Economic Research-Ekonomska Istraživanja

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rero20

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To cite this article: Manuel J. Sánchez-Franco & Manuel Alonso-Dos-Santos (2020): Exploring gender-based influences on key features of Airbnb accommodations, Economic Research-Ekonomska Istraživanja, DOI: 10.1080/1331677X.2020.1831943

To link to this article: https://doi.org/10.1080/1331677X.2020.1831943

Published online: 12 Nov 2020.

ECONOMIC RESEARCH-EKONOMSKA ISTRAŽIVANJA
https://doi.org/10.1080/1331677X.2020.1831943

Exploring gender-based influences on key features of Airbnb accommodations

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ABSTRACT

Our research aims to address the following research questions: (a) to identify guests' hidden experiences in a distribution of terms over a fixed vocabulary by analysing a bulk set of online reviews through the process of text mining, and in particular, (b) to assess if the Airbnb guest experience represented in them can be used to enhance Airbnb services. On the other hand, our study analyses the relationship between the topics identified and Airbnb pricing, and mainly measures the influence of gender as a moderating cue. In this regard, a growing body of research has emerged to examine gender differences in leisure participation. In particular, our study concludes how the guests' gender affects the contributions of listings' features in price prediction. Females are more intrinsically motivated and preferentially mention, for instance, the Airbnb accommodation's location and the gratifying (local) experiences in their narratives. On the contrary, male guests highlight hygiene and apartment facilities. To sum up, our research provides design guidelines to reflect the willingness to hire an apartment, offering insights for research and practice, and allowing the layout of pricing-recommendation systems.

ARTICLE HISTORY
Received 25 June 2020
Accepted 29 September 2020

KEYWORDS
Airbnb; price; gender; structural topic models; XGBoost; SHAP values

JEL CLASSIFICATIONS
M31; C18; C55

1. Introduction

Overall, recommendation systems are based on a sharing economy (cf. Marin Anglada & Hernández Lara, 2020) by connecting supply and demand through peer-to-peer platforms, and in particular, modify the way in which travellers contract hospitality services (cf. Sánchez-Franco et al., 2016; Sparks et al., 2016). For instance, Airbnb – a disruptive innovation in the hospitality industry – differs from traditional hotels 'in terms of booking systems, facilities, software platforms and design, and service for guests' (Sánchez-Franco, Troyano-Jiménez, et al., 2019). Recommendation systems also become an experiential opportunity for *indirect* tourism-encounters and

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generate a huge amount of *User-Generated Content* (hereinafter, UGC) – defined as 'all informal communications [communications of interpersonal relationships] directed at consumers through Internet-based technology related to the usage or characteristics of particular goods and services, or their sellers' (Westbrook, 1987, p. 261; cf. also Litvin et al., 2008; Sánchez-Franco et al., 2016; Sanchez-Franco, Cepeda-Carrion, et al., 2019; Sánchez-Franco, Troyano-Jiménez et al., 2019; Tsao et al., 2015; Xiang et al., 2015; Zhou et al., 2014, among others). In this regard, travellers consult UGC directed at them as a relevant source of information to reduce the perceived risk, instead of relying essentially on simple numeric scores (cf. Blal & Sturman, 2014; Chevalier & Mayzlin, 2006; Gretzel & Yoo, 2008; Hu et al., 2009; Li et al., 2009; Pan et al., 2007; Park et al., 2007; Park & Kim, 2008), i.e., 'simple scores oversimplify quality measures by assuming that quality is a unidimensional measure' (Lawani et al., 2019, p. 22; see also Archak et al., 2011); furthermore, scores tend to be extremely high and promote loss of informative value (Ert et al., 2016; Phua, 2019).

Accordingly, our research aim lies in evidencing the authentic interests (or features) mentioned in UGC and, consequently, associating the price of accommodations with the presence or absence (in informal narratives) of relevant and essential subjective dimensions or attributes (cf. Raguseo et al., 2017; Sánchez-Franco, Troyano-Jiménez, et al., 2019; Sparks et al., 2016). Our study analyses a huge number of reviews focused on home-like lodging conditions, responsiveness or response time of hosts, interaction with local people or authenticity at an Airbnb lodging, or distance from the city centre (e.g., Gibbs et al., 2018; Gunter & Önder, 2018; Guttentag, 2016; Guttentag et al., 2018; Johnson & Neuhofer, 2017; Mody et al., 2017; Tussyadiah & Pesonen, 2018, among others). The linguistic attributes of natural and non-structured UGC (associated with a utilitarian, enjoyable, social and home-like accommodation experience) are still largely under-explored in the home-sharing literature (Zhao et al., 2019), and in their influence on pricing decisions (cf. Sánchez-Franco, Troyano-Jiménez, et al., 2019). Although free online content is poorly structured, being *more or less* focused on a single entity or aspect of hospitality, or is multi-lingual, it becomes a standard feature for guest-facing online services that help to understand guests' preferences and demands, and guide future pricing policies of accommodation rentals to reduce inefficient pricing strategies.

Furthermore, 'although the sharing economy has becoming a global phenomenon, only limited research to date has explored demographic differences among its user base as well as between users and non-users' (Lutz & Newlands, 2018, p. 188). Overall, 'moderating factors [determined by personal traits] could account for both the limited explanatory power of and the inconsistencies between studies' (Sun & Zhang, 2006, p. 53), and precisely allow researchers to differentiate the direction or the strength of the relationship between independent and dependent variables. Here our research examines an individual-level factor: gender. Gender is indeed easy to identify and to access, and large enough to be profitable (e.g., Hanks & Mattila, 2014; Putrevu, 2001). The reluctance to recognise that gender moderates the perception of lodgings could lead to *gender blindness*, guests' dissatisfaction and inefficient pricing strategies. The assumption that hospitality services are consumed identically by males and females is indeed critically flawed (e.g., McCleary et al., 1994; Sánchez-Franco et al., 2016). Our study is thus relevant for a major understanding of the associations between gender and prices that would enable hosts to be more effective in setting appropriate pricing policies and would be a relevant key to differentiate the touristic rentals.

