Exploring Guest Satisfaction in Boston's Airbnb Market: An Economic Analysis

1. Introduction

The proliferation of the short-term rental market, with Airbnb at its helm, has piqued substantial academic curiosity, particularly within hospitality and tourism studies. This sector's expansion has led scholars to investigate the intricacies of guest satisfaction, a determinant crucial for the platform's success and the economic viability of its hosts. The scope of this research spans a comprehensive array of factors, including property attributes, host behaviors, and their broader implications on both guests and local communities.

Previous studies, such as those by Guttentag et al. (2018)[3] and Dogru et al. (2020)[2], have described the impact of amenities, location, and host responsiveness on enhancing guest satisfaction. These themes are expanded upon by Zervas et al. (2017)[6] through the lens of signaling theory, exploring the influence of host attributes, particularly superhost status, on establishing trust and perceived quality among guests. Complementing these perspectives, Gibbs et al. (2018)[3] apply the hedonic pricing model to dissect how property and location-specific features are factored into pricing strategies, subsequently affecting guest perceptions and satisfaction.

Amidst this landscape, the role of technology in mediating the hospitality experience, especially through online reviews and digital communication, has been scrutinized by Liang et al. (2017)[5]. Their work highlights the evolving nature of host-guest interactions and their impact on satisfaction levels. Despite these extensive explorations, a gap remains in holistically integrating economic theories with empirical evidence to explain guest satisfaction within the Airbnb ecosystem comprehensively.

Therefore, at the heart of this investigation is the economic question: How do market dynamics, consumer preferences, and pricing strategies within Boston's Airbnb market influence guest satisfaction? This question prompts an examination of the main response variable, review_scores_rating, and its relationship with subratings on location, communication, and value, and with relevant predictors. The study further delves into how specific predictors impact subratings on location (review_scores_location), communication (review_scores_communication), and value (review_scores_value). These subratings offer a granular view of guest satisfaction, breaking it down into components directly influenced by host and listing characteristics.

2. The Data

2.1 Description of the Data and Variables

Aiming to bridge this gap, this study leverages a dataset from Kaggle, which encompasses detailed listings, reviews, and calendar information for 3585 Airbnb listings in Boston [1]. This dataset provides an abundance of variables that describe the listings, their reviews, and the hosts, which the study will be working with.

Host characteristics such as host_has_profile_pic, host_identity_verified, host_is_superhost, host_response_rate, and host_since are investigated to understand their effects on guest satisfaction. These variables reflect the host's credibility, responsiveness, and experience, factors potentially pivotal in shaping guest experiences.

Listing features and location, including neighbourhood, amenities, price_per_guest, room_type, and property_type, are analyzed to understand their influence on guest preferences and satisfaction. This segment of the analysis explores the tangible aspects of the Airbnb experience, from the physical attributes of the listings to their geographical positioning.

Lastly, reviews, particularly comments, undergo topic modeling to extract prevalent themes discussed by guests. This qualitative analysis enriches the understanding of guest satisfaction by unveiling the topics most frequently highlighted in reviews, offering insights into guests' priorities and experiences.

By synthesizing economic theories with this rich dataset, the study endeavors to contribute to the academic discourse on hospitality and tourism while providing actionable insights for Airbnb hosts. The goal is to enhance listing optimization, thereby improving guest experiences and strengthening hosts' market positioning within the dynamic arena of short-term rentals.

2.2 Data Cleaning

The data cleaning process undertaken for this study was critical in ensuring the reliability and accuracy of the analysis. The process began with the removal of redundant variables from the listings dataset, which originally contained 95 variables. Fourteen columns deemed irrelevant to the research objectives, such as host_picture_url, were removed, reducing the dataset's dimensionality to 81 columns. This step was essential for increasing computational efficiency and simplifying data handling. Following this, the removal of reviews that were missing comments was necessary to prepare the dataset for topic modeling. Since LDA requires a complete matrix of words and frequencies, NA values representing missing or undefined data could potentially skew results and lead to errors in the analysis. Therefore, eliminating these values was crucial for maintaining the integrity of the data.

Further cleaning involved filtering out non-English reviews to ensure the coherence of topic modeling analysis. This step was vital as LDA assumes a single language to accurately identify and group thematic content. The transformation of the 'amenities' variable from a string to a list format, followed by counting the number of amenities per listing, facilitated direct comparisons across listings and provided insights into the impact of amenities on guest satisfaction. Additionally, price normalization to a per-guest basis allowed for comparisons across listings of different sizes, aiding in the pricing strategy analysis. Each of these data cleaning steps, from removing irrelevant variables to ensuring data completeness and consistency, laid the groundwork for the regression analyses that followed. This preparation was pivotal for uncovering actionable findings and exploring the factors influencing guest experiences on Airbnb.

2.3 Summary Statistics

2.3.1 Analysis of Overall Ratings Distribution

Table 1: Distribution of Airbnb Reviews by Rating Score Ranges

Rating Score Range	Number of Listings	Proportion of Total Listings (%)
0 to 25	6	0.22
26 to 50	18	0.65
51 to 75	113	4.08
76 to 100	2635	95.06

Observing the distribution of our response variable, review_scores_rating, is crucial for identifying skewness and outliers, which significantly influence the selection of statistical methods and the interpretation of results. The observed distribution reveals a notable positivity bias, with 95.06% of listings scoring between 76 to 100. This trend indicates a tendency among guests to leave overwhelmingly positive reviews, potentially influenced by social desirability factors or a reluctance to express negative feedback unless the experience was extremely unsatisfactory. Such a bias poses a significant challenge to our analysis, skewing the perception of what genuinely drives guest satisfaction. Rather than offering a balanced perspective on listings' strengths and weaknesses, the data might disproportionately highlight positive experiences, thereby ignoring areas in need of improvement.

2.3.2 Analysis of Overall Ratings Distribution by Neighborhoods

Table 2: Top 5 Most Expensive Neighborhoods:

Neighbourhood	Average Price per Guest (USD)	Average Rating
Financial District	269.65	98.25
Downtown Crossing	211.92	91.38
Back Bay	210.11	91.53
Fenway/Kenmore	206.25	89.35
West End	206.24	92.05

Table 3: Top 5 Most Affordable Neighborhoods:

Neighbourhood	Average Price per Guest (USD)	Average Rating
Mattapan	60.98	88.50
Hyde Park	74.74	93.61
Roslindale	75.41	95.57
Dorchester	75.51	89.58
Allston-Brighton	92.14	90.07

The analysis of the most expensive and most affordable neighborhoods for Airbnb in Boston reveals a nuanced picture of the short-term rental market. The top five most expensive neighborhoods, led by Harvard Square with an average price per guest of 359.00USD, do not necessarily correlate higher prices with higher ratings. Notably, Harvard Square's average rating is not available (NaN), suggesting insufficient data or a lack of reviews, which contrasts with the Financial District, where a high average price per guest (269.65USD) accompanies a high average rating (98.25). This discrepancy indicates that while guests might be willing to pay premium prices in certain areas, the perceived value or satisfaction derived from their stay is not solely determined by cost.

Conversely, the most affordable neighborhoods, with Mattapan at an average price per guest of $60.98 and the highest-rated affordable neighborhood being Roslindale at 95.57, demonstrate that lower-priced listings do not equate to lower guest satisfaction. In fact, the presence of neighborhoods like Hyde Park and Roslindale in the affordable category, both with ratings exceeding 93, suggests that guests can find high satisfaction in listings priced significantly below those in more expensive areas.

From an economic standpoint, these findings challenge the assumption that price is a direct proxy for quality or satisfaction in the Airbnb market. The variation in average ratings across different price segments underscores the importance of factors beyond price in influencing guest satisfaction. For instance, the unique characteristics of a neighborhood, the quality of the listing, and the host's attentiveness could play significant roles. As we delve deeper into what factors most influence guest satisfaction, it becomes clear that economic reasoning must account for the complexity of guest preferences and the heterogeneity of their experiences. Recognizing the varied factors that guests value, beyond just the monetary cost, will be critical in further analysis, especially when considering the impact of positivity bias on ratings. This approach ensures a more holistic understanding of the marketplace, guiding hosts on how to improve their offerings and compete effectively, not just on price but on the overall value proposition to guests.

