickly read the files. The files are consolidated and loaded into the RSQLite database. The obtained data sets contain records since 2008, which is not relevant to this study. Hence, upon exploration, the review dataset is filtered to obtain reviews for the period January'19 to December'21. To ensure the balancing of data taken from each year to, the data is selected randomly and 150000 reviews are taken from each of the years from 2019-2021. The final reviews dataset contained 450,000 reviews over 6 variables. The listings dataset contains 75 columns, all of which aren't essential to the analysis. Thus, the redundant variables are discarded.

For identifying the period to be treated as the pandemic period in this study, WHO Covid data is collected from 'The Humanitarian Data Exchange' website. The source provides authentic and real-time data for public use as verified by the United Nations.

Type	File	Number of Columns	Number of Rows	Size on Disk	Description
Online Reviews	reviews.csv.gz	7	600,006	2.68 GB	Review data from 16 cities and 15 countries.
Listing Information	listing.csv.gz	75	332,436	855.9 MB	All listing data
Calendar Information	calendar.csv.gz	7	121,332,029	5.48 GB	Calendar data for all the listings for each day of the next 365 days
Covid Data	WHO-COVID-19-global-data.csv	8	210930	9.5 MB	WHO country-wise data for reported Covid cases

Table 1: Raw data overview

3.2. Data Processing

3.2.1. Initial Cleaning and Data Processing

One of the constant issues in data analytics is finding and fixing dirty data, and failing to do so can lead to faulty analytics and unreliable judgments (Chu et al., 2016). Unstructured and unclean data can lead to misleading outcomes, rendering the analysis unusable. The Airbnb datasets are well-structured; however, several cleaning operations are undertaken to fit the data according to the purpose of the analysis. The addresses of the listings aren't consistent as some reviews lacked the names of either city, province or country. Some of the variables lacked the correct datatype. The price variable contained '$' symbol, which is not suitable for analysis. The NA values in the datasets were present in different formats. Some were empty spaces while others were presented as NA's. Variables with rates also contained the symbol '%'. After filtering the data randomly, it is cleaned into normalized tables while addressing these cleaning issues. The location variable is separated into city, province and country columns. Functions from 'stringr' library are used to make the data consistent by removing special characters. The NA values are not removed to avoid the loss of data, instead they are all made into a consistent form. The date columns are also modified to 'month-year' format for better representation. The datatypes of some variables are converted into appropriate formats. The review and listing datasets are combined into one and similar actions are performed on both calendar dataset as well as review-listing combined dataset. The obtained datasets do not have any specification for pandemic period. The WHO data for Covid-19 cases around the world is filtered down to include only the countries included in this study and the number of cases reported is visualised to estimate the time when the pandemic hit in each country.

It is observed (Figure 2) that COVID cases mostly started to be reported around March'20. Thus, the period post March'20 is treated as the pandemic period. Using this two-factor variable, the text mining analysis will be performed to understand the differences in the customer attitudes.

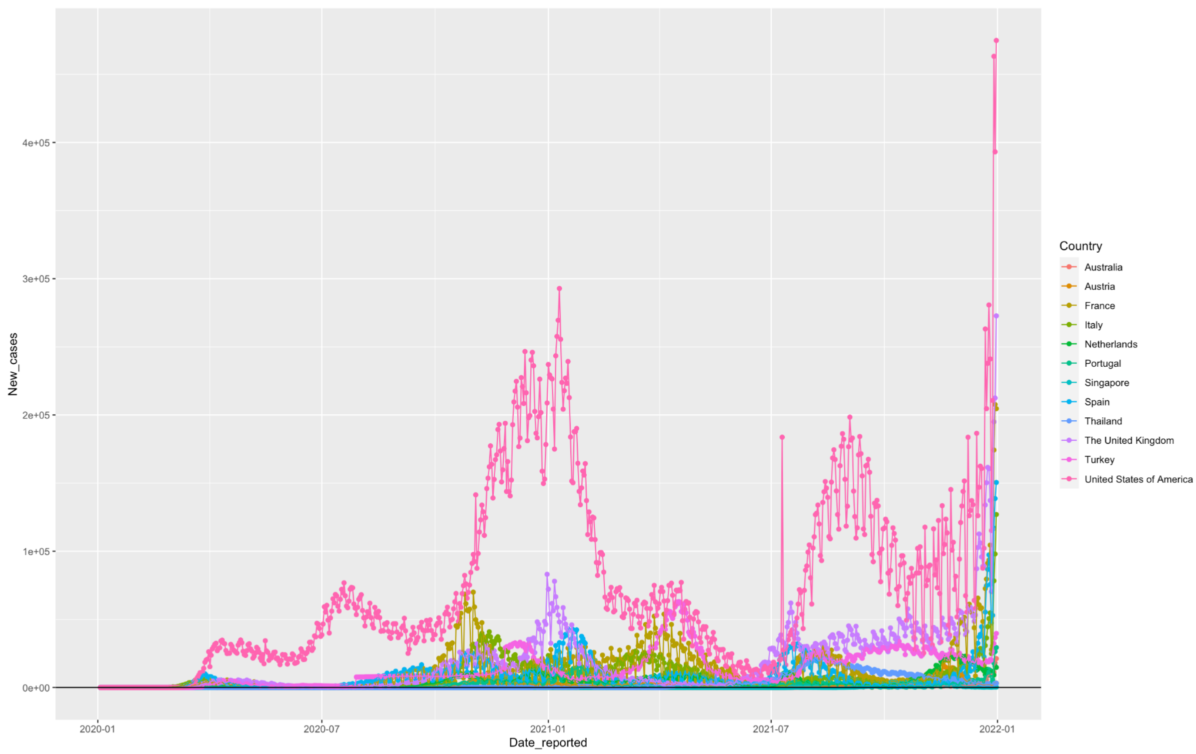

Figure 2: WHO Covid-19 cases

The data is aggregated in two master datasets after the data cleaning and preparation is completed and saved to the local disk. The initial preparation is done in RSQLite database as the large size of the datasets renders operations in R Studio too slow. After reducing the size of the datasets through filtering, the bulk of the cleaning and preparation are done in the R Studio environment.

3.2.2. Text Processing

Text mining techniques require the text data to be processed in specific methods before analysis due to the inconsistent nature of the languages used in reviews. The reviews are cleaned by removing brackets, contractions, special symbols and white spaces. To enhance efficiency, the lengths of the reviews are filtered through observing the number of words used in each review. Only reviews with 100-1200 characters are kept for analysis (Appendix B).

Texts must first be tokenized in order to be structured for subsequent analysis; otherwise, text is simply handled as an unstructured "string." (Gallagher, Furey and Curran, 2019). The collected reviews are broken up into individual words and lemmatized to their basic forms. This allows the user to perform initial text mining in order to explore the frequency of words in a corpus, which is also known as the 'Bag-of-words' process. Using this approach, it is possible to identify specific words in the documents that would have further basis for analysis.

However, not all words have meaningful interpretation when treated as its own entity and textual data often consists of highly frequent words, such as ‘at’, ‘of’, ‘an’, etc, that are part of natural language but provide no interpretation. These stop words are filtered out in order to make room for longer and more meaningful words, hence improving the data and lessening the chances of getting subpar results (Gallagher, Furey and Curran, 2019).

The reviews are also filtered based on language identification and only those in the English language are kept using the ‘udpipe’ package. The language identification is done on review and listing description texts and upon filtering, the dataset is reduced to around 87,000 reviews. Textual data produced by a crowd usually involves a lot of noise because of typos, grammatical problems, overuse of punctuation, or informal writing styles (Barbier et al., 2012). Upon obtaining the English contents, processing for spellings is attempted using the ‘hunspell’ package. Using this function, spellings are corrected both manually and through automated suggestions. Finally, the reviews are tokenized and further filtered for token lengths and tf-idf to aim for the middle 60% of the tokens that represent the mutually exclusive of common general terms and uncommon subjective terms (Appendix B). The reviews are grouped by the unique identifier, ‘listing_id’ and also the period that they belong to in terms of before or after the pandemic. This allows to perform analysis of the reviews while segregating them according to the needs of the study. The tokens from each individual review related to a single listing are grouped together for the purposes of the analysis.

3.3. Preliminary analysis and outputs

Solving the issues found in the data enables the performing of some descriptive analysis. Through looking for correlations and using statistical methods, the data is explored for indicators that would provide a direction for the core analysis.

3.3.1. Inferences from the metadata

The distributions of the metadata of Airbnb dataset (Appendix A) reveal the trends to expect in general during analysis. Overall, majority ratings of the reviews tend to be between a score of 4 to 5 in each category. This could be due to the positive attitude customers have towards Airbnb. Hence, this might not be a good indicator for spotting customer attitudes as any reviews with lower ratings will be a small minority.

The total number of reviews for the listings, counted per month, is further investigated on a timescale, and the numbers dropped noticeably around the time the pandemic started. It soon recovered, however, a second drop is seen, which might indicate a 2^{nd} wave of the pandemic. This trend is replicated when the frequency of reviews is investigated separately for each of the countries, but, in general, the number of reviews post pandemic seems higher than that before.

The majority of the room types found in the data for this study includes ‘Private Rooms’ and ‘Entire homes/apts’. Hotel rooms are not the focus of Airbnb, which is why this room type is expected to have lower demand as indicated by the lack of reviews. Finally, the listings with the instantly bookable feature are investigated, and it is found that the number of listings with such features has increased much more after the pandemic. This might indicate a trend in the way the hosts have adapted with the pandemic period by preferring to make their listings readily bookable. The inferences obtained from the distributions of the data provide a preview of things to target in the next phases of the analysis.

3.3.2. Statistical Analysis

Through the various lengths of text review, consumers' purchasing attitudes and sellers' reputations are likewise moderated (Md Altab et al., 2022). In the case of Airbnb reviews, the investigation of the correlation between review lengths and different rating categories reveals a slight positive correlation (Appendix C). However, due to the consistency of the correlations across all the rating types, this doesn't seem too promising in terms of getting insights about the customer attitudes.

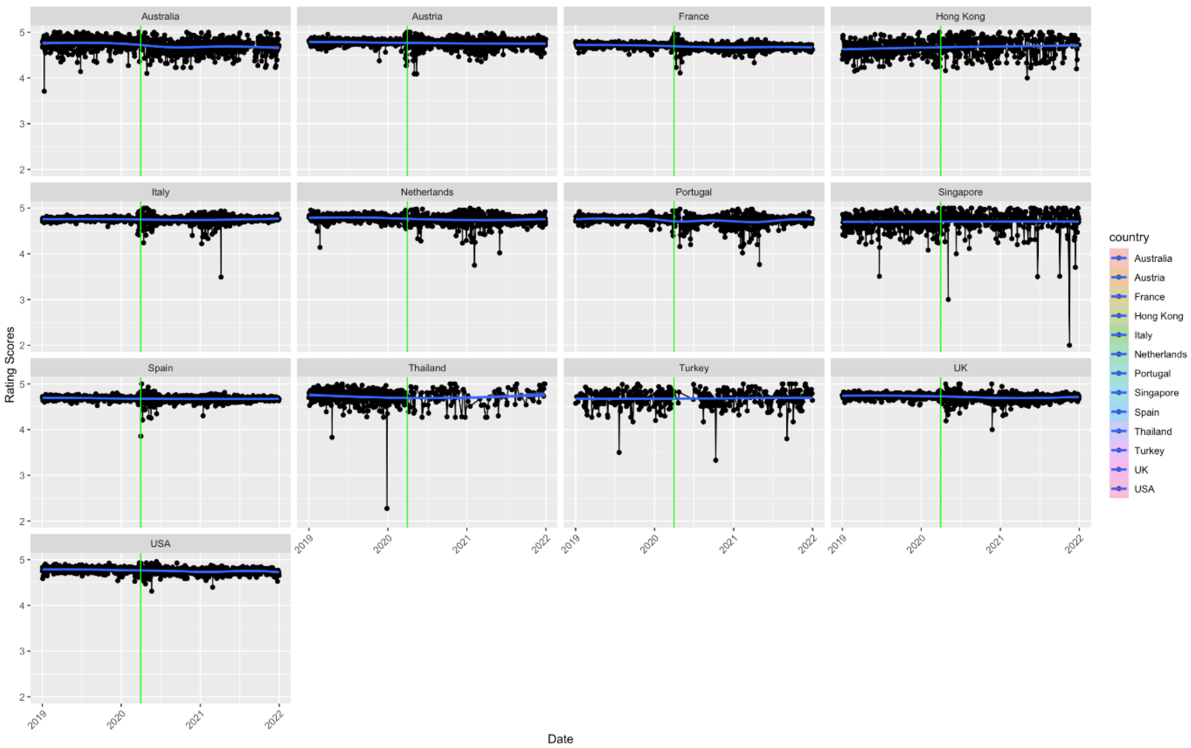

Figure 3: Country-wise rating scores from 2019-2021

Estimating the true means of the ratings as seen before the pandemic against those obtained after the pandemic gives a significant difference, dropping from 4.73 to 4.71 (Appendix C). This might indicate some changes in sentiment about the services of Airbnb. Observing the ratings on a country-basis (Figure 3) also portrays meaningful insights about how the ratings have been affected by the pandemic. It is clear that the deviations of the ratings increased noticeably right when the pandemic hit, especially in countries like France, Italy and Spain. In the case of Turkey, no rating data is found for a few months. This can be explained by the fact that there was a strict lockdown imposed there around April'20 till June'20 and that Airbnb operations would've been halted. Similar effect might've been in play in Thailand, as the number of reviews after the pandemic reduced. While most trendlines of ratings for the countries do seem to have a very slight downward slope, Hong Kong seems to have had higher ratings going into the pandemic.

The unique value proposition of Airbnb is the family-friendly and group travel-friendly stay that differentiates it from hotels. Hence, it can be expected that private rooms and shared rooms and houses are to be the most in demand room types. The ratings for each room type are regressed against time for the period of this study to investigate any changes in customer satisfaction and preference. As expected, there is no significant difference in the ratings given by customers before and after the pandemic for hotel rooms. There is a significant change in the ratings found for the other room types. The plotting of all the ratings for each room type shows a rise in variation of the ratings for entire house/apt and private rooms, whereas there seems to be a reduction of the number of ratings found for shared rooms right after the pandemic hit. However, while the ratings for entire homes/apts reduced, the true mean ratings of shared rooms increased after the pandemic.

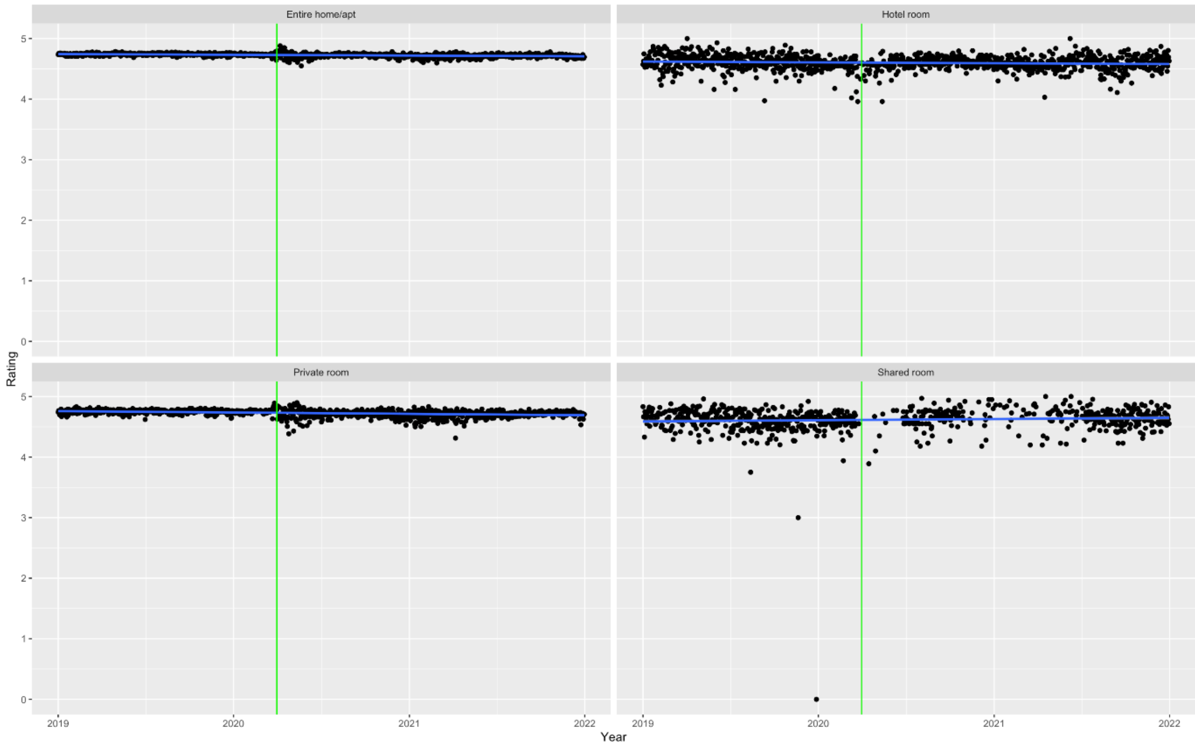

Figure 4: Ratings per room type over years

On the hosts' side too, numerous aspects are tested for differences between the two periods. It is found from the data after performing estimation tests that hosts have decided to significantly reduce the minimum nights of stay needed for making a booking for their listings, with the true mean after the pandemic being 5 nights while it was 9 nights before. At the same time, the prices of the listings have increased significantly after the pandemic by $6 on average. The combination of the rise in prices and the low demand could be the reason behind the significant increase in the days of availability of the listings, as the estimation of the number of nights the listings have been available for in 90 days increased significantly after the pandemic, from being 29 nights to 36 nights on average. However, there might not be a clear cause-effect relationship between availability and pandemic period, as it is also seen that the number of listings of hosts increase significantly after the pandemic, leading to an increase in supply while there is low demand.

3.3.3. Feature Extraction Analysis

Text feature extraction is the process of selecting words from a document section to reflect information about the content (Due Trier, Jain and Taxt, 1996). Utilising the tokenized reviews filtered based on tf-idf measures, words that could have importance in terms of pandemic are selected, through judgement, as features and tested for having effect on customer ratings. Multi-faceted observations are made to identify such words.

As seen in Appendix D, over the years, contents about communication have been mentioned frequently from 2020 through 2021, while it wasn't that frequent in 2019. This, for instance, gives an indication that customers started to be more concerned about how the hosts communicated with them during the pandemic. The word close became less used, which could indicate that the guests preferred to book an Airbnb when they were going to a distant location from their homes or that the closeness of the listing to other facilities like restaurants or stations became less of a concern after the pandemic. In 2019, there were more mentions about surroundings, such as the city itself, metros, stations, etc, while such words haven't come up later in the years. Similar nature is also seen when the words are analysed based on pre- and post-pandemic periods (Appendix D). Looking through the words by city doesn't however give much information regarding the change of word mentions based on the effect on the pandemic (Appendix D). Overall list of words indicates that, while the words used overall were positive, customers might have had some changes in their preferences while booking an Airbnb.

The selected features are: recommend, location, price, stay, host, clean, communication, availability, check and easy. Initially, these features are tested against review scores to identify their importance in the overall corpus. The regression reveals the significance of the features, with 'recommend', 'stay', 'host', 'clean', 'communication' and 'easy' having directly proportional effect on the ratings and 'location', 'price', 'communication' and 'check' having inversely proportional effect on ratings. The availability feature doesn't seem to have any significant effect on the ratings. Similar regression analysis is also performed on the features for reviews separated by periods. Except the 'easy' feature, all others turn out to be significant. On the other hand, results for reviews after the pandemic show a different result, in which 'easy' feature is significant, but 'clean' feature becomes insignificant. This could indicate that customers were looking for listings that are easy to book and were more satisfied with this feature after the pandemic than they were before the pandemic. However, they seem to be unsatisfied with the cleanliness of the bookings as revealed by the inverse proportionality of the 'clean' feature with ratings.

3.3.4. Sentiment analysis

Attitudes are the settled way of thinking about something or the way people feel about some entity, and that delves into the emotions or the mental states. The words that are mentioned in prominence are an expression of the inner mind moulded by emotions, which provides the rationale for associating word importance with attitude. Sentiment analysis further extracts the emotions behind text documents and gives a portrayal of the attitude behind a particular statement. This method allows us to get a measure of the positive or negative feelings behind a review, or even go deeper into emotions such as anger, happiness, dislike, sadness, fear, etc. Thus, with the first approach of text mining completed, the next approach undertaken is to perform sentiment analysis on the documents. Sentiment analysis uses various predefined dictionaries to match sentiments with words in text and an overall sentiment can be calculated based on the positivity and negativity of the words in a review.

Initially, a compatibility test is done to determine the dictionaries that can be used to fit the nature of the Airbnb reviews best. Four dictionaries are considered in this case: Afinn, Bing, NRC and Loughran. It is unnatural human behaviour to frequently use highly negative words in expressing themselves in any format. Hence, when the Airbnb reviews are aggregated at a higher level, it is expected that all the dictionaries have positive-leaning sentiments (Figure 5).

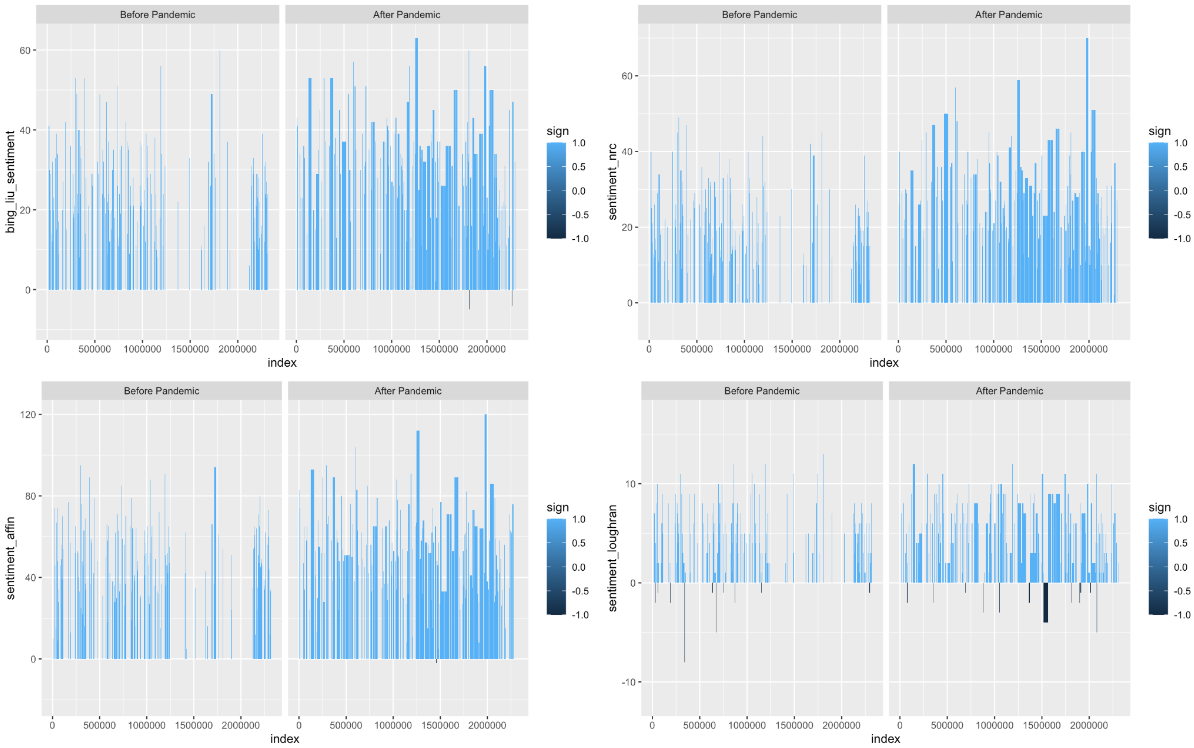

Figure 5: Sentiments of different dictionaries by pandemic periods

The sentiments from each dictionary are evaluated based on regression results against review scores. The result of the regression analysis corresponds with the observed performances of the dictionaries, with all four dictionaries having significant effect in predicting rating scores, but Bing Liu dictionary having the highest adjusted R2 of 22.5% (Appendix E)

Emotions portray the feelings induced within a customer after any particular incidence, which in the case of Airbnb, would be the experience of a booking made by a customer. It is seen from the data that these emotions have direct correlation with the ratings given by customers. The relationship is analysed through performing regression test of all the NRC feeling extracted from review text against rating scores. As per the results, it is seen that in case of Airbnb, the emotions 'anger', 'anticipation', 'fear', 'joy' and 'trust' have negative correlation with rating scores, while 'sadness' and 'surprise' have positive correlation. However, 'sadness' and 'trust' emotions do not have a significant effect on rating scores. This is visualised through the wide confidence interval seen for both these emotions as seen in figure 6. It can be ultimately perceived that, catering towards services that incite in customers the feelings of surprise could lead to higher rating scores in case of Airbnb, while issues that cause negative emotions, specially anger, disgust and fear, need to be investigated as these have significant effect and should be avoided to mitigate chances of lower ratings.

