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Causal recipes of customer loyalty in a sharing economy: Integrating social media analytics and fsQCA

Abstract

Built on the evolutionary stimulus-organism-response model, this study examines how customer encounters with different interaction mechanisms (stimuli) evoke service-quality perceptions and sentiments (organisms) that impact customer loyalty (responses) to accommodation-sharing services. It draws important service-quality dimensions and sentiments from Airbnb reviews and examines which patterns lead to the highest levels of customer loyalty. It is the first study to integrate social media analytics and fuzzy-set Qualitative Comparative Analysis to explain the attitudinal and behavioral components of customer loyalty. A distinctive aspect of the findings is the prescriptive causal recipes that allow hosts to prioritize certain resources, focusing more on the key dimensions (order winners) that most affect customer loyalty. The findings also show that configurations leading to high-level attitudinal loyalty differ from those leading to high-level behavioral loyalty in accommodation sharing.

Keywords: S-O-R model, social media analytics, fsQCA, customer loyalty, accommodation sharing, sharing economy

1. Introduction

Unlike traditional e-commerce platforms where customers communicate with providers online, sharing economy (SE) platforms digitalize offline services where customers meet service providers in person (e.g., drivers and passengers interact in ride-sharing services; hosts and guests interact when sharing a living space). While previous studies have considered SE services holistically without specifying varied levels of face-to-face interactions (Cheng & Jin, 2019; Lee & Tse, 2021), customers' evaluations change due to levels of interaction, a feature that eventually affects their satisfaction. For instance, customers' perceived safety in car-sharing varies according to the level of face-to-face interactions (Kim et al., 2019). Customers sharing a living space with hosts focus more on economic value and social interaction in accommodation sharing (Xu, 2020). In accommodation sharing, the face-to-face interaction level varies across room types, depending on whether the hosts are present during the stay (Xu, 2020). When customers (i.e., guests) rent an entire apartment without the hosts present, their face-to-face interaction is limited. Guests who rent a bedroom but share other spaces with their hosts experience higher levels of face-to-face interaction.

On the other hand, studies investigating service dimensions that affect customer behavior in accommodation sharing are not univocal. Tussyadiah (2016) reports that some customers intentionally look for places where they can avoid social interactions. Other studies, including one by Tussyadiah and Pesonen (2016), claim that certain customers desire interactions with locals during accommodation sharing. We argue that there are three possible explanations for such contradictory findings. First, customers faced with different sharing levels have diverse mindsets regarding the definition of good-quality accommodations. Thus, the dominant sharing level in samples could have biased previous findings. Second, studies that use surveys to collect data may yield findings that sample sizes or inconsistent measurements may restrict. On the contrary, this study uses social media analytics to extract

important service dimensions directly from a large number of customer reviews, overcoming the shortcomings of survey-based methods. Third, previous studies that use linear analysis to investigate individual factors do not attempt to examine the interactions among factors. Drawing on complexity theory in this context leads to the conclusion that focusing on any single service dimension is insufficient to explain customer loyalty in the SE. Fundamentally, retaining customers in the SE involves a shift in focus from individual service dimensions to interactions among them (Pappas, 2017).

Scholars have confirmed the causal complexity of customer behavior in tourism (e.g., Mehran & Olva, 2020). The two characteristics that causal complexity emphasizes are conjunction and equifinality (Ragin, 2008): the joint presence or absence of a set of variables leads to the outcome of interest (i.e., conjunction), and alternative configurations can explain the focal outcome equally effectively (i.e., equifinality). A configurational approach is particularly well-positioned to investigate the conjunction and equifinality inherent in causal complexity (Furnari et al., 2021). Consistent with most configurational studies, this study focuses on identifying how multiple explanatory factors combine to bring about an outcome of interest (Cervelló-Royo et al., 2022; Leischnig & Kasper-Brauer, 2015).

More specifically, this study aims to understand how multiple service dimensions are configured in ways that lead to high-level customer loyalty in accommodation sharing, clarifying how hosts can strategically allocate resources for service improvement. First, in contrast to chain hotels, hosts are not professional providers but individual peers who typically have fewer resources (Lee et al., 2023). Hence, prioritizing resources and focusing on a subset of service dimensions are imperative where their co-occurrence (i.e., conjunction) can affect customer behavior. Service dimensions present in the configurations constitute combined “order winners” that deserve priority. Second, hosts have different levels of control over various service dimensions (Guo et al., 2017). For instance, host-related dimensions, such as

responsiveness and friendliness, are fully controllable; however, providers cannot fully control location-related dimensions, such as neighborhood and transport connectivity. Thus, identifying alternative configurations that equally explain the outcome of interest (i.e., equifinality) can help service providers select alternative paths to better control the service dimensions that achieve the highest outcome. Accordingly, we apply configurational theorizing in this study.

In addition, this study uses the evolutionary stimulus-organism-response (S-O-R) model that Jacoby (2002) reconceptualized as its theoretical thread. It employs fuzzy-set Qualitative Comparative Analysis (fsQCA) to model how customers encountering different sharing mechanisms (stimuli) perceive service dimensions (organisms), impacting customer loyalty (responses) to accommodation-sharing providers.

This study makes two major contributions. First, it advances our understanding of the complexity of customer loyalty in accommodation sharing from a configurational perspective. To improve the explanatory power of customer loyalty, we consider the attitudinal and behavioral components of loyalty separately. Second, this study capitalizes on the wealth of online user-generated content and analyzes a substantial number of online reviews. Understanding customers' needs directly from user-generated content, such as online reviews, is vital because customers make decisions based on electronic word-of-mouth (eWOM), particularly in the platform-facilitated SE.

2. Literature review

2.1 S-O-R model for delineating customer loyalty

The S-O-R model (Mehrabian & Russel, 1974) posits external factors (stimuli) that evoke individuals' internal states (organisms), resulting in behavioral reactions (responses). It assumes that the sequence of S-O-R is linear. However, this assumption may prevent scholars from understanding dynamic relations that impact the outcome (Bigne et al., 2020). The evolutionary S-O-R model by Jacoby (2002) appears to be a better choice for explaining customer behavior (Cui et al., 2016): it uses three circles to represent S-O-R, forming a dynamic 7-sector Venn diagram, as Figure 1 shows.

Sector 1 refers to the environmental stimulus of an individual encounter. Previous studies recognize various environmental features as stimuli, including hotel ambiance (Jani & Han, 2015), perceived responsible actions associated with a destination (Su & Swanson, 2017), and restaurant attributes (Peng et al., 2017). Yet, Slama and Tashchian (1985) warn against neglecting social scape, a meaningful environmental stimulus. Social interactions are stimuli—they can trigger a person's internal state (Lin et al., 2019). Consistent with this perspective, Sector 1 conceptualizes guest–host face-to-face interaction stimuli.

