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Recommend or not: A comparative analysis of customer reviews to uncover factors influencing explicit online recommendation behavior in peer-to-peer accommodation

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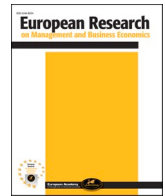
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Recommend or not: A comparative analysis of customer reviews to uncover factors influencing explicit online recommendation behavior in peer-to-peer accommodation

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ABSTRACT

In the fiercely competitive landscape of the peer-to-peer accommodation platform Airbnb, understanding customers' online recommendation behavior is essential for optimizing competitiveness and harnessing the potential of electronic word-of-mouth. This study aims to provide comprehensive insights into the factors driving customers' issuance of positive or negative recommendations based on their experiences. Leveraging 10,101 online reviews from Airbnb users, we employ the Structural Topic Model to determine latent topics relating to customers' recommendation intentions. This study reveals that positive recommendations are primarily influenced by hedonic values tied to the overall experience, including crucial aspects such as convenience for exploring points of interest, local authenticity, social interaction, and emotional fulfillment. These findings highlight the significance of providing memorable and enriching experiences to elicit positive reviews from customers. On the other hand, negative recommendations are closely linked to utilitarian values focused on practical concerns such as check-in procedures, cleanliness, comfortableness, and amenities. Understanding these utilitarian factors is vital for hosts and platform administrators to improve service quality and address potential issues that may lead to negative reviews. Furthermore, this study emphasizes the significant role of hosts in shaping both positive and negative recommendations. This research contributes valuable insights to the field of peer-to-peer accommodation, highlighting the significance of various factors influencing customers' recommendation behavior.

1. Introduction

Online customer reviews have become an indispensable element of today's digital marketplace, profoundly influencing consumer behavior and purchase decisions (Roozen & Raedts, 2018; Tan et al., 2018; Zhang et al., 2014). As a form of electronic word-of-mouth (eWOM), these reviews provide valuable information for prospective consumers evaluating products or services (Duffy, 2015; Torres et al., 2014). Unlike traditional advertising, consumers often perceive reviews as more credible and objective since they originate from peers rather than businesses with vested interests (Torres et al., 2014). This confidence in user-generated evaluations enables informed decision-making grounded in authentic experiences (Duffy, 2015). In addition, customer reviews provide insights beyond official endorsement information, including

personalized usage recommendations, first-hand accounts, and potential problems (Huifeng & Ha, 2021; Ventre & Kolbe, 2020). Access to these additional perspectives grants consumers pertinent knowledge prior to purchase. Furthermore, the information assists in assessing product quality and reliability, effectively reducing perceived purchase risk (Huifeng & Ha, 2021; Ventre & Kolbe, 2020). By enhancing knowledge and mitigating uncertainty, online reviews increase consumer confidence and conversion rates (Zhang et al., 2014).

Given the importance of online customer reviews, the role of written recommendations in customer reviews becomes even more critical. The written recommendations within customer reviews, in particular, serve as powerful endorsements that carry significant persuasive power for potential customers (Wantara & Tambrin, 2019). Customer intention to recommend reflects their willingness to positively promote a product or

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service based on their subjective user experience (Cheung & Thadani, 2012). For experience-based services like accommodation, potential customers rely heavily on the experiences shared by others through online recommendations to evaluate intangible attributes and determine suitability. This makes recommendations from existing customers especially important for creating awareness, influencing choice, and driving demand (Nusair et al., 2013). However, negative online recommendations can have profound negative impacts on a business's performance. The most immediate impact is on sales and revenue, as negative reviews reduce purchase intentions and future demand (Chevalier & Mayzlin, 2006). This effect is amplified for online businesses that depend more on digital visibility (Gruen et al., 2006). Negative recommendations also damage brand equity by diminishing brand image, trust, and reputation (Park et al., 2007). Given these risks, it is valuable for accommodation providers to understand what drives customer recommendation behavior. Identifying factors that influence the intention to recommend positive endorsements could help businesses improve their online reputation and performance.

The focus of this study is the leading peer-to-peer (P2P) accommodation platform, Airbnb. Founded in 2008 in San Francisco, Airbnb operates an online marketplace that allows individuals to list and book short-term lodging accommodations worldwide (Guttentag, 2015). In just over a decade, Airbnb has experienced exponential growth, offering over 7 million listings across more than 100,000 cities in over 220 countries (Airbnb, 2022). The rapid rise of Airbnb has captured the attention of many researchers, with online reviews emerging as a popular source of data for academic inquiry. Previous studies have explored Airbnb user behavior from various angles using customer reviews, investigating aspects such as perceptions of service quality (Ding et al., 2020; Ju et al., 2019), user experience (Sthapit & Jimenez-Barreto, 2018; Lalicic & Weismayer, 2017; Tussyadiah & Zach, 2017), loyalty behavior (Lee & Kim, 2018; Liang et al., 2018; Mao & Lyu, 2017), and other perspectives. However, the majority of these studies have predominantly focused on the macro-level perceptions of Airbnb users. Despite the extensive research in this domain, scant attention has been given to understanding the factors that influence Airbnb users when it comes to expressing their intentions to recommend or not recommend a property.

In contrast to traditional hotels that provide standardized accommodation services, Airbnb operates through a diverse community of individual hosts, placing greater emphasis on establishing an initial trust to influence customers' booking intentions. Research has demonstrated that trust is a crucial factor in the decision-making process for Airbnb users, given the risks and uncertainties involved with staying in a stranger's home (Hawlitschek et al., 2016; Guttentag, 2015). As potential guests evaluate different accommodation options, the presence of online recommendations from previous customers plays a pivotal role in shaping their perception of trust toward a listing and host (Tussyadiah & Park, 2018). Online reviews and recommendations hold significant weight in establishing trust and credibility in the sharing economy context (Tussyadiah & Pesonen, 2016), where traditional signals like brand reputation are lacking. These authentic reviews from fellow users provide valuable vicarious experiences and social cues that mitigate the risks associated with booking an Airbnb. Furthermore, the social nature of peer-generated recommendations makes them more persuasive and influential in fostering trust, as potential guests are more inclined to rely on the opinions of previous guests over marketer-created content (Xie et al., 2011).

To bridge this existing knowledge gap, we propose the following research question: What are the underlying factors that influence Airbnb users' positive and negative online recommendations? To address this question, this study employs Structural Topic Modeling (STM) to analyze Airbnb users' online reviews. STM is an increasingly utilized computational text analysis technique that can uncover latent topics and relationships within large bodies of text data (Roberts et al., 2019). Applying STM to Airbnb reviews can provide greater granularity and

insight into the sentiment drivers behind users' recommendations. Building on the importance of understanding recommendation behavior as a key indicator of customer satisfaction (Jani & Han, 2014; Ladhar, 2009), this study draws theoretical grounding from Herzberg et al.'s (1959) two-factor satisfaction theory. According to the two-factor theory, there is a fundamental distinction between the types of factors that contribute to satisfaction versus dissatisfaction. Specifically, the theory proposes that "motivation factors" tend to elicit satisfaction when present, while "hygiene factors" primarily serve to prevent dissatisfaction when absent. In the context of the present study, this implies that the attributes fostering guest satisfaction and driving positive recommendations are not simply the opposite of those that lead to guest dissatisfaction and generate negative eWOM. Drawing on Herzberg et al.'s (1959) theoretical framework, this study delineates between positive and negative recommending language to develop a richer understanding of what factors could influence Airbnb users' intentions of recommendation.

The insights drawn from this study can help Airbnb hosts improve their offerings, enhance user experiences, and build initial trust with their guests. As the home-sharing market becomes more saturated, it is crucial for hosts to differentiate themselves from the competition. Identifying the factors that influence users' intention to recommend a property can help hosts tailor their offerings and marketing efforts to stand out in a crowded market, ultimately attracting more guests and generating positive word-of-mouth. For the Airbnb platform, a deeper understanding of these important factors could lead to better recommendations and overall service improvements. From a theoretical perspective, this study advances a theoretical understanding of the mechanics of eWOM, particularly regarding experience-based products that are intangible in nature (Liang et al., 2018). Determining the topics most influential to recommendation intentions for accommodation services like Airbnb adds nuanced depth to conceptual models of eWOM. The use of STM provides a novel methodological approach to empirically deriving the factors underlying guests' recommendations. This data-driven technique enables theoretical constructs to emerge inductively from user-generated content (UGC), overcoming the limitations of applying a priori frameworks (Roberts et al., 2019).

2. Literature review

2.1. Introduction of online reviews

Owing to rapid technological advancements, "online reviews" have emerged as an ideal and efficient mode of communication, significantly displacing traditional face-to-face interactions with electronic formats (Kato, 2022; Eisingerich et al., 2015). Online reviews are perceived as valuable and evaluative information, encompassing both positive and negative comments about a given product, brand, or organization shared with current, past, and potential customers online (Kumar et al., 2023; Bartschat et al., 2022; Kiritattarkarn et al., 2020). Presently, numerous informational platforms host a substantial number of online reviews. In addition to text, these evaluations may also include photographs, videos, star ratings (typically ranging from 1 to 5 stars), and descriptions of product or service usage (Kato, 2022; Liu & Pang, 2018). Online reviews have evolved into a new form of eWOM communication, characterized by strong sociality, extensive dissemination capabilities, and greater influence than other communication forms (Fang et al., 2023; Sharma et al., 2020; Godes & Mayzlin, 2004). As a form of UGC, online reviews not only assist consumers in making informed purchase decisions but also aid managers and stakeholders in promptly enhancing the quality of their products and services. In a survey conducted in the United States, over 80 % of consumers reported reading online reviews before purchasing (Murphy, 2020). Fang et al. (2023); Bartschat et al. (2022); Wu et al. (2017), and Sun et al. (2021) regard online reviews as one of the most significant and influential information sources for customers making purchase decisions. Moreover, customers frequently seek

advice and recommendations from their peers before making a purchase (Wang et al., 2018a) and often share their experiences and reviews afterward (Liu et al., 2021). Numerous studies have demonstrated the significance of online reviews in predicting consumers' buying intentions (Yang, 2022; Naujoks & Benkenstein, 2020; Yan et al., 2018; Wu & Lin, 2017; Erkan & Evans, 2016).

