

Do travelers' reviews depend on the destination? An analysis in coastal and urban peer-to-peer lodgings

Manuel J. Sánchez-Franco  | Manuel Rey-Moreno 

Business Administration and Marketing,
Faculty of Business Management and
Economics, University of Sevilla, Avda Ramón
y Cajal n1, Sevilla, 41018, Spain

Correspondence

Manuel J. Sánchez-Franco, Business
Administration and Marketing, Faculty of
Business Management and Economics,
University of Sevilla, Avda. Ramón y Cajal, 1,
41018 Sevilla, Spain.
Email: majesus@us.es

Funding information

Research Group SEJ-494, Andalusian Regional
Government, Spain. Research Group SEJ-574,
Andalusian Regional Government, Spain.

Abstract

Our research applies a service, feature-oriented approach to deeply explore the subjective experiences shared publicly by Airbnb guests in their reviews. Our processed data set contains 73,557 reviews of Airbnb stays in coastal and urban destinations between 2017 and 2020. A topic modeling based on the BERTopic approach is applied to detect dense clusters of reviews and identify one highly relevant and interpretable topic per cluster related to core and essential sharing services and surrounding features. Our study, therefore, allows a higher understanding of the relationships between urban versus coastal destinations and guests' preferences. Furthermore, it enables hosts to differentiate the touristic short-rentals lodgings according to customer experiences.

KEYWORDS

Airbnb, BERTopic, coastal destination, peer-to-peer lodgings, topic modeling, urban destination

1 | INTRODUCTION

Peer-to-peer accommodation platforms (from now on, P2P accommodations) encourage exchanging (e.g., renting) lodgings between “ordinary people” at competitive prices through community-based online services (Dolnicar, 2017; Zach et al., 2020). P2P accommodations provide “connections between people with significant dissimilarities (i.e., weak ties), e.g., in terms of beliefs and background” (Yoganathan et al., 2021, p. 526). P2P accommodations combine commercial value and functional, enjoyable or social experiences (Gansky, 2010; Ikkala & Lampinen, 2014). Moreover, publicly sharing such experiences through elaborated user-generated content (from now on, UGC in the form of a review) creates (or fosters) an authentic image related to the destination (and its accessibility, accommodations, attractions, amenities, or activities, among others) that influence travelers' intentions.

Our research explores Airbnb, a short-term housing rental company attracting enormous interest from scholars, government

administrations, and tourism managers (cf. Geissinger et al., 2020; Guttentag & Smith, 2017). In particular, Airbnb is (a) primarily considered as a low-cost renting option (Guttentag et al., 2018; Liang, 2015), (b) now a trendy, warm, and authentic (social) option, and (c) classified under collaborative consumption (cf. Frenken et al., 2015; see also Kraus et al., 2020). In this sense, Airbnb focuses on travelers (here, guests) who enjoy multiple interactions with the host and local people and use community-based online services to reduce failure risk by freely sharing accommodations' ratings and UGC (Martins Gonçalves et al., 2018; Sánchez-Franco & Alonso-Dos-Santos, 2021).

UGC highlights utility, affective, social or symbolic features of Airbnb lodgings, reflecting consumer experiences *in natura* without any interference from researchers (cf. Sánchez-Franco et al., 2016). Although stay-related UGC is poorly structured, focuses on a singular aspect of hospitality services or is multi-lingual, it is especially relevant in tourism and hospitality to help understand guests' valid preferences described in reviews from anonymous or unfamiliar

This is an open access article under the terms of the Creative Commons Attribution-NonCommercial-NoDerivs License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial and no modifications or adaptations are made.

© 2021 The Authors. *Psychology & Marketing* published by Wiley Periodicals LLC

sources. Centered on the generator of the content, UGC entails higher levels of elaboration and greater engagement. Additionally, the Media Systems Dependency theory proposes that consumers of the content dependent upon a medium (e.g., community-based online services) are more likely to be personally changed by that community in behavior and opinion (cf. Ball-Rokeach, 1985). Law et al. (2014) note that social media develop a significant role in tourists' decision-making given the social dimension of behavior in this hospitality context. In 2017, Statistic Brain revealed that 81% of travelers find user reviews important (Luo, 2018). Although the valence (and influence) of UGC in and on review helpfulness, consumer attitude, and behavior show diverging results (cf. Filieri et al., 2021), Sparks and Browning (2011) note that the willingness to book online is higher when (hotel) reviews are predominantly positive (Del Chiappa et al., 2015; Tsoo et al., 2015).

"The influence of eWOM [here, UGC] on consumers' attitudes toward a brand and their purchase intention has been [thus] widely recognized in recent literature" (Martins Gonçalves et al., 2018, p. 807; cf. also Chevalier & Mayzlin, 2006; Godes & Mayzlin, 2004). Furthermore, "the interpretation of consumption stories or narratives is gaining more popularity within the consumer research domain" (Rahmanian, 2021, p. 47). However, "scarce research focuses on guests' expectations, predictions, goals, and desires from linguistic attributes of online textual reviews generated by customers" (Sánchez-Franco & Alonso-Dos-Santos, 2021, p. 2499). There is no conclusive evidence concerning guests' preferences—which are also traditionally examined in a biased way (cf. Mao & Lyu, 2017; Sánchez-Franco & Alonso-Dos-Santos, 2021; Tussyadiah, 2016a, 2016b; Varma et al., 2016). Furthermore, there is still a need to deepen the research debate about what guests highlight in their reviews, especially in different (touristic) environments at the country, region, or city level. "Since the type of tourists varies between cities and rural areas, the value of attributes may vary between rural and urban destinations" (Falk et al., 2019, p. 134). For instance, Moreno-Izquierdo et al. (2019) differentiate between "sun, sea, and sand" destinations—associated with sports and adventure activities, spending time at the beach—and urban areas (centered on gastronomy, arts, visits to museums and concerts, or leisure activities, such as shopping or sports).

To sum up, our study seeks to account for the limited explanatory power and the inconsistencies between studies by applying clusterisation analysis to a sample of urban and coastal destinations. It addresses a challenging examination of natural and nonstructured UGC identifying guests' experience-related latent topics. First, the paper presents the theoretical framework relevant to this study. It analyses thematic networks about Airbnb, tourism, and environments. Second, our method section describes the data collection and cleansing process. Next, it identifies topics and offers results by considering the above reasoning. Our modeling applies the BERTopic approach (cf. Grootendorst, 2020) based on Top2Vec (Angelov, 2020). Finally, the discussion section outlines the future lines of research and theoretical and managerial implications.

2 | RESEARCH OBJECTIVES

Our study addresses the following main research objectives (RO) to detect guests' experiences in their narratives (or reviews) about Airbnb stays. Overall, this will enable us to go deeper into a growing line of research by analysing the spread of sharing lodgings in geographical scope and establish a large-scale comparison. In particular, this study proposes the following research objectives:

- RO.1. To identify guests' latent semantic structures (or topics) by analysing a bulk set of UGC after an actual stay through its pre-processing (cleansing data) and data mining processing.

Our research seeks: (1) to overcome the disadvantages of probabilistic generative topic modeling, (2) to expand previous studies based on structural scales, and (3) to apply large-scale data sources following an exploratory approach. Our study is thus more reliable and accurate than statistical results based on limited sample data.
- RO.2. To explore destination-level topics (and metatopics) of an urban versus coastal nature, and their associations through a correspondence analysis. Here no model has to be hypothesized.
- RO.3. To explore the key features that travelers describe in their narratives through P2P accommodations and describe the relationship between the most relevant topics, sentiment scores, and selected destinations.

To sum up, by identifying the main topics related to guests' preferences, hosts could enhance listings' content published in Airbnb (e.g., description, summary, or photos reflecting host and guest interaction, among others). Additionally, our study aims to validate advanced natural language processing (NLP) analysis with results attained by traditional methods (cf. Cai, 2021). In this regard, following Sánchez-Franco and Alonso-Dos-Santos (2021, p. 2499) approach, our research has to 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" (see Figure 1).

3 | THEORETICAL FRAMEWORK

3.1 | Airbnb and environments at the destination level

Growing research about UGC (based on personal needs and experiences of guests) is necessary to analyse how to invest and modernize hospitality infrastructures. On the one hand, in collaborative economy contexts and hospitality-specific heterogeneity, users preferentially access free and credible information provided by anonymous consumers who know a particular product or service (Martins Gonçalves et al., 2018). On the other hand, "the content published by users on the social network sites may [also] affect other

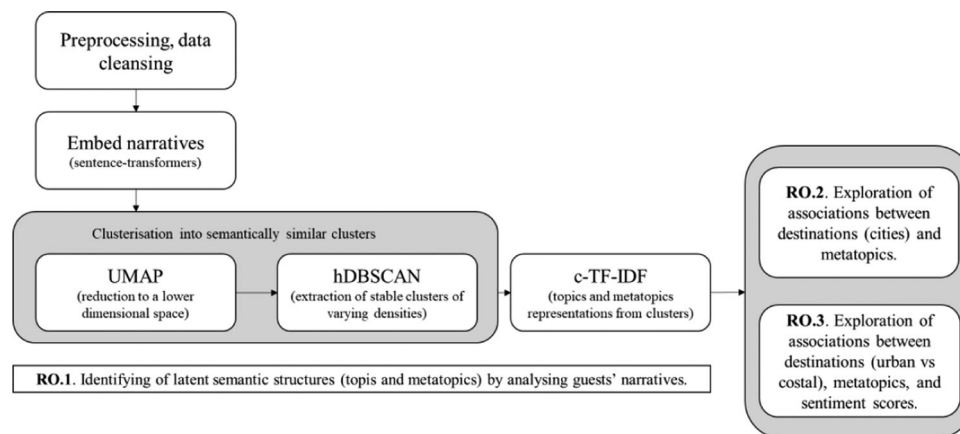


FIGURE 1 Research objectives flow

individuals' attitudes and intentions in a consumption context" (Herrero Crespo et al., 2015).

Accordingly, "social media data not only provides tourists with various traveling information on the demand side but also inspires tourism destinations to make decisions according to the tourist preferences from the supply side" (Sun et al., 2018, p. 2; see also Dickinger & Mazanec, 2008; Tsao et al., 2015; Vermeulen & Seegers, 2009). UGC "integrates a holistic tourist experience, not only with accommodations, but also all kinds of experiences and activities to carry out in the destination" (Lalicic et al., 2021, p. 11) and tends to be more empathetic and trustworthy than logic-based communications (Gretzel & Yoo, 2008). Community-based online services thus promote higher levels of elaboration (focused on the generator of the content) and greater customer engagement stemming from personal goals or values (or preferences) (cf. Brodie et al., 2011; Herrero Crespo et al., 2015). Analogous to webroomers, UGC would enhance guests' knowledge about Airbnb lodgings (features and benefits) and control decision-making (Santos & Gonçalves, 2019). Although simple signals—acting as heuristics—allow travelers to infer the unobservable cues of hospitality services (Belver-Delgado et al., 2021), scores awarded by past travelers could oversimplify quality measures by assuming that quality is a uni-dimensional measure (Archak et al., 2011; Ert et al., 2016; Lawani et al., 2019, p. 22). In contrast, NLP offers enormous capabilities of harvesting plenty of enriched UGC. It converts more valuable and credible reviews (created by non-professionals) about personal goals and values to features (or preferences), modeling semantic relationships, and showing relevant topics more efficiently than traditional text analysis (Cai, 2021).

First, most literature published to date provides promising results about the presence or absence of crucial subjective dimensions or features such as:

- Site-specific features (or structural attributes), for example, the distance from the touristy hotspots or the services and home benefits for enhancing the homely feel (e.g., household amenities and basic functionalities such as beds, wireless Internet, ample

space, and free parking, among others) (cf. Guttentag, 2015, 2016; Johnson & Neuhofer, 2017).

- Convenient location and environmental features, for example, for its comparatively low cost (cf. Guttentag, 2016; Mao & Lyu, 2017; Satama, 2014; Tussyadiah & Pesonen, 2016; Yang & Ahn, 2016) or the post-modern experiences described as authentic staying at an Airbnb lodging (cf. Guttentag et al., 2018; Liang, 2015; Mody et al., 2017; Poon & Huang, 2017), the novelty (Guttentag, 2016; Johnson & Neuhofer, 2017; Mao & Lyu, 2017), or the interaction as part of a social benefit from using Airbnb (Tussyadiah & Pesonen, 2016).