Interaction levels between tourists and hosts vary in different environmental settings, whether in restaurants, parks, and clubs or on the street (Eusébio & Carneiro, 2012). As such, we expect that types of rooms can correspond to measures of guest–host interactions. For example, when guests rent an entire apartment, the interaction level is lower because they do not physically share the same space with hosts.

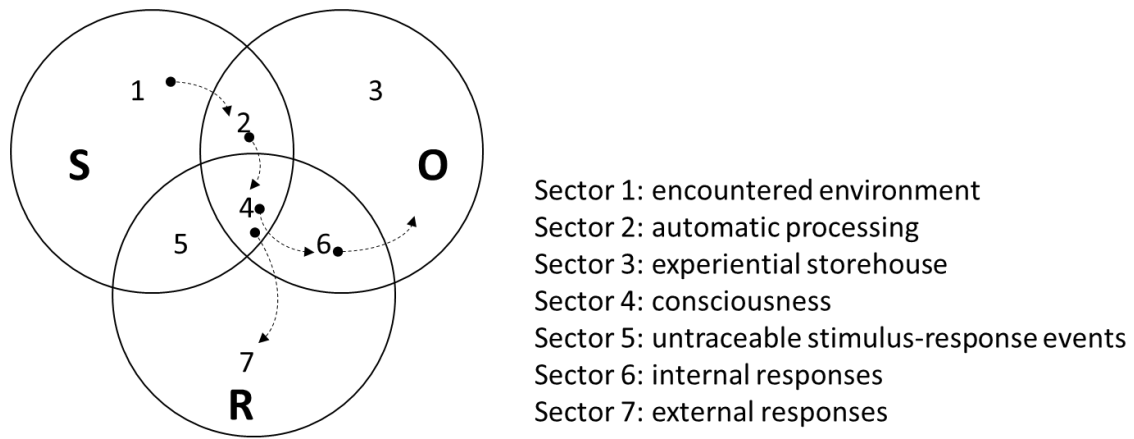


Figure 1. S-O-R model as reconceptualized by Jacoby (2002)

When processing stimuli automatically or unconsciously, the individual evolves to either Sector 2 or Sector 5. In Sector 2, individuals subconsciously process the incoming stimuli. Because of the limited capacity of human memory, individuals are likely to subconsciously filter out elements from less important stimuli, processing only their essential elements. Bigne et al. (2020) use eye-tracking to identify important pictorial elements (e.g., text, pictures) that capture individuals' attention in Sector 2. Similarly, we use topic modeling to identify important service dimensions that capture customers' attention in Sector 2. Topics that are more prevalent in the reviews indicate a higher level of importance for customers. In contrast, Sector 5 contains reactions that are difficult to trace.

Sector 4 includes individuals' emotions when they process stimuli consciously (Jacoby, 2002). For instance, in an online auction, stimuli from Sector 1 can trigger perceived enjoyment in Sector 4 (Cui et al., 2016). This study analyzes the sentiments detectable in customer reviews and uses the sentiment scores to measure customers' emotional reactions to a stimulus.

Sector 6 ("internal responses") contains outcomes from Sector 4 that are not directly visible—for example, attitudes and intentions. This study conceptualizes attitudinal loyalty as an internal response measured by customers' recommendations of services to others. Further, the output from Sector 6 will likely shift to Sector 3. When information from Sector 4 enters

Sector 6 and combines with information retrieved from Sector 3 to create a new attitude (attitudinal loyalty), long-term memory will store the attitude (Sector 3). Further, Sector 7 consists of outcomes from Sector 4 that are externally detectable, such as behavioral reactions. This study conceptualizes behavioral loyalty as an external response that can be assessed by determining whether a customer is willing to revisit the location. To conceptualize Sectors 6 and 7 as attitudinal loyalty and behavioral loyalty, respectively, this study uses topic modeling to extract topics directly from the reviews related to “recommendation” and “revisit intention.” Figure 2 summarizes our theoretical framework for investigating the two paths (1→2→4→6, and 1→2→4→7).

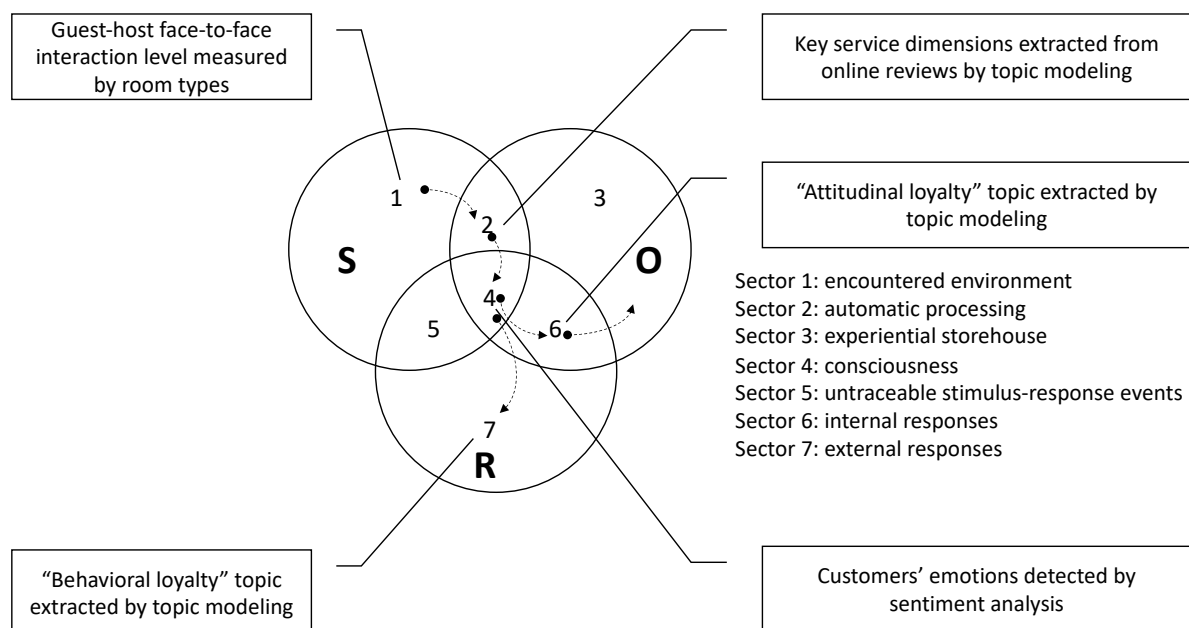


Figure 2. Conceptual framework in this study

Attitudinal loyalty can appear in a guest’s intention to encourage others to try the accommodation-sharing service, which can be assessed in terms of the extent to which a guest recommends the service to others (Donio et al., 2006). The attitudinal loyalty variable in this study measures the prevalence of recommendation-related topics extracted from online reviews.