2.3.3 Analysis of Guest Satisfaction Ratings: Downtown Versus Non-Downtown Property Types

Table 4: Property Types Distribution within Downtown Area

property_type	property_count	average_rating	proportion
Apartment	361	93.27	0.87
Bed & Breakfast	4	72.00	0.01
Boat	5	94.60	0.01
Condominium	20	94.42	0.05
House	9	97.00	0.02
Loft	4	99.00	0.01
Other	3	NaN	0.01
Townhouse	3	85.33	0.01
Villa	4	100.00	0.01
All Types	413	91.95	1.00

Table 5: Property Types Distribution outside Downtown Area

property_type	property_count	average_rating	proportion
Apartment	2251	91.21	0.71
Bed & Breakfast	37	93.21	0.01
Boat	7	88.83	0.00
Camper/RV	1	NaN	0.00
Condominium	211	94.46	0.07
Dorm	2	86.50	0.00
Entire Floor	4	100.00	0.00
Guesthouse	1	100.00	0.00
House	553	92.12	0.17
Loft	35	95.93	0.01
Other	14	88.11	0.00
Townhouse	51	95.42	0.02
Villa	2	99.00	0.00
All Types	3169	93.73	1.00

Tables 4 and 5 offer a snapshot of how different property types within and outside Boston's Downtown area rank in terms of guest satisfaction, providing data-driven insights into the dynamics of Boston's Airbnb market.

Table 4 reveals that within the Downtown area, the overall guest satisfaction ratings are consistently high across most property types, indicating that location might be a primary factor in guest satisfaction. For instance, properties like Condominiums and Houses, which are traditionally sought after, show high satisfaction ratings, which could suggest that guests place a premium on these property types when situated in a central urban location.

Outside Downtown, as shown in Table 5, the satisfaction ratings are more varied, hinting at a market where guest preferences may be influenced by factors beyond location, such as property features or value for money. For example, Guesthouses and Villas receive top ratings, suggesting that in less central areas, guests might value unique or distinctive properties that offer a different kind of experience.

The economic implications from these tables, in the context of the research question on how market dynamics, consumer preferences, and pricing strategies influence guest satisfaction, suggest a market where the central location is a strong determinant of satisfaction. However, it also indicates a market that values diversity, where outside the central area, the uniqueness and type of property become more significant, possibly affecting how hosts price and market their properties to align with these preferences. This data reflects a market that operates on both the principles of location value within the city core and the diversity of offerings in more residential or outlying areas.

2.3.4 Text Analysis - Identifying Common Words in Review Comments and Topic Modelling

Table 6: Most Common Words

Word	Count
great	40179
stay	35523
place	33024
boston	31103
apartment	28538
location	23027
clean	22974
host	22143
u	21637
room	21499
nice	18825
would	18813
comfortable	15839
house	14602
everything	13802

Building on the quantitative analysis from Tables 4 and 5, which provided a numerical understanding of guest satisfaction across different property types and locations, the study transitions to a qualitative exploration of guest reviews.

The text analysis from Table 6 highlights that "great" is the most frequently mentioned term in reviews, suggesting overall positive experiences among Airbnb guests in Boston. The prominence of the terms "location," "clean," "host," and "comfortable" indicates these are critical factors in guest satisfaction. Location affects guests' convenience and accessibility to attractions, cleanliness is a non-negotiable aspect of property quality, host interactions shape the personal experience, and comfort within the lodging is essential for a positive stay. These four aspects are evidently valued by customers and are areas where hosts can focus to optimize guest satisfaction.

Table 7: LDA Results and Interpretation

Topic	LDA Result	Interpretation
0	0.048*"u" + 0.026*"home" + 0.019*"made" + 0.014*"time" + 0.014*"even" + 0.013*"feel" + 0.011*"experience" + 0.011*"like" + 0.011*"airbnb" + 0.011*"first"	The Feeling of Home
1	0.059*"day" + 0.051*"arrival" + 0.050*"reservation" + 0.039*"host" + 0.035*"tom" + 0.035*"posting" + 0.033*"canceled" + 0.033*"jamaica" + 0.033*"automated" + 0.029*"plain"	Booking Process and Host Interaction
2	0.060*"room" + 0.055*"nice" + 0.045*"house" + 0.030*"walk" + 0.030*"really" + 0.029*"good" + 0.022*"minute" + 0.018*"station" + 0.016*"close" + 0.015*"also"	Accommodation Quality and Location
3	0.013*"night" + 0.012*"bed" + 0.012*"one" + 0.010*"didnt" + 0.009*"kitchen" + 0.009*"bathroom" + 0.008*"little" + 0.008*"small" + 0.007*"bedroom" + 0.007*"day"	Amenities and Comfort
4	0.050*"great" + 0.045*"stay" + 0.040*"place" + 0.032*"apartment" + 0.031*"boston" + 0.029*"location" + 0.023*"host" + 0.023*"clean" + 0.023*"would" + 0.017*"everything"	Overall Experience and Satisfaction

Moving from the initial identification of common words in Airbnb reviews to a deeper analysis, the research employs Latent Dirichlet Allocation (LDA) for topic modeling. This method enhances the analysis by uncovering themes within the text data, transitioning from word frequency to the distribution of topics across the documents. Through text pre-processing and the creation of a 'bag-of-words' model, LDA discerns patterns that categorize words into themes that encapsulate guest experiences.

The use of LDA reveals five themes in guest feedback, each corresponding to different facets of the Airbnb experience. These themes range from the emotional connection guests feel with their accommodations to practical considerations such as the booking process and the quality of the location. They also cover the physical comforts of the amenities provided and guests' overall satisfaction with their stay.

These themes from the LDA model align with the research question by highlighting aspects that are frequently mentioned in guest reviews and that contribute to satisfaction. Topics related to host interaction indicate its influence on the guest experience, suggesting that the host's engagement and communication are important. The themes suggest that both the tangibles like location and comfort, as well as intangibles such as the host's personal touch, are crucial in shaping guest satisfaction.

Topic modeling with LDA thus provides a more complex view of guest satisfaction, going beyond the quantitative to include the qualitative aspects of guest feedback, and offering a comprehensive understanding of what contributes to positive experiences in Boston's Airbnb market.

The results obtained from the LDA topic modeling serve as a foundation for the subsequent OLS regression analysis in Section 4.1 of the research. The themes identified by LDA, which encapsulate the various aspects of the Airbnb experience that guests commonly discuss, will be used to inform and refine the selection of variables for the regression model. This integration ensures that the OLS regression is grounded in the qualitative realities of guest feedback, enhancing the robustness and relevance of the quantitative analysis.

3. Visualizations

Building on insights from the summary statistics and text analysis, the research now incorporates visualizations to further explore identified patterns. The emphasis on visualizing temporal trends, rating distributions, and the price-review rating relationship is directly informed by preliminary findings. For instance, observed variations in satisfaction ratings suggest examining how these change over time, potentially revealing seasonal influences or the impact of policy changes on guest perceptions. Visualizing rating distributions aims to clarify the nature of guest satisfaction, particularly focusing on skewness and outliers. Lastly, the relationship between price and review ratings will be visualized to investigate if higher prices align with higher guest satisfaction, linking qualitative themes from text analysis with quantitative data. This step aims to provide a clearer, integrated view of guest satisfaction factors in Boston's Airbnb market.

