Analysing the Impact of Location, Amenities, and Host Behaviour on Airbnb Pricing and Occupancy Rates in London, England

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# 1. Introduction

## 1.1 Overview and Purpose of the Project

The hotel sector has long been the go-to for lodging, but new entrants have shaken things up and made providers adjust to stay ahead of the curve. The sharing economy has emerged as a contemporary trend. Airbnb, their major industry supplier, has grown substantially since its establishment in 2008. As per Lu (2021), Airbnb enumerated 3 million lodgings worldwide in November 2016. This scale demonstrates the significant effect Airbnb has had in a short period, together with sustained supply expansion. As a result, Airbnb is seen as a disruptor of the conventional hotel business. Airbnb has revolutionised tourism, enabling homeowners to lease their residences to travellers searching for distinctive and economical lodging (Gunter, Zekan and Milone, 2024). The price of Airbnb rentals is very variable, affected by demand, seasonality, and location-specific characteristics. Precise forecasting of rental pricing is crucial for hosts to maximise their earnings and for visitors to make educated booking choices. Airbnb has become a formidable platform, with almost three times the number of supply listings compared to the most significant global hotel operator, Marriott International. The rapid expansion of the sharing economy has underscored the need for training and education between the traditional hotel sector and the sharing economy, notably Airbnb (Di Persio and Lalmi, 2024).

AirBnB, a prevalent digital platform, enables peer-to-peer rental of residential properties, including houses and flats, for temporary lodging. Its business span includes more than 220 nations and territories worldwide, significantly impacting the hotel industry and local economies. This website provides an alternative to traditional hotel services by allowing private people to rent their homes as temporary accommodations for travellers (Camatti *et al.*, 2024). Recent studies have shown that AirBnB's market presence supplements the hospitality sector and actively influences hotel revenue dynamics. This interaction could be distilled and quantified by statistically analysing the correlation coefficient between the number of AirBnB listings and the incomeAirbnb listings and the income the hotels get from the room reservations (Gangarapu and Mernedi, 2023). Similarly, the presence of AirBnB in American metropolitan regions with a high penetration of AirBnB resulted in a 1.3% reduction in hotel booking rates and a 1.5% lower income due to booking rates compared to hotels (Lu, 2021).

A significant aspect of Airbnb being such an appealing proposition for real estate investors and entrepreneurs is that it revealed its pinnacle sales and profits in the third quarter of 2022. In this research, they examined AirBnB listing pricing in Italy, Rome, based on the Airbnb Pricing Experiment. In this paper, we endeavoured to find out what makes for a scintillating Airbnb listing and identify the factors that would impact the pricing of an Airbnb listing. They can utilise several machine learning algorithms like support vector regression, XGBoost, neural networks and natural language processing methods including TF-IDF, bag of words, and aspect-based sentiment analysis. With these methodologies, we have aimed to formulate a more superior and dependable pricing plan for AirBnB hosts using it, which could increase their hosts’ usage and profitability (Sims, Ameen and Bauer, 2019).

The hospitality platform Airbnb was established in 2008 and has since seen exponential development. In 2022, 2.9 million individuals served as hosts on Airbnb globally. Since the platform's inception, nearly one billion guests have been accommodated (Chapman, Mohammad and Villegas, 2023) despite criticism from various scholars and practitioners regarding inherent limitations of peer-to-peer experiences during the platform's initial development (Chapman, Mohammad and Villegas, 2023). The Airbnb platform operates on a two-sided market model, facilitating communication between accommodation-seeking tourists (guests) and accommodation providers (hosts). The latter are categorised into non-professional hosts, who rent properties for supplementary income rather than as a primary business, and professional hosts, such as guesthouses, hostels, and bed and breakfasts, who utilise their real estate exclusively for rental purposes (Tan *et al.*, 2024).

## 1.2 Research Question, Aim and Objectives

### 1.2.1 Research Question

* How effectively can machine learning models recommend rental items to users based on their preferences and browsing history?

### 1.2.2 Aim

The study aims to analyse the impact of location, amenities, and host behaviour on Airbnb pricing and occupancy rates in London, England.

### 1.2.3 Objectives

* To examine how different London neighbourhoods affect Airbnb listing prices and occupancy levels.
* To determine which amenities correlate with higher pricing and increased occupancy rates.
* To investigate how host responsiveness and listing accuracy impact guest reviews and occupancy.