These questions are analysed in an ambitious study of natural and non-structured UGC – extracted from Airbnb – that identifies users' experience-related topics. The research method section provides details of the data collection, data mining and findings on online home-sharing services. Finally, the discussion section outlines the future lines of research and theoretical and managerial implications.

2. Theoretical framework

Peer-to-peer economy or collaborative consumption are based on network effects that enable hosts to offer, for instance, their unoccupied houses or rooms (to other individuals) for a short-term rental, with near-zero marginal costs and reduced search costs (cf. Rifkin, 2014; Zervas et al., 2017). In particular, Airbnb 'has gained public and scholarly attention due to its disruptive effects on the hospitality industry' (Adamiak, 2019, p. 1; cf. also Guttentag, 2015; Marin Anglada & Hernández Lara, 2020). Airbnb transforms countless individuals into hospitality micro-entrepreneurs (Guttentag, 2019) who 'offer an alternative value proposition centred around cost-savings, household amenities and the potential for a more authentic local experience' (p. 819). For instance, Ert et al. (2016) name this finding based on local communities as the quest for originality.

'Individuals grant each other temporary access to underutilised physical assets, possibly for money' (Frenken & Schor, 2017, pp. 4–5; cf. also Sundararajan, 2016). And Airbnb 'provides a platform allowing hosts to rent out their homes and guests to rent them, charging both parties a fee for transactions' (Phua, 2019, p. 2051). Airbnb is indeed a commission-based web-platform for hosts and travellers where 'guests find entire apartments or single/multi-rooms at a more competitive price than hotels, coordinated through community-based services' (Sánchez-Franco, Troyano-Jiménez, et al., 2019). Guests '(…) can easily price-shop multiple accommodation options with the click of the mouse' (Gibbs et al., 2018, p. 46), the perceived price being considered as the most important driver explaining its growth and success (e.g., Choi et al., 2018; Mao & Lyu, 2017; Tussyadiah & Pesonen, 2018, among others). In this regard, although a pricing policy for Airbnb hosts entails the assessment of utility-bearing attributes or quality signs, and to what extent they matter to guests to gain value for their expenditure, research has detected inefficient pricing by Airbnb hosts due to: (1) the uniqueness of the rental services offered on Airbnb (Gibbs et al., 2018) and (2) the emotional drivers applied by non-professional hosts (cf. Ikkala & Lampinen, 2014; see also Hill, 2015; Li, Moreno, et al., 2016, among others). Li, Pan, et al. (2016) find that Airbnb non-professional hosts are apparently unable to optimally set prices. Additional research based on pricing policy guides of accommodation rentals is thus needed to: (1) highlight efficient pricing strategies as key drivers that influence guests' selection of lodgings and appropriately warrant host revenues (Guttentag & Smith, 2017; Lampinen and Cheshire, 2016; Wang & Nicolau, 2017), or at least, (2) foster acceptable price policies based, for instance, on experiential learning to overcome their initial lack of pricing capability or on the market demand level (cf. Magno et al., 2018).

In particular, few studies have been conducted to identify what subjective dimensions or attributes influence the pricing policies of Airbnb accommodations; indeed, 'the research to date related to "pricing and Airbnb" does little to explain the variables that make up the price of a listing' (Gibbs et al., 2018, p. 47; cf. also Guttentag et al., 2018). To overcome this gap in the literature, and to avoid focusing only on a low price to attract travellers, our study then adapts a Hedonic Pricing Analysis-based approach related to the presence or absence of relevant and essential 'subjective dimensions or features' (see Lancaster's theory of consumer demand; cf. also Rosen, 1974). This framework is applied to estimate the value of different attributes in price composition in the Airbnb services by studies such as Chen and Xie (2017), Gibbs et al. (2018) and Wang and Nicolau (2017), among others. Nevertheless, although previous studies examine the effects of review quantity and quality, ratings or management features on the prices of Airbnb lodgings, our research analyses linguistic attributes mentioned in online narratives by guests to predict the price of the sharing economy (Zhao et al., 2019). For instance, Airbnb is focused on guests who enjoy multiple experiences, finding cost-savings to be their primary motivator (in conjunction with location and household amenities; cf. Guttentag et al., 2018; Paulauskaite et al., 2017), and also contrasting life values, or interaction with the host and local people (e.g., Guttentag, 2016; Johnson & Neuhofer, 2017; Mody et al., 2017; Poon & Huang, 2017; Tussyadiah & Pesonen, 2018). In this sense, previous research partly identifies measurable, utility, emotional and social features from guests' perspectives, e.g., economic benefits/value for money (e.g., Mao & Lyu, 2017; Tussyadiah, 2015; Yang & Ahn, 2016), postmodern experiences based on authenticity at an Airbnb lodging (e.g., Guttentag et al., 2018; Poon & Huang, 2017), hospitality features based on home-like lodging conditions (e.g., Guttentag et al., 2018; Johnson & Neuhofer, 2017), social interactions as part of a social benefit and other benefits enjoyed from using Airbnb (e.g., Mody et al., 2017; Tussyadiah & Pesonen, 2018), or distance from the tourist centre (measured, for instance, as a major transportation hub) (cf. also Guttentag, 2016; Satama, 2014; So et al., 2018, among other authors).

Our study, therefore, applies a feature-oriented framework to identify relevant topics (a distribution of terms over a fixed vocabulary; cf. Blei, 2012; see also Blei et al., 2003) around: (1) the core sharing services (in-apartment facilities) as well as (2) the surrounding features (related to guests' desire for first-hand learning) that significantly associate with the prices of Airbnb accommodations and generate higher revenues for hosts.