3.1 Temporal Trends in Guest Satisfaction

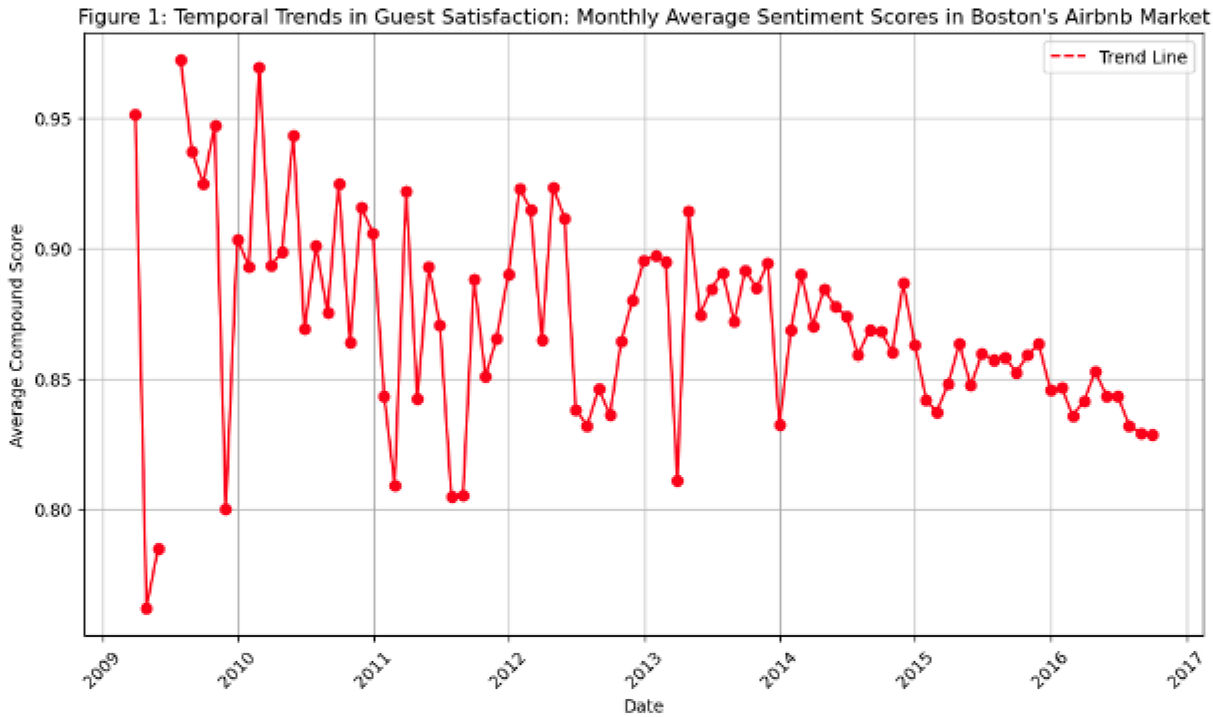


Figure 1 illustrates the monthly average sentiment scores for Boston's Airbnb market, showing a general decline over several years. This trend could indicate that as the market matures and becomes more saturated, guests' expectations may increase, leading to more critical reviews over time. Seasonal effects could also play a role, with peak tourist seasons potentially yielding higher satisfaction scores. Additionally, the economic aspect of perceived value could contribute to this trend; if prices increase without improvements in quality or service, guest satisfaction could naturally diminish. The figure suggests that both external economic factors and internal market changes are at play in shaping guest satisfaction trends in Boston's Airbnb market.

3.2 Visualizing Positivity Bias

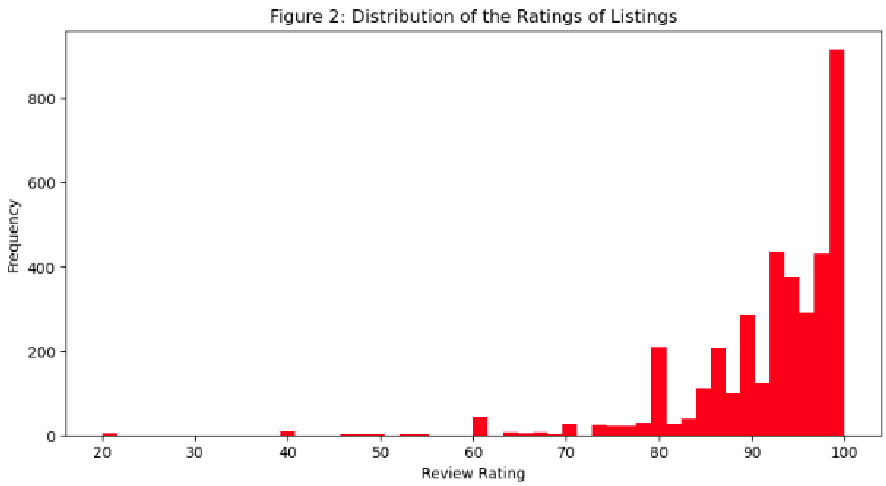


Figure 2 presents the distribution of review ratings for Airbnb listings, visually reinforcing the concept of positivity bias identified in the summary statistics. This bias is evident from the concentration of ratings towards the higher end of the scale, with a significant majority of reviews clustered around the 90-100 mark. The skew towards higher ratings aligns with the summary statistics discussion, suggesting that guests are more inclined to leave positive feedback, potentially due to social desirability or reluctance to post negative reviews. The visualization provides a clear depiction of this trend and underlines the importance of considering this bias when analyzing guest satisfaction and interpreting the factors that contribute to positive reviews in the Airbnb market.

3.3 Visualizing the Relationship between Price and Review Rating

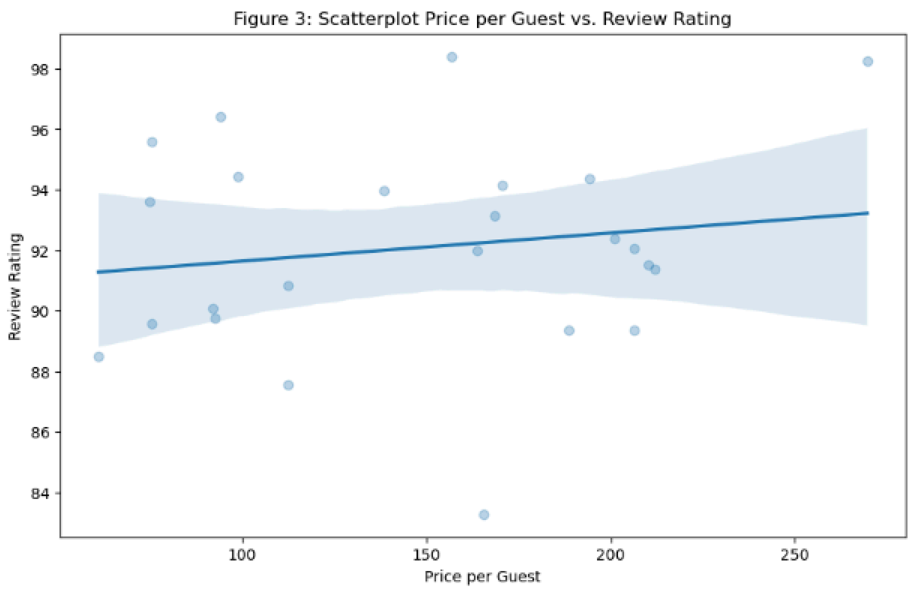


Figure 3 offers a high-level view of the relationship between price per guest and review ratings, showing a trend that higher prices may be associated with higher ratings. Yet, the scatter plot also reveals variability, with a spread of ratings across the price spectrum, indicating that other factors are likely at play. This visualization, while indicative, does not provide definitive answers about the nature or strength of the relationship between pricing and guest satisfaction. It sets the stage for a more detailed and rigorous investigation, which will be conducted in Section 4.1 with OLS Regression analysis and further explored in Section 4.2 through Machine Learning techniques. These subsequent analyses aim to dissect the intricacies of this relationship, controlling for other variables that might influence satisfaction, and to determine to what extent, if any, price per guest is a predictor of guest satisfaction in Boston's Airbnb market.

3.4 Visualizing the Temporal Variations in Sentiment Scores for Location, Cleanliness, and Comfort

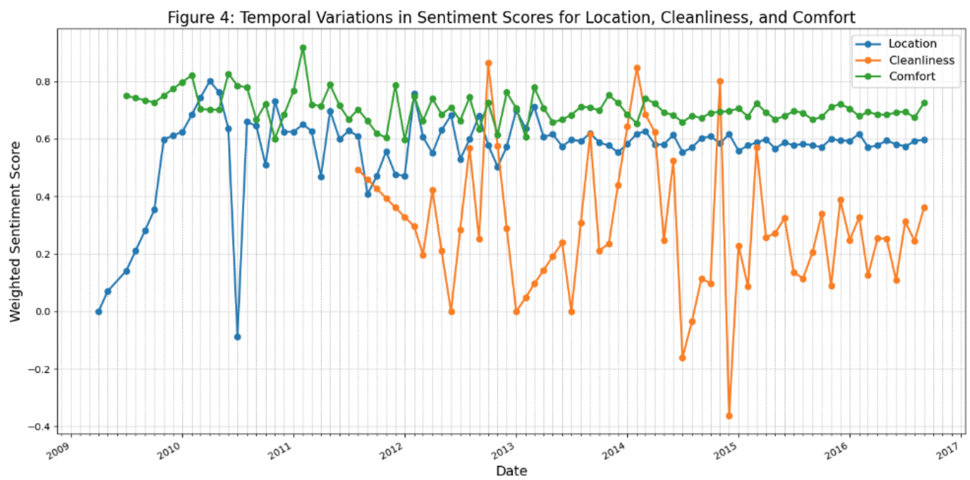


Figure 4: Temporal Variations in Sentiment Scores for Location, Cleanliness, and Comfort

Figure 4 shows sentiment trends for location, cleanliness, and comfort, aligning with themes identified from text analysis. Sentiment for location remains high, reflecting its prominence in reviews and LDA findings. Cleanliness shows high variability, indicating fluctuating guest experiences or expectations, which resonates with its frequent mention in reviews. Comfort displays a stable trend, suggesting that the expectations or experiences do not change significantly over time. This graph ties the qualitative analysis from earlier sections to a quantitative time series, laying the groundwork for deeper regression and machine learning analysis to quantify these aspects' impact on satisfaction.

