International Journal of Hospitality Management 81 (2019) 54–64

Contents lists available at ScienceDirect

International Journal of Hospitality Management

journal homepage: www.elsevier.com/locate/ijhm

# Do airbnb host listing attributes influence room pricing homogenously?

Manojit Chattopadhyay[a,*], Subrata Kumar Mitra[b]

[a] Decision science and Systems Area, Indian Institute of Management Raipur, Atal Nagar, P. O. - Kurru (Abhanpur), Raipur, (C.G.) 493661, India
[b] Finance Area, Indian Institute of Management Raipur, Atal Nagar, P. O. - Kurru (Abhanpur), Raipur, (C.G.) 493661, India

ARTICLE INFO

*Keywords:*
Variable importance
Sharing economy
Peer-to-peer accommodation
Price determinants
Random forest
Decision tree
Amenities
Regional heterogeneity
Rental platform
Airbnb listing
Room pricing
Revenue management

ABSTRACT

This research primarily contributes to the identification of the important variables that significantly influence room pricing on the Airbnb rental platform. The study adopted a comparative approach by using three different methods—OLS, random forest, and decision tree—and applied it to a vast amount of data from the Airbnb listing dataset of 11 US cities. Each individual amenity mentioned in the listing in the textual format was used as an independent variable. We also added six other common listing variables to obtain interesting insights into the influence of these variables from the perspective of the host, guest, traveler, and tourist. Apart from identifying city-specific variable importance using different models, we estimated a composite score of variable importance that may be helpful to generalize the influence of amenities and other explanatory variables in the presence of any city-specific regional heterogeneity on the shared rental platform.

## 1. Introduction

The global regression models used for investigating the influence of determinants on room pricing of Airbnb's sharing accommodation mask the spatial heterogeneity of relations (Wang and Nicolau, 2017; Zhang et al., 2011). These models possibly overlook the presence of regional (or city-specific, in the case of Airbnb rentals) variations with respect to the important explanatory variables that significantly influence the room price of peer-to-peer accommodation.

Pricing and revenue management are the two most frequently researched areas in the hospitality domain. Due to the theoretical and practical criticality of room pricing, Airbnb hosts must master room pricing to increase their profitability after satisfying guest expectations. Traditional corporate hotels and hotel chains, as well as peer-to-peer rentals, are easily searchable online. At the same time, in the absence of reputational corporate brand identity in Airbnb shared rentals, the hosts must provide some information for purposes of increasing the attractiveness of their property in terms of amenities and other pricing criteria, which are comparable and searchable. Thus, hosts in Airbnb not only fix their price but also decide the terms and conditions for providing room and services to improve their business and profits.

On the other hand, guests are also at their liberty to select the property that is most economically advantageous and serves their need satisfactorily. Every day, thousands of guests select not to rent a traditional hotel room and instead spend the night in a room listed on peer-to-peer rentals by a stranger. In the literature of hospitality and tourism, studies have shown the increasing trend of novelty seeking and collaborative consumption on sharing rental platforms based on travel bragging items (Guttentag, 2015). Tourists and guests are looking for specific amenities items offered by the hosts on these platforms (Abrate and Viglia, 2017). However, there is a lack of studies on room pricing determinants for online shared rentals. Even traditional hoteliers have paid less attention to important determinants that influence realistic room price decision (Hung et al., 2010). Therefore, the objective of this work is to investigate and identify the key determinants from various offered amenities, accompanied by some specific price indicators identified in the literature that are influential in room pricing. Additionally, this study will explore any potential city-specific generalizations of the key determinants' influence on room pricing using the Airbnb listings dataset of 11 different US cities. To the best of our knowledge, this is the first endeavor to explore key determinants for generalizability across cities in the same country, based on 143 explanatory variables relating to amenities and few other price indicators.

Also, there is a research gap regarding any generalization of key determinants' influence on room price across cities in the same country on peer-to-peer rentals. In a related work (Wang and Nicolau, 2017), room pricing determinants in 33 Airbnb cities are shown to be the same as for traditional hotels (Chen and Rothschild, 2010). Another study

* Corresponding author.
*E-mail addresses:* mchattopadhyay@iimraipur.ac.in (M. Chattopadhyay), skm@iimraipur.ac.in (S.K. Mitra).

https://doi.org/10.1016/j.ijhm.2019.03.008
Received 17 September 2018; Received in revised form 20 February 2019; Accepted 6 March 2019
0278-4319/ 

explored the main pricing factors from a limited dataset comprising 794 samples of Airbnb listings from a single city—metropolitan Nashville, Tennessee—and concluded distance from convention center as a point of sensitivity for room pricing (Zhang et al., 2017). Some of the studies confirmed the positive and significant influences of reviews, ratings, host photos, and Superhost status on room pricing (Liang et al., 2017). Due to the popularity of the Airbnb, both hosts and guests are likely to see sharing rental as cheaper in price and offer a novel experience (like igloos, castles or tree houses) than the traditional hotel accommodation. This experience as an user motivation, stimulates guests “utilitarian value” or hedonic value (Prebensen and Rosengren, 2016; Miao et al., 2014).

The success of a regression-based hedonic pricing model depends on the validity of assumptions associated with these models. However, when the dataset involves nonlinearity or hidden multicollinearity, nonparametric models are more suitable. Therefore, the present study applied RF and CTree as decision tree-based nonparametric data-mining models to deal with the nonlinearity issues in the dataset (Janitza et al., 2016). The present study employed a comparative approach by using three different methods—OLS, random forest (RF), and conditional inference tree(CTree)—applied on a vast quantity of data from the Airbnb listing dataset for 11 cities in the US (151,955 observations and 143 explanatory variables).

While most studies have usually focused on city scale we analysed price determinants across 11 cities in the same country (US). Therefore, this study extended hedonic pricing analysis at the country level comparing the results obtained from 11 different cities.

Therefore, the two main novelty aspects of the present work are: investigating the overall as well as local, city-specific dissimilarity in the relationship between room pricing and its main determinants for Airbnb rentals and application of two machine learning algorithms (RF and CTree) for exploring room price determinants.

The aim of the research was to compare the performance of the applied models that identify the influence of room price determinants, and their estimated results, to contribute to the existing literature on sharing accommodation

The present work primarily contributes to the identification of the important determinants influencing room pricing for Airbnb rentals and to discern any possibility of city-specific generalization for identified determinants in the hospitality and tourism industry. Because the long-term success of the rental industry is critically determined by pricing (Hung et al., 2010; Zervas et al., 2017), the room pricing determinants help Airbnb hosts to develop better practices by recognizing the pricing determinants that persuade guests’ readiness to pay and then fixing the room price based on guests’ insights and fulfillment of expectations. Moreover, this study explores whether the room pricing determinants are similar or locally generalizable across 11 cities in the US, which may help Airbnb hosts to undertake city-specific room pricing strategies and to develop further strategies to improve their services regarding identified main determinants that influence pricing in the underlying dynamic market situations. It is essential for Airbnb hosts to communicate the listing attributes effectively, in terms of amenities and other features that satisfy guests, and set prices for long-term success.

The rest of the study is organized as follows: The next section includes a comprehensive survey of relevant research works. Then we present the methodology, including the dataset description. Thereafter, we applied the OLS, random forest, and decision tree methods to investigate the determinants’ influential roles in affecting room price. The final section presents implications and conclusions.

## 2. Literature review

The appearance of ‘the sharing economy’ has resulted in unique growth with respect to a number of users, empowering innovative areas of socioeconomic interaction (Sundararajan, 2016). In the last few decades, the information communication technology revolution and the diffusion of smartphones and social media have tremendously influenced the digital sharing economy (Anderson, 2014; Cohen and Kietzmann, 2014; Zervas et al., 2017).

In literature there are contradictory opinions and assessments on impact of Airbnb on traditional hotel business in diverse geographical locations (Xie and Kwok, 2017). In Texas state of the US, Zervas et al. (2017) evaluated that hotel revenue reduced by 0.05% due to a 1% increase in Airbnb listings. In Manhattan, Smith Travel Research (STR) reported that Airbnb did not significantly impact hotel demand (STR, 2016). Similar studies reported insignificant impact in New York city (Alvarado et al., 2016). However, sharing rental like Airbnb has significant positive influence not only by changing the competitive scenarios in hotel industry but also through transformation of the tourism industry (Heo et al., 2019). The peer-to-peer based accommodation available in digital space is increasing the supply of rooms in a way that should foster visitation and should have encouraging influences on the larger tourism-based economy, specifically when the tourist demand is high (Guttentag, 2015). The accommodation types on Airbnb and similar platforms vary from private rooms to castles. The room price in hospitality literature has been demonstrated to be influenced by the physical features, like the location and the offered accommodation type (Monty and Skidmore, 2003). The reputational aspect of the product in sharing accommodation encompasses the various online reviews offered by guests on the platform and influences room pricing (Yacouel and Fleischer, 2012). The key benefits of the sharing economy of Airbnb may be the fostering of tourism due to short-duration rentals and the extra income that may help hosts cover mortgage expenses (Gottlieb, 2013). In the last few years, many customers from traditional hotel industry prefer more on new and trendy Airbnb rentals that are local and authentic based on the travel bragging items offered on this platform (Travel Update, 2014). In the hotel and tourism industry, travellers’ novelty seeking from room experience is a key concept that leads to innovativeness in rental offerings (Snepenger, 1987; Sirakaya et al., 2003). A limited number of studies has explored the influence of travel bragging rights regarding the offered amenities on room pricing for shared accommodation. The decision on hotel room selection is mainly influenced by room price (Hung et al., 2010; Lockyer, 2005). Therefore, various studies have explored the room pricing determinants with respect to the demand side (Becerra et al., 2013; Chen and Rothschild, 2010; Espinet et al., 2003; Lee and Jang, 2012; Schamel, 2012; Thrane, 2007; Yang et al., 2016; Guttentag et al., 2018) and supply side (Heo and Hyun, 2015; Lee, 2011; Masiero et al., 2015) in the accommodation industry. Hosts from a peer-to-peer rental platform like Airbnb are often unable to understand the actual room pricing to be influenced by their listing offerings during the setting of their room price on the rental platform (Hill, 2015). A comprehensive literature review of the influence of particular listing attributes on room price during 2016–18, encompassing a sample dataset of Airbnb listings in various countries, methodologies applied, and the dimension of explanatory variables (for exploring room pricing determinants), is presented in Table 1.