Finally, our research analyses the influence of the biological male-versus-female dichotomy as an interacting driver on: (1) how individuals differentially engage in a behaviour (cf. Holbrook, 1986), (2) information seeking and processing and communication modes (cf. selectivity hypothesis, Meyers-Levy, 1989; Meyers-Levy & Maheswaran, 1991; Meyers-Levy & Sternthal, 1991), and consequently, (3) remembering and sharing guests' experiences in tourist lodgings. Our study models a main question related to gender differences that can be translated into differential (consistent) preferences for Airbnb accommodations and their features and can have implications for their future behaviour. For instance, males tend to be self-focused (and mainly assess functional features of services, see Dittmar et al., 2004) – describing their Airbnb stays in terms of lodging facilities. Males are indeed selective processors who often rely on a subset of highly available and salient cues (i.e., tangible cues or, here, lodging facilities) when they are adopting a buying decision (Hoyer & MacInnis, 2010). On the contrary, females tend to be emotionally expressive (e.g., Kring & Gordon, 1998), more associated with higher levels of hedonic consumption (e.g., Tifferet & Herstein, 2012), and other-focused aspects – assessing family comfort, location or surrounding features (cf. Bakan, 1966). Females are more concerned about others, pursue harmonic interrelationships, and are warm and nurturing (e.g., Deaux, 1984; Gefen & Straub, 1997; Sánchez-Franco et al., 2016). Moreover, females are: (1) even more willing to take lower risks than males (Powell & Ansic, 1997), prioritise security-based features (e.g., facilities for disabled travellers or kids) and are (2) generally more cautious and act more responsibly when spending money (cf. Slama & Tashchian, 1985). Females could thus describe their Airbnb stays in terms of experience quality conceptualised as tourists' affective responses to their desired social–psychological benefits.

Females and males are therefore differently driven by expressive and communal goals, and consequently differ in the influence of 'the opportunity for customers to affiliate with other individuals during the (…) encounter' (Odekerken-Schroder et al., 2001, p. 310). Diversity and nature in the tourist motives and preferences of males and females create diversity in their leisure motives and behaviours and in their hesitation (or preferences) in decision-making. When remembering a stay, males and females are likely to engage in differential patterns of information (internal) seeking (from their memories). Gender could thus be a better explanatory variable than sex-role self-image for leisure service usage (Oh et al., 2002).

3. Research questions

Our research aims to address the following questions related to: (a) identifying guest experience-related topics (i.e., a distribution of terms over a fixed vocabulary), and (b) determining if the guest experience extracted from UGC can be applied to improving pricing policies and hospitality services. Our study in particular identifies the key features that guests describe in their narratives through community-based online services such as Airbnb, analyses the relationship between the most prevalent topics and Airbnb pricing, and estimates the effect of gender as an interacting personal trait in leisure participation and interests.

4. Research method

4.1. Data collection

New York is selected as a case study because of its competitive advantage in entertainment driven by tourism. It generates multiple feelings mentioned in online reviews by guests. The dataset is obtained from the OpenDataSoft website (available at: https://public.opendatasoft.com). The reviews are publicly accessible. And our research here filters out accommodations for: (1) less than six guests, (2) a price higher than $10 (not including cleaning fees or additional charges for guests) and (3) entire apartments.

The guests' gender is extracted by applying gender package (Mullen, 2019). Our study analyses a single language, English, to maintain consistency between the texts analysed. It applies the textcat package based on the R 3.6.1 statistical tool to recognise English in the reviews (cf. Hornik et al., 2013) and Google's Compact Language Detector 2.

Our gender-balanced dataset finally contains 30,338 reviews (54% by females), spanning the period between 2015 and 2017.

4.2. Data cleansing process

Our research addresses a cautious data cleaning process based on the following stages: (1) it discards punctuation, capitalisation, digits and extra whitespace, (2) it removes a list of common stop words – such as certain pronouns, adverbs or conjunctions – to filter out overly common terms filters, and (3) filters, tokenises and lemmatises the nouns and verbs. Moreover, following Sánchez-Franco et al. (2016), Sanchez-Franco, Cepeda-Carrion, et al. (2019), Sánchez-Franco, Troyano-Jiménez et al. (2019), all the possible variations of relevant terms (e.g., misspellings) associated with the guests' overall assessments are identified, getting rid of comments that are generic and irrelevant to the hospitality and tourism domain.

Finally, our study selects a small dictionary based on document and term frequency, i.e., the sparsity parameter is here equivalent to 0.9998 (significantly reducing the terms from 3346 to a handy and semantically appropriate volume, i.e., 401 terms).

4.3. Data mining

Our research here examines the association of the rational and experiential features in the customer reviews and identifies consistent thematic-information to understand the context of the narratives about the online home-sharing services analysed (Sánchez-Franco, Troyano-Jiménez, et al., 2019).

4.3.1. Structural topic modelling

Our study estimates the relationships between terms and reviews through a text-mining algorithm to explore latent semantic structures (Blei, 2012; Blei et al., 2003) related to 'cost-savings, household amenities or the potential for more authentic local experiences' (cf. Gutiérrez et al., 2017, p. 279). In particular, our approach focuses on structural topic modelling (hereinafter, STM), and its implementation in the STM 1.3.3 R package (Roberts et al., 2018). STM is conceptualised as an unsupervised method that allows the researchers to discover topics (inferred here from the guests' comments) that can be correlated and estimates their relationships to document metadata (explanatory covariates defined as information about each document).

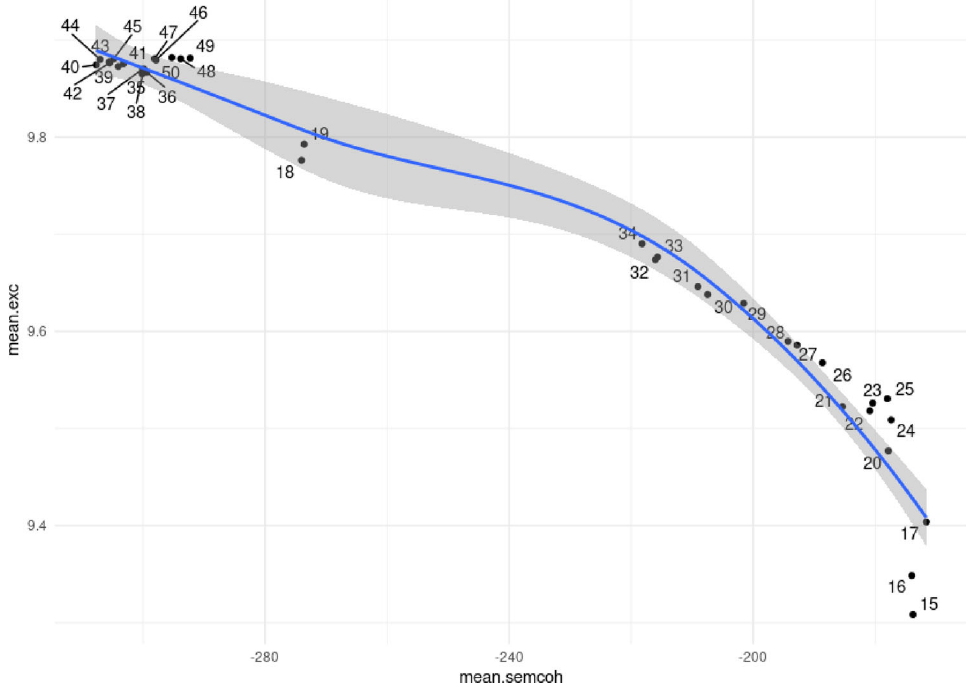

Figure 1. Semantic coherence and exclusivity values of topic models.
Source: Authors' data analysis.

