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Study of Price Determinants of Sharing Economy-Based Accommodation Services: Evidence from Airbnb.com

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Abstract: This research aims to identify price determinants for sharing economy-based accommodation services and to further use the identified price determinants to predict accommodation prices. A dataset drawn from Airbnb.com, was collected for analysis. We identify price determinants from five categories. The top five price determinants are identified as room type, city, distance to tourist attractions, number of pictures posted, and number of amenities provided. More importantly, we find that interaction effects between variables can also significantly influence price. Finally, a series of price prediction models are built based on the identified price determinants.

Keywords: sharing economy; price determinants; Airbnb.com; interaction effects; price prediction

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1. Introduction

The emergence of peer-to-peer platforms has allowed people to share excess assets and services, resulting in the rise of the term sharing economy to describe this new business model [1,2]. The sharing economy business model is booming in many industries. Examples of popular peer-to-peer platforms include Uber and Lyft in the car transportation industry and Airbnb and Roomorama in the accommodation industry [1,3]. The sharing economy in the accommodation industry is receiving particular attention from both industry and the academic world. In contrast to traditional accommodation providers, accommodation-sharing platforms collect unutilized accommodation assets from hosts and match these assets with guests who need temporary accommodation. This type of service is often referred to as a value co-creation process accomplished by hosts and guest [4,5]. One notable advantage is that the costs for hosts who provide accommodation is minimal compared to the substantial costs for traditional accommodations such as hotels [1,2,6]. The market size of accommodation-sharing platforms has increased drastically in recent years. For example, the total sales and user base of accommodation-sharing platforms in China reached 16.5 billion and 147 million by 2018, respectively, with a growth rate above 25% [7,8].

For multiple reasons, pricing decisions are crucial in determining the long-term success of the traditional accommodation industry [9]. Pricing has been shown to significantly influence consumer accommodation selections [10]. For similar reasons, pricing is also a very important aspect for sharing economy-based services. Therefore, it is important to examine the pricing determinants of sharing economy-based accommodations, which may provide useful guidelines on pricing decisions for accommodations. In addition, having a better knowledge of pricing determinants will be crucial for sharing economy platforms such as Airbnb.com. Although platforms do not make pricing decisions themselves, they do make recommendations for hosts regarding pricing. If platforms can make appropriate recommendations on pricing, sales and profitability could be increased.

Many scholars have studied the price determinants of traditional accommodation services (e.g., [9,11]). However, the results of these studies cannot be simply generalized to the sharing economy-based accommodation industry due to its distinctive characteristics;

for example, most items are personal assets, and the hosts are nonprofessional owners [12]. Several studies have examined the price determinants of sharing economy-based accommodation services, considering the influences of various factors such as hosts (e.g., [13,14]), location (e.g., [15–17]), listing attributes (e.g., [18,19]), and review ratings (e.g., [12,20]).

Despite the abovementioned studies, however, more efforts are needed to identify factors that influence the pricing of sharing economy-based accommodation services. First, several potentially important influencing factors, such as earliest time to check-in, latest time to check-out, and length of title, are absent from previous studies. Second, the interaction effects between variables are not discussed in the literature. Previous studies focused on the effects of individual variables on accommodation prices, but it is possible that the effect of one variable may depend on the value of another variable. Therefore, it is necessary to explore the interaction effects between variables. Third, based on the identified influencing factors, it is also important to build a model that can predict the appropriate price for sharing economy-based accommodation services. However, such prediction analysis is still lacking in the existing literature. Therefore, it is meaningful to reexamine price determinants in the context of sharing economy-based accommodation services.

This study has the following two-objectives.

1. This study attempts to build a framework for sharing economy-based accommodation services that identifies not only the crucial influencing factors but also the interaction terms between these factors.
2. This study seeks to build a prediction model that provides appropriate pricing decisions for sharing economy-based accommodation services.

Officially founded in mid-2008, Airbnb.com is a pioneer in the sharing economy industry and has had substantial success in the accommodation-sharing industry [21]. Drawing on a dataset from Airbnb.com, this study examines the price determinants of sharing economy-based accommodation services from five categories: (1) listing attributes; (2) listing location; (3) host attributes; (4) rental policies; and (5) listing reputation. The results show that the top five price determinants are room type, city, distance to tourist attractions, number of pictures posted, and number of amenities provided. More importantly, we find that several interaction terms also significantly influence accommodation prices. This suggests that the same factor may have different effects when other factors change. In addition, we test our prediction model using RF (random forest), SVR (support vector regression), and OLS (ordinary least square) algorithms. All three models perform well, but the RF model outperforms the other two for price prediction.

On the theoretical front, our research contributes to the literature of studies on the price determinants of sharing economy-based accommodation services. The framework we propose includes not only factors from five categories but also the interactions between different factors. To the best of our knowledge, we are the first to identify interaction terms as price determinants in the literature. The effectiveness of our framework and the interaction terms are supported by a subsequent prediction analysis.

On the practical front, our research results provide important implications for platforms, hosts, and guests. It is important for platforms and hosts to make wise decisions when pricing accommodations. Drawing on our research, guests can also make better judgments when selecting their accommodation.

2. Literature Review

2.1. Sharing Economy-Based Accommodation Services

The boom of Internet technology resulted in the sharing economy, which reduces costs and makes transactions between individuals possible [22,23]. Sharing economy-based accommodation services are popular applications of the sharing economy, which provides platforms for hosts to rent their excess accommodations to guests.

Previous studies have researched sharing economy-based accommodation services from various perspectives. First, many scholars have examined the purchase intentions of guests. These studies showed that privacy issues and financial risks negatively affect the intention to use Airbnb.com [24]. Further, since accommodations are provided by unknown individuals, trust between hosts and guests is particularly important. Thus, strengthening the trust between hosts and guests may increase guests' purchase intentions [13,14]. One way to alleviate information asymmetry and boost trust is through experience sharing by guests. One study showed that purchase decisions are influenced by social distance and shared experiences by other guests and further revealed that guests' post-purchase experience sharing activities are affected by information discrepancy and deviating experiences [25].