An Airbnb listing price based on hedonic pricing theory, can be related with presence or absence of specific listing or other attributes (Gibbs et al., 2018) and in literature various multiple regression based hedonic price models applied to explore price determinants.

The survey analysis revealed the fact that some studies extended their analysis at the country level by comparing the results from different cities. Few works on pricing determinants including hedonic pricing model in peer-to-peer rental platforms has been reported in literature (Chen and Xie, 2017; Gibbs et al., 2018; Wang and Nicolau, 2017). In hedonic price models, closeness to amenities has been revealed as price determinant (Lawani et al., 2018).

Some of the hedonic pricing models reported to measure the impact of variables like room feature, location, amenities and services, rental protocols, online review score, distance to the beach, accommodation type, extra room, number of rooms and accommodation capacity to be

**Table 1**
comprehensive review of determinants from Airbnb listings from various countries influencing on pricing and their relevant contribution through various applications.

| Author/Year | City/Country of study | Sample description | methods | Pricing determinants in Airbnb from literature |
|---|---|---|---|---|
| Amaro et al., 2018 | Germany and China | 202 samples | online surveys targeting millennials, model based on the Theory of Reasoned Action, Partial Least Squares (PLS) | Intentions to book on Airbnb, Attitude towards Airbnb, Subjective norm, Perceived risk, Economic benefits, Desire for unique accommodation and variety |
| Benítez-Aurioles, 2018 | 44 cities of the world (16 in the USA and 14 in the European Monetary Union) | Total 497,509 listings | OLS regression | Entire home, Private room, Bedrooms, Bathrooms, Accommodates, Superhost, Number of reviews, Score, Flexible cancel |
| Gunter, 2018 | San Francisco and the Bay Area of the USA | 40,060 Airbnb listings | logit and probit models | Super host as dependent variable and Super host criteria, Demand determinants, Alternative/additional measures related variable are the determinants criteria |
| Liang et al., 2018 | Canada and the USA | 395 surveys | Convenience sampling, structural equation modelling (SEM) | Transaction-based satisfaction, Experience-based satisfaction, rust in Airbnb (institution-based trust), Trust in hosts (disposition to trust), Switching intention, Repurchase Intention |
| Mauri et al., 2018 | Italy and UK | 502 listings from Milan and London | Shapley Value Regression | popularity variables along with personal reputational attributes and the description of the product being offered |
| Qiu et al., 2018 | London, UK | 41124 listings | binomial logistic model estimated using sequential Bayesian updating approach | 31 variables: include the number of reviews, the price per person per night, the location of the listing, the neighbouring |
| Abrate and Viglia, 2017 | Barcelona, Istanbul, London, Paris, and Rome | 981 samples | frontier regression model | reputation related variables |
| Gunter and Önder, 2017 | Viennese | cross-sectional data set of all Viennese Airbnb listings | cluster-robust ordinary least squares | Reviews quantity and quality and management features like identity, location and response |
| Horn and Merante, 2017 | USA, Boston | 5000 listing sample | regression | Attributes from Airbnb listings |
| Liang et al., 2017 | Hong Kong | Web craeler extracted 3830 accommodations belonging to 1872 hosts of Airbnb | Poisson regression model for count data & Tobit model | Number of review, rating, superhost badge,price, capacity,bed room,bed,exra, room rate, availability, cancel, photo, description, listing rule, legth of time |
| Zhang et al., 2017 | Metro Nashville, Tennessee | 794 samples | General Linear Model (GLM), Geographically Weighted Regression (GWR) | price, age, distance, reviews, ratings |
| Ert et al., 2016 | Stockholm | 395 samples | regression | product attributes (e.g., apartment size, location), and seller attributes (reputation, visual appearance) |
| Varma et al., 2016 | USA (202) and rest are from other countries | online survey from 347 participants and 12 in-depth interviews | ANOVA | survey questions on Factors for selection of a lodging facility in Airbnb and hotel conditions, and some other listing characteristics. |

positively price determinant (Saló and Garriga, 2011; Benítez-Aurioles, 2017; Gibbs et al., 2018; Wang and Nicolau, 2017).

Consequently, interest is evolving in this research gap due to limited knowledge of the generalizability of the relations between determinants of listing attributes and room pricing (Wang and Nicolau, 2017).

Complexity characterizes the relations between determinants and room price (Spindler et al., 2018) because in a dynamic rental market, listing variables may exert a nonlinear impact on room pricing (Espinet et al., 2003; Baggio and Sainaghi, 2011; Aziz et al., 2011). Therefore, non-parametric approaches are a better alternative to deal with the nonlinear influence of room pricing determinants (Batmaz et al., 2017). Moreover, computational complexity emerges during any traditional model implementation for investigating the generalizability of determinants' influence from millions of sample data accompanied by hundreds of explanatory variables. The sharing economy-based Airbnb rental platform also entails a huge amount of user-generated content related to the rental experiences of guests in response to the huge number of listing attributes uploaded by hosts. Thus, the existing studies lack the comprehensive research to identify key determinants from listings attributes and to model their nonlinear influence on price-determinant complex relationships on the peer-to-peer accommodation platform Airbnb.

### 2.1. Room selection-room pricing relationship in hotels and Airbnb

Extant literature has reported a wide variety of attributes like brand and hotel image, room price or value for money, physical attributes of a hotel (like property size, architect of a hotel, beautification, cleanliness, hotel facilities, hotel amenitites, aesthetic design, hotel space), room attributes, room services, hotel security, providing food and beverage, and hotel location etc that impact hotel guest in room selection-room pricing relationship in traditional hotel industry (Albayrak and Caber, 2015; Alcántara-Alcover et al., 2013; Ariffin and Maghzi, 2012; Dolnicar and Otter, 2003). Due to these large number of hotel attributes, and making them easy to follow, these hotel attributes are categorised as: physical environment and human interactions (Walls, 2013).

The guest experience in Airbnb rental selection is similar to hotel experience at relatively lesser cost (Festila and Müller, 2017). In Airbnb, some practical attributes receive more value than some experiential attributes (Guttentag et al., 2018). In literature, 'location' attribute is not found statistically significant by the Airbnb guests, however, 'amenities' and 'cost saving' reported to have positive influence and statistically significant (Tussyadiah, 2016). This inconsistency is possibly due to dearth of standards of Airbnb rentals, desire to travel and user personalities (Festila and Müller, 2017). Regardless of these contradictions, normally recognised attributes that favour the Airbnb room selection are related with monetary benefits/lesser price (Guttentag and Smith, 2017; Young et al., 2017), location (Tussyadiah, 2016), property amenities (Guttentag, 2015), cleanliness (Bridges and Vásquez, 2018), novelty experience/ interaction between host-guest (Festila and Müller, 2017) etc.

To understand the differences of attributes influence on room-selection-room pricing relationship between hotel and Airbnb customers it was reported that in Airbnb guests valued more on host-guest interaction and neighbourhoods experiences but room amenities and food and beverage influence more to the hotel customers (Belarmino et al., 2017). In another study involving survey of 630 users who experienced both Airbnb and hotel it was reported that Airbnb is superior than hotel due to the rental experiences relating to host-guest interactions, room amenities, localness, personalisation while the other attributes tend to be similar (Mody et al., 2017).

### 2.2. Pricing determinants in hotels and Airbnb

Martin-Fuentes et al. (2018) confirmed in their research that the price is most significant feature to infer the hotel classification system like 5-star, 4-star etc. The finding is in consistent with the concepts that traditional hotel classification system is a regular determinant of prices (Israeli, 2002) and the hotel room prices are in significant linear relationship with the hotel categories (Martin-Fuentes, 2016). Yang et al. (2016) reported higher rating scores given by the customer influence the price across the countries. Research reported that affiliation with branded chain are determinant of price (Yang et al., 2016; Becerra et al., 2013; Lee and Jang, 2012) but in Taipei, Taiwan and Israel influence of affiliation is not clear (Israeli, 2002; Hung et al., 2010). Hotel location is an important price determinant and consistent amongst literature (Lee and Jang, 2012; Zhang et al., 2011; Schamel, 2012). Various literature applied attributes related with diverse amenities in their hotel price determinant models (Becerra et al., 2013; Chen and Rothschild, 2010; Saló et al., 2014). Offerings of amenities like express checkout, mini-bars, television, breakfast, safes, advance booking, more housekeepers to guest ratio and hair dryers highly influence higher room price (Yang et al., 2016; Schamel, 2012; Masiero et al., 2015; Thrane, 2007; Lee and Jang, 2012). Although laundry service with lower price (Lee and Jang, 2012) and internet service influence is inconsistent (Yang et al., 2016). Extant literature has also reported that the physical features of hotel like number of rooms, hotel oldness, availability of a business center, bar, and swimming pool are price determinants (Yang et al., 2016; Thrane, 2007; Lee and Jang, 2012; Becerra et al., 2013; Chen and Rothschild, 2010). However, parking and gym found to be consistent higher price determinants (Chen and Rothschild, 2010; Yang et al., 2016).