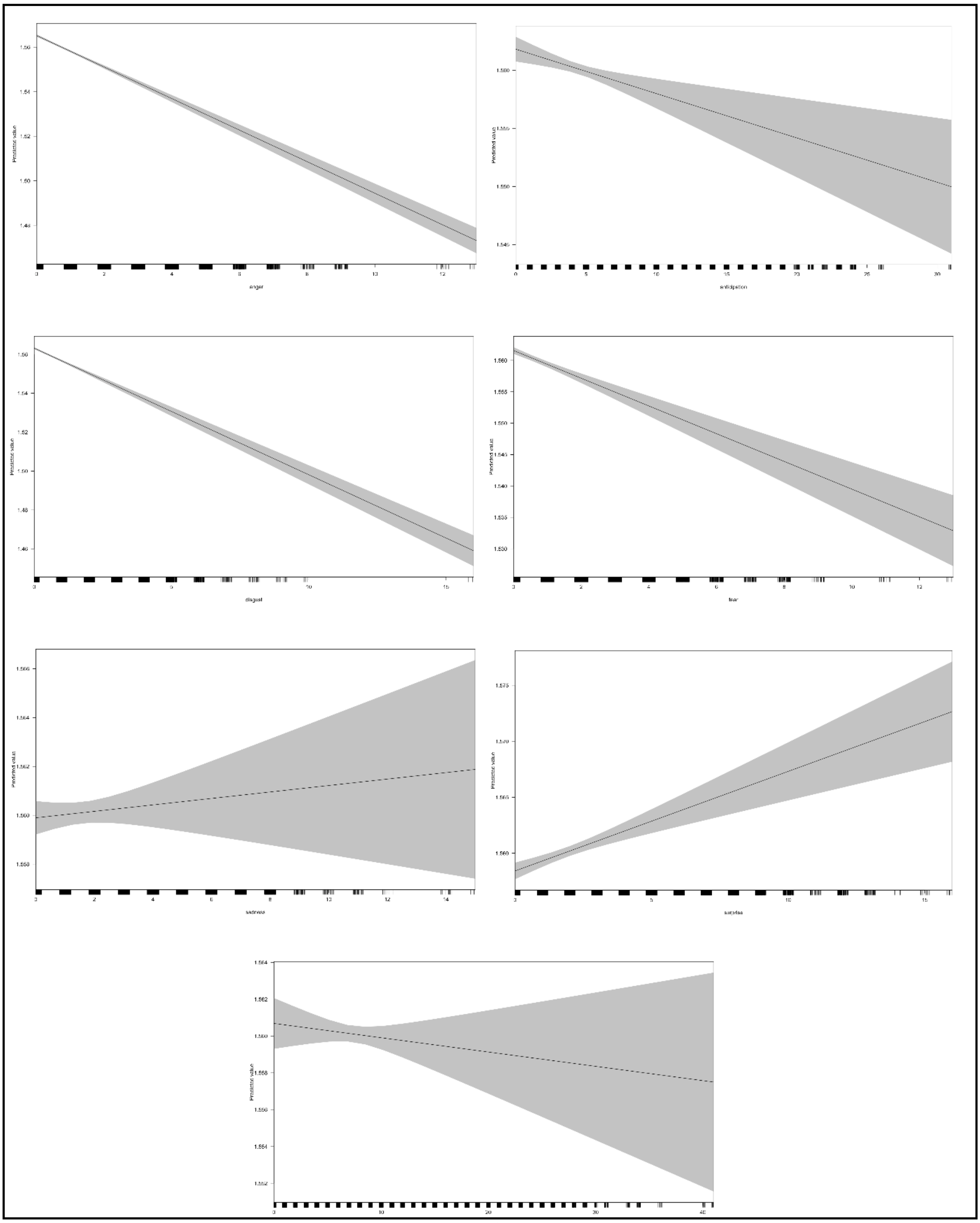

Figure 6: Relationship between emotions and rating scores

3.3.5. Topic Modelling

Another approach to text mining customer reviews is to use Latent Dirichlet Allocation (LDA) method to identify topics based on word association to get a detailed perception of the dominant matters at any given point of time. This part of the analysis will focus on deriving the differences in the dominance of the identified topics before and after the pandemic to see if there has been any effect. The cleaned texts from the initial stages are retrieved again and prepared specifically for topic modelling. As emoticons and other characters present in comments aren't relevant for topic identification, these are removed and the texts are tagged using R Studio 'udpipe' package to detect the different parts of speech. As topics are engraved in nouns, adjectives and adverbs, these are filtered out and fed into the model.

The LDA topic modelling is performed using the 'stm' model, while keeping the effect of review ratings and date of review prevalent. The optimal K value, to identify the number of topics to be searched, is defined as 7 based on high held-out likelihood, exclusivity and semantic coherence and low residuals (Appendix F). The 'selectModel' function is used with k=7 to find the best LDA integrated 'stm' topic model for better optimization.

The obtained topic model provided a range of words with high association to be clustered together under a topic. Based on observation of the 'frex' words, the topics are determined to be 'Communication', 'External Facilities', 'View/Beauty', 'Distance/Transportation', 'Value for Money/Cleanliness', 'Amenities', and 'Place/Comfort' (Appendix F). The top words for each identified topic are visualised for verification (Appendix F). The tokens captured under each topic seems intuitive. For example, the words metro, walk, station, bus, etc can be considered as 'External Facilities' to indicate that the guests might be concerned with such places when making a booking.

Based on the effect estimation of ratings, it is seen that negative ratings have been influenced by the topics 'Amenities' and 'Value for money/Cleanliness', while the more positive ratings entailed the customers being concerned with issues about 'View/Beauty' (Figure 7). While these are the topics identified based on overall reviews from the entire period of study, change of the prevalence of these topics with the onset of the pandemic is to be examined carefully.

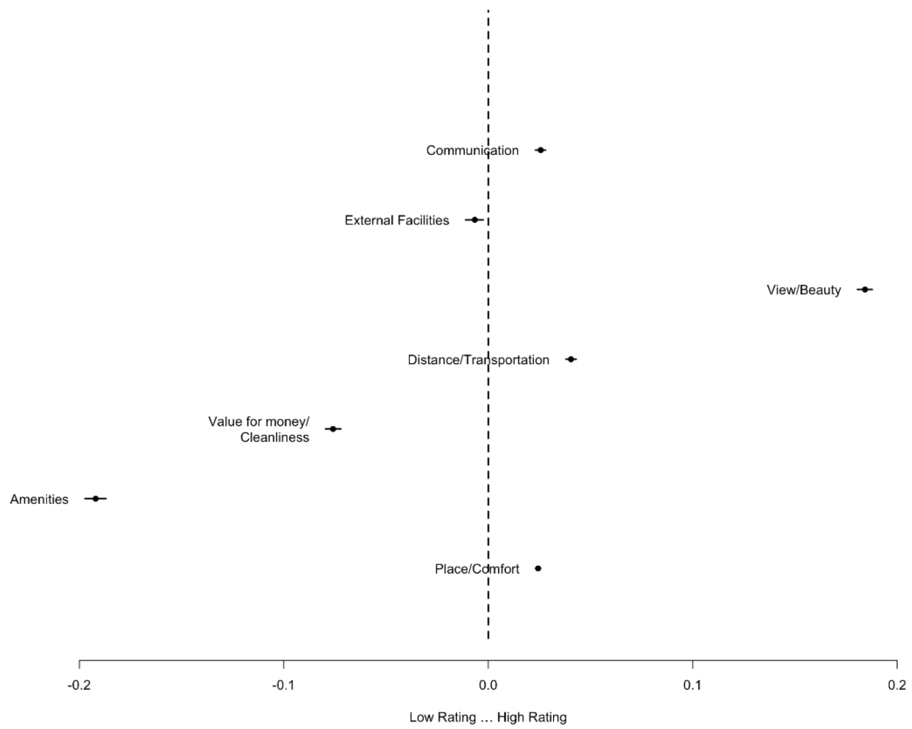

Figure 7: Effect estimation of each topic with prevalence of review ratings

3.3.6. Predictive Analysis

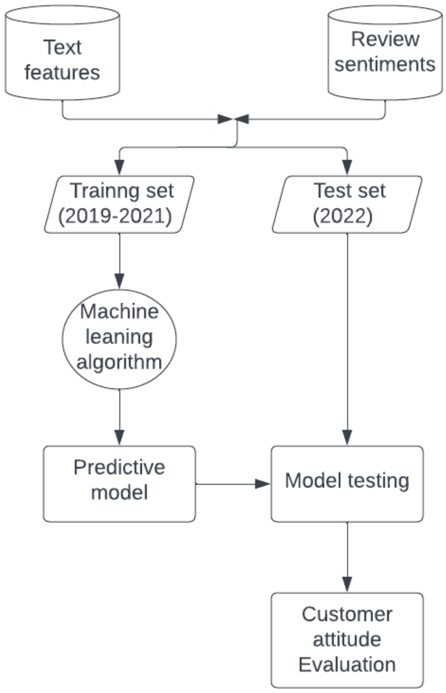

Figure 8: Predictive modelling process on review datasets

Text mining is the use of machine learning techniques on textual data while utilising Nature Language Processing (NLP). This provides the relevance of using mined data in machine learning algorithms. Due to the close correlation between ratings and customer satisfaction, the extracted sentiment scores and features can be used to train machine learning models to provide a prediction of review ratings. Hence, in this study, the analysed reviews from 2019-2021 are used as training data to train supervised learning models and evaluated against 2022 review data. Similar data preparation is performed on the test data to maintain consistency in comparison. Two models are trained, one using only pre-pandemic dataset and another using only post-pandemic dataset, and they are evaluated against the test dataset. The better model should indicate whether customer attitude changes that have been analysed in the previous sections will carry over into the future or whether customer behaviours will return to pre-pandemic state. An instance-based learning algorithm, K-nearest neighbours model, is used for this purpose. It is a non-parametric technique for text categorisation based on statistical pattern recognition to find the k-nearest neighbours of an ambiguous feature vector whose class is to be determined, given N training vectors. It is utilized to perform a predictive approach towards evaluating change in customer attitude through setting review scores, treated as multi-level factor, as the target variable for prediction.

3.4. Conclusive Analysis and Outputs

Utilising the preliminary outcomes of the analysis, this section of the study will draw findings that constitute the fundamental findings to specifically address the objectives undertaken.

3.4.1. Change of emotions with the pandemic

The preliminary analysis revealed the necessity to investigate the issued that gave rise to emotions such as anger, surprise, etc to maximize rating scores for Airbnb. Word associations with each emotion are analysed to understand what aspects of the services are the causes. This analysis is furthered by analysing whether the issues behind each emotion have remained the same after the pandemic or not. Guests are found to feel anger mostly about the heat, likely the room temperature; noise, probably from the neighbourhood of the listings; money, which would refer to the price of the bookings they make. They are also found to fear some sort of difficulty and anticipate a lot about the booking being perfect and the time, probably referring to their stay there. However, there doesn't seem to be much influence of the pandemic behind these emotions as these words have persisted in the reviews even after the pandemic. The reason behind trust being insignificant predictor of rating could be that customers have historically associated cleanliness with Airbnb even before the pandemic, so they expected sufficient sanitization measures from Airbnb by given during the pandemic. However, there also seem to be instances where guests felt disgusted by the dirty rooms too in the post-pandemic period that led to lower ratings, which could indicate that some listings might have not been maintaining the cleanliness. Another change in the words that caused surprise is the word 'money' in the post-pandemic period. This is consistent with the feature extraction analysis, that the feature 'price' did catch the guests by surprise and had a significant effect on the ratings. Despite the observed few differences in the frequent words used to express each emotion before and after the pandemic, the distributions of the emotion scores by pandemic period do not reveal a big difference, with only the significant emotions from the regression test showing slight change in their means (Figure 9)

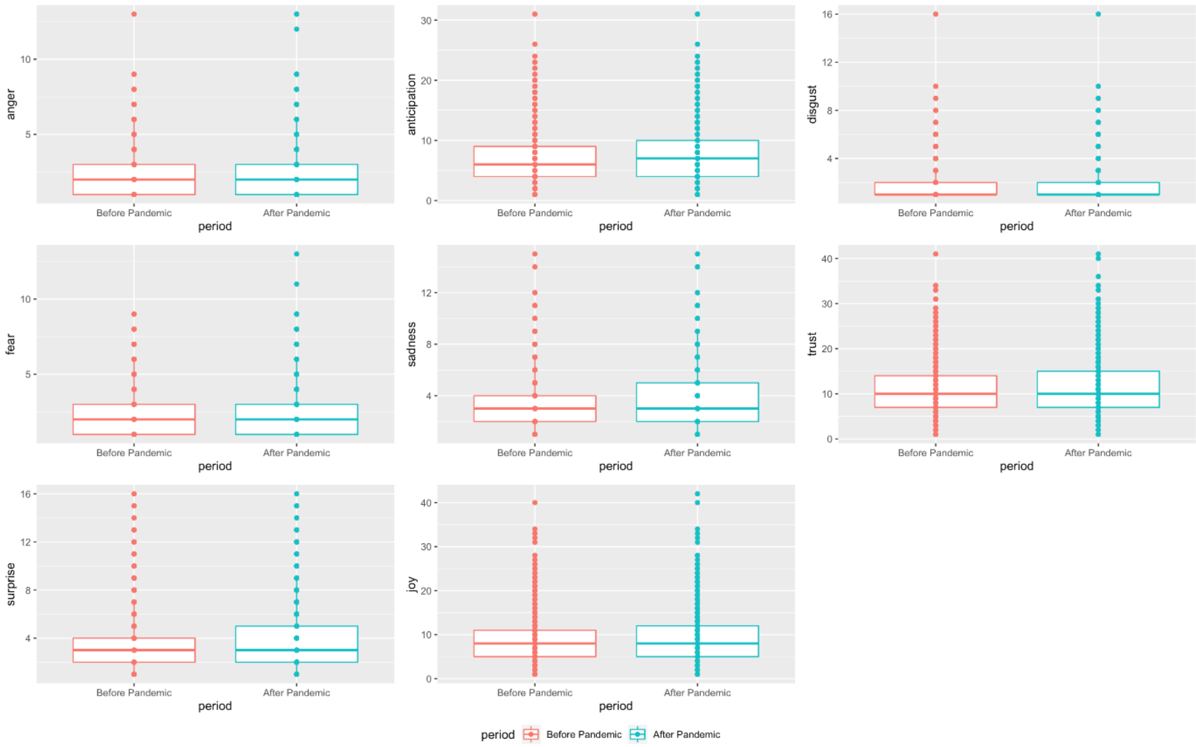

Figure 9: Changes in distributions of emotion levels with the pandemic

3.4.2. Country-wise emotion prevalence with the pandemic

In the previous results, the NRC emotions and their associated words have been analysed in terms of the period of the pandemic. In this section, the development of the emotions over the timeline of the study is examined to understand the fluctuations of each emotion based on the events that occurred. In figure 15, it is evident that the onset of COVID-19 caused a disruption in the trend of each emotion. Each of the emotion levels deviated noticeably from the stable trend that is seen before the pandemic. Guests felt anticipation, trust and joy increasingly right after the pandemic as evidenced by the upward trend of the emotion levels. This might indicate that, even though customers were anticipating about how their experience of Airbnb booking might be during the pandemic, their emotions were heightened by it too as following anticipation, good experience translated to immense joy and enhanced trust in the service. There is also indication that the pre-pandemic levels of the emotions were slowly coming back towards the end of 2021, and so was the variance in the levels. These findings are also replicated when the emotions are investigated on a country-basis (Appendix E). However, some of the countries might have experienced a considerable drop in bookings, such as in Thailand, right after the pandemic, while other countries, like Turkey, has a drop-in level right after the pandemic, but the lines pick up soon after an interval

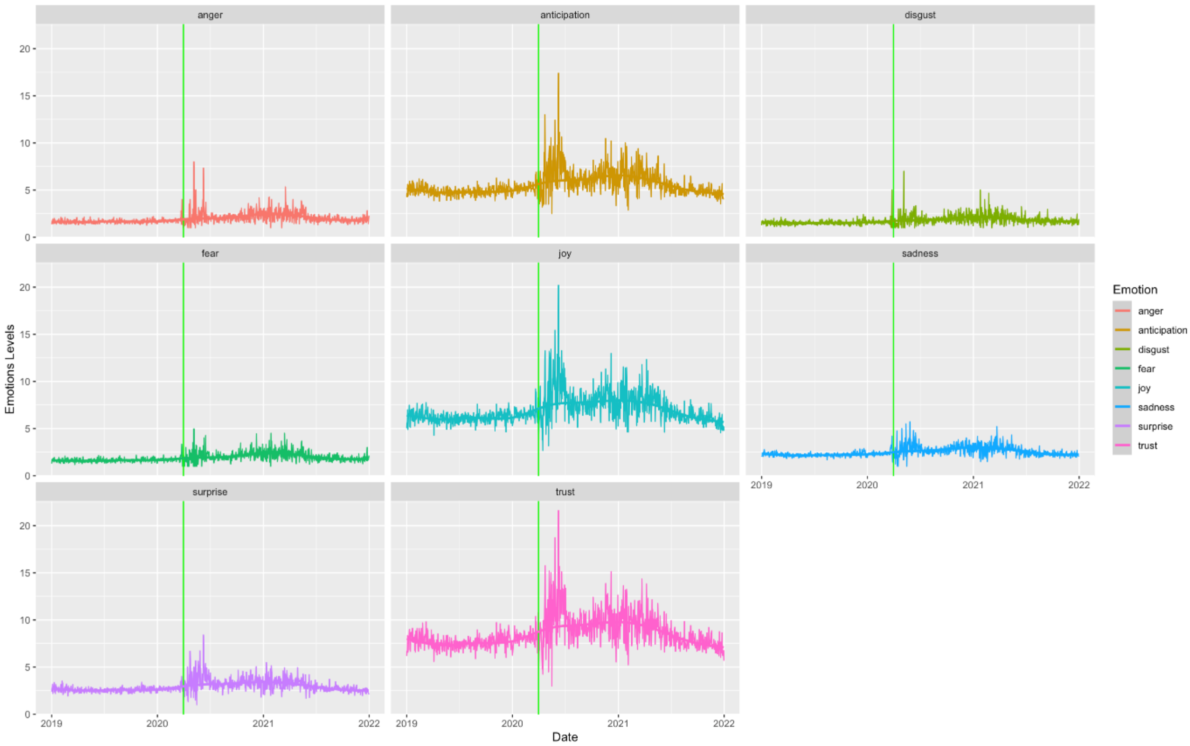

Figure 10: Overall changes of emotions during the period of study

Another finding from the analysis of the emotions on a city-level is the decrease in the percentages of positive sentiments in general after the pandemic (Figure 11). Regardless, some cities did also incite a big increase in the positive sentiments, which indicates that some cities might have handled the pandemic better than the others. It can be noted that the sentiments of Vienna, Sydney, Singapore, Rome, Porto, Paris, Melbourne, Madrid, London, Hong Kong, Barcelona, Bangkok and Amsterdam saw a reduction in percentages of positive sentiments after the pandemic. On the other hand, the remaining cities: San Francisco, New York and Istanbul saw a rise in positive sentiment after the pandemic, which could indicate that these cities were less impacted by the pandemic, or that the management of the situation in these regions was better. However, overall, the percentages of the negative sentiments remain overshadowed by that of the positive ones. Of all the countries, the most concerning condition is seen in Bangkok, which shows a massive drop in all sentiments.

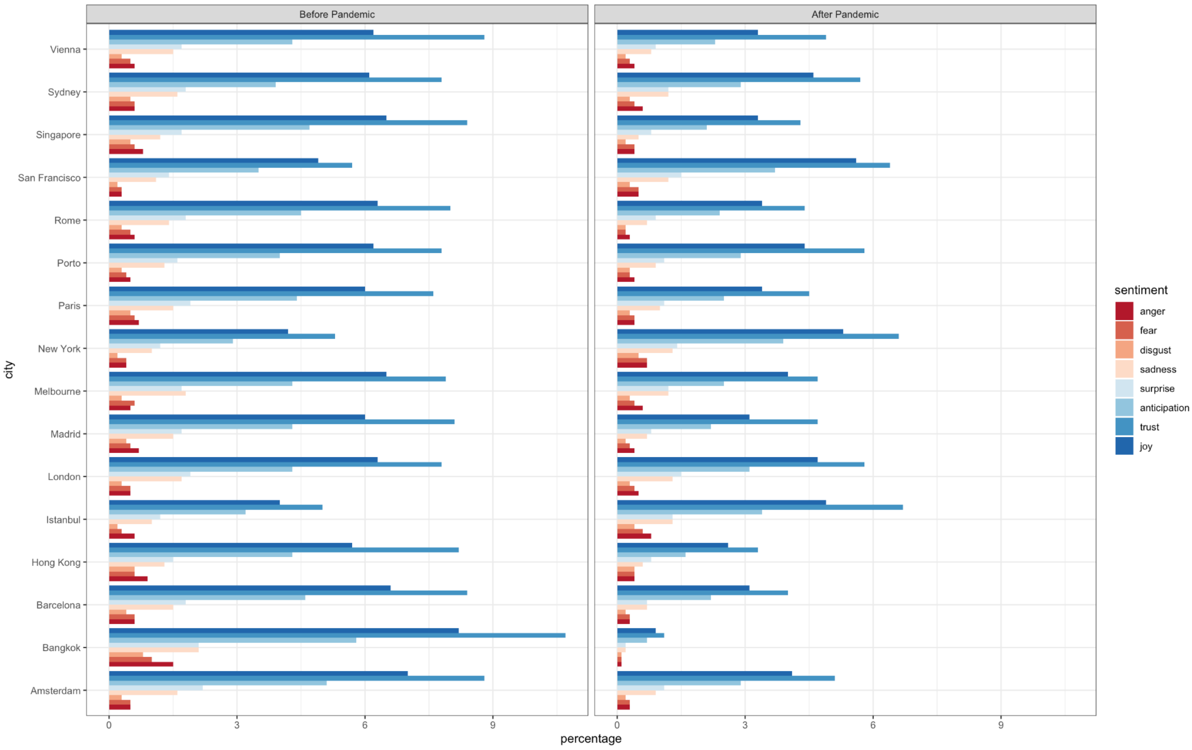

Figure 11: Country-wise comparison of emotions with the infuence of the pandemic

3.4.3. Country-wise change of polarity of sentiments

There is indication of positive sentiments after the pandemic as seen in the previous section. Hence, further investigation of the changes of polarity is performed to get a concentrated insight into how these sentiments are changing over time. In figure 12, it is found that indeed there is a decrease in the level of positive sentiments in most of the cities considered. As seen in the previous sections, the noted cities did see a drop in positive sentiments after the pandemic. When trended against time indexes (Figure 13), it is seen that there have been the highest fluctuations in the polarity levels in Amsterdam and Singapore. The polarity of sentiments in Melbourne and Sydney has been downward-trended while that in Istanbul is upward-trended. This clearly indicates how the customer perception of the services of each city varied over the period.