Several studies also investigated guests' repurchase intentions. Retaining repeat customers is particularly important in the sharing economy since existing customers can easily switch back to traditional service providers [26]. Previous studies showed that repurchase intention is affected by guests' attitude, perceived value and risk [26], trust [27], and electronic word of mouth [28].

In addition, identifying price determinants is crucial for sharing economy-based accommodation services as well. This stream of research is directly related to our study and thus will be reviewed independently in Section 2.3.

2.2. Price Determinants of Traditional Accommodation Services

Many empirical research studies have identified price determinants in the traditional accommodation industry to inform pricing strategies.

Different scholars have focused on different aspects of pricing. For example, Mattila and O'Neill [29] indicated there is a significant relationship between room prices and customer satisfaction. Israeli [30] discovered that a star rating of a hotel is a stable predictor of room prices. Employing an OLS model, Zhang, Ye, and Law [17] examined price determinants from five dimensions, including hotel class, room quality, location, cleanliness, and service. Their results showed that hotel class, room quality, and location are important price determinants but that service and cleanliness are not significant predictor of room prices. Through quantile regression analysis, Hung et al. [9] found that the ratio of the number of housekeepers to the number of guest rooms is a significant predictor of hotel prices for most quantiles, while the type of hotel (resort hotel or city hotel) is significant only for high-priced hotels (75th and 90th quantile).

In summary, as revealed by previous studies, price determinants in traditional accommodation services include star rating, location, room quality, customer satisfaction, ratio of housekeepers to rooms, and hotel type (resort or city). However, due to the distinct differences between traditional accommodation services and sharing economy-based accommodation services, the abovementioned research results cannot be simply applied to the sharing economy.

2.3. Price Determinants of Sharing Economy-Based Accommodation Services

Due to the unique features of the sharing economy, it is necessary to reexamine its price determinants. For example, one previous study showed that the host–guest relationship is much closer when using the Airbnb.com platform and that this results in higher experiential value, authenticity, sociability, and trust [18].

Considering the uniqueness of the sharing economy, scholars have identified the price determinants of sharing economy-based accommodation services from various perspectives. These price determinants can be divided into five categories: (1) listing attributes; (2) listing location; (3) host attributes; (4) rental policies; and (5) listing reputation. In particular, price determinants of listing attributes, host attributes, and rental policies categories are significantly different from traditional accommodation services [12,18]. Table 1 summarizes the major findings from previous studies on the price determinants of sharing economy-based accommodation services.

Table 1. Studies on price determinants of sharing economy-based accommodation services.

Category	Determinants	Effects	Literature
Listing attributes	Room type: entire home, private room (reference group: shared room), accommodation capacity, number of bedrooms/beds/bathrooms/pictures, wireless Internet, parking	Positive	[12,15,18–20,31]
	Breakfast, instant bookable	Mixed	Positive: [18,20,31] Negative: [12,15,18]
Listing location	Distance to density zone	Positive	[15,18]
	Distance to tourist attraction/beach, place of interest	Negative	[15,18]
	Distance to city center/hall	Mixed	Positive: [20] Negative: [12,15] Non-significant: [18]
	Distance to shopping center	n.s.	[18]
Host attributes	Host identity verified, response time, membership months	Positive	[12,18,19]
	Host profile picture	Negative	[12]
	Superhost, host listing count	Mixed	Positive: [12,15,18,20] Negative: [18] Non-significant: [19]
Rental policies	Cancellation policy (moderate plus strict)	Positive	[12,18]
	Cancellation policy: moderate (reference group: flexible)	Negative	[19]
	Cancellation policy: strict (reference group: flexible)	n.s.	[19]
	Smoking allowed	Mixed	Negative: [12] Non-significant: [15]
Listing reputation	Rating	Positive	[12,18–20]
	Number of reviews	Mixed	Positive: [20] Negative: [15,18]

The fist category of price determinants is listing attributes. First, room type is identified as an influencing factor of listing price on Airbnb.com [12,18–20]. The price is higher when the room type is an entire home or private room compared to a shared room. The number of people the location accommodates, number of bedrooms, number of bathrooms, number of beds, and number of pictures also positively impact price [12,15,18–20]. The amenities associated with higher price include wireless Internet and parking [12,15], whereas the effects of breakfast and instant booking vary by context [12,18,20,31].

The second category of price determinants is listing location. Previous studies found that prices are higher for accommodations closer to tourist attractions [15,18]. However, distance from the accommodation to the city center can have mixed effects in different contexts, including positive effects, negative effects, and non-significant effects [15,18,20].

For the category of price determinants related to host attributes, most previous studies showed that whether the host is a "superhost" can increase accommodation prices [12,15,18,20,32], with a few exceptions [19]. Further, counterintuitively, posting a profile picture of a host has a negative effect on the price [12]. In addition, verified host identity [12], rapid response [19], and longer host membership history [18] are associated with higher price.

The next category of price determinants is rental policies. Generally, a stricter cancellation policy is associated with a higher rental price [12,18], but this is not the case in Austin, Texas, in the United States [19]. Accommodations in which smoking is allowed usually charge lower prices in most cities [12], with a few exceptions [15].

Last, some factors related to listing reputation are also identified as price determinants. First, higher user ratings are shown to be associated with higher price [12,18–20]. Nonetheless, volume of reviews yields mixed effects on prices [15,18,20].

2.4. Theoretical Contributions

This study contributes to the literature on price determinants of sharing economy-based accommodations through three main accomplishments. First, to the best of our knowledge, we are among the first to propose a framework for the price determinants of sharing economy-based accommodation services, which includes factors from five categories. Notably, several factors, including earliest time to check-in, latest time to check-out, and length of title, are identified for the first time. Second, previous studies usually examined the individual effect of each price determinant. However, we examine the interaction effects between different factors and find that these effects may also be significant in influencing accommodation prices. Third, there is a lack of research on prediction analysis on sharing economy-based accommodation services prices in the existing literature. In our research, we apply the identified influencing factors and interaction terms to build a prediction model, which proves the effectiveness of our proposed framework and could provide guidance in terms of pricing decisions.