3.5 Exploring the Spatial Dynamics: Median Household Income Distribution Across Neighborhoods and its Correlation with Location Ratings

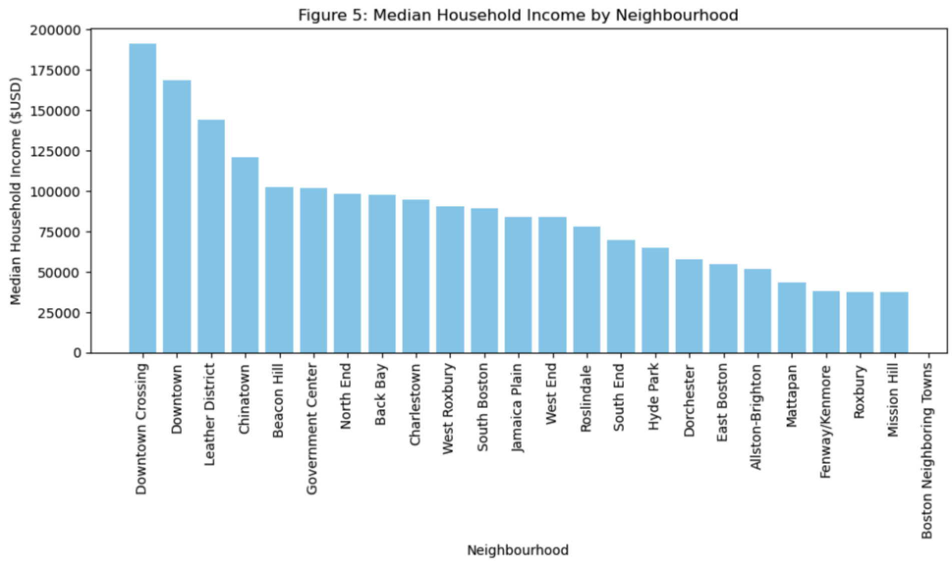


Figure 5 depicts the median household income by neighborhood, an economic indicator that could potentially correlate with the perceived quality of a location—a topic extensively discussed in the previous LDA section. As guests frequently highlight 'location' in their reviews, the implication is that neighborhoods with higher median incomes may offer characteristics that guests associate with higher quality, such as safety, convenience, and amenities.

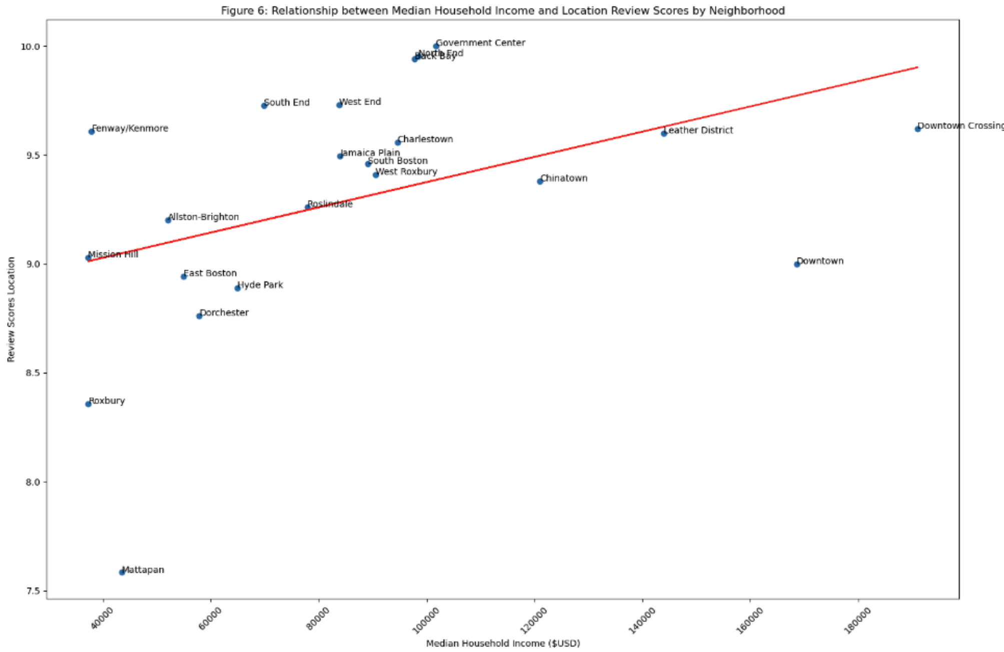


Figure 6 displays a scatterplot correlating median household income with location review scores for various Boston neighborhoods, suggesting a potential link between the economic status of an area and guests' location satisfaction. The upward trend in the plot indicates that as median household income increases, so does the average score for location reviews. This could imply that guests perceive neighborhoods with higher incomes as better locations, possibly due to associated factors like safety, amenities, and overall appeal. However, it's important to note that while there's a visual trend, the scatterplot alone cannot confirm causality or the strength of this relationship. This initial observation will be examined in depth using OLS regression and machine learning techniques in subsequent sections of the research to determine the statistical significance and to control for other variables that might influence these scores.

3.6 Visualizing Open Space Amenities Count Across Neighborhoods

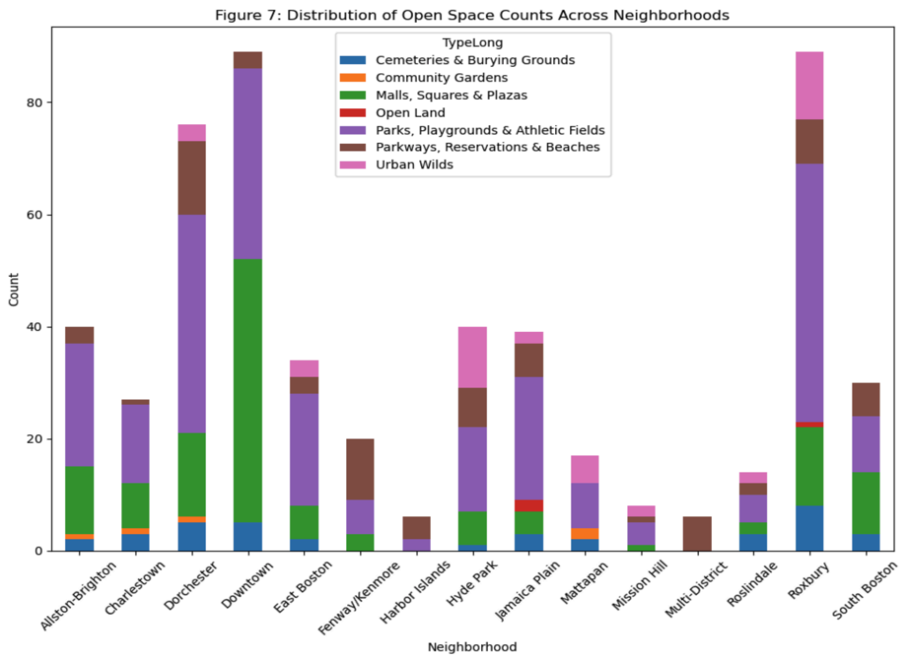


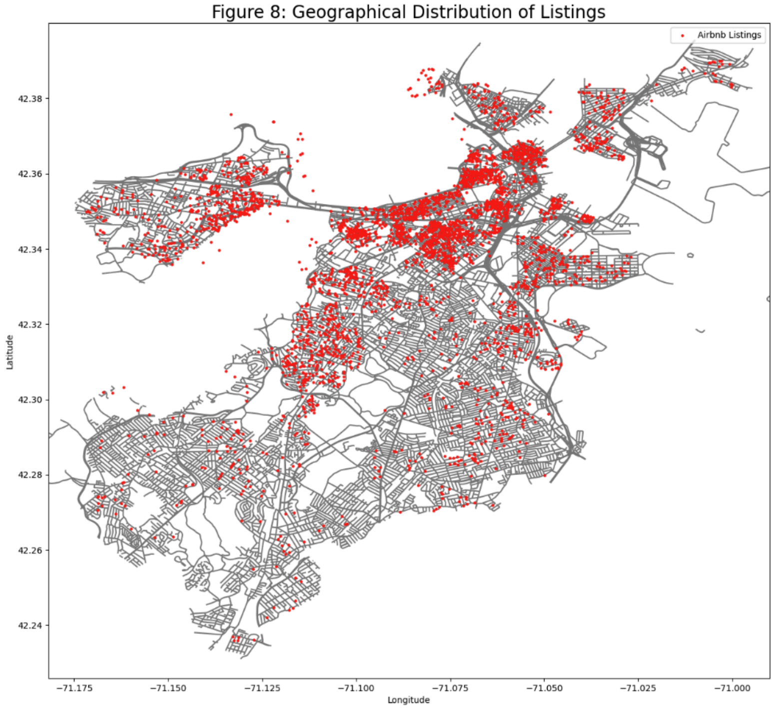
Figure 7 depicts the distribution of open space counts across Boston neighborhoods, which enriches our preliminary analysis of the 'location' aspect of the Airbnb review scores. The variety of open spaces, such as parks, community gardens, and athletic fields, could contribute to the attractiveness and satisfaction guests associate with a particular location.