In sharing economy, star ratings and branded affiliation, are unfitted to rental offers as the majority of Airbnb properties are personal residence (Guttentag, 2015). In Airbnb there are higher variations in prices. As per market rule customers relate prices with the offerings as amenities (Wang and Nicolau, 2017). A large number of customer select Airbnb because of amenities (Airbnb, 2018) which are important price determiants and guest's satisfaction (Wang and Nicolau, 2017; Gibbs et al., 2018). These amenities of Airbnb are different from hotels as Airbnb customers link amenities like washing machine, kitchen, dryer, refrigerator and household items etc in similar way as they have in their home. Amenities like bed and breakfast has been evaluated as price determiant and hot tub, a private bath, and a larger room reported to show positive influence on room price (Monty and Skidmore, 2003). Airbnb listings are related with idle property from non-professional host so it is necessary to relook the pricing determinants from traditional hotels (Botsman and Rogers, 2011). As Wang and Nicolau (2017) reported that role of location as price determinant is not established in Airbnb.

Based on the comparative distinction between traditional hotel versus Airbnb room selection and room price relationship and price determinants the present work acknowledged the necessity to relook several known features and explore to discern new price determinants of Airbnb rental listings. The objective of the study is therefore to explore whether the room pricing determinants are similar or locally generalizable across 11 cities in the US or not.

## 3. Methodology

The present research comprises two phases. In the first phase, three methods—traditional OLS, random forest tree, and conditional inference trees —were applied to test their success in modeling the relations between 143 explanatory listing attributes and room price. In the next phase, we investigated the variables' importance to identify the key determinants having a significant influence on the room price.

In statistical computing, variable importance in regression is a well-researched topic (Grömping, 2009). Traditionally, parametric regression methods are widely applied to find the room pricing determinants, as evident from the survey findings in Table 1. The RF and CTree methods have been utilized to perform regression tasks wherein 143 listing attributes were used as explanatory variables, and room price was considered the response variable, to identify determinants related to the room price via the variable importance measures computed from the both applied models.

### 3.1. Random Forest (RF)

As in real life, an ensemble of trees is a forest. A random forest is a popular and efficient model for performing classification and regression tasks (Breiman, 2001). For the computational purpose, it considers the following statistical framework (Genuer et al., 2010):

*training set* $(T) = \{(X_1, Y_1), .....,(X_m, Y_m)\}$ made of $m$ i.i.d. samples of a random vector $(X, Y)$. Where vector $X = (X^1, .....X^n)$ comprises the explanatory or independent variables $X \in \mathbb{R}^n$, *and* $Y \in y$ where $y$ is a dependent or response variable. In the regression, it is assumed that $Y = s(X) + \varepsilon$ with $E[\varepsilon|X] = 0$ and $s$ the regression function (for more detail, (Hastie et al., 2001).

RF involves a large number *ntree* of trees, such as 1000 decision trees, for better predictive performance. This large number of trees is important to achieving the objective of investigative quantities like variable importance (Breiman, 2002).

The random aspect in RF is due to the following two factors (Grömping, 2009): i) each distinct tree is generated from random samples and ii) a random sample of *mtry* candidate variables is used to generate the split in each tree. Due to this randomness in trees, each of the individual trees produces a different prediction. Thus, the mean prediction for the predictions of the individual trees is regarded as the overall prediction of the RF—because the individual trees generate multidimensional step functions. Thus, their mean also becomes multidimensional step functions that predict smooth functions because they represent a huge number of diverse trees.

### 3.2. Conditional inference trees (CTree)

Breiman et al. (1984) proposed a classification and regression trees (CART) model for splitting each node to ensure a maximum decrease in the node impurity measure (i.e., the total sum of squared deviations from node centers). In CART, initially, trees grow in large numbers but are subsequently pruned if they do not influence predictive performance based on pruning criterion. For a long time, this splitting procedure remained biased in the presence of diverse nature of regressor variables (Shih and Tsai, 2004). To overcome this bias in variable selection, CTree uses p-values attained through permutation test on function based statistics of the inputs as a condition to identify the best cutoff. The p-values are computed by applying statistical approximation or Monte Carlo simulations. The novel idea was to disentangle variable selection and splitting choice. The procedure involved in this model includes performing a global permutation test that considers a null hypothesis that no relations exist between any explanatory variables and the response variable in the node. The node does not split and becomes a terminal node when this global null hypothesis is not rejected. In other cases, for each of the variables, an individual null hypothesis is tested, and splitting is performed for the variable with minimum *p*-values (default is $p < 0.05$). Thus, overfitting or a biased variable selection is avoided (Hothorn et al., 2006).

With the above two approaches, the explanatory variables in the respective models are ordered based on their variable importance, which is determined based on the value changes in the dependent variable in response to the change in explanatory variables.

### 3.3. Dataset and variables

The three models (i.e., OLS, RF, and CTree) were applied to the sample Airbnb listings dataset from 11 cities—Austin, Boston, Chicago, DC, Los Angeles, Nashville, New Orleans, New York, San Diego, San Francisco, and Seattle—after the compilation of the relevant variable information from a third party website www.insideairbnb.com with publicly available data of Airbnb.com. Because the study involved only the US, the selected dependent variable room price (listed price per night in Airbnb.com) used the US dollar as the selected currency in our dataset. After performing data preparation, taking care of null values and missing values, etc., the total dataset used in the study consisted of 151,955 sample listings.

After exploring the literature on peer-to-peer rentals and traditional hotel room price determinants, we investigated the influence of the following selected attributes: *Accommodates*, *Bathrooms*, *Beds*, *Number of reviews*, *Review scores rating*, *Reviews per month*, and listed amenities offered by hosts. The *amenities* attribute comprised 137 diverse services offered by the hosts in Airbnb listings, and hence, it contained various services offered within the same *amenities* variable. The number of amenities was not the same across the observations in the dataset. Moreover, we employed separate data preparation by decomposing the composite amenities attribute into 137 independent offered amenities variables. The value of each amenity was considered either 1 or 0 (if amenities offered then 1 else it is 0) in each sample observation. Due to space constraints descriptive statistics related to 14 important variables as per Fig. 1 are only reported in Table 2.

### 3.4. Checking multicollinearity

In multiple regression, collinearity may exist between three or more variables even in absence of high correlation between variables that

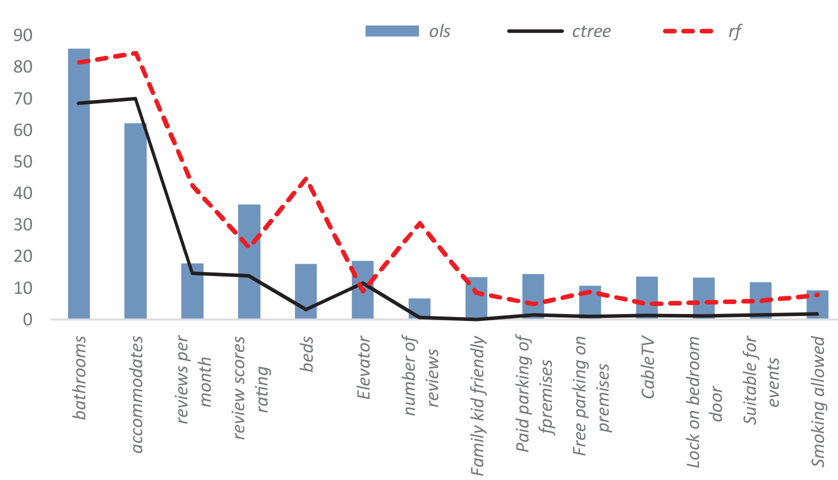


**Fig. 1.** Comparative evaluations of variable importance of the top 14 key determinants computed by three applied models.

**Table 2**
Descriptive statistics of important variables.

| Variables | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Accommodates | 3.57 | 2.48 | 1 | 26 |
| Bathrooms | 1.33 | 0.73 | 0 | 18 |
| Beds | 1.94 | 1.57 | 0 | 50 |
| CableTV | 0.33 | 0.47 | 0 | 1 |
| Elevator | 0.21 | 0.41 | 0 | 1 |
| Family kid friendly | 0.48 | 0.5 | 0 | 1 |
| Free parking on premises | 0.4 | 0.49 | 0 | 1 |
| Lock on bed room door | 0.33 | 0.47 | 0 | 1 |
| Number of reviews | 26.83 | 47.7 | 0 | 711 |
| Paid parking off premises | 0.06 | 0.24 | 0 | 1 |
| Review scores rating | 75.02 | 39.04 | 0 | 100 |
| Reviews per month | 1.49 | 2.11 | 0 | 140 |
| Smoking allowed | 0.05 | 0.21 | 0 | 1 |
| Suitable for events | 0.05 | 0.22 | 0 | 1 |

may lead to redundancy between variables. multicollinearity for a given predictor, can be measured by calculating a score known as the variance inflation factor (VIF) that represents the amount of variance of a coefficient is inflated as a result of multicollinearity in the model (Assaf et al., 2019). As a thumb rule VIF values above 10 indicate problematic amount of multicollinearity (Chatterjee and Hadi, 2015). The correlation matrix (Table 3) for the 14 important variables used in the model visibly shows the no collinearity problem. Additional indication on the multicollinearity problem in this dataset has been performed after computing VIFs for all the variables (as identified in Fig. 1) and the VIFs for all the variables are < 10.

### 3.5. Performance measures

Our objective was to perform a comparative assessment of the performance of the applied models for their explanatory and prediction capabilities while considering their parsimony (i.e., defending in contradiction of overfitting). Whereas the explanatory potential of a model can be evaluated through $R^2$ (in-sample fit measures), the evaluation of the predictability of a model applies the root mean squared error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE) (Sharma et al., 2018; Becker et al., 2013; Shmueli et al., 2016). The degree of likeness between the estimated and actual outcome is defined by $R^2$ (closer to value 1 indicates more similarity). Model-estimated values specify better confidence when the values of RMSE, MAPE, and MAE are low.