3. Methodology

3.1. Data Collection

The dataset was collected from Airbnb.com on 11 September 2019, using a Python-based crawler. We set the check-in date as October 16 and the check-out date as 17 October 2019 and all the available listing prices from the cities of Beijing, Shanghai, or Guangzhou are obtained. In total, the data collection yielded 65,130 observations. Then, to avoid observations without real transactions, we kept only the accommodations that had at least one existing review from customers [33]. Further, some observations had missing values. After getting rid of those incomplete observations, we obtained in total 16,784 observations.

Note that the listed prices for accommodations on Airbnb.com usually indicate prices for renting the entire accommodation. However, it is common that customers travel with companions, or even share accommodations with strangers [7]. Therefore, guests care more about how much they would be charged individually rather than the price for the entire property. Even in scenarios such as family travel, the average individual price (price per guest) is also an important consideration. Therefore, it is more meaningful to divide accommodation prices by capacity (number of guests that can be accommodated) to obtain the measurement of accommodation price. Note that usually accommodations serve number guests less than its capacity (2–5 guests are common for Airbnb.com). Thus, we make the following rule during the data collection process: for accommodations whose capacity is between 2 and 5, individual prices are obtained by dividing the listed prices by their capacities; for accommodations whose capacity is greater than 5, the listed price is divided by 5 to obtain individual prices.

3.2. Description of Variables

In this section, we describe the variables identified in this research in detail. Table 2 shows the variable definitions and corresponding descriptive statistics. The variables are categorized into five categories: (1) listing attributes: *Room type* (whether the accommodation is an entire home, a private room, or a shared room), *Amenities* (number of amenities provided, such as hair-dryer, swimming pool, and Wi-Fi), *Pictures* (the number of accommodation pictures provided by the host on the website), *length of title* (the listing's title length), *Instantly bookable* (whether the accommodation can be booked instantly without the host's confirmation), $Self-check-in$ (whether guests can check in themselves without the host helping), $Earliest\ check-in\ time$ (the earliest time of a day that guests can check-in), and $Latest\ check-out\ time$ (the latest time of a day that guests have to check-out); (2) listing location: *City* (where the accommodation is located: Beijing, Shanghai, and Guangzhou), *Distance to railway station* (distance between the accommodation and the nearest railway station), *Distance to subway* (distance between the accommodation and the nearest subway station), *Distance to airport* (distance between the accommodation and the nearest airport), and *Distance to tourist attraction* (distance between the accommodation and the nearest tourist attraction); (3) host attributes: *Superhost* (whether the host is a superhost on Airbnb.com), *English* (whether the host can speak English), and *Register months* (months that the host's register has existed); (4) rental policies: *Infant allowed* (whether the accommodation allows infants to stay), *Child allowed* (whether the accommodation allows children to stay), *Pets allowed* (whether the accommodation allows pets to stay), *Smoking allowed* (whether the accommodation allows guests to smoke indoors), and *Cancellation policy* (cancellation policy of an accommodation: flexible, moderate, and strict); and (5) listing reputation: *Reviews* (number of reviews an accommodation has received) and *Ratings* (overall rating of an accommodation, ranging from 1 to 5 with a 0.5 increment).

Table 2. Variable list.

	Variable Name	Mean	SD	Min.	Max.	Definition
	Log (price)	2.21	0.18	1.57	2.98	The logarithm of the average price at a given property, including tax and cleaning fees (total price/number of guests)
Listing attributes	Room type					Room type of a given property
	Entire home	0.76	0.43	0	1	
	Private room	0.22	0.42	0	1	
	Shared room (reference)	0.02	0.12	0	1	
	Amenities	16.73	4.55	0	30	Number of amenities
	Pictures	26.16	15.12	1	201	Number of pictures
	Length of title	37.28	11.94	2	64	Length of title
	Instant bookable (binary)	0.45	0.50	0	1	Offers instant booking or not
	Self-check-in (binary)	0.57	0.49	0	1	Whether guests can check themselves in
	Earliest check-in time					earliest time for check-in
	08–12 (reference)	0.04	0.20	0	1	
	13–17	0.89	0.31	0	1	
	18–01	0.004	0.07	0	1	
	flexible	0.06	0.24	0	1	
	Latest check-out time					Latest time for check-out
	00–06 (reference)	0.006	0.08	0	1	
	07–12	0.93	0.25	0	1	
	13–17	0.06	0.23	0	1	
	18–23	0.002	0.05	0	1	
Listing location	City					City that a listing is in
	Beijing	0.32	0.46	0	1	
	Guangzhou	0.20	0.40	0	1	
	Shanghai (reference)	0.48	0.50	0	1	
	Distance to railway station (km)	6.35	5.02	0	42.39	Distance to the nearest railway station
	Distance to subway (km)	0.46	0.23	0	0.99	Distance to the nearest subway
	Distance to airport (km)	18.55	9.06	1.20	77.42	Distance to the nearest airport
	Distance to tourist attraction (km)	1.71	1.32	0	5.99	Distance to the nearest tourist attraction
Host attributes	Superhost (binary)	0.54	0.50	0	1	Being a superhost: hosted at least 10 trips; maintained at least 90% response rate; received a 5-star review at least 80% of the time
	English (binary)	0.35	0.48	0	1	Is a host able to host in English
	Register months	29.87	17.49	2	116	Months that the host's register has existed
Rental policies	Infants allowed (binary)	0.54	0.50	0	1	Allows infants to stay
	Children allowed (binary)	0.72	0.45	0	1	Allows children to stay
	Pets allowed (binary)	0.14	0.35	0	1	Allows pets to stay
	Smoking allowed (binary)	0.24	0.43	0	1	Allows smoking indoors
	Cancellation policy					Cancellation policy of a listing
	Strict	0.28	0.45	0	1	
	Moderate	0.46	0.50	0	1	
	Flexible (reference)	0.27	0.44	0	1	
Listing reputation	Reviews	26.71	35.04	3	495	Number of reviews
	Ratings	4.90	0.23	1	5	Overall ratings from 1 to 5

To guarantee the robustness of the models and obtain more interpretable results, the dependent variable *price* is transformed to its logarithmic form lg*price*. Figure 1 shows that the distribution of lg*price* is close to normal. Price primarily ranges from 80 to 400 yuan, with a minimum price of 37 and a maximum price of 945. The mean is 177.7, and the median is 159.7.