Our research: (1) estimates different STM models for 10 and 50 topics to propose models that not only provide technical (managerial) insights but are also accessible (Sánchez-Franco, Troyano-Jiménez, et al., 2019); (2) applies an initialisation based on the method of moments, 'which is deterministic and globally consistent under reasonable conditions' (Roberts et al., 2018, p. 11; cf. also Roberts et al., 2016); (3) discards the models that have the lowest value for the bound (Roberts et al., 2014), and (4) assesses the trade-off between semantic coherence and exclusivity (i.e., internal consistency-cohesiveness-and differentiation or diversity criteria, see Blei et al., 2003; Gerring, 2001; Mimno et al., 2011; Roberts et al., 2014). Our study, therefore, prioritises managerial implications and, consequently, selects a *handy* number of topics, here 18 (see Figure 1 for coherence and exclusivity values of topic models).

To identify intuitive meanings of topics, these are usually conceptualised with a list of the most representative reviews that are most strongly connected to each topic (see Epigraph 4). Likewise, although the STM proposal extracts the terms that have the highest probability of occurring conditionally in the topic, the terms may not be semantically interesting (Kuhn, 2018). Bischof and Airoldi (2012) propose using the FRequency and EXclusivity metric (hereinafter, FREX), defined as the ratio of term frequency conditional in a topic to term-topic exclusivity (cf. Roberts et al., 2013, 2014). The FREX metric tries to locate terms which are both frequent in and exclusive to a topic, assuming that 'the exclusivity of words to topics is equally important for communicating content' (Bischof & Airoldi, 2012). The ω

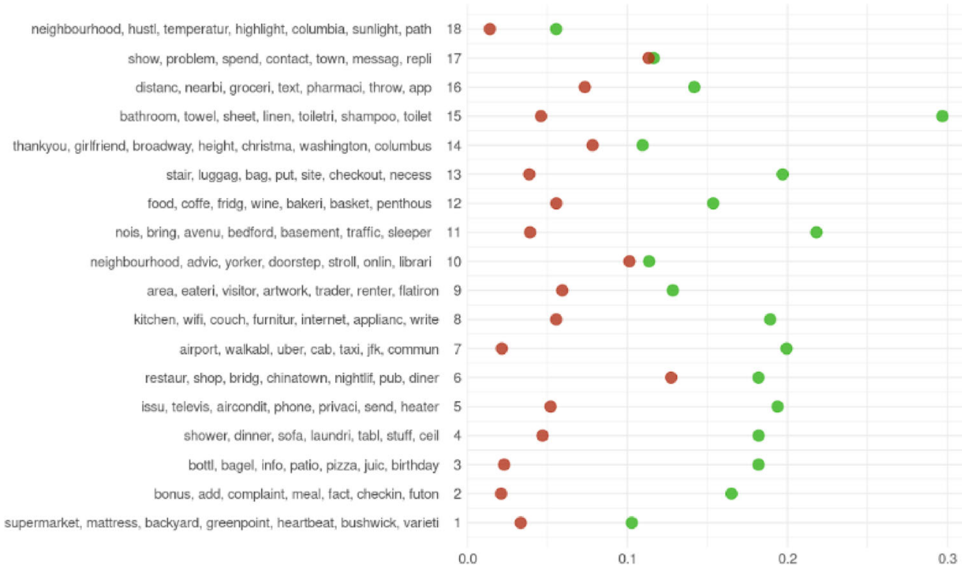

Figure 2. Graphical display of the top-7 FREX terms (by topic), estimated topic proportions (red) and Gini coefficients (green).
Source: Authors' data analysis.

weight balances the influence of FREX, and it is here set at 0.5. Figure 2 provides a summary, i.e., the average prevalence (and also the Gini coefficients), and the top-7 FREX terms.

4.3.2. Predictive analysis: extreme gradient boosting

For predictive analysis, our study analyses the topics' influence on the log-transformed price of Airbnb accommodations by applying an extreme gradient boosting (hereinafter, XGBoost). Our research uses the coefficients' root mean squared error and *R*-squared scores to validate the models and evaluate their qualities.

To ensure the effectiveness of the training process and to find the best-fitted model based on the *R*-squared value, our research splits the dataset into two subsets (cf. Climent et al., 2019; Sánchez-Franco, Troyano-Jiménez, et al., 2019): 75% of the observations (train dataset) allow us to train the XGBoost model in order to find the best combination of parameters by applying cross-validation. Our research performs a 10-fold cross-validation. The remaining 25% (validation dataset) enable us to validate the performance of the *best-fitted model* and to ensure the accuracy of the trained approach.

Following a tuning process of detecting the combinations of the best parameters and validating the performance of the fitted models, the *R*-squared value obtained with the validation dataset is 0.889 (and an RMSE of 0.1) with 100 rounds, a learning rate (η) of 0.179, a subsample equal to 0.688 and a maximum depth of each tree of 10.

