Examining the predictors of successful Airbnb bookings with Hurdle models: Evidence from Europe, Australia, USA and Asia-Pacific cities

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Abstract

Recent studies on Airbnb have examined the predictors of room prices, successful reservations and customer satisfaction. However, a preliminary investigation of the listings from twenty-two cities across four continents revealed that a significant number of Airbnb homes remained non-booked. Thus, Poisson count-regression techniques cannot efficaciously explain the effects of predictors of successful Airbnb bookings. To address this gap, we proposed a text mining framework using Hurdle-based Poisson and Negative Binomial regressions. We found that the superhost status, host response time, and communication with guests emerged as the most significant predictors irrespective of geographies. We also found that the *instant booking option* strongly influences the bookings across cities with incoming business visitors. Additionally, we presented a machine learning-based variable-importance scheme, which helps determine the top predictors of successful bookings, to design customized recommendations for attracting more guests and unique advertisement content on P2P accommodation platforms.

Keywords: *Sharing economy; Airbnb; Over-dispersion; Text analytics; Hurdle models*

1. Introduction and Motivation

The *sharing economy* phenomenon involves the activities of sharing, accessing, or renting surplus or idle capacity of products and services offered by individuals within a peer-to-peer network or community in exchange for payments or some alternative services (Hamari et al., 2015; Belk, 2014; Jiang and Tian, 2018). Also synonymous to *collaborative consumption*, it has enabled a dynamic matching between buyers and sellers to sell products and services, preferably through digital platforms (Larivière et al., 2017) across a variety of businesses, such as *taxicabs* (Uber, Lyft), *accommodation* (Airbnb, Vrbo), *food delivery* (Deliveroo, Foodpanda), and *bikes* (Lime, Mobike). The case of Airbnb is of particular interest to both industry experts and academic scholars because it attempts to generate economic benefits (Jiang and Tian, 2018) for both homeowners and travellers across diverse geographies. Also, in recent times, the idea of being able to access and use a home without the hassle of owning it has made the idea of short-term home-sharing much more attractive to consumers. This propensity of prospective consumers has prompted businesses to engage in the practice of alternative modes of consumption. Lawson et al. (2016) have concluded from their study that such business practices promote responsible consumption behaviour of guests, helps boost businesses of Airbnb hosts and at the same time benefit the society as a whole. Besides, short-term home-sharing is relatively new, and its recency warrants in-depth study of the predictors of its success as compared to other e-commerce platforms.

Existing academic research on Airbnb has examined *pricing prediction* and *strategy* (Chen and Xie, 2017; Wang and Nicolau, 2017; Cai et al., 2019; Chattopadhyay and Mitra, 2019), *potential gender bias* (Su and Mattila, 2020), *impact on the hotel industry* (Guttentag and Smith, 2017; Zervas et al., 2017), *implications for room rents* (Barron et al., 2020), *destination selection* (Tussyadiah and Pesonen, 2016); *impact on tourism employment* (Dogru et al., 2020), and *user behaviour and experiences* (Tussyadiah, 2016). Airbnb recommends that hosts should help create comfortable and reliable stays for guests by (a) being responsive, (b) readily accept requests, (c) avoid cancellations, (d) seek positive reviews [1]. Each Airbnb home is unique in feature (in terms of *host profile*, *exact location*, *neighbourhood*, *variance in price per night*, *accommodation capacity of guests*, *amenities offered*, and *reviews received from previous guests*). In contrast, conventional hotels offer reputational features through "co-created value" in the form of *brand identity*, a *pre-defined set of amenities*, and *trust* that peer-to-peer shared homes lack. Therefore, customers (or guests) also face a challenge in interpreting these attributes while searching for accommodation across different home types such as entire homes, private rooms, and shared rooms[2]. Consequently, it becomes the responsibility of both parties to enable successful *value co-creation* during the consumption of these collaborative services (Ramaswamy and Ozcan, 2018). While hosts are responsible for presenting adequate information on these attributes for their shared homes (Chattopadhyay and Mitra, 2019), that enables them to be easily identifiable on the platform; guests rely upon historical reviews for *cleanliness*, *communication*, *check-in*, *accuracy*, *exact location*, and *value-for-money* (Cheng and Jin, 2019; Xu, 2020; Zhu et al., 2020).

However, the current literature lacks a detailed examination of the predictors that lead to successful reservations for these shared homes. Further, existing models (Wang and Nicolau, 2017; Chattopadhyay and Mitra, 2019; Biswas et al., 2020; Xu, 2020) ignore the effect of previously unbooked shared homes while travellers search for lodgings. Additionally, current studies overlook the presence of geography-specific features that influence these important predictors. Therefore, this study aims to identify the key predictors of successful reservations of peer-to-peer homes, using predictors based on value co-creation and investigate their relative importance. Also, this study will explore the potential influences of these predictors on

[1] Hosting on Airbnb - What's expected of hosts?: https://www.airbnb.co.in/hospitality
[2] What do home types mean: https://www.airbnb.co.in/help/article/317/what-do-the-different-home-types-mean

successful Airbnb room reservations due to geography-specific generalizations. Broadly, we seek answers to the following research questions:

RQ1: What are the major predictors of bookings in peer-to-peer platforms?

RQ2: Do these predictors follow any generalizable pattern across different geographies?

To answer these research questions, first, we identified different *host-based* and *guest-based* predictors from the Airbnb booking platform that played a significant role during the booking decision made by a tourist. In the process, we applied appropriate text-mining techniques in conjunction with count regression and machine-learning methods to build a novel framework to extract the predictors and empirically investigate the count of Airbnb reservations. Second, we applied an assortment of count data regression that included traditional techniques such as Poisson and Negative-Binomial and advanced hurdle models. The latter kind of models for Airbnb booking data's count-nature enabled them to account for the presence of a large number of unbooked homes and seek a more plausible explanation instead of traditional data-mining models. Third, we executed variable-importance algorithms to seek the top predictors in each geographical region (represented in this study by four continents). Our study acknowledged and compared these predictors across Europe, Australia, Asia-Pacific, and North America, leading to a largely generalizable empirical framework. These investigations led to a set of actionable predictors for both hosts and guests and guided them through designing a more efficacious home-sharing experience.

The remaining part of the paper is organized as follows. Section 2 reviews the existing literature on the predictors of Airbnb bookings, theoretical background. Section 3 describes the research data, followed by the Methodology in Section 4. Section 5 discusses the results and major implications. Section 6 concludes the paper with a summary of the main findings, and finally, Section 7 presents the avenues for future research.

2. Literature Review and Theoretical Foundation

We categorized the predictors of the successful Airbnb-home reservations into the following categories, primarily based on *host-based* and *guest-based* dimensions: (a) description of the listing space and summary of the textual content, (b) host, (c) location, (d) star ratings, (e) variance in price per night, (f) home, (g) booking policy, and (h) review scores from guests. Xu (2020) also found that tourists preferred home-based signals for tangible attributes (such as superhost status, neighbourhood, accommodation capacity, number of amenities) while referring to historical reviews for intangible attributes (such as communication, cleanliness, value-for-money, exact location) before purchase decisions.

2.1. Predictors of booking a shared-home in collaborative-consumption platforms

In a collaborative-consumption platform such as Airbnb, the website acts as the key customer interface (Larivière et al., 2017) and helps create a long-lasting impression that strongly affects subsequent decisions to reserve the home. Consequently, the count of words used in the *space description* and *textual summary* to describe the listing, whether the host mentions the convenience of available amenities, transports, positive and negative sentiment polarities of the self-description are principal host-based predictors of Airbnb shared-home reservations (Zhang et al., 2018a; Liang et al., 2020). Bilgihan and Bujisic (2015) examined the influence of utilitarian and hedonic website features, customer commitment, trust, and e-loyalty for online hotel reservations. Their findings confirmed that web-design elements are essential for better customer relationship management (CRM) and successful hotel-reservations (Lawson et al., 2016). Often, compelling narratives and story-building within the description of the listing summaries and host profiles help clinch the bookings up to eight per cent higher (Pera et al., 2016; Mauri et al., 2018; Zhu et al., 2019). Additionally, scholars from the marketing and e-commerce literature acknowledge the effect of positive and negative sentiments on subsequent sales and reputation-building (Ismagilova et al., 2019). Therefore, hosts can improve the volume of reviews and booking performance by providing more comprehensive and detailed descriptions of their shared homes on the website.

Next, we present the host-based predictors that influence Airbnb home reservations. Host-based attributes on Airbnb platforms such as reputation, presence of host's profile photograph and its visual appeal (Peng et al., 2020; Zhang et al., 2021), duration of years spent on the Airbnb platform, time taken to respond to the guests 'queries, and their impact on further decision-making (Ert et al., 2016; Gunter, 2018; Zhang et al., 2018a; Ert and Fleischer, 2019). Often, the trust and reputation are enhanced through the "Superhost" badge (Mauri et al., 2018), which hosts earn through rigorous performance metrics set by Airbnb[3], such as overall ratings of more than 4.8, at least ten stays or 100 nights, less than 1% cancellation rate, and a 90 per cent response rate[4]. In addition, Ert et al. (2016) found that the presence of prominent photos could signal a higher degree of trust among potential guests, while Zhang et al. (2020) examined the effect of a pleasant smile of the Airbnb host in the profile photo and how these factors could improve the chances of reservations and subsequent revenues. On the contrary, hosts with multiple shared-homes on Airbnb could make faster revenues but indicate poor hospitality and lack of care among prospective guests (Kwok and Xie, 2019; Liang et al., 2020). Further, a single host's multiple homes imitate a traditional hotel or rental service while escaping the stern governance and associated taxes [5].

We then study "location", "neighbourhood", "price", and "listing" related predictors that influence successful Airbnb reservations (Biswas et al., 2020; Moon et al., 2019). Often, hosts present a detailed description of the location to aid prospective guests while browsing the listing since the exact location is visible only after a successful reservation. It is a crucial

[3] How do I become a Superhost : https://www.airbnb.co.in/help/article/829/how-do-i-become-a-superhost
[4] Strive for Superhost: https://www.airbnb.co.in/resources/hosting-homes/a/why-strive-for-superhost-status-50
[5] To Curb Illegal Airbnbs, New York City Wants to Collect Data on Hosts: https://nyti.ms/3gcfJdS

predictor of room reservations and has been consistently reported by scholars (Lee and Jang, 2012; Biswas et al., 2020). Additionally, a friendly neighbourhood is what guests want to book their rooms into (Han et al., 2019). Next, the overall star ratings on the Airbnb platforms play a significant role in indirectly signalling accommodation quality (Martin-Fuentes et al., 2018; Dann et al., 2019). In addition to written reviews, Airbnb expects the guest to answer the question: "Overall, how was the stay?" [6]

Next, we examine the effect of the valence of "price per night" while guests search for Airbnb rooms. Often, price is an important feature among hotel rooms that helps guests infer the quality and the luxury offered (Martin-Fuentes et al., 2016; Chen and Xie, 2017; Wang and Nicolau, 2017; Cai et al., 2019; Chattopadhyay and Mitra, 2019). But, the listed per-night price for a room is not inflexible and may vary with those of its competitors, often within the same neighbourhood. This phenomenon may prompt users to look at "the difference with the median price within a neighbourhood" while choosing Airbnb rooms for stays. Then, we study various amenities and how they influence the possibility of successful bookings on the Airbnb platform (Masiero et al., 2015; Chattopadhyay and Mitra, 2019). Customers often attempt to mentally connect to the facilities at an Airbnb home (such as coffee-maker, hairdryer, washing machine, and refrigerator) with their homes' homely feeling and familiarity. Also, they try to relate the price-per-night displayed on the website with the amenities offered at a shared-home (Wang and Nicolau, 2017; So et al., 2018). Further, the maximum capacity of a shared home adversely impacts the chances of its booking (Liang et al., 2017).