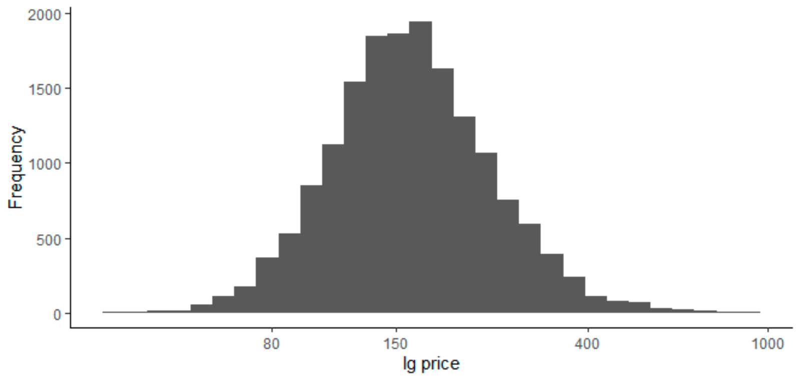
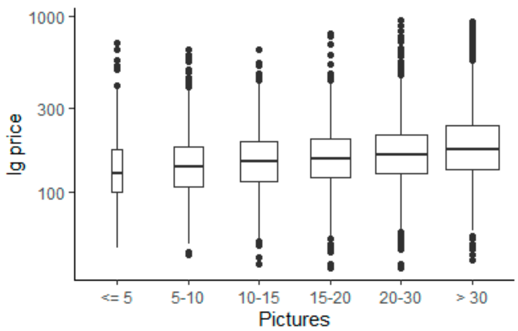
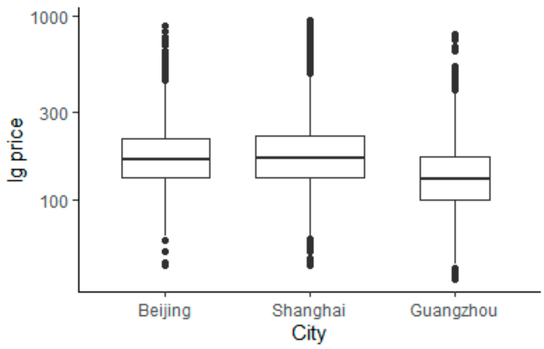


Figure 1. Histogram of lg*price*.

We then conducted a series of descriptive analyses on some variables to reveal their effects on accommodation prices. Figure 2a shows that, as the number of accommodation pictures posed on Airbnb.com (which are listing attributes) increases, prices also seem to increase, implying a potential positive effect of the number of pictures posted on accommodation price.

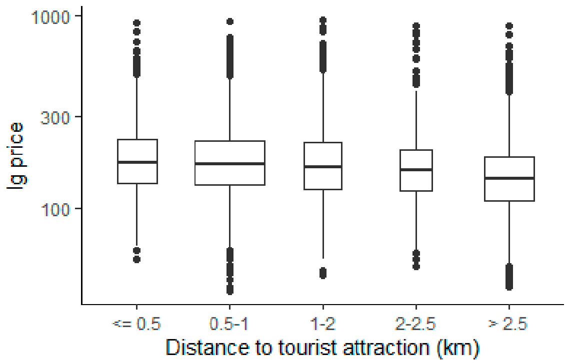


(**a**)



(**b**)

Figure 2. *Cont.*



(**c**)

Figure 2. (**a**) Relationship between the number of pictures posted and accommodation prices. (**b**) Relationship between cities and accommodation prices. (**c**) Relationship between the distance to tourist attractions and accommodation prices.

Figure 2b shows that listing location may also influence accommodation prices. Prices of properties in Guangzhou are lower than prices in Shanghai or Beijing. Figure 2c demonstrates that accommodation prices gradually decrease as the distance to the nearest tourist attractions increases, indicating a potential negative effect of distance to tourist attractions on accommodation prices.

The above descriptive analysis results reveal that different variables may have various effects on the price of sharing economy-based accommodation services. Thus, we will identify these price determinants through rigorous research methodologies in the subsequent sections.

3.3. Data Analysis

To identify the price determinants, we employed an OLS model to estimate the effects of different variables on the prices of sharing economy-based accommodation services. Since factors may have different value scales, variables were standardized to avoid imprecise estimation results [27].

We constructed two models to identify price determinants. The first model incorporates variables from five categories and estimates the main effects of each variable on accommodation price. Model 1 is specified as

$$lg\ price = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon \tag{1}$$

where lg*price* is the logarithmic form of the price of a property, β_0 is the constant term, X_i is the *i*th factor, β_i is the semi-elasticity of price with respect to X_i [18], and ε is the error term. The model indicates to what extent each factor (X_i) influences the dependent variable (lg*price*) when the other factors remain unchanged. The estimation of β_i thus indicates whether X_i has a significant effect on accommodation price.

In addition, we are also interested in exploring the interaction effects between two variables. Therefore, we built Model 2 to identify potential price determinants from interaction terms. Model 2 is specified as

$$lg\ price = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} X_i X_j + \varepsilon \quad (i \neq j) \tag{2}$$

where $X_i X_j$ represents the interaction term between the two factors X_i and X_j. Although Model 1 reveals significant factors that influence accommodation price, there may be interaction effects between two factors. Identifying these interaction terms is important in build an overarching framework for describing the price determinants of sharing economy-based accommodation services. The estimation of β_{ij} reveals whether the term $X_i X_j$ has a significant effect on accommodation price.

