What have hosts overlooked for improving stay experience in accommodation-sharing? Empirical evidence from Airbnb customer reviews

Purpose – In accommodation-sharing, hosts must provide satisfactory stay experiences for guests, who will then express intentions to re-visit (behavioral loyalty) and/or recommend the experiences to others (attitudinal loyalty) in their reviews. Through the lens of expectation-confirmation theory, this study investigates the service dimensions customers focus on in their reviews and their relationships with customer-loyalty manifestations in accommodation-sharing.

Design/methodology/approach – This study uses topic modelling to discover distinctive dimensions from Airbnb reviews from a micro perspective and map them onto overarching themes from a macro perspective, and further examines the relationships among topics using cluster analysis.

Findings – This study reveals "information" as an important theme rarely mentioned in the literature. Besides, "homeliness" is a unique dimension associated with behavioral and attitudinal loyalty toward accommodation-sharing.

Practical implications – The findings help accommodation-sharing platforms and hosts identify customer concerns and the drivers of customer loyalty in accommodation-sharing.

Originality – In the existing literature, customer perceptions and loyalty are largely determined through surveys, and the findings are not univocal due to the inconsistencies of measurement items used, the potential response bias, and limited sample sizes. This study capitalizes on the wealth of user-generated content, and extracts service dimensions and customer loyalty directly from textual reviews, overcoming previous research limitations.

Keywords – accommodation-sharing, sharing economy, expectation-confirmation theory, customer behavior, online review, text-mining

Paper type – Research paper

1. Introduction

The sharing economy (SE) uses online platforms to connect people wishing to share underutilized resources (Mody *et al.*, 2021). In recent decades, the SE has entered the hospitality sector, opening opportunities for popular start-ups, such as Airbnb, that offer accommodation-sharing (Godovykh *et al.*, 2022; Kim *et al.*, 2022). It has been estimated that online platforms enabling accommodation-sharing will generate revenues of over $100 billion by 2025 (Olson and Kemp, 2015).

Accommodation-sharing has three characteristics that separate it from the traditional hotel industry. First, it emphasizes unique local experiences by connecting with residents (De Canio *et al.*, 2020; Gassmann *et al.*, 2021), which contrasts with hotels where establishing social interactions with guests is not the intent (Lin *et al.*, 2019). Second, accommodation-sharing's targeted customers are those seeking to feel at home during their stay (Liu and Mattila, 2017; Zhu *et al.*, 2019). Sigala (2017, p. 353) described homely feelings as "something that one can never buy or get in the traditional tourism industry." Third, compared to hotels, accommodation-sharing is less standardized, as service providers are individual peers, not professional providers (Tussyadiah and Zach, 2017). Consequently, customers who choose accommodation-sharing experience different decision-making processes than those who use traditional hotels. One cannot understand the important service dimensions of stay experiences in accommodation-sharing from traditional tourism research, which in turn highlights the need to reconsider and update the distinctive dimensions of customer experiences in the SE.

Although user-generated content (UGC), such as customer reviews, is a valuable for identifying customer preferences, survey-based studies remain the norm for identifying dimensions of customer experiences (e.g., So *et al.*, 2022). However, findings from relevant surveys are not univocal. For instance, while Tussyadiah and Pesonen (2016) reported that social interactions drive customers to accommodation-sharing, Tussyadiah (2016) discovered that there are customers avoiding social interactions on purpose. These mixed findings could result from inconsistent measurement items used in surveys as well as limited sample sizes. To overcome these deficiencies, this study leverages a large amount of customer reviews to extract important service dimensions in accommodation-sharing. Accordingly, our first research question is: *What are the distinctive dimensions on which customers focus in their reviews of accommodation-sharing?*

Unlike chain-hotels, accommodation-sharing providers typically have fewer resources. Therefore, it is imperative that they prioritize resources and focus on the key service dimensions (order winners) that most affect customer satisfaction, which in turn boosts customer loyalty (Kim, 2019). Customer loyalty consists of attitudinal and behavioral components (Tabaku and Kruja, 2019). The former can be manifested in a customer's intention to recommend an SE service to other customers (Bloemer and de Ruyter, 1999), while the latter can be reflected in purchase behaviors, including the intention to reuse an SE service. To help service providers identify the key dimensions linked with attitudinal and behavioral loyalty, we formulated our second research question: *Which dimensions often co-occur with recommendation (attitudinal loyalty) and intention to re-visit (behavioral loyalty) in customer reviews of accommodation-sharing?*

To date, attention has focused largely on the study of motivations of service providers and customers as well as their satisfaction with the SE experience, whereas little focus has been on the link between service dimensions and customer loyalty. Despite the importance of building long-lasting relationships with customers to realize shared consumption in the SE, the notion of customer loyalty in the SE remains ambiguous (Shuqair *et al.*, 2019). Prior studies have been conducted to extract important service-dimension topics from customer reviews, providing useful insights for us to understand customer expectations in accommodation-sharing. Customers are generally satisfied when their expectations are confirmed. Nevertheless, from the perspective of service providers and SE platforms, what they want to achieve is not merely satisfied customers, but loyal customers. Only when customers express intention to revisit (behavioral loyalty) and/or recommend the stay to others (attitudinal loyalty), shared consumption can be realized and SE businesses can be sustained (Kim, 2019).