Second, recent research on destinations traditionally focuses on urban areas at the consolidation stage in the lifecycle model. It analyses the core and essential services located in such destinations that significantly affect the assessment of accommodation listings and generate higher revenues for hosts (Heo et al., 2019; Liang et al., 2017; Maxim, 2019, among others). In this regard, Moreno-Izquierdo et al. (2019) precisely note that most studies examine large urban cities and traditionally overlook moderating regional or city-specific features (Chattopadhyay & Mitra, 2019). Hasan et al. (2019, p. 218) point out that "coastal-based beach tourism is one of the least researched areas in tourism literature." Although urban destinations such as Hong Kong, New York, or London are overall mainstays on the list of international visitors, about 40% of the world's population lives on the coast or within the coastal area and partly depend on a combination of nature, *sun*, *sea*, and *sand*, evolving towards a service-oriented tourism-dependent economy (cf. Hasan et al., 2019; see also Sardá et al., 2009; Warton & Brander, 2017). One, therefore, expects there to be significant differences between urban and coastal destination experiences (cf. Oh et al., 2007, who examine bed-and-breakfast guests' experiences).

In particular, coastal tourism is a location-based market, and destinations compete to gain guests' preference. Tourists are attracted to coastal destinations because of a desire for escape, rest, relaxation, prestige, adventure, or social interaction. In addition, tourists enjoy exciting recreational activities indoors and outdoors

such as sport, and play in a peaceful atmosphere *along the shore* and enjoy natural resources. Coastal tourism destinations indeed fall all along an urban-rural continuum (Pahl, 1966). At one beginning of the scale, cities like New York or Chicago offer travelers social and cultural experiences. In more centered positions, destinations such as Fort Lauderdale (focused on environmental resources that attract tourists to Florida's coast, in conjunction with Miami Beach and Sarasota) or even further afield regions like Hawaii (valued for their natural beauty, flora, and fauna).

In line with previous comments, there is a gap in the literature regarding the Airbnb core or basic Airbnb features, mentioned by guests in a vast amount of UGC about their gratifying, authentic and local experiences in nonurban destinations related to indoor and outdoor activities for leisure and sightseeing. And exploring the traveler's differential topics in their P2P accommodations' narratives allows us to assess the distinctive destination image, guests' attitudes, and their intention of repeat visits. While certain factors are highlighted equally in the narratives for urban and coastal destinations, other drivers clearly distinguish the geographical destinations and correspond to guests' needs fulfilled through the destination selected, such as social-integrative-, tension-free- or affective-needs, among others. To sum up, our research, explores the images of Airbnb accommodations in urban and coastal destinations based on their attributes, as discussed in guests' narratives.

3.2 | Review of studies and thematic networks about Airbnb, tourism, and environments

Assuming the gap in the literature regarding the Airbnb experiences in nonurban destinations, a science mapping here aims at displaying (and contextualizing) the structural and dynamic aspects of our theoretical framework. A network analysis related to our main research questions could confirm our research field's structure through co-word analysis. And it could identify prominent themes that are more specialized (or emerging) and, consequently, peripheral to the mainstream work. Our study, therefore, displays a strategic diagram to categorize the detected topics for a better interpretation of the results.

With query #1, 3366 refereed articles (as the highest-ranked scientific contributions) are collected by extracting from WoS (SCI-EXPANDED, SSCI, ESCI) and Scopus and filtered according to their content. Our search focuses on the keyword "Airbnb" OR "Tourism*." It includes studies focused on P2P accommodations in the title, abstract or keywords related to widespread sharing tourism phenomena. P2P accommodation topics increasingly appear in peer-reviewed journals in 2010, and a general trend in new articles is towards examining more specialized themes (cf. Belarmino & Koh, 2019). Our data set spans the period between 2010 and 2020.

WoS Query#1-analog to Scopus query: TS
 = (AirbnbORTourism)ANDTI
 = (coastal × ORurban × ORrural × ORsun × ORbeach*).

Applying text-mining analysis carries out a careful data cleaning process based on our sub-epigraph "Data cleansing process and extracting terms." In particular, it omits terms shorter than a minimum of three characters. Our research normalizes differences between UK and US spelling. The inclusion of noisy terms in the topic modeling process could contaminate predictive performances. Our study also selects a subset of unigrams and bigrams (from now on, terms) by tf-idf metric (above the median) (cf. Sánchez-Franco et al., 2019). Our analysis finally extracts 9709 lemmatized terms.

Additionally, to create and analyse the conceptual structure of our theoretical framework, our research follows Cobo et al. (2011a, 2011b) approach. It summarizes the centrality for each community (or the strength of external ties to other topics or a theme's importance) and density for each community (or the strength of internal relations between nodes or their coherence). And finally, it displays a co-topic network or thematic map according to the quadrant in which topics are located. As one can thus observe (see Figure 2):

- **Quadrant I** (upper-right quadrant, or motor themes)
 - Community #1 (i.e., city, resident, urban tourism, rental, or neighborhood, among others) is associated with city-specific heterogeneity concerning, for instance, the (short-duration) rentals and their influence on neighborhoods. Combining high centrality and density community #1 is considered an increasingly developed theme and highly relevant for structuring our research field, thus gaining coherence and importance. If its density decreases, community #1 might be progressively identified as a transversal one, that is, the community could move to Quadrant IV over time.
 - **Quadrant II** (upper-left quadrant, or highly developed and isolated themes)
 - Communities #2 (heritage, behavior, household, or livelihood, among others) and #3 (hospitality or urbanization) are represented by specific tourist services. Both communities show a high-medium density (well-focused research) but a low-medium relevance (external links), that is, not well-connected with other fields and, consequently, specialized and peripheral (Ivory Towers).
 - **Quadrant III** (lower-left quadrant, or emerging or declining themes)
 - Community #4 (i.e., coastal tourism or coastal area) shows a *relatively* well-connected internal structure and is weakly connected to other nodes. It is thus located in an unstructured quadrant, with the potential of becoming a mainstream research theme (Quadrant I). However, coastal tourism has probably not had enough time to establish strong ties to other topics.
- In this regard, one of the most profitable industries in coastal areas is indeed tourism (European Commission, 1999; Hall, 2001). Tourism is an important economic activity, especially in many coastal areas (European Commission, 2014), and it is considered the largest segment of the global tourism industry. Inherited coastal sand-beach tourism has thus become an emerging theme in the economy (and management) literature and might evolve towards motor themes (mainstream). The coastal research domain

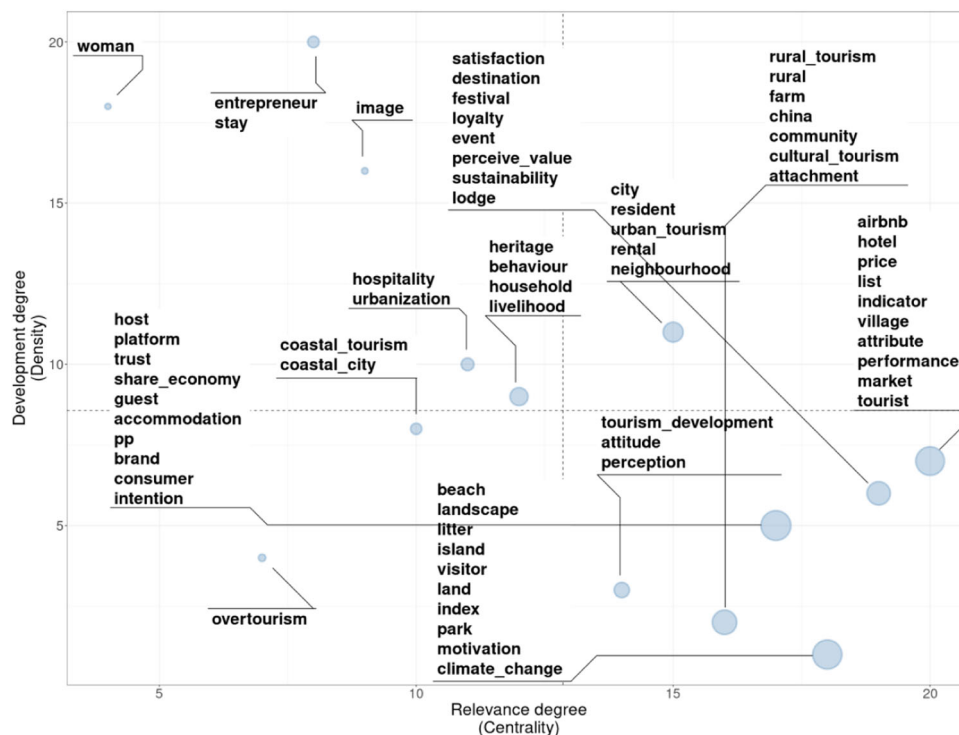


FIGURE 2 A co-topics network to compute centrality and density: 2010–2020. *Centrality, or x-axis, measures the degree of interaction of a (sub-) network with other (sub-) networks (Cobo et al., 2011a, 2011b). **Density, or y-axis, measures the internal strength of the network (Cobo et al., 2011a, 2001b). *** $p = P2P$. P2P, peer-to-peer accommodation

is therefore a peripheral topic—well-structured (medium average density) and shows limited bonds to other topics (medium average centrality) in the (communities) graph analysed. Consequently, it has developed into a potential challenge in the Destination Marketing Organisation (DMO). And it should be essentially associated with actual guests' preferences for P2P accommodations in different destinations, increasing its relevance and centrality.

Furthermore, peripheral topics produce new knowledge to be progressively shared among diverse core topics that fragment into new (cohesive) communities which coalesce around emerging research questions (Chubin, 1976). Thematic areas in Quadrant III act as peripheral nodes (with sparser connections) to the overall graph, for example, the over-tourism theme (community #5). They turn into emerging topics connected to important dimensions that progressively influence, for instance, 'Airbnb rental platform vs. hotel research' from the perspective of the hosts, guests, or government administrations (e.g., Xie & Kwok, 2017; cf. also Guttentag & Smith, 2017).

- **Quadrant IV** (lower-right quadrant, or basic and transversal themes).

Quadrant IV evidence that the field is expanding and could become a mainstream topic over time, reflecting its conceptual development. Community #6, more centrally located in the network and comprising the keywords host, platform, trust or shared economy, is a fundamental and transversal theme (with a high average centrality and a low-medium density). It is related to involvement with the Airbnb brand, customer

trust and its influence on travelers' behavior, "specifically looking at how P2P accommodations websites have successfully monetized trust, how consumers and hosts perceive trust and the issues that arise from this type of transaction" (Balarmino & Koh, 2019, p. 3). The sharing economy and Airbnb have become a transversal interest in exploring P2P platforms because of the relationship between hosts and guests, concluding in their value proposition. Both concepts could influence the development of all the other themes.

Furthermore, community #7 (as a *bandwagon* theme) is defined as Airbnb's sharing accommodation (and is related to different concepts such as Airbnb, hotel, or price host, among others). It is an (internally) underdeveloped topic (weak coherence) with a potential to develop into being significant to the domain as a whole (mainstream). 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 Gutierrez et al., 2017; Guttentag et al., 2018; Poon & Huang, 2017; Sánchez-Franco & Alonso-Dos-Santos, 2021, among others, to conclude Airbnb's role as a disruptor for the hotel industry).

Likewise, community #8 (satisfaction, destination, festival, loyalty, event or perceived value, among others) is associated with customer relationship quality and is here determined by useful, enjoyable, social and home-like accommodation experiences from interactions with local people or authenticity (e.g., Guttentag, 2016; Johnson & Neuhofer, 2017; Mody et al., 2017; Poon & Huang, 2017; Tussyadiah & Pesonen, 2016). As Guttentag et al. (2018, p. 343) point out, "Airbnb listings are quite varied, and the potential appeals of Airbnb include both practical advantages and experiential facets that

may not generally go hand-in-hand.” And, precisely, to trade-off customer satisfaction and loyalty, the preservation of local resources and consequently the local authenticity community #9 (rural tourism, farm, China, community, cultural tourism, among others) is related to rural tourism. Rural tourism entails researching residents (e.g., farm-houses), achieving sustainable development in the long run, a traditional lifestyle or quality service, or increasing competitiveness in rural areas. In this regard, community #9 is also centered on tourism development and its model is designed by, for instance, the local community that fosters rural entrepreneurship (based on financial rewards; cf. Anand et al., 2012; Wang et al., 2012) to improve service encounters during the travelers' stays.

Finally, community #10 (beach, landscape, litter, island, climate change, among others) is related to maritime areas and is defined by conservation and “a future” related to the local community. Therefore, it is a relevant theme (and influential). Although it is highly associated with sustainable development, community #10 could be considered a (weakly) coherent theme.

4 | MATERIALS AND METHODS

4.1 | Data collection

Our data set is obtained from the InsideAirbnb website (available at: <http://insideairbnb.com/>). The reviews are publicly accessible. And our research here filters out accommodations for two urban destinations (New York and Chicago) and two consolidated nature-based, sun and beach destinations (Hawaii and Fort Lauderdale). Our destinations have all the services and infrastructure necessary to accommodate the tourism industry and are relevant destinations for domestic and international visitors alike.

