

# Literature Review

A brief review of factors influencing hotel prices and their respective prediction models.

The literature review will discuss the various factors that would influence statistical models predicting prices of hotels. Such features are worth exploring given their studied effects around the governing prices of hotels within various cities and demographics. Machine learning models have been quite progressive in this respect, being able to dictate prices of hotels based on geospatial analyses, sentimental analyses of customers, the type of owners of hotel listings, seasonality and other factors that would influence such price predictions which will be further discussed through this review in light of a select few of other papers.

Price prediction models (in this context, for hotels), would serve to be beneficial for hotel owners, potentially tuning their prices to those of more reasonable standard, or those potentially joining the industry. Moreover, such models could also serve to the advantage of customers with minimal knowledge of the various attributes that govern their respective environments they travel or reside in.

There have been works on sentimental analyses and moreover the psychological factors that may influence the potential pricings of hotels and moreover the success of hotels in this respect. The article presented here ([Kayhan Tajeddini et al., 2021](#)) discusses such psychological factors in respect to hotel prices listed by owners, with their empirical results highlighting that revisits are an integral predictor of customer loyalty and thus the price of a hotel. Such an attribute can prove to be a helpful predictor in conjunction with customer loyalty for machine learning algorithms predicting hotel prices based on such behavioural theories and empirical results as discussed in their article. To an extension of the theoretical basis on the significance of behavioural predictors for customer loyalty and thus hotel prices, there have been practical attempts at using such sentimental information as markers for machine learning models ([Le Hong Trang et al., 2021](#)), with varying levels of success over different statistical models involving sentiment mining “for the problem of price prediction in online booking systems”.

Additionally, another fact that could influence statistical predictions of hotel prices would be the type of hotel rooms listed by Airbnb as discussed in this article ([Augusto-Voltes-Dorta, Agustín Sánchez-Medina, 2020](#)). The findings of the article, based on regression and ols models, suggest that several different characteristics of a hotel room, excluding its geography, can indeed produce differing price results. Moreover “[they] found statistically significant differences in the price effects of additional bathrooms, bedrooms, and guest capacities, though the last two only in off-peak and

peak periods, respectively.” This is quite significant regarding the price predictions, especially the aforementioned variations of the statistical significance in prices based on “off-peak and peak periods”.

Such variations are further expanded upon in S.Mitra’s paper ([Subrata KumarMitra, 2020](#)) where there are discussions upon the fluctuation of occupancy rates and average room rates based on the span of different seasons within the hospitality industry, similarly using regression techniques as the previous study above,

This ([Zhang, Z. et al., 2017](#)) paper suggests that price is an important factor in the hospitality economy ([Bull, A.O., 1994](#)). They propose knowing factors that affect prices is valuable information that guests can benefit from in this decentralised platform and “sharing economy.” They explore studies on factors that affect prices of Airbnb listings as discussed by Ikkala and Lampinen in ([Ikkala, T.; Lampinen, A., 2014](#)). That suggests the reputation of airbnb listings are correlated with their price. By using listings information from 33 cities, a paper by Wang and Nicolau ([Wang, D.; Nicolau, J.L., 2017](#)) identified a few of the biggest factors of price including host attributes, property attributes, amenities, rental rules and ratings of online reviews. Additionally, having a high score on online reviews can translate to higher prices in the hospitality industry ([Gutt, D.; Herrmann, P., 2017](#)).

Furthermore, hotel location has great statistical significance in predicting hotel success and thus price, as shown in this study ([LeiFang et al., 2018](#)) where a geographically weighted regression model is used to predict the possible hotel choices of consumers. This is one of the first studies made in an attempt to develop an understanding around the implications of local spatial modelling to determine the efficacy of choice predictions based on hotel locations in an urban tourism destination. The conclusions of this study were that attributes affecting hotel location choice often depend on respective regions and that surprisingly traffic isn't a significant determinant in hotel choice among urban areas. This study alongside ([KristófGyódi, ŁukaszNawaro 2020](#)) this one also both discuss the spatial dependency of prices and hotel choices of consumers.

This brief review aimed to highlight some of the major factors that influence predictive models of hotel prices, using recent papers regarding a range of statistical models and their respective results in response to respective target features. Most if not all studies involved regression analyses, for geospatial modelling to sentimental analysis. Such studies of factors that have been explored in this review have great implications and potential for further study and research for optimisation of knowledge in this field and aforementioned predictive models.