Next, we examine the influence of the "instant booking" facility, which positively induced subsequent reservations, and receiving favourable reviews (Liang et al., 2017; Wang and Nicolau, 2017). Finally, we investigate the effect of the predictors (such as cleanliness,

[6] How do star ratings work: https://www.airbnb.co.in/help/article/1257/how-do-star-ratings-work-for-stays

communication, and value-for-money) aggregated from guests ’reviews. Few of these attributes are similar to the ones which Booking.com also asks for[7]. For example, Airbnb recommends that hosts communicate clearly, promptly, and on time to maintain steady arrival of room reservations [8]. Prior studies have also highlighted the essence of these factors as fundamental elements for peer-to-peer guests (Tussyadiah, 2016; Martin-Fuentes e al., 2018). In other words, these ratings are a true reflection of the hygiene, transparency of messages, and economic value for staying at shared homes (So et al., 2018). Table 1 highlights the predictors across recent comparable studies and their research objectives.

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2.2.Theoretical Background

2.2.1. *Value co-creation in Airbnb*

In this study, we apply the “Service-Dominant” (S-D) Logic (Vargo and Lusch, 2004) that empowers *value co-creation* to examine the predictors of successful reservations at Airbnb shared-homes. Traditional services are based on “goods-dominant” (G-D) logic (Vargo and Lusch, 2004), where the primary aim is to create and deliver objects to the customer to be sold through economic exchange. According to G-D logic, the entire value is embedded into the final good during the firm’s manufacturing process, and the value of the good is indicated by the market price or what the customer is willing to pay. In such a process, the manufacturer can increase efficiency and profit through standardization of processes and economies of scale (Vargo et al., 2008). In a G-D logic, customers consume the value and must return to the supplier of goods to have access to more value with the procurement of additionals goods, deemed the sole reservoir of values (Vargo et al., 2008). Applying S-D logic in sharing-

[7] Cleanliness measures on Booking.com: https://bit.ly/3itrbTO
[8] Great communication is the key to hosting success: https://bit.ly/2SoVTCT

economy literature, scholars have reported mixed responses about *value co-creation* during Airbnb experiences among both the guest and the host. Some scholars also suggest that "customer value" in a collaborative ecosystem cannot simply be offered by the consolidation of the host attributes and the platform in a piecewise structure (value-in-exchange) as in G-D logic, but it must emerge through a rigorous and concerted effort between the guest and the host (value-in-use) (Cova et al., 2011; Vargo and Lusch, 2016; Jiang et al., 2019). Following are the major differences between G-D and S-D Logic: (a) *Value* - created by the manufacturer (G-D Logic) vs co-created by all stakeholders (S-D Logic). (b) *Value delivery* - piecewise manner from manufacturer to customer (G-D Logic) vs mutual effort by both manufacturer and customer (S-D Logic). (c) *Resources* - manufacturer's resources are operand (G-D Logic) vs value from the favourable use of operant resources, which are occasionally transmitted through operand resources (i.e. goods) (Vargo and Lusch, 2004).

Further, these collaborative-consumption platforms are driven by every stakeholder of the ecosystem, making Airbnb worthy of investigation using the S-D logic (Vargo and Akaka, 2012; Jiang et al., 2019). This novel way of thinking also suggests that guests play a significant role during the "co-creation" of value during the reservations of Airbnb shared homes and are not mere recipients of end-products or final service deliveries. According to Sheth (2020), value co-creation occurs when both the *supplier* (Airbnb host) and the *customer* (Airbnb guest) participate in a mutually symbiotic bond. Both the host and the guest contribute with resources that are inimitable and complementary to the final "value co-creation" stage, as the case for Airbnb peer-to-peer homes. For instance, prospective guests (or the *customers*) refer to historical reviews on the Airbnb shared-home submitted by prior guests to measure different dimensions such as *cleanliness*, *communication*, and *value-for-money* (Xu, 2020; Zhu et al., 2020). While, the hosts (or the *supplier*) of the shared-home co-creates service values by presenting a relevant description on the Airbnb platform, enriched with home-attributes, maintaining a trust-based ranking (in the form of “Superhost” badge), and offering ample amenities to enjoy (Van der Heijden and Bondarouk, 2020). In this manner, value co-creation occurs during an Airbnb peer-to-peer shared accommodation. A summary of the recent studies that have examined value co-creation in Airbnb is available from the authors.

2.2.2. *Theory of Consumption Values*

In this study, we also draw theoretical motivation from the Theory of Consumption Values (TCV). According to Zeithaml (1988), *customer-perceived value* refers to “the consumer's overall assessment of the utility of a product or service based on perceptions of what is received and what is given.” Sheth et al. (1991) proposed the TCV where they noted that perceived value is experiential and is consistently mirrored as a multi-dimensional construct. The five primary values that influenced consumer decision-making are namely - *functional value, social value*, *emotional value*, *epistemic value*, and *conditional value*. The functional value of an alternative relates to the perceived utility acquired through the possession of certain prominent features. A consumer enjoys a product or a service due to its superior functional and physical performance derived from these features that may not be available with its alternatives. Often, the functional value of a service is deemed to be the primary driver of consumer decision-making (Sheth et al., 1991). For example, the functional values derived from an Airbnb home include the *accommodation capacity* and *amenities offered* (figure representing these variables are available from the authors), *superhost* and the platform design embedded in the *description of the house* - all of which motivate a guest to book the home. Our study differs from Sthapit et al. (2019), who examined functional values among Airbnb guests by checking whether they found it reasonably priced.

Next, the social value of an alternative relates to the perceived utility acquired through its association with one or more social clusters. A service or a product attains social value through its relationship with various socio-economic and cultural groups. For example, the social values derived from an Airbnb home include provisioning of local cultural information, guiding guests with whereabouts in the neighbourhood, engaging in shared social practices (Johnson and Neuhofer, 2017). Often, guests display these values directly in the description of the Airbnb home (figure demonstrating this is available from the authors), or sometimes the guests may even write about these social experiences in their reviews, leading to star ratings (figure available from the authors). In this aspect, the predictors in our study improve over prior research (Jiang et al., 2019; Sthapit et al., 2019) who had examined social values among Airbnb guests through better social acceptance, improved social perception, and impression-building.

The emotional value of an alternative refers to the perceived utility acquired from its capability to stimulate emotions within the customer. A service or a product attains emotional value when linked with explicit feelings or when disseminating those feelings. For example, a traveller derives emotional values when he/she finds the Airbnb shared-home experience a pleasantly surprising and thrilling alternative to traditional hotels, leading to arousal of feelings and emotions. For instance, host-related predictors (such as *positive and negative sentiments from the home description, host response time, membership duration, total homes owned by the same host*) (figure available from the authors), and guest-related predictors (such as p*ositive and negative sentiments from guest reviews*) (Biswas et al., 2020). In this aspect, predictors in our study differ from those proposed by prior research (Zhang et al., 2018b; Sthapit et al., 2019) who had sought answers to questions such as "Airbnb makes me feel good" or "I enjoy using Airbnb service".

Next, the epistemic value of a product or service refers to the perceived utility gained through the arousal of curiosity and novelty compared to its alternatives. Recently, Airbnb has launched a new feature, *Experiences,* which "are in-person or online activities hosted by inspiring local experts and go beyond typical tours or classes by immersing guests in a host's unique world"[9]. These are a perfect example of services delivering epistemic values through knowledge-gain and curiosity. In this study, we did not find any predictor representing epistemic values.

Finally, the economic value of an alternative refers to the perceived economic utility acquired from its capability to stimulate emotions within the customer. A service or a product can deliver economic value when its benefits are higher than the cost outcomes compared to competitor services. For example, an Airbnb shared home can provide economic value with the help of the following predictors: *price difference, instant booking* and *value for money*. These predictors are unique to the past literature that examine Airbnb shared-homes with the TCV theory (Jiang et al., 2019; Sthapit et al., 2019).

3. Data Used for this Study

3.1. Data Description and Feature-Engineering

We collected the data for shared-home rentals for this study from insideairbnb[10], a third-party open-access website that sources publicly available information from the Airbnb website. Our study consisted of the shared-homes listed on Airbnb and active between October 2009 and September 2020 across the twenty-two cities in the four continents (Europe, Australia, Asia-Pacific, and North America).

We also found that a significant number of listings did not receive any bookings at all. We present these details for each city across the four continents during the collection of Airbnb data in Table 2. In our study, we chose the independent variables based on the following broad dimensions: (i) space description and textual summary (ii) host (iii) location (iv) star ratings (v) price difference (vi) home (vii) booking policy and (viii) review scores from guests. The *host-based* predictors such as *space description length*, *space description positive sentiment*,

[9] Airbnb Experience: https://www.airbnb.co.in/help/article/1581/an-introduction-to-airbnb-experiences
[10] The data behind the Inside Airbnb website: http://insideairbnb.com/get-the-data.html

space description negative sentiment and *social neighbourhood* were derived from linguistic cues using appropriate text-mining techniques. They were generated by the LIWC (Linguistic Inquiry and Word Count) software (Pennebaker et al., 2015). LIWC performs text analysis based on its inbuilt dictionary that consists of almost 6,400 words, word stems, and emoticons and is considered a well-known and reliable psychometric tool. Numerous studies confirm the validity of LIWC that examine online textual data to infer psychometric homes (Nguyen et al., 2017; McHaney et al., 2018; Biswas et al., 2020).

We present the predictors used to build our framework in Table 3. The descriptive statistics for all variables in all regions are available from the authors. We transformed "Exact Location" to a binary variable with two values: 1 (when average ratings out of 5 given by guests for "exact location" are greater than 3) and 0 (otherwise). Further, some predictors exhibited high standard deviations, such as *space description length*, *total listings*, and the *price difference*. Therefore, we normalized those predictors and log-transformed them before modelling (Liang et al., 2017; Liang et al., 2020).

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4. Research Methodology

4.1. Empirical modelling with count data for Airbnb shared-homes

Model-fitting of count data is a challenging problem in data analytics (Winkelmann, 2008). The Poisson regression model is the benchmark model for count data. Poisson regression assumes that the incidence rate of occurrence of an event is μ and is Poisson in nature, which can be determined by a set of n predictors. Hence, the number of successful bookings for the

i^{th} Airbnb home be y_i such that y_i follows a Poisson distribution with mean $\mu_{i;}$ $y_i{\sim}Po(\mu_i)$ and is given by the functional form:

$$log_e(\mu_i) = \beta_{i0} + \beta_{i1}X_{i1} + \beta_{i2}X_{i2} + \cdots + \beta_{in}X_{in} \quad (1)$$

In Eqn. (1), β_{i0} is the intercept, and the regression coefficients are β_{i1}, β_{i2}, …., β_{in}. The Poisson regression is used for fitting the expected number of home-bookings for the j^{th} Airbnb home, as follows: $E[y_i] = \mu_i = exp(\zeta_i)$ such that the link function is a natural logarithm. A similar approach is used to fit count data using Negative Binomial Regression, assuming $y_i \sim NegBinomial(\mu_i, \alpha)$, where μ_i is the mean, and α is the scale parameter. The mean is parametrized with the covariates in the regression model using a log-link function exactly as shown in Eqn. (1) above. Negative Binomial Regression is used as a generalization of the Poisson Regression, which removes the restrictive assumption that the variance is equal to the mean as in the Poisson model.