The analysis was conducted through the following procedures. First, outliers and collinearity were tested by Cook's distance and the variance inflation factor (VIF), respectively. Then, Models 1 and 2 were estimated to identify the main and interaction effects of different factors. Next, a model selection method (Bayesian information criterion, BIC) was implemented to identify important factors. Based on these factors, we then built a prediction model implementing various algorithms (OLS, SVR, and RF) for the price of sharing economy-based accommodation services.

4. Results

In this section, we present the research results for Model 1, Model 2, and the prediction model.

First, VIF scores were calculated to check for collinearity. According to Table 3, all VIF values are less than 10. Thus, collinearity between variables does not exist.

Table 3. Variance inflation factor (VIF) results.

Categories	Factors	VIF
Listing attributes	Room type	1.353618
	Amenities	1.303142
	Pictures	1.183684
	Length of title	1.14036
	Instantly bookable	1.098525
	Self-check-in	1.213097
	Earliest check-in-time	1.28976
	Latest check-out-time	1.222741
Listing location	City	6.019008
	Distance to railway station	1.236746
	Distance to tourist attraction	1.143551
	Distance to subway	1.040778
	Distance to airport	5.239556
Host attributes	Superhost	1.13907
	English	1.193011
	Register months	1.261424
Rental rules	Infants allowed	1.79103
	Children allowed	1.763774
	Pets allowed	1.131778
	Smoking allowed	1.185689
	Cancellation policy	1.148897
Listing reputation	Reviews	1.196049
	Ratings	1.094709

4.1. Price Determinants of Sharing Economy-Based Accommodation Services

The regression results from Model 1 are shown in Table 4. These results estimate the main effect of each variable on the prices of sharing economy-based accommodation. Cook's distance measure is shown in Figure 3. The results show that the model fits the data well without outliers. The adjusted R-squared value was 0.2036, indicating that 20.36% of variability in accommodation prices can be explained by the model.

Regression results by Model 1 reveal several important findings. First, as we hypothesized, each category includes at least one significant factor, which demonstrates the appropriateness of the framework we proposed. Second, most factors identified by our model have significant effects on accommodation prices. In particular, *Room type* and *City* strongly affect the price, with the highest coefficients of all variables. $Earliest\ check-in-time$, a variable absent from previous studies, is found to be significant by our model. This proves that providing guests with the convenience of early check-in could justify a price increase. Several factors are found to be insignificant. *Length of title*, which is found to have significant effects in the context of online reviews, has no significant effects on accommodation price. Further, allowing infants, pets, and children has no significant effect on accommodation price.

Table 4. Regression results from Model 1.

Category	Price Determinant	β	Std. Error	*t* Value	*p* Value	Sig.
-	Intercept	2.140	0.017	124.131	<0.001	***
Listing attributes	Room type (reference: private room)					
	Entire home	0.077	0.003	22.614	<0.001	***
	Shared room	−0.094	0.010	−9.002	<0.001	***
	Amenities	0.018	0.001	12.673	<0.001	***
	Pictures	0.022	0.001	16.363	<0.001	***
	Length of title	0.001	0.001	0.743	0.458	
	Instantly bookable (ref: no)	0.005	0.003	2.069	0.039	*
	Self-check-in (ref: no)	−0.007	0.003	−2.709	0.007	**
	Earliest check-in time (ref: 08–12)					
	13–17	0.014	0.007	2.045	0.041	*
	18–01	0.011	0.020	0.572	0.567	
	flexible	−0.006	0.008	−0.711	0.477	
	Latest check-out time (ref: 00–06)					
	07–12	−0.007	0.016	−0.459	0.647	
	13–17	0.005	0.017	0.271	0.787	
	18–23	−0.030	0.029	−1.018	0.309	
Listing location	City (ref: Shanghai)					
	Beijing	0.033	0.003	10.308	<0.001	***
	Guangzhou	−0.067	0.007	−9.116	<0.001	***
	Distance to railway station	<−0.001	0.001	−0.241	0.810	
	Distance to subway	0.005	0.001	3.680	<0.001	***
	Distance to airport	−0.015	0.003	−5.167	<0.001	***
	Distance to tourist attraction	−0.031	0.001	−23.51	<0.001	***
Host attributes	Superhost (ref: no)	0.012	0.003	4.580	<0.001	***
	English (ref: no)	0.008	0.003	2.940	0.003	**
	Register months	0.013	0.001	9.155	<0.001	***
Rental policies	Infant allowed (ref: no)	0.002	0.003	0.611	0.541	
	Child allowed (ref: no)	−0.004	0.004	−1.045	0.296	
	Pet allowed (ref: no)	−0.003	0.004	−0.748	0.454	
	Smoking allowed (ref: no)	−0.015	0.003	−4.891	<0.001	***
	Cancellation policy (ref: flexible)					
	Moderate	0.017	0.003	5.269	< 0.001	***
	Strict	0.008	0.004	2.301	0.021	*
Listing reputation	Reviews	−0.013	0.001	−9.702	< 0.001	***
	Ratings	0.012	0.001	9.467	< 0.001	***
Observations	16,784					
Adj. R-squared	0.2036					

Note: Significance levels are denoted with asterisks: *** *p* value < 0.001, ** *p* value < 0.01, * *p* value < 0.05.

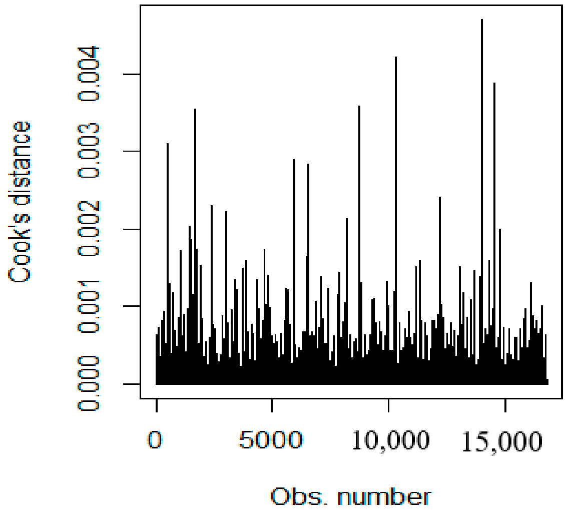


Figure 3. Cook's distance.