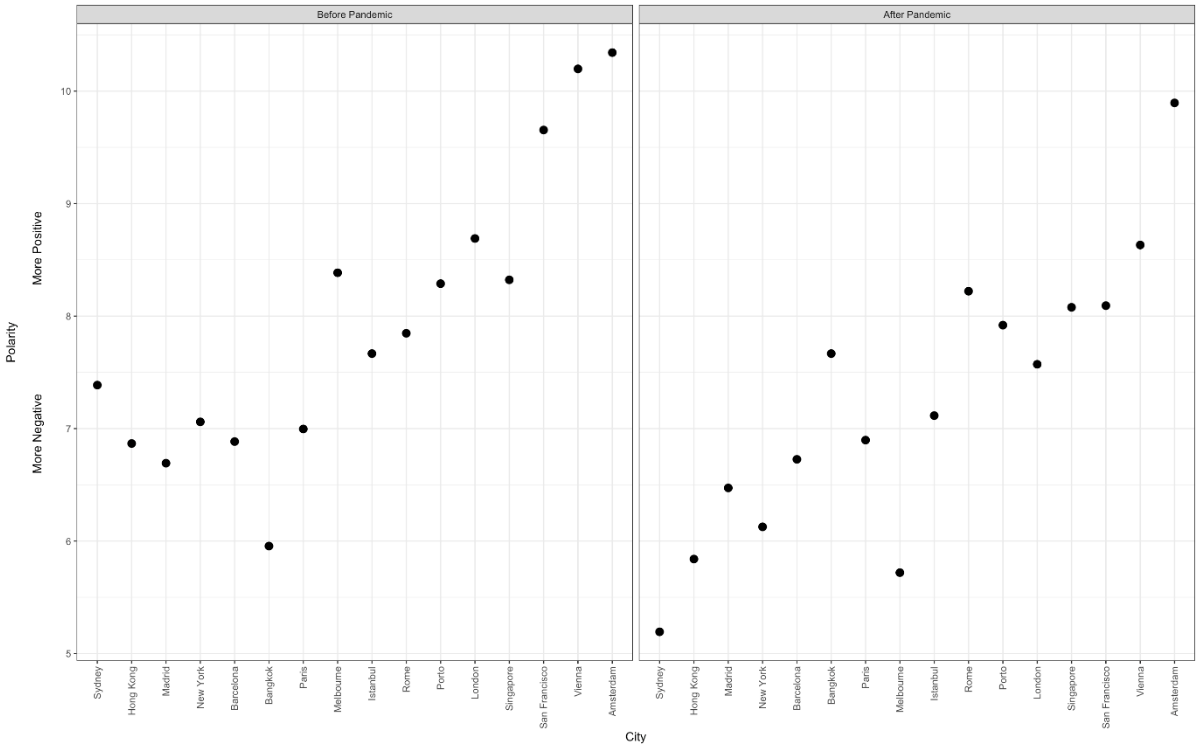

Figure 12: Changes in levels of sentiments by country during the pandemic

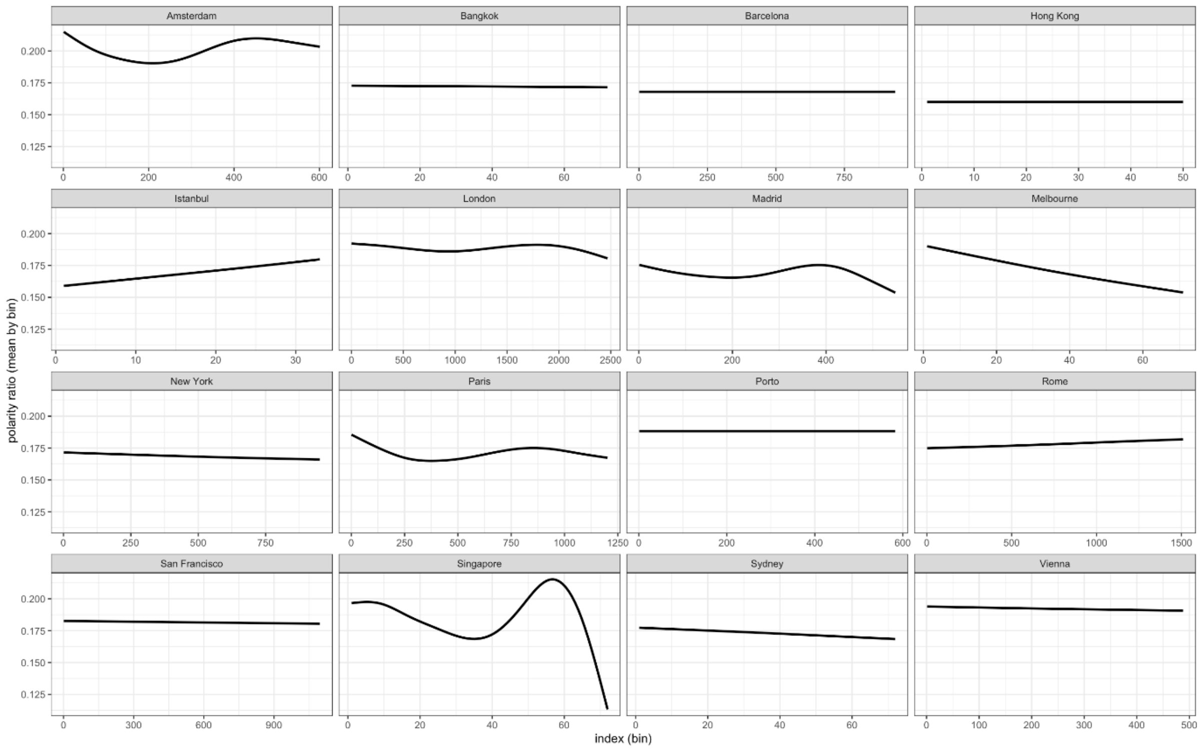

Figure 13: Country-wise temporal patterns of polarity levels

3.4.4. Temporal development of sentiments during the period of study

As part of final consideration of sentiment analysis, the outcome considered is the snapshot of monthly development of sentiments from 2019-2021 as time progresses. This gives an understanding of whether the sentiments of the reviews of guests caused a deviation from the pre-pandemic trends. Airbnb has a historical trend of generating negative sentiments at the end of the first week of every month, at half-way through the month and at the latter part of each month. These trends continued towards the post-pandemic era. The change that could be spotted is the increase of the white spaces around the March of 2021. This could hint the ambiguity that customers faced about their feelings of the situation when the pandemic hit, however, other than few sparse generations of negative sentiments from time-to-time, there doesn't seem to be any concerning change in customer attitudes following the pandemic. However, it has to be noted from the previous observations that, even if there isn't high proportion of negative sentiments towards Airbnb, the noticed change is the lowering level of positive sentiments after the pandemic.

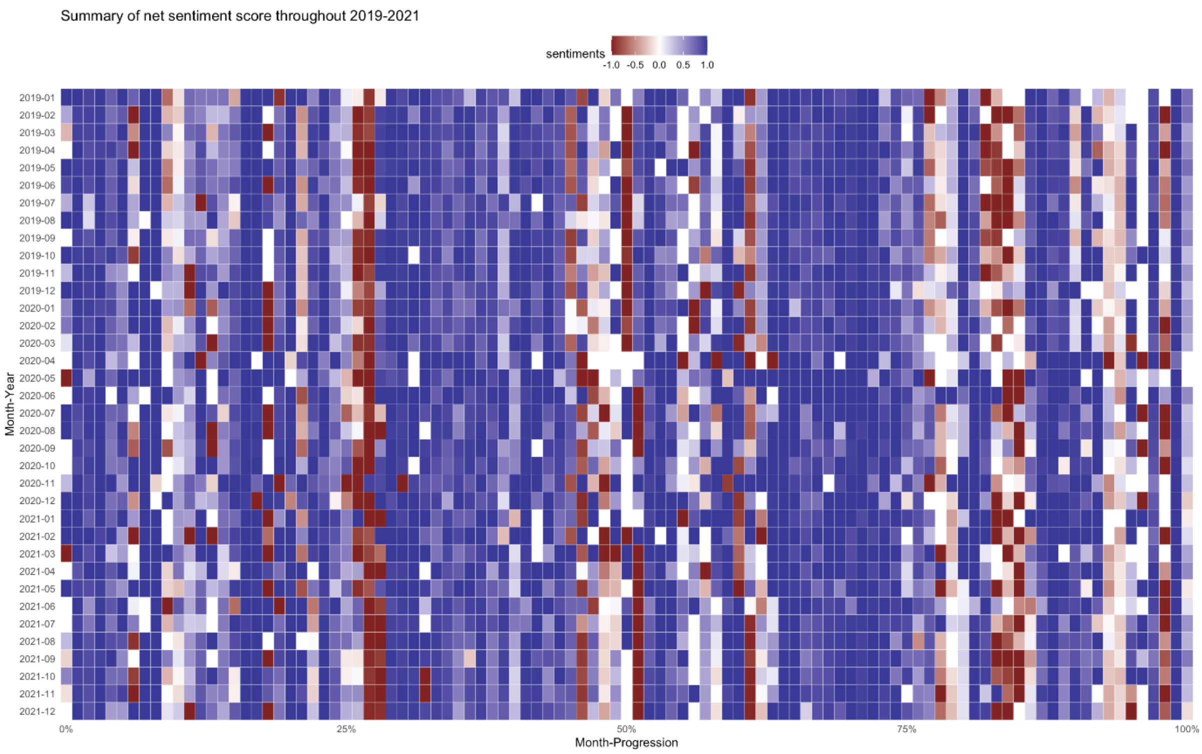

Figure 14: Monthly progression and overall trends of sentiments over the period of the study

3.4.5. Topic prevalence over time with the pandemic

From the preliminary analysis, some topics prominent in the reviews of Airbnb guests have been identified. These topics represent the attributes that are important to guests in general. Customer behaviours are susceptible to change under the influence of external factors, hence, understanding any changes in the topics most concerning to customers can be accomplished through temporal estimation of the prevalence of each topic. As defined in this study, the onset of the pandemic is taken to be the period after March'20, and the effect of pandemic on the identified topics is analysed in figure 15. It appears that the expected proportions of the topics 'Communication', 'View/Beauty' and 'Value for money/Cleanliness' are exponentially increasing around the time when the pandemic started. On the other hand, proportions of topics: 'External Facilities' and 'Distance/Transportation' are expected to decrease at the same time. These trends indicate that Airbnb customers mentioned about communication more during the pandemic, which could be during the time of booking or checking in to their rooms. Social distancing could be the contributing factor for such trend when face-to-face interactions with hosts became limited. Guests also seemed to mention about the cleanliness of their bookings increasingly during the pandemic due to safety issues. The restriction of movement and reduction in travelling do mean that customers started to be less concerned about places around the listings, such as restaurants, bus stops, etc and did not consider much about availability of transports when making a booking with Airbnb like they did before the pandemic. Apart from these, there doesn't seem to be any change in behaviour when in comes to the topics 'Amenities' and 'Place/Comfort', which indicates these were the constant expectations they had, regardless of the pandemic.

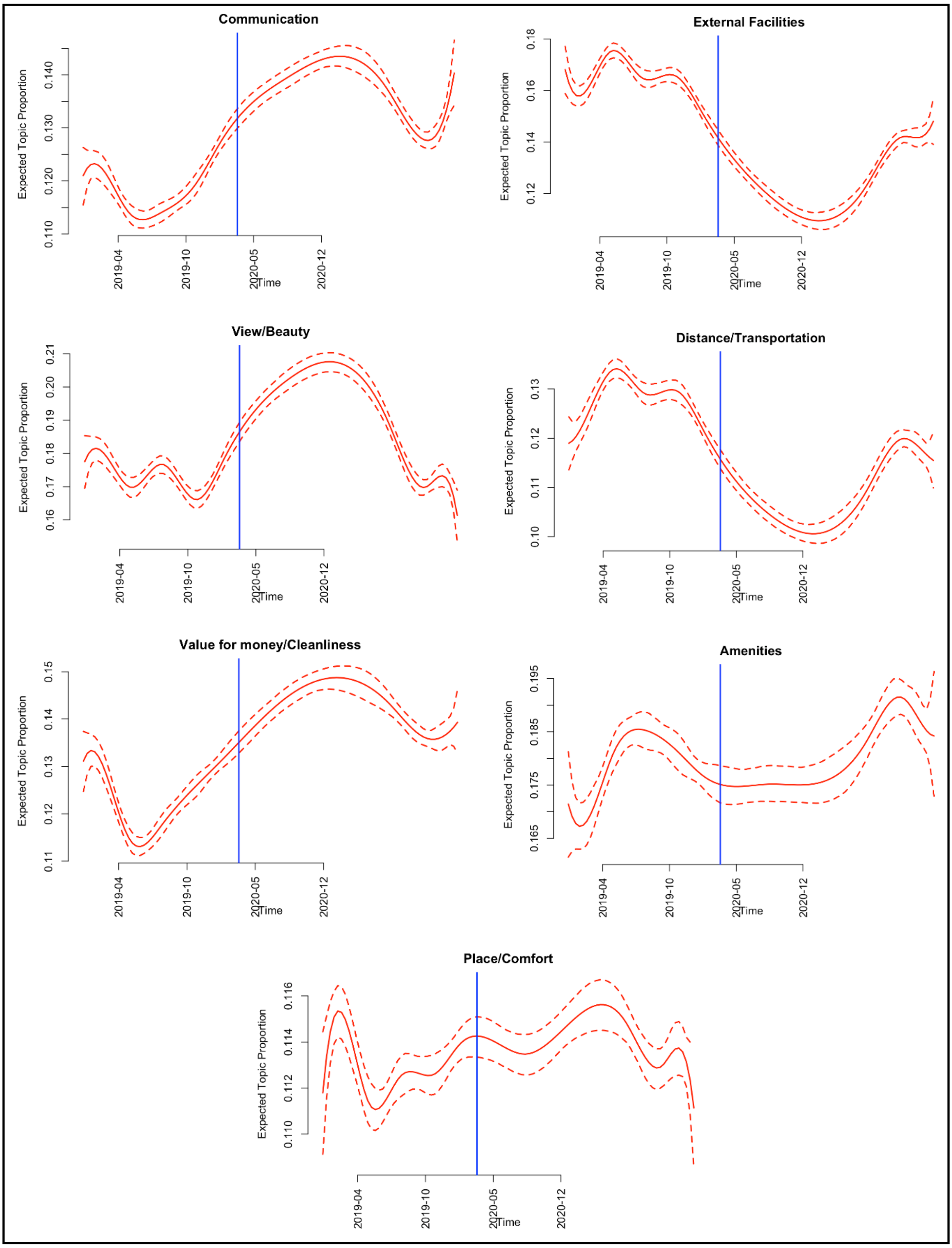

Figure 15: Temporal topic prevalence

3.4.6. Influence and change in proportions of topics for each rating level

The temporal changes of topics give insight into the changes in importance of each topic over time, translating into change in customer attitudes. The effect of any such change observed should influence the way customers rate the services. It is necessary to understand the connection between the topics and how they influence review scores. The analysis of using the effects to estimate topic proportions for each review score shows that, in general, 'Communication', 'View/Beauty', 'Distance/Transportation' and 'Place/Comfort' constitute majority of the higher rating scores, while 'Value for money/Cleanliness', 'Amenities' and 'External Facilities' have been the points of concern when customers provide lower review scores. All topics but one, 'External Facilities', have very low variation in expected proportions, indicating the dominance of the topics behind each rating.

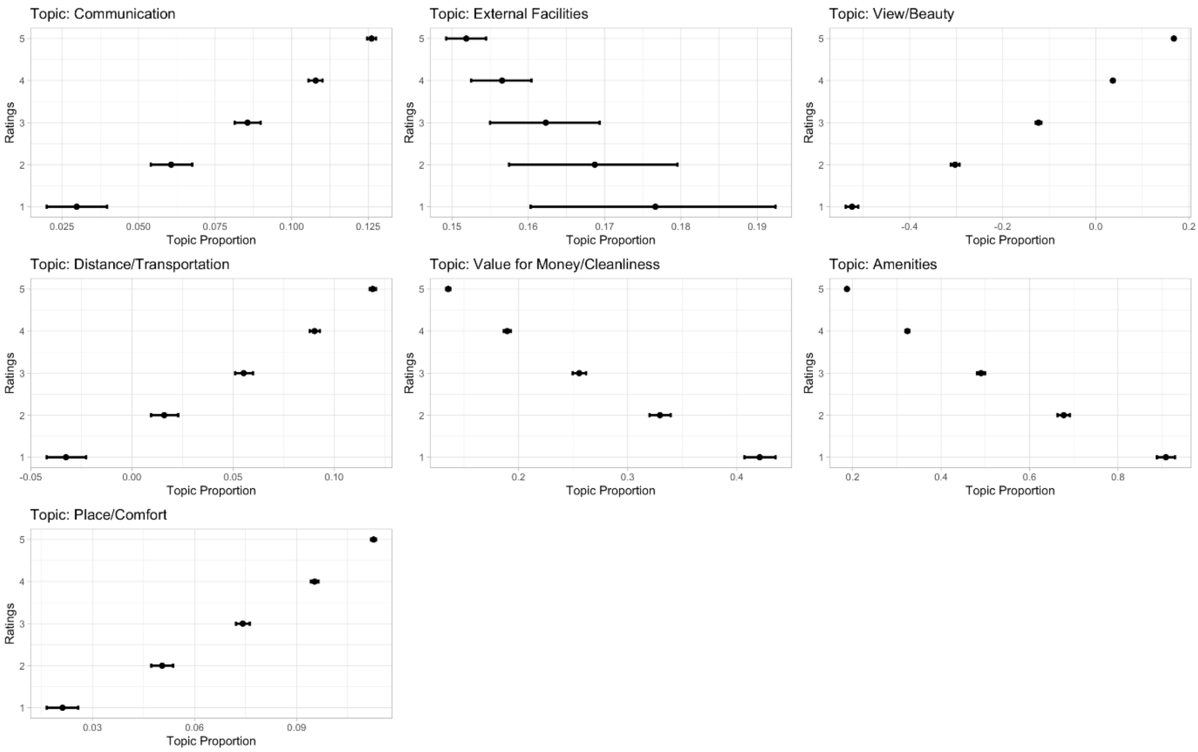

Figure 16: Topic proportions per rating level

The projection of these topic proportions over time gives a dynamic representation of whether Airbnb has improved on these issues and whether the perception of customers has changed the way they rate their experiences. Customers seems to value responsive correspondence when it comes to Airbnb, as there seems to be a slight increase in proportion of this topic for the higher rating scores after the pandemic. In terms of external facilities, customers don't seem to be much concerned about having restaurants or stations nearby their bookings during the pandemic, which is inferred from the proportions of this topic going down for all the rating levels except for score 5, which remained stable. Topics about the views or beauty of the surroundings seem undeterred by the pandemic except for its proportions in rating score 1 and 2 increasing. Customers could be valuing an escape to scenic places more when it came to booking an Airbnb during this period. There seems to be a lot of fluctuations in topic proportions of value for money/cleanliness and it is the highest in case of lower ratings. Following the pandemic, the proportions of this topic increased higher, giving an insight into the possibility of customer dissatisfaction with how Airbnb handled these aspects of their listings. 'Amenities' also prominently constitutes the lower ratings, however, there doesn't seem to be much influence of the pandemic in the topic proportions. For 'Place/Comfort' topic, there doesn't seem to be much change in proportions in the higher ratings, but they did change in the lower ratings after the pandemic, indicating that customers were satisfied with these aspects of their bookings.

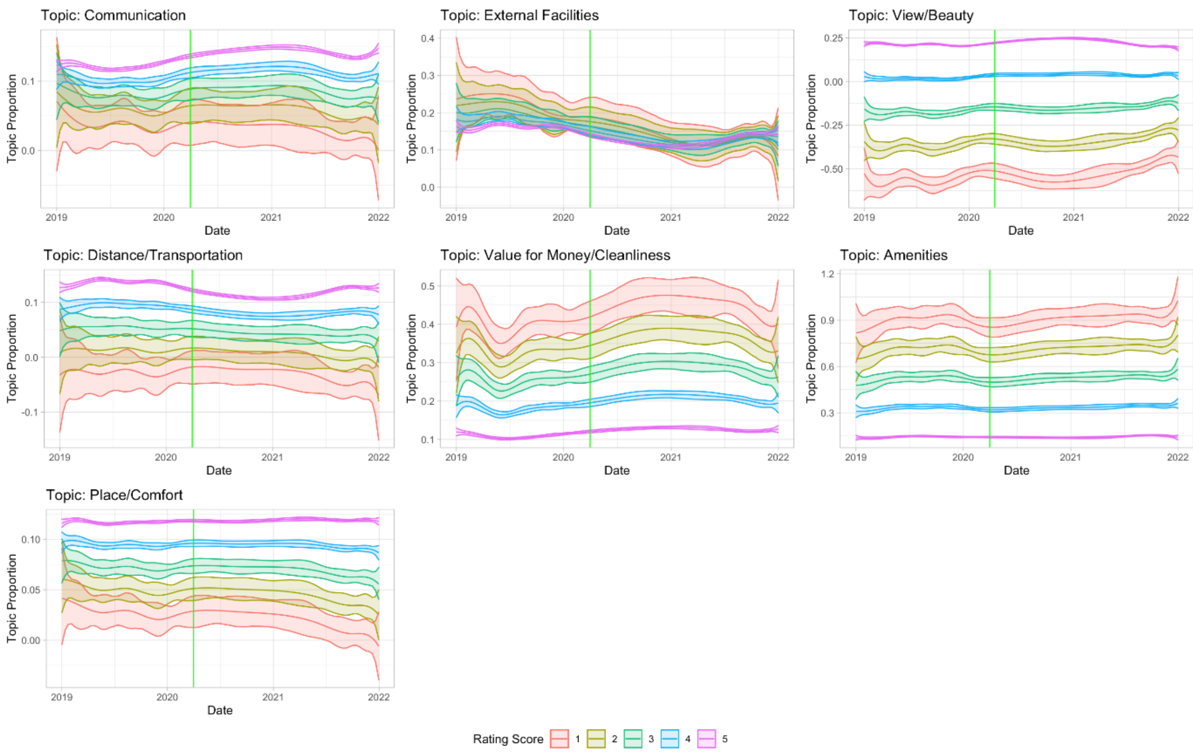

Figure 17: Topic proportion changes over time per rating level

3.4.7. Change in customer attitude evaluation through supervised learning algorithms

Significance Testing (Pre-pandemic Model vs Post-pandemic Model)		
	Accuracy	**Kappa**
p-value	8.02E-05	0.01691
df	0.02486	-0.03532

Table 2: Comparison of post-pandemic and pre-pandemic KNN models

Sentiment scores and features are used in KNN algorithms to train two sets of models using pre-pandemic and post-pandemic review data and are employed to predict ratings for test data, which is for the reviews of 2022 for this study. The comparison of the performances of the two models, in figure 18, shows that the accuracy of the model trained with pre-pandemic sentiments and textual features has a significantly higher accuracy. The kappa metric is however significantly lower than that of the post-pandemic model, but with a smaller difference. The variance of the kappa value of post-pandemic model is also quite high, leading to lower certainty. This finding indicates that the sentiments and the features identified in the test data reviews correspond better with those of the pre-pandemic ones. It is also evident from this that there has been an overall change in customer attitudes due to pandemic, which leads to the difference in performances of the models in predicting ratings of 2022 reviews.