4.2.Alternative Modelling Techniques to handle Over-dispersion

Poisson regression assumes that the mean and the variance of the distribution for y_i (the bookings received by an Airbnb home), are both equal to μ_i. However, this condition does not hold for many real-world count data, as are some of the Airbnb booking datasets in this study.

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INSERT FIGURE 1 HERE
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This incongruity is universally acknowledged as *Over-dispersion* (Winkelmann, 2008), and its presence is shown in Figure 1 for the datasets used in this study. With the help of *Dean*'*s Over-dispersion Tests* (Dean, 1992), we verified the presence of over-dispersion effects in the datasets extracted for the four continents in this study, and the results are given in Table 4. The reason for over-dispersion, in most cases, is due to the excessive zero counts. Some methods, which scholars are recently applying to handle over-dispersion among count data, are the zero-inflated regression model and the hurdle model. However, the hurdle models are more flexible and can handle both over-dispersed and under-dispersed data. Let $Y_i, i = 1, \dots, m$ be a nonnegative integer-valued random variable and suppose $Y_i = 0$ is observed with a frequency significantly higher than that, which the regular model can explain. We consider Hurdle Poisson Regression where the response variable $Y_i (i = 1, \dots, m)$ has distribution given as:

$$P(Y_i = y_i) = \begin{cases} w_0, y_i > 0 \\ (1 - w_0) \frac{e^{-\lambda_i} \lambda_i^{y_i}}{(1 - e^{-\lambda}) y_i!}, y_i > 0 \end{cases} \quad (2)$$

where $0 < w_0 < 1$ and $w_0 = w_0(z_i)$ satisfy $logit(w_0) = log(\frac{w_0}{1-w_0}) = \sum_{j=1}^{m} z_{ij}\delta_j$,

and $z_i = (z_{i1} = 1, z_{i2}, \dots, z_{im})$ is the i^{th} row of the covariate matrix Z and $\delta = (\delta_1, \delta_2, \dots, \delta_m)$ are unknown m-dimensional column vector of parameters. This function is linear, and other appropriate link functions may be used. Besides, there is interest in gathering any systematic variation in λ_i such that the value of λ_i is most commonly parametrized using a log-linear model of the following form: $(\lambda_i) = \sum_{j=1}^{m} x_{ij}\beta_j$. $\beta_j^{'}$ s are the independent variables in the regression model, and m is the number of the independent variables. In this study, we apply the regular Poisson, Negative Binomial and their hurdle-at-zero versions to model the "count of bookings" for each Airbnb listing. Therefore, Eqns. 3(a) and 3(b) give the set of equations to represent the hurdle model, the mean component and the mixture probability:

$$\mu_i(CountofBookings)$$
$$= exp(\beta_0 + \beta_1 SpaceDescriptionLength_i + \beta_2 SpaceDescriptionPositiveSentiment_i$$
$$+ \beta_3 SpaceDescriptionNegativeSentiment_i + \beta_4 Superhost_i$$

$$+\beta_5 ProfilePhotograph_i + \beta_6 Membership_i + \beta_7 ResponseTime_i$$

$$+\beta_8 TotalListings_i +$$

$$\beta_9 ExactLocation_i + \beta_{10} SocialNeighbourhood_i$$

$$+\beta_{11} Stars_i + \beta_{12} PriceDifference_i + \beta_{13} Accommodates_i$$

$$+\beta_{14} Facilities_i + \beta_{15} InstantBooking_i + \beta_{16} Cleanliness_i$$

$$+\beta_{17} Communication_i + \beta_{18} ValueforMoney_i$$

- Equation 3(a)

And,

$$\lambda_i(CountofBookings)$$

$$= exp(\beta_0 + \beta_1 SpaceDescriptionLength_i + \beta_2 SpaceDescriptionPositiveSentiment_i$$

$$+\beta_3 SpaceDescriptionNegativeSentiment_i + \beta_4 Superhost_i$$

$$+\beta_5 ProfilePhotograph_i + \beta_6 Membership_i + \beta_7 ResponseTime_i$$

$$+\beta_8 TotalListings_i +$$

$$\beta_9 ExactLocation_i + \beta_{10} SocialNeighbourhood_i$$

$$+\beta_{11} Stars_i + \beta_{12} PriceDifference_i + \beta_{13} Accommodates_i$$

$$+\beta_{14} Facilities_i + \beta_{15} InstantBooking_i + \beta_{16} Cleanliness_i$$

$$+\beta_{17} Communication_i + \beta_{18} ValueforMoney_i$$

- Equation 3(b)

4.3.Pairwise correlation and multicollinearity checks

Next, we calculated the pairwise correlations and the variance inflation factors (VIF) for the 14 numerical predictors from our proposed empirical framework. Subsequently, we also verified whether the pairwise correlation values remained within the permissible limits (close to 0.5), and the VIF-s remained within the allowable limit of 10 (Lin, 2008). In this study, our objective is to distinctly examine the booking datasets of each of the four continents. Therefore, we verified these values individually for each of the geographies. A thorough analysis of the parities correlation between the variables is done along with checks on VIF values to ensure there was no multicollinearity. The pairwise correlations and VIFs in all regions are available from the authors.

5. Results and Discussion

This section presents the results from various count regression models to explain the count of successful Airbnb home-bookings across each geography in Tables 5, 6, 7, and 8. Then, we also present a combined analysis of these geographies in Table 9. Finally, we present a comparison of predictors for Airbnb home-bookings across geographies in Table 10.

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5.1. Findings from main results

To study the determinants of bookings for Airbnb, we applied the proposed count regression models. We also explored Hurdle-at-zero models to account for the inflated frequency of zero counts of bookings (i.e. no bookings), leading to over-dispersion in the count data. The model-fitting results are based on host characteristics, review ratings of the listing, listing characteristics, textual data from the description of the shared-home provided by the host, exact location of the listing, neighbourhood, price variance, and booking policy.

Tables 5-8 show the results from the explanatory models on Airbnb home-bookings in Europe, Asia-Pacific, the USA and Australia. The results reveal that the *length of the description of space* (given by the word count) seems to encourage successful bookings for Europe (coeff.: 0.236, p-value < 0.0001). Therefore, if the description consists of more words to describe the home, it is more likely to attract bookings from potential guests - a finding echoed by previous studies (Bilgihan and Bujisic, 2015; Zhang et al., 2018a; Liang et al., 2020). While exploring the textual content of the home description, we find that there is minimal influence of sentiments extracted from the space description and summary bookings for any Airbnb home across all geographies. Further, any host would write only positive words about his own home; thereby, the prospective guest finds it too flattering to be true. Therefore, the coefficient is negative (coeff.: -0.035 for Europe, p-value < 0.0001, -0.030 for the US, p-value < 0.0001, -0.024 for Asia-Pacific, p-value < 0.0001, -0.024 for Australia, p-value < 0.0001), while the coefficient of negative sentiment is positive consistently (coeff.: 0.014 for Europe, p-value < 0.0001, 0.020 for the US, p-value < 0.0001, 0.016 for Asia-Pacific, p-value < 0.0001, 0.022 for Australia, p-value < 0.0001) (Ma et al., 2018). Such contrasting sentiments extracted from product description are reflected in the e-commerce literature (Ismagilova et al., 2019). If the Airbnb host writes something critical, truthful, or practical while describing the home, potential guests take it positively and appreciate the hosts' truthfulness. This contrasting effect of sentiments would tend to increase the chance of a successful booking.

Next, we examined the hosts who received the "Superhost" badge. Hosts attain a "Superhost" badge if they complete a minimum of 10 stays in a year, are quick in responding to guest queries, have received 5-star ratings across at least eighty per cent of all reservations, and rarely cancelled a confirmed booking. This study introduced a dummy into the model with "Superhost" equals 1 when the host has the Superhost badge and 0 otherwise. Results show that the coefficient estimates for "Superhost" are consistently positive across all geographies.

Thus, guests find it more assuring to book a home where the host has been ratified, also supported by previous literature (Liang et al., 2017; Gunter, 2018; Mauri et al., 2018). The Airbnb CEO, Brian Chesky, has echoed similar feelings to describe the business of shared-homes.[11] However, the magnitude of the coefficients is higher for European cities (coeff.: 0.869, p-value < 0.0001) than others (coeff.: 0.0.699 for Australia, p-value < 0.0001, 0.649 for Asia-Pacific, p-value < 0.0001, and 0.695 for the US, p-value < 0.0001).

Another important host-based characteristic is whether the *host has a profile photo* on the listing website or not. This study introduced a dummy variable to account for, which has a consistently positive coefficient for all continents. Therefore, a host who displays the picture on the home-listing website creates an unobserved bond of trust between himself/herself and the prospective guest, and the guest can mentally relate the name of the person to a physical face for the place they would rent (Ert et al., 2016; Barnes, 2020; Peng et al., 2020; Zhang et al., 2021). This phenomenon is especially true for shared accommodation as they are bound to co-create a more personalized consumer experience and value than traditional hotels. The magnitude of the coefficients is highest for Australian cities (coeff.: 6.286, p-value < 0.0001) and lowest for Asia-Pacific cities (coeff.: 0.148, p-value < 0.0001) (China and Japan in this study). These finding for Asia-Pacific cities also match the prevalence of the existing difficulty of facial recognition among Chinese iPhone users[12]. Often Chinese home-sharing firms have been known to launch facial recognition-based locks specifically for travellers in China[13].

Next, we investigate *the response times of the host* to the queries raised by potential guests. The host response time has been categorized as "within an hour", "within few hours", "within a day", "no response" to the query and accept a booking. We would expect guests to be favouring hosts who respond quickly. Prompt response from the host within an hour or a few

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[11] In The Business of Trust: https://news.airbnb.com/in-the-business-of-trust/
[12] Chinese users claim iPhone X face recognition can't tell them apart: https://bit.ly/3gi8ik0
[13] Chinese Airbnb competitor rolls out facial recognition locks: https://yhoo.it/3xpdv0v

hours will tend to generate more positive bookings and responses from prospective guests. Our results also reveal similar effects for all four continents. The four continents have positive and highly statistically significant coefficient estimates for *host response time within an hour* (coeff.: 0.174 for Europe, p-value < 0.0001, 0.220 for Australia, p-value < 0.0001, 0.268 for Asia-Pacific, p-value < 0.0001, and 0.253 for the US, p-value < 0.0001). However, as more time elapses between a customer's query and the host's response, it seems to discourage the final booking decision. Comparing the four geographies, the host response time (within an hour) shows the strongest influence on booking in Asia-Pacific (China and Japan in this study) (coeff.: 0.268, p-value < 0.0001). It can be possibly because Airbnb has more competition in China from local peer-to-peer home-sharing platforms than in other geographies[14]. The same is also true for USA-based cities where the number of hotels and temporary accommodations is high, leading to a higher competitive market [15]. The coefficient values for host response time (within an hour, few hours, within a day) are much lower than what host response time (no response) shows. Thus, the host response time (no response) elicits an immensely negative effect on the guest's future booking decision. If the host does not respond at all, it is going to have an adverse impact.