# 2. Background

## 2.1 Introduction to Airbnb

In recent years, the sharing economy has experienced tremendous growth to platforms such as Airbnb, which have revolutionised the lodging sector. Therefore, the sharing economy refers to individuals dealing with each other's resources, commodities, and services on online platforms or communities to maximise underused assets' usage. Airbnb has a crucial impact on how individuals search for and rent rooms through its volatile pricing of Airbnb (Gunter, Zekan and Milone, 2024). Conventional lodging rates do not change as they are not tied to demand or seasonal variations to current or distinctive listing attributes, but Airbnb rates vary based on each. Unpredictability poses a unique boxing problem for the pursuers and seekers of this optimal equilibrium between cost-effectiveness and value (Lu, 2021). This difficulty has become more and more necessary to incorporate data science. The availability of historical data on Airbnb can be beneficial for researchers to get some interesting inferences about price patterns, consumer preferences, and market dynamics. These observations are the starting point for creating precise and accurate algorithms to forecast Airbnb listing values (Di Persio and Lalmi, 2024).

The forecasting of Airbnb listing pricing is precise and comes with substantial consequences and benefits to both the hosting and the hosted party in the sharing economy. Hosts are better able to improve their listings by applying accurate pricing forecasts in competition with the market trend or property characteristics (Chapman, Mohammad and Villegas, 2023). It helps them optimise their income potential and improves the company's success. In addition, hosts get insights into the factors that lead to pricing fluctuations to follow a follow a wiser path, for instance, to decide about property enhancements, amenities, and other announced attributes (Gangarapu and Mernedi, 2023). Precise pricing forecasts, however, help visitors in the sharing economy by providing transparency and letting them choose better according to their budget, taste, and need for amenities. In the sharing economy, where resources are exchanged for resources among people, precise pricing forecasts allow visitors the best options to lodge and travel efficiently based on timing. With open-mindedness, their overall pleasure and experience with the sharing economy through the Airbnb platform improve (Sims, Ameen, and Bauer, 2019).

## 2.2 Selection Criteria for Papers

The evidence in this study regarding the selection criteria for papers focuses on relevance, methodological rigour, and some contribution to understanding the dynamics of Airbnb pricing. Using the ones that look into the factors affecting the price of stay on Airbnb and occupancy rates, especially in urban areas like London. Attention was drawn to the studies using advanced analytical techniques (such as machine learning and regression models) to extract inferences from the massive datasets. Moreover, research that examined the interactions between location, amenities, and host behaviour was focused on to guarantee a comprehensive analysis of variables that are important in determining the performance of Airbnb rental. This approach would like to synthesise various perspectives and methods to understand the subject thoroughly.

## 2.3 Critical Analysis of Key Papers

### 2.3.1 Paper 1: “Airbnb listings’ performance: Determinants and predictive models”.

In his study of Airbnb listing performance in Thessaloniki, Greece, Kirkos (2022) explores the determinants of occupancy rate, bookings, and revenue of Airbnb listings. It employs data mining methodologies to learn the factors that deterministically influence customer purchase intention and the listing performance and the development of a predictive model (Kirkos, 2022). The study takes an AI-derived inducer on a dataset of variables related to host, lodgings, rules and guest ratings. One of the key findings is the fundamental role of the host in determining listing success, which also implied that Random Forest was the most effective classification model. It provides little for hosts, managers or regulatory bodies.

However, the study's main limitation is that it is constrained to the geographical scope, that is, Thessaloniki, Greece. It does not generalise the findings to other markets with dissimilar cultural, economic or tourism features (Kirkos, 2022). Second, the study identifies key determinants and a predictive model. However, external factors like seasonality, macroeconomic conditions and local events may significantly affect Airbnb's performance and could not be fully considered. Additionally, a rapidly changing market means that anticipated trends in past data may not act in the same manner. The findings are future research topics such as expanding geographic scope, using external variables in the analysis, and employing more dynamic modelling techniques to increase robustness and applicability (Kirkos, 2022).

### 2.3.2 Paper 2: “Machine Learning for short-term property rental pricing based on seasonality and proximity to food establishments."

Cervera, de Esteban Curiel and Pérez-Bustamante Yábar (2024) examine how machine learning might help predict short-term rental pricing, particularly seasonality and the distance to food establishments, within Madrid. The dataset of 220 Airbnb properties is used to study through factor analysis and clustering of the properties to determine seasonal pricing trends and the effect on nearby eating options. The results imply that hosts could also increase revenue management by integrating food amenities into their pricing policies. While it is well documented in the study, there are also limitations (Cervera, de Esteban Curiel and Pérez-Bustamante Yábar, 2024). A limitation of the geographical focus on Madrid limits the generalisability of the results to other cities of different cultural and economic contexts. Madrid's food scene and tourism patterns may be unique to this particular place; therefore, the predictive models developed may not fit for generic application. Furthermore, while the study correctly points out the relevance of seasonality and the proximity to food establishments, it may fail to consider other essential factors related to the rental prices, such as local events, transportation access, or property-associated attributes like size and condition.

