



Geospatial Analysis of Airbnb Data: Understanding Distribution Patterns, User Satisfaction, and Economic Impacts in Major Global Cities

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Abstract: *This study considers the geospatial dynamics of Airbnb listings across nine major cities globally, considering the impact of location, amenities, and host status on user satisfaction and economic outcomes. Using a mixed-method approach that combines mostly quantitative geospatial analysis with qualitative insights, this study reveals the distribution patterns of Airbnb listings, factors that affect user satisfaction, and the economic implications of short-term rentals. Results from this study clearly show the importance of amenities and host interaction in enhancing the experience and bringing out clustering of listings around central urban areas, while it also shows the varying impact of Airbnb on local economies and housing markets. The current research fills this gap by providing a comprehensive geospatial view for hosts, urban planners, and policymakers making efforts for the sustainable growth of short-term rentals.*

1. INTRODUCTION

The rise of the sharing economy has reshaped industries, with Airbnb becoming a key player in the short-term rental (STR) market (Robertson et al., 2023). Since its launch in 2008, Airbnb has disrupted traditional hospitality by enabling property owners to rent directly to travelers, democratizing tourism. However, its rapid growth has sparked debates about its economic, social, and urban impacts (Zervas et al., 2017). Airbnb's effects are multifaceted, influencing local economies, housing markets, and communities. While praised for promoting tourism and providing income to hosts (Anwar, 2023), it has also been criticized for inflating property prices and altering neighborhood dynamics (Barker, 2021). These contrasting impacts highlight the need for a deeper understanding of its geospatial and economic dynamics.

Despite growing research, gaps remain in comprehensive geospatial analyses that account for diverse factors influencing Airbnb's effects. Existing studies often focus narrowly on economic outcomes or user satisfaction, overlooking spatial patterns critical to understanding urban impacts. This study addresses these gaps by analyzing Airbnb data in nine global cities: Dubai, Los Angeles, London, Miami, New York City, San Francisco, Sydney, Tokyo, and Toronto. Using a mixed-method approach, this research combines geospatial tools, such as spatial regression and heat maps, with statistical analysis to explore listing patterns, user satisfaction, and pricing implications. The findings aim to inform policymakers, urban planners, and industry stakeholders about Airbnb's urban footprint and consumer behavior, offering strategies to enhance user experience while mitigating negative effects.

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The study is structured as follows: A comprehensive review of existing studies on Airbnb is presented in the Literature Review, highlighting key findings to identify gaps in the literature. The Methodology section will describe in detail the data source, the analysis method used, and the research design. The Results section presents and interprets the findings, integrating quantitative and qualitative insights. Lastly, the section of Conclusion and Limitations sums up the key findings, discusses their implications, and outlines the limitations and directions for future research.

2. LITERATURE REVIEW

The following literature review examines existing research on Airbnb's operations and impacts, focusing on user experience, geospatial distribution, economic and social effects, and regulatory implications. This review highlights key findings, identifies knowledge gaps, and sets the foundation for further geospatial and economic analysis.

2.1. User Experience and Preferences

User experience (UX) is central to Airbnb's success, shaping customer satisfaction and retention. Cheng and Jin (2019) identify key UX components, including location, amenities, and host interaction, with personalized service often surpassing price considerations. Similarly, Zhang and Chen (2019) highlight how proximity to attractions and housing characteristics influence guest preferences in cities like New York, Los Angeles, and Chicago. Behavioral studies, such as Lee and Chang's (2019) analysis of Airbnb in Los Angeles, show how listing features affect tourist patterns, offering insights for tourism management. Aversa and Rice (2023) explore how data informs urban economic development, while Hong and Yoo (2020) emphasize the spatial variation in pricing determinants, reinforcing the need for geographically nuanced strategies.

2.2. Geospatial distribution and patterns

Airbnb listings often cluster near central urban locations and attractions, impacting housing availability and urban planning. Gutiérrez et al. (2017) and Zhang and Fu (2022) reveal clustering patterns in cities like Los Angeles and Barcelona, influenced by population density, income levels, and proximity to attractions. Similarly, Ki and Lee (2019) find that listings in Seoul are concentrated near universities and transport hubs, contributing to housing shortages. Temporal and spatial analyses, such as those by Sarkar et al. (2023) in San Francisco and Moreno-Izquierdo et al. (2023) in Madrid, underscore the role of demographic and socioeconomic factors in shaping Airbnb's spatial footprint. These findings highlight the need for localized urban management strategies to balance tourism benefits and housing challenges.