We then explore the impact of the t*otal number of listings* owned by the hosts. Some Airbnb hosts have multiple homes listed in their names, and often they are located in different parts of the same city. When the number of listings under each host is more (generally more than one listing in a hosts name), it adversely affects the guests' decision to book. A prospective guest looks for homes that the host well manages. Moreover, when there are multiple homes in a hosts' name, it is consistently perceived to hurt their bookings, as they perceive a lack of proper care from the host during the stay (Xie and Mao, 2017; Kwok and Xie, 2019). Additionally,

[14] Annual transaction value of home sharing market in China from 2015 to 2019: https://bit.ly/3pDjJXP
[15]Number of Airbnb users in USA: https://www.statista.com/statistics/346589/number-of-us-airbnb-users/

regulators and municipal authorities are critical of multiple Airbnb homes being managed by a single host, which may operate like a hotel chain and not a standalone home-sharing facility that does not pay lodging taxes and tourism revenues but enjoys the facilities funded by them[16].

Another salient characteristic of an Airbnb listing is its exact location.[17] This study introduced a dummy variable to measure the effect of the *exact location*, which reports a positive coefficient estimate in the Hurdle Regression performed for all four continents. This finding supports the claim that the location of a home is precise as described by the host in the Airbnb website, and the previous travellers have verified it after their stays; thus, chances of successful bookings increase manifold. Similarly, the effect of social neighbourhoods is strongly positive on bookings for all four continents. Among them, Asia-Pacific (coeff.: 0.076, p-value < 0.0001) and the USA (coeff.: 0.077, p-value < 0.0001) demonstrate the highest positive impact with a statistically significant coefficient for both of them.

On the other hand, it has the least impact on bookings in Australia (coeff.: 0.009, p-value < 0.0001), possibly due to the sparse population density. On the contrary, European cities (coeff.: 0.026, p-value < 0.0001) report a higher impact of socially active neighborhood towards Airbnb shared-home bookings. Therefore, when hosts write socially relevant content in the neighbourhood description, such as "very friendly and social neighbourhood", "cosy neighbourhood", it bolsters the chances of booking.

Star ratings assigned by travellers after their Airbnb also stays a statistically significant predictor of Airbnb bookings (Ma et al., 2018). A potential customer often looks at home reviews and overall ratings (represented by stars) during information search for a home. Moreover, the star ratings immediately become a crucial factor during the successful booking of a listing[18]. Our study finds that the effect of stars is consistently positive and increasing for

[16] The economic costs and benefits of Airbnb: https://bit.ly/3g9TkxN
[17] How do star ratings work ? https://www.airbnb.co.in/help/article/1257/how-do-star-ratings-work-for-stays
[18] Explaining 5 star ratings to guests: https://bit.ly/3iDF55E

all cities across continents, and they are strongest for Australia (coeff.: 1.797, p-value < 0.0001) and weakest for Europe (coeff.: 1.003, p-value < 0.0001).

With the rise in the number of homes listed by Airbnb, localities have more homes listed in the same neighbourhood (Wang and Nicolau, 2017; So et al., 2018). Similar findings have been reported in the hotel pricing literature (Maseiro et al., 2015). Therefore, the *price per night* is a significant factor for a potential guest to consider before reservations. We compared the absolute difference between the *price per night* of a listing and all listings' median price in the neighbourhood. In the case of Asia-Pacific cities (coeff.: -0.015, p-value < 0.0001), we found an affinity of "price-stickiness" among guests leading to a reduced number of bookings when "price per night" for an Airbnb home deviated excessively from the median price in the neighbourhood. However, it positively affected Airbnb reservations for cities (coeff.: 0.123 for Europe, p-value < 0.0001, 0.043 for Australia, p-value < 0.0001, and 0.139 for the US, p-value < 0.0001) in other continents, possibly because price acted as a surrogate of quality among hotels and lodgings (Chattopadhyay and Mitra, 2019).

Among other home-related characteristics, the listings that can accommodate more people seem to attract fewer tourists. Therefore, we found that the *accommodation capacity* had a consistent negative coefficient estimate for all four continents. With options of accommodating more people at an Airbnb shared-home, the chances of a booking might decrease. For many tourists, hotels can easily provide accommodations with attached bathrooms with bedrooms, but Airbnb homes with limited bedrooms or bathrooms might not have the option and miss such opportunities. Therefore, the Airbnb shared-homes that can accommodate fewer guests, with a few bathrooms that are commensurate with bedrooms, can attract more business.

Next, we look at whether the homes have the option of *instant booking* or if the host needs to approve a prior reservation request and how it affects the booking decision. This study introduced a dummy variable, which takes the value as *one* when the Airbnb shared-home allows instant booking or *zero* otherwise. The coefficients for this variable are consistently positive for all four continents; thus, *instant booking* would tend to increase the chances of booking decision. The effect of *instant bookings* in business travel is stronger, whereas it is weaker for leisure travellers, who might plan and make reservations accordingly. The coefficient for *instant booking* is the highest for the USA (coeff.: 0.346, p-value < 0.0001) and lowest for Asia-Pacific (coeff.: 0.015, p-value < 0.0001). It could be possible that the guests arriving at the cities in Asia-Pacific are well prepared and plan; therefore, last-minute reservations have a minimal impact. In contrast, cities in the USA such as New York and Seattle see much footfall from business travellers, a higher positive impact.

Next, *review ratings on the cleanliness* of the home have a positive effect on future reservations that it may receive (Cheng and Jin, 2019; Xu, 2020). The coefficient estimates are also consistently positive for each of the four continents (coeff.: 0.579 for Europe, p-value < 0.0001, 0.407 for Australia, p-value < 0.0001, 0.216 for Asia-Pacific, p-value < 0.0001, and 0.921 for the US, p-value < 0.0001). However, the results suggest that guests arriving at Asia-Pacific cities (coeff.: 0.216, p-value < 0.0001) are less careful about cleanliness than those in the USA (coeff.: 0.921, p-value < 0.0001) are. The coefficient estimates for *value for money* positively affect subsequent Airbnb bookings for Europe (coeff.: 0.046, p-value < 0.0001), Australia (coeff.: 0.307, p-value < 0.0001), and the USA (coeff.: 0.260, p-value < 0.0001) and negatively impact the Asia-Pacific cities (coeff.: -1.280, p-value < 0.0001). This finding might imply that guests in Asia-Pacific tend to book at slightly higher-priced Airbnb homes where the price might be considered a surrogate for quality (So et al., 2018). Simultaneously, *communication* holds a consistent top-five rank among significant predictors (coeff.: 1.470 for Europe, p-value < 0.0001, 0.738 for Australia, p-value < 0.0001, 1.487 for Asia-Pacific, p-value < 0.0001, and 1.323 for the US, p-value < 0.0001) (see Figure 4), and so potential guests expect that the hosts ask them a few follow-up questions after every booking request (Ert and

Fleischer, 2019; Xu, 2020). They must not be rude or too inquisitive but ensure that the Airbnb shared-home is a good fit, leading to an outstanding shared-home experience.

5.2.Findings from the Interaction Effects

Finally, we have endeavoured to look at the full model across all four continents from where we have chosen the 20 cities for this study (see table 9). In studying the main effects of the variables chosen for the study five different count regression models were chosen, namely, Poisson, Quasi-Poisson, Negative-Binomial, Hurdle-at-zero Poisson and Hurdle-at-zero Negative-Binomial. Based on the comparison between the AIC of these models, it is seen that the Hurdle-at-zero Negative-Binomial model performs the best (with the lowest AIC). Thus, in order to study the interaction effects, we have resorted to using the Hurdle-at-zero Negative-Binomial regression model. Some very interesting insights emerge from this model in the form of interaction between the variables. Defining the four continents as factors, we have looked into the interaction with some of the variables whose main effects have been statistically significant. The variables chosen are a *super-host* badge, *exact location*, *price difference* and *instant booking.* In fitting the model, we use Australia as the benchmark category and other continents (Asia-Pacific, Europe and the US). Looking at the coefficients of the interaction terms, we can see that Australia, Asia (coeff.: -0.611), and the US (coeff.: -0.074) have a lower impact of the super-host badge on successful bookings of Airbnb listings. But although in the case of Asia, this difference between Asia and Australia is significant statistically (p-value < 0.01), it is not significant in the US. Europe, on the other hand, shows a significantly higher impact of super-host badge on Airbnb bookings when compared to Australia (coeff.: 0.254) (p-value < 0.01).

Next, when comparing the impact of exact location we find that Asia (coeff.: -0.589), Europe (coeff.: -0.159) and the US (coeff.: -0.143) all have lower influence on Airbnb booking as compared to Australia. Although Asia and the US have a significant effect (p-value < 0.01), the same is not true for Europe. This observation can be attributed to the fact that Australia is sparsely populated and the connectivity by public transport may not be very good. This requires the exact location of the listing to be known to the prospective guest to plan accordingly.

Moving on to the next variable, *price difference*, we conclude from the regression result that as compared to the benchmark category of Australia, Asia (coeff.: 0.046), Europe (coeff.: 0.203) and the US (coeff.: 0.005). Though Europe has a significantly higher impact (p-value < 0.01), Asia has a comparatively lower significance (p-value < 0.1). And there is no statistical significance found between the impact of price difference on bookings between the US and Australia.

Finally, for the instant bookable quality of listings, Asia (coeff.: -1.841) seems to have a lower significance (p-value < 0.01) as compared to Australia, probably due to the much higher density of listings found in Asia. However, Europe and the US show a significantly higher impact of instant bookable on successful properties booking. This might be because many European and US cities see many business travellers arriving at very short notice for whom, being able to book instantly into an Airbnb is more attractive.

5.3.Feature Selection

In data analytics, as we are dealing with in this study, the significance of the variable importance schemes are paramount. Researchers generally undertake them after fitting the appropriate regression techniques. These schemes help us better understand the effects of specific independent variables on the dependent variable while building the regression models (Chattopadhyay & Mitra, 2019). Here we applied the *varImp()* function for GLM setting from the *caret* package in R to improve our prediction models and retain only the top 10 important features (see Figure 2). For an LM/GLM model-based approach, *varImp()* creates an aggregate importance score by applying the absolute value of the t-statistic for each model parameter and then ranks the features accordingly. In our study, the Poisson, Quasi-Poisson, Negative

Binomial, and Hurdle-at-zero Poisson and Negative Binomial models were fitted using GLM, we obtained the variable importance scores from these models that helped in the selection of important features.

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INSERT FIGURE 2 HERE
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6. Implications of this study and Concluding Remarks

6.1. Contributions to Theory

Our study has several theoretical contributions, mainly towards the *Value Co-Creation Theory* (Vargo and Lusch, 2004) and the *Theory of Consumption Values* (Sheth et al., 1991) in the context of "shared-home bookings". First, this study extends the following aspects of the *Value Co-Creation Theory.* (a) Identifies the presence of a value co-creation mechanism promoted by the guests and the hosts for a given Airbnb shared-home experience. Contrary to the hotel industry, where much of the customer value strongly depends on the hotel chain, affiliation, and is pre-existing within the hotel room, each Airbnb home is unique in its service-offering and service experience. This arrangement promotes a unique value co-creation activity. (b) While the host of the shared-home (or the supplier) can co-create service values through displaying a detailed description on the Airbnb platform that is balanced in both positive and negative sentiments, enriched with amenities for the guest (or the consumer), or responding quickly to the guest's queries; the guest participates in value co-creation by reading historical reviews (e.g. *cleanliness*, *communication,* and *value-for-money*) on the Airbnb shared-home posted by past guests and later publishes own experience after the shared-home stay. Eventually, the host earns credits (e.g. *superhost badge*) based on these reviews and subsequently attracts more guests through the trustworthiness built during the value co-creation. While few academic studies reveal these value co-creation activities in shared homes, especially on Airbnb, they are yet to acknowledge its host-level and guest-level predictors precisely using real Airbnb transaction data. This is the primary theoretical contribution to the existing research on shared accommodation.