The purpose of this study is to capitalize on the wealth of UGC to identify topics related to loyalty directly from the reviews themselves, and investigate how they are related to other service-dimension topics based on the co-occurrence of relevant keywords. Service providers and SE platforms can shift more attention to improve service dimensions that are closely linked with loyalty. Although some SE companies, such as Airbnb, have created significant success, some are struggling and losing customers (Jia *et al.*, 2020). By empirically examining Airbnb customers' experiences directly from the reviews, this study provides useful findings that help service providers and SE platforms understand customer concerns and prioritize resources for loyalty formation.

2. Literature Review

2.1 Theoretical background

We use expectation-confirmation theory (ECT) as our theoretical basis. It posits that customer satisfaction is determined by pre-purchase expectation, and confirmation of said expectation following the product or service's actual consumption (Oliver, 1980). During consumption, customers develop perceptions of the product or service's performance. They evaluate the perceived performance against their prior expectations to identify the extent to which these are confirmed. Eventually, they form a level of satisfaction based on the confirmation of expectation, which is an essential part of shaping customer loyalty (Kim, 2019).

ECT has been widely used in information system research to explain customer behavior. Bhattacherjee (2001) proposed that an individual's intention to continue information technology (IT) usage is dependent on satisfaction, expectation confirmation, and post-adoption expectation in the form of perceived usefulness. Lee *et al*. (2010) extended ECT by including the user's behavioral intention to adopt IT, and contextualized ECT in e-learning. Moreover, some scholars shifted their focus to marketing and service research. Tsao (2013) used ECT to explain customers' impulsive purchases of products promoted by showgirls in exhibits. Fu *et al*. (2018) integrated ECT and satisfaction-loyalty theory to examine customer loyalty to public transit. We should note that, in service research, customer loyalty is often associated with service quality (Lalicic and Weismayer, 2018), which is operationalized as a gap between a service's expectation and actual perception. Jia *et al*. (2020) is one of the few studies to have used ECT in the SE context. Through the theoretical lens of ECT, they investigated customer perception of how an SE service meets their demand, and how to maintain platform loyalty. While their results demonstrated ECT's role in explaining customer behavior, their context was limited to bike-sharing. According to Constantiou *et al*. (2017), there are fundamental differences between bike-sharing and other SE services in terms of rivalry between platform participants and the control exerted by platform owners. Consequently, the existing literature's findings cannot sufficiently advance our knowledge of customer behavior in other SE contexts, and the need remains to expand ECT to other SE contexts.

2.2 Customer reviews and behaviors in the SE

With the advent of online platforms, customers can now easily share their travel experiences and opinions on service quality. This provides researchers with an effective alternative for understanding consumer evaluation of service quality—especially compared to conventional survey methods. UGC, such as online reviews, are invaluable data sources for service providers to understand customer expectation and satisfaction. Drawing upon ECT, customers' SE service expectations influence perceived quality, which in turn affects satisfaction. If hosts can capitalize on the wealth of online reviews to identify the contributory factors of positive stay experiences, they can prioritize resources to align with customer expectations, and foreground the quality of the key service aspects that most explain customer behavior.

Recently, more researchers have started identifying service dimensions from customer reviews. Lee and Tse (2021) analyzed Airbnb reviews using topic modelling to identify service attributes, such as homeliness, transport, restaurants and shops, check in/out, cleanliness, bed and sleep quality, physical amenities, hot water, and host responsiveness. They applied sentiment analysis and closely examined negative reviews so as to identify areas for service improvement. Zhang (2019a) compared Airbnb and hotel reviews, and identified unique topics for the former, including late check-in, patio and deck view, kitchen supplies, host helpfulness and response, door lock/key, and sleep/bed condition. In a later study, Zhang (2019b) identified a further 16 topics. However, different researchers identify different topics. One reason for this is that text-mining approaches are exploratory, meaning that topics are discovered without explicit expectations. Besides, we acknowledge that a larger number of topics does not always mean more service dimensions. Instead, certain topics may be granular sub-topics, which could be combined to form a main theme. In fact, when identifying service areas for improvement, from a practical perspective, it is easier and more effective for hosts to focus on a few main themes rather than a large set of different topics. Hence, merging topics into larger themes or concepts may be useful. For instance, based on the words in Airbnb reviews, Brochado *et al*. (2017) identified eight themes, namely stay, host, place, location, apartment, room, city, and home. Sutherland and Kiatkawsin (2020) found 43 topics, which they merged into 4 aspects: evaluation, location, accommodation unit, and management. Lee (2022) identified 20 topics from Airbnb reviews, and mapped them into the 4 customer value dimensions.