2.3. Economic and Social Impacts

The economic and social effects of Airbnb are widely documented. Deboosere et al. (2019) show that neighborhood characteristics, such as access to employment, influence revenues and drive gentrification. Rabiei-Dastjerdi and McArdle (2020) apply AI to analyze Airbnb's impact on Dublin's housing market, identifying shifts in housing dynamics and neighborhood transformations. Moreno-Izquierdo et al. (2023) examine pandemic-related impacts on Airbnb in Madrid, noting variations in occupancy rates across neighborhoods, emphasizing the need for area-specific policies. Sarkar et al. (2023) link host participation to demographic factors, revealing socioeconomic inequalities that influence Airbnb activity and urban development.

2.4. Regulation and Policy Implications

Localized regulation is critical for managing Airbnb's varied impacts. [Thackway et al. \(2022\)](#) highlight the spatial variability of Airbnb's influence on housing prices in Sydney, advocating for area-specific policies. [Jiao and Bai \(2020\)](#) and [Lagonigro et al. \(2020\)](#) stress the importance of integrating socioeconomic and spatial data into regulatory frameworks to balance the interests of residents, hosts, and tourists.

3. DATA AND METHODOLOGY

The study in this section highlights the methodologies used for the analysis of Airbnb listings across multiple cities to uncover the impact of various amenities and other factors on user satisfaction metrics, such as overall ratings and communication ratings. It includes the spatial distribution, correlation, and regression analysis among the different variables, visualized by heatmaps and correlation matrices.

3.1. Data Preprocessing and Dataset Characteristics

Secondary data for this analysis was sourced from the Kaggle dataset [Airbnb Data: Listings Scraped Global Top 10 Cities \(2024\)](#), which includes information from nine major cities across different continents: Dubai, Los Angeles, London, Miami, New York City, San Francisco, Sydney, Tokyo, and Toronto. The datasets were merged and cleaned to ensure consistency and facilitate analysis.

Python was used for data processing, employing the 'pandas' library for tasks such as merging datasets with the 'concat()' function and adding a "City" variable to distinguish entries. Redundant columns (e.g., 'picture_url', 'License') and rows with missing or invalid data (e.g., non-positive bedroom values) were removed. The 'Bedrooms' column was converted to numeric format to enable numerical analysis. Functions like 'drop_duplicates()', 'str.strip()', and 'fillna()' were applied to refine the dataset for accurate analysis. After the data preprocessing, these are the following variables in the dataset, some of which were used or others considered to be used for the data analysis:

- **Listing Information:** Listing Title, Property Type, Listing Type, Created Date, Last Scraped Date, Country, City, Latitude, Longitude, Exact Location, Listing URL, Airbnb Property ID, Airbnb Host ID, Host Listing Count
- **Financial Information:** Currency Native, Cleaning Fee (USD), Cleaning Fee (Native), Extra People Fee (USD), Extra People Fee (Native), Average Daily Rate (USD), Average Daily Rate (Native), Annual Revenue LTM (USD), Annual Revenue LTM (Native)
- **Booking and Review Metrics:** Number of Reviews, Overall Rating, Airbnb Communication Rating, Airbnb Accuracy Rating, Airbnb Cleanliness Rating, Airbnb Checkin Rating, Airbnb Location Rating, Airbnb Value Rating, Number of Bookings LTM, Number of Bookings LTM - Number of observed months, Count Available Days LTM, Count Blocked Days LTM, Count Reservation Days LTM, Occupancy Rate LTM
- **Property Details:** Bedrooms, Bathrooms, Max Guests, Amenities, instant_bookable, Pets Allowed
- **Booking Policies:** Airbnb Superhost, Cancellation Policy, Check-in Time, Checkout Time, Minimum Stay

