Modelling and Analysing the Impact of COVID-19 on Airbnb

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Abstract— **In this study, we investigate the impacts of the COVID-19 pandemic on Airbnb, a major sharing economy platform, identifying significant changes and trends left in its passing wake, and focusing on the differences in changes by different property types. We investigate possible shifts in the popularity of entire and shared properties, changes in the geographic distribution of listings in neighbourhoods across cities, and the sentiment of reviews left by guests. By analysing data collected from a diverse range of 20 cities globally, and by considering both the listings left by hosts and reviews left by guests, we present an extensive and detailed analysis of the state of the platform in the post-pandemic era, that highlights the marked extent of the platform's evolution.**

I. Introduction

The sharing economy is an economic model wherein people provide access to underutilised assets and services, sharing the cost of ownership and improving utilisation efficiency [1]. Airbnb is a prime example of this system, allowing people to share and rent accommodations through an online platform.

As of 2019, Airbnb spans over 191 countries and 81,000 cities with 7 million listings [2]. In 2023, the company's annual revenue reached an all-time high of $9.9 billion, with an estimated 265 million users making 448 million bookings worldwide within one year [3]. Airbnb's annual revenue and booking figures have doubled in the past 4 years, and with rapid expansion in emerging markets such as India and the Middle East [2], Airbnb has demonstrated a strong performance and continues on an upward trajectory.

On the platform, hosts can choose to let, or guests can choose to rent, properties from one of four property types: 'Entire place', 'Private room', 'Shared room' and 'Hotel room'. Our research solely comprises properties that are 'Entire place' and 'Private room', due to the low numbers of 'Shared' and 'Hotel' rooms in comparison. We refer to an 'Entire place' as an 'entire-use' property and a 'Private room' as a 'shared-use' property, as it represents a private room within a property shared with other guests and/or the host. Guests who are attracted to the idea of having an authentic experience and interaction with their host or other guests can book shared-use properties at an affordable price [4]. On the other hand, those looking for a place with the comforts of their own home, but without the need to share with others, can choose to book an entire property instead.

On 11th March 2020, the World Health Organization (WHO) declared COVID-19 a pandemic [5], causing a global emergency with severe travel restrictions such as quarantines and lockdowns [6].

The goal of our investigation was to study the impact of the COVID-19 pandemic on Airbnb, across 20 cities around the world, and how it caused changes in Airbnb users' behaviour. We chose a diverse set of cities across 4 continents, to maintain a global outlook throughout our investigation, rather than just a Western representation.

Our main aim with our research was to close the knowledge gap on the global impact of the COVID-19 pandemic on the Airbnb platform - to understand changes in user behaviour. A previous study investigated the impact of COVID-19 on Airbnb, utilising data only from 2018 to the end of 2020 [7]. We investigated further, using all available data from January 2016 to December 2023, to fully understand the impact of the pandemic on Airbnb.

We came up with three research questions to understand the impact of COVID-19 on the Airbnb platform.

RQ1: *How has the COVID-19 pandemic affected guests' preference toward entire-use/shared-use properties?*

RQ2: *How has the COVID-19 pandemic affected the geographical neighbourhood distribution of Airbnb listings in cities?*

RQ3: *How has the COVID-19 pandemic impacted traveller review sentiments?*

To fully understand the state of Airbnb in the post-pandemic period, we conducted a quantitative analysis using data from 20 cities globally. Our approach used data scraped from Airbnb, including guest reviews, property listings and geography data, which was analysed with a variety of methods.

As expected, Airbnb's activities were negatively impacted during the start of the pandemic, with both the number of reviews and new listings dropping sharply. This was followed by a recovery period when Airbnb activities gradually recovered to pre-pandemic levels. Having evaluated our findings, we observed significant growth in the Airbnb platform as a whole post-pandemic, with multiple cities exceeding pre-pandemic forecasts. We first found that users' property type preferences shifted from shared-use properties to entire-use properties. Additionally, both entire and shared-use properties became more geographically spread out in the majority of cities. Finally, we found that the sentiment of guest reviews was more negative post-pandemic; both entire and shared-use reviews showed a general decrease in sentiment scores.

Our paper is structured as follows: in section II, we present a review of the current state of the research on Airbnb. Following that, in section III and section IV, we explain our research questions and experimental design including our metrics. In sections V and VI we analyse and discuss the results of our study. Finally, in section VII we address some of the limitations of our work, providing potential directions for future research, after which we conclude in section VIII with a summary of our findings.

II. Related Work

Academics have taken a strong interest in studying the sharing economy business model, due to its significant growth in popularity [8, 9]. Major companies such as Airbnb, Uber and Fiverr have emerged providing a platform for peer-to-peer interaction between users. Computer scientists have taken an interest in this field from two angles, focusing on the technical aspect, primarily studying the algorithms used in matchmaking between consumers and suppliers, and another from a Human-Computer Interaction (HCI) point of view, wherein they study the interactions between the users and the platforms which facilitate these interactions [10]. In this paper, we explore the HCI aspect of Airbnb.

A field of interest in the sharing economy is understanding the spatial distribution of Airbnb listings and their influence on supply and demand. Prior research [11, 12] has predominantly focused on Western cities, having found listings to be clustered around tourist attractions and the city centre. Study [13] Expanded this further by exploring non-Western cities in Asia and Latin America, generally finding similar distribution patterns in non-Western cities, except in Latin America where listings were even more concentrated around the city centre. Meanwhile studies [14] and [15], explored the socio-economic impacts of Airbnb's spatial distribution. Research [14], revealed that Airbnb's presence has caused an increase in the price of rental properties in London, benefiting homeowners. On the contrary, [15] found a strong correlation between gentrification and Airbnb's presence, suggesting that Airbnb could be causing inequality - opposing the sharing economy's aims of reducing it. In our study, we aimed to explore spatial inequality further, as we quantified changes in the spatial distribution of Airbnb properties in neighbourhoods pre and post-pandemic. Researchers have also taken an interest in studying interactions between different demographics and inequality exists amongst them [16–20]. Using graphical analysis, [17, 19], found evidence of strong homophilic interactions. Meanwhile, [16] and [20] revealed that African-American guests and hosts tend to be discriminated against. [16, 17, 19] Relied on AI tools to obtain ethnicity, age and gender through profile pictures, which only accurately classify a small range of ethnicities, as such discriminating further against minority groups.