Table 1 summarizes the service dimensions of accommodation-sharing discussed in existing studies. Based on the inherent meaning of each dimension, we categorize them into three overarching themes: host, amenities, and location. This categorization scheme is in line with Cheng and Jin (2019), Ju *et al*. (2019), and Tussyadiah and Zach (2017), among others. Cheng and Jin (2019) used content analysis to identify four major themes within Airbnb reviews, namely location, amenities, host, and recommendation. While recommendation is a theme, Cheng and Jin (2019) did not consider it a service dimension, but rather the outcome of the other three themes. Ju *et al*. (2019) analyzed 16,430 online reviews and generated a list of Airbnb's service quality attributes. These attributes were largely from four themes: host, room/house, location, and neighborhood. Similarly, Tussyadiah and Zach (2017) explored online reviews' key content and themes to explain the major service dimensions of accommodation-sharing sought by guests. They found that the most frequently mentioned dimensions were associated with location, host, and property.

Table 1. Service dimensions in accommodation-sharing in existing literature

Themes	Service dimensions	References
Host	Help from host	Ju *et al*. (2019), Lee *et al*. (2019), Situmorang *et al*. (2018), Zhang (2019a, 2019b), Zhu *et al*. (2019)
	Socialization and interaction	Lalicic and Weismayer (2018), Moon *et al*. (2019), Xu (2020)
	Check-in/out arrangement	Lee (2022), Sutherland and Kiatkawsin (2020), Zhang (2019a, 2019b)
Amenities	Household facilities	Lee *et al*. (2019), Wang and Jeong (2018), Xu (2020), Zhang (2019b)
	Value for money	Lee (2022), Liang *et al*. (2018), Ranjbari *et al*. (2020), Tussyadiah (2016)
	Housekeeping	Lee and Tse (2021), Sutherland and Kiatkawsin (2020), Zhang (2019a, 2019b)
	Pet	Sutherland and Kiatkawsin (2020), Zhu *et al*. (2019)
Location	Neighborhood safety	Ju *et al*. (2019), Sutherland and Kiatkawsin (2020), Zhu *et al*. (2019)
	Transport	Ju *et al*. (2019), Lee and Tse (2021), Zhang (2019a)
	Shops and restaurants	Lee (2022), Zhang (2019a)
	Convenience	Situmorang *et al*. (2018), Zhu *et al*. (2019)

2.3 Customer loyalty in the SE

Owning to the intense competition in the hospitality industry, scholars have suggested service providers focusing on developing long-lasting relationships with customers (Tajeddini *et al*., 2022). In the SE, customers can easily switch to conventional lodging facilities (Mody *et al*., 2022). Hence, fostering customer loyalty is crucial for both hosts and SE platforms as it leads to shared consumption and positive WOM (Kim, 2019).

There is an academic consensus that customer satisfaction and service quality are prerequisites of customer loyalty (Kandampully and Suhartanto, 2000). In the case of Airbnb, Kim (2019) found that customer loyalty is jointly shaped by customer satisfaction and trust. Some studies, on the other hand, have questioned the robustness of the relationship between customer satisfaction and loyalty, and have suggested that other service dimensions may play a role in loyalty formation (Skogland and Siguaw, 2004). Lalicic and Weismayer (2018) found that service quality, and social and authentic experiences, are significant antecedents of customer loyalty toward Airbnb. Lee and Kim (2018) revealed that hedonic value has a positive impact on satisfaction and loyalty of Airbnb users while utilitarian value influences only on satisfaction. While relevant existing studies provide useful insights regarding customer loyalty in the SE, the results are mixed. For instance, Lalicic and Weismayer (2018) found that perceived economic benefits have no impact on the level of loyalty to an Airbnb. On the other hand, Liang et al. (2018) revealed that price sensitivity does increases behavioral loyalty. These contradictory findings could be due to surveys' inconsistent measurement items, the potential response bias, and limited sample sizes. Although there are studies leveraging a large amount of customer reviews to overcome these limitations, they mainly focused on extracting service-dimension topics (e.g., Lee, 2022; Tussyadiah and Zach, 2017). The link between service dimensions and customer loyalty is underdiscussed. Cheng and Jin (2019) analysed Airbnb reviews and extracted service themes and recommendations. Their analysis showed that location and host have greater influence over Airbnb users' recommendations that can be used as proxies of attitudinal loyalty. Yet, previous studies asserted that it is inadequate to explain customer loyalty when behavioral loyalty is ignored (Watson IV *et al*., 2015). In hospitality, there are instances when customers do not make a hotel reservation but still hold a favorable attitude toward the hotel (Toh *et al*., 1993). They might recommend a hotel to others, but feel that it is too expensive to use regularly. Consequently, it is imperative to consider both the behavioral and attitudinal manifestations of customer loyalty.