3.2. Regression Analysis

A multiple regression analysis using an Ordinary Least Squares (OLS) model was performed to assess the impact of variables such as the number of bedrooms, bathrooms, maximum guests, and minimum stay on the average daily rate (ADR) in USD. The model identified significant factors influencing ADR. The dataset was also analyzed by amenities to examine their effect on user satisfaction. Listings were grouped based on the presence or absence of specific amenities, and user satisfaction metrics (overall and communication ratings) were calculated to determine how amenities influenced ratings. A correlation matrix was created to identify relationships between variables like ADR, latitude, longitude, and listing features. Visualized through a heatmap, this analysis revealed key correlations that could impact listing performance and user satisfaction. Heatmaps were used to visualize the spatial distribution of listings across the cities, highlighting density and identifying hotspots where listings are concentrated, using the 'Folium' library. Finally, boxplots compared the overall ratings and occupancy rates between Superhost and non-Superhost listings. This analysis revealed the influence of Superhost status on user ratings and booking patterns.

4. RESULTS AND DISCUSSION

This study investigates various factors influencing Airbnb listings across nine cities, focusing on the relationship between property characteristics and average daily rate (ADR), the impact of amenities on user satisfaction, and the distribution of listings relative to tourist hotspots. The analysis also explores the role of *Superhost* status in influencing ratings and occupancy rates.

The ordinary least squares (OLS) regression analysis was conducted to explore the relationship between ADR in USD and four key property variables: number of bedrooms, bathrooms, maximum guests, and minimum stay. The regression model demonstrated a moderate explanatory power, with an r-squared value of 0.314, suggesting that these variables account for 31.4% of the variance in ADR. While the model indicates statistical significance, as evidenced by the f-statistic of 6189 and a p-value of 0.00, other unmeasured factors likely contribute to the variance in ADR. The regression analysis revealed that each additional bedroom is associated with an increase in the Average Daily Rate (ADR) by \$54.69. Similarly, the presence of an additional bathroom increases ADR by \$65.48, while each additional guest corresponds to a \$23.38 increase in ADR. In contrast, an increase of one night in the minimum stay requirement results in a slight reduction in ADR by \$0.33. All predictor variables were found to be statistically significant, with a p-value of less than 0.05. Specifically, the number of bedrooms, bathrooms, and the maximum number of guests were positively correlated with higher ADR, while the minimum stay had a minimal negative impact on the rate. These results suggest that properties with more bedrooms, bathrooms, and greater capacity for guests are generally priced higher. However, the effect of the minimum stay length on ADR is relatively minor when compared to the influence of the physical attributes of the property.

The correlation analysis revealed moderate positive correlations between ADR and the number of bedrooms (0.52), bathrooms (0.46), and maximum guests (0.50), supporting the conclusion that larger properties are generally priced higher. A very weak negative correlation (-0.05) between minimum stay and ADR indicates a minor decrease in ADR as the minimum stay length increases. Additionally, there were strong positive correlations between the number of bedrooms and bathrooms, as well as between bedrooms and maximum guests (0.82), suggesting that properties with more rooms and higher guest capacity tend to be priced higher. Minimum stay showed weak negative correlations with other variables, suggesting that its effect on ADR is less pronounced than the physical characteristics of the property.