Likewise, our research filters out a price lower than 10 US dollars (not including cleaning fees or additional charges for guests). To preserve the amateur character of the host and facilitate comparisons, our study selects only hosts with a single listing. In addition, Airbnb listings are considered outliers when the number of guests lies outside the interval formed by the 5 and 95 percentiles. In this regard, our study removes all listings higher than six guests. Large apartments could indeed have a *shocking* influence on the analyses.

Additionally, our study analyses a single language, English, to maintain consistency between the texts analysed. Our research applies textcat 1.0-7 package in R for this purpose. Our data set is also truncated just before the outbreak of the COVID-19 pandemic to prevent anomalies, that is, between 2017 (March 1, 2017) and 2020 (March 1, 2020).

Our data set yields a total of 73,557 records. See Figure 3 for the spatial distribution of our Airbnb data set by region or city.

4.2 | Data cleansing process and extracting terms

Although it is not strictly mandatory under the BERTopic approach, following Sánchez-Franco et al., (2016, 2019), our research here (1)

checks the spelling of narratives and removes duplicates, (2) discards punctuation, capitalization, digits, and extra whitespaces, (3) removes a list of common stop words to filter out overly common terms and a customized list of proper nouns, (4) fixes contractions, and compound terms, (5) tokenises and lemmatizes the terms, and (6) becomes text in ASCII, and standardizes it by lowercasing. Our data set contains an average of 61.5 terms per narrative and a standard deviation of 50.1 terms. Our analysis applies dplyr 1.0.2, stringr 1.4.0 and quanteda 2.1.2 packages in R, and textclean 0.9.3, textstem 0.1.4, and hunspell 3.0.1 packages in R, among others, for these purposes.

To briefly describe our dictionary, our study applies the keyness metric, which emphasizes the vocabulary (9497 terms) that most differentiates reviews from one group (here, urban destination) in comparison to the other (here, coastal destination). The higher the keyness, the more “key” a term is. The chi-squared value (χ^2) is used for computing keyness metric, and is provided by the quanteda 2.1.2 package in R software. Figures 4a,b display the χ^2 values in the x-axis (with $p < 0.001$) for each (key-)term. “Subway,” “train,” or “neighborhood” (followed by apartment, public transport, bus, walk, or bar) are the main features in urban destinations, being the terms with the highest χ^2 values, and being mentioned 6441, 3320, and 7482 times (term frequency), respectively. Likewise, as our research comments above, the main urban attractions are based on cultural heritage (such as visiting museums and concerts or leisure activities such as sports). On the other hand, the importance of “pool,” “view,” “snorkel,” or “beach chair” or “cottage” for coastal destinations is clearly shown by its first positions, which are mentioned 6160, 4958, 1743 and 1267 and 1175 times, followed by “sunset,” “beach towel,” “swim,” or “surfboard.” Diverse terms such as tropical, grill, paradise or barbecue represent exotic gastronomy and local authenticity and are related to lunch beach or condo amenities such as patio or backyard (see Figures 4a,b).

Moreover, our study estimates the similarity between our Document-Term matrix (DTM) and a numeric vector with weights formed by a set of positive or negative terms (here, AFINN sentiment lexicon) based on an embedding matrix (containing the v element from a singular value decomposition on DTM). The results are provided by the udpipe 0.8.4-1 package in R software and shown in Figures 5a,b. Overall, the terms most associated with positive terms are mainly related to location and neighborhood amenities. This result is because travelers assess highly (and frequently) features of the surroundings or neighborhood “ambience.” For instance, “*an Airbnb apartment is close to the transportation system in an urban destination,*” or “*an Airbnb apartment is in an authentic neighborhood close to shops, touristic attractions, and local experiences such as beach food.*” On the contrary, terms more related to negative terms are about in-apartment amenities, cleanliness and comfort, and hosts' (social) interactions related to check-in or “homely feelings”—without exception according to the tourist destination.

Finally, while the description of terms has some appealing clues to identify terms that are discriminative for documents in the collection, “the approach brings a relatively small reduction in description length and reveals little in the way of inter- or intra-document

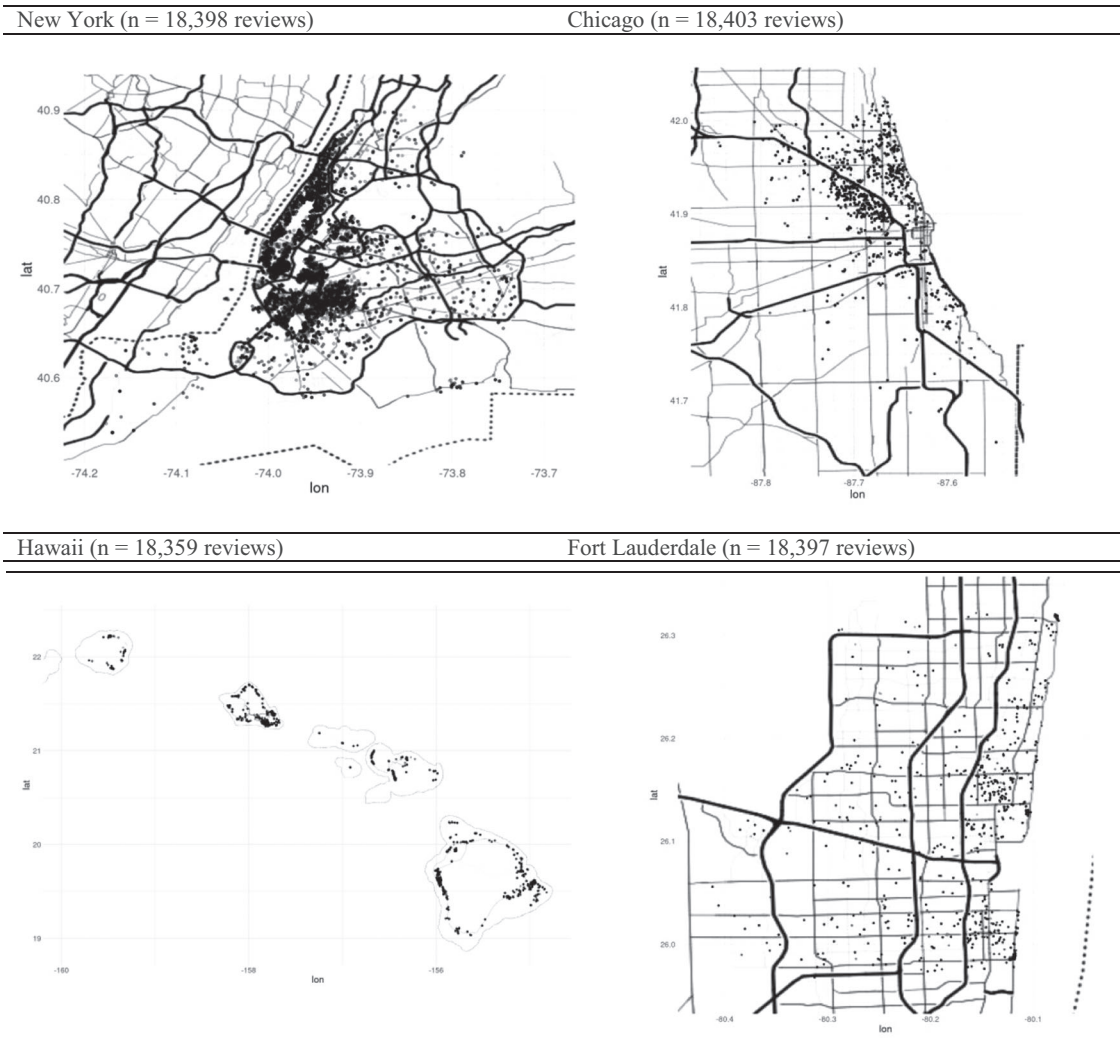


FIGURE 3 Spatial distribution of Airbnb lodgings data set by region or city

statistical structure” (Blei et al., 2003, p. 994). Therefore, the discovery of distinct latent semantic structures (or topics) and their similarities are additionally necessary.

5 | DATA MINING

Our research applies a text-mining algorithm to extract dense semantic structures (or topics) from a continuous semantic space. Overall:

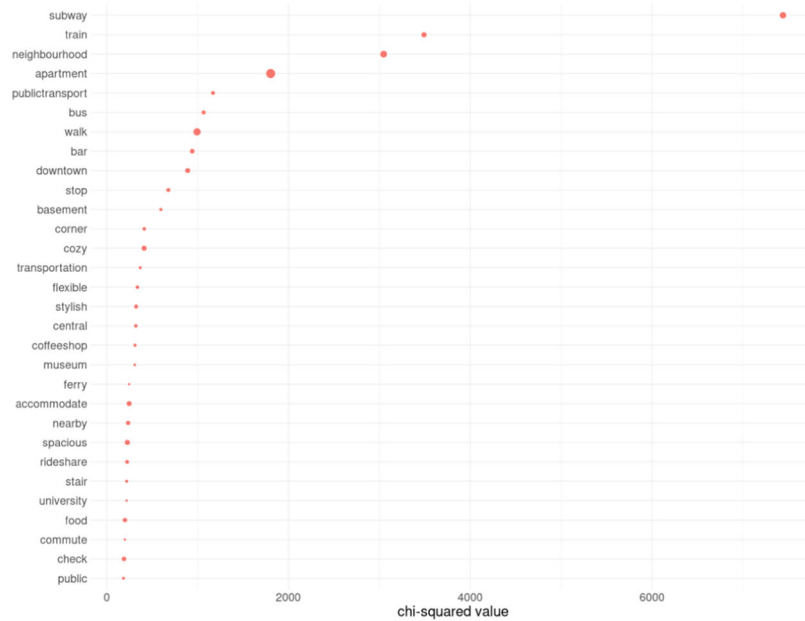
- Our study compares the terms' importance between identified clusters of document vectors, which are more informative and representative than latent dirichlet allocation (LDA) or probabilistic latent semantic analysis (PLSA) outputs. Additionally, LDA and PLSA could not fit into short texts appropriately due to severe data sparsity.
- Our analysis rejects using a bag-of-words representation of narratives and considers the ordering and semantic relationships between terms.

- Compared to LDA or PLSA, our fine-tuning approach fits a small number of parameters.

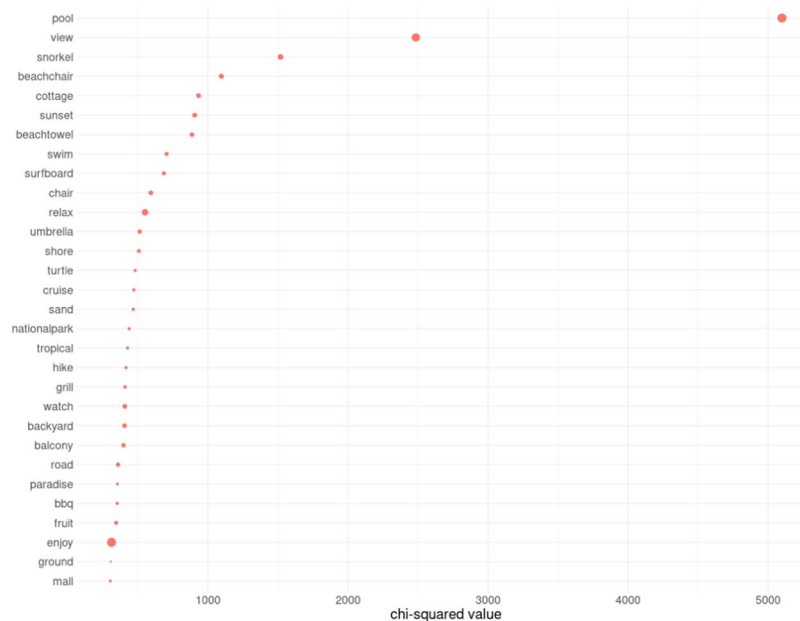
In particular, following BERTopic's approach (Grootendorst, 2020) based on Top2Vec (Angelov, 2020), our research firstly transforms our corpus into 768-dimensional vectors leveraging a pre-trained sentence transformer model optimized for semantic textual similarity (Reimers & Gurevych, 2019; cf. sentence-transformers package in Python 3.8).