Second, this study draws on the *Theory of Consumption Values* to reveal different customer-perceived values from an Airbnb shared-home and maps them with the chosen predictors as follows: (a) *functional value - the* attractiveness of shared-home, platform design, accommodation capacity, and amenities offered, (b) *social value* - whether the neighbourhood is sociable and friendly, cleanliness and communication review scores awarded by guests after Airbnb stay which also served as social interaction. (c) *emotional value* - positive and negative sentiment contents of the home description on the web platform, review sentiments, and (d) *economic value* - price difference, value-for-money scores, and instant booking. This is the second theoretical contribution of this study.

6.2. Contributions to Managerial Practices

Our study provides several actionable insights for managers as well as prospective guests. First, it gives an idea about forecasting the number of customer reviews received by P2P property reservations, which can help the hosts, highlight various qualities of their listings to potential guests who search for shared homes online. In addition, using the insights, prospective guests can make informed decisions if they are aware of the factors to look for in a shared home and thus help both parties make decisions better.

Second, with the massive growth in the shared-home rental industry in recent times, new management firms are emerging to assist Airbnb hosts in improving their short-term rentals' booking performance. Some of many such businesses are Evolve and Turnkey in North America and Guest-Ready in Europe. The recommendations from our study will help them make the listings more appealing to prospective guests.

Third, it emerges from our study that guest-specific and host-specific predictors are significant in affecting successful bookings of an Airbnb listing. This finding can help develop unique marketing strategies for tourists by highlighting features of shared property owners and the reviews posted by users. Accordingly, the advertisement contents can be displayed on various media for shared-home rental to attract prospective guests and hosts.

Fourth, from our extensive geography-specific study of the variables that affect Airbnb bookings, we have made a list of highly significant ones and compare them across four continents (please see Table 10). This study finds that the super host badge is highly influential in all four continents. And, so is the average consumer review on the communication between guest and host. The same is also true for length (word count) of space description, i.e. longer the description of the property provided by the host, the higher are the number of successful bookings of such listings. In addition, however, there are variables strictly significant in a particular continent. For instance, the price difference is mostly an important factor in Europe and the US, whereas the number of amenities provided by the host is a deciding factor in successful booking in Australia and Asia-Pacific but not in Europe or the US. The contrasting evidence from the significant variables helps make recommendations tailor-made for each geographic region.

6.3. Conclusion

Our study reveals several interesting insights, including identifying significant factors contributing to the successful room-reservations on the Airbnb peer-to-peer shared-home platform. In particular, we identified host-based (such as *superhost, membership seniority, instant booking, and accommodation capacity*) and guest-based (such as *star ratings, exact location, and review scores for cleanliness, communication, value-for-money*) for booked as well as non-booked rooms on peer-to-peer accommodation platforms through co-creation of consumer values (Camilleri and Neuhofer, 2017; Ramaswamy and Ozcan, 2018). Next, through the variable-importance scheme developed in this study, we presented a set of actionable recommendations across the four geographies - Europe, Australia, Asia-Pacific, and the USA. To our knowledge, this is the first study that examines the predictors of successful Airbnb reservations and their subsequent effects for both booked and non-booked rooms, generalizes their impact across multiple geographies of the world.

Explicitly, this study recognized the prominence of the following predictors to explain the count of successful bookings at Airbnb shared-homes across the four continents: *space description* and *textual summary*, *host*, *location*, *star ratings*, *price difference*, *home*, *booking policy*, and *review scores from guests*. Among *space description* and *textual summary* attributes, the *length of space description* is significant, while there is a minimal influence of sentiments for any Airbnb home across all geographies. Next, among *host-based* predictors, *superhost badge* and *response-time* are the strongest influencers, while the effect of *host profile-photo* is not strong across all continents. When a single host manages multiple homes, potential travellers perceive it adversely. Further, star ratings positively affect room reservations for all geographies. We find a strong “price-stickiness” effect among the Asia-Pacific cities that cause bookings to decrease when the *price per night* deviates too much from the neighbourhood median price. Cities with many business visitors are strongly affected by instant booking options, while other cities are not much affected. In contrast, *accommodation capacity* has a consistently negative effect on the subsequent Airbnb reservations. Finally, guest review scores reveal that good communication and quick response to the queries posted by potential guests can strongly motivate successful reservations on Airbnb across all geographies.

7. Future Scope of Research

Despite these significant insights, our study has a few limitations. First, we examined the predictors of successful Airbnb reservations within a cross-sectional framework. Future research could incorporate seasonality, economic shocks (such as the COVID-19 pandemic), Zhang et al. (2020), and other significant externalities to extend this study. Second, we expected that tourists were impervious to the effects of the host country-level culture while searching for potential accommodations on Airbnb. However, future research could explore the effects of Hofstede's cross-country cultural dimensions of the hosts and the guests while booking Airbnb peer-to-peer homes. Third, there were probably some guests who stayed at Airbnb shared homes but did not leave any comments. Thus, neither explicit nor implicit predictors could be calculated for such bookings. According to the data collected for the study, this particular phenomenon could not be accounted for. Fourth, in this study, we have used a lexicon-based approach, i.e. LIWC (Hartman et al., 2019), to extract the length of space description and the positive and negative sentiment content of space description. However, scholars can further consider more robust text-classification methods (Berger et al., 2020) to enrich the study.

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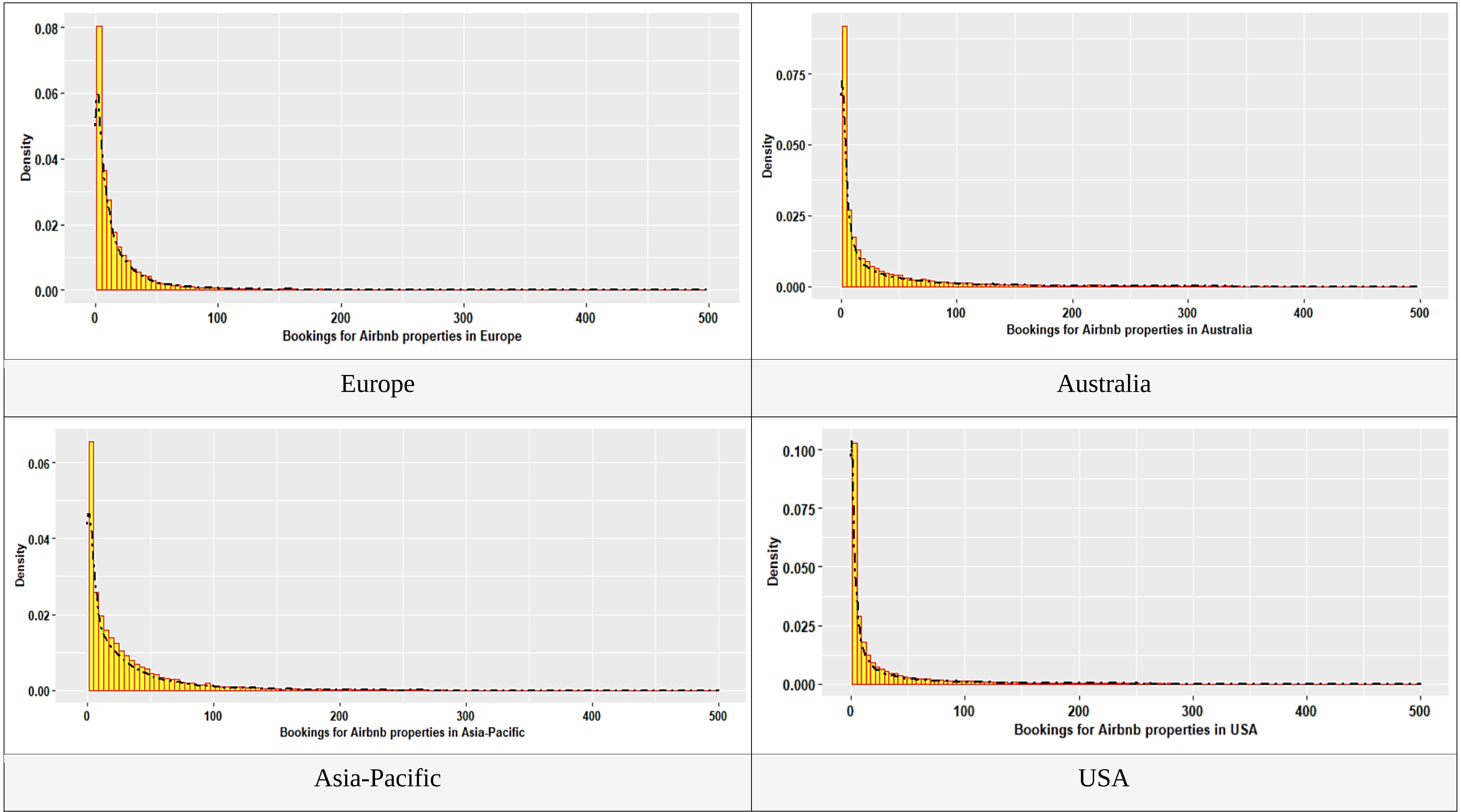

Figure 1: Density plots for "Count of Bookings received by Airbnb homes"