## 4. Results and discussion

The open-source R environment (R Foundation for Statistical Computing, 2016) on a Windows system with an Intel core and 2.5 GHz processor was used for conducting all experiments applying the OLS regression, random forest, and CTree models. The results of the variable influence of 143 explanatory variables (described in Section 3.2) on room pricing were estimated using OLS regression applied to full samples of the whole dataset, and separately, the 11-individual city-specific individual samples were used to implement the RF, CTree, and OLS regression models. The full dataset comprised 151,955 observations. The individual city-specific samples included Austin (11,134), Boston (5,954), Chicago (6,861), DC (8,720), Los Angeles (38,835), Nashville (5,234), New Orleans (4,608), New York (47,679), San Diego (10,494), San Francisco (4,680) and Seattle (7,756). With the aim of deciding if a specified variable was a significant determinant of room pricing, a comparison of the results of variable importance was performed across variables, models, and cities.

We have applied *partykit* and *randomForest* r packages for implementing the RF and CTree machine learning algorithms. Followings are parameter settings for CTree: significance level ($\propto$=0.05), Maximum depth ($maxdepth = Inf$), test statistic ($teststat = quad, max$) method for p-value (*testtype*); and for RF: Number of trees ($ntree = 500$), Number of eligible variables ($mtry = \sqrt{d}$) where d is number of independent variables. The stopping criterion is only controlled by $\propto$. The hyperparameter teststat, testtype and mincriterion govern how the global null hypothesis of independence between independent variables and the dependent variable is tested. A split is recognized when the sum of the weights in both nodes is greater than minsplit. The parameter $mtry > 0$ represents that a RF like 'variable selection', or mtry input variables are randomly selected at each node. For all the 11 cities data applied using CTree model, the number of trees are 51 and number of variables at each split are 47 and the Table 4 presents mean residual sum of square (RSS) as optimal criteria in the parameter selection and model selection. Smaller RSS specifies a better fit of the model to the data.

### 4.1. OLS regression applied on full samples

Initially, a traditional OLS regression model was applied to detect relationships between a dependent variable and a set of 143 independent variables for the entire sample (151,955 observations) of the listing dataset. The estimated 53 variables that only had a statistical influence on room price from the OLS regression model implementation are shown in Table 5. Due to a shortage of space, only statistically significant variables are presented.

### 4.2. Variable importance considering the 11 separate samples from individual cities

As with OLS regression, we also attempted to perform analysis using the RF and CTree models on the full samples of the dataset (151,955

**Table 3**
. Correlation matrix of important variables.

| Variables | Acco | Bath | Beds | Cable | Elev | Kid | FPark | Lock | Rnum | PPark | Rscore | Rmonth | Smoke | Event |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Accommodates (Acco) | 1.00 | | | | | | | | | | | | | |
| Bathrooms (Bath) | 0.59 | 1.00 | | | | | | | | | | | | |
| Beds | 0.51 | 0.57 | 1.00 | | | | | | | | | | | |
| CableTV (Cable) | 0.18 | 0.13 | 0.15 | 1.00 | | | | | | | | | | |
| Elevator (Elev) | −0.05 | −0.06 | −0.06 | 0.05 | 1.00 | | | | | | | | | |
| Family kid friendly (Kid) | 0.38 | 0.18 | 0.30 | 0.16 | 0.02 | 1.00 | | | | | | | | |
| Freeparking on premises (FPark) | 0.28 | 0.23 | 0.23 | 0.09 | −0.12 | 0.16 | 1.00 | | | | | | | |
| Lock on bed room door (Lock) | −0.06 | 0.00 | −0.04 | −0.10 | −0.06 | −0.06 | 0.02 | 1.00 | | | | | | |
| Number of reviews (Rnum) | 0.01 | −0.07 | 0.00 | 0.12 | −0.11 | 0.12 | 0.02 | −0.03 | 1.00 | | | | | |
| Paid parking off premises (PPark) | 0.01 | −0.02 | 0.00 | 0.04 | 0.12 | 0.00 | −0.15 | 0.04 | 0.06 | 1.00 | | | | |
| Review scores rating (Rscore) | 0.04 | −0.04 | 0.04 | 0.09 | −0.09 | 0.10 | 0.02 | 0.03 | 0.29 | 0.07 | 1.00 | | | |
| Reviews per month (Rmonth) | 0.04 | −0.06 | 0.03 | 0.02 | −0.08 | 0.07 | 0.03 | 0.12 | 0.58 | 0.10 | 0.36 | 1.00 | | |
| Smoking allowed (Smoke) | −0.05 | −0.01 | −0.04 | −0.04 | 0.00 | −0.03 | 0.02 | 0.03 | −0.03 | −0.03 | −0.06 | −0.05 | 1.00 | |
| Suitable for events (Event) | 0.18 | 0.14 | 0.14 | 0.01 | −0.02 | 0.10 | 0.09 | 0.01 | −0.02 | −0.01 | −0.05 | −0.03 | 0.16 | 1.00 |

**Table 4**

CTree model outputs (No. Inner nodes/terminal nodes and Length/ width/ depth of tree) for 11 cities.

| City | No. Inner nodes/ terminal nodes | Length/ width/ depth | Mean of squared residuals |
|---|---|---|---|
| Austin | 43/44 | 87/44/10 | 129325.2 |
| Boston | 49/50 | 99/50/10 | 15704.04 |
| Chicago | 38/39 | 77/39/10 | 10605.27 |
| DC | 38/39 | 77/39/10 | 100136 |
| Los Angeles | 37/38 | 75/38/10 | 77256.09 |
| Nashville | 30/31 | 61/31/9 | 29776.04 |
| New Orleans | 30/31 | 61/31/9 | 44351.26 |
| New York | 35/36 | 71/36/9 | 34765.19 |
| San Diego | 41/42 | 83/42/10 | 31178.31 |
| San Francisco | 14/15 | 29/15/7 | 39889.33 |
| Seattle | 48/49 | 97/49/10 | 25324 |

observations). However, due to the computational burden involved with such a huge quantity of data, we undertook implementation of the three models on city-specific samples. Thus, we carried out a model implementation, regarding price as the dependent variable, and 143 explanatory variables for all three models were applied individually for each of the 11 cities. Thereafter, we analyzed the estimated variable importance of the 143 variables for the 11 cities separately. The estimated variable importance score was converted to a 0–100 scale, where 100 represents the variable with the highest importance.

Table 6 presents the variable importance score of all cities observed using OLS regression. It can be seen from Table 6 that for the city of Austin, the number of *bathroom* was assigned the highest variable importance score (100), followed by *review scores rating* (48.3), and so on. When comparing variable importance across various cities, 6 out of 11 cities have shown number of bathrooms to be the most important variable for determining room pricing. As separate regression was used for each of the 11 cities, variable importance scores given in the table are not strictly comparable across the cities. Nevertheless, we produced the average score of the 11 cities for each individual variable to obtain a comprehensive understanding. While each individual column reveals variable importance for each city separately, the average of this score can be taken as a broad measure of the variable importance of 11 cities in general. The top five attributes demonstrated to have the highest average score were *Bathrooms, Accommodates, Review scores rating, Elevator,* and *Reviews per month*. Amongst the amenities, *Elevator* and *Freeparking on premises* proved to be the most important determinants.

Similar identification of important variables with respect to the RF and CTree models can be identified from Table 7 and 8 respectively.

### 4.3. Comparative performance of three models

Because the model outputs are quite different for each city sample, we analyzed the performance of the models using the four statistical measures. The results are given in Table 9.

Amongst the three competing models, RF was found to be better because of its comparatively lower error measures and higher $R^2$ values across all of the cities.

### 4.4. Overall variable importance scores by aggregating scores from three applied models

Because the variable importance score differs across the models, we compared the average score of variable importance obtained from the three different models and plotted the same in Fig. 1 to get an overall idea of variable importance across the 11 US cities. We estimated composite score by taking the arithmetic mean of the individual cities' variable importance scores. According to these composite scores, the top 10 important room-price determinants from OLS approach are as follows: *Bathrooms, Accommodates, Review scores rating, Elevator, Reviews per month, Beds, Paid parking off premises, Indoor fireplace, Cable TV,* and *Family kid friendly*. Similarly, the top 10 room-price determinants from RF based on the composite scores were found to be: *Accommodates, Bathrooms, Beds, Reviews per month, Number of reviews, Review scores rating, Elevator, Free parking on premises, Family kid friendly, Smoking allowed.* Based on composite scores, the top 10 room-price determinants from CTree approach were identified: *Accommodates, Bathrooms, Reviews per month, Review scores rating, Elevator, Wifi, Pool, Coffee maker, Beds and Internet.*

In Fig. 1, the graph illustrates the agreement on the variable importance of the top 14 determinants computed from the application of three applied models on listing dataset. Interestingly, the graph shows that all the three models agree on the topmost influence of *Bathrooms, Accommodates, Review score rating* on *Room Pricing*. However, *Reviews*

**Table 5**

Results of OLS regression model showing the estimated 53 variables which only have statistical influence on room price.