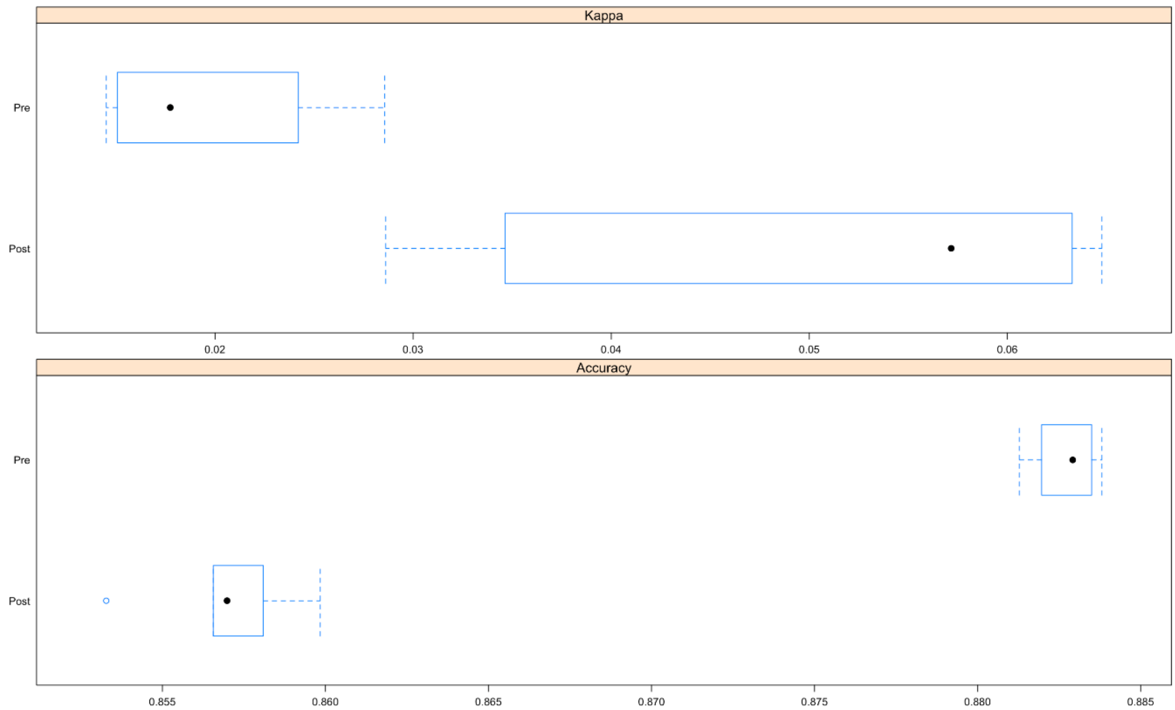

Figure 18: Topic proportion changes per rating level during the period of study

4. Interpretations and Recommendations

From the analysis performed, it is evident that the pandemic had an influence on customer behaviour as well as on the activities of the hosts of Airbnb. These have been proven quantitatively through appropriate regressions and significance tests of the acquired metadata relationships and text mining outcomes.

Overall, the number of bookings made during the pandemic went down in most countries, with Airbnb guests preferring private rooms and private homes/apts on the platform. However, the reduction in rating scores indicate their dissatisfaction with the service during the pandemic. This could be due to the significant increase in prices, as well as other attributes as identified by text mining results.

Guests increasingly valued cleanliness over the pandemic period and ratings are inversely related to this feature, meaning that lower ratings could be due to expectations about cleanliness of their bookings not being met. This could have led to the increased anticipation guests displayed before their stay. However, when this expectation was met, guests increasingly felt joy and trust towards the service. But due to the confusion caused by the nature of the pandemic, sudden destabilising effect in all emotions has been found. While even during the pandemic, overall sentiment towards Airbnb remained primely positive, the level of positivity did reduce noticeably in all the cities in the study but not sufficiently enough to cause concern or deviate far from historical trend as seen over the years before COVID-19.

The continuation of the positive ratings and sentiments towards Airbnb even during the pandemic however doesn't warrant complacency, as customer preferences did change about their bookings. Apart from cleanliness of the places, which would obviously be due to increasing health and safety concerns, customers increasingly valued good communication with hosts to facilitate easy and quick booking and checking in. And while considering other factors such as transportation and other services around the location of the bookings, though these were important influencing factors before, have not been as consequential during the pandemic when making booking decisions. Customers were more into finding an escape during the extended stay-indoors mandates all around by looking for places with better views and beauty.

Such change in preferences translated directly into the ratings. As they increasingly valued good communication with hosts and appreciated better views, major proportions of the reasons behind providing a higher rating was due to Airbnb being able to meet these expectations effectively. It is evident that even the topic of cleanliness dominated the reviews with lower ratings, indicating a major issue to be addressed by Airbnb; this issue has consistently been identified in all the steps of analysis performed in the study.

The changes in attitudes remained consistent across most of the countries, with demand of Airbnb services suddenly falling around March'20, recovering soon after to be followed by another drop and then finally picking up well at the latter part of the year. The sentiment changes were also replicated in each, with a few exceptions, such as in Istanbul, Bangkok and Singapore, indicating that some cities might've performed better during the pandemic. This could be due to the differences in the national policies around the world.

However, while the overall analysis detects various changes in customer attitudes during the pandemic and their impacts on ratings, the changes being significant, there are indications that the pre-pandemic attitudes might be returning, based on the predictive algorithms used in the analysis. Temporal projections of the sentiments and topic models show that trends have tended to return to the pre-pandemic levels at the end of 2021, providing basis for deducing that the changes might be temporary. While that is the case, the adaptation of behaviours of customers with the pandemic era might persist even if they don't translate into ratings. Such cases could be how customers became much less concerned with external facilities around the location of their bookings and the increase in sensitivity towards cleanliness and communication. While Airbnb might not require to substantially change the nature of their services due to the observed transitory changes in customer attitudes, they must persevere to address the attributes that customers have started to increasingly value following the pandemic to not damage the trust that customers have in Airbnb by default since the pre-pandemic era.

Thus, from the analysis, it can be concluded that the sharing economy has been impacted by COVID-19 through reduced demand and change in customer attitudes, but it has also survived. There are indications that the pre-pandemic momentum can pick up again, however, adaption to modified customer needs should be addressed to ensure the retaining of customer and client trust.

5. Conclusion and future scope of work

The conducted work addresses all the proposed research questions with relevant deductions have been made. Systematic analysis of Airbnb reviews through implementing multiple approaches to converge findings into unified comparison of two different periods is accomplished. Each output is statistically examined to ensure strong basis for drawing conclusions. Alongside technical adaptation, inferences are made through judgemental theorisation. Ultimately, using predictive algorithms, the findings are gauged against real data to provide a verdict about the impact of the changes caused by the pandemic as observed.

Previous literatures have focused on Airbnb from various perspectives considering the economic and operational impact of COVID-19. Other papers on text mining take unilateral approaches towards analysing texts or takes a descriptive path. Compared to those, this article implements three different text analytics techniques alongside statistical examination of the findings and brings all the elements together to provide a one-step ahead prediction to validate the trend to expect moving on from the pandemic. Some limitations of this study would be the unavailability of Airbnb's internal data, which could provide insights into the exact strategies that were undertaken to tackle the pandemic by the company. Such insights would be beneficial towards performing more focused analysis on reviews to extract their effectiveness.

The scope of this work could extend towards giving a generic conclusion about the overall impact of the pandemic on the sharing economy as well as the tourism industry. The reasons behind any changes in customer attitude could be applicable to other companies in the same industry, and further analysis of the same nature on others can provide basis for comparison to get a deeper understanding of customer behaviours.

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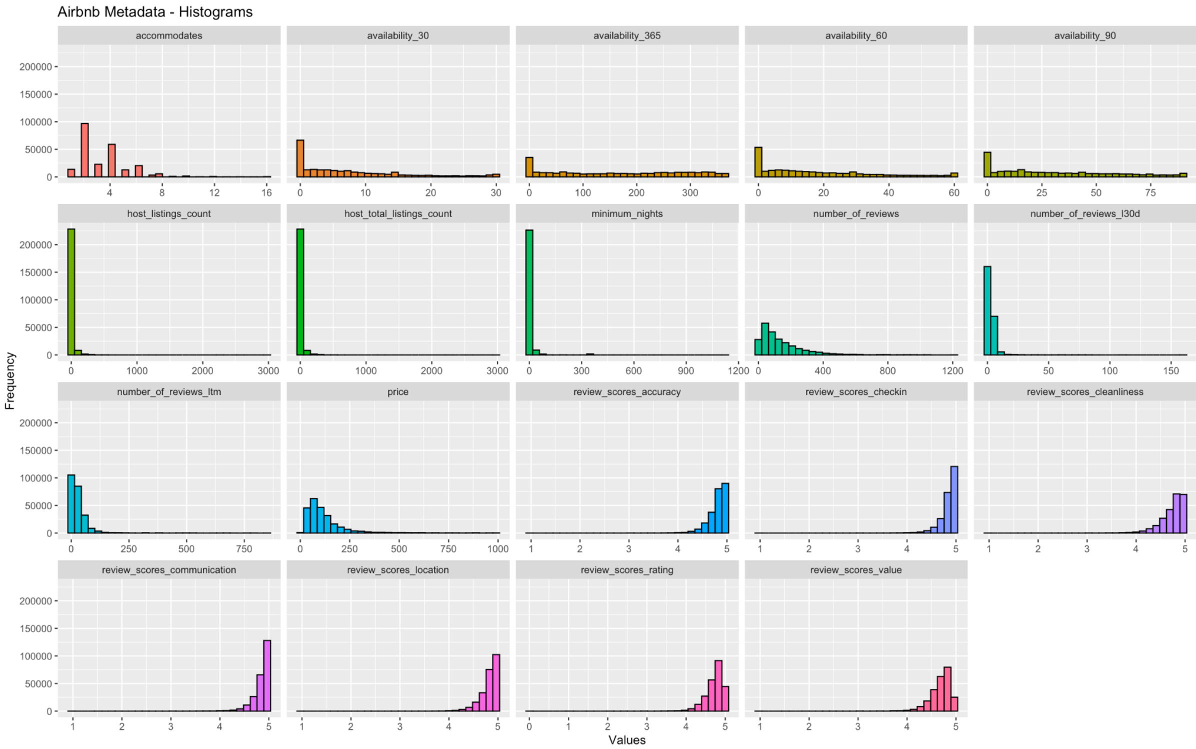
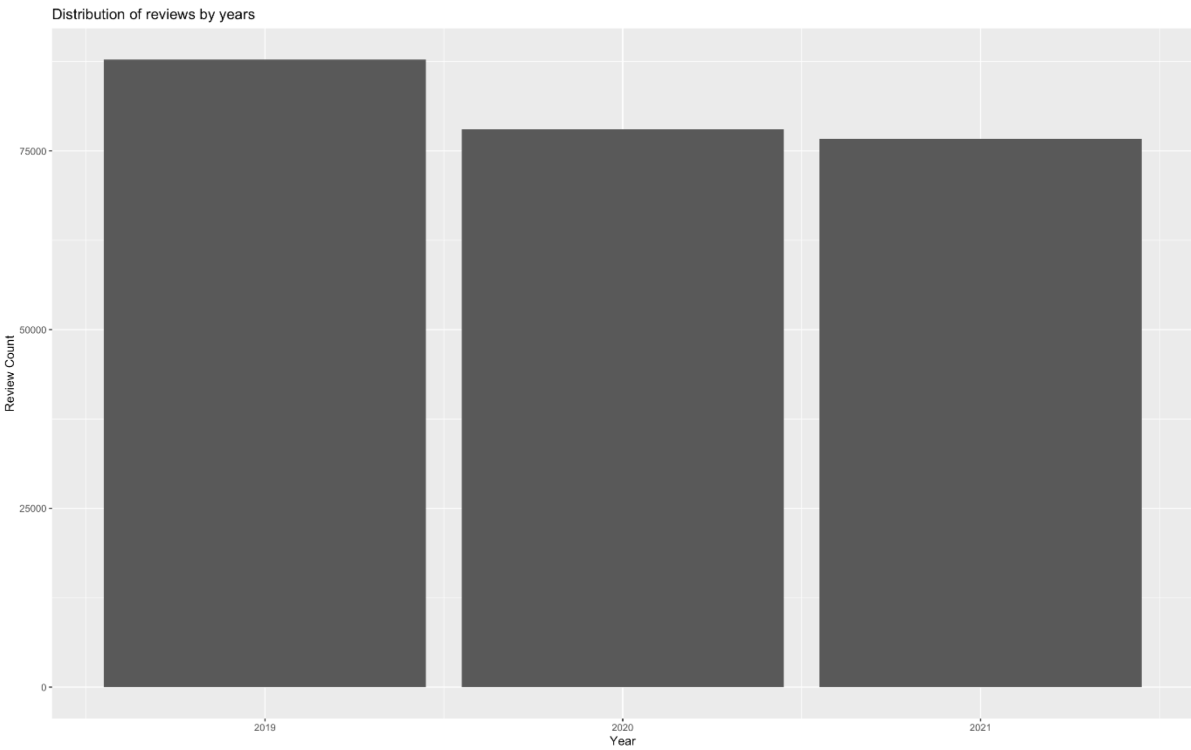
7. Appendix

7.1. Appendix A – Distributions of Data

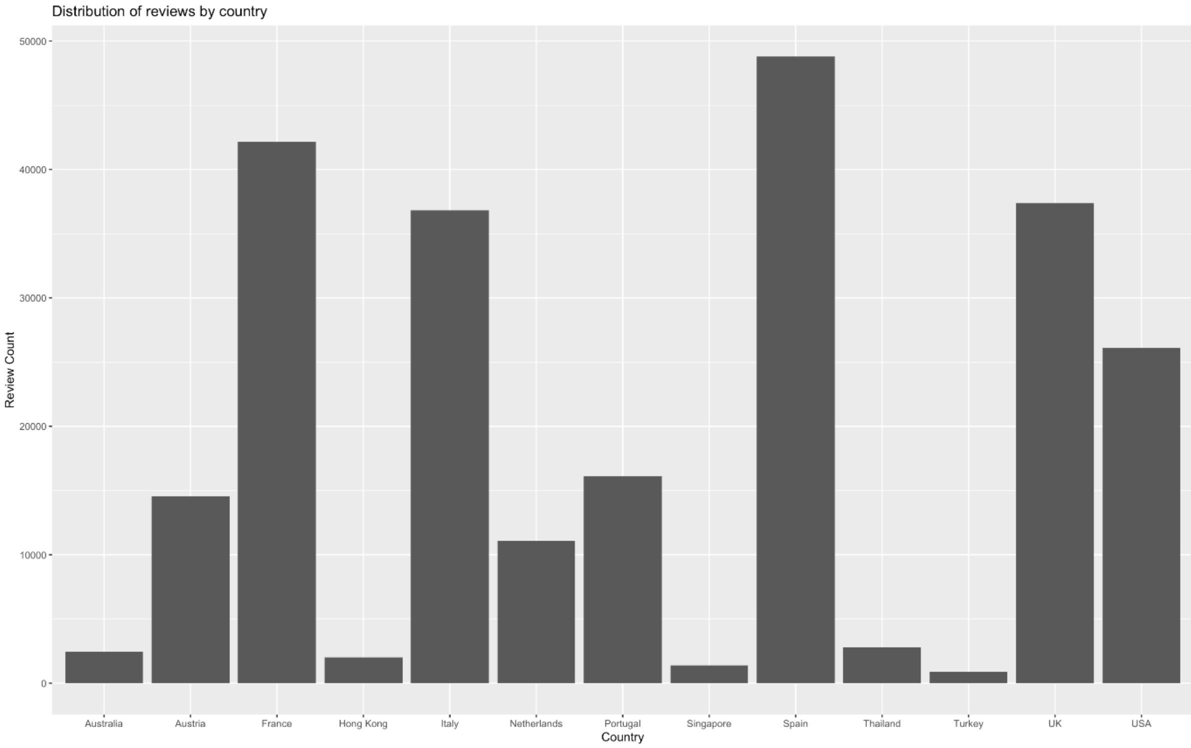
7.1.1. Metadata distributions



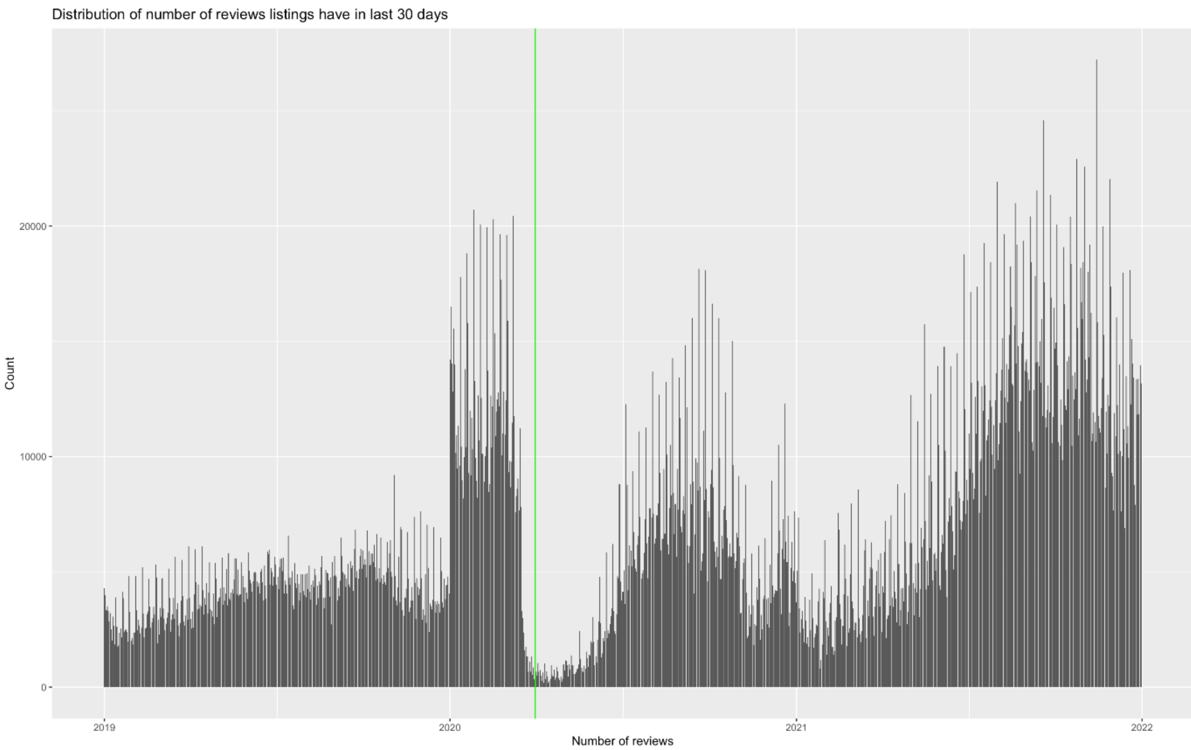
7.1.2. Number of reviews collected from each year



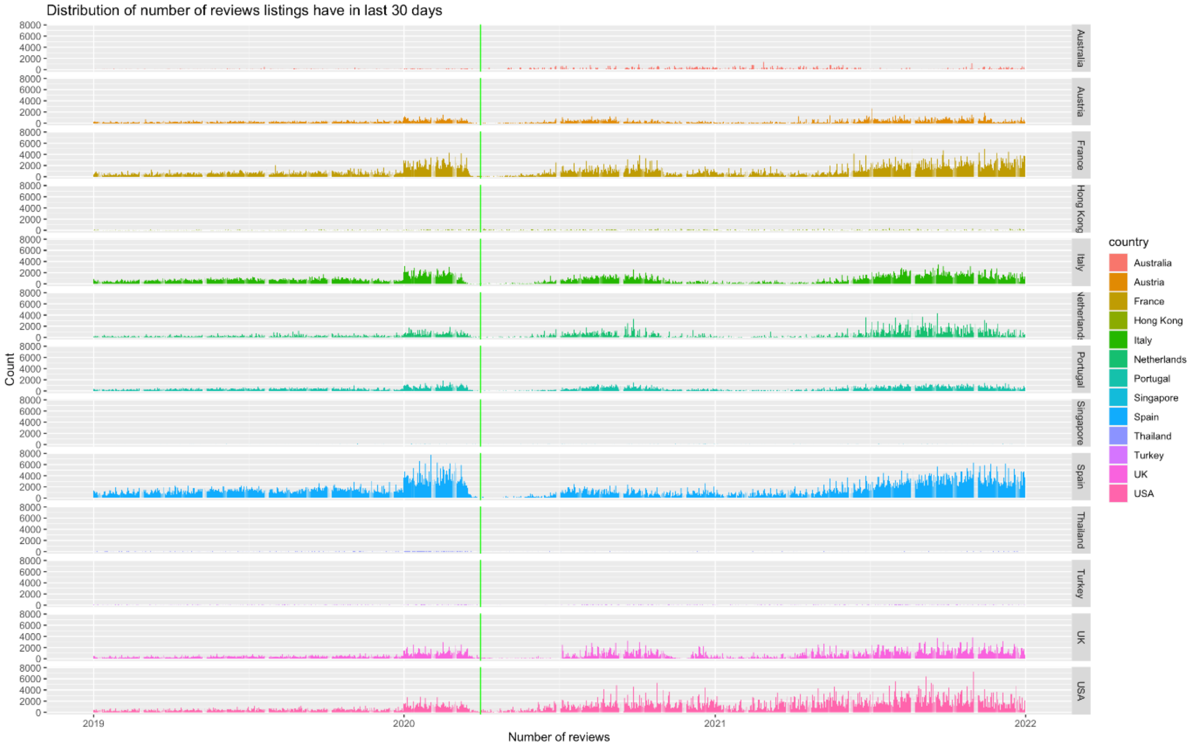
7.1.3. Number of reviews collected per country