5. Findings

Figure 3 represents the range and distribution of the impacts that each topic has on the model output applying the additive feature attribution method, i.e., SHapley

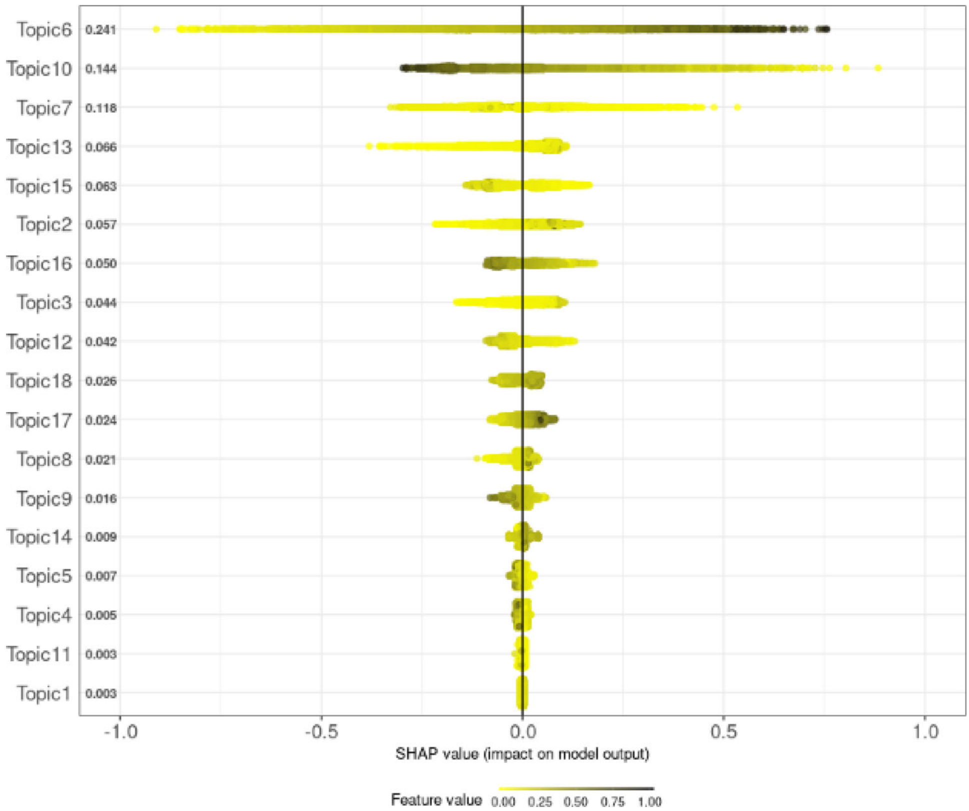

Figure 3. Feature importance displayed by local SHAP values.
Source: Authors' data analysis.

Additive exPlanations (hereinafter, SHAP values; cf. Lundberg & Lee, 2017). SHAP decomposes the prediction of an individual observation into components attributable to each feature to find a better identification of (globally and locally) influential features. SHAP: (1) illustrates the importance of a feature by comparing what a model predicts with and without the feature, (2) is accurate with human intuition, and (3) guarantees consistency in feature rankings (Lundberg & Lee, 2017). In short, each SHAP value represents a descriptive approximation of the predictive model and describes how much each topic in our model contributes, either positively or negatively, to increasing (or decreasing) the price-levels of Airbnb accommodations.

The most influential topics in our model output are, in this order, 6, 10, 7, 13, 15 and 2. The main results are set out below:

- Having a high proportion of terms assigned to topic 6 (concerning the selected model) is associated with high and positive values on the target (Airbnb price). In particular, topic 6 is formed by terms related to distance to restaurants, cafés, eateries, or bistros, among others. Topic 6 shows the greatest importance, e.g., guests preferentially (and unsurprisingly) pay more (less) for entire apartments in conveniently (or inconveniently) rated locations. The following is a sample of original representative comments for topic 6:

[1] 'Great location in downtown NYC ideal for first time stay – close to shopping, comedy, bars, amazing restaurants, coffee shops … well worth it for the private rooftop if you are travelling in the warmer months!'.

[2] 'This place was very close in walking distance to nightlife, public transit, restaurants, and shops. It was in a great location if you are looking to see major New York attractions. Great place!'.

[3] 'We had a great time renting Chester and John's place. They were such gracious hosts. They were very accommodating and very attentive. The place is comfortable and spacious and conveniently located to public transportation, shopping and restaurants. City Hall, Soho, Chinatown, and Little Italy are all within walking distance. We can't wait to stay again!'.

- Topic 10 (based on walking in a nice way related to authentic local experience) shows the opposite association in guests' reviews – terms assigned to the topic 10 are higher mentioned in narratives of accommodations with lower prices. Previous research suggests that specific traveller segments could find it valuable to lodge outside of highly touristy environments and enjoy the advantages of residential areas (cf. Guttentag et al., 2018). 'Although location greatly impacts pricing strategy, sharing apartments in a disadvantageous location for tourism should also provide a distinct and convincing Airbnb value proposition' (Sánchez-Franco, Troyano-Jiménez, et al., 2019). The following is a sample of original representative comments for topic 10:

[1] 'We rented the apartment for a week while visiting New York, and thanks to the location of the apartment we discovered Brooklyn as well! The neighbourhood was pleasant, just as the connection to Manhattan. The apartment is in good shape, clean, with enough room for 4 persons. Lior and Lee left us a good guide to Brooklyn and also gave some good advices on places to visit, including some very good restaurants. We did not meet Lior and Lee, but online contact ran smoothly. We can recommend this place to anyone looking for an address in Brooklyn! Janny, Dirk, Rinke & Bas'.

[2] 'I had a wonderful experience at Jordan's flat. It was beautiful, open, clean and rustic, exactly as advertising. I enjoyed being in the neighbourhood as its very fun and cool bohemian shops. I learned that the neighbourhood is the graffiti capital of the world. So, if you're looking for a ritzy neighbourhood, this isn't it. If you want a neighbourhood with a lot of character, then check it out. This takes away nothing from her apartment though. It's really fun and comfortable. Jordan was amazing to work with and I really enjoyed my stay'.

[3] 'Very nice if you like to feel like a New Yorker. The neighbourhood is nice. Only make sure to arrange the check in with anticipation'.

- The general trend of (relatively) long tails reaching only to the left (topic 7 located in reviews suggesting that hosts share their knowledge and expertise, e.g., transport systems, e.g., cabs, Uber, airport, among other terms) shows that a higher prevalence of this feature (highlighted in the guests' comments) is significantly associated with accommodations with lower prices. The following is a sample of original representative comments for topic 7:

[1] 'Sophie was very welcoming and helpful. She offered us a lot of local tips and hints and helped with ordering a taxi for the airport (Uber was very expensive). We really enjoyed her apartment, which was spacious and cosy. Highly recommended!'