2.2. Online recommendation

Within the diverse content of online reviews, the explicit act of recommending or not recommending specific products or services has a particularly profound impact on prospective customers' purchasing decisions. Chen (2008) conducted a comprehensive analysis of customers' online purchasing behavior and found that recommendations from fellow consumers held a more pronounced influence on decision-making compared to expert recommendations. Additionally, Filieri et al. (2015) emphasize the paramount importance of online recommendations in shaping consumer choices, asserting that customers often regard their peers' opinions as more credible and trustworthy than information disseminated directly by service providers. This observation underscores the ever-increasing role of online recommendations in molding consumer perceptions and preferences. In the context of the accommodation industry, previous studies have established a connection between guests' intentions to recommend and their overall satisfaction levels (Jani & Han, 2014; Ladhar, 2009; Zeithaml et al., 1996). This satisfaction is predominantly derived from the perceived performance outcome and service quality throughout the consumption process (Parasuraman et al., 1988; Oliver, 1980). As a result, it becomes crucial to pinpoint the specific service or product attributes that govern customers' online recommendation behavior, given that the evaluation of these attributes fundamentally determines the quality of the lodging experience (Anderson & Fornell, 2000). By identifying these attributes, industry professionals can optimize customer satisfaction and foster a positive reputation, ultimately enhancing their competitive advantage in the market.

2.3. Airbnb service attributes

Table 1 provides a list of service attributes investigated in prior studies, reflecting the dimensions that Airbnb guests frequently evaluate and discuss when sharing their experiences in online reviews. The pattern observed in the key service attributes for Airbnb users' experiences showcases the diverse nature of factors that contribute to guest satisfaction and perception. Notably, the service attributes related to hedonic value are more prominently highlighted in the studies, indicating the increasing recognition of their role in shaping positive guest experiences. Among the listed service attributes, "host-guest interaction," "authentic local experience," "accommodation quality," and "location" emerge as primary contributors to hedonic value. These attributes focus on providing guests with enjoyable, emotionally enriching, and personally gratifying experiences beyond the functional aspects of the service (Lee & Kim, 2018). In contrast, utilitarian attributes such as "safety," "cleanliness," "accuracy," "amenities," "price," and "convenience" also play important roles in guest satisfaction and service quality (Li et al., 2021; Volgger et al., 2019). Unlike traditional hotels, which typically offer standardized services and amenities, Airbnb's unique P2P accommodation model introduces distinctive attributes that set it apart in the hospitality industry. For instance, Airbnb's focus on providing authentic local experiences is a key service attribute that differentiates it from traditional hotels (Gutierrez et al. (2017). By staying in residential neighborhoods and private homes, guests have the opportunity to immerse themselves in the local culture, creating a more genuine and memorable travel experience compared to the more standardized hotel environment (Li et al., 2021). In addition, Airbnb's pricing model is often more flexible than traditional hotels, allowing hosts to set their rates based on various factors, such as location,

Table 1
A summary of Airbnb service attributes.

Service attribute	Description	Key findings	References
Host-guest interaction	Communication, responsiveness, and hospitality of the Airbnb host	A primary determinant of guest satisfaction Exerting a significant impact on the perceptions of trust and the sense of being welcomed among Airbnb users.	Liang et al. (2018) Tussyadiah and Zach (2017)
Accommodation quality	Comfort, maintenance, and quietness	Airbnb users demonstrate a greater inclination to attend to negative performance attributes of accommodation quality rather than its positive aspects.	Ding et al. (2021)
Location	Neighborhood safety, proximity to attractions, transportation	Favorable locations in proximity to amenities foster positive sentiments. The geographical situation can exert an impact on the pricing of an Airbnb listing.	Sthapit and Jimenez-Barreto (2018) Chica-Olmo et al. (2020); Falk et al. (2019)
Authentic local experience	Feeling immersed in local community and culture	Guests highly value Airbnb's distinctive selling proposition. Perceived authenticity holds considerable significance in shaping the accommodation experience and contributing to overall satisfaction.	Lee et al. (2020); Gutierrez et al. (2017) Lalicic and Weismayer (2017)
Amenities	Facilities and amenities available at the listing	The availability of amenities contributes to an enhanced perception of value.	Mao and Lyu (2017); Varma et al. (2016)
Price	Perceived value and reasonableness of price paid	The assessment of price value plays a pivotal role in the selection of an Airbnb accommodation.	Mao and Lyu (2017); So et al. (2018)
Convenience	Ease of booking, check-in/out, platform usage	Customers' attitudes towards the Airbnb website are influenced by their perceived usefulness of the platform. The flexibility of check-in/out options provided by Airbnb serves as a distinguishing feature compared to traditional hotel establishments.	Wang and Jeong (2018) Medeiros et al. (2022); Yu et al. (2022)

(continued on next page)

first determined the total number of reviews with negative recommendations for each city. We then randomly selected an equal number of reviews showing the intention to recommend from that same city, matching the negative review count. Through this process, we generated a final sample of 10,101 Airbnb customer reviews for further analysis. Table 3 provides a summary of this balanced dataset by city. The sample had an equivalent representation of both positive and negative recommendation intentions across different cities, which allows for a more rigorous comparative analysis between the drivers of recommendation versus non-recommendation-based reviews.

In this study, we used the R programming language to conduct a comprehensive analysis of textual data. R offers numerous benefits for data manipulation, statistical modeling, and visualization, making it an ideal tool for academic researchers. Throughout the analysis, we employed a range of R packages to achieve different objectives. For instance, we utilized the “syuzhet” package to measure the multiple emotional sentiments conveyed by the NRC (National Research Council) in the text data. This approach provides a more detailed understanding of Airbnb users’ experiences by capturing a broad spectrum of emotions. The “TM” (Text Mining) package played a crucial role in the pre-processing of textual data. It facilitated the cleaning and preparation of the corpus for further analysis by offering various functions for tasks such as stop word removal, stemming, and tokenization. To conduct topic modeling, we employed the “Topicmodel” package, which provides robust algorithms for uncovering latent themes and patterns within the text.

3.2. STM model setup

The primary advantage of the STM lies in its capacity to integrate covariates into the topic modeling process. In this study, we focus on a

crucial variable that influences topic prevalence (i.e., the likelihood of assigning a review to a specific topic) within our STM framework. This variable is a binary indicator that signifies whether Airbnb users intend to recommend or not recommend a particular accommodation. By incorporating this variable, the STM can account for the potential influence of users’ intentions on the topics discussed in reviews.

In the topic modeling analysis, determining a suitable number of topics to be estimated is a crucial task. There is no one-size-fits-all approach to this decision, as the literature recommends using both statistical measures and human judgment (Schmiedel et al., 2019; Roberts et al., 2014). In our study, we adopted a method that involved estimating a range of models with varying numbers of topics, from 10 to 40. To assess the goodness-of-fit of these models, we examined several criteria, including held-out likelihood, residual analysis, average exclusivity, and semantic coherence, employing methodologies described by Wallach et al. (2009), Taddy (2012), and Roberts et al. (2016). By analyzing the statistical performance of different topic models depicted in Fig. 1, we decided to construct five models with 20 to 25 topics, allowing for exploration at different levels of granularity.

As shown in Fig. 2, we identified a subset of topic models that fit the data particularly well by comparing their scores on average semantic coherence and exclusivity. Semantic coherence measures the consistency and interpretability of the topics, while exclusivity evaluates the degree to which topics can be distinguished from one another. To determine the optimal number of topics, we used our own judgment, examining the cohesiveness and exclusivity of the topics in the set of non-dominated models. Upon thorough examination, we ultimately chose 23 topics as the optimal number for our analysis, as this selection yielded topics that were more interpretable and exhibited minimal overlap. This decision aligns with recommendations from the literature, which emphasizes the importance of balancing the number of topics to