Some interesting findings regarding listing location are revealed by the results. Intuitively, accommodations closer to tourist attractions, airports, subways, and railway stations will be more expensive due to the convenience of transportation. As expected our results show that *Distance to airports* and *Distance to tourist attractions* negatively affect accommodation prices. However, *Distance to railway station* has no significant effect, while *Distance to subways* has a positive effect on accommodation prices. This may be because, unlike airports and tourist stations, railway stations are typically located in the city centers, where the infrastructure may be old and crime rates may be high. In contrast, being closer to subways usually means being closer to business districts, where the living quality may be relatively low due to traffic jams and noise. However, listing locations may have different effects in different cities, which we will explore in the subsequent section.

In addition, it would be beneficial to identify several important factors from the significant factors whereby hosts can focus on these key determinants to improve the quality of listings and provide better living experiences to the guests [34]. Thus, we identified the top five price determinants to be *Room type*, *City*, *Distance to tourist attraction*, *Pictures*, and *Amenities* (Table 5). Based on these top five factors, hosts and guests can make a quick evaluation of accommodation prices.

Table 5. Top five price determinants of accommodation prices.

Rank	Price Determinant	Category	Magnitude of Effect
1	Room type (reference: private room) Shared room Entire home	Listing attributes	 −9.4% 7.7%
2	City (reference: Shanghai) Guangzhou Beijing	Listing location	 −6.7% 3.3%
3	Distance to tourist attraction	Listing location	−3.1%
4	Pictures	Listing attributes	2.2%
5	Amenities	Listing attributes	1.8%

As shown in Table 5, the top price determinant is *Room type*. We found that entire homes have the highest price whereas shared rooms have the lowest price when other factors remain unchanged. Shared rooms are priced 9.4% lower than private rooms, while private rooms are priced 7.7% lower than entire homes. This demonstrates that privacy and independence are valued by guests. The second important price determinant is *City*. Our data were collected from three tier-1 cities in China: Beijing, Shanghai, and Guangzhou. We found that sharing economy-based accommodations are priced differently in these three cities. Specifically, accommodations in Beijing are priced 3.3% higher than in Shanghai, while accommodations in Guangzhou are priced 7.7% lower than in Shanghai. This may reflect the relative differences in the living costs and volume of visitors among the different cities.

The third important price determinant is *Distance to tourist attraction*. Guests of sharing economy-based accommodations such as Airbnb.com are usually tourists instead of business travelers. Being closer to tourist attractions means convenience regarding traffic, which therefore results in higher prices. The fourth important price determinant is the number of accommodation pictures posed on Airbnb.com. This is consistent with the descriptive analysis shown in Figure 2a. The results show that as more pictures are posted, the price increases. This may be because accommodations with more pictures increase trust with their guests. However, in the case of low-quality accommodations, posting photos has the opposite effect. This can be verified by testing the interaction effects. The fifth important price determinant is the number of amenities provided by the accommodation. This is intuitive in that more amenities, such as Wi-Fi, a fridge, and a hairdryer, offer conveniences to guests and therefore increase the price.

In summary, Model 1 does a good job in identifying important factors that influence accommodation prices. However, several more complicated effects call for a more sophisticated model that takes interaction effects into account. First, counterintuitive results are observed for listing locations effects, including distance to subways and distance to railway stations. Further investigation into the effects of these variables across different cities may help to gain deeper insights. Second, Model 1 indicates that more accommodation photos lead to higher prices. However, whether this observation holds true among all three different accommodation types will be of further interest to the providers of accommodations. Therefore, it is crucial to answer these important questions by considering interaction effects.

4.2. Price Determinants of Sharing Economy-Based Accommodation Services with Interaction Effects

Variables may have interaction effects on sharing economy-based accommodation prices that are missing from Model 1. In this section, we investigate the interaction effects between variables. In particular, we test the interaction effects between the number of accommodation pictures posted and room type and the interaction effects between the listing location (including distance to subway and distance to railway station) and city.

Table 6 shows the regression results from Model 2. It shows that the main variable effects are similar to the results from Model 1. The adjusted R-squared reached 0.2072, slightly higher than that of Model 1, indicating that more variability in accommodation prices can be explained by Model 2.

The interaction terms *Picures* $\times$ *Entire room* and *Picures* $\times$ *Shared room* are negatively significant, demonstrating the existence of interaction effects. Specifically, when the room is a private room, the *Picures* coefficient is 0.039. When the room is an entire home or a shared room, the *Picures* coefficients are 0.019 and -0.008, respectively. Therefore, when more pictures of accommodations are uploaded, the prices of entire homes and private rooms increase, while the prices of shared rooms decrease. This may be attributed to the fact that entire homes and private rooms are usually in better condition than shared rooms. Therefore, more pictures of shared rooms will lower guests' expectations, which in turn lead to lower prices.

Table 6. Regression results of Model 2.