Recommendation-related topics are similar to eWOM. A satisfactory service encounter leads to positive eWOM; an unsatisfactory encounter causes negative eWOM. As such, Sector 6 would conceptualize eWOM as a response outcome from an individual's moods, perceptions, and cognitions (Sector 4). Behavioral loyalty can manifest in purchase behaviors, including repurchase intention (Lee & Wong, 2021). We define this variable as the desire of a guest to stay in the same place again. The prevalence of revisit intention-related topics extracted from online reviews measures behavioral loyalty (Sector 7).

2.2 Antecedent conditions that influence customer experiences in accommodation sharing

Customer experience in accommodation sharing is one of the areas of SE that has been investigated the most, and “authentic encounter” often emerges as its main component (Cheng, 2016). Guttentag (2015) discovers that accommodation sharing's distinct appeals relate to price, amenities, and authenticity. Ju et al. (2019) reveal that major factors influencing customer satisfaction include host, room/house, location, and neighborhood. Some researchers highlight the importance of economic value in the SE (Böcker & Meelen, 2017; Guttentag, 2015). Although accommodation sharing may cost more than hotels, there are additional benefits, such as a sense of home and travel tips from locals, that traditional hotels do not provide.

Despite the various interpretations, factors that influence customer experience remain vague, requiring a more coherent and comprehensive understanding based on both macro and micro-perspectives. To do so, we analyze a large data set of online reviews from Airbnb to unpack key service dimensions from a micro-perspective and then map them to overarching themes from a macro-perspective. The three overarching themes, namely “Host,” “Amenities,” and “Location” (Cheng & Jin, 2019), characterize the macro-perspective for two reasons. First, the textual reviews yield the three themes, while other themes (e.g., risk perspective) suggested by prior studies may not be as easily extracted. Second, the themes in Cheng and Jin (2019)

are sufficiently generalized to link with previous studies' notable findings. Table 1 organizes the service dimensions that recent studies identify into three themes.

2.3 Configurational approach and fsQCA

Our understanding of how service dimensions affect customer experiences and loyalty has gaps. We suggest that customers rely on different mixtures of dimensions to evaluate their experiences and form loyalty. The literature gives little regard to how service dimensions form configurations of conditions that could substitute for one another as paths to high-level customer loyalty. Insufficient comparisons across different interaction levels compound this difficulty. For example, customers staying in different room types experience diverse interaction mechanisms and may evaluate attributes differently (Lee, 2022). The same factors or configurations of factors will not likely explain the high-level loyalty among customers in different room types. This study aims to identify these configurations.

We apply fsQCA to find combinations of factors that increase loyalty, allowing us to go beyond single-factor explanations. Scholars in tourism recognize the value of fsQCA for gaining insight into the combination patterns of causal factors in simulating outcomes, such as the intention to purchase (Pappas, 2017) and recommendations (Mehran & Olya, 2020). Yet, the measurements and determinations of such intentions as the outcome in fsQCA largely occur through close-ended measures in survey studies. There has been no consistent way to measure intentions, and the potential response bias in surveys makes it difficult to assess the extent to which customers truly mean their intentions.

Compared to using measurement items in surveys to assess customer intentions, extracting them directly from textual reviews offers a relatively unified means of assessment. Customers revealing their intentions explicitly and voluntarily strongly signals their reliability (Liu & Beldona, 2021). Using such words as "I recommend" in an online review suggests that

their satisfaction has reached a point that motivates them to encourage others to follow suit (Guerreiro & Rita, 2020). Zhang and Mao (2012) use regression analysis to identify relationships between hotel attributes and customer intentions to revisit and recommend. They apply content analysis to textual reviews and find that words related to functional attributes (e.g., “room,” “location,” “price”) indicate “customer intention to recommend” and “revisit.” Their content analysis coincides with findings from the regression analysis, suggesting that textual reviews can serve as sources for determining customer intentions. Accordingly, this study not only takes a configurational approach to the empirical analysis, handling the causal complexity inherent in customer loyalty. It also uses reviews to identify the combination patterns of key aspects that can predict high-level customer loyalty, overcoming prior studies’ limitations.

3. Research methodology

Figure 3 shows the four phases of this study’s research methodology. Each phase is explained in detail below.