The presence of abundant and varied open spaces within a neighborhood may enhance guests' perception of location quality, offering opportunities for recreation and relaxation that could positively impact their overall experience. In contrast, neighborhoods with fewer open spaces might score lower on location satisfaction if guests value access to natural and recreational areas as part of their stay.

This distribution aligns with the findings from the text analysis where 'location' was identified as a key theme. The bar chart provides a visual reference for the availability of open spaces, which can be a factor in determining the desirability of a neighborhood in the eyes of Airbnb guests. This information will be utilized in the OLS regression and machine learning sections to further explore the quantitative relationship between the availability of open space amenities and the location aspect of guest satisfaction scores.

3.7 Mapping the Geographical Distribution of Listings and Overall Ratings

Figure 8: Geographical Distribution of Listings



The map displays a visualization of Airbnb listings in Boston, with red dots marking the location of each property. The clusters of red dots are noticeably denser in certain areas like Downtown, Back Bay, and along the Charles River, suggesting these are the most popular neighborhoods for Airbnb rentals, most likely due to their appeal to tourists and accessibility. The distribution of listings across the city provides a snapshot of the short-term rental market landscape, highlighting areas where guests are most likely to stay during their visit to Boston.

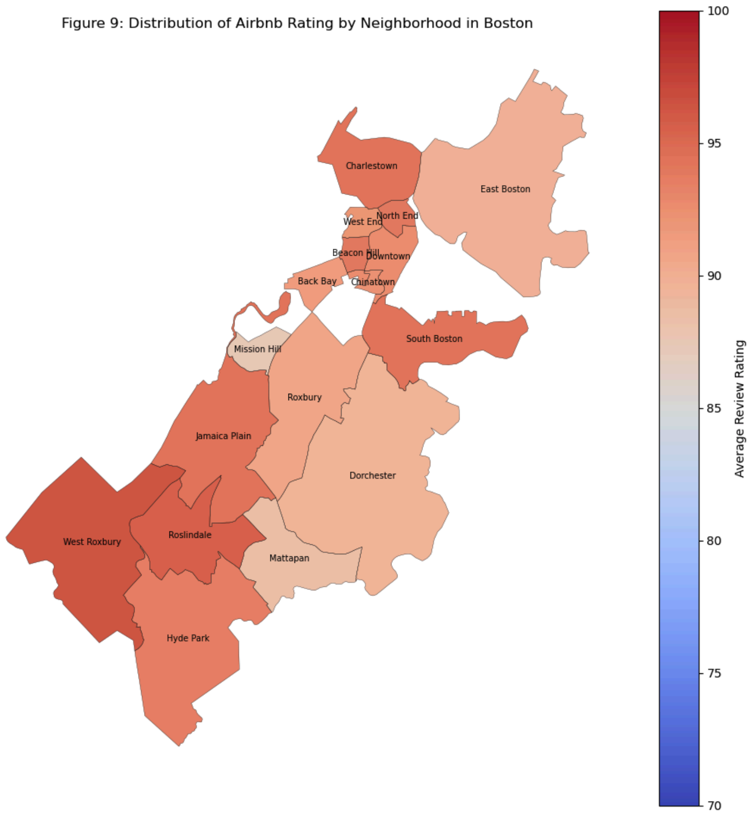


Figure 9: Distribution of Airbnb Rating by Neighborhood in Boston

The provided plot shows the distribution of the average ratings across different neighborhoods in Boston. Note that since there is an overwhelmingly high proportion of positive ratings across all reviews, the color range is deliberately adjusted from [0, 100] to [70, 100] to make the color variations between neighborhoods more distinguished for visualization purposes. As discussed previously, this overwhelmingly positive rating can be explained by 'positivity bias' proposed by previous literature, where people have a tendency to leave positive reviews [2].

Despite the presence of positivity bias—wherein guests are generally predisposed to leave positive feedback—the slight variations in the ratings are still telling. The map shows that Charlestown, Jamaica Plain, Roslindale, and West Roxbury have the highest overall ratings in their review. While West End, Hyde Park, Mattapan, and Mission Hill have the lowest overall ratings.

Charlestown's historical significance and iconic landmarks may imbue a sense of charm and nostalgia in guests' experiences, thereby nudging ratings upward. Jamaica Plain, with its eclectic mix of culinary delights and cultural diversity, could engage guests in a way that compels them to share more enthusiastic reviews. Similarly, Roslindale and West Roxbury are perceived as serene, family-friendly locales offering a respite from the city's hustle—this tranquility can translate into slightly more positive reviews.

In contrast, neighborhoods like West End, Hyde Park, Mattapan, and Mission Hill, though still positive, have registered lower relative ratings. These areas, possibly due to a denser urban environment, fewer tourist attractions, or a stronger local rather than tourist presence, may not elicit the same level of enthusiasm in reviews.

4. OLS Regression and Machine Learning

4.1 OLS Regression Results

Section 4.1 delves into the complexity of guest satisfaction on Airbnb by assessing the relationship between overall ratings and sub-ratings on check-in, communication, location, and value. These elements were identified in section 2.3.4 topic modeling as critical in shaping guests' overall perception of their stay. Utilizing regression analysis, the study seeks to measure the marginal utility provided by each sub-rating, which reflects the added satisfaction from improving specific aspects of the stay.

The inquiry also examines host-related factors, like responsiveness and verified identity, to understand their effect on communication ratings, drawing on signaling theory to explain how these elements can act as signals of quality in a market where asymmetrical information is prevalent.

In considering the impact of location, this research applies hedonic pricing, hypothesizing that guests assess the location rating based on neighborhood attributes, potentially reflecting in their willingness to pay more for certain locations.

Furthermore, the study scrutinizes the concept of value for money, analyzing how the cost per guest and the type of property affect the perceived value of the stay.

The goal is to identify key drivers of satisfaction and provide actionable insights for hosts to enhance their listings, supported by an economic perspective on guest behavior and market dynamics.

4.1.1 Investigating the Correlations between Overall Rating and Sub-ratings on check-in, communication, location, and value

This section examines the influence of specific aspects of an Airbnb stay—check-in, communication, location, and value—on overall guest satisfaction. The hypothesis posits that high ratings in these individual categories correlate with a more favorable overall experience.

For the first regression analysis, overall rating is used as the dependent variable, with the four sub-ratings serving as independent predictors. The analysis will quantify the contribution of each sub-rating to the overall satisfaction score.

The outcomes will elucidate the most influential factors in determining guest satisfaction. Understanding these key drivers allows hosts to target improvements effectively. This analysis is designed to distill actionable insights, guiding hosts on which service enhancements are most beneficial for elevating the overall guest experience.

Table 8: Regression Results: Overall Rating and Subratings

	Dependent variable: review_scores_rating
	(1)
const	-3.659***
	(1.198)
review_scores_checkin	1.952***
	(0.129)
review_scores_communication	2.346***
	(0.139)
review_scores_location	0.927***
	(0.100)
review_scores_value	4.974***
	(0.097)
Observations	4887
R^2	0.659
Adjusted R^2	0.659
Residual Std. Error	4.509 (df=4882)
F Statistic	2357.744*** (df=4; 4882)
Note:	*p<0.1; **p<0.05; ***p<0.01

The regression analysis reveals critical insights into the role of specific aspects of an Airbnb stay in influencing overall guest satisfaction:

1. Positive contributions from all four aspects—check-in, communication, location, and value—are observed, aligning with expectations that higher individual aspect ratings correlate with higher overall satisfaction.
2. The 'value' aspect has the most significant coefficient, suggesting a substantial impact on the overall rating. Each one-point increase in the 'value' rating is associated with an equivalent increase in the overall satisfaction score.
3. The 'location' aspect has the smallest coefficient, indicating its relative impact on overall satisfaction is less compared to other aspects.
4. The R-squared value signifies a moderate correlation between these sub-ratings and the overall rating, pointing to a strong collective influence of these aspects on guest satisfaction.

The subsequent section will delve into the determinants of each aspect, exploring what drives guest perceptions and how these can be optimized for enhanced guest experiences.

4.1.2 Regression Analysis on Key Aspects

4.1.2.1 Communication

The analysis of host factors on the 'communication' aspect of guest satisfaction in Airbnb experiences has yielded discernible results through regression modeling. This section focuses on how a host's status, experience, actions, and response speed relate to guests' communication ratings.