Additionally, training of the model on historical data could make it difficult to adjust to fast changes in the market or unanticipated circumstances, e.g. an economic downturn or a shift in consumer preferences (Cervera, de Esteban Curiel and Pérez-Bustamante Yábar, 2024). A broader dataset, which includes other locations and other factors affecting pricing dynamics, would benefit future research more.

### 2.3.3 Paper 3: “A Sustainable Rental Price Prediction Model Based on Multimodal Input and Deep Learning—Evidence from Airbnb”

Tan *et al.* (2024) propose a sustainable rental price prediction model for Airbnb listing by leveraging multimodal inputs and deep learning techniques. None of these suggests that property features, host characteristics, reputation, and location are not significant determinants for pricing strategies for hosts. Using different data sources, such as property descriptions and images, the model is better integrated with a mean absolute percentage error (MAPE) of 5.57% compared to the simpler models (Tan *et al.*, 2024). However, the research has some notable limitations. Firstly, the reliance on data from a single city, Amsterdam, restricts the generalisability of the findings to other markets with different dynamics and cultural contexts. TheThe structure of Amsterdam's rental market is not unlike that of other cities (which could lead to the predictive model not being applied to different geographical locations). Furthermore, although the study incorporates multimodal inputs, it does not consider the different variables in pricing (e.g. economic fluctuations or local events that could dramatically influence demand) (Tan *et al.*, 2024).

Furthermore, due to the complexity of the deep learning model, its practical implementation by hosts without relevant technical abilities might be challenging. Users need to know how different factors can influence pricing decisions through the model. However, deep learning models are typically seen as the 'black box', making it hard for hosts to draw actionable insights (Tan *et al.*, 2024). In future research, rental price predictions could be extended to broader datasets in several cities and with more contextual variables to make predictions more robust and applicable in different contexts.

### 2.3.4 Paper 4: “Predicting Listing Prices In Dynamic Short Term Rental Markets Using Machine Learning Models”.

Chapman, Mohammad, and Villegas (2023) utilise a machine learning model to predict listing prices in a dynamic short-term rental market. In their study, they investigate the tight interaction of several factors that influence Airbnb pricing, namely location, property characteristics, season, and demand, and the effectiveness of different models in reflecting that complex interplay between the factors. The research intends to guide hosts and guests in making informed pricing and booking strategy decisions. This is, however, difficult without access to the full content of the study (Chapman, Mohammad, and Villegas, 2023). Some things can be inferred from the title and abstract of the article. The study's findings might be limited depending on the very particular datasets used, therefore, the models might not generalise to different geographical places or periods. Short-term rental markets are dynamic, and training models on historical data might not be enough to adapt to changes in the demand or market conditions in a short time.

Moreover, predicting correctly is not the only criterion, as model interpretability isery important. While machine learning models can predict tremendously well, they are often opaque. They do not provide much insight into the underlying drivers of the pricing decision (Chapman, Mohammad and Villegas, 2023). A significant drawback of this lack of interpretability is that models are not always practical for hosts because they would likely need to trust in predictions they do not entirely understand. Future research could focus on designing methods that can improve the model's interpretability at the cost of predictive accuracy so that machine learning-based pricing tools for the short-term rental market can be usable and adopted. Another possible addition is the inclusion of real-time data and dynamic updates of the models, which allows it to be more adaptable when the market changes (Chapman, Mohammad and Villegas, 2023).

## 2.4 Summary of Literature Review

The literature review established that location, amenities, and host behavior play a vital role in influencing Airbnb prices and occupancy rates. On the other, it assesses how much Airbnb is capable of contributing to the field of tourism and economic development. This has been proven by studies that show geographic factors, and neighbourhood characteristics are deciding factors in rental prices. It adds that the more desirable the amenities, the greater the occupancy rates and prices. Guests' satisfaction and review of a listing are influenced by host responsiveness and listing accuracy. Increasingly, machine learning techniques are used to build models that can be used within pricing strategies. However, models remain challenging to interpret, and the findings are generalisable from market to market. As the review points out, pricing in the Airbnb ecosystem is highly complex.

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