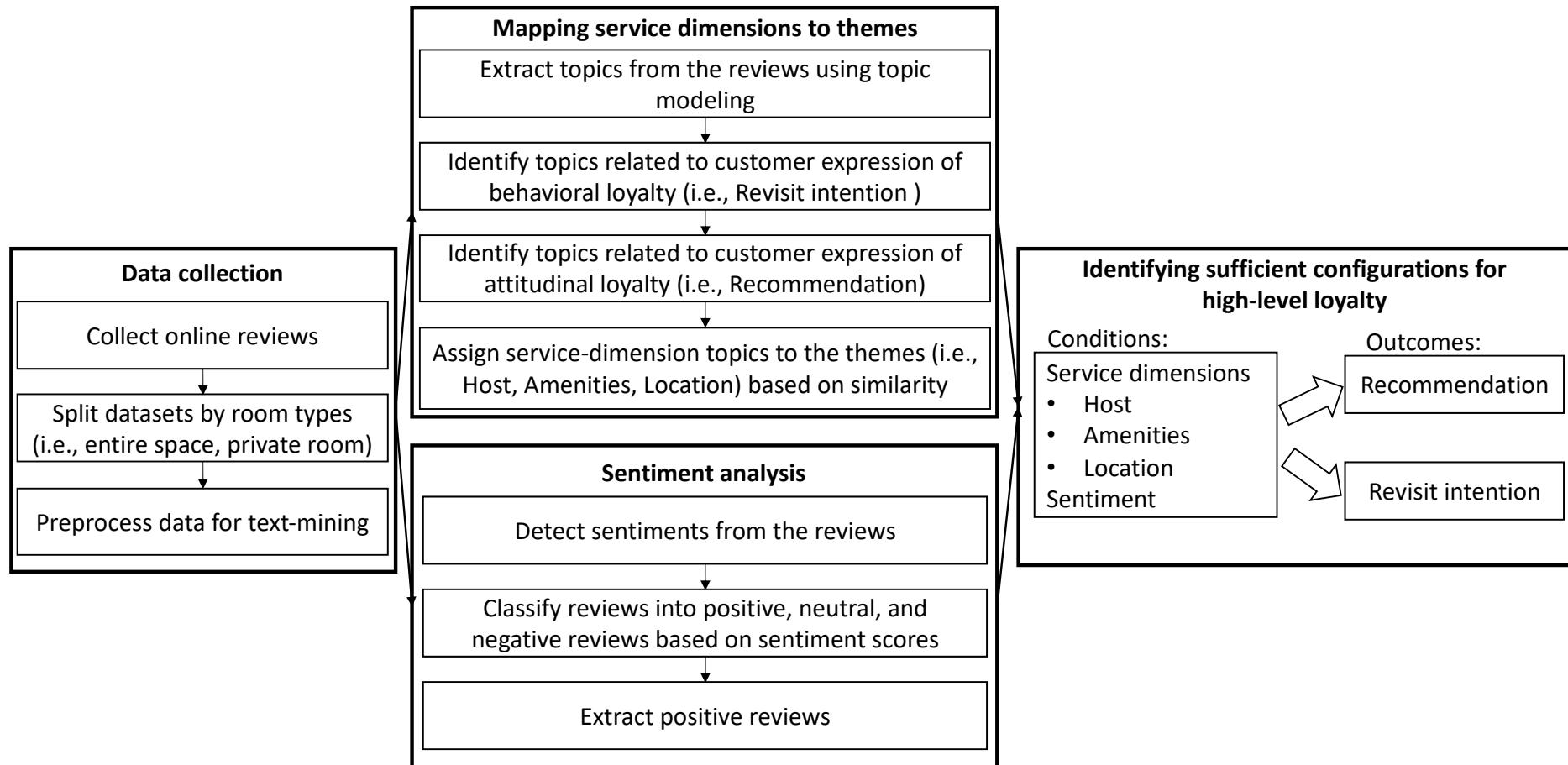


Figure 3. Research methodology

3.1 Data collection

This study uses data from Insideairbnb.com, an independent website that allows access to publicly available information about a city’s Airbnb listings. We chose London because it is one of the most popular cities for tourists and has a large number of registered Airbnb hosts. We retrieved 111,711 online reviews written by guests who used Airbnb services in London from January to April 2020. The listing ID associated with each review was merged with the listing records that reveal room types. We removed non-English reviews and those the Airbnb platform automatically generated because of booking cancellations, leaving 90,586 reviews. We applied sentiment analysis to draw sentiments directly from the reviews and removed reviews without sentiments from the study, leaving 80,602 reviews.

Airbnb offers four room types—Entire Place, Private Room, Shared Room, and Hotel Room—with 40,552, 38,872, 498, and 680 reviews, respectively. We excluded reviews related to hotel rooms because traditional hotel service providers do not participate in the SE. The same was true of reviews related to shared rooms—many were hostel rooms that real estate professionals managed, hence, outside the scope of this study. Notably, the content of shared-room reviews could have been related to guest–guest interactions, which this study did not consider. As a result, only reviews of “entire space” and “private rooms” were within the scope of this study. These two room types were balanced (i.e., 51% “entire space” and 49% “private room”) in our data set. Thus, the models have no bias against either type.

Python executed data pre-processing, such as tokenization and stop-word removal. Subsequently, we used the spaCy en model for lemmatization to connect each word to its dictionary form. In addition, we removed words that do not carry inherent meaning.

3.2 Mapping service dimensions to themes

A service dimension of accommodation sharing can emerge as a latent topic the reviews hide. The distribution of words that customers use in the reviews characterizes each dimension, i.e., “topics.” Latent Dirichlet allocation (LDA) is a state-of-the-art technique used for topic modeling in Airbnb reviews (Lee, 2022). As a generative probabilistic model of a corpus, it considers each document a mixture of latent topics, each characterized by its word distribution (Blei et al., 2003). Since LDA does not make any assumptions regarding the grammatical structure of the text and is efficient in discovering topics from a large number of documents, it is suitable for analyzing Airbnb reviews (Situmorang et al., 2018; Zhang, 2019). This study uses the Gensim library in Python to construct LDA models.

Each topic is identified based on the logical connection among keywords and is then classified into two categories: (i) service dimensions and (ii) outcomes of the service dimensions. The service dimensions are mapped to three overarching themes, namely “host,” “amenities,” and “location,” as identified by Cheng and Jin (2019). The keywords of each service dimension are compared with the keywords of each theme listed in Cheng and Jin (2019, pp. 68–69). The more they have in common, the more similar they are. Each topic is assigned to its most similar theme.

The similarity measure is based on the Jaccard coefficient, which is widely used to assess the overlap between dimensions from two sources, x and y (Guo et al., 2017; Zhang, 2019). The formula for the Jaccard coefficient is:

$$\frac{a}{a + b + c}$$

where a is the number of dimensions that exist in both x and y , b is the number of dimensions that only exist in x and c is the number of dimensions that only exist in y .

3.3 Sentiment analysis

The VADER library in Python incorporates five heuristics for sentiment analysis that make it particularly suitable for social media content. It generates a compound value from -1 to +1 as a measure of sentiment polarity. However, when many words appear in a single review, the value will be close to -1 or +1. To address this, we apply VADER at the sentence level, and the overall sentiment of a review is the average value of all its sentences.

3.4 Identifying sufficient configurations of high-level loyalty

Selecting cases in fsQCA should be purposeful in the sense that they are homogeneous enough to be comparable while maintaining heterogeneity over a minimum number of cases. This study selected only positive reviews because they share enough background characteristics to be comparable within the outcome of interest (i.e., high-level loyalty). Accordingly, we used a total of 70,433 cases for the analysis: 36,760 cases belonged to the “entire space” setting, and 33,673 belonged to the “private room” setting.

The presence of an asymmetrical relationship can warrant the use of fsQCA (Hughes et al., 2019). Table 2 shows the results of the contrarian case analysis, where the bottom left and top right cases (i.e., gray cells in the table) represent the contrarian cases running counter to the main effect. A higher rank for the three service-dimension conditions means guests pay more attention to a given service, as the literature suggests that host, amenity, and location are three important factors driving customer loyalty. Table 2 shows that 41.31% (i.e., 3.96% + 2.96% + 3.90% + 10.54% + 2.51% + 6.34% + 2.72% + 8.38%) of cases rate “host” as less important (i.e., Rank < 3) while making a high-level recommendation (i.e., Rank > 3) or indicate the high-level importance of “host” along with a low-level recommendation. They represent contrarian cases. The percentage of contrarian cases is 44.29% for the relationship between “amenities” and “recommendation” and 44.30% for the relationship between “location” and “recommendation.” Similarly, the percentages of contrarian cases are 32.27%,

30.86%, and 32.97%, respectively, for the relationships between each service-dimension condition and revisit intention.