| Variables | Estimate | t-value |
|---|---|---|
| Bathrooms | 129.65 | 87.59*** |
| Accommodates | 37.93 | 59.45*** |
| Review scores rating | −0.75 | −30.92*** |
| Beds | −14.57 | −15.65*** |
| Suitable for events | 51.90 | 13.52*** |
| Indoor fireplace | 33.85 | 13.00*** |
| Pool | 32.00 | 9.56*** |
| Hottub | 30.49 | 8.95*** |
| Wifi | −43.27 | −8.34*** |
| Paid parking off premises | 28.31 | 7.60*** |
| CableTV | 15.25 | 7.45*** |
| Buzzer wireless intercom | 20.70 | 7.40*** |
| Kitchen | −23.83 | −7.24*** |
| Reviews per month | −3.87 | −7.21*** |
| Free parking on premises | −15.38 | −7.10*** |
| Lock on bed roomdoor | −13.14 | −6.83*** |
| Essentials | −24.82 | −6.75*** |
| Doorman | 29.06 | 5.45*** |
| Smokedetector | −17.03 | −5.33*** |
| Shampoo | 11.81 | 5.23*** |
| Private livingroom | −14.08 | −4.78*** |
| Bathtub | −14.79 | −4.58*** |
| Microwave | −20.70 | −4.38*** |
| Family kid friendly | 8.88 | 4.37*** |
| Coffeemaker | 17.84 | 4.34*** |
| Elevator | 11.17 | 4.26*** |
| Extra pillows and blankets | −13.26 | −3.71*** |
| Dryer | −24.62 | −3.65*** |
| Dishes and silverware | 23.55 | 3.62*** |
| Baby sitter recommendations | 23.93 | 3.61*** |
| Fireplace guards | −32.61 | −3.52*** |
| Free street parking | −8.12 | −3.31*** |
| 24hourcheckin | −8.58 | −3.25*** |
| Beach essentials | 21.29 | 3.25*** |
| Carbonmonoxide detector | 7.08 | 3.23*** |
| Pocketwifi | 23.53 | 3.17*** |
| Safetycard | −8.00 | −3.09*** |
| Washer | 19.33 | 2.86*** |
| Luggage drop off allowed | 7.40 | 2.74*** |
| translationmissing:enhosting_amenity_49 | 9.54 | 2.65*** |
| Waterfront | 32.62 | 2.63*** |
| Paid parking on premises | −13.60 | −2.58*** |
| Beachfront | 34.78 | 2.49** |
| Building staff | 26.49 | 2.47** |
| Airconditioning | 5.88 | 2.45** |
| Private entrance | 4.98 | 2.26** |
| Smoking allowed | −9.04 | −2.24** |
| Selfcheckin | −22.27 | −2.23** |
| Number of reviews | −0.05 | −2.17** |
| Full kitchen | 20.04 | 2.04** |
| Internet | −4.34 | −2.02** |
| Disabled parking spot | −20.15 | −2.00** |
| Firstaidkit | −3.96 | −1.96** |

***Note:*** *** and ** denotes significant at 1% and 5% levels respectively.

**Table 6**
top 14 variable importance results from OLS from the listing attributes across 11 cities in the US.

| Variables | Austin | Boston | Chicago | D C | Los Angeles | Nashville | New Orleans | New York | San Diego | San Francisco | Seattle | Average score |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Bathrooms* | 100.0 | 74.3 | 72.5 | 68.4 | 100.0 | 100.0 | 100.0 | 64.8 | 100.0 | 64.6 | 100.0 | 85.9 |
| *Accommodates* | 42.8 | 100.0 | 100.0 | 71.2 | 37.4 | 1.4 | 47.1 | 100.0 | 41.5 | 100.0 | 42.8 | 62.2 |
| *Review scores rating* | 48.3 | 37.4 | 23.3 | 100.0 | 23.5 | 37.6 | 19.6 | 17.9 | 33.1 | 12.3 | 48.3 | 36.5 |
| *Elevator* | 9.6 | 49.3 | 33.2 | 4.4 | 4.0 | 35.9 | 25.2 | 17.7 | 10.7 | 5.3 | 9.6 | 18.6 |
| *Reviews per month* | 3.3 | 38.0 | 28.2 | 2.2 | 3.2 | 33.3 | 29.4 | 10.8 | 7.8 | 35.5 | 3.3 | 17.7 |
| *Beds* | 1.4 | 3.3 | 22.1 | 20.2 | 17.6 | 55.0 | 44.3 | 16.4 | 6.7 | 4.9 | 1.4 | 17.6 |
| *Paid parking off premises* | 5.9 | 53.9 | 12.8 | 5.0 | 0.7 | 5.7 | 13.6 | 19.0 | 13.6 | 21.7 | 5.9 | 14.4 |
| *Indoor fireplace* | 4.4 | 13.1 | 26.0 | 19.2 | 3.7 | 17.1 | 12.0 | 24.3 | 8.3 | 19.4 | 4.4 | 13.8 |
| *CableTV* | 12.8 | 38.3 | 16.6 | 9.4 | 2.7 | 3.0 | 10.7 | 14.0 | 10.5 | 19.5 | 12.8 | 13.7 |
| *Family kid friendly* | 1.1 | 57.1 | 29.1 | 21.9 | 4.1 | 1.3 | 10.2 | 0.9 | 6.4 | 15.4 | 1.1 | 13.5 |
| *Lock on bed room door* | 10.4 | 47.7 | 11.5 | 8.4 | 3.1 | 4.5 | 4.9 | 22.6 | 4.9 | 18.5 | 10.4 | 13.4 |
| *Fire extinguisher* | 3.3 | 53.1 | 24.3 | 3.1 | 0.9 | 5.4 | 19.0 | 4.9 | 1.7 | 12.4 | 3.3 | 12.0 |
| *Suitable for events* | 2.6 | 28.6 | 18.2 | 10.0 | 8.7 | 15.1 | 13.6 | 18.2 | 9.6 | 3.3 | 2.6 | 11.9 |
| *Buzzer wireless intercom* | 24.0 | 22.7 | 4.1 | 0.3 | 4.0 | 1.7 | 5.6 | 4.5 | 13.6 | 25.7 | 24.0 | 11.9 |

*per month* and *Beds* considered as more influential in RF.

Even if there are differences on variable importance computed by RF model among eleven cities in the USA, some of the determinants still agree as similar key determinants across the models.

### 4.5. Variable importance in the presence of city specific regional heterogeneity

The performance of the RF model ($R^2$) is better for all the eleven city-based models to explain the variable importance. Therefore, we discuss any presence of city specific regional heterogeneity of the important room price determinants from the RF results in Table 7. For example, *Accommodates* is found to be the top most important price determinant (based on variable importance score) in the cities Boston, Chicago, DC, New York, San Francisco, and Seattle. Next, *bathrooms* is the top most important variable for Austin, Chicago, Los Angeles, Nashville, and San Diego. Chicago city has shown to approximately equal top importance for both *Accommodates* and *Bathrooms.* The *Reviews per month* shown to be the most important variable for New Orleans and second most important for New York city. Whereas, *Review score rating, Number of reviews* including the *Reviews per month* are shown to have less importance in Los Angeles, San Diego and Seattle than the other cities. So far, the amenities variables are concerned, *Elevator* has identified with more variable importance score in Boston, New York, and Nashville. The amenity listings *Private living room, Wifi, Smoke detector, Airconditioning, Free parking* are most important in New York city. *Wifi* are important variables in cities like Seattle, Boston, and New York. Amongst some of the interesting observations of amenities, *Private living room* is a more important variable in New York even than *Review score rating* and *Bed.* In San Francisco, *Smoking allowed* is top second important variable after *Accommodates*. Boston is shown to have more *Family kid friendly* importance than *Review scores rating.* The *Free parking on premises* is shown to have more variable importance in DC and Nashville.

## 5. Theoretical and practical implications

The study contributes to the extant literature in the following ways: it contributes to the tourism & hospitality management domain for contemplating the accommodation industry as small-travel and tourism business (Wang and Hung, 2015). The focus of the study is to identify key price determinants from a huge number of host listing attributes of a sharing rental platform and to explore city-specific generalization for identified determinants across eleven US cities. As we have mentioned both in the introduction and literature sections, that long-term success of the rental industry is significantly determined by pricing and Airbnb hosts will be able to develop improved practices through identification of key price determinants that persuade guests' readiness to pay and then fixing room price based on guests' insights and fulfilment of expectations. The study also reveals locally generalizable determinants across 11 cities in the US, which may help Airbnb hosts to undertake city-specific room pricing strategies. These strategies may help them to improve their services regarding identified key listings that influence pricing in the underlying dynamic market situations. It is crucial for Airbnb hosts to communicate effectively on the listing attributes, in terms of amenities and other attributes that satisfy tourists, and set prices for long-term sustainability.

Inter-disciplinary perspectives of the present research also contribute theoretically in varied domains like travel, tourism, marketing and new digital economy (Ye et al., 2009; Zhu and Zhang, 2010; Liang et al., 2017; Gibbs et al., 2018; Benötez-Aurioles, 2018). Sharing rentals of network economy is also leading to the emerging growth of the

**Table 7**
top 14 variable importance results from RF from the listing attributes across 11 cities in the US.

| variables | Austin | Boston | Chicago | D C | Los Angeles | Nashville | New Orleans | New York | San Diego | San Francisco | Seattle | Average score |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Accommodates* | 69.22 | 100.00 | 100.00 | 100.00 | 37.63 | 76.75 | 90.59 | 100.00 | 54.87 | 100.00 | 100.00 | 84.46 |
| *Bathrooms* | 100.00 | 60.94 | 99.84 | 97.73 | 100.00 | 100.00 | 83.11 | 72.36 | 100.00 | 52.22 | 30.78 | 81.54 |
| *Beds* | 48.40 | 47.68 | 58.22 | 36.91 | 22.57 | 78.68 | 63.62 | 43.18 | 36.51 | 35.06 | 20.81 | 44.69 |
| *Reviews per month* | 32.12 | 54.59 | 48.29 | 30.32 | 10.98 | 46.57 | 100.00 | 72.85 | 15.23 | 39.28 | 15.38 | 42.33 |
| *Number of reviews* | 24.23 | 47.64 | 41.81 | 52.59 | 9.24 | 27.23 | 27.28 | 44.16 | 13.55 | 27.14 | 21.04 | 30.54 |
| *Review scores rating* | 12.27 | 30.31 | 19.99 | 18.35 | 8.04 | 17.12 | 29.53 | 76.39 | 7.17 | 27.71 | 4.09 | 22.81 |
| *Elevator* | 2.94 | 27.79 | 10.65 | 7.78 | 5.11 | 14.26 | 2.73 | 15.23 | 7.97 | 2.26 | 2.01 | 8.97 |
| *Freeparking on premises* | 3.33 | 5.44 | 3.30 | 12.05 | 1.61 | 16.48 | 1.99 | 23.47 | 3.87 | 19.45 | 5.88 | 8.81 |
| *Family kid friendly* | 7.58 | 31.98 | 11.43 | 10.11 | 4.23 | 4.73 | 2.11 | 7.79 | 6.22 | 7.41 | 0.79 | 8.58 |
| *Smoking allowed* | 1.48 | 1.53 | 1.34 | 2.76 | 3.94 | 0.22 | 0.43 | 1.35 | 1.09 | 73.59 | 0.15 | 7.99 |
| *Private living room* | 0.67 | 2.68 | 1.56 | 2.29 | 0.83 | 0.83 | 0.60 | 60.41 | 0.94 | 0.70 | 0.12 | 6.51 |
| *Wifi* | 1.26 | 7.57 | 3.22 | 1.58 | 2.95 | 2.52 | 0.24 | 32.84 | 4.19 | 0.35 | 13.89 | 6.42 |
| *Smokedetector* | 2.62 | 5.66 | 1.46 | 4.80 | 2.95 | 5.35 | 0.45 | 40.70 | 2.52 | 0.37 | 3.34 | 6.38 |
| *Airconditioning* | 0.50 | 7.46 | 3.55 | 3.57 | 1.63 | 4.58 | 0.25 | 37.52 | 1.94 | 4.23 | 0.70 | 5.99 |