Another quantitatively researched area investigated user experiences and sentiment through textual and statistical analysis of reviews and ratings. Papers [21–23] performed sentiment analysis on Airbnb reviews, generally finding that overall - Airbnb review sentiment is quite high. [21] Compared the computed Airbnb and Hotel review sentiments across cities in Brazil, finding that Airbnb has a higher guest sentiment. Meanwhile [24–29] set out to perform topical analyses, applying techniques such as LARA, LDA and Hierarchical Clustering to investigate important aspects of guests' stays in Airbnb properties. A common limitation of [24–29], was that non-English reviews were discarded, preventing it from understanding local sentiment. Our investigation closed this gap, as we translated non-English reviews using VADER's embedded translation tool to study changes in sentiment pre and post-pandemic.

The COVID-19 pandemic had a massively negative impact on the hospitality industry [30]. Meanwhile, the impact on Airbnb has not been significantly explored; [7, 31] aimed to close that gap by investigating the impact of COVID-19 on Airbnb.

However, [7, 31] were quite limited in data and localised - using data only until the end of 2020, and primarily focusing on Western cities. With our study, we aimed to close this gap by analysing data until the end of 2023, allowing us to gain a greater insight into the changes in Airbnb post-pandemic. We also investigated 20 cities worldwide - gaining a global perspective on the impact of COVID-19 rather than a Western outlook.

III. Research Questions

To investigate the impact of COVID-19 on the Airbnb sharing economy platform, we performed a quantitative analysis of the Airbnb data available, to answer our three key research questions. When answering each question, we also considered the differences between entire and shared-use properties, to analyse the changes in experiences for property hosts and guests.

- **RQ1:** *How has the COVID-19 pandemic affected guests' preference toward entire-use/shared-use properties?* We investigate any shifts in preference to identify if hosts and guests exhibit different behaviour post-pandemic, possibly preferring to avoid interaction with other travellers and hosts, or perhaps becoming more receptive to greater interaction.
- **RQ2:** *How has the COVID-19 pandemic affected the geographical neighbourhood distribution of Airbnb listings in cities?* We investigate the change in the geographic distribution of Airbnb listings, to see if hosts exhibit different behaviour post-pandemic, whether offering a greater spread of listing locations or becoming even more concentrated in urban cores.

RQ3: *How has the COVID-19 pandemic impacted traveller review sentiments?* We assess the sentiment of guest reviews to investigate whether satisfaction levels with Airbnb accommodations have changed after the pandemic and whether guests express different levels of satisfaction between shared and entire-use properties.

IV. Experiment Design

A. Data

To perform our investigation into the impact of COVID-19 on Airbnb, we first selected 20 cities across 4 geographic regions, of different sizes, economic statuses and cultures to provide a diverse dataset of hosts and guests. We summarise this list of cities and key statistics in Table I [32–46].

Since our investigation explores the changes to the platform as a result of the pandemic, we defined 3 time periods into which we divide our data: pre-pandemic, intra-pandemic and post-pandemic. We define the start of the COVID-19 pandemic as 1st February 2020, as travel restrictions first started to be introduced in countries in February, and the end as 1st July 2022, by which point the travel restrictions and quarantines had ended in most countries. As such, we define the *pre-pandemic period* as 1st January 2016 to 1st February 2020, the *intra-pandemic period* as 2nd February 2020 to 30th June 2022, and the *post-pandemic period* as 1st July 2022 to 31st December 2023.

On Airbnb, hosts post a *listing* of their property, which includes the host's name, property type, location, availability, neighbourhood and more. *Reviews* are voluntarily left by guests upon completion of their stay at properties, and include a review date, various numerical scores, and a textual comment. To answer our three research questions, we analysed the listings and reviews we obtained for the 20 cities from 2016 to 2023, with listings informing our understanding of hosts' behaviour, and reviews that of guests. For listings, we obtained the ID, property type, neighbourhood, geographical coordinates, and date of first review; for reviews, the ID of the listing being reviewed, the review date, and the textual comment. We did not store any personally identifiable information such as names or account identifiers, and any listings scraped incorrectly (improperly formatted or missing data) were deleted as part of our data cleaning process.

B. Method and Metrics

We describe the methods used to investigate each research question in turn, and the relevant metrics we computed to perform the analysis.

RQ1: *Shift in property type preferences*

To investigate changes in guest preferences towards property type, we computed the following 2 metrics for each property type, city, and calendar month:

- Number of new listings added to the platform by hosts.
- Number of reviews left by guests.

Real occupancy records of properties are not made publically available by Airbnb, however, guests leave reviews for stays approximately 68% of the time [47], therefore the number of reviews left by guests could instead be used as a proxy for the number of stays in properties of each type, reflecting guest preferences of property type. Listings do not have a specific date on which they were first added to the platform, therefore the date of the first review acts as a proxy, to enable counting of the number of new listings in a given calendar month or period.

To investigate general changes in preferences pre and post-pandemic, we compared the total number of new listings and reviews for the entire and shared-use properties in each period.