Table 2 also shows that 24.44% of cases have low-level sentiment polarity with a high-level recommendation or high-level sentiment polarity with a low-level recommendation, running counter to the main positive relationship between sentiment polarity and recommendation. Also, 20.78% of cases have low-level sentiment polarity and high-level revisit intention or high-level sentiment polarity and low-level revisit intention, contrary to the main effect. The mean of all these percentages (i.e., 41.31%, 44.29%, 44.30%, 32.27%, 30.86%, 32.97%, 24.44%, and 20.78%) is 33.90%, meaning that more than one-fourth of the total are contrarian cases, indicating an asymmetrical relationship that calls for fsQCA (Woodside, 2014).

This study used the fsQCA 2.5 software program to conduct fsQCA. We used the direct method that Ragin (2008) suggests to convert values into fuzzy membership values based on the threshold for full membership, the threshold for full non-membership, and the threshold for the crossover point.

4 Results and discussion

4.1 Topics extracted from the reviews

We tried different numbers of topics t until the coherence value c declined. We selected the model with $t = 16$, marking the end of the growth of the coherence scores, as Figure 4 shows. Table 3 summarizes the topics identified from the reviews—three related to customer loyalty. Topic 1 was “come back,” which represents behavioral loyalty. Topics 9 and 16 concern “recommendation,” and they are grouped together to represent attitudinal loyalty. One of the significant differences between them is that the word “host” ranks second in the keyword list

for Topic 9 but 11th for Topic 16. This indicates that Topic 9 is more relevant to the host recommendation, while Topic 16 is more relevant to the Airbnb listing recommendation.

Figure 5 shows the inter-topic distance map. A circle represents a topic, while the circle's size is proportional to the topic's relative prevalence. Having relatively large circles with limited overlapping areas throughout the map could indicate a good LDA model.

Circles overlap when common keywords are associated with the topics. For instance, the overlap between Topics 10 and 15 can be justified because both topics relate to the host's behavior; hence, the existence of common keywords. Another interesting observation is that Topic 16 significantly overlaps with Topic 11, which relates to the cleanliness and comfort of the Airbnb listing. This result shows that the recommendation within Topic 16 emphasizes the Airbnb listing itself, further reinforcing our abovementioned observations regarding the differences between Topics 9 and 16. Since most overlapping areas have logical explanations, we chose the LDA model with $t = 16$ for this study.

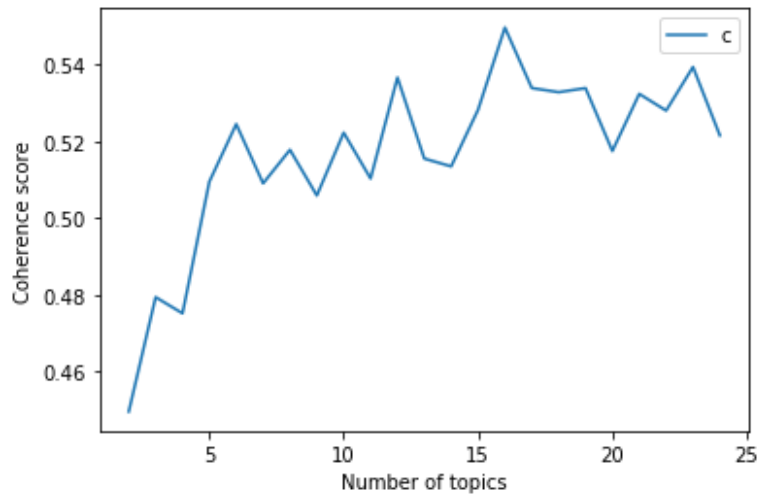


Figure 4. LDA model performance in terms of coherence score

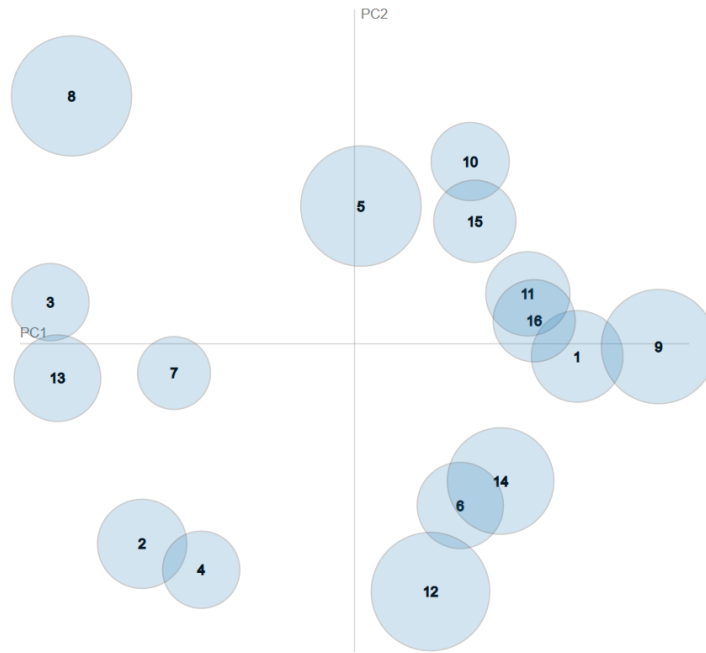


Figure 5. Visualization of topic linkages

We then grouped topics related to service dimensions into three themes: host, amenities, and location. Table 4 shows the similarities between topics and themes based on the Jaccard coefficient. Based on the similarity measures, we assigned seven topics to the “Amenities” theme: “Room space,” “Facilities,” “Well-equipped,” “Value for money,” “Picture description,” “Cleanliness and comfort,” and “Shower issue and noise at night.” We assigned four topics to the “Host” theme: “Sense of home,” “Check-in/out arrangement,” “Hospitality,” and “Responsiveness.” We assigned two topics to the “Location” theme: “Transport” and “Easy to access.”

4.2 Detection of customer sentiments from the reviews

The compound value that VADER returns grows according to increases in sentiment. Using -0.05 and 0.05 as the cutoff points, it classifies the sentiment into negative, neutral, and positive. Verification entails comparing it against customer rating, a unidimensional rating from 0 to 100 that guests register when they post a review, reflecting their overall satisfaction.

Figure 6 shows that for the reviews with relatively higher ratings (over 75), the compound scores are generally higher. On the other hand, for the reviews with relatively lower ratings (below 40), the compound scores are mostly negative, meaning that the associated sentiments are negative, showing our VADER model's reliability.