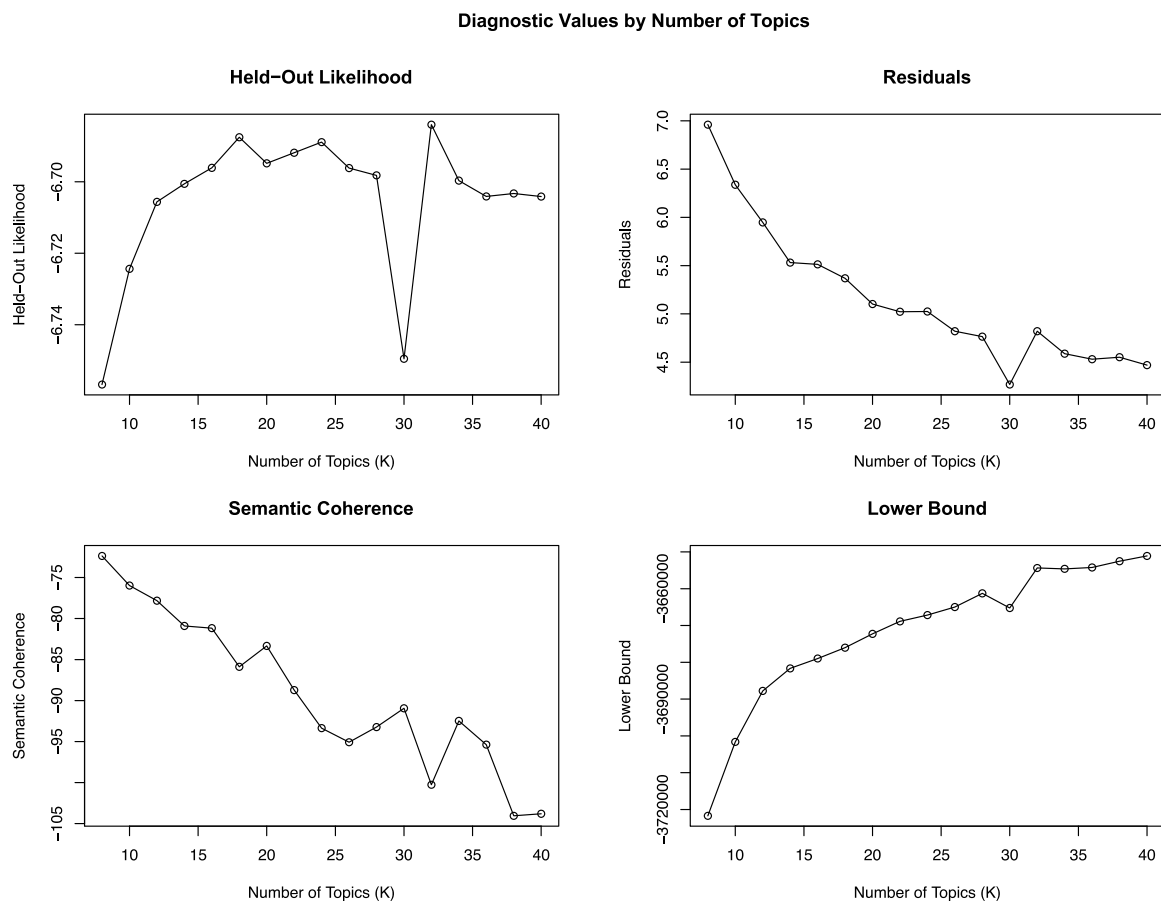


Fig. 1. Statistical performance of topic models.

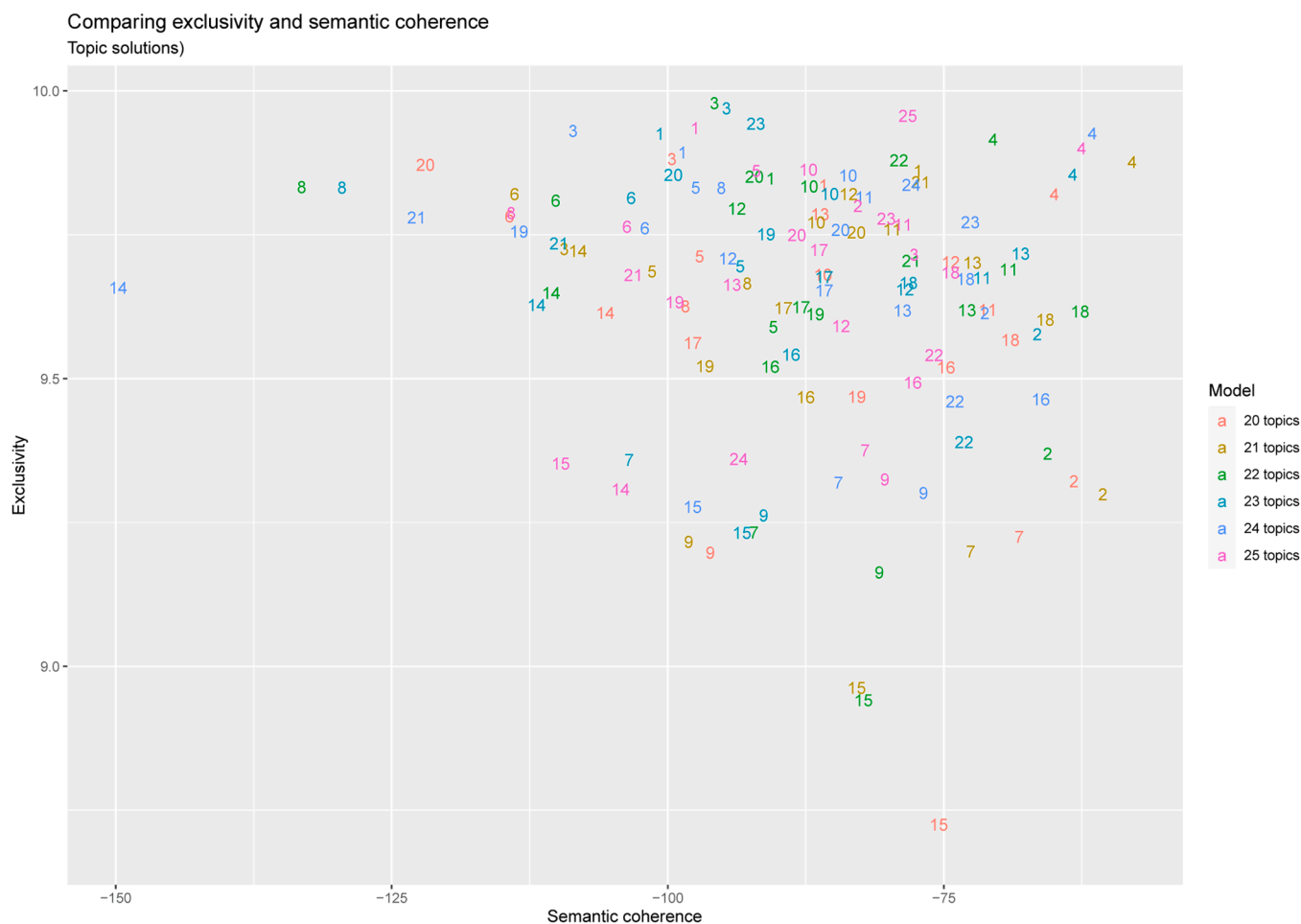


Fig. 2. Topic model performance by exclusivity and semantic coherence.

ensure both interpretability and distinctiveness (Griffiths and Steyvers, 2004; Blei et al., 2003).

4. Findings

4.1. Comparative word distribution analysis

Fig. 3 presents a visual depiction of the word distribution based on their usage patterns in two distinct types of reviews, which provides insights into the general linguistic characteristics and differences between the two groups of reviews. The plot includes words that occur at least four times to ensure statistical significance. The proximity of each word to the red line indicates the neutrality of word usage, with words close to the line being commonly mentioned by both review groups. Conversely, words positioned farther away from the line indicate a significant difference in usage between the two groups, suggesting that these words are more strongly associated with either the intention to recommend or not recommend accommodations. For instance, the words “cozy,” “decorate,” “stylish,” and “thoughtful” are positioned further away from the red line, indicating that they are highly characteristic of reviews with the intention to recommend the property. These words likely represent specific positive aspects of the accommodation experience, such as the coziness of the room, the appealing decor, the stylish design, and the thoughtful amenities provided by the property. Conversely, words such as “dirty,” “refund,” “smell,” and “roach” are also situated away from the red line, suggesting that they are strongly associated with reviews expressing a negative intention to recommend. These words likely highlight issues and concerns related to cleanliness,

dissatisfaction with the service leading to refund requests, unpleasant odors, and possible encounters with pests.

4.2. Sentiment analysis

This study conducted sentiment analysis on Airbnb user reviews to compare the emotional content associated with reviews expressing positive and negative recommendations. To achieve this, we utilize the widely adopted NRC sentiment lexicon, renowned for its comprehensive analysis of sentiment in text. Leveraging the NRC lexicon offers the advantage of a deeper examination of sentiment, enabling a more diverse understanding of the emotional differences conveyed in the text. The NRC lexicon includes approximately 14,000 English words, each assigned sentiment scores for eight distinct emotions: anger, fear, anticipation, trust, surprise, sadness, joy, and disgust, as demonstrated in Fig. 4, inspired by Plutchik’s (1980) wheel of emotions.