We then performed a time-series analysis, investigating if property type preferences post-pandemic followed pre-pandemic growth, so we could infer if the pandemic significantly altered previous trajectories. Prophet [48] modelling was applied similarly as in [49]: for each city and property type, a model of the number of reviews and new listings was trained on pre-pandemic time-series data. The mean difference between the prophet model's *forecast* and the post-pandemic *actual* number of new listings/reviews for each property type, each month, was computed as per eq. 1 with $N = 17$, the number of months in the post-pandemic period. This allowed us to determine if post-pandemic, the number of monthly reviews and new listings was greater, less than or followed pre-pandemic predictions.

$$\text{meanDifference} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\text{actual}_i - \text{forecast}_i}{\text{actual}_i}\right) \tag{1}$$

Finally, we computed the change in predictability of customer demand from pre to post-pandemic, to understand whether post-pandemic usage of shared and entire-use properties was forecastable. Using eq. 2 we computed the pre and post-pandemic permutation entropy [50] of the weekly number of reviews - where p_π represents the probability of permutation π. Permutation entropy was computed using the weekly number of reviews instead of monthly, because weekly reviews can better identify short-term patterns that monthly data might omit.

$$\text{PermutationEntropy} = -\sum_{\pi} p_\pi \log(p_\pi) \tag{2}$$

Next, using eq. 3 and eq. 4, we computed pre (P_B) and post-pandemic predictability (P_A) and change in predictability. Predictability ranges from $0 \leq$ Predictability ≤ 1, where a value closer to 1, represents high predictability. The change in predictability provided insight into whether the post-pandemic trajectory was forecastable - if it followed similar patterns to pre-pandemic, or whether there had been a post-pandemic shift due to different Airbnb usage.

$$\text{Predictability} = 1 - \text{PermutationEntropy} \tag{3}$$

$$\Delta P\% = \left(\frac{P_{\text{A}} - P_{\text{B}}}{P_{\text{B}}}\right) \times 100 \tag{4}$$

Continent	City	Population	GDP (Billion USD)	Number of Listings	Number of Reviews
North America	New York	8,335,897	2,048.4	23,202	889,657
	San Francisco	808,437	729.1	5,194	342,240
	Austin	974,447	222.0	11,238	555,696
	Boston	650,706	571.7	2,763	174,057
	Nashville	683,622	187.8	7,307	610,945
	Toronto	3,025,647	430.9	13,676	480,257
Europe	Barcelona	1,627,559	188.7	12,067	746,366
	Milan	1,362,256	248.1	17,764	733,845
	Munich	1,471,508	231.7	4,712	146,529
	Istanbul	15,840,900	142.6	21,754	458,248
	London	8,135,667	663.5	61,993	1,526,722
	Riga	614,618	24.9	1,986	102,155
Asia and Oceania	Hong Kong	7,346,100	382.3	3,101	90,556
	Bangkok	8,421,212	174.0	12,684	339,554
	Singapore	5,637,022	520.9	1,594	32,611
	Melbourne	4,585,537	159.0	18,100	719,562
South America	Mexico City	22,167,521	142.8	21,910	1,004,870
	Rio de Janeiro	6,211,223	144.1	23,572	663,722
	Belize	28,264	3.4	2,105	57,972
	Santiago	6,562,300	254.4	8,704	301,404

TABLE I: Studied Cities

RQ2: *Changes in geographic neighbourhood distribution*

To investigate whether the geographical distribution of listings had been impacted, we calculated the percentage change in Gini Coefficient as our metric. From the listing data, we calculated the number of listings on a per city, per neighbourhood, per property type basis, for each of the three time periods. As listings remain on Airbnb permanently, by default, pre-pandemic listings are a subset of post-pandemic listings. To prevent the same listing from being counted in both the pre-pandemic and post-pandemic data, we used the review date field of the listing data to define the last time a listing was "active", and used this date to determine whether a listing should fall in the pre, intra, or post-pandemic periods.

We then calculated the Gini Coefficient on a per-city, per-property-type basis, for the pre and post-pandemic periods. A Gini Coefficient value of zero indicates complete equality (listings are distributed perfectly between neighbourhoods), while a Gini Coefficient of one indicates complete inequality (all listings are concentrated in a single neighbourhood). To calculate the Gini Coefficient we compared the difference in the number of listings across neighbourhoods, in the same city and of the same property type. This was computed using eq. 5 below where n is the number of neighbourhoods in the city, X_i is the cumulative sum of the sorted values for the number of listings in each neighbourhood, up until the ith value, and X_n is the total sum of the number of listings for all neighbourhoods in the city, i.e. the final value in the cumulative sum.

$$Gini = \frac{n + 1 - 2 \cdot \frac{\sum_{i=1}^{n} X_i}{X_n}}{n} \tag{5}$$

Finally, with the pre and post-pandemic Gini Coefficients calculated for each city, we computed the percentage change in Gini Coefficient, from the pre-pandemic Gini values to post-pandemic, using eq. 6. A positive percentage change in Gini Coefficient indicated that inequality increased post-pandemic, and vice versa.

$$\%\ \text{Change in Gini} = \left(\frac{\text{Gini}_{\text{After}} - \text{Gini}_{\text{Before}}}{\text{Gini}_{\text{Before}}} \right) \times 100 \tag{6}$$

RQ3: *Changes in guest review sentiment*

To investigate whether the pandemic had an impact on guest experience, we analysed the review comments. Because of guests' propensity to leave high ratings [51], they do not reliably reflect true guest satisfaction. Therefore, we analysed the content of reviews left by guests, which offer greater detail, and review sentiment in each city was compared in the pre and post-pandemic periods.

To measure review sentiment, we initially considered two tools to compute the sentiment value of reviews in natural language: VADER (Valence Aware Dictionary for Sentiment Reasoning) [52] and TextBlob [53]. We used sample Airbnb reviews and applied both tools to them. To compare the results of the two tools, four annotators labelled the sentiment of reviews on a scale of 1 to 10, indicating extremely negative to extremely positive. With VADER we obtained very high accuracy as the results were very close to the labelled scores. With TextBlob we achieved significantly lower accuracy, especially for reviews with more complex structures, such as those with double negatives and sarcasm. As a result, we selected VADER as our sentiment analysis tool.

Prior to computing sentiment, non-English reviews were translated to English using VADER's embedded translation tool, to allow for a wider range of travellers to be represented in our study. After running the reviews through VADER we obtained data on sentiment scores ranging from -1 to 1, representing extremely negative to extremely positive reviews.