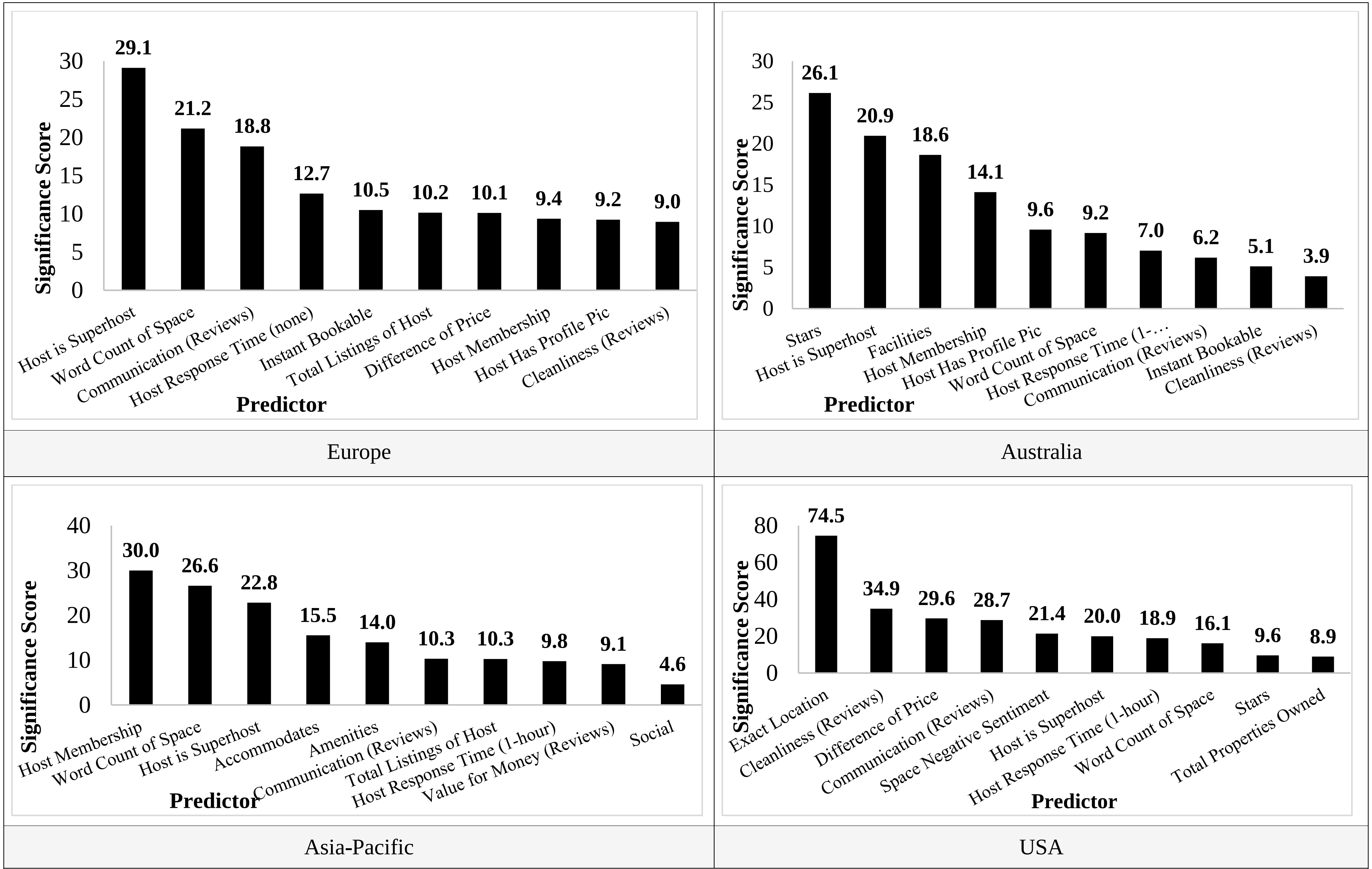

Figure 2: Top ten predictors using Hurdle Negative Binomial for Airbnb

Table 1: Summary of recent literature examining different dimensions of Airbnb homes

	Category	Predictors	Academic Sources	Objective
Host-based	Space Description	Length of title	Liang et al. (2020); **This Study**	Booking Analysis
		Title sentiments	**This Study**	Booking Analysis
		Presence of photo	Ert et al. (2016); Barnes (2020)	Pricing Analysis, Host Trust
			Zhang et al. (2021)	Revenue Analysis
			This Study	Booking Analysis
	Profile	Attractiveness of Photo	Ert and Fleischer (2019)	Host Trust
		Superhost status	Liang et al. (2017); Wang and Nicolau (2017); Xie and Mao (2017); Chattopadhyay and Mitra, (2019); Ert and Fleischer (2019); Barnes (2020)	Host Trust, Pricing Analysis
			This Study	Booking Analysis
		Membership duration	Xie and Mao (2017)	Revenue Analysis
			This Study	Booking Analysis
		Multiple homes	Kwok and Xie (2019); Liang et al. (2020)	Revenue Analysis
			This Study	Booking Analysis
		Response time	**This Study**	Booking Analysis
		Respone Rate	Xie and Mao (2017)	Revenue Analysis
	Home Location	Exact location	**This Study**	Booking Analysis
		Sociable neighbourhood	**This Study**	Booking Analysis
	Price	Price per night	Cai et al. (2019); Wang and Nicolau, (2017); Chattopadhyay and Mitra (2019); Ert and Fleischer (2019)	Pricing Analysis
		Differential price with other Airbnbs in locality	Kwok and Xie (2019)	Revenue Analysis
			This Study	Booking Analysis
	Home Facilities	Room Type	Wang and Nicolau (2017); Xie and Mao (2017); Chattopadhyay and Mitra (2019);	Pricing Analysis

		Bed Type	Wang and Nicolau, (2017); Xie and Mao (2017); Chattopadhyay and Mitra (2019); Ert and Fleischer (2019)	Pricing Analysis; Host Trust
		Guest Capacity	**This Study**	Booking Analysis
		Facilities	Wang and Nicolau 2017); Chattopadhyay and Mitra (2019)	Pricing Analysis
			This Study	Booking Analysis
		Attractiveness of Photo	Ert and Fleischer (2019)	Host Trust
	Booking and Cancellation	Instant Booking	Wang and Nicolau (2017)	Pricing Analysis
			This Study	Booking Analysis
		Cancellation Rules	Wang and Nicolau (2017); Chattopadhyay and Mitra (2019)	Pricing Analysis
Guest -based				
	Historical reviews by guests	Cleanliness	**This Study**	Booking Analysis
		Communication	**This Study**	Booking Analysis
		Value for money	**This Study**	Booking Analysis
		Review sentiments	Biswas et al. (2020)	Booking Analysis
	Overall Ratings	Stars Received	Wang and Nicolau (2017); Xie and Mao (2017); Chattopadhyay and Mitra (2019)	Pricing Analysis
			This Study	Booking Analysis
		Differential Star Ratings	**This Study**	Booking Analysis
	Total Reviews	Total Reviews	Ert et al. (2016);	Pricing Analysis
			Zhang et al. (2018a)	Host Trust
		As Proxy for Bookings	Biswas et al. (2020); **This Study**	Booking Analysis

Table 2. Geographical details of the cities for Airbnb shared-homes

	City	No. of Listings	Non-booked Listings	Date Compiled
Europe	Amsterdam	18,782	2,291	09 October, 2020
	Athens	9,455	2,184	25 October, 2020
	Barcelona	19,896	5,878	12 October, 2020
	Copenhagen	8,528	2,301	27 October, 2020
	Dublin	7,965	1,448	19 October, 2020
	Geneva	1,979	446	27 October, 2020
Australia	Melbourne	20,007	4,465	11 October, 2020
	Sydney	34,276	9,610	11 October, 2020
	Tasmania	4,818	360	07 October, 2020
	Western Australia	9,257	2,035	26 October, 2020
Asia Pacific	Beijing	27,439	12,455	26 October, 2020
	Hong Kong	7,209	3,232	25 October, 2020
	Shanghai	35,572	16,602	26 October, 2020
	Tokyo	11,715	2,396	27 October, 2020
USA	Austin	10,305	2,687	19 October, 2020
	Boston	3,254	891	24 October, 2020
	Chicago	6,295	1,141	24 October, 2020
	Hawaii	21,523	5,498	19 October, 2020
	New York	44,666	10,518	05 October, 2020
	Seattle	4,335	827	25 October, 2020

Table 3. Variables used to build our framework – brief descriptions, and literature sources

S. No.	Variable	Brief Description	Literature Source
Independent Variable			
Space Description and Textual Summary			
1	Length of Space Description	Count of words used in space to describe Airbnb listing (Numeric)	Zhang et al., 2018a; Liang et al., 2020
2	Positive Sentiment of Space Description	Positive sentiment content of home Space (Numeric)	Ma et al. (2018)
3	Negative Sentiment of Space Description	Negative sentiment content of home Space (Numeric)	Ma et al. (2018)
Host			
4	Is Superhost	Being a super host (Binary)	Liang et al. (2017); Gunter (2018)
5	Profile Photo	Presence of host's profile photo on Airbnb listing details (Binary)	Ert et al. (2016); Zhang et al. (2021)
6	Membership	The duration of years spent by the host on Airbnb (Numeric)	Self-developed for this study
7	Response Time	How soon the host responds to queries (Categorical)	Developed from Liang et al. (2020)
8	Total Listings	Count of total homes owned by the host (Numeric)	Liang et al. (2017); Xie and Mao (2017)
Location			
9	Exact Location	Location is Exact (Binary)	Self-developed for this study
10	Social Neighbourhood	Socially relevant content in description of neighbourhood (Numeric)	Self-developed for this study
Star Rating			
11	Stars	Average star rating (out of 5) assigned to Airbnb listing (Numeric)	Martin-Fuentes et al. (2018)
Price per Night			
12	Price Difference	The difference from the median price in a neighbourhood (Numeric)	Self-developed for this study
Home			
13	Accommodation Capacity	Number of people that can be accommodated in the Airbnb listing (Numeric)	Liang et al. (2017)

14	Facilities	Number of unique amenities offered at the Airbnb listing (Numeric)	Chattopadhyay and Mitra (2019)
Booking Policy			
15	Instant Booking	Whether the Airbnb listing allows instant booking (Binary)	Wang and Nicolau (2017)
Review from Guests			
16	Cleanliness	Avg. rating (out of 5) for cleanliness given by guests (Numeric)	Ju et al. (2019)
17	Communication	Avg. rating (out of 5) for communication given by guests (Numeric)	Xu (2020)
18	Value for Money	Avg. ratings (out of 5) for value-for-money set by guests (Numeric)	Ju et al. (2019)
Dependent Variable			
19	Count of Bookings	Proxied by the number of customer reviews received by the Airbnb listing (Numeric)	Xu (2020); Liang et al. (2020)

Table 4. Dean's Over-dispersion Test for Count of Airbnb Bookings

	Europe	**Australia**	**Asia-Pacific**	**USA**
Mean	24.75	25.08	6.26	22.46
Variance	2995.24	2314.04	286.71	2177.58
Dean's PB Statistic[#]	4909.20***	5028.1***	1823.00***	5440.00***
Dean's PB2 Statistic[#]	4909.30***	5028.3***	1823.20***	5440.10***
No. of Observations	66,605	68,358	81,935	90,378

* $p<0.1$; ** $p<0.05$; *** $p<0.001$; [#]Based on Dean (1992)

Table 5. Explanatory models for Airbnb home-bookings in Europe

	Dependent variable*: Successful Bookings*				
	Po	**QP**	**NB**	**H-P**	**H-NB**
Space Description and Textual Summary					
Length of Space Description	0.236***	0.236***	0.221***	0.235***	0.236***
	(0.002)	(2.269)	(0.009)	(0.002)	(0.117)
Space Positive Sentiment	-0.082**	-0.082**	-0.030*	-0.086**	-0.035*
	(0.002)	(2.227)	(0.009)	(0.002)	(0.010)
Space Negative Sentiment	0.022**	0.022**	0.018*	0.022**	0.014*
	(0.001)	(1.776)	(0.009)	(0.002)	(0.010)
Host					
Host Is Superhost (*Yes*)	0.768***	0.768***	0.774***	0.792***	0.869***
	(0.004)	(4.112)	(0.025)	(0.003)	(0.029)
Host has Profile Photo (*Yes*)	12.127***	12.127***	2.169**	12.373***	1.557**
	(0.109)	(106.228)	(0.274)	(0.091)	(0.168)
Host Membership	0.741***	0.741***	0.417**	0.759***	0.450**
	(0.005)	(5.632)	(0.017)	(0.005)	(0.026)
Host Response (*within an hour*)	0.090***	0.090***	0.130**	0.101***	0.174**
	(0.011)	(11.775)	(0.062)	(0.010)	(0.076)
Host Response (*within few hours*)	-0.163***	-0.163***	-0.091**	-0.154***	-0.067
	(0.011)	(12.362)	(0.065)	(0.011)	(0.080)
Host Response (*within a day*)	-0.268***	-0.268***	-0.180**	-0.253***	-0.187
	(0.011)	(12.720)	(0.066)	(0.011)	(0.086)
Host Response (*none*)	-0.842***	-0.842***	-0.846***	-0.830***	-0.906***
	(0.011)	(11.444)	(0.058)	(0.010)	(0.071)
Total Listings	-0.372***	-0.372***	-0.321***	-0.409***	-0.375***
	(0.012)	(0.012)	(0.030)	(0.011)	(0.036)
Location					
Exact Location (*Yes*)	0.112***	0.112***	0.063*	0.109***	0.055*
	(0.012)	(0.012)	(0.069)	(0.012)	(0.082)
Social Neighbourhood	0.113**	0.113**	0.024**	0.012***	0.026**
	(0.011)	(0.011)	(0.009)	(0.002)	(0.010)
Star Rating					
Stars	0.983***	0.983***	0.450***	1.058***	1.003*
	(0.007)	(0.007)	(0.070)	(0.014)	(0.114)