Second, a Uniform Manifold Approximation and Projection for Dimension Reduction (UMAP; cf. McInnes et al., 2018) is applied to our vectors to create a lower-dimensional embedding of document vectors through the umap-learn 0.5.1 package in Python 3.8 (McInnes et al., 2018). UMAP performs significantly better than t-SNE at maintaining both the data local and global structures. Our proposal reduces the vectors to 20-dimensions (from now on, 20d-UMAP) and measures distances between data points by cosine-similarity. Experimentation and related literature here recommend 15-nearest neighbors to emphasize local structures. And the effective minimum distance between embedded points is set at 0.01. Next, to find such dense documents areas, the

(a) Urban destination



(b) Coastal destination



† Point size: term frequency.

FIGURE 4 Text analytics based on *keyness metric*

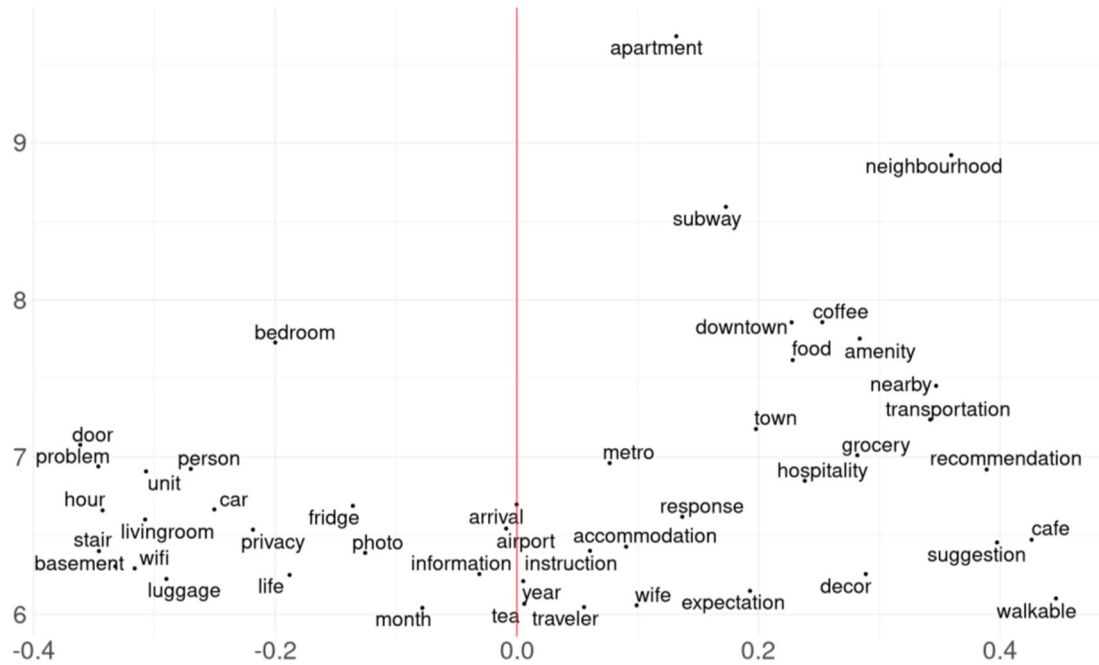
20d-UMAP embedding is clustered with Hierarchical Density-Based Spatial Clustering of Applications with Noise algorithm (from now on, hDBSCAN; Campello et al., 2013; McInnes & Healy, 2017). hDBSCAN extends DBSCAN and extracts stable clusters of varying densities (with arbitrary shapes and sizes and noisy points). The minimum size of clusters is set at 200. Likewise, the number of samples or density threshold (i.e., the minimum number of samples required before an area can be

considered dense and a point to be considered a core point is set at 25). Our analysis employs the hdbscan 0.8.27 package in Python 3.8.

Thirdly, one topic vector per cluster is identified in the following steps:

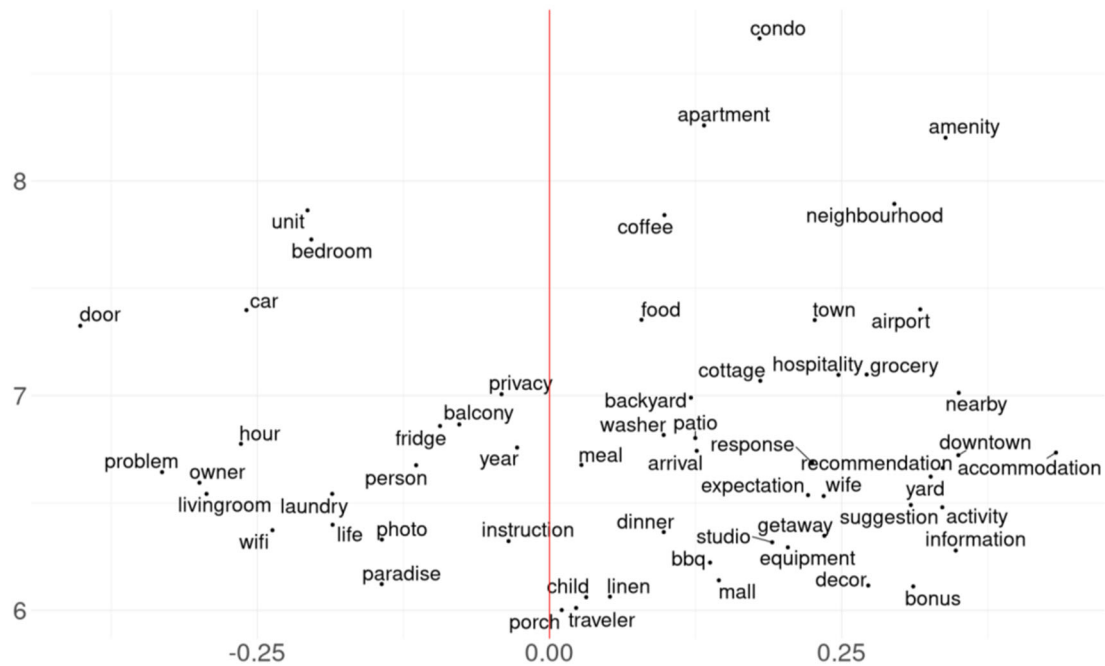
- Our analysis converts the documents in each cluster into a single document per cluster.

(a) Urban destination



†x-axis: polarity / y-axis: logarithmic frequency.

(b) Coastal destination



†x-axis: polarity / y-axis: logarithmic frequency.

FIGURE 5 Text analytics based on semantic similarity. List of terms with the highest logarithmic frequency

- Our study compares the importance scores for terms within a cluster by a class-based TF-IDF approach (from now on, c-TF-IDF, with c being the identified clusters). The higher the c-TF-IDF score, the more representative it is of its topic.
- Our study also compares the c-TF-IDF vectors between topics, merges the most similar ones, and finally re-calculates the c-TF-IDF vectors. As a result, our research reduces the number of topics from 34 topics (named from 0 to 33) to 14 compact (and semantic) metatopics (named from A to N).

Finally, our approach builds a bi-dimensional space to easily visualize the continuous representation of metatopics, applying 2d-UMAP approximation (see Figure 6). Additionally, Figures 7a,b display the most representative terms -in each topic (Figure 7) and metatopic (Figure 7)- based on their c-TF-IDF scores, and allow to compare topic (or metatopic) representations to each other.

6 | RESULTS

Figure 8 precisely displays the condensed clustering tree extracted from hDBSCAN, where λ represents the weight of the edges. The topic 0 (metatopic A) initially breaks the complex condensed clustering tree, and it is related to travel companions. The next branch from the condensed clustering tree identifies topic 2 (or

metatopic B) related to the transportation system (e.g., bus, downtown, subway, walk for transport or train), and topic 4 (or metatopic C). Topic 4 is mainly about the journey from a tourist's residence until arriving at their destination (e.g., flight, airport or cruise as the beginning of the Airbnb experience). Finally, most of the following significant branches from the clustering tree are related to metatopics, mainly about convenient location, apartment surroundings, experiential features, outdoor facilities, or in-household benefits.

Second, our results identify the topics that accumulate the highest number of reviews. Topic 24 (6587 reviews), included in metatopic J, represents around 15%. It is about ease of access to a transportation hub or "walkability" in destinations. Metatopic B includes topic 2 (1024 reviews, i.e., 2.40%). Both topics are stronger among those in urban destinations such as New York or Chicago. Metatopic I includes Topic 23 (4192 reviews, i.e., 9.83%), and it is semantically close to guests' non-economic satisfaction (e.g., love, experience, or awesome), that is, customers rely on their entire (and gratifying) experience when forming intentions and making revisit decisions. Topic 16 (3314 reviews, i.e., 7.77%) in metatopic G mainly concerns overall apartment features and location. Topic 32 (2512 reviews, i.e., 5.89%), included in metatopic N, is semantically close to topic 33 (1875 reviews, i.e., 4.39%). Topics 32 and 33 are related to coastal views from the shore or boardwalk and peaceful experiences in coastal destinations.

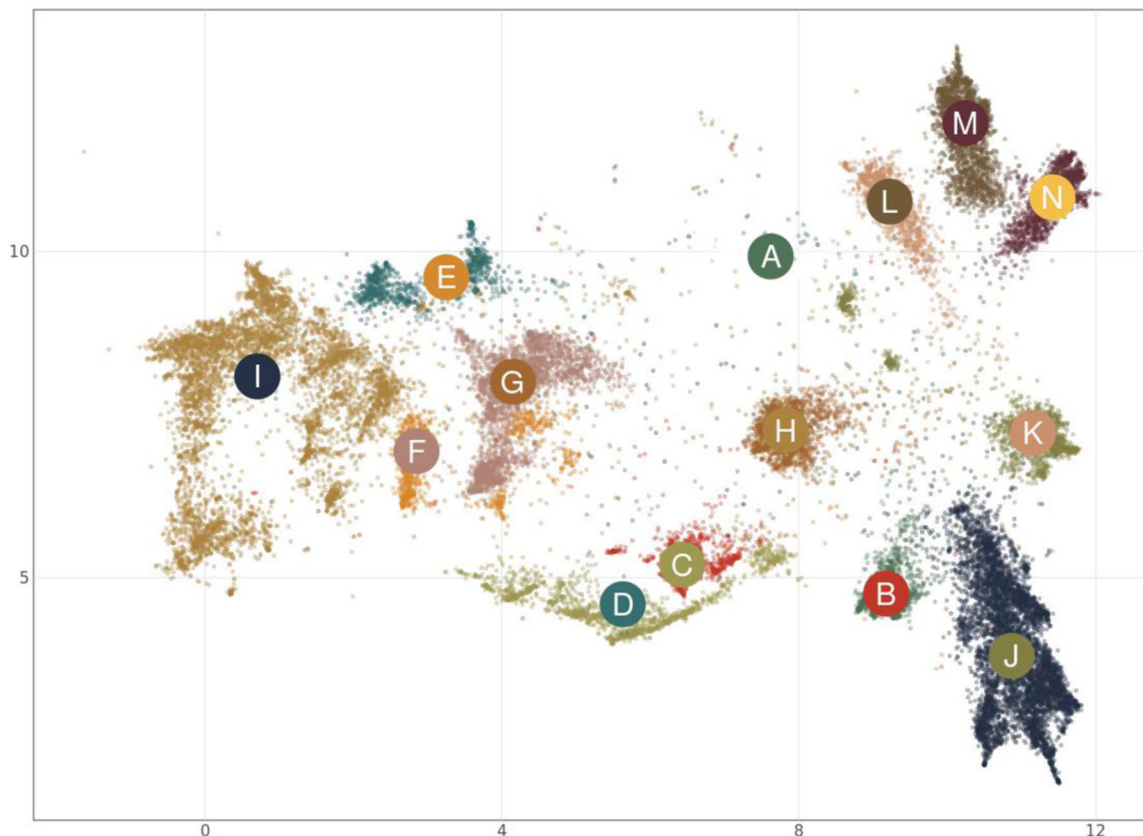
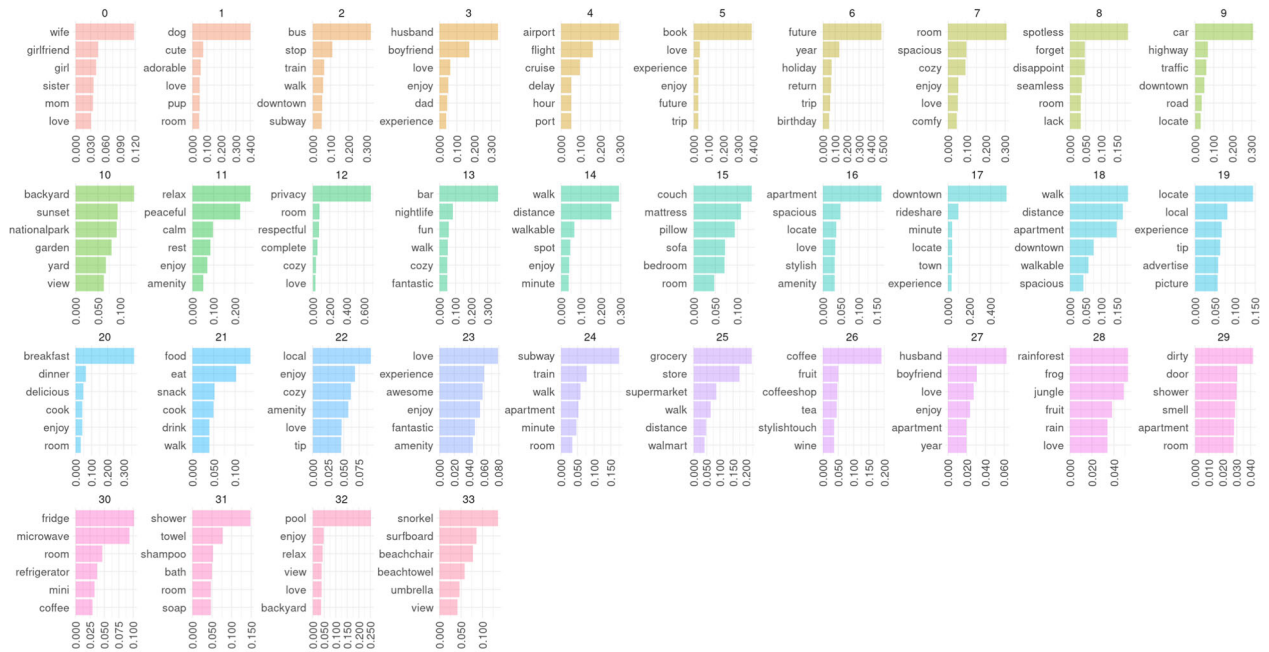