We analysed the data by grouping sentiment scores based on city and property type and calculating the average monthly sentiment score for each group. We then computed the percentage change in sentiment scores to compare pre and post-pandemic review sentiment. A positive percentage change in sentiment scores indicated an increase in review sentiment since the pandemic, and vice versa.

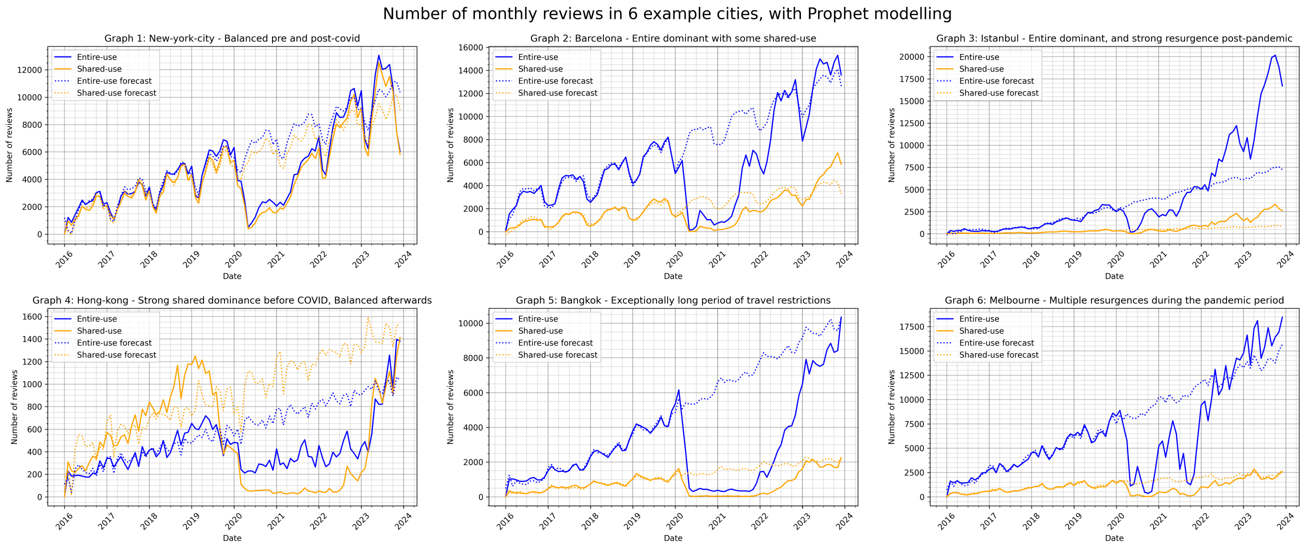

Fig. 1: Graphs of the number of monthly reviews (solid lines) in the 6 example cities for entire and shared-use, including prophet modelling (dashed lines).

V. Results

RQ1: *Shift in property type preferences*

To investigate whether there has been a shift in preferences between shared and entire-use properties, we directly compared the total number of reviews/new listings in the pre and post-pandemic periods by property type. We introduce the idea of dominant and balanced cities: we classified cities as *balanced* if the number of shared and entire-use reviews/new listings were within the range 33% to 66%, e.g., 40% shared-use, 60% entire-use. On the other hand, cities were entire-use dominant if over 66% of new listings or reviews were for entire-use, and vice-versa for shared use.

We plotted the number of reviews and new listings each month by property type from the pre-pandemic to post-pandemic periods for each city, alongside the prophet modelling predictions, and compared their results. We found that for the 20 cities, 6 distinct patterns of behaviour emerged, with certain trajectories and preferences distinctly similar in certain cities, and some patterns shared in cities within the same geographic region. To save space, we do not include the full set of 20 graphs, instead, we refer to Figure 1 which contains 6 example city graphs which demonstrate the observed behaviour for the number of monthly reviews in each city by property type.

Graph 1 of Figure 1 demonstrates balanced preferences both pre and post-pandemic, behaviour unique to New York City, London and Munich. Graph 2 shows consistent entire dominance, but with some shared use properties - found in Barcelona, San Francisco, Boston, Toronto and Belize. Graph 3 demonstrates complete entire-use dominance, with a very strong resurgence post-pandemic - evidenced by the solid blue entire-use line vastly exceeding the forecast shown as a dashed line, and a shorter period of reduced activity as a result of the pandemic, compared to others. Istanbul, Mexico City, Santiago, Austin, Nashville, Milan and Rio de Janeiro experienced this pattern.

Graph 4 is perhaps the most interesting, showing reasonably strong shared-use dominance pre-pandemic, and an extended period of intra-pandemic downturn, before recovering with a shift to balanced guest demand. This is observed in Hong Kong and Singapore. Graph 5 - Bangkok, shows a similarly long period of pandemic difficulty, instead with strong entire-use dominance both pre and post-pandemic. Finally, Graph 6 - Melbourne and Riga, shows definitive entire-use dominance, but also a distinctive peak and drop in the number of reviews in the middle of the intra-pandemic period.

In general, the graphs for new listings followed similar trends as the reviews. One of the cities that showed differences was Barcelona: the graph of reviews for Barcelona was categorised as ‘Entire dominant with some shared-use’, however, its graph of new listings was better categorised as ‘Balanced pre and post-covid’. The graph of 6 distinct patterns for new listings is attached in the Appendix for completeness but is not included within the body to save space.

Our graphical findings were supported by the percentage comparisons calculated for each city. We found that before the pandemic for reviews, of the 20 cities: 15 favoured entire, 3 were balanced - New York City, London and Munich, and 2 were shared-use - Hong Kong and Singapore. Post-pandemic, Hong Kong and Singapore became balanced and Munich became entire, therefore there were 16 entire, 4 balanced and no shared-use dominant cities. Listings showed a similar but stronger pattern of shifting, pre-pandemic there were 12 entire, 7 balanced - New York City, San Francisco, Boston, Barcelona, Munich, London and Hong Kong, and only Singapore shared. Post Pandemic, only Barcelona and Hong Kong remained balanced, with the other 18 cities entire-dominant.