[2] 'Miss Dy was a gracious hostess at this cosy, basic space in the garden level of the house. With easy access by cab or Uber to JFK, it was the perfect location for our overnight layover. When our flight from London sat on the runway at JFK for 45 minutes, we messaged Miss Dy, who graciously waited up for us'.

[3] 'Fantastic accommodation. Margarita arranged a taxi to and from JFK airport which all went smoothly. Taxi driver was very punctual. Smith St. in Brooklyn is fabulous. There's everything you need on your doorstep. It's also a welcome break from the hustle and bustle of Manhattan. The subway is minutes away and only a short ride into the island itself. The apartment is beautiful, spacious and bright with everything you need. Would definitely recommend this place to friends and family. Margarita kept in touch throughout our stay. Thank you for a lovely holiday'.

- The evolution of (relatively) long tails reaching only to the left (topic 13, or accessibility filters related to entire apartments' stairs, or facilities to check-out) evidences that terms assigned to the topic 13 are more mentioned in narratives of Airbnb apartments with lower prices. The following is a sample of original representative comments for topic 13:

[1] 'Great location to access the subway station and several bus routes. This apartment is very clean and safe. The housekeeper, Pascual, really maintains this room well. Besides, Elizabeth did do me a favour to put my luggage until the check-out date's evening. Especially after 9-11, it is impossible to find the luggage storage in New York. It is really a good experience to stay at Elizabeth's cosy apartment'.

[2] 'Mikes place is very nice and worked out well for our family. It was surprising to us that this apartment is nestled in between stores and restaurants … you wouldn't guess this apartment with a nice little courtyard exists when looking at the entrance to access the apartment! If your flight into NYC is earlier than check in or flighty out us after checkout, you do have to find alternate arrangements for bag storage. We paid to store our bags ATA a hotel so we could continue touring without lugging around our suitcases. All in all, Mikes place is a very nice place to call your home away from home for a few days!'

[3] 'This was a wonderfully convenient location. It was also comfortable and clean. Vincent was responsive to all of our needs. The only thing that was disappointing was the staircase from the first floor to the second floor. It was extremely narrow and a bit scary trying to negotiate it. It was more like a spiral ladder than a staircase. I would not recommend anyone staying in this apartment that has any problems with climbing. It's very difficult to carry anything up or down the stairs. I needed to hold onto the rails and descend the stairs going backwards in order to avoid hitting my head or losing my balance. But young types in their twenties and thirties should have no trouble whatsoever. Even with the stairs, I would stay there again'.

- Topic 15 (based on in-apartment or toilet facilities, e.g., shampoo, linen, bed, bathroom, toothbrush, washcloth, pillow, among other amenities) evidences that higher topic prevalence over documents is significantly associated with accommodations with lower prices. The following is a sample of original representative comments for topic 15:

[1] 'This place is very affordable with 'great great' location; however, it needs a few improvements such as hand towels, sheets, pillows, kitchen towels, toilet paper, and paper towels. Also, communication wasn't always easy due to a language barrier. If you don't mind any of these challenges, it is a great place to stay. Enjoy NY!'

[2] 'If you are able, stay here. MJ has a beautiful place, so tastefully decorated, and he really gets the details. He had an extra toothbrush, soaps, shampoo and conditioner, he let me use his hairdryer, and when I arrived, I noticed that even the toilet paper was folded into a point. His room is so relaxing and quite frankly, I kind of wished I could take the bed home with me because it was so comfortable. He also helped me with where to go and the secrets of traveling for cheap all over the city. Don't go anywhere else and waste your time. Stay at his place and you will love your New York experience!'

[3] 'This apartment is well located and in a nice old brown stone. The host was responsive and we were able to get keys easily. The apartment itself is basic, clean and has all you need for a short stay. The size is not much more than a large hotel room with kitchen. The wood floor and windows could use a bit of repair. The furnishings were very basic, maybe from the free pile? But the real bummer was the thin synthetic sheets. The bed linens were rough and uncomfortable. The bathroom is clean and had plenty of towels, but we ran out of hot water after one short shower. *All in all* … upon our return to NYC one week later we booked a great hotel on Hotel Tonight for significantly less per night and the sheets were much more comfortable'.

- Topic 2 shows that extreme values of this feature (i.e., in-apartment facilities) are significantly related to higher prices of Airbnb accommodations. The following is a sample of original representative comments for topic 2:

[1] 'Beautiful apartment with a nice kitchen and very comfy bed. My only complaint is that when I went to utilize the nice kitchen, I found a lack of some of the most basic kitchen-tools so it was quite hard to cook a meal! Otherwise, no complaints'.

[2] 'Great place inside! Great location!! Futon in living room was only bad thing. We had 2 people sleeping on it. When one got up, it unbalanced the futon, elevating one side and having the other person roll right off the futon. Still a great deal!'

[3] 'Great location! A few blocks from subway stops on 59th and Lex and 63rd and Lex, and walking distance to Central Park. We stayed with our two kids who slept on the futon and we had breakfast in the apartment every morning. The only challenge is that the main room with the kitchen/futon/dining is tight on space, so you have to fold up the futon and move the dining table out of the corner in order to eat'.