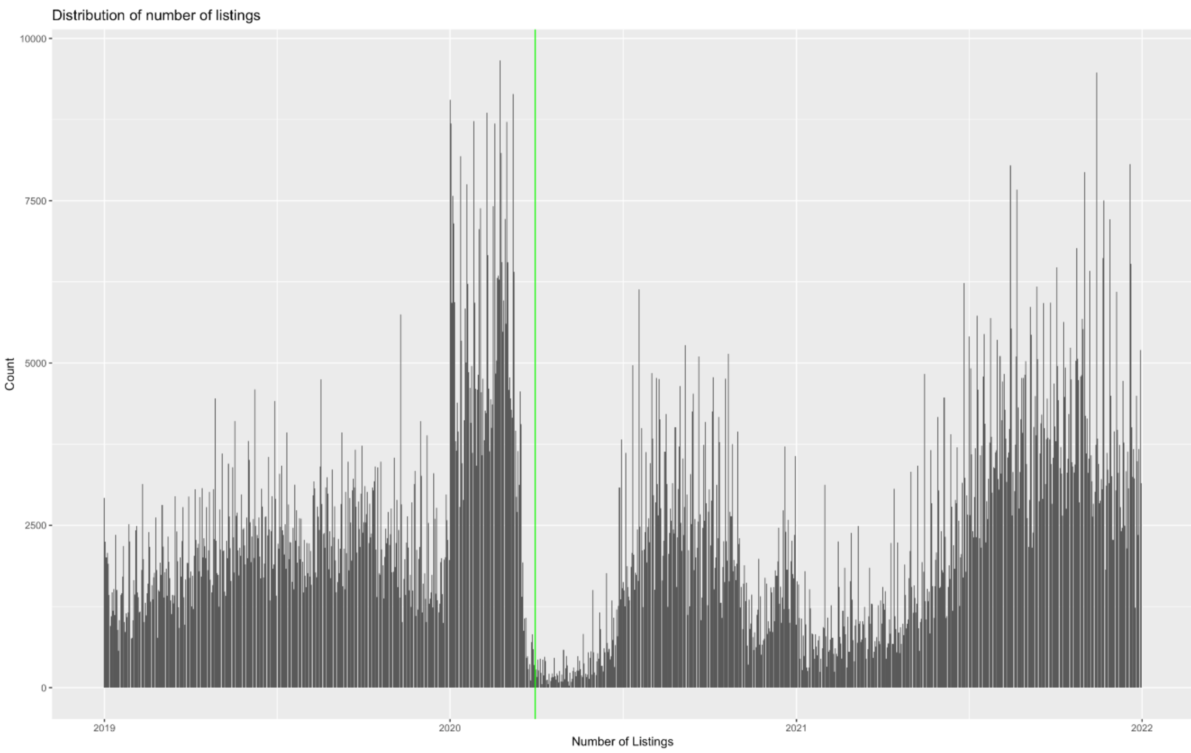
7.1.4. Distribution of number of reviews listings had in 30 days



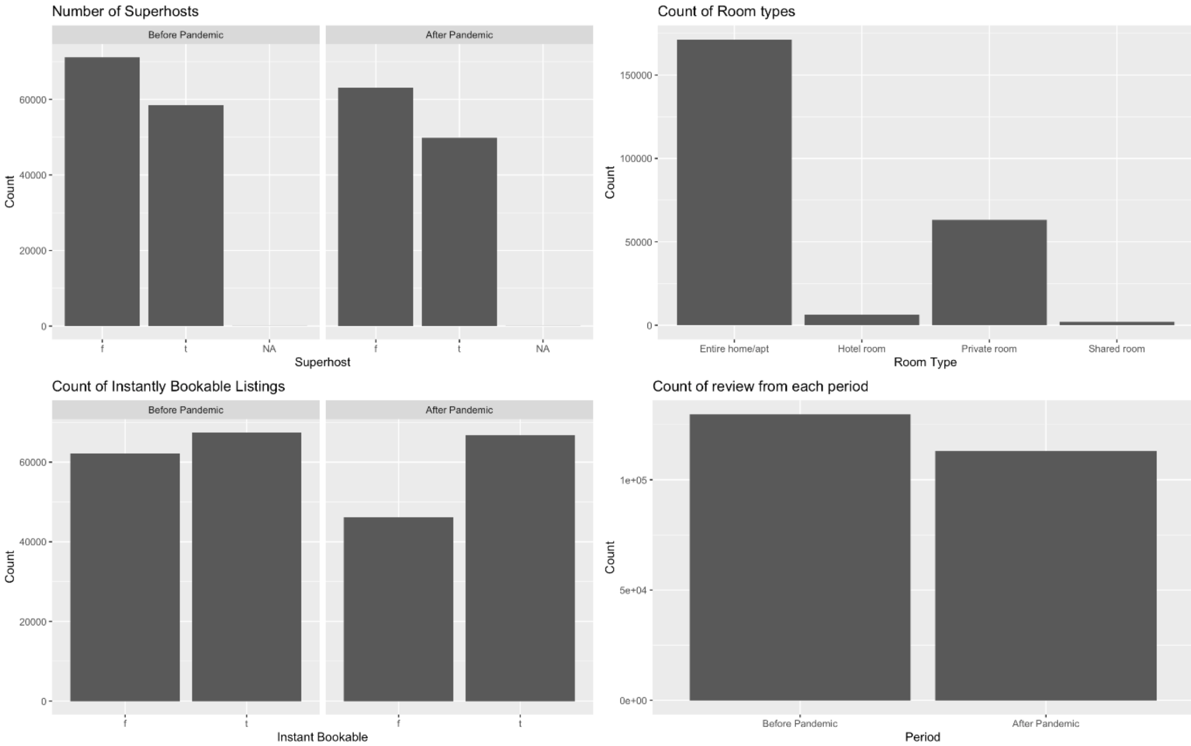
7.1.5. Distributions of number of reviews listings had in 30 days by country