**Table 8**
top 14 variable importance results from CTrees from the listing attributes across 11 cities in the US.

| variables | Austin | Boston | Chicago | D C | Los Angeles | Nashville | New Orleans | New York | San Diego | San Francisco | Seattle | Average score |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Accommodates* | 46.0 | 100.0 | 100.0 | 56.1 | 17.6 | 15.8 | 83.4 | 100.0 | 50.0 | 100.0 | 100.0 | 69.9 |
| *Bathrooms* | 100.0 | 44.5 | 60.7 | 42.4 | 100.0 | 100.0 | 100.0 | 43.4 | 100.0 | 48.4 | 13.3 | 68.4 |
| *Review per month* | 36.7 | 11.1 | 27.2 | 1.9 | 0.6 | 33.3 | 24.6 | 0.7 | 13.7 | 7.6 | 2.2 | 14.5 |
| *Review scores rating* | 13.0 | 6.2 | 3.2 | 100.0 | 2.1 | 8.3 | 0.5 | 3.8 | 12.7 | 1.0 | 0.0 | 13.7 |
| *Elevator* | 2.4 | 46.7 | 7.9 | 0.2 | 0.0 | 27.7 | 6.9 | 15.7 | 11.1 | 0.1 | 8.2 | 11.5 |
| *Wifi* | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 4.7 | 1.9 | 0.0 | 41.9 | 4.4 |
| *Pool* | 0.0 | 0.0 | 0.0 | 0.0 | 32.8 | 0.0 | 4.1 | 0.0 | 8.7 | 0.0 | 0.0 | 4.1 |
| *Coffeemaker* | 0.0 | 39.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 3.6 |
| *Beds* | 0.0 | 0.0 | 0.0 | 0.6 | 0.0 | 17.8 | 11.8 | 0.0 | 0.9 | 0.0 | 3.1 | 3.1 |
| *Internet* | 1.6 | 24.3 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 2.4 |
| *Smoking allowed* | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 18.3 | 0.0 | 1.7 |
| *Gym* | 0.0 | 14.8 | 0.6 | 0.3 | 0.0 | 0.0 | 0.0 | 0.2 | 0.0 | 0.0 | 2.1 | 1.6 |
| *Hotwater* | 0.0 | 2.5 | 0.0 | 13.2 | 0.0 | 0.5 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 1.5 |
| *Suitable for events* | 0.0 | 5.7 | 1.3 | 0.0 | 0.6 | 0.0 | 0.0 | 6.7 | 1.8 | 0.0 | 0.0 | 1.5 |
| *Longterm stays allowed* | 0.1 | 14.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.5 | 1.4 |

**Table 9**
Comparative performance measures for city specific model implementation.

| City | Method | RMSE | MAE | MAPE | $R^2$ |
|---|---|---|---|---|---|
| Austin | OLS | 382.05 | 171.05 | 224.1 | 34.50% |
| | CTREE | 369.8 | 144.84 | 49.43 | 38.60% |
| | RF | 188.85 | 67.71 | 22.27 | 84.00% |
| Boston | OLS | 133.8 | 76.68 | 76.66 | 32.30% |
| | CTREE | 128.06 | 66.51 | 37.17 | 37.90% |
| | RF | 63.3 | 29.43 | 16.12 | 84.80% |
| Chicago | OLS | 118.25 | 60.08 | 124.43 | 35.40% |
| | CTREE | 113.31 | 55.01 | 39.52 | 40.70% |
| | RF | 56.91 | 23.82 | 16.58 | 85.00% |
| DC | OLS | 300.54 | 145.69 | 235.64 | 29.50% |
| | CTREE | 278.22 | 114.88 | 43.22 | 39.60% |
| | RF | 142.52 | 54 | 19.2 | 84.10% |
| Los Angeles | OLS | 285.07 | 111.86 | 469.93 | 36.30% |
| | CTREE | 264.63 | 82.73 | 41.8 | 45.10% |
| | RF | 135.64 | 38.26 | 17.73 | 85.60% |
| Nashville | OLS | 166.55 | 89.87 | 74.89 | 40.80% |
| | CTREE | 163.61 | 74.82 | 34.17 | 42.90% |
| | RF | 94.8 | 32.88 | 14.53 | 80.80% |
| New Orleans | OLS | 200.66 | 79.86 | 96.77 | 33.60% |
| | CTREE | 201.28 | 73.94 | 35.52 | 33.20% |
| | RF | 100.57 | 31.24 | 14.48 | 83.30% |
| New York | OLS | 209.88 | 66.74 | 75.03 | 16.10% |
| | CTREE | 206.68 | 63.27 | 42.47 | 18.60% |
| | RF | 117.82 | 31.12 | 18.5 | 73.60% |
| San Diego | OLS | 201.64 | 98.19 | 55087.55 | 46.60% |
| | CTREE | 190.81 | 84.63 | 38.05 | 52.20% |
| | RF | 93.51 | 37.6 | 16.84 | 88.50% |
| San Francisco | OLS | 320.49 | 184.97 | 83.28 | 26.30% |
| | CTREE | 225.78 | 83.3 | 36.17 | 27.20% |
| | RF | 119.81 | 36.5 | 14.56 | 79.50% |
| Seattle | OLS | 232.42 | 69.47 | 165.28 | 17.40% |
| | CTREE | 225.56 | 56.02 | 32.8 | 22.20% |
| | RF | 127.72 | 25.41 | 13.94 | 75.10% |

vacation rental industry. There is also an increasing trend of novelty seeking and collaborative consumption on sharing rental platforms based on travel bragging items (Guttentag, 2015). The guests are looking for specific amenities items offered by the hosts on these platforms and as there is a lack of knowledge on room price determinants on sharing accommodation, this work a valuable foundation to contribute in this domain. As a sub-domain of travel and tourism, the traditional accommodation industry is going to be disrupted significantly in the era of new digital economy, and the price determinants of traditional hotels are either changing or replaced by newer attributes as the host's own property is listed for rent on peer-to-peer rentals.

The major practical contribution from the work is on the most targeted focus of the host on a reduced number of key pricing determinants and thus, the host can able to increase their average profit after taking care guest's rental experience. The satisfied, improved rental experience from travellers will also improve review rating and finally pull more attraction on the peer-to-peer online rentals. The host can also compare their listings with neighboring host and alongwith the demand information they can dynamically adjust their pricing and improve their occupancy rate.

## 6. Conclusion

The study developed an approach to identify the relationships between determinants and room pricing in Airbnb, peer-to-peer rentals using six variables chosen based on previous literature and 137 amenities offered by the hosts. The work Implemented OLS regression using full samples of the listing dataset and found 53 explanatory variables significantly determining the room pricing. To explore better model fitment, we applied two tree-based models: random forest tree and CTree. Unlike OLS, these two models could not be implemented on the full listing samples due to higher computational burden from the existing algorithm embedded in built-in applications executed on both R and Matlab environment. To overcome this issue we have used the city-specific samples for all the three model implementation. Therefore, we have three models, and each model applied independently on 11 city samples. Out of the three models, random forest is found to be better performing based on all the measures of performance from the above 11 independent city specific implementations. Nevertheless, we estimated variable importance scores using all the models applied to 11 city specific samples. To obtain a composite score applicable for the entire country (USA), the city-specific variable importance scores for a respective individual variable is averaged for each model (OLS, CTree, and random forest). The composite scores using all the three models are presented graphically to obtain a comprehensive visual understanding of the variable importance of the determinants influencing room pricing in the USA in general. Although ranking of variable importance marginally differs across models still the key determinants identified through the random forest are generalizable from the same findings of the variable's influence obtained from the other two models.

The tourists want to enjoy the good experience from the versatile listings including amenities offered by the hosts as matched with their looked-for rentals (Liang et al., 2017). The present research offers important insights into the complex relationships between Airbnb room price and host listing attributes including amenities on peer-to-peer rentals for eleven cities. The insights from key room price determinants from a huge host listing attributes will help Airbnb hosts to offer improved services and amenities to satisfy the guests and simultaneously hosts will be able to fix room price to avoid vacancy or increase margin after taking care the identified key listing attributes. The study indicates that Airbnb customers are sensitive to both quality and quantity parameters for paying premium room price which may have some possible theoretical and practical implication in the domains of hospitality, travelling and tourism and marketing. From consumer behavior point of view, the study contributes possibly a new perspective for the emerging growth of vacation rentals in setting room price and choice of rentals in different cities for the peer-to-peer accommodation. The study clearly indicates that for some cities Airbnb users ready to pay a premium price based on consideration of certain host listings consistently as important attributes. The study reveals that the nature of listings and the criteria of tourist guest as variable importance for selecting shared accommodation are different from traditional hotels as well as for different cities. The guests of Airbnb rentals are more influenced by room price than the guests of traditional hotels (Guttentag, 2015). Thus, as an inexpert host compared to the professional manager of traditional hotels, the hosts require to understand the significant pricing determinants which help them to list attractive offer to attract tourist guests.