Attitudinal loyalty can be manifested in a customer's intention to recommend a product, brand, or service to others (Bloemer and de Ruyter, 1999). Identifying this customer intention in one way to assess attitudinal loyalty (Donio *et al*., 2006). In other words, customers' recommendations, as expressed in reviews, can be considered an attitudinal manifestation of loyalty. Behavioral loyalty, on the other hand, can be displayed in purchase behaviors, such as repurchase intention. Accordingly, a customer's desire to re-visit a lodging establishment could be considered as a behavioral expression of loyalty. Recently, more researchers have delineated attitudinal and behavior intentions when explaining customer behavior in the SE. For instance, Lee and Wong (2021) used WOM and purchase intention to measure attitudinal loyalty and purchase intention in ride-hailing, respectively. They found that WOM significantly impacts purchase intention. Moon *et al*. (2019) investigated the factors of recommendation intention and continuous intention to use in accommodation-sharing based on the roles of guest and host. They discovered that hosts and guests have different perceptions of interactions, which ultimately affect their satisfaction, recommendation intention, and continuous intention to use. Nevertheless, the results of these studies were based on a limited number of survey respondents.

3. Methodology

The research methodology is shown in Figure 1, which consisted of three phases: UGC collection, text analytics, and knowledge discovery. In UGC collection, we collected user-generated reviews from the accommodation-sharing platform Airbnb. We considered each review as a document containing textual data. In text analytics, we retrieved the text, followed by tokenizing it to covert each word into a distinct attribute. The number of occurrences of each word was then calculated, and a term-frequency matrix was generated for co-occurrence and similarity analysis. Based on the co-occurrence of words, we identified distinct topics and formed clusters. In the last phase, knowledge discovery, the information obtained from the previous phase was used to improve the company's strategies and decision-making processes. This involved the visualization of the results for decision makers to derive insights and recommendations for improving their businesses and customer experiences.