7.1.6. Distribution of number of listings

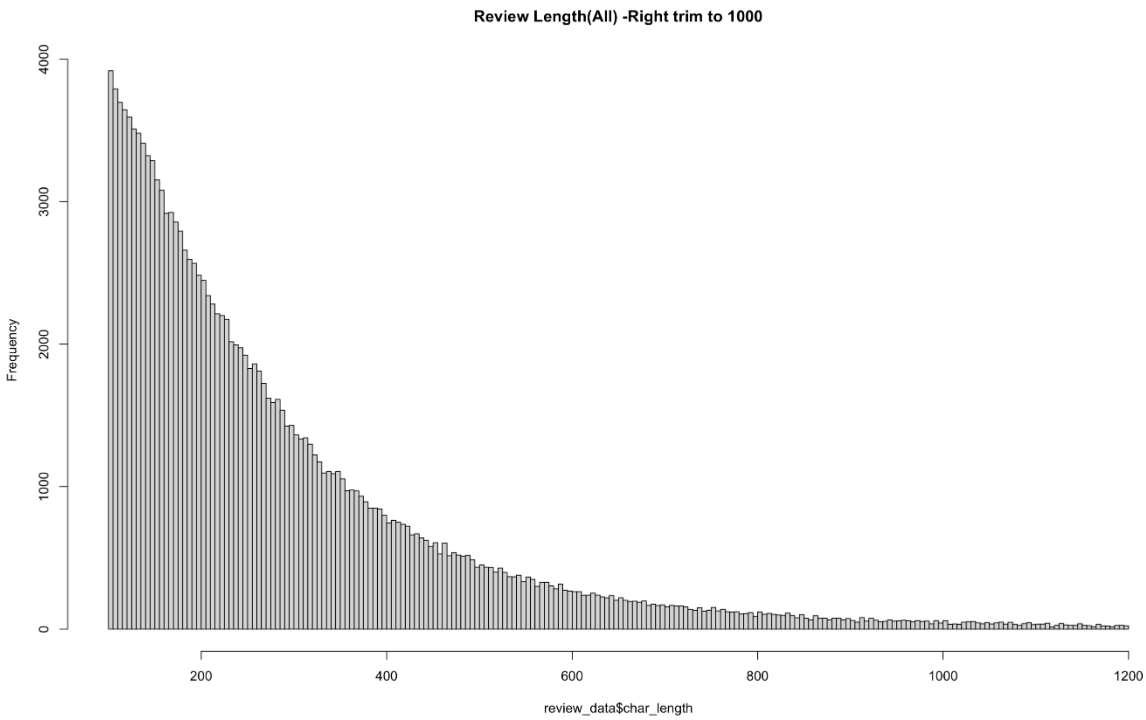


7.1.7. Other distributions

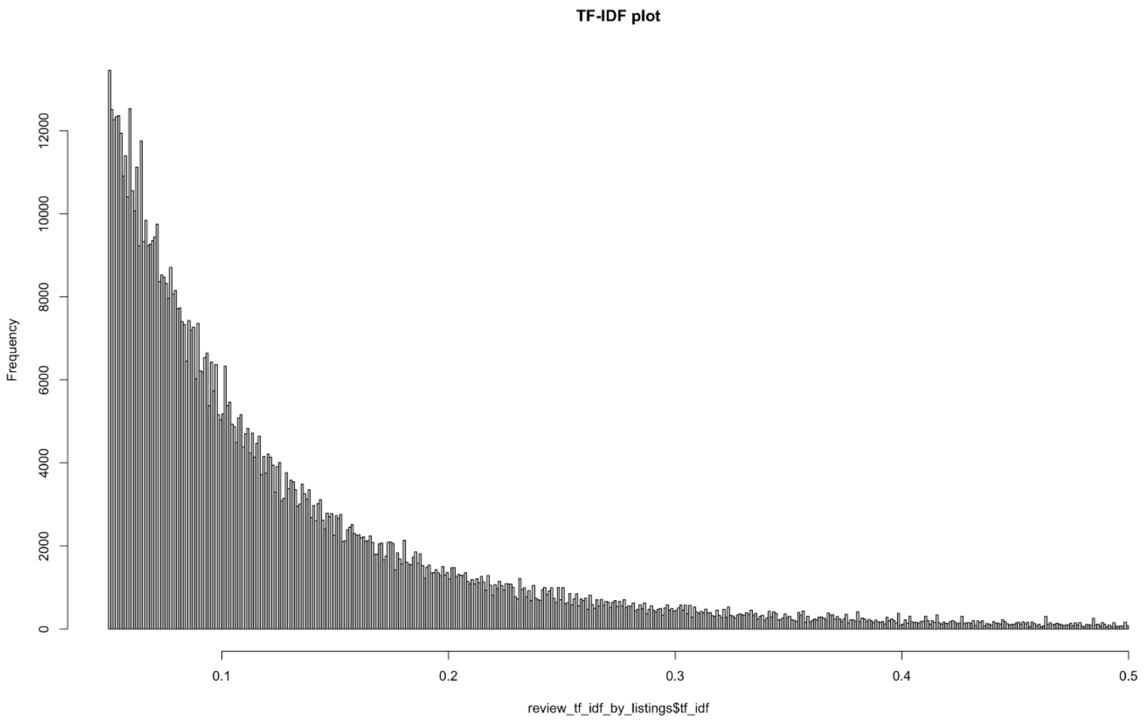


7.2. Appendix B - Text Cleaning

7.2.1. Distribution of character lengths after filtering

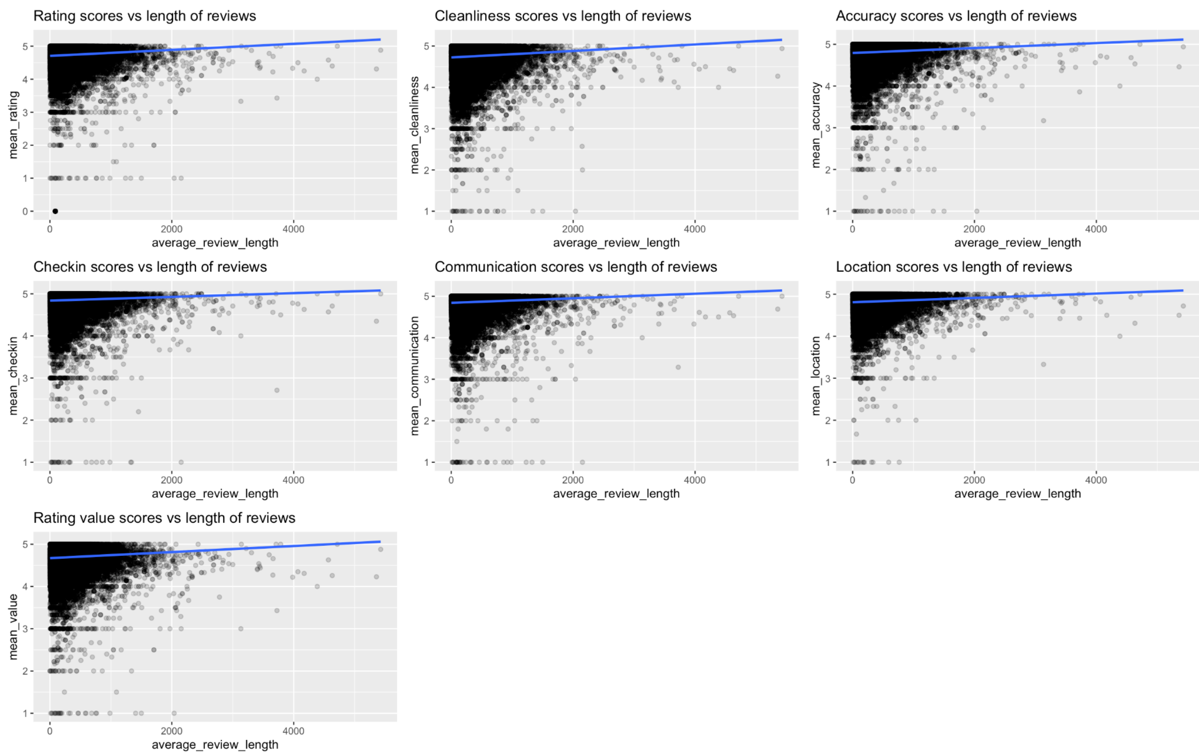


7.2.2. Final tf-idf after trimming

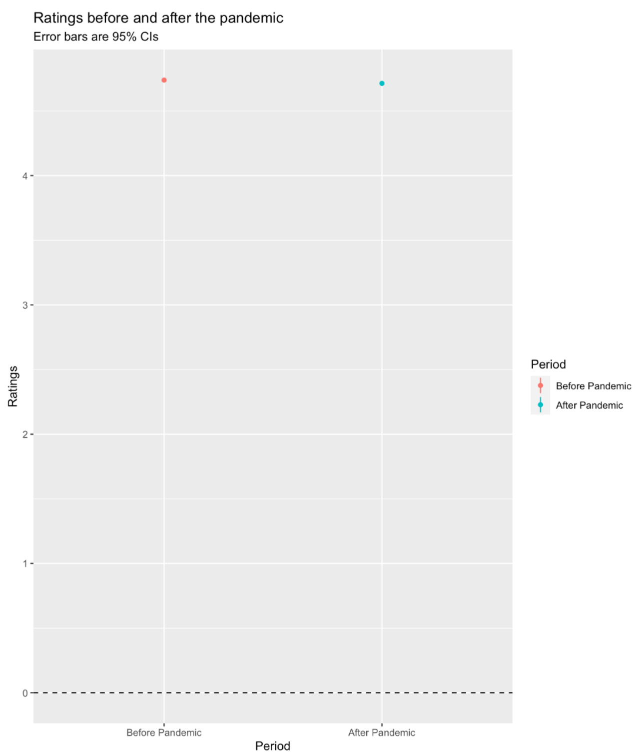


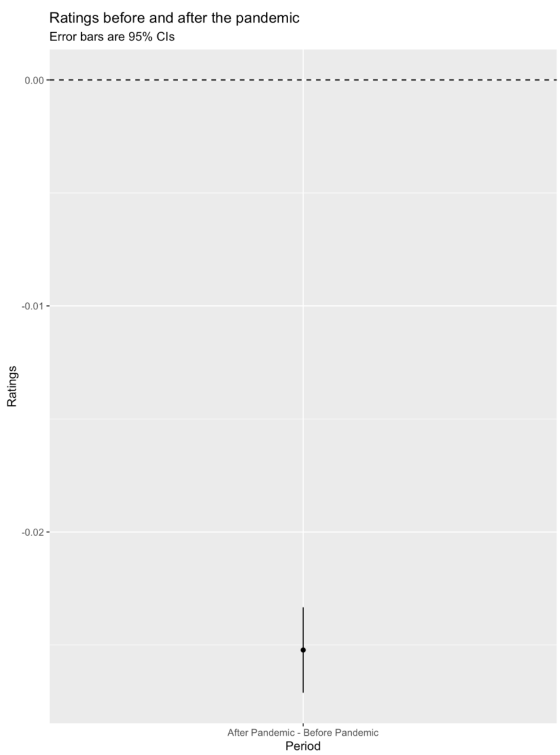
7.3. Appendix C – Preliminary Findings

7.3.1. Character lengths vs review scores

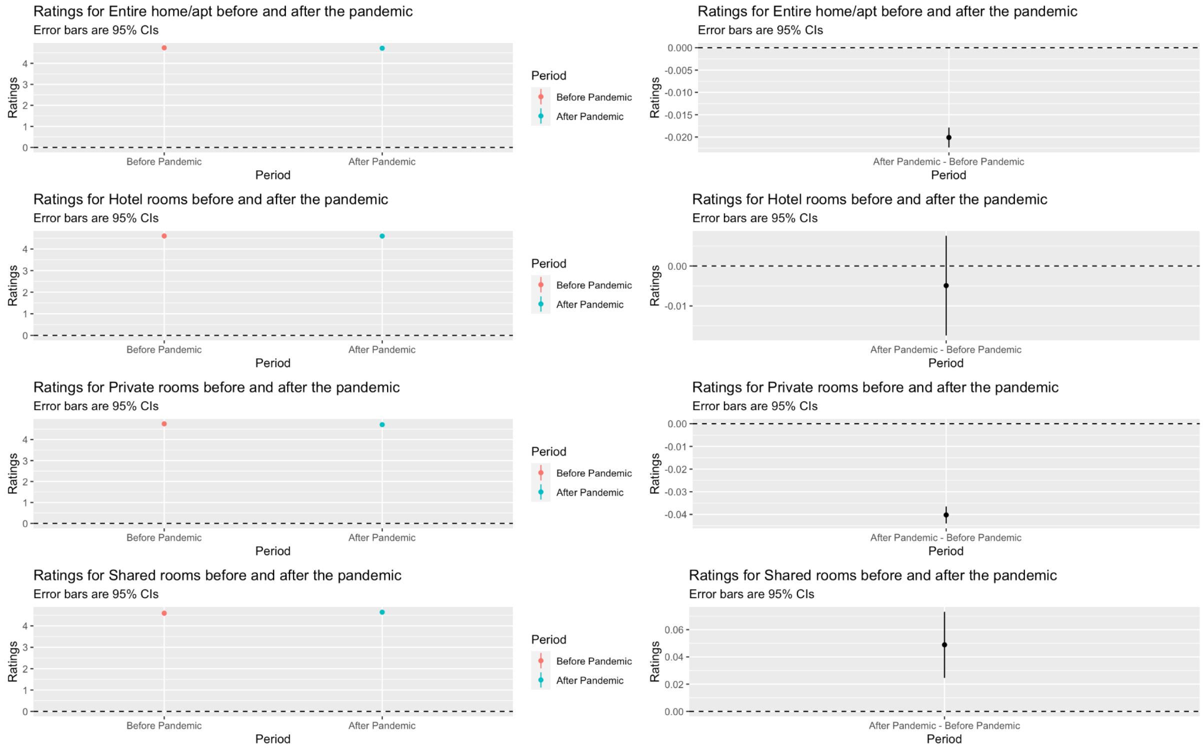


7.3.2. Difference testing for ratings before and after pandemic



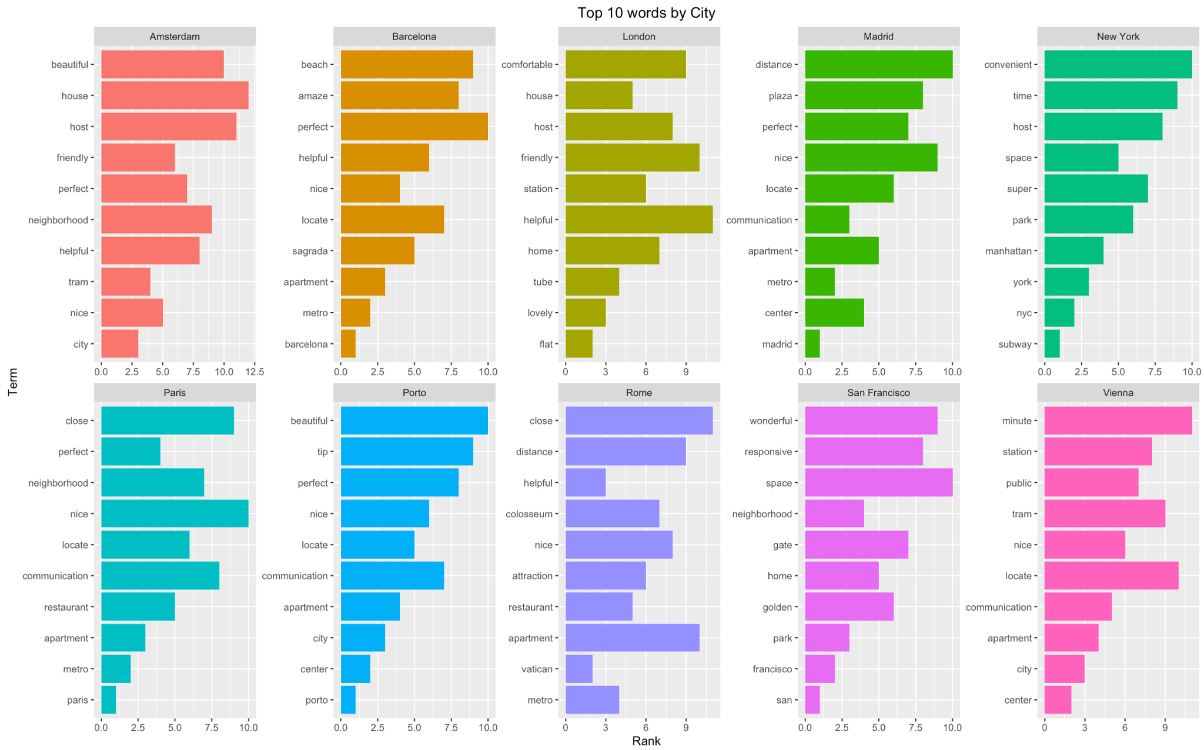


7.3.3. Difference testing for ratings before and after pandemic by room types

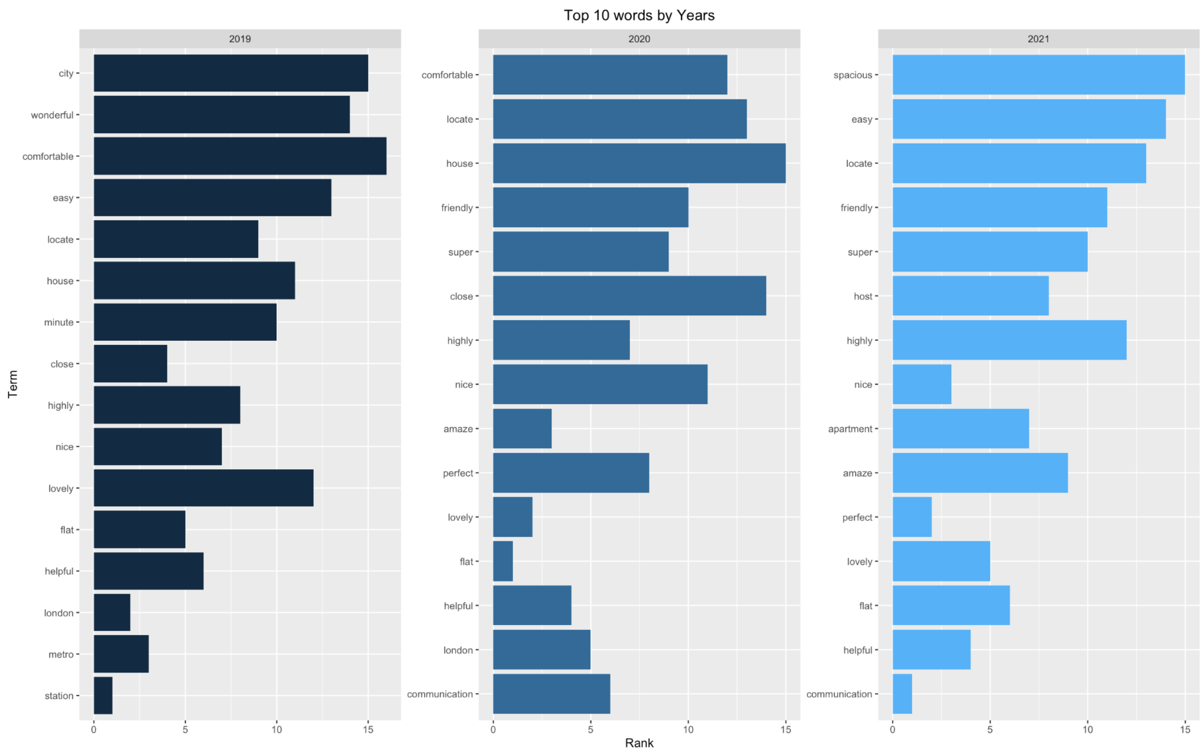


7.4. Appendix D – Feature Extraction Analysis

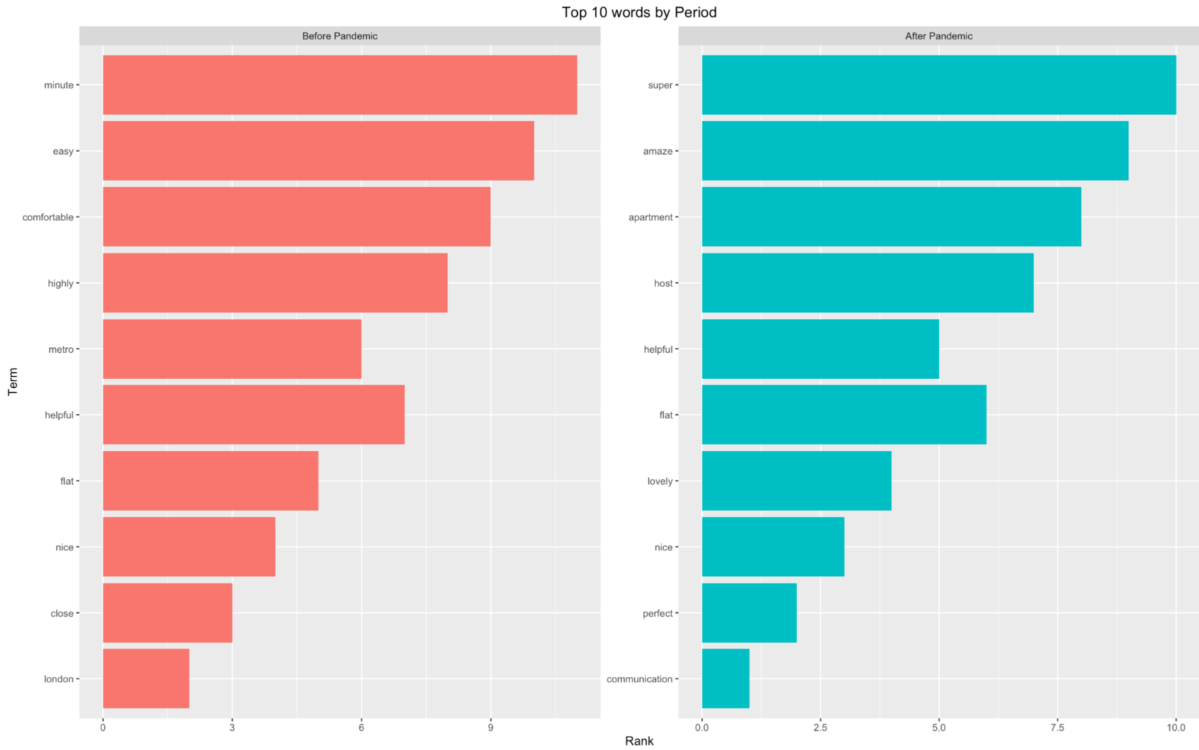
7.4.1. Top words by City



7.4.2. Top words by years



7.4.3. Top words by periods

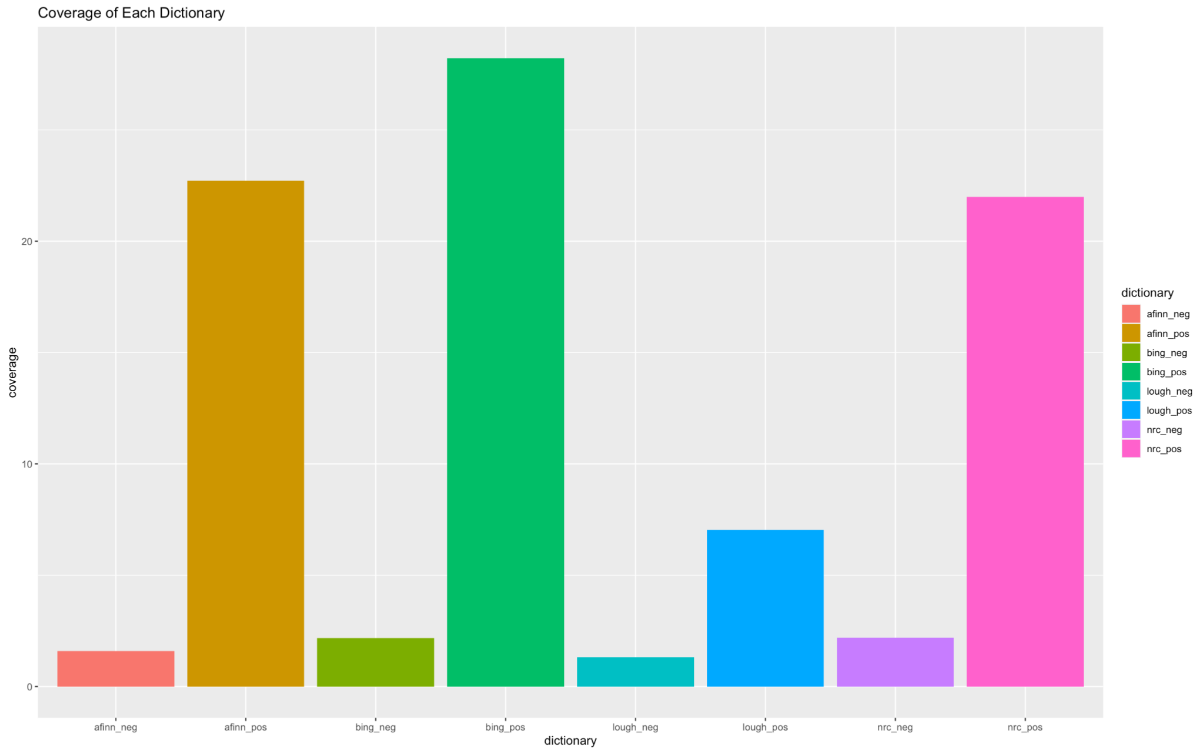


7.4.4. Regression summary of features against review scores

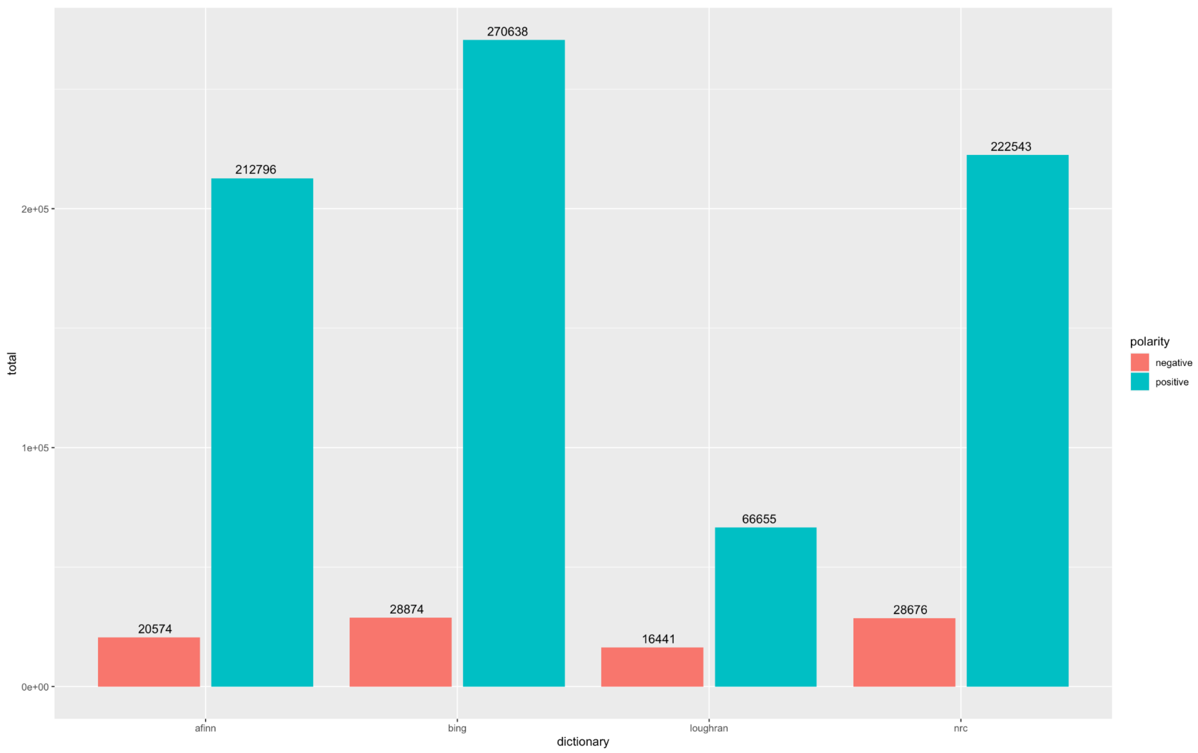
	Dependent Variable: Review Scores Rating					
	Overall		Pre-Pandemic		Post-Pandemic	
Features	**Value**	**Observation**	**Value**	**Observation**	**Value**	**Observation**
Recommend	0.313***	64,522	0.300***	38,025	0.351***	26,497
Location	(-0.169***)	64,522	(-0.234***)	38,025	(-0.112***)	26,497
Price	(-0.935***)	64,522	(-0.873***)	38,025	(-0.975***)	26,497
Stay	0.282***	64,522	0.273***	38,025	0.278***	26,497
Host	0.450***	64,522	0.410***	38,025	0.509***	26,497
Clean	0.058***	64,522	0.106***	38,025	(-0.032)	26,497
Communication	(-0.159***)	64,522	(-0.176***)	38,025	(-0.145***)	26,497
Availability	*(-0.063)*	64,522	(-0.077)	38,025	0.173	26,497
Check	(-0.321***)	64,522	(-0.311***)	38,025	(-0.337***)	26,497
Easy	0.081***	64,522	(-0.039)	38,025	0.131***	26,497
*Note: *p<0.1; **p<0.05; ***p<0.01*						

7.5. Appendix E – Sentiment Analysis

7.5.1. Sentiment dictionary coverages



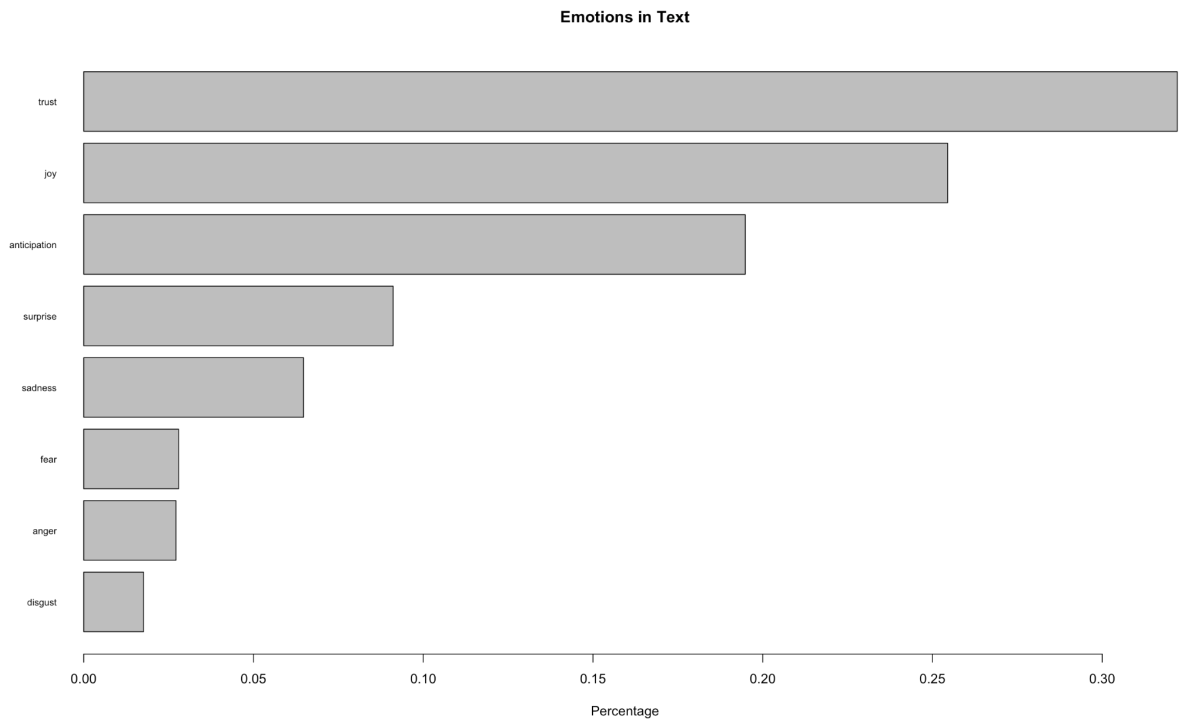
7.5.2. Sentiment dictionary polarities



Loughran dictionary seems to pick up on a lot of negative sentiment in the Airbnb reviews. The dictionary that covers the highest available sentiment in the Airbnb reviews is Bing, Afinn and NRC. Bing and NRC are the two top dictionaries that detect the most positive and negative sentiments.

7.5.3. NRC emotions

The NRC emotions as detected in the reviews give an understanding that the customers of Airbnb associate high trust with the business. Overall emotions are positive, with trust and joy being the most commonly detected emotion. Anticipation is also found as a notable emotion in the reviews, which could be due to customers feeling that way about their bookings before checking in. Other emotions such as disgust, anger, fear, even though are found in low percentages, are investigated.

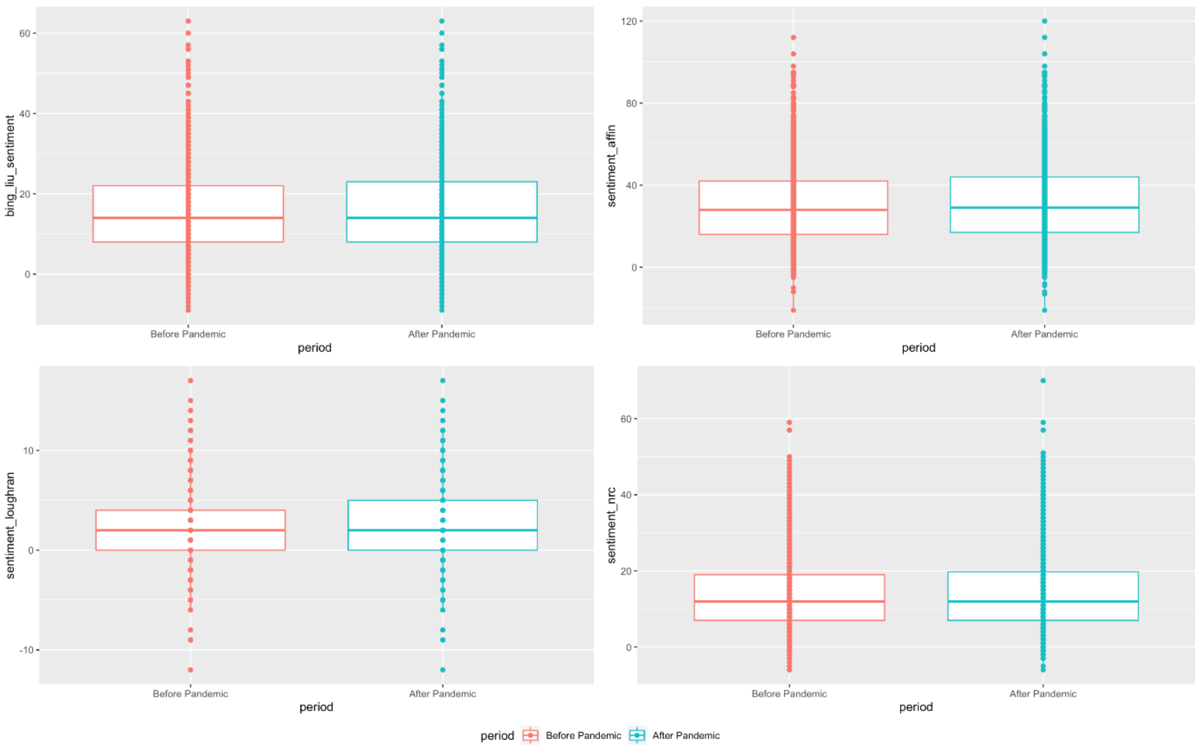


7.5.4. NRC emotions vs review score ratings regression summary

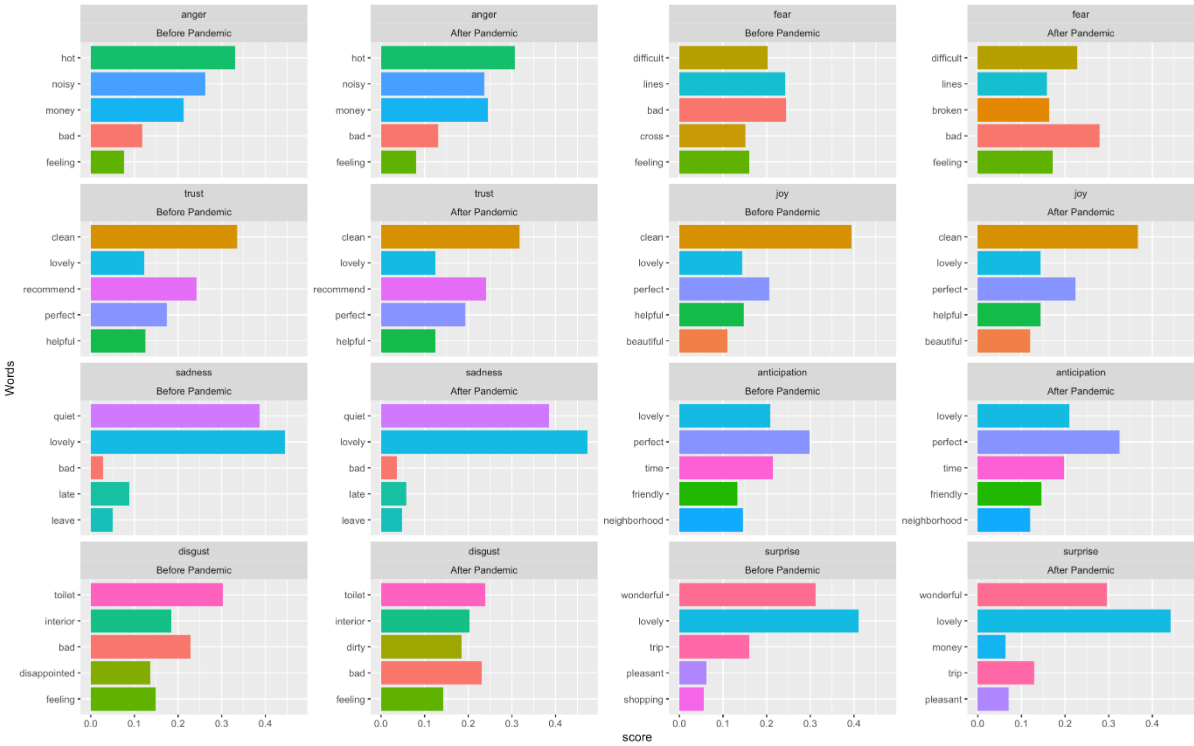
	Dependent Variable: Review Scores Rating	
	Overall	
Features	Value	Observation
Anger	(-0.007***)	78,118
Anticipation	(-0.0004***)	78,118
Fear	(-0.007***)	78,118
Joy	(-0.002***)	78,118
Sadness	0.0001	78,118
Surprise	0.001***	78,118
Trust	(-0.0001)	78,118
		Note: *p<0.1; **p<0.05; ***p<0.01

7.5.5. Comparing dictionaries through regression analysis and sentiment distributions

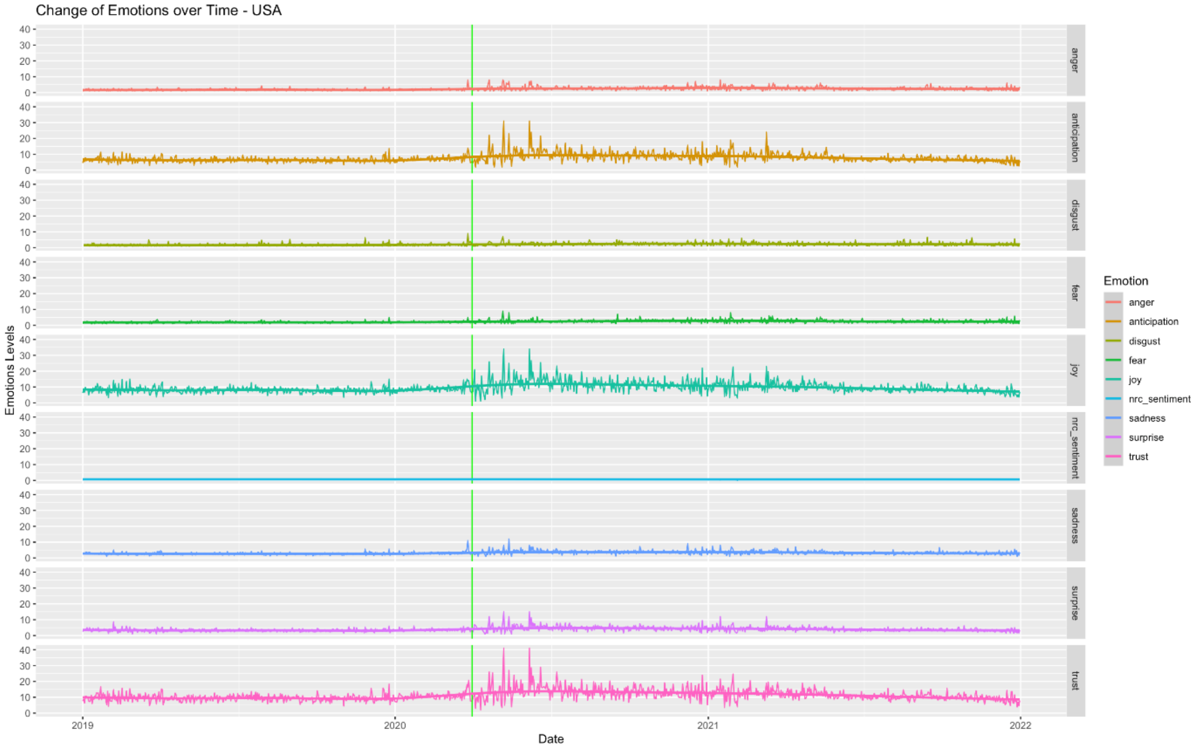
	Dependent Variable: Review Scores Rating	
Dictionary	**Value**	**Adjusted R2**
Bing	0.011***	0.225
NRC	0.011***	0.165
Affin	0.006***	0.208
Loughran	0.030***	0.164
		*Note: *p<0.1; **p<0.05; ***p<0.01*