Moreover, our study analyses how the biological male-versus-female dichotomy differently processes, evaluates and retrieves information, and makes judgements in

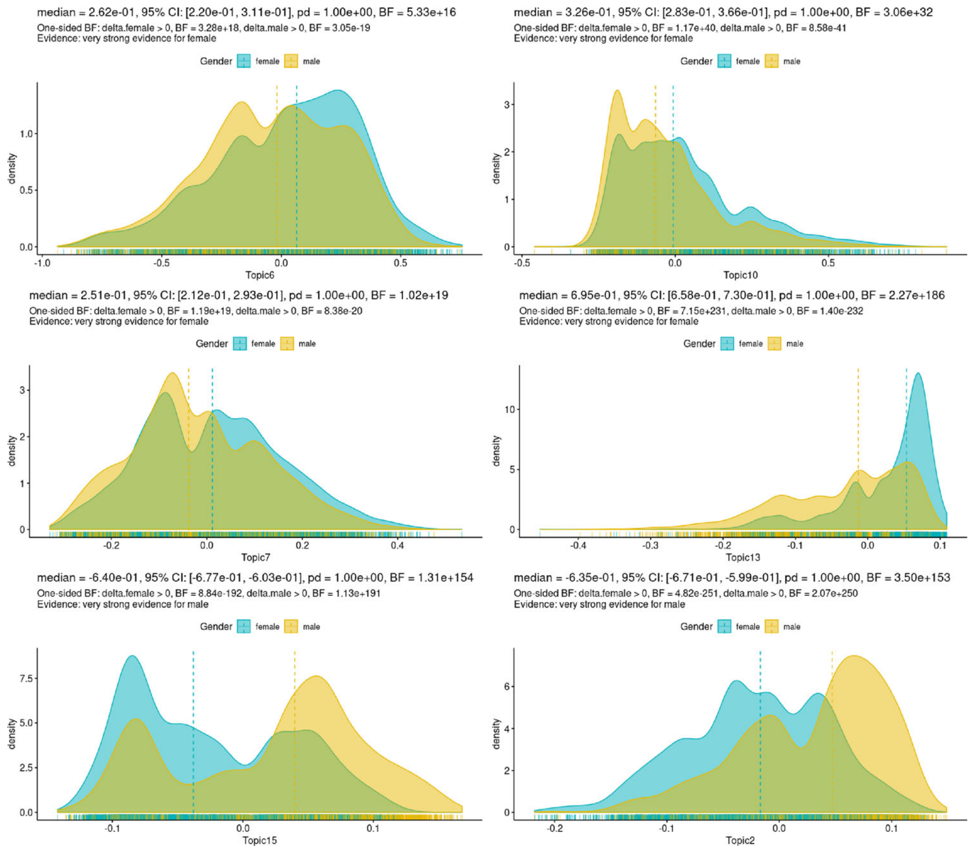

Figure 4. Density plot with median lines (and marginal rug).
(*) Bayesian *t*-tests are calculated using the BayesFactor package (Morey & Rouder, 2018), within the R environment (R Core Team, 2018).
Source: Authors' data analysis.

different ways (cf. Holbrook, 1986; Hoyer & MacInnis, 2010). Our research (about home-sharing services) precisely reveals the differential gender-based influence of the identified topics on Airbnb pricing by the comparison between two means based on a Bayesian analog of an unpaired *t*-test.

On the one hand, our study compares two models: (H_0) the null hypothesis under the assumption that the standardised effect sizes for each group (males and females) are equal and (H_1) the alternative hypothesis under the assumption that the effect is present. For instance, in the case of topic 6 the results provide strong evidence against the null hypothesis (see $BF = 5.33e+16$, in Figure 4). The SHAP values (of topic 6) have also a probability of 1 (see *pd* parameter) of being negative ($median = 2.62e-01$, 95% CI $[2.20e-01, 3.11e-01]$).

On the other hand, it is also reasonable to propose the following additional question: 'How strong is the evidence that, for instance, the average SHAP values (related to Airbnb pricing) of topic t_i differ in their association with the price between males and females?' Applying the one-sided hypothesis test, and using a zero-centred

Cauchy prior with scale $1/\sqrt{2}$ for effect size (see Morey & Rouder, 2018), the numerator is restricted to H1: $\delta_{\text{females}} > 0$, and the denominator is restricted to H1: $\delta_{\text{males}} > 0$. The main results are set out below:

- In accordance with topics 6 and 10, the corresponding Bayes factor ratio (see $BF_{\text{female}} > BF_{\text{male}}$ in Figure 4) provides greater evidence for the female-group relative to the male-group. In other words, location (topic 6) and authentic (and safe) Airbnb encounters (topic 10) show a higher association with the listings' pricing among females in comparison with males. The narratives of higher-priced apartments written by females (in comparison to males' narratives) are thus more focussed on highlighting, for instance, an authentic local neighbourhood *with a lot of character* (e.g., with opportunities for family bonding), and safe environments. Staying at an Airbnb property (not necessarily located close to tourist hotspots) offers authentic and local experiences and becomes a key feature in using peer-to-peer accommodation.
- In terms of topic 13, females assess the availability of complimentary outdoor amenities related to more accessible service for people with disabilities more than males. In this regard, females are more likely to be searching for leisure experiences with security as a priority (cf. above topic 10, based on walking in a nice way related to an authentic local experience) in comparison with males, and are more concerned about efficiency and timeliness than males (cf. topic 7, located in reviews suggesting that hosts share their knowledge and expertise).
- In terms of males' preferences for in-apartment facilities, topic 15 and topic 2 show a higher association with Airbnb prices among males – even though females are traditionally primary home-carers. Males are here focused on the importance of hygiene, quality or room amenities serving as *surrogates* for more comprehensive processing (topic 15). Also, males are more likely to complain about tangible (functional) cues than females (topic 2) (cf. also Sánchez-Franco et al., 2016). A possible explanation lies in that males focus on highly available (and apparent) cues, and preferably select objective (and salient) cues such as physical (core) attributes (cf. Meyers-Levy, 1989).

To sum up, females are more intrinsically motivated (e.g., Holbrook, 1986) – i.e., females comment (based on prior knowledge, memories and experiences) on an Airbnb accommodation according to a stimulating and amazing atmosphere – and assess the gratifying (local) experiences. On the contrary, male guests highlight hygiene and apartment facilities (as the main associations with Airbnb prices) in their narratives.