FIGURE 6 Metatopics by merging the most similar ones and visualized by reducing embeddings to two-dimensional space

(a)

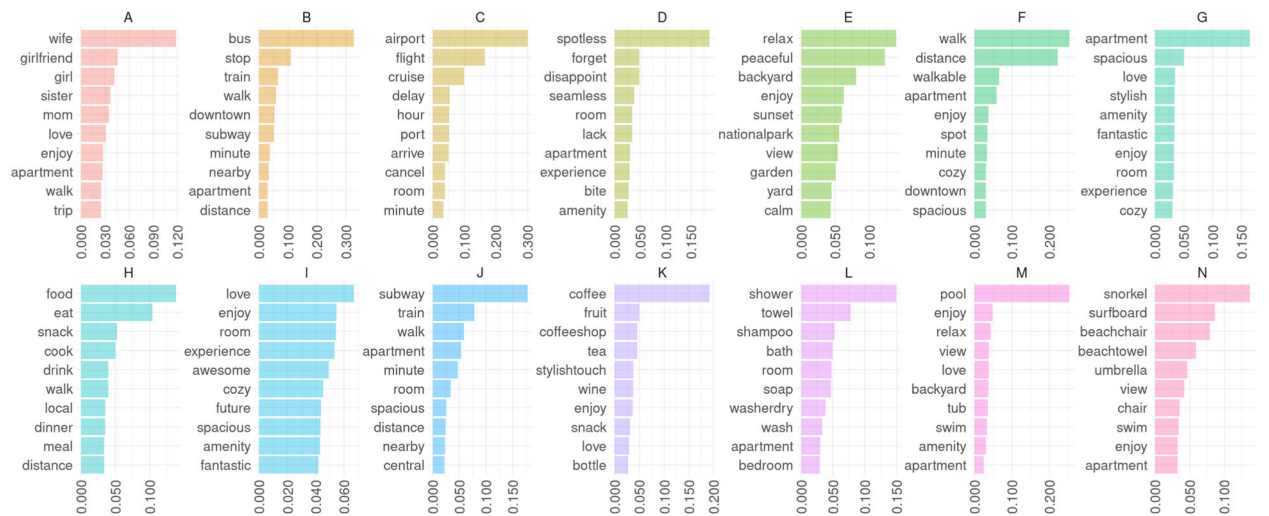
Topics.



† x-axis: tf-idf values.

(b)

Metatopics .



† x-axis: tf-idf values.

FIGURE 7 Top terms per cluster based on their c-TF-IDF scores

Third, beyond adjectives that guests have used and their intensity (e.g., amazing or loved, among others) and metatopics previously mentioned, our study comments the metatopics. In particular,

- Metatopic A (topic 0) is related to travel companions.
- Metatopic B (topic 2 above public transportation such as train, subway, or bus system) is semantically related to metatopic C (topic 4 above transport hubs such as airport or port).

- Metatopic D, consisting of topic 8, is related to cleanliness or comfort and in-household amenities.
- Metatopic E, consisting of topics 10, 11, and 12, is preferably related to a peaceful, calm, and respectful stay.
- Metatopic F (e.g., topic 14) is overall related to walking for transport (walkability). It is also semantically close to topics 19 or 22.
- Metatopic G (e.g., topics 15 and 16) is related to the room, space and location, and stylish touch.

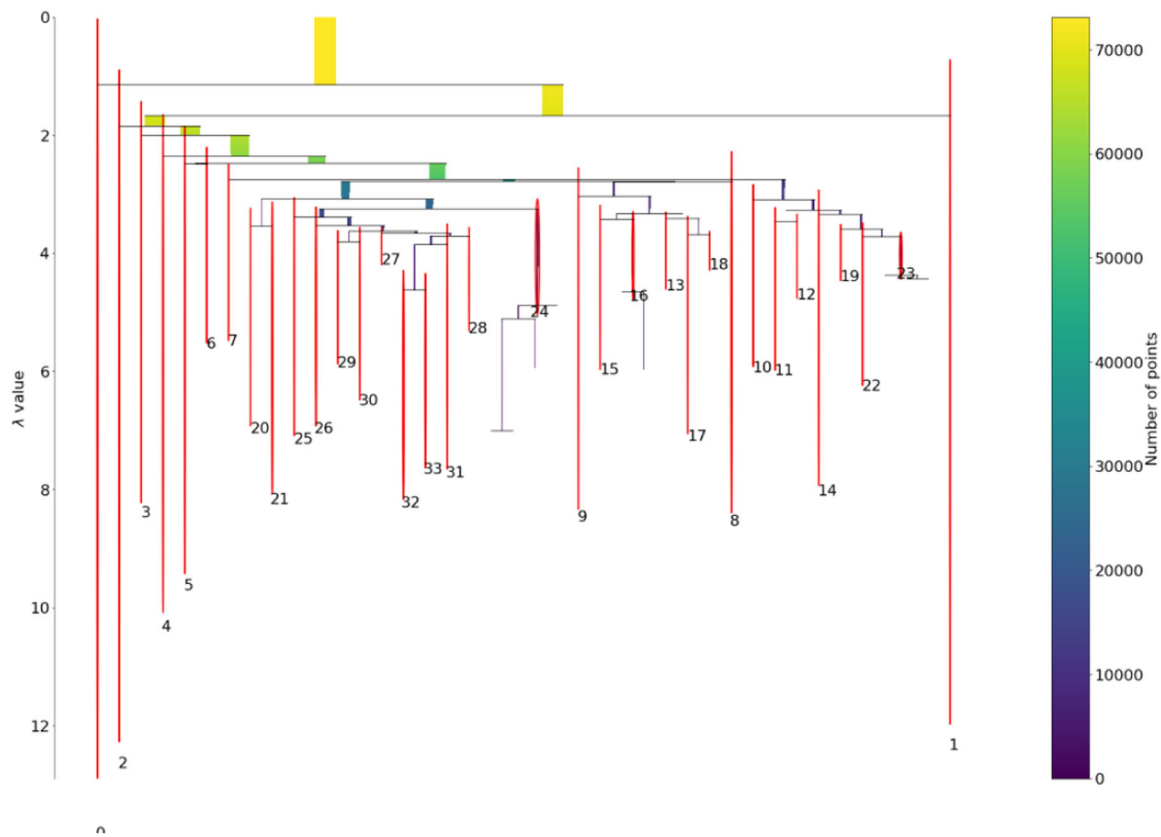


FIGURE 8 Topics identified and visualized by condensed clustering tree produced by hDBSCAN. hDBSCAN, Hierarchical Density-Based Spatial Clustering of Applications with Noise algorithm

- Metatopic H is related to local gastronomy and initially constitutes a compact sub-tree consisting of topics 20 and 21 that are also semantically close to topic 25 (grocery or supermarket) or 26 (coffee shop).
- Metatopic I (semantically close to metatopic E) is composed of two sub-trees comprising topics 6 and 7, and 19, 22, and 23. It is mainly about confidence quality, meeting expectations and review quality or pictures, and consequently, relationship quality or guests' attitudinal loyalty associated with tourists' intentions to recommend a place or Airbnb resources.

Moreover, metatopic I is also related to the homely atmosphere (represented in hosts' pictures) or stylish touch that allows parties to meet the needs and expectations (e.g., apartments with their rooftop deck in New York or Chicago or homely cottage in the nature area). Topics 22 and 23—near topic 19—share semantic space with (perceived) authenticity and local experiences in P2P accommodation environments leading to customer satisfaction.

- Metatopic J (topic 24) is about ease of access to a transportation hub or “walkability” in destinations.
- Metatopic K, consisting of topics 26 and 30 (and 29), is associated with easy access to out- and in-home food-related amenities (e.g., neighborhood amenities such as eating establishments and neighborhood coffee shops and attractions citing restaurants, bars, or pubs).

Furthermore, metatopic K, close in 2d-UMAP mapping to metatopic L, descends from topic 27 (e.g., husband or boyfriend as key terms) and topic 31 (bathroom facilities). In this regard, males are closely focused on the quality of practical household benefits (e.g., not only functional amenities such as a full kitchen, washing machine and dryer, multiple bathroom facilities, or cleanliness and comfort) but also here with outdoor amenities serving as surrogates for more comprehensive processing (cf. Sánchez-Franco & Alonso-Dos-Santos, 2021).

- Topics 32 and 33 relate to outdoor amenities in coastal surroundings and form the metatopics M and N, respectively. Metatopics M and N are mainly associated with natural resources. They represent esthetic and recreational activities in a *sun, sea, sand* environment, for example, snorkeling or surf, among others, and additionally swimming-related facilities such as pool, backyard, or beach amenities, that is, towels, umbrellas, or beach chairs.

To further elaborate on the results presented above, our study executes a correspondence analysis (CA) to describe-explore (and easily and symmetrically visualize) the different associations (or similarities) between destinations and metatopics. Our research employs FactoMineR 2.4 and factoextra 1.0.7 packages in R for this purpose. A χ^2 statistic (20,150, $df = 39$, $p < 2e-16$) identifies the similarities in metatopics across our four cities. The results affirm that

the associations are not random. The two-dimensional space explains 87.62% of the variance (>80%). The singular values (eigenvalues) of the dimensions are 0.391, 0.128, and 0.073 (see Figure 9).

Although our analysis cannot confirm a high discriminant value, it cautiously concludes that

- New York is mainly associated with metatopic J. This denotes the ease of access to transportation systems and the closeness to the apartment or distance to the subway, bus or train, and walkability. Traveler segments could find it valuable (and are willing to pay more) to lodge outside of a tourist neighborhood and enjoy the amenities of residential areas.
- Reviews about Airbnb Chicago contain comments about apartment closeness to downtown and hot attractions (metopic B). In this regard, the guests mention terms associated with bus, train, subway, walk, or nearby.
- The most distinguishing metatopics of Hawaii's reviews mainly relate to ocean views (e.g., sunset) from the backyard, shore or boardwalk, natural resources and sports (metatopics E and N). These topics are mainly associated with Hawaiian culture and lifestyle (snorkeling, surf, swim, etc.). Therefore, their position in Figure 9 clearly shows their importance in coastal destinations. Likewise, the arrows suggest a slight association between Hawaii and metatopic K, that is, local gastronomy.

- Fort Lauderdale narratives are highly related to outdoor amenities related to *sun, sea, and sand* (metatopic M) and close to transportation systems to initiate (or end) guests' journeys (metatopic C) from their place of residence until arriving at their destination, or to enjoy cruise tourism to visit, for instance, beaches of the Bahamas, among others. The transportation system can thus be essential for being both practical and for being pleasing.

Fourth, our study focuses on the mechanisms through which UGC denotes guests' satisfaction or polarity scores towards Airbnb stay. A tourism experience could indeed be holistic, personal, and situational (Kalbach, 2016) and positive or negative. In particular, sentiment analysis, as a sub-field of NLP, enables us "to determine the 'sentiment' of the [...] author of a piece of text, and can range from negative to positive as scored on whatever scale the particular sentiment analysis software chooses to use" (Pitt et al., 2018, p. 1012). Sentiment analysis highlights, for instance, where an Airbnb stay has failed to deliver services or, in contrast, where Airbnb hosts seduced guests to provide positive word of mouth or revisit intentions.