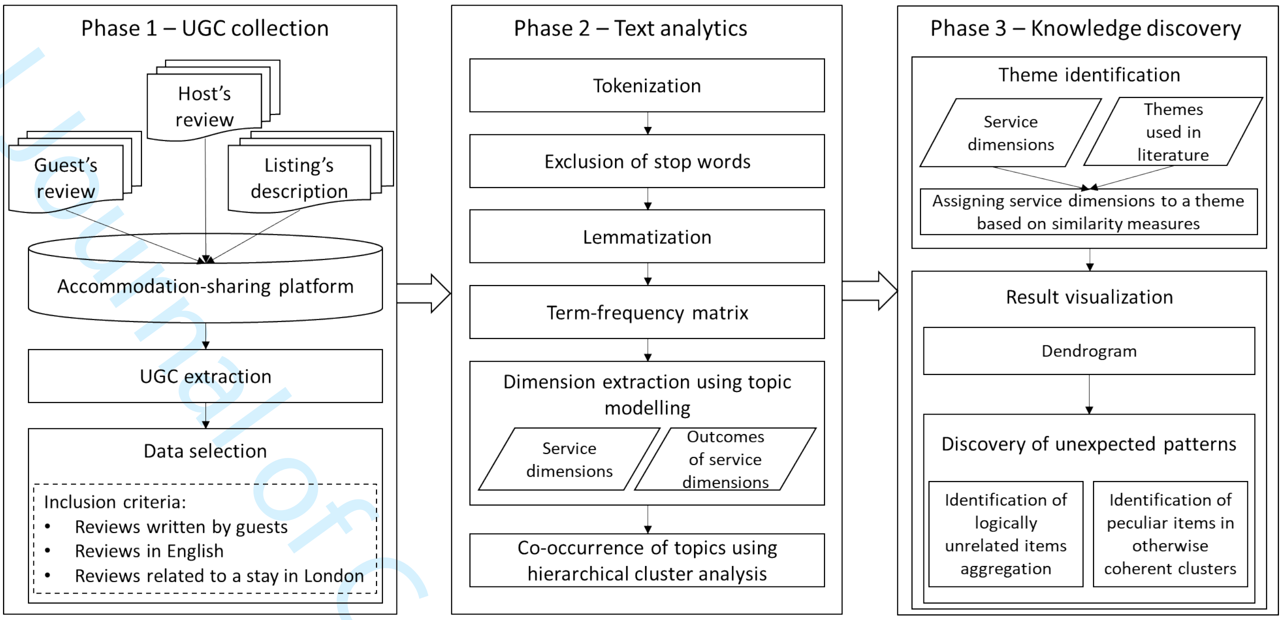

Figure 1. Research methodology

3.1 UGC Collection

This study analyzes customer reviews from Airbnb, one of the largest accommodation-sharing platforms in tourism. After each stay, both the guest and host are encouraged to post a public review of their experience on the other's page (Zervas *et al*., 2017). Both are prohibited from removing reviews unless they violate Airbnb's content policy (Lee *et al*., 2019). Compared to reviews on other social media platforms, virtual communities, or such websites as TripAdvisor, Airbnb reviews have a high research value as they have the characteristics of authenticity, allowing researchers to learn customers' real feelings (Guo *et al*., 2017; Xu *et al*., 2019).

The selection criteria for Airbnb reviews include: (i) the reviews are written by guests, not hosts; (ii) the reviews are written in English; (iii) the reviews are related to a stay in London. We chose London due to its being one of the world's most popular tourist destinations with a large number of Airbnb-registered hosts. It is also an international city, which business and leisure visitors likely visit more than once, meaning that our text analytics and findings will be useful for the hosts to understand consumer expectations. We limited the review year to 2016, the final year before Airbnb entered the luxury segment. Since Airbnb bought Luxury Retreats, a high-end vacation rental company, in 2017, it has been offering a new rental tier that includes expertly designed homes with high-end amenities. Reviews of luxury properties should be excluded from this study for two reasons. First, customers seeking luxury have different expectations from those seeking regular properties which are the context of this study. Second, many hosts that provide luxury properties are professional property agents, rather than individual hosts. This contradicts to our definition of the SE. To avoid mixing reviews from both regular and luxury segments, we only considered reviews from 2016. In addition, we used all data throughout the entire year of 2016 to avoid bias.

We collected 206,613 reviews posted by guests who used Airbnb services in London in 2016. We noticed two types of automated postings due to booking cancellations of by the guests and the hosts. These were: “The reservation was canceled X day(s) before arrival. This is an automated posting” and “The host canceled this reservation X day(s) before arrival. This is an automated posting,” respectively. Since the automated postings were of no value to the analysis, we omitted them from the study, thus reducing the dataset to 201,321. After removing the non-English reviews, we were left with a total of 175,318.

To understand the data, we used a word cloud, as shown in Figure 2, to get a visual representation of the most frequent words. The word size is proportional to the count of the word. One can easily identify the words that customers often use in their reviews. It is a useful tool for obtaining insights for prioritizing customer concerns for service design and improvement (Lee *et al.*, 2019). Further, the frequency of the top 30 frequent words is visualized in Figure 3.