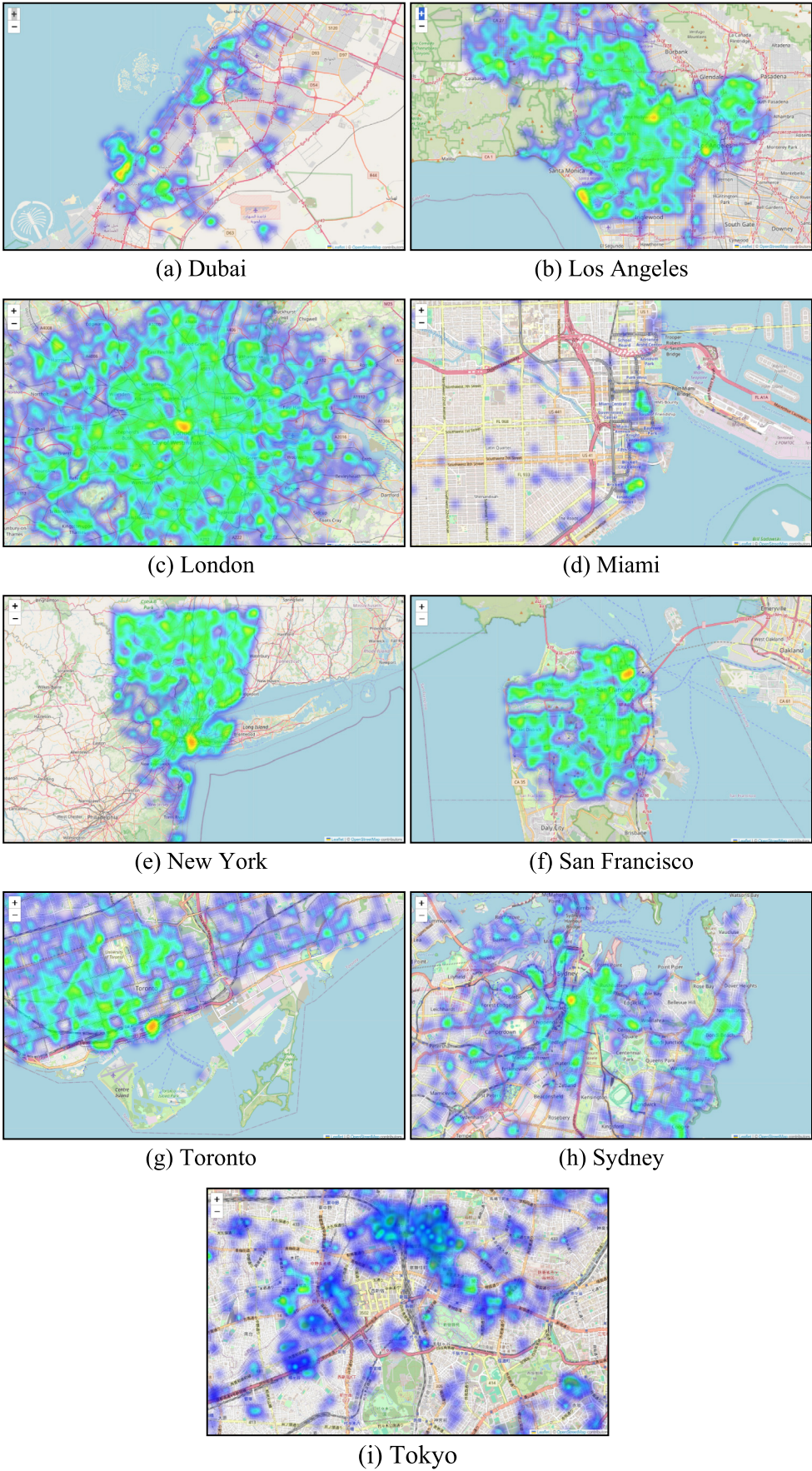


Figure 1. Airbnb listings heatmap across the world
Source: Own processing

4.1. Impact of Amenities on User Satisfaction

The analysis of the impact of amenities on user satisfaction revealed notable trends across various cities. In Dubai, listings without air conditioning received higher ratings for both overall satisfaction (4.67) and communication (9.50), suggesting that air conditioning may not be a critical factor in this city. Other amenities such as iron, essentials, and wi-fi were found to positively influence ratings, while the lack of a tv slightly improved them. In London, heating and essentials were strongly linked to higher ratings (both with an overall rating of 4.74), confirming their importance for guest satisfaction. Similarly, in Miami, listings with essentials, wi-fi, air conditioning, and hangers received higher ratings, highlighting the significance of these amenities. In New York city, properties with heating, essentials, smoke alarms, and hangers were rated higher than those without, indicating that these features are highly valued by guests. The presence of air conditioning showed a smaller, though positive, effect on ratings. Sydney and San Francisco exhibited similar trends, where amenities like essentials, smoke alarms, and hangers were associated with higher user satisfaction. In Tokyo, basic cooking amenities, air conditioning, and essentials such as hangers had a significant positive impact on ratings, with dishes and silverware showing the most pronounced effect. In Toronto, heating, smoke alarms, essentials, and safety features such as carbon monoxide alarms contributed to higher ratings for both overall satisfaction and communication. The presence of hangers also improved satisfaction, albeit to a lesser extent. In los angeles, similar patterns emerged, with safety features and essential amenities leading to higher satisfaction ratings. However, the impact of hangers was more nuanced, showing a higher communication rating but slightly reducing the overall rating.