## **Citations**

Trang, L. H., Huy, T. D., & Le, A. N. (2021). Clustering helps to improve price prediction in online booking systems. *International Journal of Web Information Systems*, 17(1), 45–53. <https://doi.org/10.1108/ijwis-11-2020-0065>

Tajeddini, K., Mostafa Rasoolimanesh, S., Chathurika Gamage, T., & Martin, E. (2021). Exploring the visitors' decision-making process for Airbnb and hotel accommodations using value-attitude-behavior and theory of planned behavior. *International Journal of Hospitality Management*, 96, 102950. <https://doi.org/10.1016/j.ijhm.2021.102950>

Voltes-Dorta, A., & Sánchez-Medina, A. (2020). Drivers of Airbnb prices according to property/room type, season and location: A regression approach. *Journal of Hospitality and Tourism Management*, 45, 266–275. <https://doi.org/10.1016/j.jhtm.2020.08.015>

Fang, L., Li, H., & Li, M. (2019). Does hotel location tell a true story? Evidence from geographically weighted regression analysis of hotels in Hong Kong. *Tourism Management*, 72, 78–91. <https://doi.org/10.1016/j.tourman.2018.11.010>

Boto-García, D., Mayor, M., & De la Vega, P. (2021). Spatial price mimicking on Airbnb: Multi-host vs single-host. *Tourism Management*, 87, 104365. <https://doi.org/10.1016/j.tourman.2021.104365>

Mitra, S. K. (2020). Estimating the duration of different seasons and their impact on hotel room prices. *International Journal of Hospitality Management*, 90, 102604. <https://doi.org/10.1016/j.ijhm.2020.102604>

Gyódi, K., & Nawaro, Ł. (2021). Determinants of Airbnb prices in European cities: A spatial econometrics approach. *Tourism Management*, 86, 104319. <https://doi.org/10.1016/j.tourman.2021.104319>

Leoni, V., & Nilsson, W. (2021). Dynamic pricing and revenues of Airbnb listings: Estimating heterogeneous causal effects. *International Journal of Hospitality Management*, 95, 102914. <https://doi.org/10.1016/j.ijhm.2021.102914>

Marchenko, A. (2019). The Impact of Host Race and Gender on Prices on Airbnb. *Journal of Housing Economics*, 101635. <https://doi.org/10.1016/j.jhe.2019.101635>

Barnes, S. J., & Kirshner, S. N. (2021). Understanding the impact of host facial characteristics on Airbnb pricing: Integrating facial image analytics into tourism research. *Tourism Management*, 83, 104235. <https://doi.org/10.1016/j.tourman.2020.104235>

Zhang, Z., Chen, R., Han, L., & Yang, L. (2017). Key Factors Affecting the Price of Airbnb Listings: A Geographically Weighted Approach. *Sustainability*, 9(9), 1635. <https://doi.org/10.3390/su9091635>

Lampinen, A.; Cheshire, C. Hosting via Airbnb: Motivations and financial assurances in monetized network hospitality. In Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, San Jose, CA, USA, 7–12 May 2016; pp. 1669–1680. <https://doi.org/10.1145/2858036.2858092>

Ikkala, T.; Lampinen, A. Defining the price of hospitality: networked hospitality exchange via Airbnb. In Proceedings of the Companion Publication of the 17th ACM Conference on

Computer Supported Cooperative Work & Social Computing, Baltimore, MD, USA, 15–19 February 2014; pp. 173–176. <http://dx.doi.org/10.1145/2556420.2556506>

Wang, D.; Nicolau, J.L. Price determinants of sharing economy based accommodation rental: A study of listings from 33 cities on Airbnb.com. *Int. J. Hosp. Manag.* 2017, 62, 120–131. <http://dx.doi.org/10.1016/j.ijhm.2016.12.007>

Gutt, D.; Herrmann, P. Sharing Means Caring? Hosts' Price Reaction to Rating Visibility. Available online: [http://aisel.aisnet.org/cgi/viewcontent.cgi?article=1053&context=ecis2015\\_rip](http://aisel.aisnet.org/cgi/viewcontent.cgi?article=1053&context=ecis2015_rip) (accessed on 11 September 2017)

Bull, A.O. Pricing a Motel's Location. *Int. J. Contemp. Hosp. Manag.* 1994, 6, 10–15. [[Pricing a Motel's Location](#)]