Price per Night					
Price Difference	0.432∗∗∗	0.432∗∗∗	0.122∗∗∗	0.429∗∗∗	0.123∗∗∗
	(0.013)	(7.412)	(0.013)	(0.003)	(0.012)
Home					
Accommodation Capacity	-0.029∗	-0.029∗	-0.072∗	-0.033∗	-0.087∗
	(0.001)	(2.113)	(0.009)	(0.002)	(0.009)
Facilities	0.069∗∗∗	0.069∗∗∗	0.067∗∗∗	0.077∗	0.095∗
	(0.017)	(1.913)	(0.009)	(0.002)	(0.011)
Booking Policy					
Instant Booking (*Yes*)	0.257∗∗∗	0.257∗∗∗	0.270∗∗∗	0.246∗∗∗	0.262∗∗∗
	(0.003)	(3.970)	(0.020)	(0.003)	(0.025)
Review from Guests					
Cleanliness (Reviews)	0.428∗∗∗	0.428∗∗∗	0.468∗∗∗	0.389∗∗∗	0.579∗∗∗
	(0.002)	(10.775)	(0.044)	(0.009)	(0.064)
Communication (Reviews)	1.428∗∗∗	1.428∗∗∗	1.436∗∗∗	0.920∗∗∗	1.470∗∗∗
	(0.001)	(14.062)	(0.053)	(0.012)	(0.078)
Value for Money (Reviews)	0.063∗∗∗	0.063∗∗∗	0.032∗	0.047∗∗∗	0.046∗
	(0.004)	(10.486)	(0.044)	(0.009)	(0.071)
Intercept	-9.151∗∗∗	-9.151∗∗∗	-7.414∗∗∗	-9.160∗∗∗	-7.252∗∗∗
	(0.110)	(17.110)	(0.279)	(0.091)	(0.178)
Observations	66,605	66,605	66,605	66,605	66,605
Log-Likelihood	-298,955.297	-	-67,589.257	-294,317.900	-65,610.620
Theta	-	-	0.9219	-	0.6037
AIC	597,956.594	-	135,226.514	588,727.700	131,315.200

Note: Note: ∗p<0.05; ∗∗p<0.01 ∗∗∗p<0.001;; Standard errors in parenthesis;
Po=Poisson; QP=Quasi-Poisson; NB=Negative Binomial; H-P=Hurdle Poisson; H-NB=Hurdle Negative Binomial

Table 6. Explanatory models for Airbnb home-bookings in Australia

	Dependent variable*: Successful Bookings*				
	Po	**QP**	**NB**	**H-P**	**H-NB**
Space Description and Textual Summary					
Length of Space Description	0.125∗∗∗	0.125∗∗∗	0.146∗∗∗	0.127∗∗∗	0.182∗∗∗
	(0.003)	(0.034)	(0.015)	(0.003)	(0.019)
Space Positive Sentiment	-0.030∗∗∗	-0.030∗∗∗	-0.022∗∗	-0.032∗∗∗	-0.024∗
	(0.002)	(0.029)	(0.013)	(0.002)	(0.019)
Space Negative Sentiment	0.019∗∗∗	0.019∗∗∗	0.019∗	0.019∗∗∗	0.022∗
	(0.002)	(0.025)	(0.012)	(0.002)	(0.018)
Host					
Host Is Superhost (*Yes*)	0.596∗∗∗	0.596∗∗∗	0.567∗∗∗	0.632∗∗∗	0.699∗∗∗
	(0.004)	(0.051)	(0.028)	(0.004)	(0.036)
Host has Profile Photo (*Yes*)	8.208∗∗∗	8.208∗∗∗	6.069∗∗	8.620∗∗∗	6.286∗∗∗
	(0.107)	(1.396)	(0.267)	(0.108)	(0.363)
Host Membership	0.264∗∗∗	0.264∗∗∗	0.250∗	0.274∗∗∗	0.304∗∗∗
	(0.002)	(0.030)	(0.012)	(0.002)	(0.021)
Host Response (*within an hour*)	0.067∗∗∗	0.067∗∗∗	0.184∗∗∗	0.045∗∗∗	0.220∗∗∗
	(0.011)	(0.150)	(0.069)	(0.011)	(0.091)
Host Response (*within few hours*)	-0.057∗∗∗	-0.057∗∗∗	-0.175∗∗∗	-0.032∗∗	-0.208∗∗
	(0.012)	(0.158)	(0.076)	(0.012)	(0.100)
Host Response (*within a day*)	-0.215∗∗∗	-0.215∗∗∗	-0.284∗∗∗	-0.192∗∗∗	-0.282∗∗
	(0.013)	(0.168)	(0.079)	(0.013)	(0.104)
Host Response (*none*)	-0.453∗∗∗	-0.453∗∗∗	-0.510∗∗∗	-0.423∗∗∗	-0.632∗∗
	(0.011)	(0.149)	(0.067)	(0.011)	(0.089)
Total Listings	-0.169∗∗∗	-0.169∗∗∗	-0.068∗∗	-0.192∗∗∗	-0.026∗
	(0.012)	(0.053)	(0.025)	(0.004)	(0.035)
Location					
Exact Location (*Yes*)	0.010∗	0.010∗	0.002	0.003	0.005
	(0.012)	(0.080)	(0.044)	(0.006)	(0.058)
Social Neighbourhood	0.011∗∗	0.011∗∗	0.002	0.012∗∗	0.009∗∗
	(0.011)	(0.025)	(0.012)	(0.002)	(0.015)
Star Rating					
Stars	1.221∗∗∗	1.221∗∗∗	1.587∗∗∗	0.821∗∗∗	1.797∗∗∗
	(0.007)	(0.216)	(0.089)	(0.015)	(0.093)

Price per Night					
Price Difference	0.264∗∗∗	0.264∗∗∗	0.031∗∗	0.265∗∗∗	0.043∗∗
	(0.006)	(0.083)	(0.016)	(0.006)	(0.014)
Home					
Accommodation Capacity	-0.004∗	-0.004∗	-0.001	-0.003∗	-0.005∗
	(0.002)	(0.024)	(0.012)	(0.002)	(0.016)
Facilities	0.209∗∗∗	0.209∗∗∗	0.285∗∗∗	0.214∗∗∗	0.365∗∗∗
	(0.002)	(0.028)	(0.014)	(0.002)	(0.019)
Booking Policy					
Instant Booking (*Yes*)	0.126∗∗∗	0.126∗∗∗	0.162∗∗∗	0.121∗∗∗	0.154∗∗∗
	(0.004)	(0.046)	(0.023)	(0.004)	(0.030)
Review from Guests					
Cleanliness (Reviews)	0.359∗∗∗	0.359∗∗∗	0.244∗∗∗	0.323∗∗∗	0.407∗∗∗
	(0.011)	(0.148)	(0.068)	(0.011)	(0.103)
Communication (Reviews)	0.849∗∗∗	0.849∗∗∗	1.050∗∗∗	0.439∗∗∗	0.738∗∗∗
	(0.015)	(0.203)	(0.077)	(0.014)	(0.119)
Value for Money (Reviews)	0.347∗∗∗	0.347∗∗∗	0.319∗∗∗	0.315	0.307
	(0.013)	(0.168)	(0.076)	(0.012)	(0.127)
Intercept	-6.935∗∗∗	-6.935∗∗∗	-6.536∗∗∗	-6.965∗∗∗	-6.847∗
	(0.111)	(1.457)	(0.287)	(0.113)	(0.388)
Observations	68,358	68,358	68,358	68,358	68,358
Log-Likelihood	-349,875.171	-	-66,246.141	-243,651.200	-44,586.530
Theta	-	-	0.7448	-	0.3917
AIC	699,796.343	-	132,540.283	487,394.400	89,267.060

Note: ∗p<0.05; ∗∗p<0.01 ∗∗∗p<0.001;; Standard errors in parenthesis;
Po=Poisson; QP=Quasi-Poisson; NB=Negative Binomial; H-P=Hurdle Poisson; H-NB=Hurdle Negative Binomial

Table 7. Explanatory models for Airbnb home-bookings in Asia-Pacific

	Dependent variable*: Successful Bookings*				
	Po	**QP**	**NB**	**H-P**	**H-NB**
Space Description and Textual Summary					
Length of Space Description	0.310∗∗∗	0.310∗∗∗	0.146∗∗∗	0.127∗∗∗	0.392∗∗∗
	(0.003)	(0.009)	(0.015)	(0.003)	(0.014)
Space Positive Sentiment	-0.043∗∗∗	-0.043∗∗∗	-0.022∗∗	-0.032∗∗	-0.024∗∗
	(0.002)	(0.008)	(0.013)	(0.002)	(0.018)
Space Negative Sentiment	0.038∗∗∗	0.038∗∗∗	0.019∗	0.039∗∗	0.016∗
	(0.001)	(0.005)	(0.012)	(0.002)	(0.013)
Host					
Host Is Superhost (*Yes*)	0.511∗∗∗	0.511∗∗∗	0.567∗∗∗	0.632∗∗∗	0.649∗∗∗
	(0.005)	(0.018)	(0.028)	(0.004)	(0.028)
Host has Profile Photo (*Yes*)	0.075	0.075	0.069∗∗	0.120∗	0.148∗
	(0.167)	(0.552)	(0.267)	(0.108)	(0.589)
Host Membership	0.294∗∗∗	0.294∗∗∗	0.250∗	0.274∗∗∗	0.447∗∗∗
	(0.002)	(0.008)	(0.012)	(0.002)	(0.002)
Host Response (*within an hour*)	0.396∗∗∗	0.396∗∗∗	0.184∗∗	0.245∗∗∗	0.268∗∗∗
	(0.011)	(0.038)	(0.069)	(0.011)	(0.048)
Host Response (*within few hours*)	-0.235∗∗∗	-0.235∗∗∗	-0.175∗∗	-0.192∗∗	-0.275∗∗
	(0.015)	(0.050)	(0.076)	(0.012)	(0.070)
Host Response (*within a day*)	-0.259∗∗∗	-0.259∗∗∗	-0.284∗∗	-0.192∗∗	-0.310∗∗
	(0.016)	(0.054)	(0.079)	(0.013)	(0.075)
Host Response (*none*)	-0.311∗∗∗	-0.311∗∗∗	-0.510∗∗	-0.423∗∗	-0.489∗∗
	(0.016)	(0.051)	(0.067)	(0.011)	(0.066)
Total Listings	-0.420∗∗∗	-0.420∗∗∗	-0.068∗∗	-0.392∗∗∗	-0.120∗∗∗
	(0.008)	(0.028)	(0.025)	(0.004)	(0.041)
Location					
Exact Location (*Yes*)	0.091∗∗∗	0.091∗	0.502	0.083	0.487
	(0.023)	(0.077)	(0.044)	(0.006)	(0.225)
Social Neighbourhood	0.080∗∗∗	0.080∗∗∗	0.052∗∗	0.046∗∗	0.076∗∗∗
	(0.002)	(0.007)	(0.012)	(0.002)	(0.016)
Star Rating					
Stars	0.886∗∗∗	0.886∗∗∗	1.587∗∗∗	0.821∗∗∗	1.272∗
	(0.029)	(0.096)	(0.089)	(0.015)	(0.191)