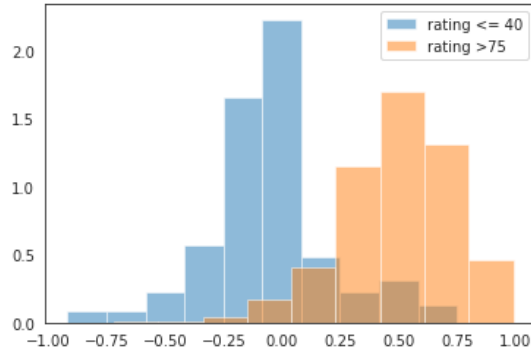


Figure 6. Compound values and the unidimensional customer ratings of the reviews

4.3 Configurational analysis

In fsQCA, the values of the three thematic causal conditions and the two outcomes are the prevalence of the mapped topics determined by LDA. In addition, the value of the sentiment causal condition is the compound value VADER returns. Statistical information can serve for calibration (Park & Mithas, 2020). The original values that cover 5%, 25%, and 50% of the data values are set as the point of full non-membership, the crossover point, and the point of full membership, respectively. For “Host” and “Amenities,” the values that cover 5%, 10%, and 25% of the data values are used. Tables 5 and 6 are the truth tables for high-level recommendation and revisit intention for different room types when the consistency threshold is set at 0.8.

Tables 7 and 8 summarize the results. In fsQCA, conditions may be present in a configuration (denoted by ●), absent (denoted by ⊗), or labeled “do not care” (denoted by ○). The solution coverage refers to the extent to which the configurations can explain the outcome.

A value above 0.7 means that our solutions cover a substantial percentage of the outcome. Given the impact of the consistency threshold on the configuration results, we performed a sensitivity analysis by changing the consistency threshold. When generating the configurations for “high recommendation” in the case of “entire space,” the results are the same when the consistency threshold is set between 0.78 and 0.84. When generating the configurations for “high revisit intention” in “entire space,” there is no difference in the final results when the consistency threshold is increased up to 0.87. While the QCA literature suggests the minimum threshold value to be above 0.8, in this case, lowering the threshold has no impact on the results because all the raw consistency values, as the truth table shows, are above 0.8. When generating the configurations for “high recommendation” and “revisit intention” in the “private room” setting, the consistency threshold can be increased up to 0.81 and 0.91, respectively, without affecting the results. In these two cases, lowering the threshold to below 0.8 also has no impact on the results; all the raw consistency values are above 0.8.

Our results confirm the conjunction and equifinality inherent in the complex formation of customer loyalty in accommodation sharing. We find that the joint presence and absence of service dimensions and positive sentiment can generate high-level customer loyalty. For instance, high scores for “host” combined with “location” generate high customer loyalty (configurations PA1 and PB2). This kind of configuration can function as a causal recipe that guides the hosts in creating the conditions that result in loyal customers.

Further, alternative solutions can lead to the same outcome. For instance, in an “entire space” setting, the presence of “location” can be combined with the absence of “amenities” (configuration EA1) or “host” (configuration EA2) or the presence of positive sentiment (configuration EA3) to generate high-level recommendations. However, our results reveal that the solutions differ depending on room type, suggesting that guests facing different interaction mechanisms would evaluate attributes differently and require different causal conditions to

generate loyalty. For instance, the presence of “location” can generate high revisit intention in the “entire space” setting (configuration EB1), but it is not sufficient to generate the same outcome in the “private room” setting. Guests who prefer staying in a private room are more inclined to engage with hosts; hence, “hosts’ behavior” appears as a dominant aspect in the evaluation. According to our results, both “location” and “host” should be present in order to generate high revisit intention in the “private room” setting.

“Location” is present in all the configurations. This result contradicts previous studies suggesting that locational benefits are insignificant in affecting customer satisfaction and the future intention to use accommodation sharing (Tussyadiah, 2016). Some studies claim that guests are well informed that accommodation sharing occurs in residential areas, implying that locational benefits, such as closeness to food and beverage establishments, bars, and shops, would be lower than stays in areas where hotels predominate. Yet, from a micro-perspective, our study considers locational benefits in terms of the ease of access to the property and public transport connectivity. Our results show that guests tend to evaluate these two locational benefits when they recommend the place or express the intention to revisit it. This finding could indicate that the density of buildings in residential areas is higher than in hotel areas; hence, finding suitable listings in residential areas has challenges. Moreover, accommodation-sharing services do not have a front desk or receptionist to answer guests’ navigation inquiries, explaining the importance of convenient transportation to the location.

5. Implications and conclusion

5.1 Theoretical implications

This study extends the conventional S-O-R model by going beyond its linear sequence to explain the complexity and dynamic interrelationships among causal factors related to customer loyalty. Unlike most previous studies that used survey results to examine the linear

effect of individual factors, we integrate social media analytics and fsQCA to obtain valuable insights into customer loyalty in accommodation sharing. Our findings show that the causal recipes for attitudinal and behavioral loyalty differ under various sharing mechanisms. We expand upon previous studies that debate customer behavior but rarely differentiate between the attitudinal and behavioral components of customer loyalty.

Further, unlike studies that consider accommodation sharing as a single service, regardless of interaction levels, we categorized accommodation-sharing services based on the level of sharing. Our results show that guest evaluations depend on the interaction level, which may seem straightforward but confirms a significant drawback of many existing studies that assume customer expectation and behavior in the SE to be independent of sharing level. In contrast, we provide a foundation for understanding customer behavior in accommodation sharing by identifying the combination patterns of causal conditions in creating customer loyalty following the level of sharing. Our findings are in the form of configurations that “contrast from the types of insights that one can gather by relying only on insights from the conventional econometric approaches that focus on the effect of just one or two causal variables, and how a unit change in them may affect a certain performance outcome” (Park & Mithas, 2020, p. 104).

5.2 Managerial implications

This study reveals the configurations of conditions that can explain recommendation (attitudinal loyalty) and intention to revisit (behavioral loyalty) in accommodation-sharing customer reviews. Though we understand that delivering a service and improving customer sentiments can help retain customers, individual accommodation-sharing hosts are not professional service providers and, thus, usually have fewer resources for improving services.

As a result, it is crucial for them to prioritize resources and focus more on the key service dimensions (order winners) that most affect customer loyalty.

The findings suggest two distinct market segments with different focuses during service evaluation. In contrast to those who physically share space with hosts, guests renting an entire space do not focus much on the “host” aspect in their evaluations. Hosts need to offer this guest segment a friendly and private atmosphere where they can avoid social interactions and avoid unnecessarily checking up on them during the day (Farmaki & Stergiou, 2019). On the other hand, for guests who share their living space, hosts can put more effort toward a flexible check-in/out, hospitality standards, responsiveness, and creating a sense of home.