Here, to identify and categorize the guests' opinions, our approach applies an unsupervised lexicon-based approach using TextBlob, that is, a Python library for different NLP tasks such as sentiment extraction. TextBlob offers two metrics: (1) polarity that is

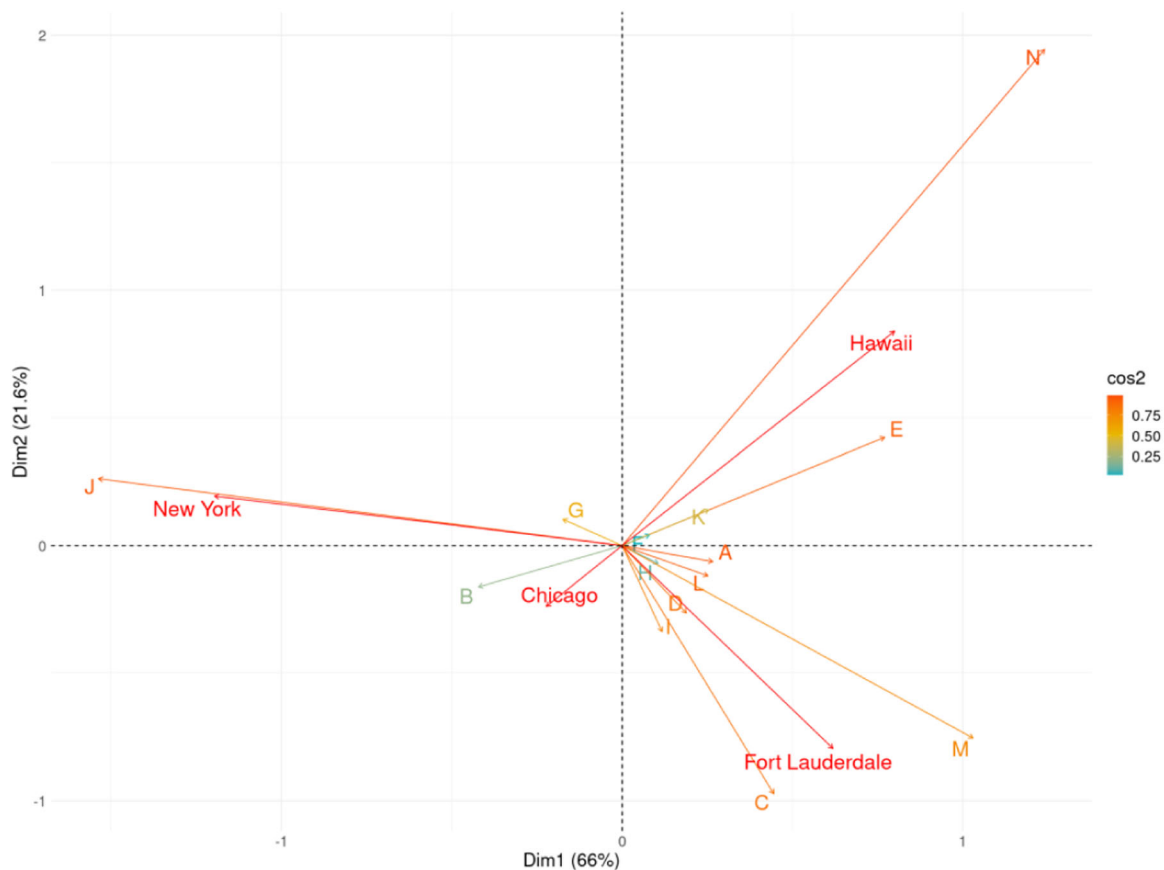


FIGURE 9 Correspondence analysis: Results

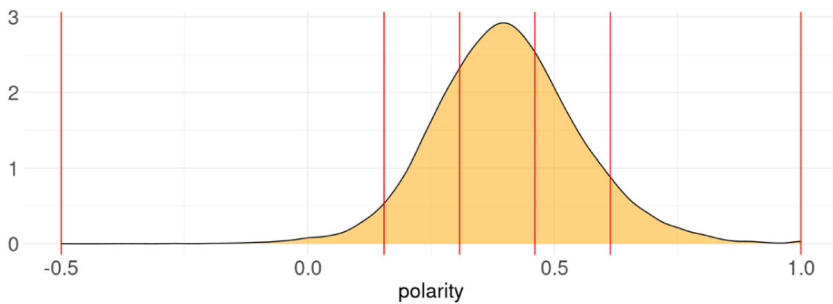


FIGURE 10 Density plot of polarity variable

a value that ranges within $[-1, \text{negative}, +1, \text{positive}]$, and (2) subjectivity that is also a value that lies in the range of $[0, \text{objective}, 1, \text{subjective}]$. Additionally, our analysis discretises the polarity scores into five intervals grouping by the standard deviation method (see Figure 10). Subsequently, it displays a mosaic plot indicating deviations from a specified independence model in a high-dimensional contingency table, that is, $(\text{metatopics} + \text{discretised polarity}) \times \text{destination}$. Each cell is a rectangular area of size proportional to the corresponding observed cell frequency. The colors encode the χ^2 residuals of the cell concerning the model of mutual independence, that is, colors measure the distance of each cell from independence, that is, colors measure the distance of each cell from independence, that is, colors measure the distance of each cell from independence. If the residual is less (greater) than -2 ($+2$), the observed frequency of the cell is less (greater) than the expected frequency. Blue (red) here means a positive (negative) sentiment. Our analysis applies `vcd` 1.4-8 package in R for this purpose (see Figure 11).

Next, our study summarizes the main results below:

- In urban destinations, guests tend to provide positive word of mouth and revisit intentions about “walkability” (F), the apartment and its stylish touch (G), and, as in coastal destinations, the relationship quality (I). On the other hand, metatopic J (i.e., the ease of access to a transportation hub) shows observed frequencies higher than expected in each sentiment cell excepting the fifth cell (most favorably).
In contrast, guests rate public transportation, such as train, subway, or bus system (metatopic B), less favorably. The less favorably polarized cells (2 and 3 points out of 5) are significantly higher than expected.
- In coastal destinations, guests positively evaluate critical topics associated with peaceful, calm, and respectful Airbnb stays (E). Metatopics M and N also show observed frequencies higher than expected in each sentiment cell. They are also related to swimming-related facilities and esthetic and recreational activities in a sun, sea, and sand environment. Contrariwise, guests mention less favorably the aspects above transport hubs such as airports or port (C).
- In urban destinations, guests favorably mention their attitudinal loyalty and intention to recommend Airbnb (I).
- Finally, although our correspondence analysis cannot confirm a high discriminant value between destinations concerning metatopics A, L, or D, coastal guests less favorably report topics related to travel companions (A) and husband or boyfriend as key terms (L), or the cleanliness, comfort, and in-household facilities (D).

7 | CONCLUSION

To understand the relevant topics expressed by guests in their narratives and how they could impact managers' decisions, our research applies a text-mining algorithm to discover dense semantic structures in a continuous semantic space. Our processed data set contains 73,557 reviews between 2017 and 2020. Using techniques for the NLP and the BERTopic approach, our research goes beyond the previous literature results about Airbnb accommodation features. It allows us to gather information needed in a reliable, authentic, and efficient way (behaving as problem solvers) and look for fun-related experiences (acting as travelers; cf. Del Chiappa et al., 2015). According to the previous literature, an extensive data set offers a low likelihood of error, and UGC is trustworthy for adjusting new services in specific destinations.

Additionally, our study goes beyond previous research by incorporating a regional or city dimension. By displaying associations between metatopics and assuming that rural areas seem to have a higher level of heterogeneity (cf. Falk et al., 2019), our research combines urban tourism (as a mainstream) and coastal tourism (as an emerging theme). Thus, our study is relevant to analyse the interacting effects of urban—or coastal—destinations on the features of Airbnb accommodations' influence on travelers' decisions. It offers guidelines to (1) implement an integrated marketing and communications strategy that attracts target markets and (2) foster positive behavioral intentions regarding relationship quality. Furthermore, the proposed method allows managers to non-confuse planning decisions and enhance the heterogeneous distinctiveness of diverse destinations using advanced topics modeling approaches.

8 | DISCUSSION

8.1 | Theoretical implications

Travelers visit destinations with distinct motivations to engage in activities that offer them specific benefits (hedonic, symbolic, and social) and vary due to the singular offers of each destination. In this regard, our research proposes vital insights into how different travelers' segments assess a short-rental listing in their online travel reviews (Lalicic et al., 2021) and differentiates the direction or strength of the associations between metatopics and

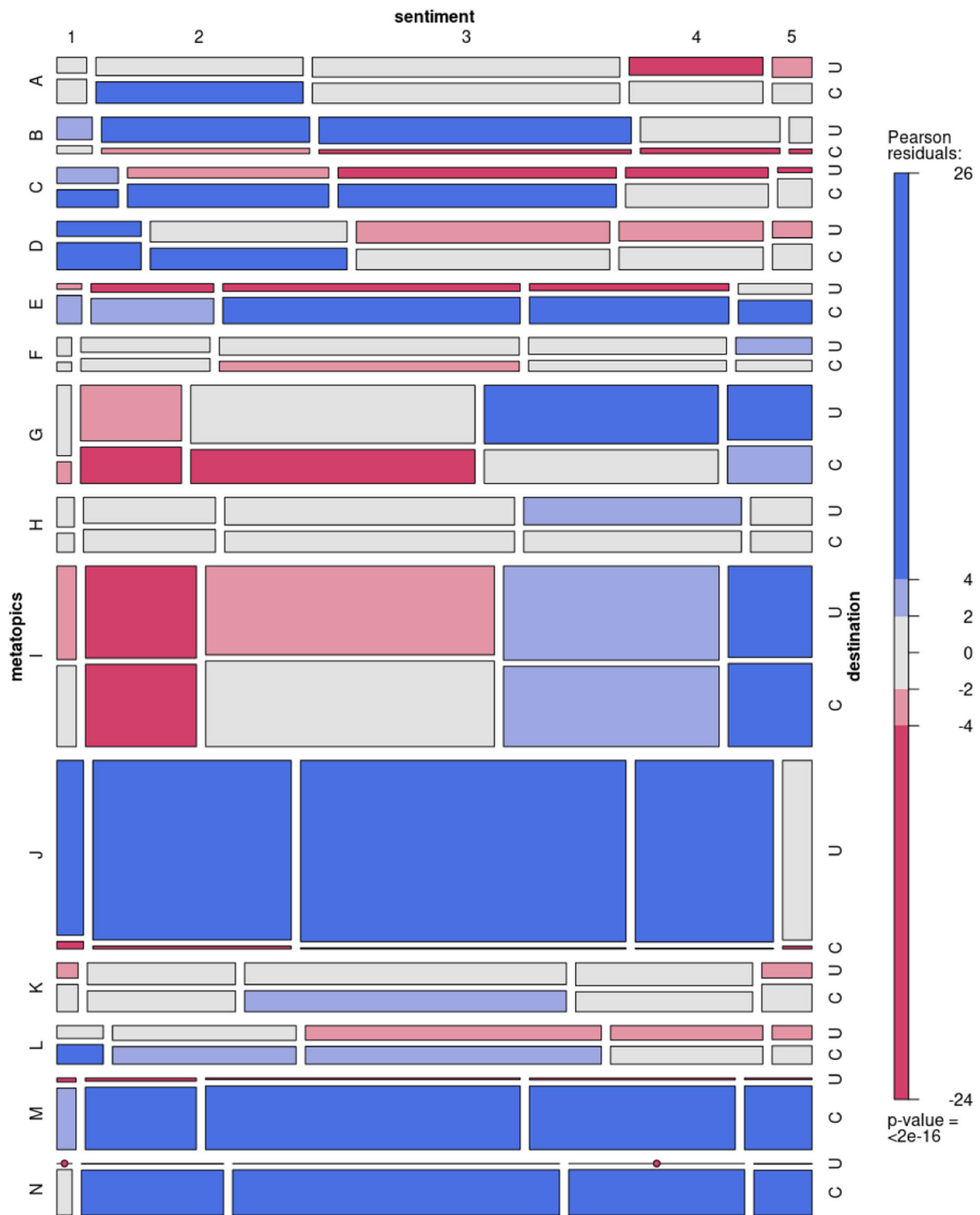


FIGURE 11 Mosaic plot
 †. C, coastal destination; U, urban destination

destinations. In particular, our analysis expands the research stream to emerging scholar areas, adequately combining geographical factors related to tourists' accommodation trends and functional, hedonic, and authentic local lifestyle experiences. "Although Airbnb and the sharing economy are global phenomena, their impact has a more than evident local component" (Morenozquierdo et al., 2019).