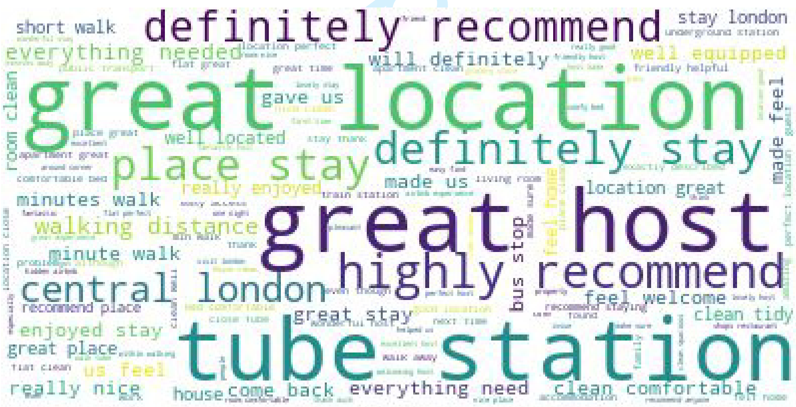

Figure 2. Word cloud

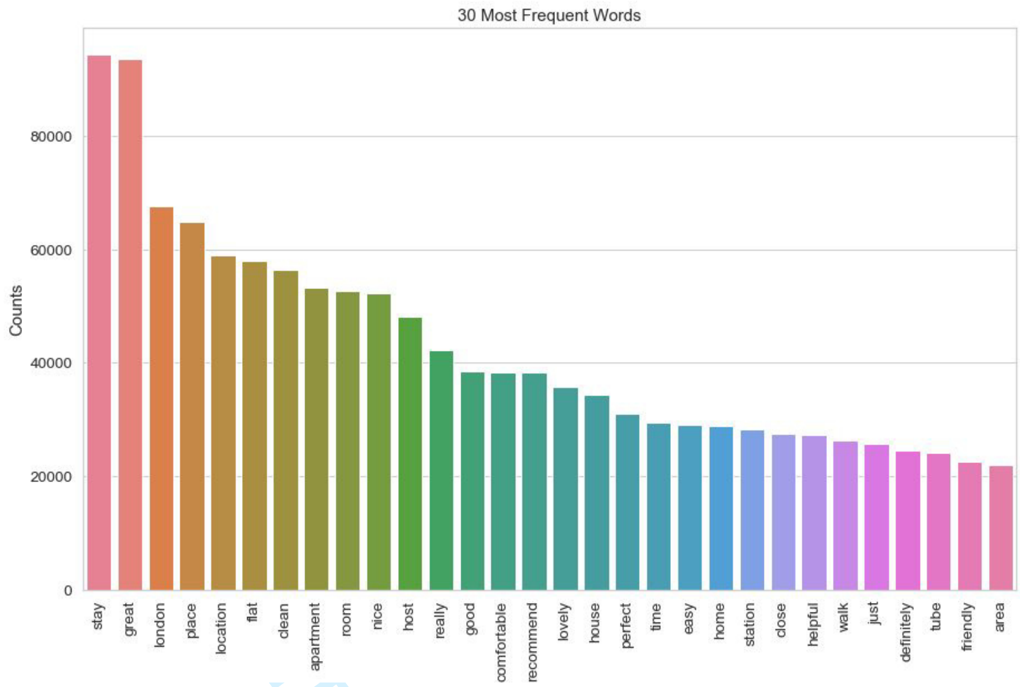

Figure 3. The top 30 frequent words in the reviews

3.2 Text analytics

We required text-mining approaches to discover hidden patterns in the reviews. Following tokenization (i.e., discretizing words within a document), each document became a sequential collection of tokens (words). We then filtered stop words that contained no specific meaning need, followed by lemmatization (i.e., resolving words to their dictionary form). Moreover, we found it necessary to impose structure on the text by creating a term-frequency matrix wherein the columns consisted of all the tokens found in all documents, and the cell of the matrix was the term frequency in which a token appeared. Term frequency refers to the ratio of the number of times a token appears in a given document to its total number of terms. Once a term-frequency matrix is formed, standard data-mining techniques can be applied to perform text-mining.

During topic modelling, we viewed a service dimension of accommodation-sharing as a latent construct distributed over a vocabulary of words used by customers to describe their Airbnb experiences, which we referred to as a "topic". State-of-the art techniques to identify topics from reviews include Latent Dirichlet Allocation (LDA) and Factor Analysis (FA). LDA is a generative probabilistic model of a corpus. It treats each document as a mixture of latent topics, each of which is characterized by a distribution over words (Blei *et al*., 2003). LDA has previously been used to discover topics from Airbnb reviews (Lee, 2022). However, because of LDA's probabilistic nature, we noticed that high frequency words were associated with numerous topics. This is a limitation of LDA as it affects the interpretation of the topics. On the other hand, FA can be used to extract topics stored in the form of dictionaries. Based on the term-frequency matrix, FA with a Varimax rotation can be computed to extract a number of factors. All words with a factor loading higher than a specific threshold are then retrieved as part of the extracted topic. Since existing studies do not usually justify the choice of the topic modelling techniques, Péladeau and Davoodi (2018) compared LDA and FA for topic extraction. They found that FA can generate topics perceived by human coders more coherently than LDA. Moreover, FA offers additional benefits over LDA. First, unlike LDA, which generates different solutions with different starting states, FA can generate the same solution when the same options are used. Second, FA is more capable of extracting topics that are less correlated with one another. This is due to the Varimax rotation, which potentially removes items associated with too many topics and instead selects items loading strongly on only a few factors (or topics) (Péladeau and Davoodi, 2018). Accordingly, we chose FA for topic modelling—which can also be implemented in QDA Miner software.

After topic modelling, we applied cluster analysis to build topic clusters based on their co-occurrence. This assumes that the more often the topics co-occur, the more similar or related they are. Hierarchical cluster analysis can be used to form clusters by grouping similar topics, up until the formation of a single large cluster.

3.3 Knowledge discovery

When identifying key service areas for improvement, it is more practical for the hosts to focus on a few key themes rather than a large set of varying topics. Hence, it would aid hosts for the topics to be merged into larger themes or concepts. Based on the literature review, we identified three overarching themes that can be categorized into existing service dimensions: host, amenities, and location. The topics were assigned to the most similar theme based on keywords. We based the similarity measure on the Jaccard coefficient (Everitt *et al*., 2001), which has been widely used to assess the overlap between dimensions from two sources. For instance, Guo *et al*. (2017) used it to test the degree of overlap between the dimensions extracted from their analysis of hotel reviews with those used in prior studies. Zhang (2019a) used it to compare dimensions between Airbnb and hotel reviews. The Jaccard coefficient indicates the proportion of categories that match between two sources, i.e., the topic and theme in this study. The formula for the Jaccard coefficient is:

$$\frac{x}{x+y+z}$$

where *x* is the number of dimensions present in both sources, *y* is the number of dimensions contained only in the first, and *z* is the number of dimensions that only exist in the second.