Along with OLS regression, we used random forest and CTree models not applied in the tourism and hospitality industries. We have tried to estimate a composite score that may be helpful in getting the generalizability of the influence of amenities and other explanatory variables in the presence city specific regional heterogeneity on a shared rental platform.

The present work has achieved an important contribution by considering a composite amenities variable consisting of a huge number of amenities offered on shared rental business. Each of individual amenities used in our model as independent variables apart from six other common variables to get an interesting insight of the influence of specific amenities offered from the perspective of the host, guest, travellers, tourists as well as researchers on Airbnb platform.

Similar to other research, the present study also involves limitations. The dependent variable in our study has considered the listing price (Abrate et al., 2011; Gibbs et al., 2018) rather than the actual price on which rental was sold. Nevertheless, we also acknowledge that the present study has not considered any qualitative determinants (like socio-psychological parameters) that might have influence on room pricing on sharing rental. There is also scope to consider a global price determinant model for obtaining a more generalizable variable importance for listings on Airbnb platform globally across the countries.

## Acknowledgement

The authors would like to thank the editor and the anonymous reviewers for providing valuable feedback through their constructive comments during revising the manuscript.

## References

Abrate, G., Viglia, G., 2017. Personal or product reputation? Optimizing revenues in the sharing economy. J. Travel. Res. https://doi.org/10.1177/0047287517741998.
Airbnb, 2018. Fast Facts. (Accessed on 22, April, 2018. https://press.atairbnb.com/fast-facts.
Albayrak, T., Caber, M., 2015. Prioritisation of the hotel attributes according to their influence on satisfaction: a comparison of two techniques. Tour. Manag. 46, 43–50.
Alcántara-Alcover, E., Artacho-Ramírez, M.Á., Martínez-Guillamón, N., Campos-Soriano, N., 2013. Purpose of stay and willingness to stay as dimensions to identify and evaluate hotel experiences. Int. J. Hosp. Manag. 33, 357–365.
Alvarado, C., Hennis, S., Haywood, J., 2016. STR: Airbnb's Impact on NYC's Boroughs. (Accessed 30, December 2018. http://www.hotelnewsnow.com/Articles/30455/STRAirbnbs-impact-on-NYCs-boroughs.
Amaro, S., Andreu, L., Huang, S., 2018. Millenials' intentions to book on Airbnb. Curr. Issues Tour. 1–15. https://doi.org/10.1080/13683500.2018.1448368.
Anderson, Donald N., 2014. "Not just a taxi"? For-profit ridesharing, driver strategies, and VMT. Transportation 41 (5), 1099–1117.
Ariffin, A.A.M., Maghzi, A., 2012. A preliminary study on customer expectations of hotel hospitality: influences of personal and hotel factors. Int. J. Hosp. Manag. 31 (1), 191–198.
Assaf, A.G., Tsionas, M., Tasiopoulos, A., 2019. Diagnosing and correcting the effects of multicollinearity: bayesian implications of ridge regression. Tour. Manag. 71, 1–8.
Aziz, H.A., Saleh, M., Rasmy, M.H., Elshishiny, H., 2011. Dynamic room pricing model for hotel revenue management systems. Egypt. Inform. J. 12 (3), 177–183. https://doi.org/10.1016/j.eij.2011.08.001.
Baggio, R., Sainaghi, R., 2011. Complex and chaotic tourism systems: towards a quantitative approach. Int. J. Contemp. Hosp. Manage. 23 (6), 840–861. https://doi.org/10.1108/09596111111153501.
Batmaz, I., Karagoz, P., Serdar, G., 2017. A comparative study on learning to rank with computational methods. In: IEEE International Conference on Big Data (Big Data). IEEE. pp. 1898–1906 (2017, December).
Becerra, M., Santaló, J., Silva, R., 2013. Being better vs. Being different: differentiation, competition, and pricing strategies in the Spanish hotel industry. Tour. Manag. 34, 71–79. https://doi.org/10.1016/j.tourman.2012.03.014.
Becker, J.-M., Rai, A., Rigdon, E., 2013. Predictive validity and formative measurement in structural equation modeling: embracing practical relevance. Thirty Fourth International Conference on Information Systems 1–19. https://doi.org/10.1146/annurev.clinpsy.1.102803.144239. (January 2016).
Benítez-Aurioles, B., 2017. Price and Booking Determinants in the Peer-to-Peer Market of Tourist Accommodation. The Case for Airbnb in Barcelona. Doctoral dissertation. CEMFI, Spain Master Thesis.
Benítez-Aurioles, B., 2018. Why are flexible booking policies priced negatively? Tour. Manag. 67, 312–325. https://doi.org/10.1016/j.tourman.2018.02.008.
Botsman, R., Rogers, R., 2011. What's mine is yours: how collaborative consumption is changing the way we live Vol. 5 Collins, London.
Breiman, L., 2001. Random forest. Mach. Learn. 45 (1), 5–32. https://doi.org/10.1016/j.compbiomed.2011.03.001.
Breiman, Leo, 2002. Manual on Setting up, Using, and Understanding Random Forests v3. 1. URL:. http://oz.berkeley.edu/users/breiman/Using_random_forests_V31(2002).
Breiman, L., Friedman, J., Olshen, R., Stone, C., 1984. Classification and Regression Trees. Wadsworth & Brooks/Cole Advanced Books & Software, Pacific California.
Bridges, J., Vásquez, C., 2018. If nearly all Airbnb reviews are positive, does that make them meaningless? Curr. Issues Tourism 21 (18), 2057–2075.
Chatterjee, S., Hadi, A.S., 2015. Regression Analysis by Example. John Wiley & Sons.
Chen, C.F., Rothschild, R., 2010. An application of hedonic pricing analysis to the case of hotel rooms in Taipei. Tour. Econ. 16 (3), 685–694. https://doi.org/10.5367/000000010792278310.
Chen, Y., Xie, K.L., 2017. Consumer valuation of Airbnb listings: a hedonic pricing approach. Int. J. Contemp. Hosp. Manage. 29 (9), 2405–2424. https://doi.org/10.1108/IJCHM-10-2016-0606.
Cohen, B., Kietzmann, J., 2014. Ride on ! Mobility business models for the sharing economy ride on ! mobility business models for the sharing economy. Organ. Environ. 27 (3), 279–296. https://doi.org/10.1177/1086026614546199.
Dolnicar, S., Otter, T., 2003. Which hotel attributes matter? A review of previous and a framework for future research. Griffin, T., Harris, R. (Eds.), Proceedings of the 9th Annual Conference of the Asia Pacific Tourism Association (APTA), 1 176–188.
Ert, E., Fleischer, A., Magen, N., 2016. Trust and reputation in the sharing economy: the role of personal photos in Airbnb. Tour. Manag. 55, 62–73. https://doi.org/10.1016/j.tourman.2016.01.013.
Espinet, J.M., Saez, M., Coenders, G., Fluvia, M., 2003. Effect on prices of the attributes of holiday hotels: a hedonic prices approach. Tour. Econ. 9 (2), 165–177. https://doi.org/10.5367/000000003101298330.
Festila, M., Müller, S., 2017. The impact of technology-mediated consumption on identity. The Case of Airbnb Paper Presented at the Proceedings of the 50th Hawaii International Conference on System Sciences. (2017).
Genuer, R., Poggi, J.-M., Tuleau-Malot, C., 2010. Variable selection using random forests. Pattern Recognit. Lett. 31 (14), 2225–2236. https://doi.org/10.1016/j.patrec.2010.03.014.
Gibbs, C., Guttentag, D., Gretzel, U., Morton, J., Goodwill, A., 2018. Pricing in the sharing economy: a hedonic pricing model applied to Airbnb listings. J. Travel Tour. Mark. 35 (1), 46–56. https://doi.org/10.1080/10548408.2017.1308292.
Gottlieb, C., 2013. Residential short-term rentals: should local governments regulate the "Industry"? Plan. Environ. Law. https://doi.org/10.1080/15480755.2013.766496.
Grömping, U., 2009. Variable importance assessment in regression: linear regression versus random forest. Am. Stat. 63 (4), 308–319. https://doi.org/10.1198/tast.2009.08199.
Gunter, U., 2018. What makes an Airbnb host a superhost? Empirical evidence from San Francisco and the Bay Area. Tour. Manag. 66, 26–37. https://doi.org/10.1016/j.tourman.2017.11.003.
Gunter, U., Önder, I., 2017. Determinants of Airbnb demand in Vienna and their implications for the traditional accommodation industry. Tour. Econ. https://doi.org/10.1177/1354816617731196. 135481661773119.
Guttentag, D., 2015. Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector. Curr. Issues Tour. 18 (12), 1192–1217. https://doi.org/10.1080/13683500.2013.827159.
Guttentag, D., Smith, S., Potwarka, L., Havitz, M., 2018. Why tourists choose airbnb: a motivation-based segmentation study. J. Travel. Res. 57 (3), 342–359. https://doi.org/10.1177/0047287517696980.
Hastie, T., Tibshirani, R., Friedman, J., 2001. The elements of statistical learning. Math. Intell. 27 (2), 83–85. https://doi.org/10.1198/jasa.2004.s339.
Heo, C.Y., Hyun, S.S., 2015. Do luxury room amenities affect guests' willingness to pay? Int. J. Hosp. Manag. 46, 161–168. https://doi.org/10.1016/j.ijhm.2014.10.002.
Heo, C.Y., Blal, I., Choi, M., 2019. What is happening in Paris? Airbnb, hotels, and the Parisian market: a case study. Tour. Manag. 70, 78–88.
Hill, D., 2015. How much is your spare room worth? IEEE Spectr. 52 (9). https://doi.org/10.1109/MSPEC.2015.7226609.
Horn, K., Merante, M., 2017. Is home sharing driving up rents? Evidence from Airbnb in Boston. J. Hous. Econ. 38, 14–24. https://doi.org/10.1016/j.jhe.2017.08.002.
Hothorn, T., Hornik, K., Zeileis, A., 2006. Unbiased recursive partitioning: a conditional inference framework. J. Comput. Graph. Stat. 15 (3), 651–674.