Moreover, post-modern travelers precisely seek emotional, authentic, and unique experiences. And guests' narratives contain the genuine relationship with the host, the accommodation features and amenities, and their relevant experiences that impact future perceptions of the destination image (Lin et al., 2019; Shi et al., 2019). Understanding the hospitality service features for each destination (coastal or urban) from the demand side is thus of paramount

relevance for DMO. "While other sources of travel reviews (e.g., TripAdvisor) have been used to assess destination image and experiences, P2P accommodation reviews are often left aside" (Lalicic et al., 2021). To sum up, guests' narratives are here employed and analysed to understand which accommodation attributes guests mainly mention to develop tourism strategies to foster destinations' history and image. And although there are, overall, interdisciplinary themes in each narrative related to an Airbnb stay, our study applies NLP techniques and consequently detect cohesive stay-related features that are most informative.

Most research assesses tourist preference by adopting small group opinion-based methods (Sun et al., 2018) to explore whether customers' preferences determinants are locally generalizable across different destinations. Contrariwise, our analysis analyses a bulk set of UGC after an actual stay through its preprocessing (cleansing data) and data mining processing and subsequently applies a novel topic modeling to summarize a global dense semantic structure from a continuous semantic space and uses a product, feature-oriented approach. It focuses on a non-supervised hierarchical clustering of reduced embeddings to identify documents very similar in each cluster (or topic) of varying densities. In this regard, our study uses pre-trained embeddings to extract a latent semantic structure or topics (in a large collection of documents) which are more informative than topics proposed by the classic LDA or PLSA models, among others. Our analysis efficiently detects areas of highly similar documents and does not predefine the number of topics, nor does it prefit multiple parameters as LDA does. As a result, our study identifies metatopics as easily interpretable and representative.

To sum up, following BERTopic approach (Grootendorst, 2020; cf. also Top2Vec, Angelov, 2020), our analysis exemplifies the relevance of using novel techniques to interpret the semantic structures hidden in data. Furthermore, according to the approximate similarities between the topics shown in the 2d-UMAP mapping, our method also displays how the destination shapes the UGC about Airbnb stays, consistent with our primary research objective, that is, the guests' narratives offer valuable information to subsequent travelers. Accordingly, our study recommends using BERTopic to identify recurring themes discussed in the corpora and can be used as a baseline for future research.

8.2 | Managerial implications

Our results are relevant for urban and coastal tourism development and a higher understanding of the essential relationships between destinations and P2P accommodations. In particular, it enables hosts to enhance marketing strategies and differentiate touristic short-rentals lodgings and travel experiences. Our findings thus provide practical results for Airbnb managers that should facilitate the conditions of a touristic experience based on services and activities (e.g., lodgings and attractions), and consequently, embellish the holistic experiences of the place visited (Cetin & Bilgihan, 2016).

In particular, people seek relaxation and recreation at the coast. Coastal Airbnb guests refer to recreational activities that include informal pleasures, swimming, surfing, snorkeling, and other sun-and-beach leisure activities. Guests highlight (in their reviews) amenities and services through which visitors pursue their comfort and enjoyment (e.g., hot tub, pool, and jacuzzi) or enjoy proximity to the beach, fresh air or nature tourism in conjunction with scenic esthetics (cf., metatopic E). Beyond the heterogeneity of coastal tourists, nature authenticity is essential. In particular, metatopics M and N are here preferential, that is, recreation on the beach experiences and ocean view of the natural surroundings. They are related explicitly to gratifying activities such as surfing associated with Hawaiian culture and lifestyle. Sports and adventure, relaxation or experiencing nature are also distinct preferences of tourists staying in nature destinations. These experiences create a sense of "place" and foster destination appeal.

Moreover, post-modern travelers precisely seek emotional, authentic, and unique experiences. Airbnb hosts should therefore (1) monitor guests' reviews, (2) promote these exotic and local authenticity aspects in their listing descriptions using, for instance, customized photography reflecting host and guest interactions (e.g., gratifying hosts' interactions related to check-in or "homely feelings"), and (3) create and intensify a favorable destination branding to differentiate their hospitality offerings. In addition, proximity to the ocean is a crucial attraction because of the implied closeness to the recreational activities offered on the beaches. In this regard, metatopic I identifies the homely atmosphere (represented in hosts' pictures) or stylish touch that allows parties to meet their needs and expectations.

The length of stay at any urban tourism destination is shorter than in beach surroundings which are more holiday-dependent. Consequently, guests (e.g., older tourists and those with a disability) assess metatopics (e.g., F or J) that enhance their visitor transport experience based on speed, safety and comfort, that is, efficient mobility and experiential connectivity (and inter-modality, e.g., walking—feasible only for short distances—cycling, with cycling support infrastructure—or public transport, among others). In urban destinations, tourism is the movement of travelers between main attractions. Guests who remain in urban destinations could desire cultural and traditional activities and educational and social factors (e.g., gastronomic culture). It is thus related to accommodation location measured as the distance from the apartment, tourist attractions and transportation hubs. In addition, walkable facilities and services of urban destinations allow enjoying short breaks or an extended weekend. For example, New York relates to shopping, sightseeing and theatre-going, and Chicago to the arts scene, cultural- and architecture-attractions.

A significant objective of transport policy is to achieve a sustainable, coordinated and integrated public transportation system and combine it with private transportation services, for example, Uber or Lyft related to transportation, taxis or shuttles. Overall urban guests could pay more (less) for entire apartments in highly (lowly) rated locations than coastal destinations, that is, guests partially focus

on which transport type to use at the destination. The inherent density of the metatopics based on transportation systems and neighborhood amenities that facilitate the flow of guests between features of the tourist experience (e.g., nightlife attractions) is (here) highly associated with urban destinations.

Finally, hospitality features based on home-like lodging conditions (e.g., household amenities and basic functionalities such as overall homely feel or functional amenities related to kitchen and bathroom, among others) are standard features influencing guests' decisions without establishing significant differences by type of destination.

9 | LIMITATIONS

Several limitations need to be acknowledged. First, "big data's characteristics of incompleteness, inaccessibility, and non-representativeness are generally problematic for academic research" (Cai, 2021, p. 7). Our study in isolation cannot thus firmly determine the motivations (e.g., cultural or sun, sea, and sand motives) for the traveler's stay. Second, although a representation of topics changes over time, future research should assess whether the topics and metatopics found in urban and coastal destinations are stable as time goes on. Third, the bias towards positive reviews unbalances our analysis of latent semantic structures. Again, however, future contributions should overcome them to yield generalizable results. Moreover, future research could compare our results with those achieved by other topic modeling approaches.

Finally, the essence of the sharing economy is conceptualized as obtaining, giving, or sharing access to goods and services without expecting any return. While Airbnb may not strictly conform to the sharing economy concept (Eckhardt & Bardhi, 2015), in our opinion, our study is closely aligned with the idea of the collaborative economy narrative. It analyses a commercial exchange (rentals) between amateur host and guest (cf. Palgan et al., 2017). Amateur hosts grant each other temporary access to underutilised physical assets such as a second homes (cf. Frenken & Schor, 2017). Second homes are likely used to take advantage of an opportunity for passive income and rent them out through community-based online services. Future research should, however, critically interrogate the sharing economy concept concerning the accommodation-sharing platform Airbnb.

ACKNOWLEDGMENTS

Research Group SEJ-494, Andalusian Regional Government, Spain.
Research Group SEJ-574, Andalusian Regional Government, Spain.

ORCID

Manuel J. Sánchez-Franco  <http://orcid.org/0000-0002-8042-3550>

Manuel Rey-Moreno  <http://orcid.org/0000-0002-7542-1542>

REFERENCES

- Anand, A., Chandan, P., & Singh, R. (2012). Homestays at Korzok: Supplementing rural livelihoods and supporting green tourism in the Indian Himalayas. *Mountain Research and Development*, 32(2), 126–136.
- Angelov, D. (2020). Top2vec: Distributed representations of topics. *arXiv*, 2008, 09470.
- Archak, N., Ghose, A., & Ipeirotis, P. G. (2011). Deriving the pricing power of product features by mining consumer reviews. *Management Science*, 57, 1485–1509.
- Ball-Rokeach, S. J. (1985). The origins of individual media-system dependency: A sociological framework. *Communication Research*, 12(4), 485–510.
- Belarmino, A., & Koh, Y. (2019). A critical review of research regarding peer-to-peer accommodations. *International Journal of Hospitality Management*, 84(January), 1–15.
- Belver-Delgado, T., San-Martín, S., & Hernández-Maestro, R. M. (2021). The influence of website quality and star rating signals on booking intention: Analyzing the moderating effect of variety seeking. *Spanish Journal of Marketing—ESIC*, 25(1), 3–28.
- Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research*, 3, 993–1022.
- Brodie, R. J., Hollebeek, L. D., Juric, B., & Ilic, A. (2011). Customer engagement: Conceptual domain, fundamental propositions, and implications for research. *Journal of Service Research*, 34(10), 251–271.
- Cai, M. (2021). Natural language processing for urban research: A systematic review. *Heliyon*, 7(3), e06322.
- Campello, R. J. G. B., Moulavi, D., & Sander, J. (2013). Density-based clustering based on hierarchical density estimates. In J. Pei, V. S. Tseng, L. Cao, H. Motoda, & G. Xu (Eds.), *Advances in knowledge discovery and data mining. PAKDD 2013. Lecture notes in computer science* (Vol. 7819). Springer.
- Cetin, G., & Bilgihan, A. (2016). Components of cultural tourists' tourists' experiences in destinations. *Current Issues in Tourism*, 19(2), 137–154.
- Chattopadhyay, M., & Mitra, S. K. (2019). Do Airbnb host listing attributes influence room pricing homogenously? *International Journal of Hospitality Management*, 81, 54–64.
- Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, 43(3), 345–354.
- Chubin, D. E. (1976). State of the field. The conceptualisation of scientific specialties. *The Sociological Quarterly*, 17(4), 448–476.
- Cobo, M. J., López-Herrera, A. G., Herrera-Viedma, E., & Herrera, F. (2011a). An approach for detecting, quantifying, and visualising the evolution of a research field: A practical application to the fuzzy sets theory field. *Journal of Informetrics*, 5(1), 146–166.
- Cobo, M. J., López-Herrera, A. G., Herrera-Viedma, E., & Herrera, F. (2011b). Science mapping software tools: Review, analysis, and cooperative study among tools. *Journal of the American Society for Information Science and Technology*, 62(7), 1382–1402.
- Del Chiappa, G., Lorenzo-Romero, C., & Alarcón-del-Amo, M. C. (2015). The Influence of user-generated content on tourists' tourists' choices. *Tržište/Market*, 27(2), 221–236.
- Dickinger, A., & Mazanec, J. (2008). Consumers' preferred criteria for hotel online booking. In P. O'Connor, W. Höpken, & U. Gretzel (Eds.), *Information and communication technologies in tourism 2008, Innsbruck* (pp. 244–254). Springer Wien.
- Dolnicar, S. (2017). *Peer-to-peer accommodation networks: Pushing the boundaries*. Goodfellow Publishers.
- Eckhardt, G. M., & Bardhi, F. (2015). The sharing economy isn't about sharing at all. *Harvard Business Review*, 28, 1–360.
- Ert, E., Fleischer, A., & Magen, N. (2016). Trust and reputation in the sharing economy: The role of personal photos on Airbnb. *Tourism Management*, 55(1), 62–73.
- European Commission. (1999). *Towards a European integrated coastal zone management strategy: General principles and policy options*. European Commission.