Category	Price Determinant	β	Std. Error	*t* Value	*p* Value	Sig.
-	Intercept	2.152	0.017	125.296	<0.001	***
Listing attributes	Room type (reference: private room)					
	Entire home	0.073	0.003	21.024	<0.001	***
	Shared room	−0.116	0.012	−9.322	<0.001	***
	Amenities	0.018	0.001	12.572	<0.001	***
	Pictures	0.039	0.003	14.166	<0.001	***
	Length of title	0.001	0.001	0.418	0.676	
	Instantly bookable (ref: no)	0.006	0.003	2.140	0.032	*
	Self-check-in (ref: no)	−0.007	0.003	−2.500	0.012	*
	Earliest check-in time (ref: 08–12)					
	13–17	0.013	0.007	1.952	0.051	▪
	18–01	0.009	0.020	0.445	0.656	
	flexible	−0.006	0.008	−0.697	0.486	
	Latest check-out time (ref: 00–06)					
	07–12	−0.013	0.016	−0.809	0.419	
	13–17	−0.001	0.017	−0.043	0.966	
	18–23	−0.032	0.029	−1.078	0.281	
Listing location	City (ref: Shanghai)					
	Beijing	0.031	0.003	9.527	<0.001	***
	Guangzhou	−0.074	0.008	−9.709	<0.001	***
	Distance to railway station	0.000	0.002	0.243	0.808	
	Distance to subway	0.003	0.002	1.644	0.100	
	Distance to airport	−0.012	0.003	−4.128	<0.001	***
	Distance to tourist attraction	−0.030	0.001	−22.608	<0.001	***
Host attributes	Superhost (ref: no)	0.012	0.003	4.404	<0.001	***
	English (ref: no)	0.009	0.003	3.131	0.002	**
	Register months	0.012	0.001	8.975	<0.001	***
Rental policies	Infant allowed (ref: no)	0.001	0.003	0.309	0.757	
	Child allowed (ref: no)	−0.003	0.004	−0.880	0.379	
	Pet allowed (ref: no)	−0.003	0.004	−0.760	0.448	
	Smoking allowed (ref: no)	−0.016	0.003	−5.072	<0.001	***
	Cancellation policy (ref: flexible)					
	Moderate	0.017	0.003	5.291	<0.001	***
	Strict	0.009	0.004	2.490	0.013	*
Listing reputation	Reviews	−0.013	0.001	−9.926	<0.001	***
	Ratings	0.012	0.001	9.474	<0.001	***
Interactions	Pictures × room type (entire home)	−0.020	0.003	−6.668	<0.001	***
	Pictures × room type (shared room)	−0.047	0.013	−3.670	<0.001	***
	Distance to subway × city (Beijing)	0.008	0.003	2.890	0.004	**
	Distance to subway × city (Guangzhou)	−0.008	0.003	−2.382	0.017	*
	Distance to railway station × city (Beijing)	−0.005	0.003	−1.704	0.088	▪
	Distance to railway station × city (Guangzhou)	−0.008	0.007	−1.190	0.234	
Observations	16,784					
Adj. R-squared	0.2072					

Note: Significance levels are denoted with asterisks: *** p value < 0.001, ** p value < 0.01, * p value < 0.05, ▪ p value < 0.1.

In terms of interaction effects between listing locations and cities, we find that *Distance to subway* × *Beijing* was positively significant and that *Distance to subway* × *Guangzhou* was negatively significant. Further, the coefficient of *Distance to subway* for the city of Shanghai was 0.003, the coefficient of *Distance to subway* for Beijing is 0.011 and the coefficient of *Distance to subway* for Guangzhou is −0.005. This suggests that in Beijing, accommodations closer to subways are usually priced lower. However, in Guangzhou, the reverse effect is observed, and accommodations closer to subways are usually priced higher. This may be due to differences in urban planning styles in different cities.

The interaction between *Distance to railway station* and *city* shows no significant effects for Shanghai and Guangzhou. However, the *Distance to railway station* × *Beijing* interaction is negatively and marginally significant ($p = 0.088$). This suggests that there may be a weak negative effect of distance to railway stations on accommodation prices in Beijing.

4.3. Prediction Model

From Model 1 and Model 2, we identified several price determinants of sharing economy-based accommodation services. The results can provide important implications for relevant practitioners, including platforms, hosts, and guests. However, if we could predict accommodation prices based on various factors, the results would be of great interest and value to the industry as a whole. Thus, in this section, we will build a prediction model that predicts accommodation prices based on the price determinants identified above. One the on hand, such prediction models can help platforms, hosts, and guest to better evaluate accommodation prices. On the other hand, the prediction performance can show the effectiveness of the above identified price determinants.

The prediction models are implemented through the following procedures. First, the model selection process is conducted. Based on the identified price determinants, we employ stepwise regressions with bidirectional elimination (BIC) such that poorly fitted factors are eliminated from the prediction model. The dataset is then split into a training set (70%) and a testing set (30%). Three prediction methods are then adopted: ordinary least square (OLS), support vector regression (SVR), and random forest (RF). To show how interaction terms boost the prediction performance, we implement each prediction method both with and without interaction terms, resulting in a total of six models.

After the model selection process, we obtain the following prediction model without interaction terms.

$$\begin{aligned} lg\ price = {} & \beta_0 + \beta_1\ Room\ type + \beta_2\ Amenities + \beta_3\ Pictures + \beta_4\ Cities \\ & + \beta_5\ Distance\ to\ tourist\ attraction + \beta_6\ Distance\ to\ subway + \beta_7\ Distance\ to\ airport \\ & + \beta_8\ Superhost + \beta_9\ Register\ months + \beta_{10}\ Smoking\ allowed + \beta_{11}\ Cancellation\ policy \\ & + \beta_{12}\ Reviews + \beta_{13}\ Ratings \end{aligned} \tag{3}$$

The prediction model with interaction terms is shown as below.

$$\begin{aligned} lg\ price = {} & \beta_0 + \beta_1\ Room\ type + \beta_2\ Amenities + \beta_3\ Pictures + \beta_4\ Cities \\ & + \beta_5\ Distance\ to\ tourist\ attraction + \beta_6\ Distance\ to\ subway + \beta_7\ Distance\ to\ airport \\ & + \beta_8\ Superhost + \beta_9\ Register\ months + \beta_{10}\ Smoking\ allowed + \beta_{11}\ Cancellation\ policy \\ & + \beta_{12}\ Reviews + \beta_{13}\ Ratings + \beta_{14}\ Pictures \times Room\ type \\ & + \beta_{15}\ Distance\ to\ subway \times Cities \end{aligned} \tag{4}$$

Table 7 shows the performance of each prediction model. We use three measures of the prediction performance: Root Mean Square Error (RMSE), Mean Square Error (MSE), and Mean Absolute Error (MAE). The results show that the RF method performs the best among all three prediction methods (with or without interaction terms). The SVR method is the second best, and OLS displays the worst performance. Further, we find that the prediction models with interaction terms always have a better prediction performance than those without interaction terms regardless of what method is employed (OLS, RF, or SVR). This again shows the importance of considering interaction effects when identifying the price determinants of sharing economy-based accommodation services.