These initial findings provided clear evidence to suggest that hosts and guests generally preferred entire-use properties and that post-pandemic, there has been a significant shift away from shared-use properties, with cities becoming more balanced or entire-use dominant.

Next, to consider how closely the number of monthly reviews and new listings in each city followed pre-pandemic trajectories, we trained the prophet models (also shown on Figure 1) for entire and shared-use for each city, and computed the mean difference between the actual and forecasted results. We defined that a mean difference less than -0.05 corresponded to below-forecast growth, -0.05 to 0.05 followed the forecast, and greater than 0.05 exceeded it.

For entire-use properties, 10 out of 20 cities experienced a greater number of monthly reviews than predicted in the post-pandemic period characterised by graphs 3 and 4; 5 cities followed the forecast - New York City, Mexico City, Barcelona, San Francisco and Riga, while 5 were below - Toronto, Singapore, Hong Kong, Bangkok and Belize. New listings had even stronger growth for entire-use properties post-pandemic, with 19 cities experiencing growth exceeding the pre-COVID-19 forecast, with only Belize again receiving below-forecast new listings.

Meanwhile, shared-use properties had weaker review growth, with only 5 cities exceeding - Barcelona, Istanbul, Riga, Rio de Janeiro and Santiago, 5 following - London, Munich, Austin, New York City and Toronto, and the remaining 10 cities below forecast. On the other hand, listings experienced similarly strong growth as entire-use, with 16 cities exceeding the forecast, only Hong Kong following, and 3 performing worse - Boston, Singapore and Belize. This similar level of growth in the number of new listings suggests that the Airbnb platform as a whole is experiencing stronger growth post-pandemic, with hosts listing their properties at a higher rate than before, both for entire-use, and shared-use properties.

We found that the predictability post-pandemic decreased in all cities and property types by 5-7% as shown in Figure 2, implying that the significant disruption caused by the pandemic remained prevalent. Furthermore, a change in predictability also indicated a shift in Airbnb usage - correlating with a shift in user preference from shared to entire-use properties. Munich was amongst those cities that experienced the greatest decrease in predictability, this aligned with the city's shift in guest preference from 'balanced' guest preference pre-pandemic to entire-use post-pandemic. This post-pandemic change in predictability shows a transformation in Airbnb consumer priorities and demands.

From our investigation into RQ1, we found that in the post-pandemic era, guests and hosts increasingly favoured entire-use properties, with clear trends of shared-use cities becoming balanced, and balanced entire-use dominant. We observed growth in the number of guests staying in entire-use properties significantly exceeding pre-pandemic predictions, while shared-use properties in half of the analysed cities failed to exceed or follow pre-pandemic forecasts. Overall, our results suggest that there has been a shift post-pandemic towards entire-use properties.

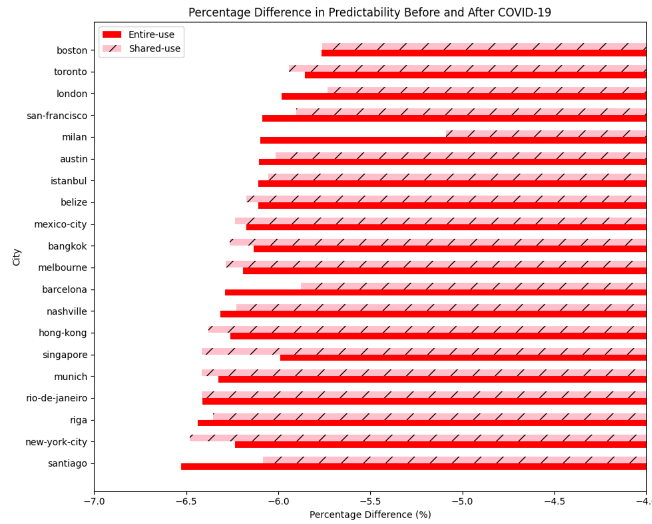

Fig. 2: Percentage difference in predictability pre-pandemic to post-pandemic.

RQ2: *Changes in geographic neighbourhood distribution*

To visualise the impact that COVID-19 had on the geographical distribution of Airbnb listings, we plotted diverging bar charts for the percentage change in Gini Coefficient pre and post-pandemic, as shown in Figure 3. Cities with a positive percentage change (coloured in red), such as Mexico City and Singapore, saw an increase in listing inequality, meaning that listings became more concentrated within select neighbourhoods. Meanwhile, cities with a negative percentage change (coloured in green), such as San Francisco and Nashville, saw a decrease in inequality, i.e., the listings became more evenly distributed between neighbourhoods.

We found that for entire and shared-use listings, the overall trend was that inequality of listing distributions between neighbourhoods had decreased post-pandemic.

For entire-use listings on the left of Figure 3, 15 out of 20 cities exhibited a decrease (or no change) in inequality of listing distributions. Interestingly, we found evidence of a strong regional trend in North America, where all 6 cities exhibited decreases in inequality post-pandemic. Specifically, San Francisco demonstrated the greatest decrease in inequality of all cities investigated, while Milan saw the greatest increase in inequality.

For shared-use listings on the other hand (right of Figure 3), we no longer observed the regional trend evident in North American entire-use listings, instead finding no obvious regional trends. Overall, we again found strong evidence of a decreasing inequality trend, with 15 out of the 20 cities investigated, exhibiting an inequality decrease, for shared-use listings post-pandemic. Interestingly, leading the way for inequality decreases was once again San Francisco.

While for both entire and shared-use listings, the same overall number of cities showed inequality decreases, the magnitude of percentage decreases for shared-use listings was much greater than that of their entire-use counterparts.