The results of sentiment analysis are shown in Figs. 5 and 6. Users who recommended the listing consistently employed words associated with trust, joy, and anticipation, suggesting a positive emotional experience throughout their stay. Conversely, those who did not recommend the listing utilized a greater number of words related to negative emotions, such as sadness, fear, disgust, and anger, indicating a negative emotional experience during their Airbnb experience. These findings align with Barsky and Nash’s (2002) finding that feelings of joy and anticipation were strong predictors of customer delight and positive eWOM, while feelings like anger and disgust were associated with customer dissatisfaction. The results are also consistent with the work of Sirakaya and Woodside (2005), who demonstrated a direct correlation

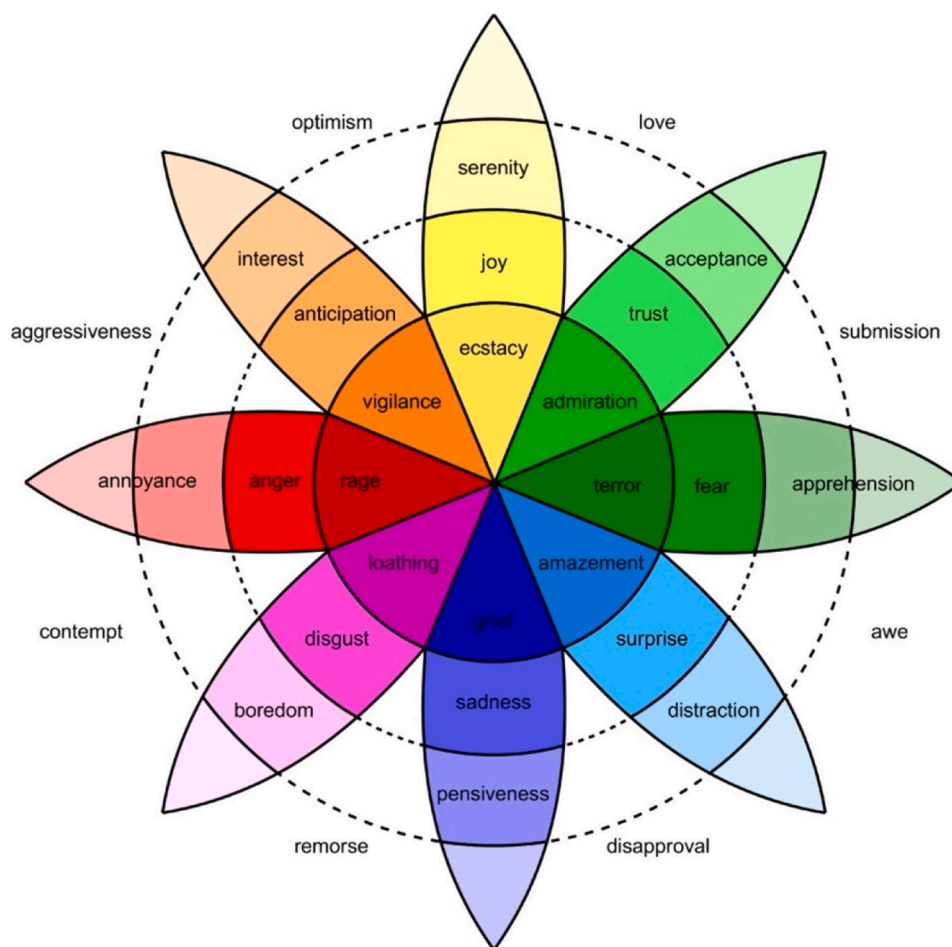


Fig. 4. The wheel of emotions (Plutchik, 1980).

reported being disappointed with the lack of accurate information on the number of beds provided, which has resulted in an unpleasant experience. A significant number of reviews indicate that the lodging is overpriced and, therefore, not recommended for a comfortable stay.

Topic 3 (noise and sleep quality) is related to the problem of noise disturbance in lodging, particularly in relation to the quality of sleep. Many guests have reported experiencing noise-related issues, such as hearing footsteps, loud music, and sounds from neighboring accommodations, which have hindered their ability to sleep. Reviews indicate that noise can be a particularly significant issue for individuals who are light sleepers and that thin walls and upstairs accommodations can exacerbate the problem. Topic 4 (location) is about the convenience of the location and the accurate descriptions of the location. Based on the highest probability words, this topic appears to be about a place to stay in specific cities, with positive comments about the location, cleanliness, and overall experience. Reviews recommend the location to anyone visiting the area and express a desire to return. The FREX words reinforce the positive sentiment with references to the cute, cozy, and communicative aspects of the accommodations, as well as the convenience of the location for downtown activities.

Topic 5 (building maintenance) is about issues related to the maintenance of the buildings where the properties are located. The most important issues mentioned in the reviews are related to the building's infrastructure, security, access, and maintenance problems. The Highest Prob and FREX words suggest that guests had issues with the building's structure, elevators, key fobs, lock codes, and security. Guests also mentioned problems with the unit's cleanliness, including issues with cockroaches and mold/mildew. Topic 6 (group stay) is related to staying in a house with a yard suitable for groups, families, and children. The

reviews mention the availability of outdoor space, such as the backyard and driveway, and indoor space, like the master bedroom and porch. They also discuss the suitability of the space for kids to play games and hang out. Additionally, the reviews mention the availability of space for dogs, which suggests that the location is pet-friendly.

Topic 7 (host attitude) is related to the negative experiences that Airbnb guests have encountered in their interactions with their respective hosts. The related top words include *negative*, *strict*, *accuse*, *aggressive*, *unfortunate*, and *picky*. As evidenced by representative reviews, guests have frequently expressed dissatisfaction with the negative attitudes of certain hosts, which in turn has served as a key reason for not recommending the property. The complaints mentioned in the reviews suggest that negative host attitudes may manifest in a variety of ways, including poor communication, unprofessional behavior, and a lack of responsiveness to guest needs and concerns. Topic 8 (safety concern) is related to the features of the rental property that might impact the stay of different types of guests, including families with children and young adults. Based on the Highest Prob terms of this topic, it appears that guests may have had concerns regarding the safety of the property, such as steep stairs, narrow or rough mobility, smoke, and old age. The representative reviews provide further context on these features. Some reviews mentioned the suitability of the property for families with children, as there were plenty of indoor and outdoor toys available. However, another review advises against renting the property for families with young children due to the steep staircase and noise concerns from the tenant downstairs. The reviews also highlight other features of the property, such as unique architectural features, large and spacious rooms, high-quality appliances and amenities, and proximity to local attractions.

Recommend

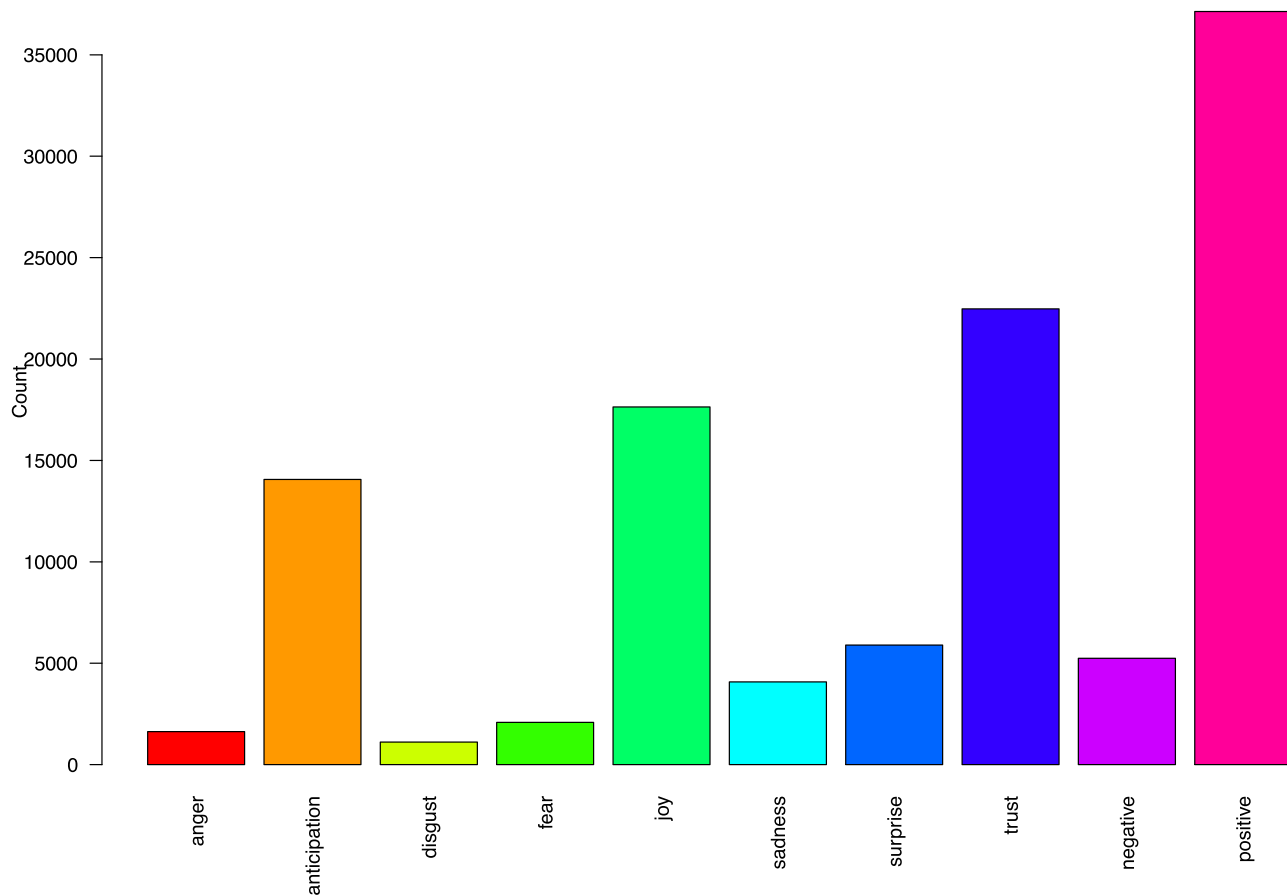


Fig. 5. Sentiment analysis of Airbnb reviews with positive recommendations.

Topic 9 (island experience) is about a beautiful island experience. The reviews highlight the natural beauty of the island, including volcanoes, rainforests, and fruit trees. The guests enjoyed their stays in various properties, including cabins, cottages, and a treehouse, and appreciated the seclusion and privacy they provided. The reviews also mention the warm hospitality of the hosts, who provided treats and notes, helped the guests get situated, and offered tours and massages. Topic 10 (seaside experience) is related to vacation experiences in beachfront condos, resorts, and locations with beautiful ocean views. The reviews frequently mention amenities such as beach gear, including chairs, umbrellas, and boogie boards, as well as pools, sunset views, and convenient locations for walking to nearby attractions or restaurants.