Hung, W.T., Shang, J.K., Wang, F.C., 2010. Pricing determinants in the hotel industry: quantile regression analysis. Int. J. Hosp. Manag. 29 (3), 378–384. https://doi.org/10.1016/j.ijhm.2009.09.001.
Israeli, A.A., 2002. Star rating and corporate affiliation: their influence on room price and performance of hotels in Israel. Int. J. Hosp. Manag. 21 (4), 405–424.
Janitza, S., Tutz, G., Boulesteix, A.L., 2016. Random forest for ordinal responses: prediction and variable selection. Comput. Stat. Data Anal. 96, 57–73. https://doi.org/10.1016/j.csda.2015.10.005.
Lawani, A., Reed, M.M.R., Mark, T., Zheng, Y., 2018. Reviews and Price on Online Platforms: Evidence From Sentiment Analysis of Airbnb Reviews in Boston. Regional Science and Urban Economics.
Lee, C.G., 2011. The determinants of hotel room rates: another visit with Singapore's data. Int. J. Hosp. Manag. 30 (3), 756–758. https://doi.org/10.1016/j.ijhm.2010.09.010.
Lee, S.K., Jang, S.C., 2012. Premium or discount in hotel room rates? The dual effects of a central downtown location. Cornell Hosp. Q. 53 (2), 165–173. https://doi.org/10.1177/1938965512441056.
Liang, S., Schuckert, M., Law, R., Chen, C.C., 2017. "Be a "Superhost": the importance of badge systems for peer-to-peer rental accommodations.". Tour. Manag. 60, 454–465. https://doi.org/10.1016/j.tourman.2017.01.007.
Liang, L.J., Choi, H.C., Joppe, M., 2018. Exploring the relationship between satisfaction, trust and switching intention, repurchase intention in the context of Airbnb. Int. J. Hosp. Manag. 69, 41–48. https://doi.org/10.1016/j.ijhm.2017.10.015.
Lockyer, T., 2005. Understanding the dynamics of the hotel accommodation purchase decision. Int. J. Contemp. Hosp. Manage. 17 (6), 481–492. https://doi.org/10.1108/09596110510612121.
Martin-Fuentes, E., 2016. Are guests of the same opinion as the hotel star-rate classification system? J. Hospitality Tourism Manage. 29, 126–134.
Martin-Fuentes, E., Fernandez, C., Mateu, C., Marine-Roig, E., 2018. Modelling a grading scheme for peer-to-peer accommodation: stars for Airbnb. Int. J. Hosp. Manag. 69, 75–83.
Masiero, L., Nicolau, J.L., Law, R., 2015. A demand-driven analysis of tourist accommodation price: a quantile regression of room bookings. Int. J. Hosp. Manag. 50 (1), 8. https://doi.org/10.1016/j.ijhm.2015.06.009.
Mauri, A.G., Minazzi, R., Nieto-García, M., Viglia, G., 2018. Humanize your business. The role of personal reputation in the sharing economy. Int. J. Hosp. Manag. 73, 36–43. https://doi.org/10.1016/j.ijhm.2018.01.017.
Miao, L., Lehto, X., Wei, W., 2014. The hedonic value of hospitality consumption: evidence from spring break experiences. J. Hospitality Marketing Manage. 23 (2), 99–121.
Mody, M., Suess, C., Dogru, T., 2017. Comparing apples and oranges? examining the impacts of Airbnb on hotel performance in Boston. Boston Hospitality Rev. 5 (2), 1–15.
Monty, B., Skidmore, M., 2003. Hedonic pricing and willingness to pay for bed and breakfast amenities in Southeast Wisconsin. J. Travel. Res. 42 (2), 195–199. https://doi.org/10.1177/0047287503257500.
Prebensen, N.K., Rosengren, S., 2016. Experience value as a function of hedonic and utilitarian dominant services. Int. J. Contemp. Hospitality Manage. 28 (1), 113–135.
Qiu, R.T., Fan, D.X., Liu, A., 2018. Exploring the Booking Determinants of the Airbnb Properties: An Example of the Listings of London. Information and Communication Technologies in Tourism Springer, Cham, pp. 44–51.
R Foundation for Statistical Computing, 2016. R: A Language and Environment for Statistical Computing, vol. 1 R Foundation for Statistical Computinghttps://doi.org/10.1007/978-3-540-74686-7.
Saló, A., Garriga, A., 2011. The second-home rental market: a hedonic analysis of the effect of different characteristics and a high-market-share intermediary on price. Tour. Econ. 17 (5), 1017–1033.
Saló, A., Garriga, A., Rigall-I-Torrent, R., Vila, M., Fluvià, M., 2014. Do implicit prices for hotels and second homes show differences in tourists' valuation for public attributes for each type of accommodation facility? Int. J. Hosp. Manag. 36, 120–129.
Schamel, G., 2012. Weekend vs. Midweek stays: modelling hotel room rates in a small market. Int. J. Hosp. Manag. 31 (4), 1113–1118. https://doi.org/10.1016/j.ijhm.2012.01.008.
Sharma, P.N., Morgeson III, F.V., Mithas, S., Aljazzaf, S., 2018. An Empirical and Comparative Analysis of E-government Performance Measurement Models: Model Selection Via Explanation, Prediction, and Parsimony. Government Information Quarterly.
Shih, Y.S., Tsai, H.W., 2004. Variable selection bias in regression trees with constant fits. Comput. Stat. Data Anal. 45 (3), 595–607. https://doi.org/10.1016/S0167-9473(03)00036-7.
Shmueli, G., Ray, S., Velasquez Estrada, J.M., Chatla, S.B., 2016. The elephant in the room: predictive performance of PLS models. J. Bus. Res. 69 (10), 4552–4564. https://doi.org/10.1016/j.jbusres.2016.03.049.
Sirakaya, E., Uysal, M., Yoshioka, C.F., 2003. Segmenting the Japanese tour market to Turkey. J. Travel. Res. 41 (3), 293–304. https://doi.org/10.1177/0047287502239038.
Snepenger, D.J., 1987. Segmenting the vacation market by novelty-seeking role (Alaska). J. Travel. Res. 26 (2), 8–14. https://doi.org/10.1177/004728758702600203.
Spindler, C., Woll, O., Schober, D., 2018. Sharing Is Not Caring: Backward Integration of Consumers (No. 18-006). ZEW-Zentrum für Europäische Wirtschaftsforschung/ Center for European Economic Research.
STR, 2016. STR Chain Scales. (Accessed on 30, December, 2018). http://www.strglobal.com/Media/Default/Documents/STRGlobalChainScales2016.pdF.
Sundararajan, Arun, 2016. The Sharing Economy: the End of Employment and the Rise of Crowd-based Capitalism. Mit Press.
Thrane, C., 2007. Examining the determinants of room rates for hotels in capital cities: the Oslo experience. J. Revenue Pricing Manage. 5 (4), 315–323. https://doi.org/10.1057/palgrave.rpm.5160055.
Travel Update, 2014. Luxury Travelers Increasingly Request Airbnb-like Rentals; It's About Bragging Rights - Travel Update With Barb. Date Accessed:2018-08-05. https://travelupdate.boardingarea.com/luxury-travelers-increasingly-request-airbnb-like-rentals-bragging-rights/.
Tussyadiah, I.P., 2016. Factors of satisfaction and intention to use peer-to-peer accommodation. Int. J. Hosp. Manag. 55, 70–80.
Varma, A., Jukic, N., Pestek, A., Shultz, C.J., Nestorov, S., 2016. Airbnb: Exciting innovation or passing fad? Tourism Manage. Perspect. 20, 228–237. https://doi.org/10.1016/j.tmp.2016.09.002.
Walls, A.R., 2013. A cross-sectional examination of hotel consumer experience and relative effects on consumer values. Int. J. Hosp. Manag. 32, 179–192.
Wang, D., Nicolau, J.L., 2017. Price determinants of sharing economy based accommodation rental: a study of listings from 33 cities on Airbnb.cOm. Int. J. Hosp. Manag. 62, 120–131. https://doi.org/10.1016/j.ijhm.2016.12.007.
Xie, K.L., Kwok, L., 2017. The effects of Airbnb's price positioning on hotel performance. Int. J. Hosp. Manag. 67, 174–184.
Yacouel, N., Fleischer, A., 2012. The role of cybermediaries in reputation building and price premiums in the online hotel market. J. Travel. Res. 51 (2), 219–226. https://doi.org/10.1177/0047287511400611.
Yang, Y., Mueller, N.J., Croes, R.R., 2016. Market accessibility and hotel prices in the Caribbean: the moderating effect of quality-signaling factors. Tour. Manag. 56, 40–51. https://doi.org/10.1016/j.tourman.2016.03.021.
Ye, Q., Law, R., Gu, B., 2009. The impact of online user reviews on hotel room sales. Int. J. Hosp. Manag. 28 (1), 180–182. https://doi.org/10.1016/j.ijhm.2008.06.011.
Zervas, G., Proserpio, D., Byers, J.W., 2017. The rise of the sharing economy: estimating the impact of Airbnb on the hotel industry. J. Mark. Res. 54 (5), 687–705.
Zhang, H., Zhang, J., Lu, S., Cheng, S., Zhang, J., 2011. Modeling hotel room price with geographically weighted regression. Int. J. Hosp. Manag. 30 (4), 1036–1043. https://doi.org/10.1016/j.ijhm.2011.03.010.
Zhang, Z., Chen, R.J.C., Han, L.D., Yang, L., 2017. Key factors affecting the price of Airbnb listings: a geographically weighted approach. Sustainability (Switzerland) 9 (9). https://doi.org/10.3390/su9091635.
Zhu, F., Zhang, X., 2010. Impact of online consumer reviews on sales: the moderating role of product and consumer characteristics. J. Mark. 74 (2), 133–148.