6. Conclusion

Our research analyses physical attributes, experiential or social experiences that influence Airbnb users' encounters by analysing a bulk set of online reviews through exploratory and predictive approaches. Our study improves practices in the sharing economy by identifying the subjective topics highly related to the price of Airbnb listings (e.g., location or authentic local experiences, among others), and joining them with the moderating effect of gender. In particular, a Bayesian analog of an unpaired *t*-test shows that gender is a significant moderator, i.e., guests' gender has an influence on the main Airbnb lodging features ordered according to their association with pricing policies. Specifically, females are here more associated with higher levels of hedonic consumption (e.g., Tifferet & Herstein, 2012). Females' reviews mainly focus on a stimulating and amazing atmosphere (topics 6 and 10) and consequently assess the gratifying experiences of the destination selected (described by Guttentag et al., 2018; Poon & Huang, 2017, among others). Moreover, females are even more willing to take lower risks than males (Powell & Ansic, 1997), assessing advantages for disabled travellers or kids (topic 13), or being more concerned about efficiency and timeliness than males (cf. topic 7). On the other hand, males' reviews tend to be on self-focused functional features of services (e.g., hygiene and apartment facilities based on home-like lodging conditions, i.e., topics 15 and 2) – described as a 'home away from home' by Guttentag et al. (2018) or Johnson and Neuhofer (2017), among others.

Our research therefore contributes to the literature on users and customer behaviour, offering insights for research and practice, and allowing the design of pricing-recommendation systems. Although previous studies have assessed gender as a moderating factor from an attitudinal viewpoint and its influence on behavioural intentions (e.g., moderating the relationship between customer satisfaction and loyalty or repurchasing behaviour, cf. Homburg & Giering, 2001; Mittal & Kamakura, 2001), our study goes further considering the moderating effect of gender on differentiating the direction or the strength of the relationship between Airbnb lodgings (subjective) features and pricing policies.

7. Research limitations

The bias towards positive reviews on, for instance, Airbnb, guides scholars to analyse themes that are highly valued by travellers. Moreover, cultural scripts or demographic features of guests such as age or income affect customer narratives. Following Sanchez-Franco, Cepeda-Carrion, et al. (2019), our research does not analyse the less frequent terms in the long tail of the distribution. Finally, other destinations (e.g., destinations with different cultural scripts, patterns of tourism seasonality or touristic attractions) should also be studied in order to generalise the conclusions.

8. Implications

Our research contributes to the literature on the sharing economy, fostering insights for theoretical and managerial implications concerning the effect of gender on key features of accommodation and deriving predictions and future recommendations. Our study concludes how the gender of guests affects the presence (or prevalence) of key features of accommodations and it is thus consistent with the proposal that the guests' narratives offer valuable information to future guests affecting their desires.

Our study proposes a method: (1) to explore the usefulness of analysing tourist-host (authentic) encounters based on the sharing economy as a global phenomenon with a rapid growth potential and, subsequently, (2) to predict how well the experiential encounters meet guests' predictions – i.e., as a viable alternative to staying in a hotel, hostel or bed and breakfast. Our research could be understood as a heuristic for theory building, applying an inductive perspective of reasoning, to obtain clues that may point researchers and practitioners in a promising direction.

In this regard, although previous studies examine the effects of number of reviews, ratings and host photos on the prices of Airbnb lodgings, little research focuses on guests' expectations, predictions, goals and desires from the linguistic attributes of online textual reviews generated by customers to holistically determine the price of the sharing economy (Zhao et al., 2019). To understand how the main topics influence pricing strategies in practice and the degree to which they could impact the model output, our research applies an interesting (predictive) approach based on XGBoost regressors and SHAP values. SHAP values become a unified measure of feature importance that help scholars and Airbnb hosts (when setting the prices of accommodations) interpret predictions not across the entire population but at an individual level.

Furthermore, our study contributes to the literature on guests' behaviour on online home-sharing services and detects lines of research on service recommendation systems. Although hospitality features that determine travellers' choices have been previously researched, the linguistic attributes of online textual reviews (associated with a utilitarian, enjoyable, social and home-like accommodation experience), their associations with pricing policies, and the relevance of gender in UGC are still largely under-explored in the home-sharing literature. Our research here identifies relevant topics about: (1) the basic sharing services (or the central value proposition, cf. Johnson & Neuhofer, 2017) preferred by males (i.e., core attributes of entire apartments reflecting physical features that guests crave at Airbnb lodgings), as well as (2) location and surrounding features (e.g., neighbourhood amenities – e.g., eating establishments and shopping facilities or safety) preferred by females. Our results are consistent with previous research on the tourist population that females are more concerned about relationships with others and security (cf. Deaux, 1984; Gefen & Straub, 1997; McCleary et al., 1994; Meng & Uysal, 2008). Females assess (more than males) 'natural scenery and having recreational activities, such as attending festivals/museums, visiting historical sites, sightseeing and shopping' (cf. Meng & Uysal, 2008, p. 462).

Our results are also close to those obtained by Dittmar et al. (2004, p. 440; cf. relational and item-specific processing; see also Iacobucci & Ostrom, 1993) that propose that males are more functional in their buying attitudes. Male guests here evaluate after engaging in detailed and comprehensive examination about in-apartment aspects, while female guests evaluate the aspects related to location and neighbourhood amenities. Following Sánchez-Franco et al.'s (2016) research about online customer service reviews in urban hotels, 'males describe their experiences in terms of the core product; that is to say, a hotel room [here, Airbnb apartment] that offers the fundamental functional benefits that the guest is seeking (e.g., a place to sleep)' (p.

1177). On the other hand, females prefer staying at Airbnb lodgings where hosts become a main social contact, and the comfort, design and safety are prioritised. Following Johnson and Neuhofer (2017), 'hosts are required to share their skills and expertise […] such as the provision of local routines and cultural information, direct assistance to guests and engaging in shared social practices with guests'. To avoid focusing only on low prices to attract travellers, hosts should thus communicate (in their descriptions and photos) key features focusing on gender differences, and, for instance, provide (for females) interaction with local people or authenticity through experience-based programmes (cf. also Mao & Lyu, 2017).

To sum up, our study assumes the influence of gender as an interaction cue and concludes that females and males differ in the influences of the utility, emotional or social attributes or quality signs, and to what extent these matter to guests to gain value for their expenditure. Our findings significantly influence the key design of accommodations and generate higher revenues for hosts. The effects of gender on the importance of a range of hospitality experiences are therefore a critically valuable finding for Airbnb hosts. Hosts should assess guests' needs according to their gender to help in designing Airbnb accommodations, and their offer to future guests. Hosts need to adopt a more segmented approach that enables them to attract and satisfy gender-based guests.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This study was supported by SEJ494, Research Group, Government of Andalusia, Spain.

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