Table 9: Regression Results: Factors Affecting Communication Rating

	Dependent variable: review_scores_communication	
	(1)	(2)
_within a day		-0.018
		(0.035)
_within a few hours		-0.112***
		(0.028)
_within an hour		0.107***
		(0.028)
const	9.756***	9.636***
	(0.188)	(0.024)
host_has_profile_pic	-0.096	
	(0.188)	
host_identity_verified	0.067***	
	(0.021)	
host_is_superhost	0.295***	
	(0.029)	
host_since_months	-0.002***	
	(0.000)	
host_total_listings_count	-0.001***	
	(0.000)	
Observations	4887	4887
R^2	0.063	0.021
Adjusted R^2	0.062	0.020
Residual Std. Error	0.622 (df=4881)	0.636 (df=4883)
F Statistic	65.159*** (df=5; 4881)	34.931*** (df=3; 4883)
Note:		*p<0.1; **p<0.05; ***p<0.01

Model 2, examining hosts' experience and actions, shows that superhost status and identity verification have a positive impact on communication scores, underscoring the importance of credibility and proven hosting quality. Notably, the lack of significance for a host's profile picture suggests that it does not markedly influence guests' perceptions of communication quality.

Model 3, focusing on response speed, indicates a clear preference for prompt replies. Hosts who respond within an hour are rewarded with higher communication scores, highlighting the premium guests place on swift interactions. The lack of significance for response times within a day suggests that responsiveness is binary in guests' perceptions: responses are either prompt, within an hour, or not.

Both models demonstrate modest R-squared values, suggesting that while these factors are important, they do not fully capture the breadth of elements that influence guests' communication satisfaction. This suggests that other, unmodeled aspects of the communication experience, such as the content of communication, guests' expectations, and perhaps the platform's features like instant booking, also play crucial roles.

4.1.2.2 Location

Table 10: Regression Results: How Public Spaces affect Location Rating

	Dependent variable: review_scores_location	
	(1)	(2)
Community Gardens	-0.160***	-0.138***
	(0.032)	(0.032)
Malls, Squares & Plazas	0.006***	0.007***
	(0.001)	(0.001)
Open Land	0.139***	0.150***
	(0.021)	(0.021)
Parks, Playgrounds & Athletic Fields	-0.016***	-0.016***
	(0.001)	(0.001)
Urban Wilds	-0.100***	-0.098***
	(0.005)	(0.005)
const	9.756***	9.734***
	(0.021)	(0.022)
is_downtown		0.013
		(0.078)
is_downtown*Community Gardens		-0.000***
		(0.000)
is_downtown*Malls, Squares & Plazas		-0.007***
		(0.003)
is_downtown*Open Land		0.000***
		(0.000)
is_downtown*Parks, Playgrounds & Athletic Fields		0.016**
		(0.007)
is_downtown*Urban Wilds		0.000***
		(0.000)
Observations	4887	4887
R^2	0.163	0.167
Adjusted R^2	0.163	0.166
Residual Std. Error	0.643 (df=4881)	0.642 (df=4878)
F Statistic	190.800*** (df=5; 4881)	122.211*** (df=8; 4878)
Note:		*p<0.1; **p<0.05; ***p<0.01
		Model 1 AIC: 9563.35, BIC: 9602.32
		Model 2 AIC: 9549.05, BIC: 9608

Table 11: Regression Results: How Neighborhood Wealth Affects Location Rating

	Dependent variable: review_scores_location
	(1)
const	9.029***
	(0.030)
med_household_income_K	0.006***
	(0.000)
Observations	4887
R^2	0.059
Adjusted R^2	0.059
Residual Std. Error	0.682 (df=4885)
F Statistic	305.031*** (df=1; 4885)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 10 offers insights into how the proximity of an Airbnb listing to various types of nearby places influences its attractiveness. Community gardens are unexpectedly associated with slightly lower location scores, suggesting they may not be a primary draw for guests. In contrast, proximity to shopping venues like malls and plazas tends to elevate guests' location ratings, which could reflect a preference for convenience and accessibility to retail and entertainment options. Open spaces, generally, add to the location appeal, affirming a guest preference for natural surroundings.

In downtown areas, the proximity to shopping doesn't have the same positive impact, likely because such amenities are expected and ubiquitous in urban centers. Here, the unique draws of a downtown location may lie elsewhere, perhaps in cultural venues or dining experiences not captured by the model.

The R-squared values from the models indicate that open space variables account for about 20% of the variance in location scores, with slight improvements when downtown specifics are included. The lower AIC in model 5 compared to model 4 suggests a better fit without overcomplicating the model, despite a higher BIC which hints at the cost of additional complexity.

Subsequent analysis, as indicated by Table 11, uses median household income as a proxy for neighborhood quality, focusing on downtown listings where income variance is notable. The modest increase in location rating with each $1,000 rise in median household income suggests other unmodeled factors may have significant roles in guests' perceptions of location quality. These could range from historical prestige to modern amenities or the intangible 'feel' of a neighborhood, prompting further investigation in the regression and machine learning sections.

4.1.2.3 Amenities & Comfort

Table 12: Regression Results: How Amenities Count and Room Type Affect Overall Rating

	Dependent variable: review_scores_rating
	(1)
amenities_count	0.349***
	(0.023)
const	86.354***
	(0.410)
is_private_room	0.275
	(0.241)
is_shared_room	1.250
	(0.853)
Observations	4887
R^2	0.045
Adjusted R^2	0.045
Residual Std. Error	7.544 (df=4883)
F Statistic	76.988*** (df=3; 4883)
Note:	*p<0.1; **p<0.05; ***p<0.01

In exploring the impact of amenities and room type on overall ratings, the analysis reveals that the number of amenities a listing provides has a quantifiable effect on guest satisfaction. With a coefficient of 0.349 in the regression model, each additional amenity is associated with a marginal but significant increase in the overall rating. This increment, while modest, suggests that amenities contribute positively to the guest experience.

The regression findings also highlight that the type of room—whether private or shared—does not significantly alter the overall satisfaction score, indicating that guests' satisfaction may be less about privacy levels and more about the quality and availability of amenities or other aspects of their stay. This aspect of the analysis suggests that hosts might consider focusing on enhancing their listings with additional amenities rather than converting shared spaces to private ones to improve guest satisfaction.

4.1.2.4 Value for Money

Table 13: Value Perception Disparities: Downtown vs. Non-downtowr

	Dependent variable: review_scores_value
	(1)
const	9.185***
	(0.019)
is_downtown	0.018
	(0.034)
price_per_guest	-0.000
	(0.000)
Observations	4887
R^2	0.001
Adjusted R^2	0.000
Residual Std. Error	0.835 (df=4884)
F Statistic	1.377 (df=2; 4884)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 14: Impact of Property Type on Guest Perception of Value

	Dependent variable: review_scores_value
	(1)
_Bed & Breakfast	-0.013
	(0.115)
_Boat	0.036
	(0.186)
_Condominium	0.262***
	(0.048)
_Dorm	-0.622
	(0.415)
_Entire Floor	0.042
	(0.415)
_Guesthouse	0.878*
	(0.480)
_House	0.144***
	(0.037)
_Loft	0.355***
	(0.097)
_Other	-0.157
	(0.152)
_Townhouse	0.199**
	(0.100)
_Villa	0.281
	(0.222)
const	9.122***
	(0.014)
Observations	4887
R^2	0.013
Adjusted R^2	0.010
Residual Std. Error	0.830 (df=4875)
F Statistic	5.676*** (df=11; 4875)
Note:	*p<0.1; **p<0.05; ***p<0.01

Upon examining the regression coefficients in Table 13, it's evident that the 'price_per_guest' variable is statistically significant, suggesting that higher prices correspond to lower perceived value. However, the effect size is minimal (less than 0.01) on the value rating scale of 10. Additionally, listings outside downtown areas do not exhibit a higher perceived value compared to those within downtown locales, on average.

In Table 14, a comparison of perceived value across various property types with apartments as the base group reveals significant differences. Condominiums, houses, and lofts exhibit notably higher perceived values than apartments. On average, condominiums receive a 0.34 higher rating, houses receive a 0.144 higher rating, and lofts receive a 0.355 higher rating in terms of perceived value compared to apartments.

4.1.2.5 OLS Regression Results Summary

This analysis uncovers the intricate relationship between Airbnb guests' overall satisfaction and their ratings across key dimensions such as check-in, communication, location, and value, grounded in economic principles.

Firstly, the positive impact of all four aspects on overall ratings underscores the potential for enhancing overall guest satisfaction by improving specific service areas. Notably, the significant influence of value suggests that guests prioritize receiving good value for their money, aligning with the economic principle of consumer surplus.

The importance of host qualities, such as superhost status and verified identity, in enhancing communication ratings highlights the role of trust and reliability, akin to signaling theory, where hosts signal quality to mitigate information asymmetry.