The relationships among themes can be further visualized using different techniques for direct, and ease of, interpretation. Typically, it can be presented using a dendrogram in which frequently co-occurring topics are combined and formed into a cluster at the beginning of the agglomeration process, whereas seldomly occurring or stand-alone topics are combined at the end. While cluster analysis can form coherent, logically-related groups of items to replicate a known reality, paying closer attention to the grouping of logically-unrelated items can lead to the discovery of new knowledge. In this study, we adopted two methods for identifying unexpected patterns: First, an aggregation of logically-unrelated items at an early stage of the clustering process; and second, peculiar items in an otherwise coherent cluster. While whether the associations discovered represent known fact, trivial new knowledge, or potentially important discoveries depend on the judgment and experience of the domain experts, we hope to provide useful recommendations for improving business decisions.

4. Results

4.1 Topics extracted from reviews

As shown in Table 2, we used QDA Miner software to discover 12 topics, classified into either: (i) service dimensions that influence customer experiences in Airbnb accommodation; and (ii) customer loyalty, which is the outcome of the service dimensions. We identified the following 10 service dimensions: "room," "public transport," "homeliness," "check in/out arrangement," "street noise," "neighborhood," "clear information," and "description accuracy." The two outcomes were "come back" and "highly recommend."

Table 2. The 12 topics that are extracted from the reviews

Class	Topic	Keywords
Service dimension	Room	Bathroom; Bed; Bedroom; Clean; Equip; Kitchen; Large; Nice; Room; Well
	Public transport	Away; Bus; Distance; Minute; Public; Station; Stop; Transport; Transportation; Tube; Walk
	Homeliness	Feel; Home; Lovely; Welcome
	Check in/out arrangement	After; Allow; Arrive; Check; Early; Flight; Late; Leave; Luggage; Morning; Out
	Street noise	Night; Noise; Noisy; Sleep; Street; Window
	Hot water	Bed; Coffee; Hot; Shower; Tea; Towel; Water
	Neighborhood	Restaurant; Shop; Pub; Bar; Store; Grocery; Cafe
	Clear information	Clear; Give; Information; Instruction; Provide
	Description accuracy	Describe; Exactly; Photo; Picture; Show
	Responsiveness	Always; Answer; Question; Quickly; Respond
Customer loyalty	Come back	Again; Back; Come; Definitely
	Highly recommend	Anyone; Highly; Recommend

4.2 Mapping topics onto the themes

We mapped the extracted service dimensions onto three overarching themes: “location,” “host,” and “amenities.” The keywords of each service-dimension topic were compared with those of the themes listed in Cheng and Jin (2019, pp. 68–69). Where more keywords overlapped in both the topic and the theme, we considered the latter two to be more similar to each other. Each topic was then assigned to the most similar theme. Based on the Jaccard coefficient, the similarities between each topic and each theme were computed as shown in Table 3.

Table 3. Similarities between service-dimension topics and themes

	Location	Amenities	Host
Room	0%	29.17%	0%
Public Transport	11.11%	0%	0%
Homeliness	0%	0%	17.64%#
Check in/Out Arrangement	0%	0%	0%
Street Noise	6.06%	3.85%	0%
Hot Water	2.86%	12.0%	0%
Neighborhood	9.09%*	0%	0%
Clear Information	0%	0%	0%
Description Accuracy	0%	0%	0%
Responsiveness	0%	0%	0%

"welcome" from the topic and "welcoming" from the theme is considered a match

* "cafe" from the topic and "cafes" from the theme is considered a match; "shop" from the topic and "shops" from the theme is considered a match

Three topics were assigned to the theme "location": public transport, street noise, and neighborhood. Two topics assigned to "amenities": room and hot water. Lastly, one topic was assigned to the theme "host": homeliness. Four topics could not be assigned to any theme: check in/out arrangement, clear information, description accuracy, and responsiveness. Each is then manually examined so as to determine whether they can be thematically matched. If not, new themes can be created. Additional references, such as Zhang (2019a), can also be used in this process.

We found that "responsiveness" was closely related to the topic "host's response," as defined by Zhang (2019a), with a similarity value of 50%. Zhang (2019a, p. 663) suggested that this topic implies that "Airbnb guests want to interact with hosts; thus, hosts should respond to and interact with guests so that guests can gain authentic experiences in the local community." As this topic related to hosts' behavior, it was logical to assign "responsiveness" to the theme "host."