Table 7. Comparison of the three prediction models.

	Without Interactions			With Interactions		
	OLS	**SVR**	**RF**	**OLS**	**SVR**	**RF**
RMSE	0.1615	0.1550	0.1382	0.1613	0.1554	0.1379
MSE	0.0261	0.0240	0.0191	0.0260	0.0242	0.0190
MAE	0.1268	0.1199	0.1065	0.1267	0.1201	0.1063

5. Discussion

This study investigates the price determinants of a leading sharing economy-based accommodation platform, Airbnb.com, and derives four main findings that are discussed in more detail below.

First, we build a framework to identify factors that influence accommodation prices. The framework is mainly based on five categories proposed by previous studies. To the best of our knowledge, we are among the first to integrate factors from different categories into a single framework, and we also introduce several new variables into the framework. For example, we find that the earliest check-in time has a significant influence on accommodation price.

Second, Model 1 shows that the top five determinants are room type, city, distance to tourist attractions, number of pictures posted, and number of amenities provided. First, we find that room type is the most powerful determinant on accommodation price, which is similar to the results found in previous studies [12,18–20]. This reflects the idea that guests value private space when making bookings. When choosing shared rooms, guests must share with other guests or even strangers, therefore, privacy and security are a big concern. For private rooms, guests have their independent bedrooms but may share bathrooms and living rooms with others. When renting an entire home, guests enjoy independent bedrooms, living rooms, and bathrooms and are thus willing to pay a higher price.

The city where the accommodation is located is found to be the second most important price determinant. This suggests that different living costs across cities may lead to different accommodation prices. Previous studies also showed that the prices of sharing economy-based accommodations differ between cities [35].

The distance of an accommodation to tourist attractions, which is the third important determinant, is negatively associated with accommodation price. This may be because guests use sharing economy-based accommodation platforms for the purposes of tourism rather than business. Therefore, being close to tourist attractions makes it more convenient for tourists and thus leads to higher prices. A previous study also found that distance to tourist attractions negatively influences accommodation price based on a dataset from Hong Kong [18]. Our research further verifies that this effect also exists for other cities, namely, Beijing, Shanghai, and Guangzhou.

More accommodation pictures and more amenities are also found to lead to higher accommodation prices. This is consistent with a previous study, which found that more accommodation pictures posted is an indication of professionalism for the listing and thus can increase price [20]. Further, more amenities can enhance guests' experience, and thus, hosts can charge higher prices.

Third, the results of Model 2 reveal the importance of considering interaction effects when identifying price determinants. Most previous studies focus on the influence of each variable on accommodation prices. However, we find that the interaction effect between two variables may also have significant effects. Failure to capture these interaction effects may result in an oversimplification of pricing. Interestingly, we find that there are interaction effects between the number of accommodation pictures and room type and between the listing location and city. One counterintuitive result is that more accommodation pictures does not always increase price. We find that prices increase with the number of pictures of accommodations for entire homes and private rooms but that more pictures decreases the price for shared rooms. One plausible explanation is that pictures for better accommodations induce more interest from guests, whereas pictures of worse accommodations have the opposite effect. Another counterintuitive finding is that being closer to subways may lead to lower prices. Accommodations closer to the subway are usually cheaper in Beijing. However, being closer to the subway increases accommodation prices in Guangzhou. This shows that guests may have opposite preferences for the same attribute in different cities. Thus, ignoring interaction effects in the model results in missing important insights.

Finally, we verify the effectiveness of the price determinants identified by Model 1 and Model 2 through prediction models. The prediction results show that the incorporation of interaction terms increases the prediction power. Further, we find that the nonlinear models (RF and SVR) slightly outperform the linear model (OLS). The prediction models we proposed provide important implications for platforms, hosts, and guests. For the platform and host, the prediction results could advise them on appropriate pricing strategies. Guests could also use the results to quickly filter out overpriced accommodations.

6. Conclusions

The sharing economy has been booming in recent years and has brought innovation to many industries. One notable example is the accommodation industry. Famous sharing economy-based accommodation services providers include Airbnb.com and HomeAway. One distinct difference between sharing economy-based accommodation services and traditional accommodation services is that asset owners share their own property with guests with platforms acting as intermediaries. Therefore, the pricing of such sharing economy-based accommodations may be different from that of traditional accommodations.

This paper aims to explore the factors that influence sharing economy-based accommodation prices. We first build a framework including factors from five categories. In particular, some factors such as earliest check-in time is newly identified by our research. We then build Model 1 to explore the effect of each variable on accommodation prices. Model 1 identifies several price determinants, of which the top five are further evaluated. The interaction effects between factors were included in Model 2, which revealed how the interaction between two variables can influence accommodation prices. Based on the price determinants identified by Models 1 and 2, we further build a series of prediction models to estimate accommodation prices given the price determinants.

Our theoretical contributions not only lie in the framework proposed by this research but also in the fact that this research represents one of the earliest attempts to investigate interaction terms as price determinants. The results of Model 2 show that several significant interaction terms are price determinants. Without such an analysis, important insights would be missed. Further, this study is one of the first to implement prediction models for sharing economy-based accommodation prices. The prediction results support the effectiveness of the price determinants identified by this research, including both the variables and the interaction terms.

Our research results could also provide important insights to platforms, hosts, and guests. Hosts can use several strategies to help raise prices. For example, they may allow for an earlier check-in time, which is shown to increase price. Hosts may also post more pictures of their properties if they are renting entire homes or private rooms. However, hosts renting shared rooms should be cautious about posting more pictures. For guests, our results may help them to evaluate the appropriateness of prices for properties. Platforms such as Airbnb.com may benefit from our research in that they may use our models to provide price estimates for asset owners.

There are several limitations to this study. First, our dataset was collected from Airbnb.com from three first-tier cities in China. Future studies might collect data from more cities and verify the results in a broader context. Second, this study was conducted based on cross-sectional data, and thus, the dynamic effects between price determinants and accommodation prices may be ignored. Future studies should collect data for multiple time periods and extend this research by including panel data regressions.

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