Topic 11 (proximity to points of interest) focuses on the convenience and location of the accommodations, with words such as *walk*, *subway*, *restaurant*, *neighborhood*, and *minute*, indicating that the reviews highlight the importance of easy access to amenities and attractions. The representative reviews mention the proximity to subway stations and public transportation, shops, restaurants, and attractions within walking distance. The FREX words such as *metro*, *train*, *subway*, *restaurant*, and *shop* further support the idea that the reviews emphasize the location and convenience of the accommodations. The proximity to amenities and attractions can significantly enhance the guest experience, and hosts who offer convenient and accessible accommodations are more likely to receive positive reviews and recommendations. Topic 12 (transportation) is related to the availability of transportation near the property. Guests appreciate properties that are located in areas with easy access to public transport or highways for easy driving. Properties situated near parks or scenic routes are also popular, as guests can enjoy a peaceful walk or jog. Another crucial factor is the distance of the

property from their points of interest. Guests appreciate properties that are situated in areas that are conveniently located to reach their destinations with ease. The word *drive* is frequently mentioned, and guests tend to appreciate a short drive time to their destination. The availability of parking is also an essential factor to consider for guests who are driving.

Topic 13 is about guests' evaluation of Airbnb hosts' helpfulness, with a specific emphasis on the usage of the top words *helpful*, *host*, and *flexible*. Based on representative reviews, certain attributes emerge as crucial indicators of their helpfulness. In particular, guests are highly appreciative of hosts who respond promptly to their inquiries and concerns. This is particularly important in instances where guests may encounter unforeseen challenges, such as delayed flights or travel disruptions. Another important factor in evaluating host performance is their level of flexibility. This entails the ability to accommodate guests' requests and needs, even if they deviate from the standard operating procedures. In relation to Topic 14 (hospitality and supportiveness of hosts), the Highest Prob words such as *always*, *answer*, *available*, *tip*, *everything*, and *give* are indicative of the host's willingness to provide support and assistance to the guests. Representative reviews provide insight into how the hosts were hospitable and supportive towards their guests. For instance, Airbnb hosts demonstrate a willingness to share tips and recommendations with their guests. This can include advice on local attractions, restaurants, and other points of interest, as well as practical tips on navigating the local area, which is often highly appreciated by guests.

Topic 15 (issues with accommodation quality) is related to the issues guests encountered during their stay, particularly related to the quality of the accommodation. The Highest Prob words indicate that guests had

Not recommend

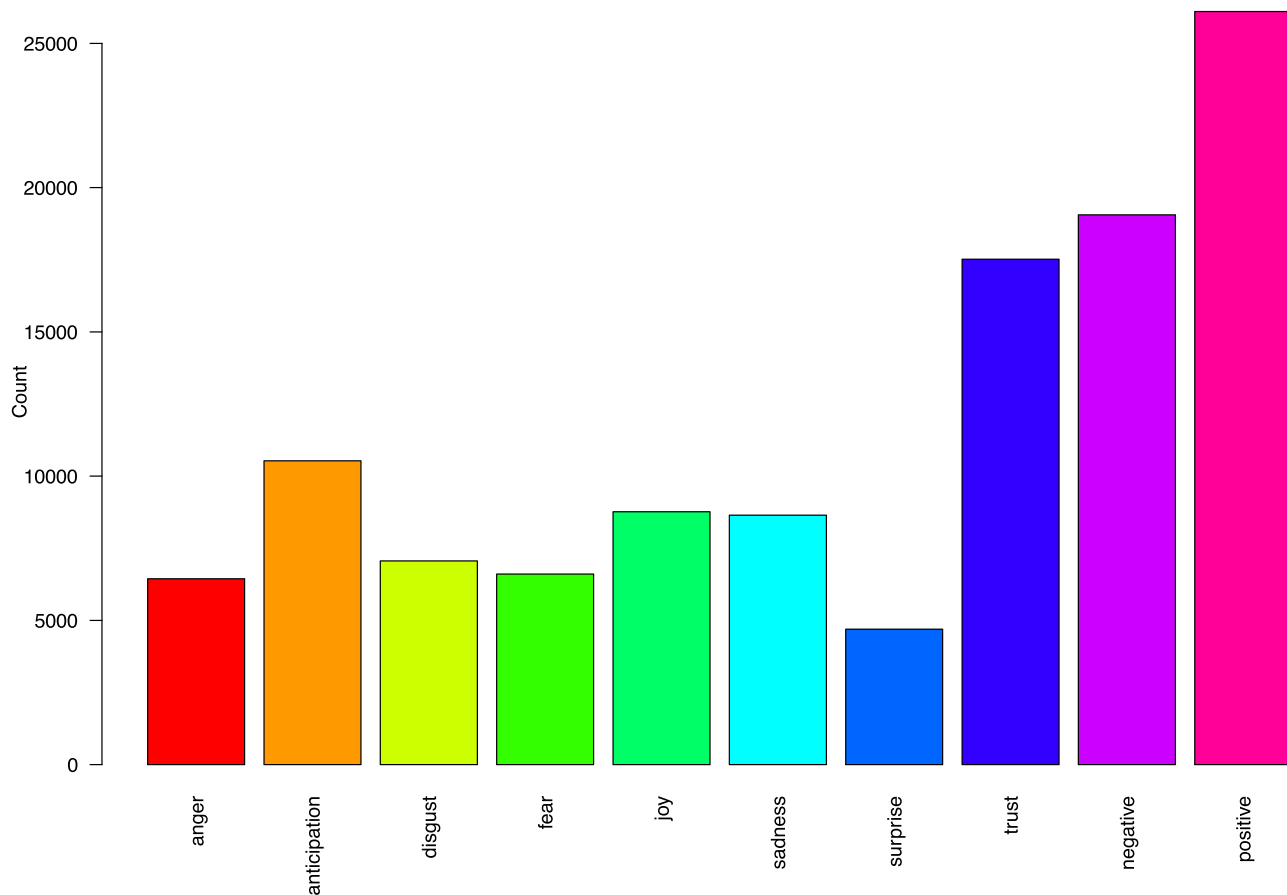


Fig. 6. Sentiment analysis of Airbnb reviews with negative recommendations.

problems with the water supply, shower, and toilet and faced issues related to hot and cold temperatures, bad smells, bugs, and cockroaches. The top FREX words further emphasize the issues with pests such as ants, roaches, and cockroaches and problems related to leaks, clogs, and the heating and cooling system. The representative reviews illustrate the various issues guests encountered during their stay. The reviews highlight serious problems related to water damage, mold, sewage fumes, and leaking roofs. Guests also faced issues related to pests such as ants, roaches, and cockroaches and experienced problems with the heating and cooling system, resulting in uncomfortable temperatures. The reviews also indicate that guests were not adequately informed about the issues prior to their arrival, and some hosts were not willing to offer any compensation for the problems faced during their stay.

Topic 16 (food and drinks) is related to the thoughtful supply of food and drinks by the host. Analysis of the most frequent and highest probability words associated with this topic reveals that guests highly value the comfort and cleanliness of the space, with particular emphasis placed on the bed and bathroom. Additionally, guests appreciate the complimentary coffee and snacks, as well as decorations that contribute to the overall ambiance of the space. Topic 17 (cleanness) is related to the cleanliness and condition of the place. The highest probability words include *clean*, *place*, *dirty*, *bathroom*, *bed*, *good*, and *smell*, indicating that people tend to evaluate the quality of Airbnb accommodations based on these factors. The FREX words include *stain*, *filthy*, *dirty*, *dust*, *dirt*, *dusty*, *outdate*, *curtain*, *carpet*, *hair*, *paint*, *furniture*, *rug*, *tear*, *gross*, *disgust*, *sheet*, *picture*, and *sticky*, which further emphasizes that people frequently complain about cleanliness and the condition of the furniture and amenities. The representative reviews provided to interpret this topic suggest that the Airbnb accommodations did not match the

advertised pictures, indicating a misrepresentation of the quality of the place. Many people have reported issues related to cleanliness, such as filthy floorboards, dirty walls, and stains on furniture. Broken and outdated furniture is also a common complaint. Some guests have also mentioned bad smells, such as mildew or vomit-like odors, and broken bathroom fixtures.

Topic 18 (home-like experience) centers around the idea of positive experiences and hospitality in Airbnb stays. Words such as *home*, *stay*, *feel*, *beautiful*, *wonderful*, and *welcome* suggest a focus on the feeling of being welcomed into a comfortable and inviting space. Additionally, terms like *book*, *family*, *time*, *love*, and *visit* imply a sense of personal connection between the guest and the host. The FREX words in this topic further emphasize the importance of exceeding expectations and going beyond what is typical in terms of hospitality. Words like *truly*, *beyond*, *hospitality*, *exceed*, and *memorable* indicate a desire to create a special and memorable experience for guests. Representative reviews on this topic showcase the importance of feeling at home, being well taken care of, and building personal connections with hosts. Topic 19 (check-in/out flexibility) is related to the degree of flexibility afforded to Airbnb guests by their respective hosts, particularly with regard to changes in travel plans, such as flight delays or cancellations. The prevalence of such discussions in Airbnb reviews is indicative of the importance that travelers place on the flexibility and adaptability of their accommodation arrangements in the face of unforeseen circumstances. Topic 20 (cooking facilities) is focused on the quality of the kitchens and cooking facilities in the listed accommodations. The Highest Prob and FREX words associated with the topic are consistent with this interpretation. The highest prob words *good*, *kitchen*, *cook*, *nice*, and *studio* all relate to the quality and features of the kitchen and cooking facilities, while

Table 2

Topic summary.