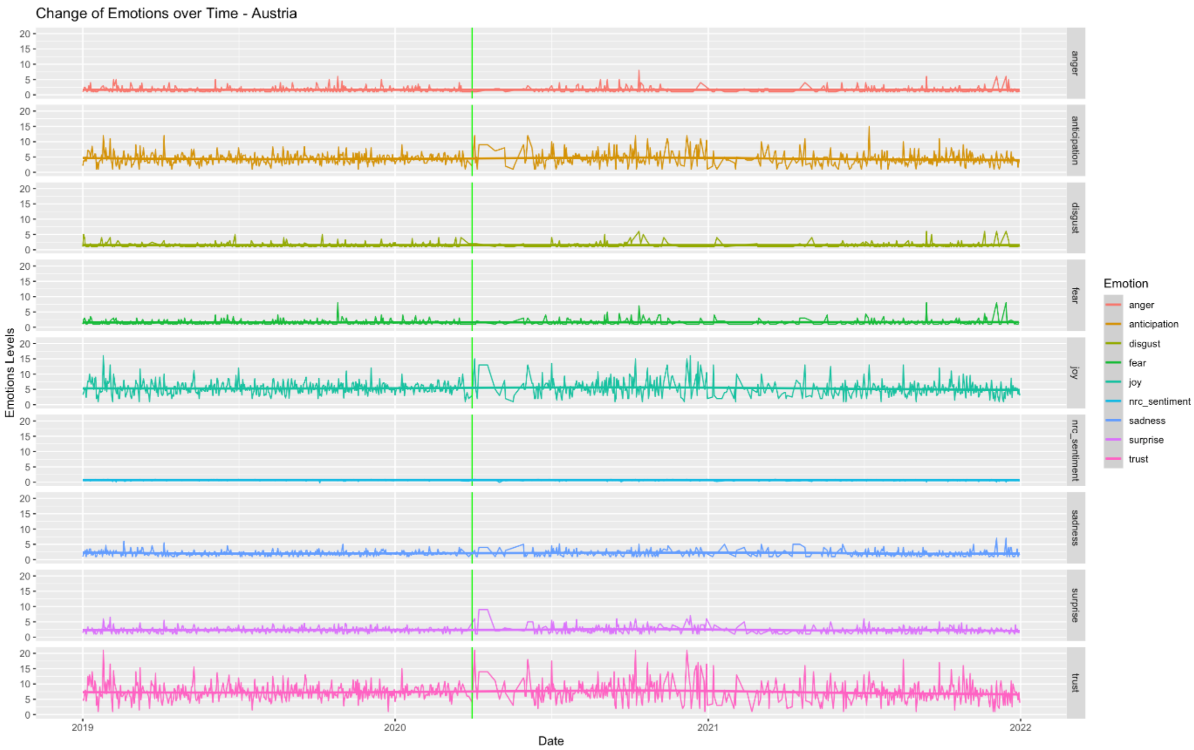


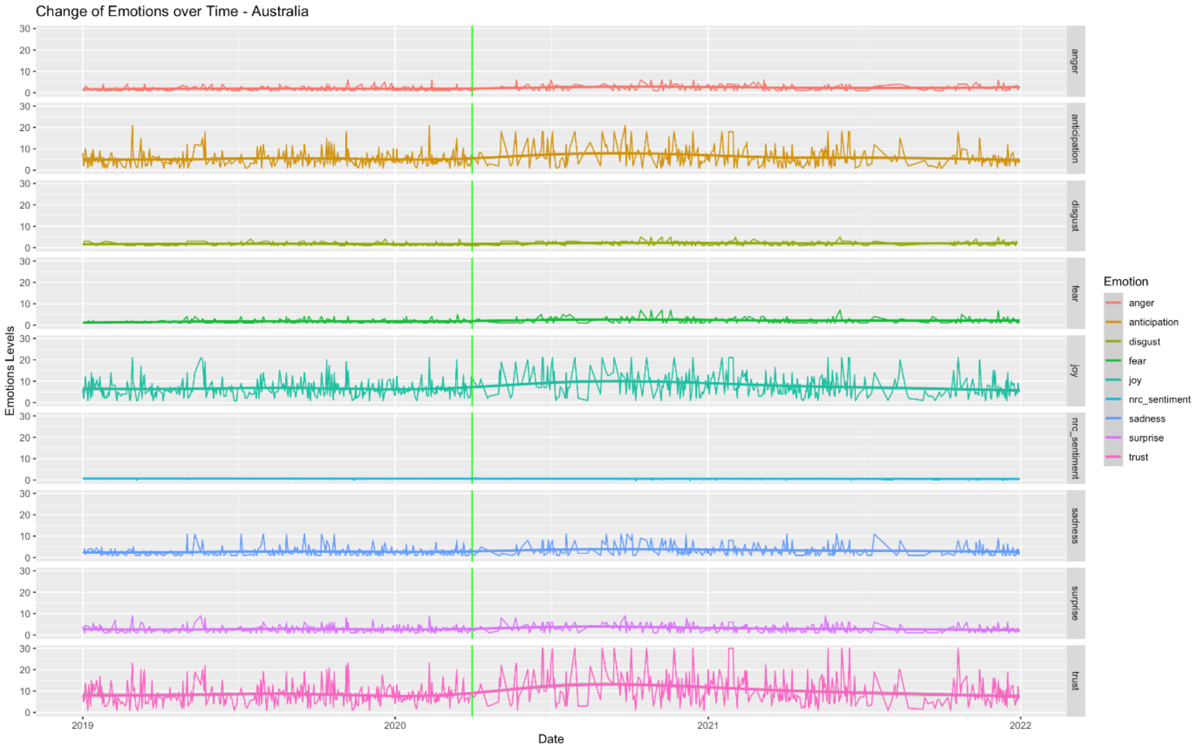
7.5.6. Frequent words per emotion and comparison with that of the pandemic period

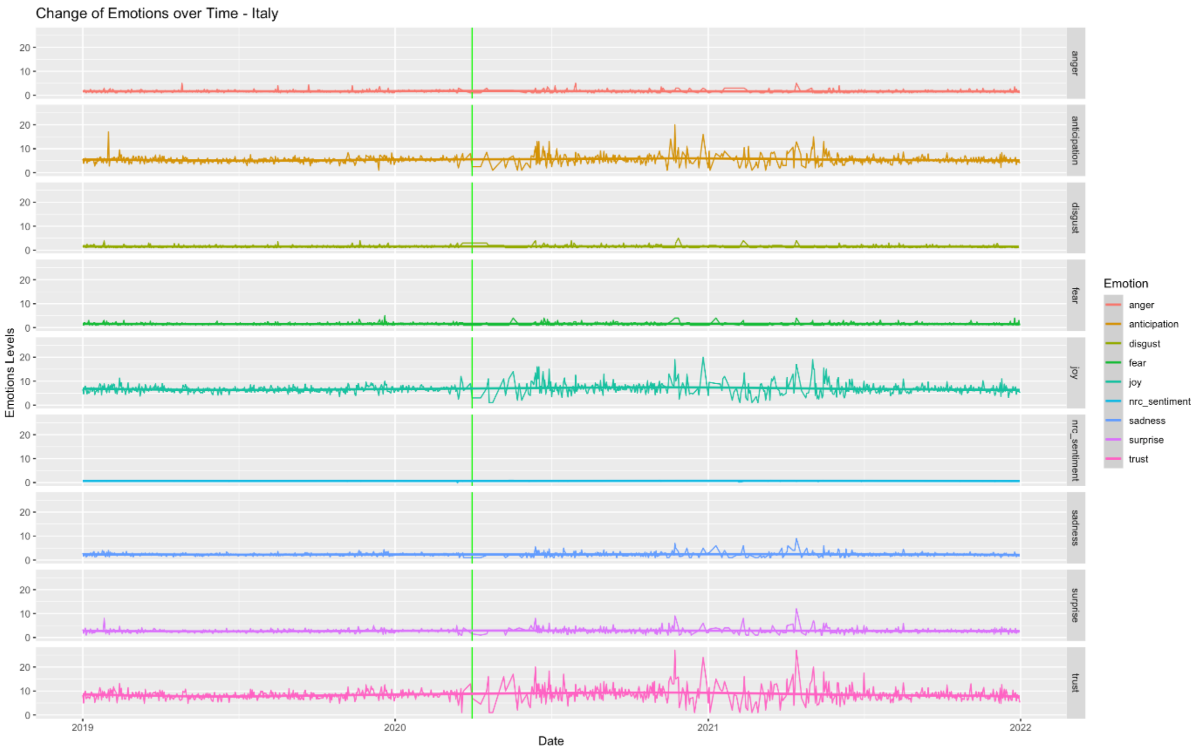


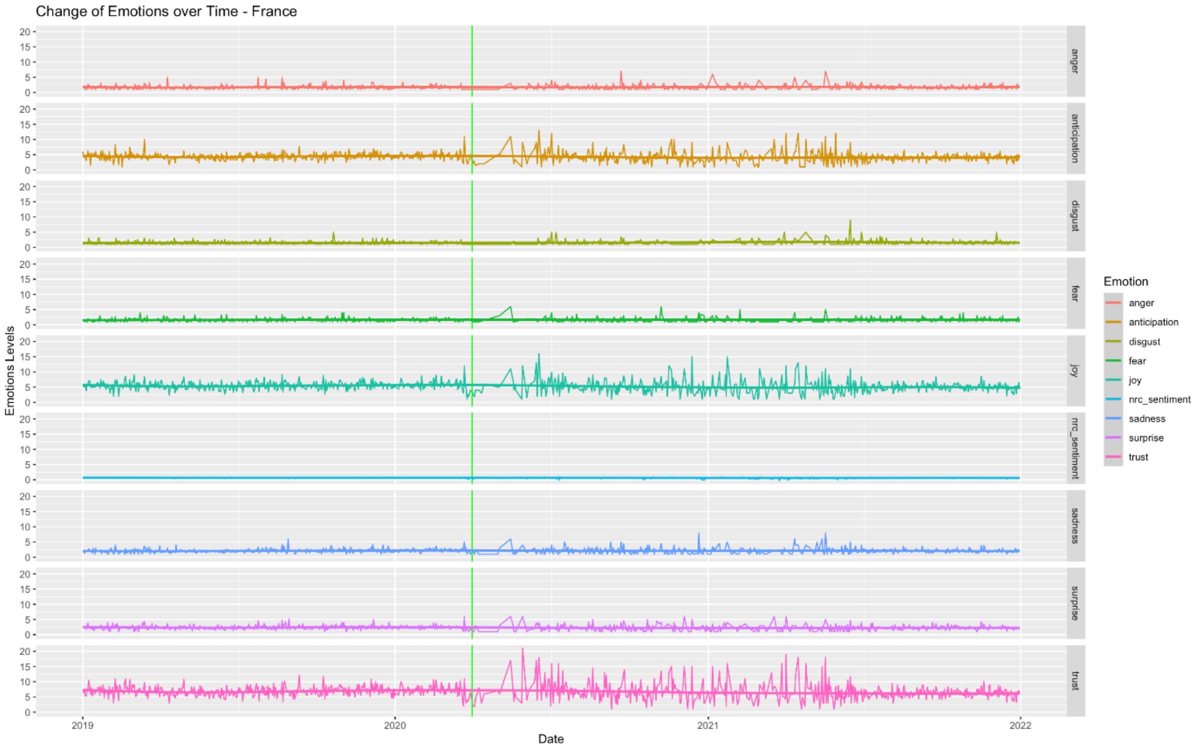
7.5.7. Country-wise changes of emotion over the study period

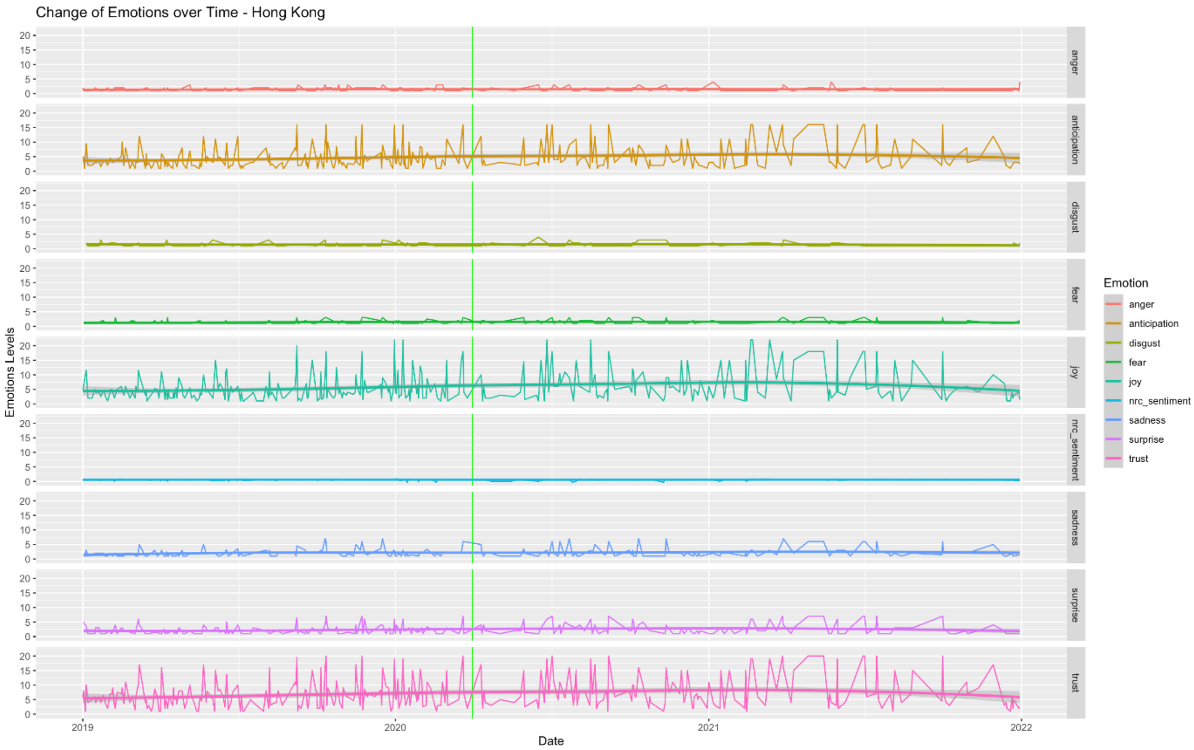


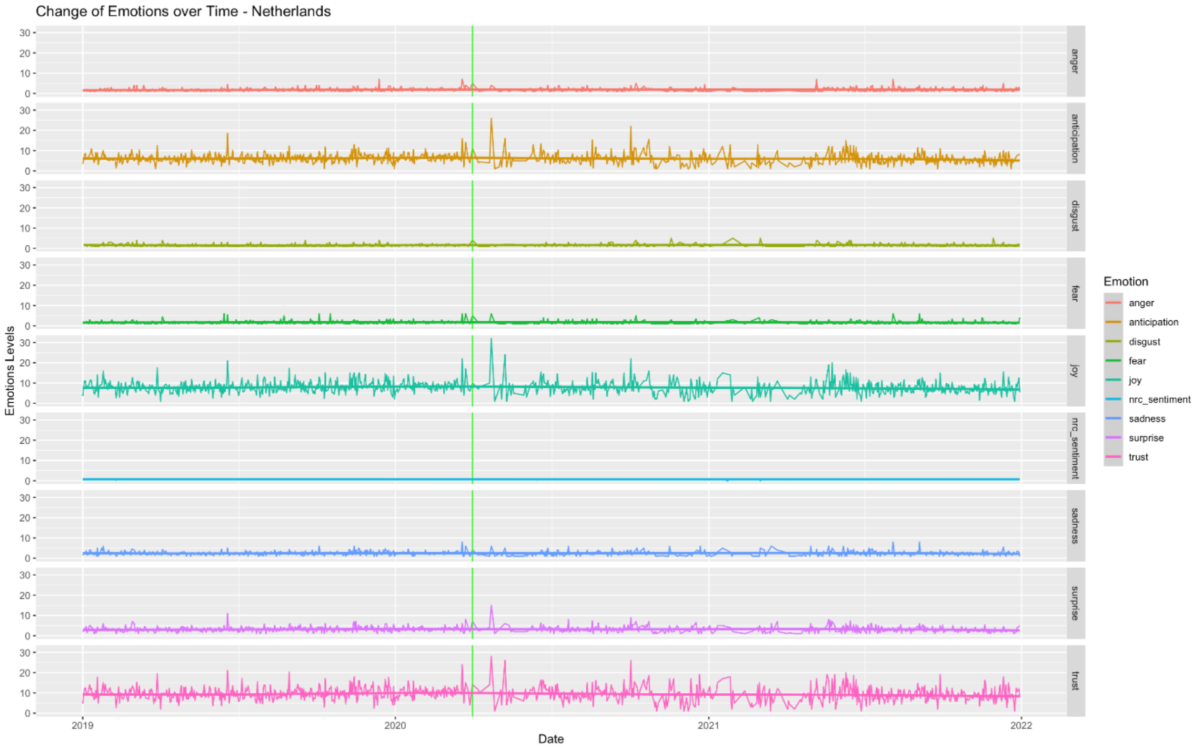


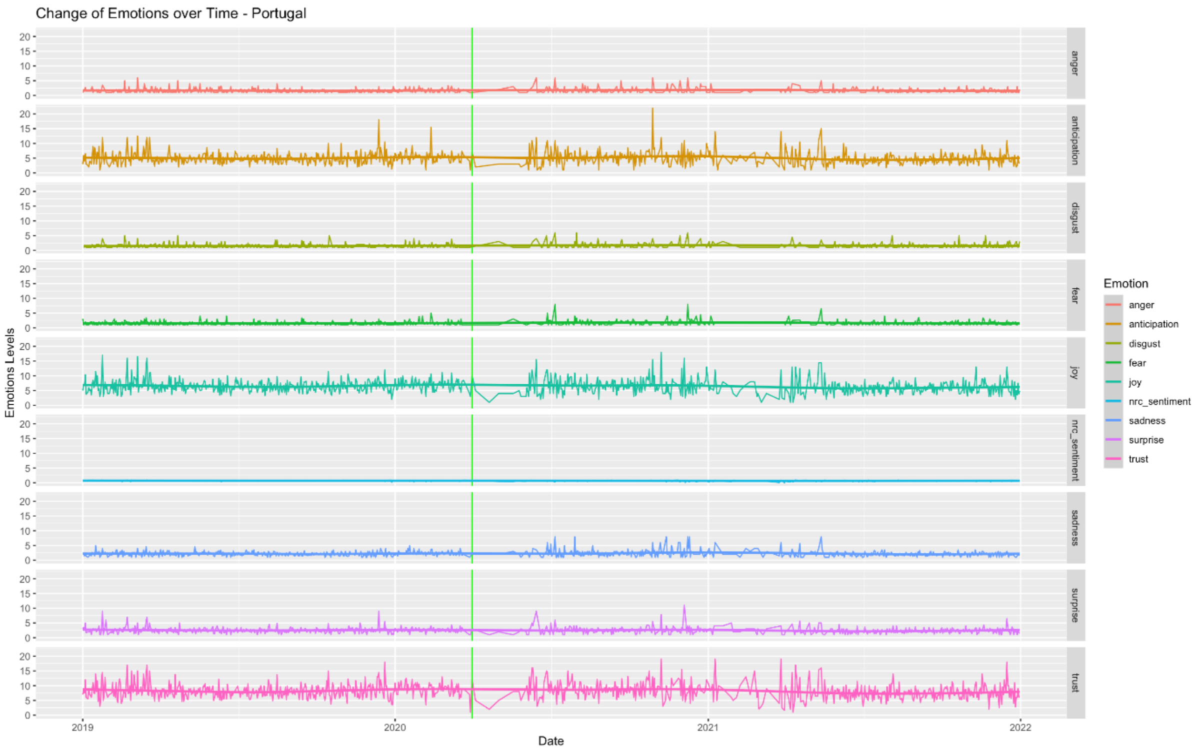

Change of Emotions over Time - Australia
Emotions Levels
Date
anger
anticipation
disgust
fear
joy
nrc_sentiment
sadness
surprise
trust
Emotion
anger
anticipation
disgust
fear
joy
nrc_sentiment
sadness
surprise
trust
2019
2020
2021
2022

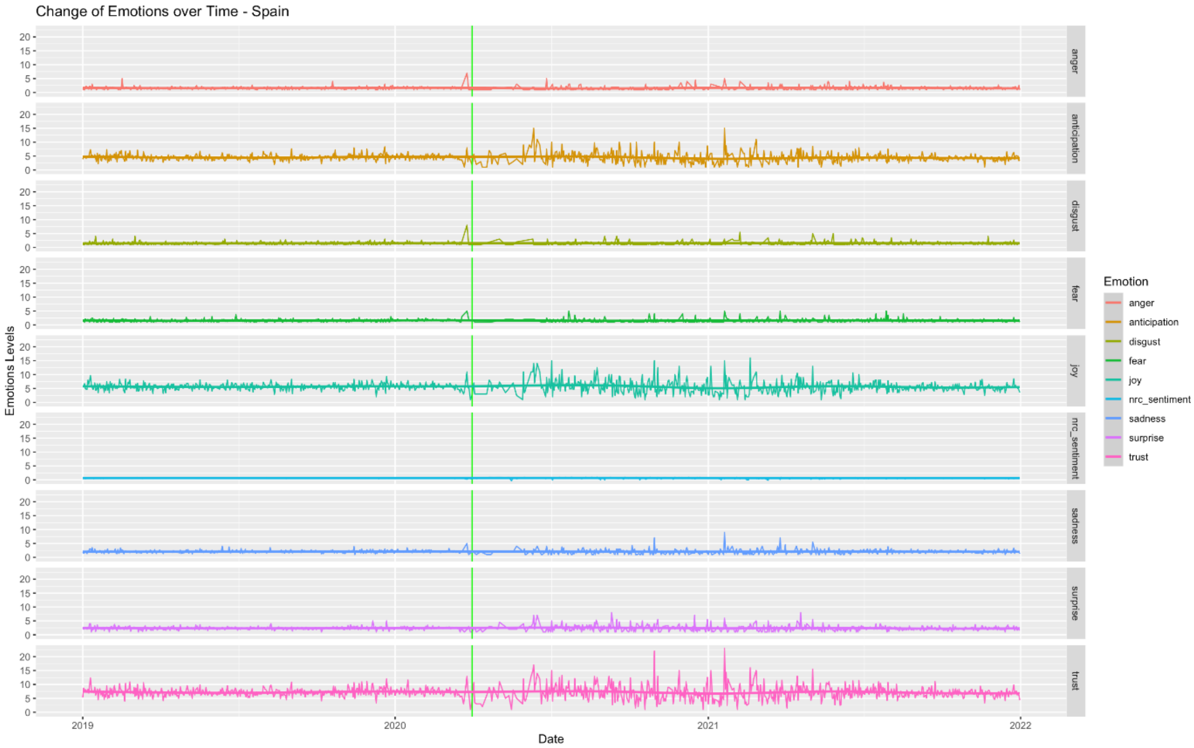

Change of Emotions over Time - Italy
Emotions Levels
Date
anger
anticipation
disgust
fear
joy
nrc_sentiment
sadness
surprise
trust
Emotion
anger
anticipation
disgust
fear
joy
nrc_sentiment
sadness
surprise
trust
2019
2020
2021
2022