Price per Night					
Price Difference	-0.065∗∗∗	-0.065∗∗	-0.031∗∗	-0.265∗∗∗	-0.015∗∗∗
	(0.006)	(0.020)	(0.016)	(0.006)	(0.013)
Home					
Accommodation Capacity	-0.136∗∗∗	-0.136∗∗∗	-0.101∗	-0.083∗	-0.227∗
	(0.004)	(0.012)	(0.012)	(0.002)	(0.014)
Facilities	0.140∗∗∗	0.140∗∗∗	0.285∗∗∗	0.214∗∗∗	0.216∗∗∗
	(0.002)	(0.028)	(0.014)	(0.002)	(0.015)
Booking Policy					
Instant Booking (*Yes*)	0.025∗∗∗	0.025∗∗∗	0.162∗∗∗	0.121∗∗∗	0.015∗
	(0.005)	(0.017)	(0.023)	(0.004)	(0.028)
Review from Guests					
Cleanliness (Reviews)	0.008	0.008	0.244∗∗∗	0.323∗∗∗	0.216∗∗∗
	(0.025)	(0.082)	(0.068)	(0.011)	(0.138)
Communication (Reviews)	2.204∗∗∗	2.204∗∗∗	1.050∗∗∗	1.439∗∗∗	1.487∗∗∗
	(0.029)	(0.094)	(0.077)	(0.014)	(0.144)
Value for Money (Reviews)	-0.937∗∗∗	-0.937∗∗∗	-0.619∗∗∗	-0.915∗	-1.280∗∗∗
	(0.027)	(0.091)	(0.076)	(0.012)	(0.141)
Intercept	-0.707∗∗∗	-0.707	-1.036∗∗∗	-1.965∗∗∗	-1.118∗
	(0.168)	(0.555)	(0.287)	(0.113)	(0.595)
Observations	81,935	81,935	81,935	81,935	81,935
Log-Likelihood	-122,728.267	-	-48,748.567	-121,721.500	-45,061.650
Theta	-	-	0.8951	-	0.3629
AIC	245,502.535	-	97,545.134	243,535.000	90,217.300

Note: ∗p<0.05; ∗∗p<0.01 ∗∗∗p<0.001;; Standard errors in parenthesis;
Po=Poisson; QP=Quasi-Poisson; NB=Negative Binomial; H-P=Hurdle Poisson; H-NB=Hurdle Negative Binomial

Table 8. Explanatory models for Airbnb home-bookings in USA

	Dependent variable*: Successful Bookings*				
	Po	**QP**	**NB**	**H-P**	**H-NB**
Space Description and Textual Summary					
Length of Space Description	0.232∗∗∗	0.232∗∗∗	0.211∗∗∗	0.234∗∗∗	0.259∗∗∗
	(0.001)	(0.009)	(0.007)	(0.001)	(0.009)
Space Positive Sentiment	-0.020∗∗∗	-0.020∗∗∗	-0.026∗∗	-0.018∗∗	-0.030∗∗
	(0.001)	(0.008)	(0.007)	(0.001)	(0.008)
Space Negative Sentiment	0.027∗∗∗	0.027∗∗∗	0.017∗∗∗	0.027∗∗∗	0.020∗∗∗
	(0.001)	(0.006)	(0.006)	(0.001)	(0.008)
Host					
Host Is Superhost (*Yes*)	0.505∗∗∗	0.505∗∗∗	0.569∗∗∗	0.539∗∗∗	0.694∗∗∗
	(0.002)	(0.014)	(0.016)	(0.002)	(0.019)
Host has Profile Photo (*Yes*)	0.404∗∗∗	0.404∗∗∗	0.998∗	0.369∗∗	1.368∗∗∗
	(0.020)	(0.121)	(0.109)	(0.020)	(0.154)
Host Membership	0.614∗∗∗	0.614∗∗∗	0.658∗∗∗	0.611∗∗∗	0.750∗∗
	(0.001)	(0.007)	(0.007)	(0.001)	(0.010)
Host Response (*within an hour*)	0.276∗∗∗	0.276∗∗∗	0.206∗∗∗	0.287∗∗∗	0.253∗∗∗
	(0.006)	(0.006)	(0.033)	(0.006)	(0.042)
Host Response (*within few hours*)	-0.007	-0.007	-0.127∗∗∗	-0.007∗∗	-0.144∗∗
	(0.006)	(0.006)	(0.035)	(0.006)	(0.045)
Host Response (*within a day*)	-0.058∗∗∗	-0.058∗∗∗	-0.174∗∗	-0.046∗∗	-0.189∗∗
	(0.006)	(0.006)	(0.037)	(0.006)	(0.047)
Host Response (*none*)	-0.718∗∗∗	-0.718∗∗∗	-0.768∗∗	-0.699∗∗	-0.876∗∗
	(0.006)	(0.035)	(0.031)	(0.006)	(0.040)
Total Listings	-2.472∗∗∗	-2.472∗∗∗	-1.537∗∗∗	-2.700∗∗∗	-2.256∗∗∗

	(0.020)	(0.123)	(0.050)	(0.021)	(0.076)
Location					
Exact Location (*Yes*)	0.003	0.003	0.006	0.003	0.0192
	(0.002)	(0.012)	(0.623)	(0.002)	(0.016)
Social Neighbourhood	0.035***	0.035***	0.044***	0.035**	0.076***
	(0.001)	(0.005)	(0.006)	(0.001)	(0.016)
Star Rating					
Stars	0.760***	0.760***	0.338***	0.794***	0.921***
	(0.009)	(0.057)	(0.053)	(0.009)	(0.096)
Price per Night					
Price Difference	0.179***	0.179***	0.042**	0.184***	0.139***
	(0.003)	(0.020)	(0.008)	(0.003)	(0.009)
Home					
Accommodation Capacity	-0.040***	-0.040***	-0.048***	-0.039*	-0.055*
	(0.001)	(0.006)	(0.006)	(0.001)	(0.008)
Facilities	0.039***	0.039***	0.010**	0.039*	0.008***
	(0.001)	(0.007)	(0.006)	(0.001)	(0.007)
Booking Policy					
Instant Booking (*Yes*)	0.288***	0.288***	0.345***	0.276***	0.346*
	(0.002)	(0.014)	(0.013)	(0.002)	(0.017)
Review from Guests					
Cleanliness (Reviews)	0.584	0.584	0.708***	0.536***	0.921***
	(0.007)	(0.043)	(0.035)	(0.002)	(0.057)
Communication (Reviews)	1.109***	1.109***	1.229***	0.577***	1.323*
	(0.007)	(0.057)	(0.041)	(0.009)	(0.144)
Value for Money (Reviews)	0.462***	0.462***	0.268***	0.386	0.260
	(0.008)	(0.050)	(0.040)	(0.008)	(0.072)
Intercept	2.275***	2.275***	2.692***	2.616***	2.927***
	(0.021)	(0.127)	(0.113)	(0.021)	(0.159)
Observations	90,378	90,378	90,378	90,378	90,378

Log-Likelihood	-608,184.575	-	-138,267.113	-600,376.300	-133,024.000
Theta	-	-	0.8379	-	0.4606
AIC	1,216,415.151	-	276,582.226	1,200,845.000	266,142.100

Note: $*p<0.05$; $**p<0.01$ $***p<0.001$;; Standard errors in parenthesis;
Po=Poisson; QP=Quasi-Poisson; NB=Negative Binomial; H-P=Hurdle Poisson; H-NB=Hurdle Negative Binomial

Table 9. Explanatory models for Airbnb home-bookings combined across geographies

	Dependent variable*: Successful Bookings*
	H-NB
Space Description and Textual Summary	
Length of Space Description	0.369***
	(0.007)
Space Positive Sentiment	-0.0002
	(0.006)
Space Negative Sentiment	0.028***
	(0.006)
Host	
Host Is Superhost (*Yes*)	0.953***
	(0.035)
Host has Profile Photo (*Yes*)	-1.879***
	(0.187)
Host Membership	-0.151***
	(0.007)
Host Response (*within an hour*)	0.987***
	(0.048)
Host Response (*within few hours*)	0.941***
	(0.052)
Host Response (*within a day*)	0.949***
	(0.053)
Host Response (*none*)	0.534***
	(0.051)
Total Listings	-0.248***
	(0.023)
Location	
Exact Location (*Yes*)	0.241***
	(0.065)
Social Neighbourhood	0.038***
	(0.006)
Star Rating	
Stars	0.601***
	(0.042)

Price per Night	
Price Difference	-0.049***
	(0.016)
Home	
Accommodation Capacity	-0.019***
	(0.006)
Facilities	0.119***
	(0.007)
Booking Policy	
Instant Booking (*Yes*)	0.124***
	(0.029)
Review from Guests	
Cleanliness (Reviews)	0.086*
	(0.042)
Communication (Reviews)	0.989***
	(0.048)
Value for Money (Reviews)	-0.356***
	(0.051)
Interaction Effects	
Host Is Superhost * Asia	-0.611***
	(0.046)
Host Is Superhost * Europe	0.254***
	(0.049)
Host Is Superhost * USA	-0.075
	(0.041)
Exact Location * Asia	-0.589*
	(0.249)
Exact Location * Europe	-0.159
	(0.124)
Exact Location * USA	-0.143*
	(0.068)
Price Difference * Asia	0.046*
	(0.021)
Price Difference * Europe	0.203***
	(0.020)

Price Difference * USA	0.005
	(0.018)
Instant Booking * Asia	-1.841∗∗∗
	(0.039)
Instant Booking * Europe	0.486∗∗∗
	(0.040)
Instant Booking * USA	0.085∗∗∗
	(0.035)
Intercept	2.805∗∗∗
	(0.193)
Observations	307,276
Log-Likelihood	-2,96,300
Theta	0.3051
AIC	5,92,668

Note: ∗p<0.05; ∗∗p<0.01 ∗∗∗p<0.001; Standard errors in parenthesis; H-NB=Hurdle Negative Binomial

Table 10. Comparison of predictors for Airbnb home-bookings across geographies

	Europe	Asia Pacific	Australia	USA
Space Description and Textual Summary				
Length of Space Description	✓	✓	✓	✓
Space Positive Sentiment	X	✓	✓	✓
Space Negative Sentiment	X	X	X	✓
Host				
Host Is Superhost (*Yes*)	✓	✓	✓	✓
Host has Profile Photo (*Yes*)	✓	X	✓	X
Host Membership	✓	✓	✓	X
Host Response (*within an hour*)	X	✓	✓	✓
Host Response (*within few hours*)	X	X	X	X
Host Response (*within a day*)	X	X	X	X
Host Response (*none*)	✓	X	X	X
Total Listings	✓	✓	X	✓
Location				
Exact Location (*Yes*)	X	X	X	✓
Social Neighbourhood	✓	✓	X	X
Star Rating				
Stars	X	X	✓	✓
Price per Night				
Price Difference	✓	X	X	✓
Home				
Accommodation Capacity	X	✓	X	X
Facilities	X	✓	✓	X
Booking Policy				
Instant Booking (*Yes*)	✓	X	✓	X
Review from Guests				
Cleanliness (Reviews)	✓	X	✓	✓
Communication (Reviews)	✓	✓	✓	✓
Value for Money (Reviews)	X	✓	X	X

Note: The choice of predictors and non-predictors in the table above is based on the variable importance scores and statistical significance of the explanatory variables. Actionable insights can be drawn from the list of most important explanatory variables, specific to each continent.