Topic no.	Topic proportions	Top words	Topic label	Herzberg Factor
1	0.025	Highest Prob: towel, wash, dry, laundry, washer, machine, kitchen, fridge, microwave, toilet FREX: dry, washer, dish, wash, pot, paper, soap, machine, shampoo, maker	Amenities and facilities	Hygiene
2	0.06	Highest Prob: room, bed, bathroom, stay, people, small, place, price, sleep, night FREX: room, price, uncomfortable, hotel, mattress, bed, desk, hostel, restroom, small	Room comfortableness	Hygiene
3	0.032	Highest Prob: noise, night, sleep, hear, loud, upstairs, light, neighbor, noisy, sound, FREX: noise, upstairs, loud, sleeper, noisy, hear, neighbor, music, earplug, sound	Noise and sleep quality	Hygiene
4	0.112	Highest Prob: place, stay, everything, need, perfect, location, super, clean, definitely, nice, FREX: downtown, super, exactly, place, perfect, definitely, cute, awesome, quick, everything	Location	Motivator
5	0.033	Highest Prob: unit, build, park, door, front, street, issue, lock, key, elevator FREX: build, elevator, unit, security, code, sign, lock, lobby, secure, garage	Building maintenance	Hygiene
6	0.028	Highest Prob: house, family, group, large, kid, yard, dog, backyard, space, area, FREX: house, group, yard, backyard, driveway, game, kid, dog, fence, together	Group stay	Motivator
7	0.029	Highest Prob: guest, host, review, list, stay, issue, clean, previous, experience, rule FREX: rule, previous, guest, review, write, read, negative, picky, accuse, aggressive	Host attitude	Both
8	0.017	Highest Prob: stair, child, step, old, apartment, young, problem, smoke, foot, steep FREX: young, stair, steep, bill, child, narrow, climb, woman, smoke, summer	Safety concern	Hygiene
9	0.033	Highest Prob: island, stay, beautiful,	Island experience	Motivator

Table 2 (continued)

Topic no.	Topic proportions	Top words	Topic label	Herzberg Factor
10	0.043	experience, property, cottage, love, big, drive, enjoy FREX: volcano, hilo, cabin, van, nature, tree, farm, frog, bird, cottage Highest Prob: beach, condo, view, great, pool, chair, walk, ocean, resort, snorkel FREX: condo, boogie, resort, turtle, gear, snorkel, beach, pool, umbrella, ocean	Seaside experience	Motivator
11	0.096	Highest Prob: great, walk, restaurant, neighborhood, easy, subway, location, minute, close, distance FREX: station, metro, train, subway, restaurant, cafe, distance, bar, neighborhood, museum	Proximity to points of interest	Motivator
12	0.028	Highest Prob: park, car, drive, great, min, time, location, day, walk, north FREX: north, truck, min, car, bike, road, shore, highway, drive, park	Transportation	Motivator
13	0.069	Highest Prob: apartment, host, great, good, location, stay, clean, experience, enough, helpful FREX: excellent, apartment, helpful, accommodation, host, enough, flexible, prompt, communication, process	Host helpfulness	Both
14	0.020	Highest Prob: always, question, need, available, answer, local, tip, everything, property, host, FREX: always, tip, chat, answer, terrace, favorite, brilliant, question	Hospitality and supportiveness of host	Both
15	0.044	Highest Prob: water, stay, shower, issue, hot, bug, night, smell, day, window FREX: ant, roach, cockroach, bug, leak, dead, kill, crawl, spray, clog	Issues with accommodation quality	Hygiene
16	0.045	Highest Prob: comfortable, bed, space, coffee, clean, room, enjoy, touch, comfy, bathroom, FREX: snack, comfy, decorate, wine, thoughtful, beautifully, art, tea, touch, chocolate	Food and drinks	Motivator

(continued on next page)

Table 2 (continued)

Topic no.	Topic proportions	Top words	Topic label	Herzberg Factor
17	0.045	Highest Prob: clean, place, dirty, look, picture, floor, stain, break, bathroom, bed FREX: stain, filthy, dirty, dust, dirt, dusty, cleanliness, outdate, curtain, carpet	Cleaness	Hygiene
18	0.057	Highest Prob: home, stay, feel, make, beautiful, like, wonderful, welcome, family, time FREX: home, truly, beyond, forward, hospitality, exceed, birthday, pleasure, expectation, memorable	Home feeling	Motivator
19	0.029	Highest Prob: make, late, day, sure, early, flight, feel, arrive, night, luggage FREX: flight, luggage, late, upgrade, checkout, sure, airport, nervous, early, departure	Check-in/out flexibility	Motivator
20	0.035	Highest Prob: good, kitchen, cook, nice, studio, comfortable, stock, bed, equip, bedroom FREX: studio, cook, equip, meal, fully, stock, kitchen, size, appliance, apartment	Cooking facilities	Motivator
21	0.021	Highest Prob: work, wifi, issue, call, service, stay, day, time, phone, internet FREX: internet, wifi, remotely, connection, company, slow, connect, app, phone, work	Internet connectivity	Hygiene
22	0.070	Highest Prob: host, tell, check, say, day, leave, book, ask, never, refund FREX: cancel, refund, tell, finally, rude, refuse, reservation, send, suppose, customer	Check-in issues	Hygiene
23	0.019	Highest Prob: bite, little, stay, leave, really, time, may, know, note, nice FREX: bite, little, note, comment, fine, slightly, month, anyway, surprise, may	Pest issues	Hygiene

comfortable, bed, equip, bedroom, place, stay, and bathroom relate to the general comfort and amenities of the accommodations. Similarly, the FREX words studio, equip, cook, meal, fully, stock, and kitchen are all directly related to the kitchen and cooking facilities. Representative reviews indicate that guests appreciated the well-equipped kitchens with essential appliances and basic food items.

Table 3

Summary statistics of the review sample.

Review type City	Positive recommendation	Negative recommendation	Total Number of Reviews
Asheville	210	210	420
Austin	630	630	1260
Boston	283	283	566
Dallas	226	226	452
Denver	271	271	542
Hawaii	1441	1441	2882
New York	1485	1485	2969
Portland	173	173	346
Washington	332	332	664
		Total	10,101

Topic 21 (internet connectivity) is about issues related to the Internet, Wi-Fi, and app connectivity. There are also complaints about slow response time, unresponsiveness, and poor management. The representative reviews indicate that many guests have faced issues related to internet connectivity, and it is also observed that the management and staff were slow to respond and not helpful in resolving these issues. Topic 22 (check-in issues) is mainly related to guests' unpleasant experiences, which pertain to check-in issues. A thorough analysis of the representative reviews has found that the check-in process can be a major source of frustration and inconvenience for guests and can result in negative feedback on the platform. One of the primary issues reported by guests is the lack of clear communication from hosts regarding the check-in process. Guests also reported instances where hosts had not provided adequate information on how to access the property, resulting in confusion and delays upon arrival. Another area of concern related to check-in is the lack of flexibility offered by hosts. Topic 23 (pest issues) is related to negative feedback given by guests on Airbnb regarding the quality of their stay due to issues related to pests. Through a thorough analysis of representative reviews on this topic, it has become apparent that guests who complain about pest issues also tend to highlight the sanitary conditions of the property. The presence of pests in a property can be indicative of unsanitary conditions, which can have a detrimental impact on the comfort and safety of guests. Common pests that are often reported by guests include bed bugs, cockroaches, rodents, and other insects.

4.5. Topic distribution analysis

In this study, we utilized STM to examine the impact of users' intention to recommend on the prevalence of topics discussed in Airbnb reviews. Specifically, we included a binary variable denoting whether or not the user recommended the service as a covariate in our model. By employing STM, we were able to estimate the proportion of each topic associated with the positive and negative recommendations, and subsequently perform statistical tests to determine if there were significant differences between them. For instance, if the proportion of a particular topic was found to be significantly higher in reviews associated with non-recommendation intentions than in those associated with recommendation intentions, this topic may be considered a factor influencing guests' decision to not recommend the service.