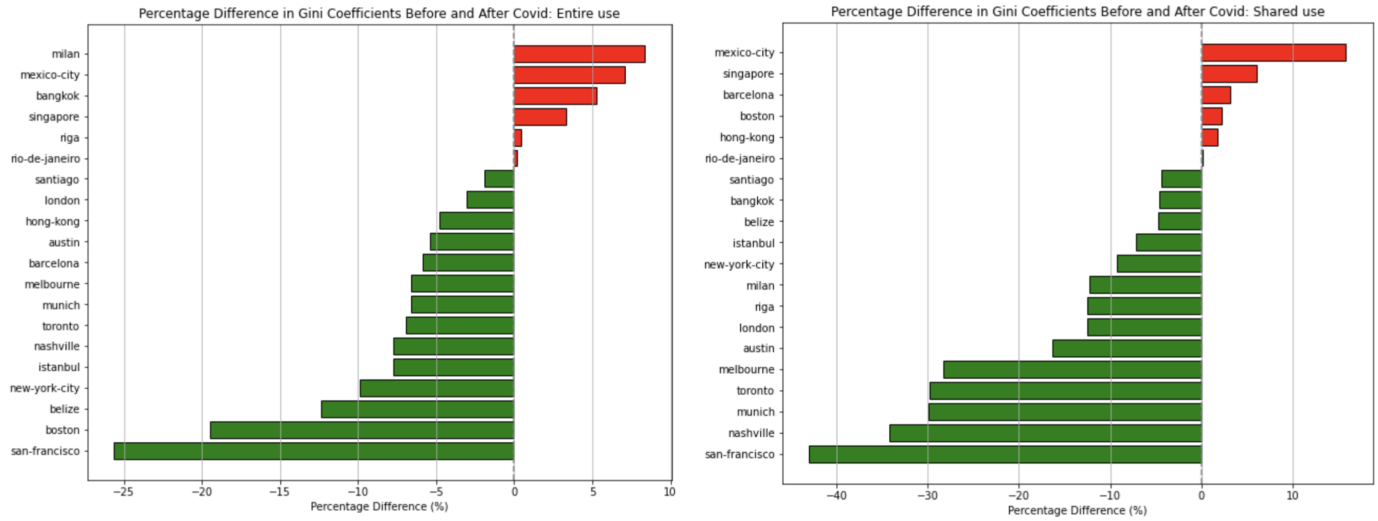

Fig. 3: Percentage change in Gini Coefficient per city for both entire-use listings and shared-use listings.

This was specific to inequality decreases, whereas inequality increases were of roughly the same magnitude for entire and shared-use listings, with the exception being Mexico City, which experienced a far greater increase in inequality for shared-use listings compared to entire-use.

In summary, our key findings for RQ2, were that both entire use and shared use listings saw a general trend of decreasing inequality post-pandemic, reflected by 15 out of 20 cities for both property types. However, the observed inequality decreases for shared-use property types was of a far greater magnitude than the inequality decreases for entire-use listings. This means that post-pandemic, shared-use listings had a greater tendency to be spread out between neighbourhoods of a city, than their entire use counterparts.

RQ3: *Changes in guest review sentiment.*

To investigate whether there have been changes in review sentiment post-pandemic, we once again plotted diverging bar charts, this time showing the percentage changes in sentiment scores for both property types pre and post-pandemic, as shown in Figure 4. Cities that experienced an increase in sentiment scores are coloured in green, whereas those with decreasing scores are coloured in red.

Our results showed a downward trend in sentiment scores for property types across most cities. Specifically, sentiment scores decreased in 19 out of 20 cities for entire-use properties and in 18 out of 20 for shared-use. Both property types shared similar regional trends, with some of the greatest declines in sentiment in South American cities including Mexico City, Santiago, and Rio de Janeiro. Among them, Santiago saw the largest drop in sentiment scores by nearly 50% for both property types. The negative impact of the pandemic on sentiment is also evident in certain European cities, namely Istanbul, Munich, and Barcelona. In contrast, studied cities in North America, Asia and Oceania were only slightly affected by the pandemic, with most cities seeing percentage declines within 10%.

Comparing the sentiment percentage change between entire-use and shared-use properties, we found that the pandemic had a more negative impact on guest satisfaction levels for shared-use properties, reflected by a greater overall reduction in sentiment scores. This disparity is particularly prominent for cities with smaller declines in sentiment, namely those in North America, Asia, and Oceania.

Exceptions to this trend were observed in Hong Kong and Bangkok. Hong Kong experienced an increase in sentiment scores for both property types, with a nearly 30 percent increase for shared-use properties, while Bangkok experienced a slight increase in sentiment scores for shared-use properties.

In conclusion, studying RQ3, we found a general decline in review sentiment for both entire-use and shared-use properties, with shared-use properties experiencing a more significant drop. These key results indicate reduced guest experience in Airbnb stays, especially for shared-use properties.

VI. Discussion

RQ1: *Shift in property type preferences*

While investigating the shift in property-type preferences, we identified certain interesting patterns or behaviours. The 3 cities in Asia that we investigated, Singapore, Hong Kong and in particular Bangkok, experienced significantly longer periods of downturn compared to those in other regions. These cities had post-pandemic recoveries between the summer of 2022 and spring 2023, compared to summer 2021 for North America, Europe and South America. Graphs 4 and 5 in Figure 1 illustrate the contrast, likely resulting from the much later lifting of COVID-19 travel restrictions [54, 55]. This late resurgence was reflected in the Prophet investigation, with the 3 Asian cities consistently below forecast for the number of guest reviews. Following current trajectories, these cities already have or will likely exceed pre-pandemic forecasts.