5.3 Conclusion

This study examines the complex underpinnings of customer loyalty in accommodation sharing, specifically the level of face-to-face interactions between guests and hosts, and offers theoretical and methodological innovations. From a theoretical perspective, this study provides an understanding of customer loyalty in the SE, taking a configurational point of view to overcome the drawbacks of prior studies. To improve the explanatory power of customer loyalty, we delineate its two major components: attitudinal and behavioral loyalty. Built upon the advanced S-O-R model, this study reveals that the combinations of factors that lead to attitudinal loyalty differ from those leading to behavioral loyalty, with novel results.

From a methodological perspective, this study integrates social media analytics and fsQCA to identify important service dimensions and customer intentions from user-generated content. Currently, fsQCA remains a relatively new method in the domain of information systems. It is more prevalent in social sciences and marketing, where data for fsQCA are mainly drawn from surveys, interviews, and vignette-based experiment. Although secondary data are becoming more popular for fsQCA studies, most are structured data. Our study demonstrates

using unstructured data to identify important conditions and outcomes for fsQCA. As all the variables used in fsQCA are data-driven, researchers from other domains can easily adopt our methodological framework.

The study has two limitations. First, the data used were limited to Airbnb reviews from London in 2020, and factors leading to customer loyalty in our context have poor generalization potential across other contexts. Thus, our findings cannot be directly applied to other contexts without exercising caution. Second, although this study focuses on positive reviews, negative reviews may reveal critical factors that damage customer loyalty. One future research direction is to examine negative reviews, applying our methodology but using low-level loyalty as the outcome of interest and comparing results.

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List of Tables

Table 1. Accommodation-sharing service dimensions in the existing literature

Themes (macro-level)	Service dimensions (micro-level)	References
Host	Problem-solving features (i.e., helpfulness, communication, responsiveness)	Ju et al. (2019), Lee et al. (2019), Situmorang et al. (2018), Zhang (2019), Zhu et al. (2019)
	Friendly, pleasant, and welcoming host who provides a sense of home and offers fresh snacks, breakfast, or tea	Lee et al. (2019), Situmorang et al. (2018), Zhang (2019), Zhu et al. (2019)
	Social connection (i.e., guest–host relationship, interaction and engagement, local tips from hosts)	Guttentag (2015), Situmorang et al. (2018), Xu (2020)
	Flexibility of check-in/out arrangement	Lee et al. (2019), Sutherland and Kiatkawsin (2020), Zhang (2019)
Amenities	Household amenities	Guttentag (2015), Lee et al. (2019), Situmorang et al. (2018), Xu (2020)
	Less expensive but suitable amenities (i.e., value for money)	Tussyadiah (2016)
	Cleanliness and comfort	Lee and Tse (2021), Sutherland and Kiatkawsin (2020), Zhang (2019)
	Animal / Pet	Sutherland and Kiatkawsin (2020), Zhu et al. (2019)
	Picture description and accuracy	Sutherland and Kiatkawsin (2020)

Location	Safe neighborhood	Ju et al. (2019), Sutherland and Kiatkawsin (2020), Zhu et al. (2019)
	Public transport connectivity	Ju et al. (2019), Lee and Tse (2021), Zhang (2019)
	Shops and restaurants	Situmorang et al. (2018), Zhang (2019)
	Convenience and easy-to-find	Situmorang et al. (2018), Zhu et al. (2019)

Table 2. Results of the contrarian case analysis

		Recommendation								Revisit Intention					
		Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Total			Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Total
Host	Rank 1	0.32%	5.83%	1.74%	3.96%	2.96%	14.81%	Host	Rank 1	7.13%	0%	3.56%	0.58%	3.53%	14.81%
	Rank 2	0.22%	7.78%	3.75%	3.90%	10.54%	26.19%		Rank 2	0.45%	0%	17.67%	2.35%	5.73%	26.19%
	Rank 3	1.72%	5.58%	4.17%	4.22%	3.71%	19.39%		Rank 3	8.80%	0%	3.18%	3.20%	4.21%	19.39%
	Rank 4	2.51%	6.34%	3.97%	4.14%	2.32%	19.28%		Rank 4	9.72%	0%	4.03%	1.73%	3.81%	19.28%
	Rank 5	2.72%	8.38%	4.57%	3.99%	0.66%	20.33%		Rank 5	10.36%	0%	5.09%	1.88%	3.00%	20.33%
	Total	7.49%	33.91%	18.21%	20.21%	20.19%	100%		Total	36.46%	0%	33.52%	9.75%	20.27%	100%
		Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Total			Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Total
Amenities	Rank 1	0.42%	5.86%	1.75%	4.81%	6.90%	19.75%	Amenities	Rank 1	5.16%	0%	8.32%	0.47%	5.80%	19.75%
	Rank 2	1.10%	3.83%	3.99%	3.74%	6.97%	19.64%		Rank 2	5.93%	0%	5.57%	3.43%	4.71%	19.64%
	Rank 3	2.11%	6.21%	3.59%	4.60%	3.95%	20.45%		Rank 3	8.92%	0%	5.38%	1.71%	4.44%	20.45%
	Rank 4	2.39%	7.18%	4.15%	3.95%	2.37%	20.03%		Rank 4	9.17%	0%	5.49%	1.87%	3.50%	20.03%
	Rank 5	1.46%	10.83%	4.73%	3.10%	0.00%	20.13%		Rank 5	7.28%	0%	8.77%	2.27%	1.82%	20.13%
	Total	7.49%	33.91%	18.21%	20.21%	20.19%	100%		Total	36.46%	0%	33.52%	9.75%	20.27%	100%
		Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Total			Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Total
Location	Rank 1	0.00%	1038%	2.88%	7.70%	6.88%	27.83%	Location	Rank 1	9.92%	0%	9.21%	1.03%	7.67%	27.83%