Fig. 7 plots the estimated changes in the topic proportions when shifting from reviews showing recommendation and non-recommendation intentions. The dots are the mean values of the estimated differences, and the bars are the 95 % confidence intervals for the difference. It is found that the topics that are more frequently mentioned in reviews with positive recommendation intentions are related to the convenience of the property, such as its "proximity to points of interest," "location," and availability of "food and drinks." Additionally, the behavior of hosts appears to be a crucial factor in eliciting positive recommendations, with topics such as the creation of a "home feeling," the "host helpfulness," and the "hospitality and supportiveness of the

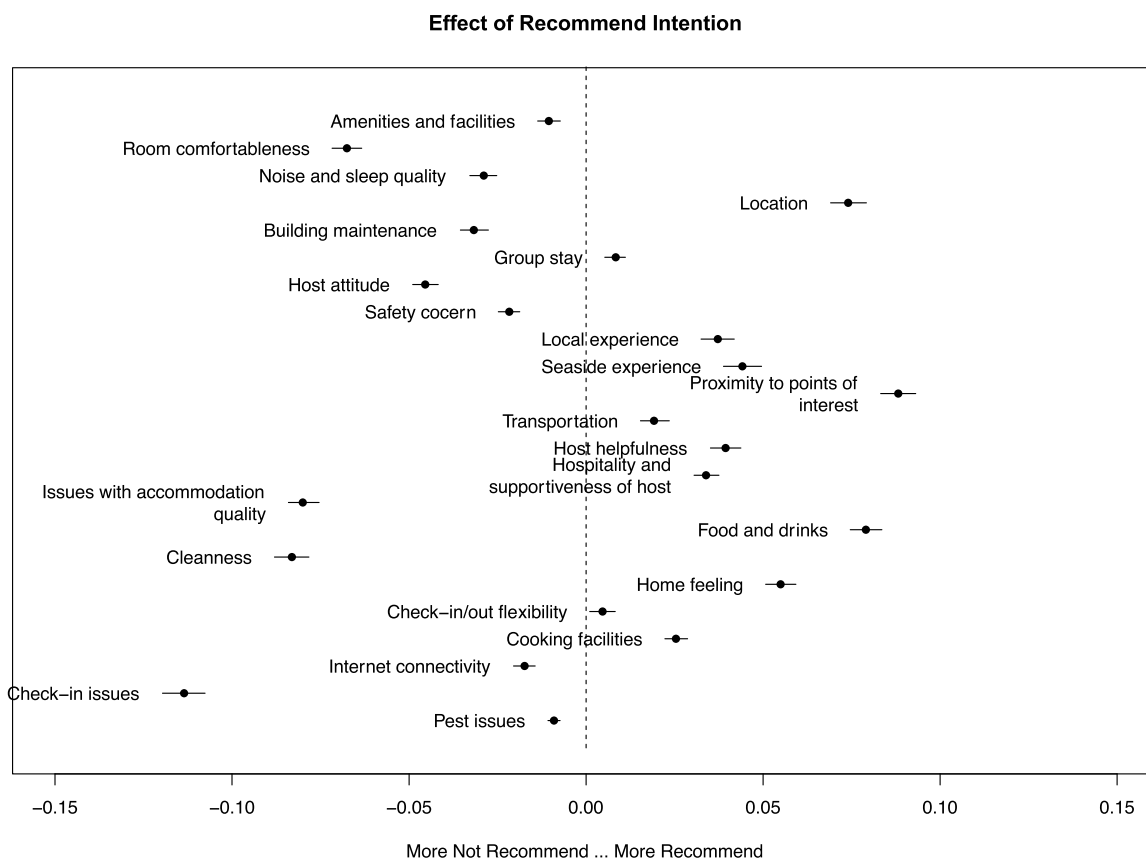


Fig. 7. Change in topic prevalence based on the recommendation intentions.

host” frequently mentioned in favorable reviews. Moreover, some users express their recommendation of the property based on the unique and authentic experiences provided, such as the opportunity to immerse oneself in the “local experience” or enjoy a “seaside experience.” Conversely, reviews indicating non-recommend intentions tend to highlight issues that detract from the overall experience. A notable example is the presence of “check-in issues,” which appear significantly more in negative reviews. Furthermore, negative reviews often mention topics related to the room experience, such as “issues with accommodation quality,” “cleanness,” “room comfortableness,” and “noise and sleep quality.” These factors appear to be important in influencing a guest’s decision to post negative recommendations about a property.

4.6. Topic correlation analysis

The topic correlation network in Fig. 8 provides an overview of topics that are often discussed together. The sub-cluster in the upper left of the figure centers around the topics of “location” and “local experience.” The “location” topic is closely linked with “proximity to points of interest” and “food and drinks,” indicating that these are important factors for guests when considering the location of their accommodations. On the other hand, the “local experience” topic is connected with “group stay,” “transportation,” and “seaside experience,” suggesting that guests are interested in more immersive and authentic experiences when visiting a new location. However, the cluster located in the bottom right of the figure presents topics that are often discussed by guests who do not recommend the property. This cluster revolves around “room comfortableness” and “host attitude.” The topic of “room comfortableness” is linked with several negative factors that contribute to an unpleasant lodging experience, such as “pest issues,” “cleanness,” and “noise and sleep quality.” Clearly, guests prioritize a comfortable and clean environment when selecting lodging options. As for “host

attitude,” this topic is closely connected with unpleasant “check-in issues,” which indicates that guests value a positive attitude from hosts before or during their stay.

5. Discussion

This section presents and discusses the key findings concerning Airbnb users’ intentions to recommend accommodations. The implications, conclusions, and suggestions for future researchers are provided.

5.1. Research findings

Table 4 provides a summary of the service attribute-related topics that were found to potentially influence Airbnb users’ tendencies to provide either positive or negative recommendations. The findings highlight the significance of the initial phase, namely the check-in process prior to the stay, in shaping users’ intentions to recommend accommodations. During this phase, users’ encounters with unpleasant experiences can impact their recommendation intentions. Notably, these experiences often stem from the behavior and attitude exhibited by the hosts, as revealed by the topic correlation analysis. The analysis demonstrates a close association between the topics of “check-in issues” and “host attitude.” The behavior and attitude of the hosts hold considerable sway over users’ perceptions during the check-in process. If hosts are perceived as poor or unfriendly during this crucial period, it detrimentally affects users’ inclination to recommend the rented place. Another prevalent issue frequently mentioned in user reviews pertains to difficulties encountered during the check-in process, specifically instances where guests were unable to check in due to the unavailability of rooms. Additionally, some guests reported that the property they had booked was unexpectedly canceled during the check-in period, often without prior notice. Such circumstances not only disrupt guests’ travel plans but

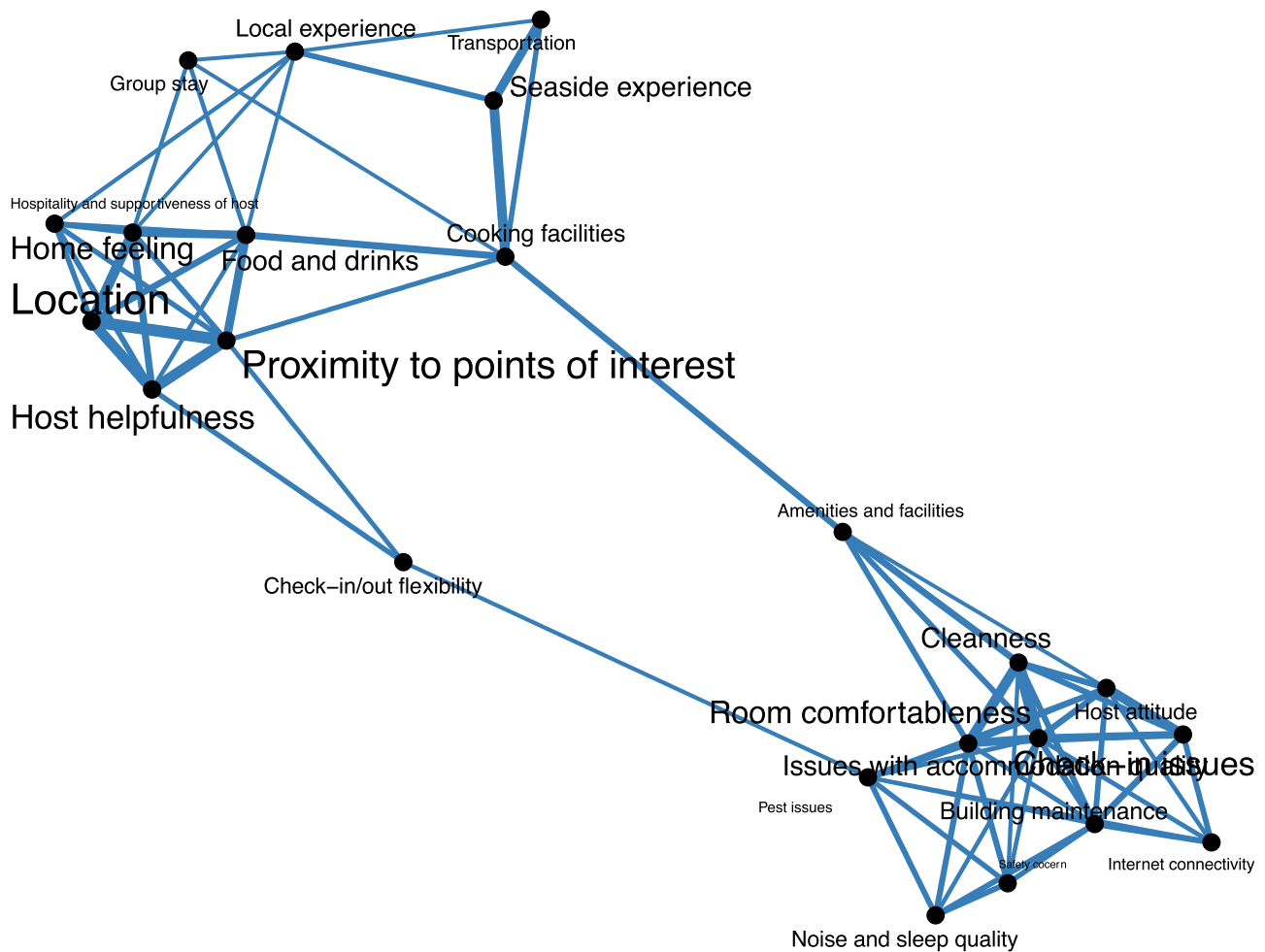


Fig. 8. Topic correlation map.

Table 4
A summary of major findings.