Riga and Melbourne exhibited unique behaviour, with both cities experiencing a significant peak in entire-use reviews

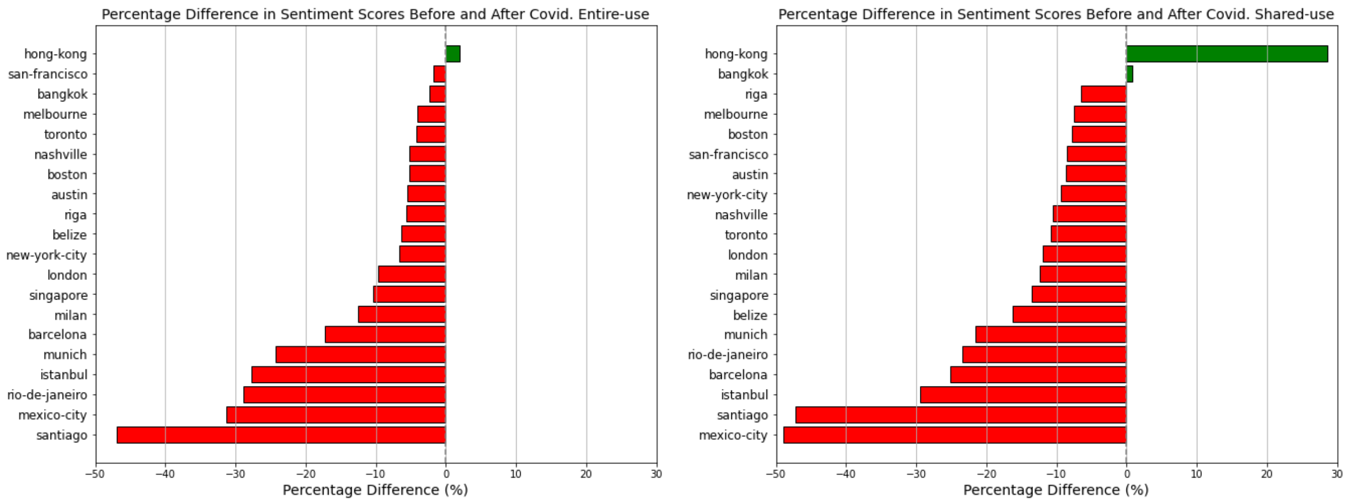

Fig. 4: Percentage change in sentiment scores before and after Covid for entire-use and shared-use property types.

during their pandemic periods, in summer 2020 in Riga and summer 2021 for Melbourne, before a sudden drop to levels similar to the start of the pandemic. In both cases, restrictions were lifted during the pandemic, before later being reimposed [56, 57], likely resulting in the rise, then drop in guest reviews. The same did not occur for shared-use properties, likely because restrictions meant that hosts could not share their properties with multiple guests.

RQ2: *Changes in geographic neighbourhood distribution*

Our Gini Coefficient calculations revealed a trend post-pandemic of inequality in Airbnb listing distributions decreasing. However, decreased inequality could stem from historically busier neighbourhoods becoming quieter in terms of Airbnb listing activity, or vice-versa, where historically quieter neighbourhoods have become busier. Given the travel restrictions imposed by many countries during the pandemic, it seems that the former scenario is more likely, since hosts may not have been able to continue operating under the economic downturn brought on by travel restrictions.

Of the 20 cities studied, only two cities, namely Mexico City and Singapore, experienced increases in inequality for both entire-use and shared-use listings. For the same possible reason inequality decreased, we would still expect pandemic travel restrictions to result in fewer listings overall. As a more tourism-dependent city [58], the reason for Mexico City's increased inequality may have been that with travel restrictions in place, only properties in the most popular tourist neighbourhoods could remain profitable enough for hosts. On the other hand, Singapore, as a business hub [59], may have seen increased inequality as the stricter and longer travel restrictions, as discussed in RQ1, meant that tourism fell drastically, while the number of Airbnb properties located in neighbourhoods near the central business district may have remained constant, thereby taking a comparatively greater share of the listings across the city.

Additionally, San Francisco stood out as a city that saw a huge decrease in Gini Coefficient for both entire-use listings, and shared-use listings, reflecting a shift towards a more even distribution of listings overall. This could be a result of the high cost of living San Francisco, with the highest rent in the U.S [60], possibly pushing hosts in quieter neighbourhoods to list their properties on Airbnb to earn supplemental income.

Another key finding was that generally, the scale on which inequality had decreased for shared use listings was far greater than that of entire use listings. During the pandemic, there was a significant shift in traveller preferences towards accommodation with greater privacy [61]. As a result, we might expect that demand for shared use listings dropped more than demand for entire use listings, which was more heavily felt by more popular Airbnb neighbourhoods, explaining our observed results.

RQ3: *Changes in guest review sentiment*

Our main findings from investigating review sentiment are that the pandemic had a negative impact globally on guest satisfaction, especially for shared-use properties. Among all cities studied, we found that South American cities suffered the greatest, characterised by the large drop in sentiment scores post-Covid. The sharp decline may be attributed to the severe pandemic outbreaks in South America [62], which have led to stricter travel regulations. As popular tourism destinations, Airbnb listings in these cities were more likely to be affected by such restrictions.

Overall, the downward trend in review sentiment for Airbnb stays is as expected, as the limitations on services and adherence to health guidelines could have led to less pleasant experiences. It is also not surprising that shared-use properties were more affected by the pandemic. This could have been because guests faced more inconveniences and felt greater stress about sharing spaces with others, fearing the risk of infection.

VII. Limitations & Future work

We highlight here certain limitations in our research that should be addressed in possible future research, for which we also make some suggestions.

One of the greatest limitations of our research is focusing primarily on major metropolitan/urban cities generally in developed countries. As a result, we lacked insights into how the pandemic impacted less crowded or smaller cities, cities in developing countries, or rural areas. Future work should explore the impact of COVID-19 on Airbnb in suburban and rural environments and compare the results with the conclusions in this study to identify any differences. Specifically, there were several cities which we were not able to collect Airbnb data for, namely cities in Africa and the Middle East, where there is low Airbnb activity.