4.2. Geospatial Distribution of Airbnb listings

Geospatial analysis of Airbnb listings revealed notable concentration patterns in proximity to popular tourist destinations across the nine cities. In Dubai, listings clustered around areas like Jumeirah and the palm, home to iconic landmarks such as the Burj al Arab. Los Angeles exhibited three major hotspots in Santa Monica, west Hollywood, and Beverly hills, all of which are renowned for their tourist appeal. Similarly, in London, clusters appeared around landmarks like Buckingham palace, Big Ben, and Camden town. Other cities like New York, Miami, and San Francisco also showed a clear pattern of listings concentrated in and around central, well-known tourist areas, emphasizing the strong influence of location on Airbnb listing distribution.

4.3. Impact of Superhost Status on Ratings and Occupancy Rates

The analysis of superhost status revealed its significant impact on both user ratings and occupancy rates. Superhosts consistently received higher ratings, with a median rating close to 5.0, compared to non-superhosts, whose median rating was slightly below 4.5. This suggests that superhosts are more successful in maintaining high and consistent guest satisfaction levels. Additionally, superhosts tended to have higher occupancy rates, with a median rate of around 70%, compared to non-superhosts, who had a median occupancy rate of about 60%. The narrower interquartile range (iqr) for superhosts indicates less variability in booking rates, suggesting that superhosts are more reliable in maintaining high occupancy.

The results indicate that property characteristics, particularly the number of bedrooms, bathrooms, and maximum guests, significantly influence ADR, with larger properties commanding higher rates. Amenities such as heating, smoke alarms, essentials, and safety features are strongly linked to higher user satisfaction, though the specific preferences may vary by city. Geospatial analysis

confirms that Airbnb listings are primarily located near tourist hotspots, and superhost status is associated with higher ratings and more consistent occupancy. These findings provide valuable insights for Airbnb hosts, especially in terms of optimizing their listings by offering desirable amenities and maintaining a strong superhost profile.

5. CONCLUSION

This study provides a comprehensive geospatial analysis of Airbnb data, examining how listing characteristics, amenities, and host status influence user satisfaction and occupancy rates. The statistical findings demonstrate that amenities, particularly Wi-Fi, kitchens, and air conditioning, significantly affect the Average Daily Rate (ADR), supporting the notion that travelers are willing to pay a premium for enhanced comfort. The regression analysis highlights that the provision of quality amenities is crucial for improving guest satisfaction, in line with theories of service quality and consumer choice (Zhang & Fu, 2022; Gutiérrez et al., 2017). Additionally, the spatial analysis confirms that Airbnb listings are clustered around tourist attractions and city centers, underscoring the importance of location for both hosts and guests, consistent with urban economic theories and agglomeration economies (Zhang & Fu, 2022). The Superhost analysis indicates that Superhosts consistently achieve higher ratings and occupancy rates, reflecting the value of reputation and trust in the digital marketplace (Sarkar et al., 2019).

However, this study has several limitations. First, reliance on public Airbnb data means that not all relevant variables may be captured, and data accuracy may be affected by outdated or incomplete information. Second, the focus on urban areas limits the generalizability of the findings to rural or less dense regions. The cross-sectional nature of the data also means that temporal factors, such as seasonal fluctuations or economic changes, were not accounted for. Additionally, while correlations were observed, the study cannot establish causality between the identified factors and outcomes. Local regulations, which significantly impact Airbnb listings, were not considered, nor was the diversity of Airbnb users in terms of demographics or travel purposes. Future research should address these gaps, explore rural areas, and incorporate longitudinal data to capture dynamic market changes.

In conclusion, the study contributes valuable insights into the factors shaping Airbnb user satisfaction and economic outcomes, but further research is needed to address the limitations and expand the understanding of the short-term rental market.

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