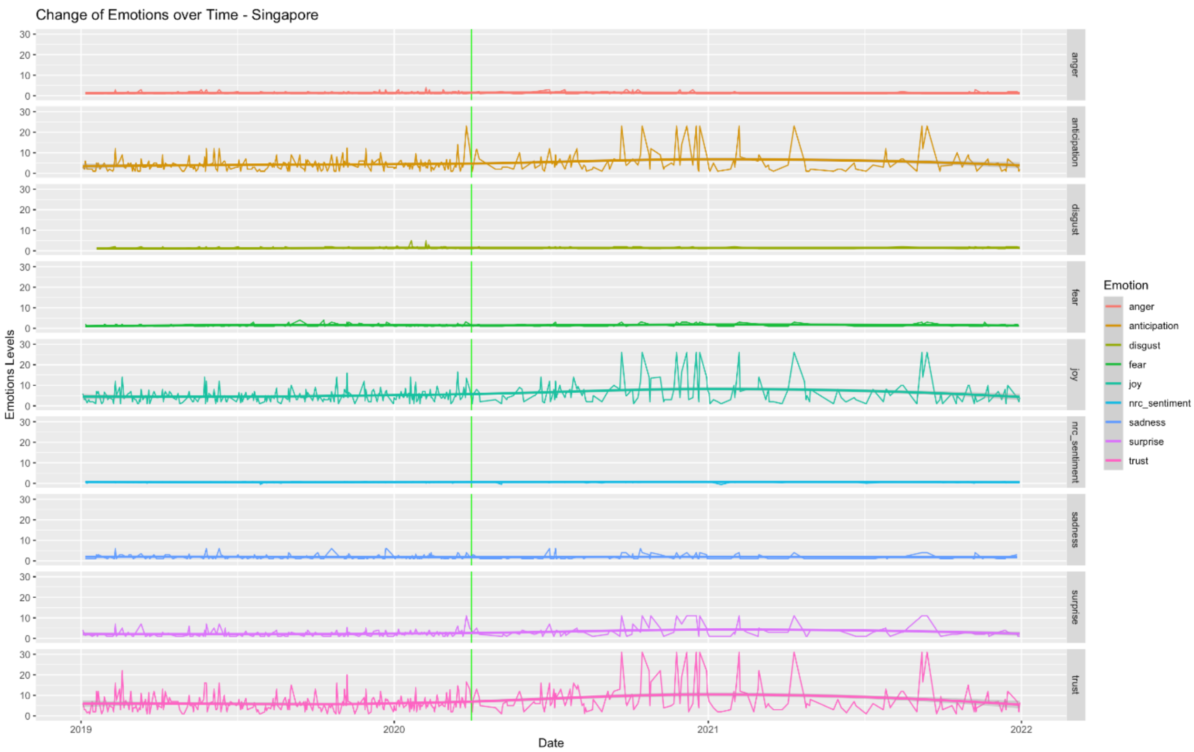

Change of Emotions over Time - France
Emotions Levels
Date
Emotion
anger
anticipation
disgust
fear
joy
nrc_sentiment
sadness
surprise
trust
2019
2020
2021
2022


Change of Emotions over Time - Hong Kong
Emotions Levels
Date
Emotion
anger
anticipation
disgust
fear
joy
nrc_sentiment
sadness
surprise
trust
2019
2020
2021
2022


Change of Emotions over Time - Netherlands
Emotions Levels
Date
2019
2020
2021
2022
anger
anticipation
disgust
fear
joy
nrc_sentiment
sadness
surprise
trust
Emotion
anger
anticipation
disgust
fear
joy
nrc_sentiment
sadness
surprise
trust

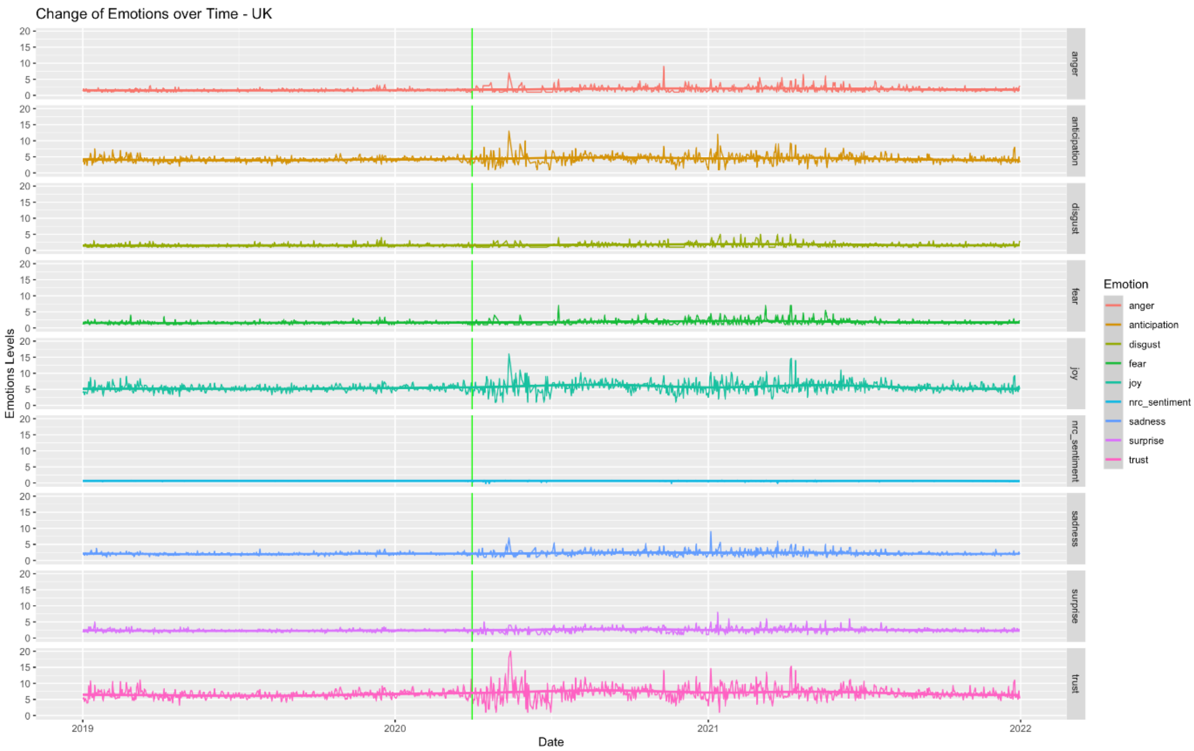

Change of Emotions over Time - Portugal
Emotions Levels
Date
2019
2020
2021
2022
anger
anticipation
disgust
fear
joy
nrc_sentiment
sadness
surprise
trust
Emotion
anger
anticipation
disgust
fear
joy
nrc_sentiment
sadness
surprise
trust


Change of Emotions over Time - Spain
Emotions Levels
Date
2019
2020
2021
2022
anger
anticipation
disgust
fear
joy
nrc_sentiment
sadness
surprise
trust
Emotion
anger
anticipation
disgust
fear
joy
nrc_sentiment
sadness
surprise
trust


Change of Emotions over Time - Singapore
Emotions Levels
Date
2019
2020
2021
2022
anger
anticipation
disgust
fear
joy
nrc_sentiment
sadness
surprise
trust
Emotion
anger
anticipation
disgust
fear
joy
nrc_sentiment
sadness
surprise
trust

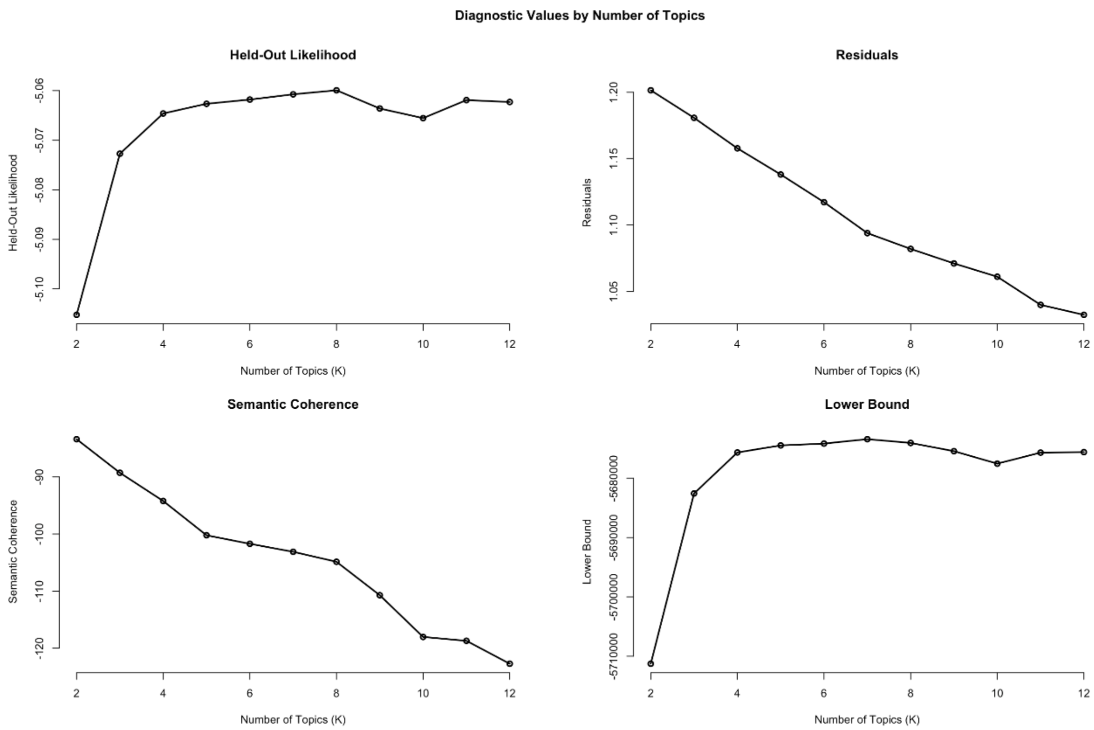

Change of Emotions over Time - Thailand
Emotions Levels
Date
2019
2020
2021
2022
anger
anticipation
disgust
fear
joy
nrc_sentiment
sadness
surprise
trust
Emotion

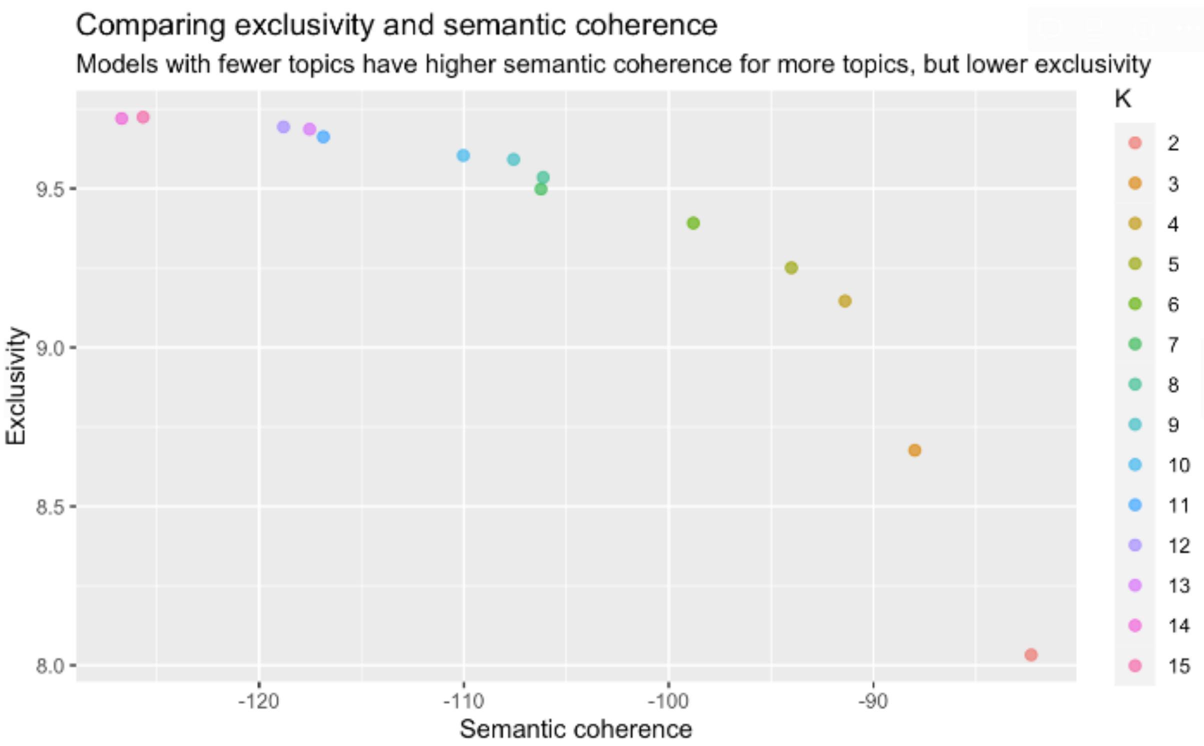

Change of Emotions over Time - Turkey
Emotions Levels
Date
2019
2020
2021
2022
anger
anticipation
disgust
fear
joy
nrc_sentiment
sadness
surprise
trust
Emotion



7.6. Appendix F – Topic Modelling

7.6.1. Selecting the optimum K for topic modelling





7.6.2. Summary of identified topics

Topic	Topic Label	Proportion	Frex Words
1	Communication	12.5	quick, time, response, communication, clear
2	External Facilities	14.4	walk, station, minute, bus, metro, away, train
3	View/Beauty	17	beautiful, amazing, wonderful, view, absolutely
4	Distance/Transportation	11.7	walking, public, access, distance, easy, transport
5	Value for Money/Cleanliness	13.3	value, house, comfy, exactly, warm, good, money
6	Amenities	19	bathroom, bedroom, bit, floor, small, window, noise
7	Place/Comfort	12.1	place, spot, perfect, question, quiet, great

7.6.3. Dominant words for each topic

Communication

External Facilities

View/Beauty

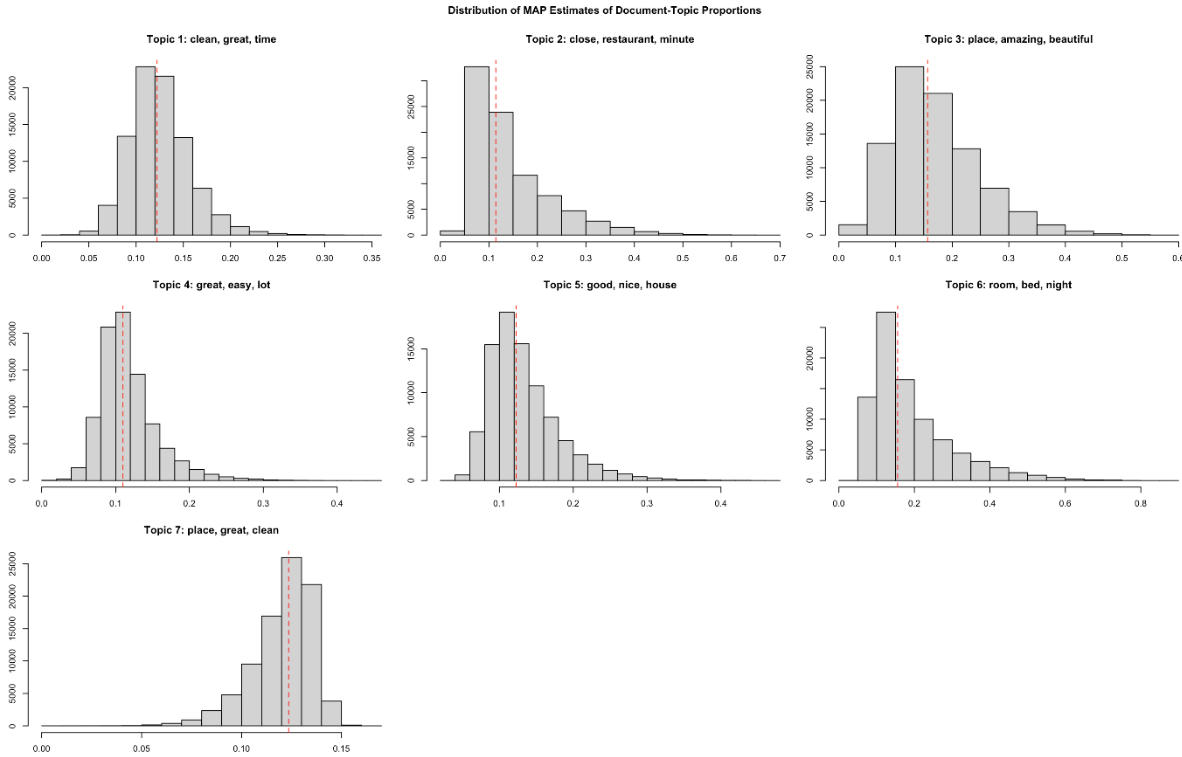
Distance/Transportation

Value for money/Cleanliness

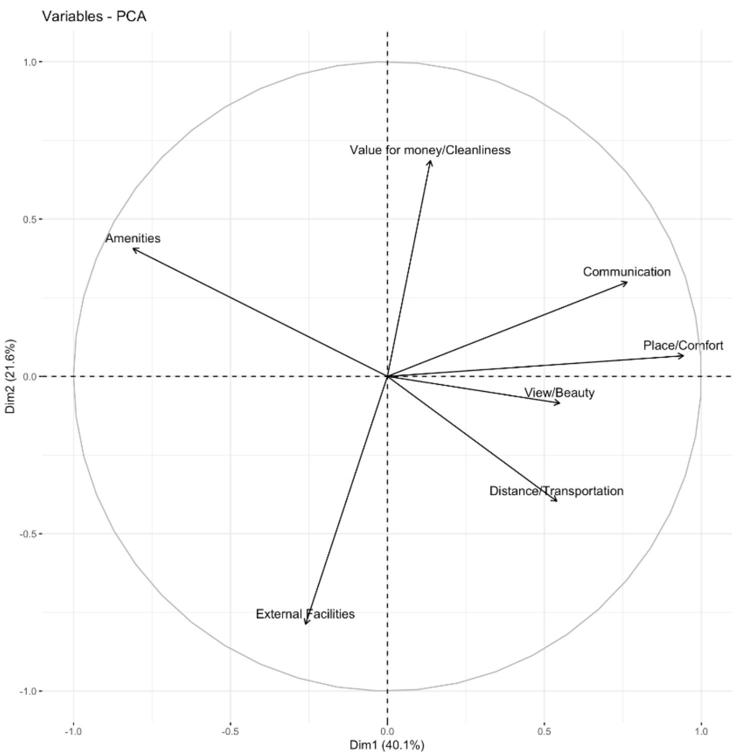
Amenities

Place/Comfort

7.6.4. Topic distributions over documents

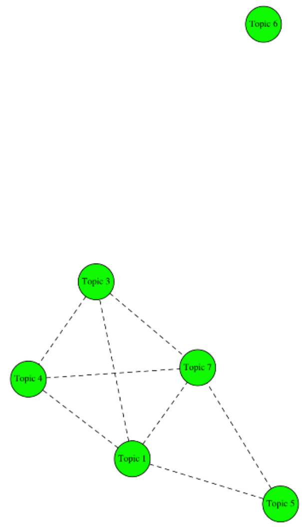


7.6.5. Factor Component Analysis (PCA)



PCA test is able to explain almost 62% of the total variance in topics. The test also says that there isn't too much multi-collinearity between the topics and can be considered individually.

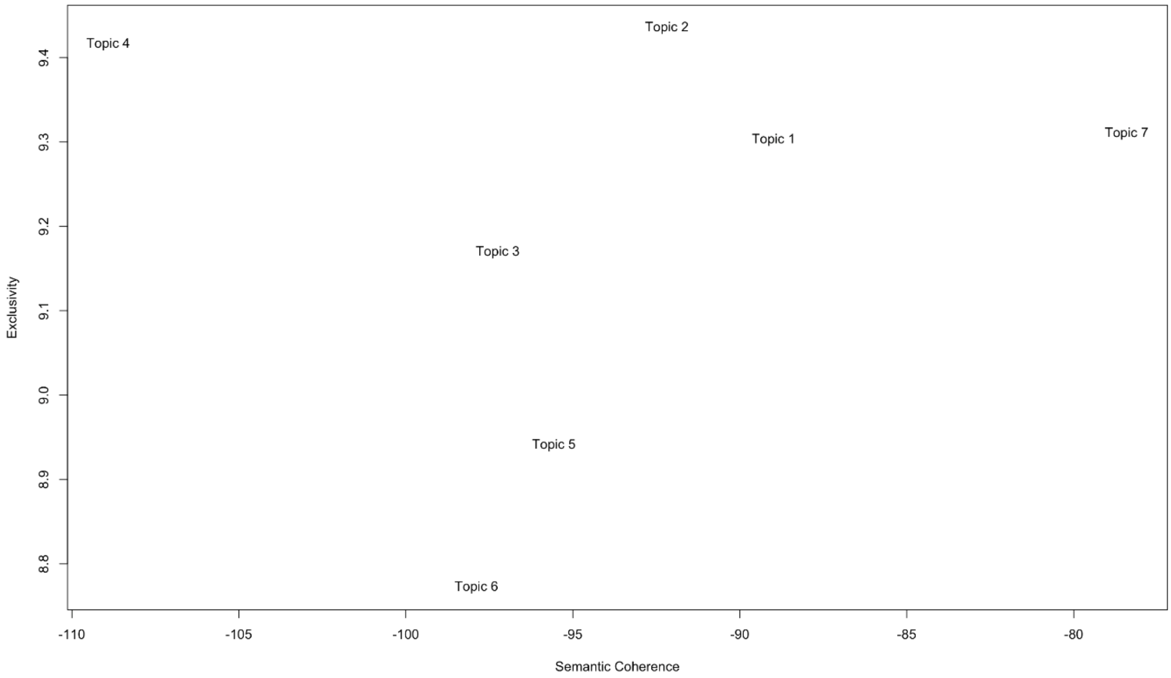
7.6.6. Topic associations



In terms of correlation, topic 2 and 6 seems the most exclusive ones, while other topics have some association with each other as shown by the topic association test.

7.6.7. Top words per topic

7.6.8. Topic quality by exclusivity vs semantic coherence



7.7. Appendix G – Predictive Analysis

7.7.1. Topic quality by exclusivity vs semantic coherence