- European Commission. (2014). *A European strategy for more growth and jobs in coastal and maritime tourism*. European Commission.
- Falk, M., Larpin, B., & Scaglione, M. (2019). The role of specific attributes in determining prices of Airbnb listings in rural and urban locations. *International Journal of Hospitality Management*, 83, 132–140.
- Filieri, R., Javornik, A., Hang, H., & Niceta, A. (2021). Environmentally framed eWOM messages of different valence: The role of environmental concerns, moral norms, and product environmental impact. *Psychology & Marketing*, 38(3), 431–454.
- Frenken, K., Meelen, T., Arets, M., & Glind, P. V. (2015). Smarter regulation for the sharing economy. *The Guardian*. www.theguardian.com/science/political-science/2015/may/20/smarter-regulation-for-the-sharing-economy
- Frenken, K., & Schor, J. (2017). Putting the sharing economy into perspective. *Environmental Innovation and Societal Transitions*, 23, 3–10.
- Gansky, L. (2010). *Why the future is sharing*. Penguin Group.
- Geissinger, A., Laurell, C., & Sandström, C. (2020). Digital disruption beyond Uber and Airbnb—Tracking the long tail of the sharing economy. *Technological Forecasting and Social Change*, 155, 119323.
- Gibbs, C., Guttentag, D., Gretzel, U., Morton, J., & Goodwill, A. (2018). Pricing in the sharing economy: A hedonic pricing model applied to Airbnb listings. *Journal of Travel & Tourism Marketing*, 35(1), 46–56.
- Godes, D., & Mayzlin, D. (2004). Using online conversations to study word-of-mouth communication. *Marketing Science*, 23(4), 545–560.
- Gretzel, U., & Yoo, K. H. (2008). Use and impact of online travel reviews. *Information and Communication Technologies in Tourism*, 8, 35–46.
- Grootendorst, M. (2020). BERTopic: Leveraging BERT and c-TF-IDF to create easily interpretable topics. <https://doi.org/10.5281/zenodo.4430182>.
- Gutierrez, J., García-Palomares, J. C., Romanillos, G., & Henar Salas-Olmedo, M. (2017). The eruption of Airbnb in tourist cities: Comparing spatial patterns of hotels and peer-to-peer accommodation in Barcelona. *Tourism Management*, 62, 278–291.
- Guttentag, D. (2015). Airbnb: Disruptive innovation and the rise of an informal tourism accommodation sector. *Current Issues in Tourism*, 18(12), 1192–1217.
- Guttentag, D. (2016). *Why tourists choose Airbnb: A motivation-based segmentation study underpinned by innovation concepts* (Unpublished Doctoral Dissertation), University of Waterloo, Canada.
- Guttentag, D., Smith, S., Potwarka, L., & Havitz, M. (2018). Why tourists choose Airbnb: A motivation-based segmentation study. *Journal of Travel Research*, 57(3), 342–359.
- Guttentag, D. A., & Smith, S. L. (2017). Assessing Airbnb as a disruptive innovation relative to hotels: Substitution and comparative performance expectations. *International Journal of Hospitality Management*, 64, 1–10.
- Hall, C. M. (2001). Trends in ocean and coastal tourism: The end of the last frontier? *Ocean & Coastal Management*, 44(9–10), 601–618.
- Hasan, M. K., Abdullah, S. K., Lew, T. Y., & Islam, M. F. (2019). The antecedents of tourist attitudes to revisit and revisit intentions for coastal tourism. *International Journal of Culture, Tourism and Hospitality Research*, 13(2), 218–234.
- Heo, C. Y., Blal, I., & Choi, M. (2019). What is happening in Paris? Airbnb, hotels, and the Parisian market: A case study. *Tourism Management*, 70, 78–88.
- Herrero Crespo, A., San Martín Gutiérrez, H., & Hernández Mogollón, J. M. (2015). Perceived influence on behavior of user-generated content on social network sites: An empirical application in the hotel sector. *Revista Española de Investigación de Marketing ESIC*, 19(1), 12–23.
- Ikkala, T., & Lampinen, A. (2014). Defining the price of hospitality: Networked hospitality exchange via Airbnb. In *Proceedings of the companion publication of the 17th ACM conference on computer supported cooperative work & social computing*. ACM, Baltimore, MD, pp. 173–176.
- Johnson, A.-G., & Neuhofer, B. (2017). Airbnb—An exploration of value co-creation experiences in Jamaica. *International Journal of Contemporary Hospitality Management*, 29(9), 2361–2376.
- Kalbach, J. (2016). *Mapping experiences: A complete guide to creating value through journeys, blueprints and diagrams*. O'Reilly Media.
- Kraus, S., Li, H., Kang, Q., Westhead, P., & Tiberius, V. (2020). The sharing economy: A bibliometric analysis of the state-of-the-art. *International Journal of Entrepreneurial Behavior & Research*, 26(8), 1769–1786.
- Lalicic, L., Marine-Roig, E., Ferrer-Rosell, B., & Martin-Fuentes, E. (2021). Destination image analytics for tourism design: An approach through Airbnb reviews. *Annals of Tourism Research*, 86, 103100.
- Law, R., Buhalis, D., & Cobanoglu, C. (2014). Progress on information and communication technologies in hospitality and tourism. *International Journal of Contemporary Hospitality Management*, 26(5), 727–750.
- Lawani, A., Reed, M. R., Mark, T., & Zheng, Y. (2019). Reviews and price on online platforms: Evidence from sentiment analysis of Airbnb reviews in Boston. *Regional Science and Urban Economics*, 75, 22–34.
- Liang, L. J. (2015). *Understanding repurchase intention of Airbnb consumers: perceived authenticity, EWOM and price sensitivity* (Unpublished Master's Thesis). University of Guelph.
- Liang, S., Schuckert, M., Law, R., & Chen, C. C. (2017). Be a “Superhost”: The importance of badge systems for peer-to-peer rental accommodations. *Tourism Management*, 60, 454–465.
- Lin, P. M. C., Fan, D. X. F., Zhang, H. Q., & Lau, C. (2019). Spend less and experience more: Understanding tourists' social contact in the Airbnb context. *International Journal of Hospitality Management*, 83, 65–73.
- Luo, Y. (2018). *What Airbnb Reviews Can Tell us? An Advanced Latent Aspect Rating Analysis Approach* (Graduate Theses and Dissertations), 16403.
- Mao, Z., & Lyu, J. (2017). Why travellers use Airbnb again?: An integrative approach to understanding travelers' repurchase intention. *International Journal of Contemporary Hospitality Management*, 29(9), 2464–2482.
- Martins Gonçalves, H., Miranda Silva, G., & Gomes Martins, T. (2018). Motivations for posting online reviews in the hotel industry. *Psychology & Marketing*, 35(11), 807–817.
- Maxim, C. (2019). Challenges faced by world tourism cities—London's perspective. *Current Issues in Tourism*, 22(9), 1006–1024.
- McInnes, L., & Healy, J. (2017). Accelerated hierarchical density-based clustering. In *2017 IEEE international conference on data mining workshops (ICDMW)*, 33–42.
- McInnes, L., Healy, J., & Melville, J. (2018). UMAP: Uniform manifold approximation and projection. *Journal of Open Source Software*, 3(29), 861.
- Mody, M. A., Suess, C., & Lehto, X. (2017). The accommodation experiencescape: A comparative assessment of hotels and Airbnb. *International Journal of Contemporary Hospitality Management*, 29(9), 2377–2404.
- Moreno-Izquierdo, L., Ramón-Rodríguez, A. B., Such-Devesa, M. J., & Perles-Ribes, J. F. (2019). Tourist environment and online reputation as a generator of added value in the sharing economy: The case of Airbnb in urban and sun-and-beach holiday destinations. *Journal of Destination Marketing & Management*, 11, 53–66.
- Oh, H., Fiore, A. M., & Jeoung, M. (2007). Measuring experience economy concepts: Tourism applications. *Journal of Travel Research*, 46, 119–132.
- Pahl, R. E. (1966). The rural-urban continuum. *Sociologia Ruralis*, 6, 299–327.
- Palgan, Y. V., Zvolaska, L., & Mont, O. (2017). Sustainability framings of accommodation sharing. *Environmental Innovation and Societal Transitions*, 23, 70–83.
- Pitt, C., Mulvey, M., & Kietzmann, J. (2018). Quantitative insights from online qualitative data: An example from the health care sector. *Psychology & Marketing*, 35(12), 1010–1017.

- Poon, K., & Huang, W. (2017). Past experience, traveller personality and tripographics on intention to use Airbnb. *International Journal of Contemporary Hospitality Management*, 29(9), 2425–2443.
- Rahmanian, E. (2021). Consumption narratives: Contributions, methods, findings and agenda for future research. *Spanish Journal of Marketing–ESIC*, 25(1), 46–84.
- Reimers, N., & Gurevych, I. (2019). Sentence-BERT: Sentence embeddings using Siamese BERT-networks. In *Proceedings of the 2019 conference on empirical methods in natural language processing*, November 3–7 (pp. 3982–3992). Hong Kong, China.
- Sánchez-Franco, M. J., & Alonso-Dos-Santos, M. (2021). Exploring gender-based influences on key features of Airbnb accommodations. *Economic Research-Ekonomska Istraživanja*, 34(1), 2484–2505.
- Sánchez-Franco, M. J., Navarro-García, A., & Rondán-Cataluña, F. J. (2016). Online customer service reviews in urban hotels: A data mining approach. *Psychology & Marketing*, 33(12), 1174–1186.
- Sánchez-Franco, M. J., Navarro-García, A., & Rondán-Cataluña, F. J. (2019). A naive Bayes strategy for classifying customer satisfaction: A study based on online reviews of hospitality services. *Journal of Business Research*, 101, 499–506.
- Santos, S., & Gonçalves, H. M. (2019). Multichannel consumer behaviors in the mobile environment: Using fsQCA and discriminant analysis to understand webrooming motivations. *Journal of Business Research*, 101, 757–766.
- Sardá, R., Mora, J., Ariza, E., Avila, C., & Jimenez, J. A. (2009). Decadal shifts in beach user sand availability on the Costa Brava (Northwestern Mediterranean Coast). *Tourism Management*, 30(2), 158–168.
- Satama, S. (2014). *Consumer adoption of access-based consumption services. Case AirBnB* (Unpublished Master's Thesis). Aalto University, Finland.
- Shi, S., Gursoy, D., & Chen, L. (2019). Conceptualising home-sharing lodging experience and its impact on destination image perception: A mixed method approach. *Tourism Management*, 75, 245–256.
- Sparks, B. A., & Browning, V. (2011). The impact of online reviews on hotel booking intentions and perception of trust. *Tourism Management*, 32(6), pp 1310–1323.
- Sun, Y., Ma, H., & Chan, E. H. W. (2018). A model to measure tourist preference towards scenic spots based on social media data: A case of Dapeng in China. *Sustainability*, 10, 43.
- Tsao, W. C., Hsieh, M. T., Shih, L. W., & Lin, T. M. (2015). Compliance with eWOM: The influence of hotel reviews on booking intention from the perspective of consumer conformity. *International Journal of Hospitality Management*, 46, 99–111.
- Tussyadiah, I. P. (2016a). Strategic self-presentation in the sharing economy: Implications for host branding. *Information and Communication Technologies in Tourism*, 2016, 695–708.
- Tussyadiah, I. P. (2016b). Factors of satisfaction and intention to use peer-to-peer accommodation. *International Journal of Hospitality Management*, 55, 70–80.
- Tussyadiah, I. P., & Pesonen, J. (2016). Drivers and barriers of peer-to-peer accommodation stay—an exploratory study with American and Finnish travellers. *Current Issues in Tourism*, 21(6), 703–720.
- Varma, A., Jukic, N., Pestek, A., Schultz, C. J., & Nestorov, S. (2016). Airbnb: Exciting innovation or passing fad? *Tourism Management Perspectives*, 20, 228–237.
- Vermeulen, I. E., & Seegers, D. (2009). Tried and tested: The impact of online hotel reviews on consumer consideration. *Tourism Management*, 30(1), 123–127.
- Wang, C., Chen, K., & Chen, S. (2012). Total quality management, market orientation and hotel performance: The moderating effects of external environmental factors. *International Journal of Hospitality Management*, 31, 119–129.
- Warton, N. M., & Brander, R. W. (2017). Improving tourist beach safety awareness: The benefits of watching Bondi Rescue. *Tourism Management*, 63(3), 187–200.
- Xie, K. L., & Kwok, L. (2017). The effects of Airbnb's price positioning on hotel performance. *International Journal of Hospitality Management*, 67, 174–184.
- Yang, S., & Ahn, S. (2016). Impact of motivation in the sharing economy and perceived security in attitude and loyalty toward Airbnb. *Advanced Science and Technology Letters*, 129, 180–184.
- Yoganathan, V., Osburg, V., & Bartikowski, B. (2021). Building better employer brands through employee social media competence and online social capital. *Psychology & Marketing*, 38(2), 524–536.
- Zach, F. J., Nicolau, J. L., & Sharma, A. (2020). Disruptive innovation, innovation adoption and incumbent market value: The case of Airbnb. *Annals of Tourism Research*, 80, 102818.

How to cite this article: Sánchez-Franco, M. J., Rey-Moreno, M. (2021). Do travelers' reviews depend on the destination? An analysis in coastal and urban peer-to-peer lodgings. *Psychology & Marketing*, 1–19.

<https://doi.org/10.1002/mar.21608>