The positive effect of response speed on communication ratings underscores the value of time in service quality, indicating that quicker responses are perceived as better service, potentially leading to higher satisfaction.

The regressions results in section 4.1.2.2 on location ratings, considering amenities and neighborhood socioeconomic status, suggests a hedonic pricing model, wherein guests assign varying values to different location features, impacting their overall location satisfaction.

Furthermore, the analysis reveals a nuanced relationship between price per guest and perceived value, illustrating the economic concept of diminishing returns, where higher prices may not always result in higher perceived value. The varied perceived value across property types also reflects diverse guest preferences, indicative of different utility derived from various accommodation types.

In summary, these findings indicate that guest satisfaction on Airbnb is influenced by a combination of factors including value for money, trust and reliability of hosts, timely communication, and specific location features. These insights underscore the importance for hosts to prioritize delivering value and maintaining high service standards to enhance guest satisfaction, guided by principles such as consumer surplus, signaling theory, and utility maximization.

4.2 Machine Learning

Section 4.1 OLS Regression delves into the impact of specific variables on Airbnb guest satisfaction. It transitions to machine learning techniques such as regression trees and random forests, to examine how these factors influence overall rating scores. Shifting focus from subratings to the overall score, it aims to discern the direct effects of amenities count, pricing, room type, neighborhood economic status, urban proximity, host characteristics, response speed, and property type on satisfaction.

Modeling the overall rating considers variables such as amenities count, price per guest, and room type, capturing guests' trade-offs between comfort, privacy, and cost, directly affecting satisfaction and perceived value. Location indicators, like median household income and downtown proximity, alongside community amenities, reflect neighborhood desirability and accessibility, shaping guest preferences and ratings.

Host-related attributes, such as host tenure, superhost status, and response rate, signal experience, reliability, and service commitment, critical for guest trust and satisfaction. Response time and property type provide insights into service quality and unique experiences, impacting guest perceptions and overall ratings.

Economically, these variables align with supply-demand dynamics, utility maximization, and market segmentation, influencing guest decision-making and competitive positioning. By incorporating a broad range of factors, the model comprehensively addresses the complex determinants of guest satisfaction and the economic landscape of Airbnb listings.

4.2.1 Decision Tree

Transitioning to the section on Decision Tree, this study embraces a non-parametric methodology that can adeptly capture the complex, non-linear relationships and interactions between variables without the restrictive assumptions inherent in linear models.

A Decision Tree works by partitioning the data into subsets based on decision rules inferred from the predictor variables, which allows for a piecewise approximation of the underlying relationship. This approach not only mitigates the influence of outliers and the problem of non-constant variance but also provides a clear, interpretable structure for our model.

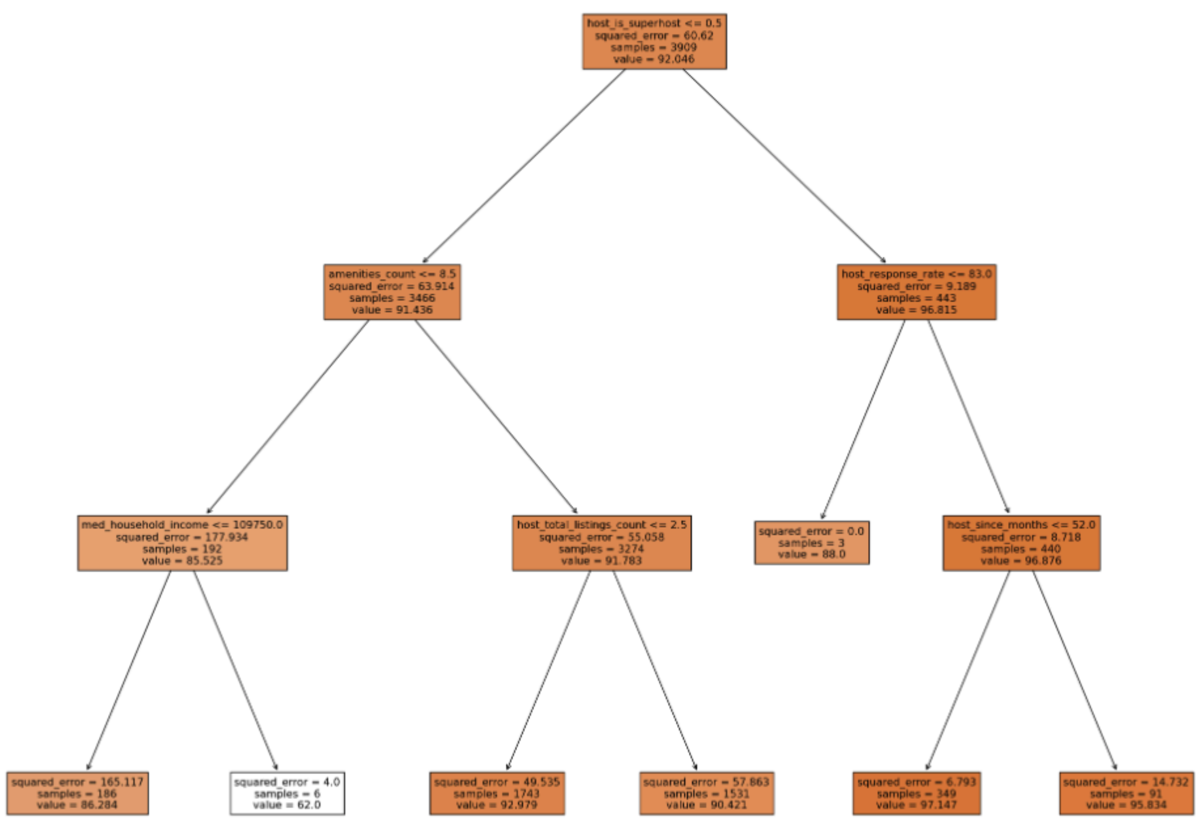
The objective function for the regression tree can be represented as:

$$\text{Objective Function: } \sum_{i=1}^{N} (y_i - f(x_{i1}, x_{i2}, \ldots, x_{ip}))^2$$

where:

y_i is the actual overall rating score of the i-th listing,
$f(x_{i1}, x_{i2}, \ldots, x_{ip})$ is the prediction function of the regression tree for the i-th listing,
$x_{i1}, x_{i2}, \ldots, x_{ip}$ are the input variables for the i-th listing, including 'amenities_count', 'price_per_guest', etc.,
N is the total number of listings in the dataset.

Figure 10: Decision Tree Visualization for Predicting Overall Rating

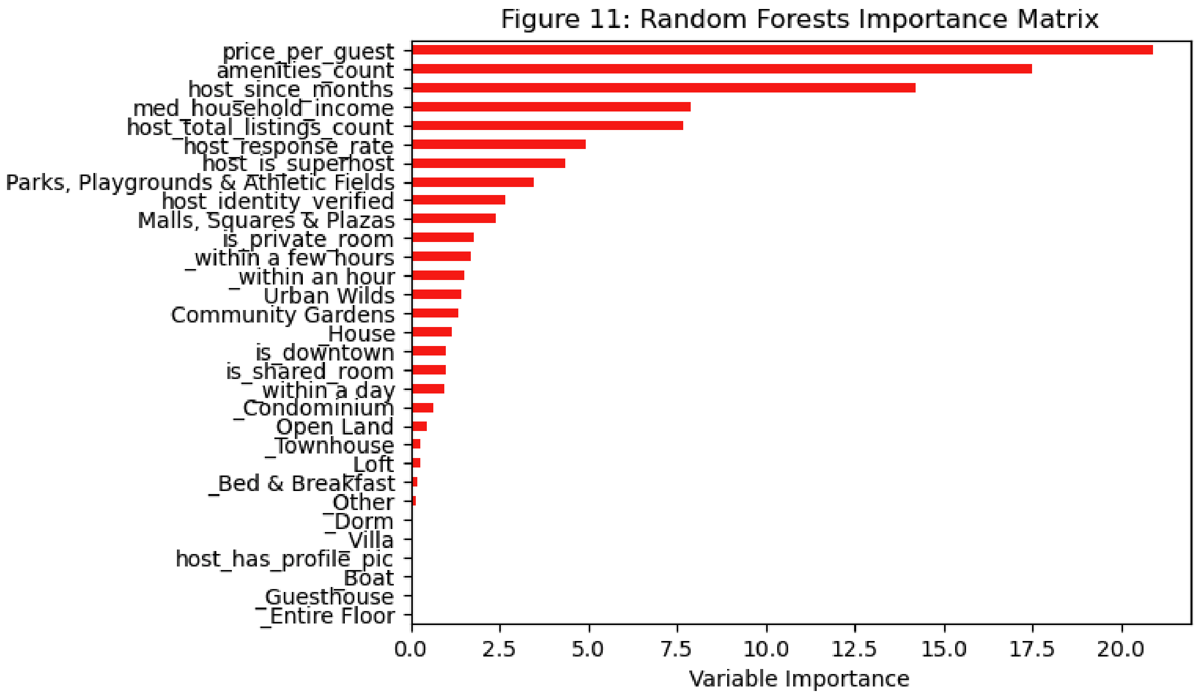


The regression tree analysis provides a clear and intuitive way to understand the primary factors influencing overall ratings and offers predictions for various scenarios.