	Rank 2	0.03%	5.08%	0.37%	2.09%	5.51%	13.08%		Rank 2	0.04%	0%	10.00%	0.03%	3.01%	13.08%
	Rank 3	1.90%	1.88%	7.04%	2.78%	5.48%	19.07%		Rank 3	5.27%	0%	4.26%	5.98%	3.56%	19.07%
	Rank 4	3.54%	6.22%	4.30%	4.33%	1.86%	20.26%		Rank 4	11.13%	0%	3.63%	1.64%	3.86%	20.26%
	Rank 5	2.01%	10.35%	3.62%	3.32%	0.47%	19.76%		Rank 5	10.10%	0%	6.43%	1.07%	2.17%	19.76%
	Total	7.49%	33.91%	18.21%	20.21%	20.19%	100%		Total	36.46%	0%	33.52%	9.75%	20.27%	100%
		Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Total			Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Total
Sentiment	Rank 1	2.90%	8.22%	4.22%	3.01%	1.65%	20.00%	Sentiment	Rank 1	9.75%	0%	5.50%	2.05%	2.70%	20.00%
	Rank 2	2.00%	7.30%	4.21%	4.08%	2.41%	20.00%		Rank 2	8.73%	0%	5.54%	1.83%	3.90%	20.00%
	Rank 3	1.44%	6.25%	4.14%	4.43%	3.74%	20.00%		Rank 3	7.68%	0%	5.83%	2.04%	4.45%	20.00%
	Rank 4	0.80%	5.91%	2.98%	4.43%	5.87%	20.00%		Rank 4	6.04%	0%	7.02%	2.56%	4.37%	20.00%
	Rank 5	0.35%	6.23%	2.66%	4.26%	6.51%	20.00%		Rank 5	4.25%	0%	9.64%	1.26%	4.85%	20.00%
	Total	7.49%	33.91%	18.21%	20.21%	20.19%	100%		Total	36.46%	0%	33.52%	9.75%	20.27%	100%

Table 3. Topics identified from the reviews

Topic number	Topic name	Topic keywords
1	Come back (Revisit intention)	Nice, place, clean, host, back, super, really, stay, come, room
2	Room space	Room, bathroom, kitchen, clean, large, bedroom, big, share, small, nice
3	Facilities (such as towel, floor, and window)	Flat, work, new, bedroom, well, towel, stay, need, floor, unit
4	Well-equipped	Well, flat, bed, locate, equip, kitchen, comfortable, bedroom, quiet, area
5	Sense of home	Home, stay, feel, make, place, time, go, need, want, day
6	Value for money	Good, place, great, value, stay, nice, clean, money, communication, apartment
7	Picture description	Picture, price, look, exactly, place, expect, photo, room, bit, quite
8	Check-in/out arrangement	Host, day, check, time, apartment, leave, say, Airbnb, get, night
9	Recommendation	Great, host, location, recommend, stay, place, highly, clean, amazing, lovely
10	Hospitality	Touch, thank, lovely, host, stay, hospitality, thoughtful, coffee, tea, little
11	Cleanliness and comfort	Stay, enjoy, lovely, apartment, clean, comfortable, thank, place, definitely, check

12	Transport	Station, close, walk, minute, tube, bus, show, restaurant, place, stay
13	Shower issue and noise at night	Shower, bed, door, problem, location, noise, bit, issue, fine, work
14	Easy to access	Great, easy, location, check, apartment, access, stay, perfect, flat, restaurant
15	Responsiveness	Quick, host, respond, question, check, stay, quickly, response, apartment, always
16	Recommendation	Really, stay, great, perfect, place, location, recommend, time, enjoy, nice

Table 4. Similarity measures between service-dimension topics and themes

Service Dimension	Amenities	Host	Location*
Room space	0.24	0	0
Facilities, such as towels, floor, and windows	0.13	0	0.02
Well-equipped	0.2	0	0.02
Sense of home	0.03	0.08	0.02
Value for money	0.13	0.03	0
Picture description	0.06	0	0
Check-in/out arrangement	0.03	0.05	0.02
Hospitality	0.03	0.06	0.02
Cleanliness and comfort	0.10	0.03	0
Transport	0.03	0	0.13
Shower issue and noise at night	0.10	0	0.05
Easy to access	0.03	0.03	0.05
Responsiveness	0.03	0.05	0

**“shops” and “restaurants” from the theme are converted to “shop” and “restaurant” for mapping to our LDA results*

Table 5. Truth table for high-level recommendation and revisit intention in “entire space”

Host	Amenities	Location	Sentiment	Number	Recommendation	Raw Consistency
0	0	1	0	35	1	0.977
0	0	1	1	177	1	0.976
1	0	1	1	2,099	1	0.926
1	0	1	0	487	1	0.926
0	1	1	1	1,698	1	0.906
0	1	1	0	634	1	0.883
1	1	1	1	23,947	1	0.849
1	1	1	0	7,683	0	0.777
Host	Amenities	Location	Sentiment	Number	Revisit Intention	Raw Consistency
0	0	1	0	35	1	0.961
0	0	1	1	177	1	0.937
1	0	1	0	487	1	0.934
0	1	1	0	634	1	0.900
1	1	1	1	23,947	1	0.898
1	0	1	1	2,099	1	0.893
1	1	1	0	7,683	1	0.883
0	1	1	1	1,698	1	0.879

Table 6. Truth table for high-level recommendation and revisit intention in “private room”

Host	Amenities	Location	Sentiment	Number	Recommendation	Raw Consistency
1	0	1	0	431	1	0.956
1	0	1	1	2,014	1	0.941
1	1	1	1	23,574	1	0.864
1	1	1	0	7,654	1	0.818
Host	Amenities	Location	Sentiment	Number	Revisit Intention	Raw Consistency
1	0	1	0	431	1	0.956
1	1	1	1	23,574	1	0.931
1	0	1	1	2,014	1	0.927
1	1	1	0	7,654	1	0.915

Table 7. Sufficient configurations for a high-level recommendation of the service

Room type		Outcome: Recommendation (Attitudinal loyalty)		
		EA1	EA2	EA3
Entire space	Configuration	EA1	EA2	EA3
	Host	○	⊗	○
	Amenities	⊗	○	○
	Location	●	●	●
	Positive sentiment	○	○	●
	Raw coverage	0.143	0.146	0.683
	Unique coverage	0.013	0.019	0.454
	Consistency	0.891	0.875	0.823
	Solution coverage	0.717		
	Solution consistency	0.817		
Private room	Configuration	PA1		
	Host	●		
	Amenities	○		
	Location	●		
	Positive sentiment	○		
	Raw coverage	0.829		
	Unique coverage	0.829		
	Consistency	0.807		
	Solution coverage	0.829		
	Solution consistency	0.807		

Table 8. Sufficient configurations for high revisit intention

Room type		Outcome: Revisit intention (Behavioral loyalty)
Entire space	Configuration	EB1
	Host	○
	Amenities	○
	Location	●
	Positive sentiment	○
	Raw coverage	0.817
	Unique coverage	0.817
	Consistency	0.796
	Solution coverage	0.817
	Solution consistency	0.796
Private room	Configuration	PB1
	Host	●
	Amenities	○
	Location	●
	Positive sentiment	○
	Raw coverage	0.824
	Unique coverage	0.824
	Consistency	0.882
	Solution coverage	0.824
	Solution consistency	0.882