Review type	Topic	Review type	Topic
Positive recommendation	Amenities and facilities	Negative recommendation	Location
	Room comfortableness		Group stay
	Noise and sleep quality		Local experience
	Building maintenance		Seaside experience
	Host attitude		Proximity to points of interest
	Safety concern		Transportation
	Issues with accommodation		Host helpfulness
	quality		
	Cleanness		Hospitality and supportiveness of host
	Internet connectivity		Food and drinks
	Pest issues		Home feeling
	Check-in issues		Check-in/out flexibility
			Cooking facilities

may also give rise to complications regarding refunds or alternative accommodations. However, it is important to note that even though a smooth check-in/out experience is considered crucial, it may not

guarantee users' intentions to recommend the accommodation. One potential reason for this is that providing flexibility during the check-in/out period, which is commonly practiced, may not be as appreciated by users as one might expect.

During the stay stage, two key aspects emerge as influential factors in Airbnb users' online recommendation behavior: the convenience provided by the property and the in-room experience. The convenience offered by the property plays a crucial role in triggering users' recommendations. Specifically, three topics have emerged as prevalent among Airbnb users when discussing their experiences: "proximity to points of interest," "food and drinks," and "location." The prominence of these topics indicates the importance of location-related factors in users' recommendation decisions. Users highly value accommodations that are conveniently situated near popular attractions, landmarks, restaurants, and entertainment venues (Sthapit & Jimenez-Barreto, 2018). There are two additional topics that have emerged as significant factors related to convenience and Airbnb users' recommendation behavior. These topics are "local experience" and "seaside experience." The concept of a "local experience" has gained importance in the Airbnb context. Users often seek accommodations that provide them with an authentic and immersive experience of the local culture, customs, and lifestyle (Liang et al., 2018). They appreciate properties that are situated in neighborhoods or areas where they can easily explore local attractions, interact with residents, and engage in activities that showcase the unique characteristics of the destination. A positive local experience, where users feel connected to the destination and its culture, has been found to impact their recommendation intentions positively (Guttentag et al., 2018). Similarly, the "seaside experience" has emerged as a relevant

topic, particularly for properties located in coastal or beachside destinations. Users often prioritize accommodations that offer convenient access to the beach or waterfront areas. The proximity to the seaside and the availability of activities such as swimming, sunbathing, and water sports significantly influence users' recommendation decisions (Ding et al., 2020).

Many reviews from Airbnb users emphasize the crucial role of the in-room experience in determining the suitability of an Airbnb listing for long-term living. This study further reveals that negative in-room experiences have a significant impact on users' decisions to refrain from recommending accommodations in their reviews. In terms of hygiene, encountering unclean or poorly maintained accommodations. Factors commonly mentioned in relation to cleanliness include dirty or unkempt rooms, unclean bedding or bathrooms, and an overall lack of cleanliness. Another issue that frequently arises is the presence of pests, such as ants, roaches, and other unwanted creatures, which users often complain about. Comfort is another crucial factor. When users come across uncomfortable or subpar sleeping arrangements, such as uncomfortable beds or insufficient bedding, they are more likely to express their dissatisfaction in their reviews. This, in turn, reduces the likelihood of recommending the accommodation. Excessive noise, whether originating from outside sources or within the property itself, can also disrupt users' sleep and overall experience. Users who experience sleep disturbances tend to mention this problem in their reviews, which can negatively impact their intention to recommend the accommodation. Another aspect of the in-room experience relates to issues with facilities and equipment. This includes problems like water leaks and shower malfunctions, which can significantly affect users' convenience and comfort. The presence or absence of essential facilities and equipment in accommodations is a crucial factor for users when evaluating the suitability of a place for long-term stays. This aspect holds significant weight in the decision-making process of Airbnb users when considering whether to recommend a particular accommodation.

5.2. Practical implications

The findings of this study provide valuable insights and practical implications for both Airbnb platform management and property hosts. Understanding the factors that influence users' intention to recommend can improve the overall user experience, enhance customer satisfaction, and ultimately contribute to improved business performance. While most of the attributes that could contribute to Airbnb users' positive recommendations are related to the location of properties, which is fixed and challenging for hosts to change, there are still ways to leverage the benefits of the location to attract potential customers. For Airbnb hosts, they can emphasize the proximity to popular tourist attractions, restaurants, and other points of interest that are valued by Airbnb users. By providing specific names and detailed experiences associated with nearby places, hosts can capture customers' attention and create a compelling narrative about the convenience and unique experiences that the location offers. To avoid negative recommendations, it is paramount for Airbnb hosts to prioritize providing a satisfying check-in experience. The findings of this study clearly indicate that the topic of "check-in issues" appeared significantly more in the reviews showing negative recommendations. A smooth and efficient check-in experience sets a positive tone for guests' entire stay and can significantly impact their satisfaction level (Zhang, 2019). Hosts should pay close attention to the check-in process and take proactive measures to minimize any potential issues guests may encounter. Furthermore, factors influencing the comfort and overall in-room experience are significant contributors to guest dissatisfaction and the likelihood of customers posting non-recommendatory content. Specifically, concerns related to a dirty environment, noise disturbances, and bedding quality emerged as prominent factors, which provide Airbnb hosts with specific directions to focus on when developing strategies aimed at improving the lodging experience of customers.

The findings provide valuable insights for the Airbnb platform that can guide platform management in enhancing the overall user experience and driving business performance. The study highlights the significance of factors influencing users' intention to recommend accommodations. Understanding these factors can aid in refining the platform's recommendation algorithms. By incorporating insights from user reviews and sentiment analysis, the platform can better match users with accommodations that align with their preferences and priorities, increasing the likelihood of positive recommendations. It is suggested that the platform implement robust systems for monitoring user experiences and feedback. By regularly analyzing continuously updated reviews, the platform can proactively address any recurring issues and identify areas for improvement. This approach can contribute to enhanced customer satisfaction and encourage more positive recommendations. In this study, host behavior has been found to play an important role in influencing Airbnb users' intentions to recommend or not recommend a property. The specific attributes related to Airbnb host behavior can help Airbnb develop effective host performance metrics and guidance to ensure positive guest experiences.

5.3. Theoretical implications

The distinct attributes influencing Airbnb users' intentions to recommend or not recommend accommodations provide compelling evidence to support Herzberg's two-factor theory, which elucidates the difference between satisfiers and dissatisfiers in shaping individuals' satisfaction levels (Herzberg et al., 1959). The congruence between the study's findings and Herzberg's two-factor theory demonstrates the universality of this theory in different contexts beyond the workplace. This aligns with other studies that have applied the two-factor theory to various domains, including customer satisfaction and user experience (Li et al., 2023; Meneses et al., 2023). It reinforces the notion that individuals' satisfaction and dissatisfaction are influenced by different sets of factors, and understanding this distinction is crucial for effectively managing user experiences and improving overall satisfaction levels in various settings.

Moreover, this study extends previous Airbnb research by exploring the motivations of Airbnb users regarding posting recommendation comments, which play an essential role in customers' purchase decisions (Filieri et al., 2015). By investigating the contrasting motivations of users who recommend accommodations and those who express an intention not to recommend, this study enhances our understanding of the underlying factors that drive users' attitudes and behaviors on the platform.

Furthermore, the findings of this study demonstrate that users who provide positive recommendations on Airbnb prioritize hedonic values, such as enjoyment, pleasure, and satisfaction, in their evaluations. This aligns with research on hedonic consumption, which suggests that individuals are motivated by the emotional and experiential aspects of products and services (Hirschman & Holbrook, 1982). On the other hand, users who express dissatisfaction and reluctance to recommend primarily focus on the fulfillment of their utilitarian needs, such as functionality, reliability, and practicality. This finding is consistent with the theory of utilitarian consumption, which posits that individuals seek products and services based on their functional benefits and problem-solving capabilities (Holbrook & Hirschman, 1982). This alignment with existing research in the field of consumer behavior highlights the interplay between hedonic and utilitarian motivations in consumer decision-making. It underscores the importance of considering both emotional and functional aspects in understanding user attitudes and behaviors on online platforms like Airbnb.

5.4. Conclusions

In conclusion, this study contributes significant insights into the motivations and decision-making processes of Airbnb users when it

comes to recommending accommodations in their reviews. The findings indicate a notable distinction between users who offer positive recommendations and those who express dissatisfaction. Positive recommendations tend to be driven by a higher emphasis on hedonic values, such as enjoyment and satisfaction. At the same time, negative reviews focus more on fulfilling utilitarian needs, such as functionality and practicality. This study also highlights the pivotal role of host behavior in shaping users' intentions to recommend or not recommend accommodations. Negative reviews often mention the theme of "host attitude," while positive reviews emphasize "host helpfulness" and the "hospitality and supportiveness of the host." This highlights the direct influence of host behavior on user perceptions and subsequent recommendations.

5.5. Limitations and suggestions for future research

Despite the significant contributions of this study, it is essential to acknowledge its limitations. One notable limitation is the focus solely on reviews from the United States. This narrow scope may hinder the generalizability of the findings to other regions and countries. Cultural, social, and economic factors can play a substantial role in shaping users' perceptions and preferences regarding the in-room experience, and these factors may differ significantly in diverse geographical contexts. Therefore, future research should aim to collect data from a more diverse range of countries or regions to obtain a broader and more representative understanding of Airbnb users' perspectives worldwide. Another limitation of the current study is the lack of differentiation among users based on property type or other relevant characteristics. Different types of accommodations, such as apartments, houses, or shared spaces, may offer unique in-room experiences that can influence users' evaluations and recommendations differently. For example, the in-room experience of a shared space like a dormitory may be different from that of a private house. Therefore, future research could explore how the in-room experience and users' recommendations vary across different types of properties, which could offer a deeper understanding of the factors that influence users' intentions to recommend or not recommend accommodations based on specific property types.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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