Figure 10 illustrates that a host's superhost status significantly impacts overall ratings, with guests generally providing more positive ratings when the host holds this designation. This likely stems from the trust and high-quality experience associated with Airbnb's superhost program. Additionally, host responsiveness emerges as crucial, with listings receiving faster responses, particularly exceeding 83% of response times, tending to have higher satisfaction scores. This underscores the importance of communication in the hospitality experience, with being a superhost indicating a level of care and service highly valued by guests. Moreover, the amenities count significantly influences guest satisfaction, with listings offering more than 8.5 amenities receiving lower scores, suggesting diminishing marginal utility beyond a certain point.

Another layer of insight relates to the economic aspects of pricing and neighborhood effects. The regression tree suggests that guests opting for more expensive listings, particularly those above $525 per guest, tend to be among the most satisfied, indicating a willingness to pay a premium for an exceptional experience. This aligns with luxury market dynamics, where higher prices often correlate with elevated guest expectations. Furthermore, there is a marginal preference for stays in neighborhoods with higher median incomes, indicating a slight inclination toward upscale or perceived safer areas. Interestingly, while one might expect higher costs to dampen satisfaction, the data reveals that at the upper end of the market, higher prices are associated with greater satisfaction, highlighting the influence of perceived value over raw price figures. This insight is particularly valuable for hosts targeting the premium segment, emphasizing the importance of aligning prices with the luxury experience guests anticipate.

4.2.2 Random Forests



The importance matrix from the Random Forest model indicates that 'price per guest', 'number of amenities provided', and 'duration of the host's experience' are the three most significant variables for model prediction accuracy. This contrasts with the single regression tree's findings, where 'whether the host is a superhost' ranks as the most influential variable for predicting the overall rating, with 'number of amenities' and 'host response rate' following in importance. The Random Forest model also ranks these latter two variables highly, within the top five for variable importance. The divergence between the models' results underscores the differences in how they assess feature influence on the target variable. The ensemble method of Random Forest, which aggregates outcomes from multiple decision trees, provides a broader analysis of data and feature interactions, potentially offering a more reliable estimation of feature importance.

The differences and similarities in the results from the regression tree and the Random Forest importance matrix can be traced back to several factors. The structure of the models is a primary consideration; Random Forest's method of combining insights from many trees offers a layered understanding of how features interact to affect predictions. This approach diminishes the impact of anomalies, presenting a comprehensive view of feature significance. Conversely, a regression tree provides a straightforward perspective on the influence of individual features, which may not fully capture complex interactions. Additionally, the variation in feature importance between the models highlights how certain features may have varying degrees of influence based on the modeling approach. For example, the 'superhost' status might significantly affect guest perceptions in a linear decision-making model. However, in the multifaceted decision-making environment of Random Forest, which considers a wider dataset, 'price per guest' and 'amenities provided' appear as consistently critical factors across various Airbnb listings

4.3 Comparison of Models

The comparison of machine learning models reveals a progressive improvement in performance from Linear Regression through to Random Forest, as evidenced by Mean Squared Error (MSE) and R-squared metrics. Linear Regression, with the highest MSE and lowest R2 Score, suggests a limited ability to capture complex data relationships, likely due to its assumption of linearity between predictors and the target variable. The Decision Tree model, showing a marginal enhancement in both metrics, indicates a better grasp of non-linear relationships, though its vulnerability to overfitting may constrain its predictive accuracy. The introduction of ensemble methods, starting with Bagging, marks a significant leap in model performance. By leveraging multiple learners to reduce variance and improve prediction robustness, Bagging demonstrates a substantial decrease in MSE and increase in R2 Score, underscoring the efficacy of ensemble strategies in handling complex data patterns. The Random Forest model, an extension of Bagging with additional randomness in selecting features for splitting nodes, achieves the lowest MSE and highest R2 Score among the evaluated models. This highlights its superior capability in generalizing the learned patterns to new data, thereby providing the most accurate and reliable predictions.

Figure 12: Model Comparison

	Model	MSE	R2 Score
0	Linear Regression	50.140844	0.090588
1	Decision Tree	49.933917	0.094341
2	Bagging	37.518201	0.319527
3	Random Forest	37.356104	0.322467

The comparison of machine learning models reveals a progressive improvement in performance from Linear Regression through to Random Forest, as evidenced by Mean Squared Error (MSE) and R2 Score metrics. Linear Regression, with the highest MSE and lowest R2 Score, suggests a limited ability to capture complex data relationships, likely due to its assumption of linearity between predictors and the target variable. The Decision Tree model, showing a marginal enhancement in both metrics, indicates a better grasp of non-linear relationships, though its vulnerability to overfitting may constrain its predictive accuracy. The introduction of ensemble methods, starting with Bagging, marks a significant leap in model performance. By leveraging multiple learners to reduce variance and improve prediction robustness, Bagging demonstrates a substantial decrease in MSE and increase in R-squared, underscoring the efficacy of ensemble strategies in handling complex data patterns. The Random Forest model, an extension of Bagging with additional randomness in selecting features for splitting nodes, achieves the lowest MSE and highest R-squared among the evaluated models. This highlights its superior capability in generalizing the learned patterns to new data, thereby providing the most accurate and reliable predictions.

5. Conclusion

The investigation into what drives guest satisfaction in Boston's Airbnb market has provided a detailed look at how specific factors—amenities, host communication, location, pricing, and property type—play pivotal roles. Through the application of economic theories and principles, alongside statistical and machine learning analyses, this study has revealed the intricate balance between supply and demand dynamics, consumer behavior, and market segmentation within the Airbnb ecosystem.

First, amenities were found to significantly influence guest satisfaction, highlighting the principle of diminishing marginal utility. Guests value a certain level of convenience and comfort provided by amenities up to a point, after which additional amenities do not contribute as significantly to satisfaction. This suggests that hosts should focus on providing essential, high-quality amenities that align with guest expectations rather than increasing the sheer quantity of amenities.

Host-guest communication emerged as another critical factor, aligning with the signaling theory. Hosts who are responsive and engage positively with guests signal trustworthiness and reliability, thereby reducing information asymmetry and increasing guest satisfaction. The superhost status acts as a credible signal of a high-quality hosting experience, further enhancing guest trust and satisfaction.

The study also underscored the importance of location, applying the hedonic pricing model to understand its impact on satisfaction. Guests are willing to pay a premium for properties located in desirable areas, indicating that location attributes are significantly valued. This preference for location reflects the economic concept of positional goods, where the value is derived from the property's relative position or desirability within a certain context or neighborhood.

Pricing strategy plays a complex role, demonstrating the relationship between perceived value and cost. The analysis suggests that pricing must be carefully considered to reflect the value provided. Economic principles of price elasticity and consumer surplus are at play, with guests evaluating the trade-off between price and the quality of their stay, indicating a nuanced relationship between pricing, expectations, and satisfaction.

Lastly, the influence of property type on guest satisfaction highlights market segmentation and consumer preferences within the Airbnb market. Different guest segments have distinct preferences and willingness to pay, which can be catered to by offering various types of properties. Understanding these segments allows hosts to tailor their offerings more effectively, maximizing utility for both hosts and guests.

In conclusion, this research has delineated the multifaceted nature of guest satisfaction in Boston's Airbnb market through an economic lens, offering actionable insights for hosts. By focusing on quality amenities, effective communication, strategic pricing, and understanding the economic underpinnings of guest preferences, hosts can enhance guest satisfaction and improve their competitive standing in the market. This study not only contributes to the academic understanding of the short-term rental market but also provides practical guidelines for hosts aiming to optimize their offerings in the ever-evolving Airbnb ecosystem.

An area for further exploration is the price elasticity of demand within the Airbnb market. A focused study on how price fluctuations impact booking volume could yield critical insights into optimal pricing strategies for hosts. Investigating price sensitivity not only informs individual pricing decisions but also provides broader economic understanding of consumer behavior in the sharing economy. Such an analysis could reveal the thresholds at which guests are willing to trade off between cost and the perceived value of an Airbnb experience, guiding more nuanced and dynamic pricing models.

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