As time progresses, it would be sensible to carry out a study that employs similar methodologies as ours, to determine if post-pandemic trends in growth, change in sentiment, and geographic inequality have remained constant, or change over time. Our analysis only utilised a year and a half of post-pandemic data, therefore it would be wise to repeat the study after 2 to 5 years and compare 4 years of pre-pandemic data with 4 years of post-pandemic data, for a more balanced analysis.

We now consider the limitations relating to the investigation of each research question, rather than as a whole. The conclusions that we came to for RQ1 only considered the number of reviews and new listings. We did not consider if the pandemic was the key reason for the shift, or if other factors, such as rising prices as a result of housing crises in various cities [63] were responsible. Future investigations could aim to investigate why we observed the general shift from shared to entire-use properties.

In RQ2, our use of the Gini Coefficient does not capture the full intricacies of the geographical distribution of Airbnb listings, since some spatial information is not preserved. A high Gini Coefficient indicates that listings are concentrated within a specific neighbourhood, however, we could not tell whether this was in the city centre, or in the suburbs, from this metric alone. Two cities with similar Gini Coefficients can have very different spatial patterns of listings. As a result, although we knew whether the inequality in a city had increased or decreased, we could not tell how this change came about. Decreased inequality could occur from fewer listings in popular neighbourhoods, or more listings in quieter neighbourhoods.

Finally, when studying review sentiment in RQ3, we did not distinguish between English and non-English reviews. From a linguistic perspective, English and non-English reviewers may have different speech habits and writing styles, while from a cultural perspective, those from different backgrounds may express different views and opinions about the same listing and service. Future work could investigate whether there are indeed differences between review sentiment expressed by English and non-English speakers, which could be more reliably controlled for in globally reaching studies as our own. In addition to studying review sentiment, future work could also investigate how the topics (e.g., location, staff) discussed in the reviews changed post-pandemic to gain a more comprehensive understanding of COVID-19's impact on guest experience.

VIII. Conclusion

In this study, we applied a quantitative approach to assess the impact of the COVID-19 pandemic on Airbnb, covering a globally diverse range of 20 cities across 4 geographic regions. Through time-series analysis with Prophet modelling and predictability computation, we investigated shifts in preferences between shared and entire-use properties. We then computed Gini coefficients to evaluate changes in the geographic distribution of Airbnb listings. Lastly, we applied VADER to compute guest review sentiments, assessing variations across different cities.

Our research highlighted an existing preference for entire-use Airbnb properties, with a post-pandemic shift from shared-use options widening the gap. Airbnb experienced stronger but more unpredictable growth in property listings across all types post-pandemic. Furthermore, our analysis showed a decrease in geographic neighbourhood inequality for both property types across the majority of cities - implying that the spread of Airbnb is expanding beyond initial hot spots in cities. Finally, we observed a decline in review sentiment in most cities, with shared-use properties experiencing the most significant reduction.

Overall, our results showed that post-pandemic, the Airbnb platform has experienced significant changes - in particular the shift in property types, leading to a rise in the number of hosts listing entire properties, and guests staying in them. Moving forward, Airbnb should continue to evaluate how it wishes to position itself, either following its roots as a part of the sharing economy, promoting the sharing of private rooms in shared-use properties and encouraging interactions between hosts and guests, or continue its transition towards a platform economy, providing a cheaper and less-regulated alternative to hotels [64].

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Appendix

In the appendix, we include the 6 example graphs for the categories for listings. We did not have space to include them in the body of the report, as such they should not be assessed. We include the figure for completeness only.

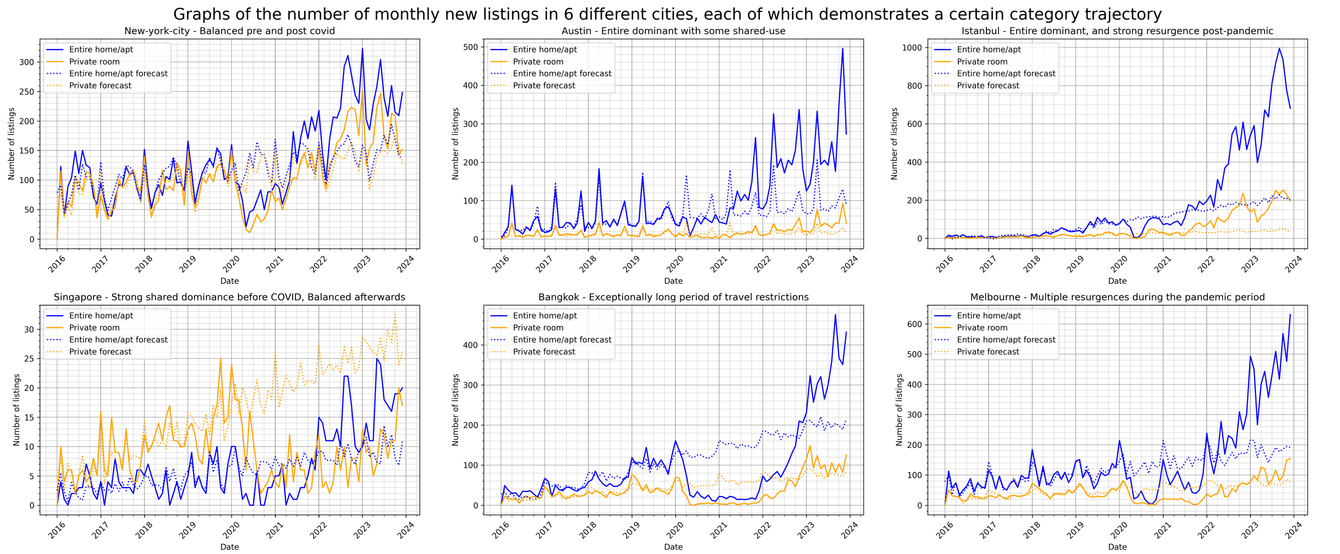

Fig. 5: Number of new listings in 6 cities with prophet modelling. This graph shows that the graphical results follow six distinct patterns. However, the category can differ for reviews and new listings in the same city.