Moreover, "check-in/out arrangement" was close to the topic "late/evening check-in" defined by Zhang (2019a), with a similarity value of 16.67%. According to Zhang (2019a, p. 664), the "late check-in" topic suggests that "hosts should provide a smooth check-in process to guests, especially for those who may arrive late at the place." As this also related to host's behavior, we deemed it logical to assign "check-in/out arrangement" to the theme "host."

To the best of our knowledge, the remaining two topics, “clear information” and “description accuracy,” have seldom been discussed in the literature. As they contain keywords related to the quality of the Airbnb’s listing information, we grouped them together to generate a new theme named “Information.” The key findings are identified and summarized in Table 4, based on our careful examination of the reviews related to each theme.

Table 4. Findings of each theme

Theme	Findings	Sample reviews
Location	(1) Location convenience is usually measured in terms of public transportation connectivity, and neighborhood amenities, such as cafés, restaurants, and pubs. (2) "Street noise" is generally considered a drawback and is associated with the quality of sleep. It is unfavorable to guests especially when the street noise occurs at night, thus disturbing their sleep.	"Pros: The location of the apartment is really great with restaurants, public transportation and bars just around the corner." "… I can hear the noise on the street and next door whole night. There were young people having party so loud all the night. None of us could sleep that night, although we are so tired after a long trip…"
Amenities	(1) Guests comment on the rooms (kitchen, bedroom, bathroom, or entire apartment) in terms of comfort, cleanliness, and the access to internet and appliances. (2) As guests are charged for the cleaning fee for each booking, they expect up-to-standard cleanliness. (3) Not all the listings in London supply hot water in the bathroom. An unstable supply of hot water is considered a disadvantage to guests.	"We felt so let down by the cleanliness of the flat when we stayed there last week. The smell of mold in the vault area and second bathroom was so strong that we had to hold our breath… Don't forget we were charged a cleaning fee and sadly the service has not been carried out…" "… the worst part is the shower. There is no water pressure and at times we didn't have any warm water at all. So I wouldn't recommend to stay at this place, since the value for money is not given."
Host	(1) Guests are happy when they feel as if they are at home. The construction of homely feelings depends on the room types.	"… My first Airbnb experience was above all expectations. [Host] is an excellent host and made it feel like home. [Host] is genuine,

	(2) Guests expect good responsiveness from the host not only during the stay, but also a few days before arrival. Pre-arrival interaction is part of their service evaluation.	welcoming and accommodating and her knowledge of London and the local area is second to none….” “…The host didn't respond to initial messages/questions written 3 days prior to arrival until the day of arrival, leaving us to question if we actually had a secure reservation or not…”
Information	(1) Guests are unhappy when the facilities are not as described online nor up to a convenient standard. (2) Guests appreciate clear instructions on how to use appliances (e.g., washing machines and dryers) and check-in processes.	“…this is really not up to scratch when you imply in your listing you have wifi, which was not true when listed, and people like us whose work is internet based picked your place because of this…” “…The flat was spotlessly clean and instructions for all the appliances (washing machine, dishwasher, cooktop, oven, etc) were in a kitchen drawer. We did notice that the cooktop had some damage but used it repeatedly without problem…”

4.3 Co-occurrence analysis of topics

To identify topics more associated with customer loyalty, we referred to “highly recommend” and “come back” as representing the outcomes of service dimensions. If guests are satisfied with the stay, they are more likely to recommend the Airbnb or express their desire to return in their reviews. Figure 4 shows the dendrogram based on the co-occurrence of topics. We removed single-word clusters to concentrate only on strong associations.

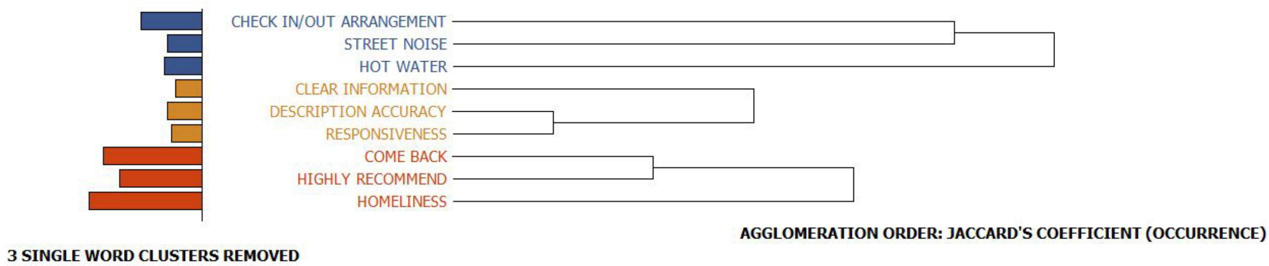

Figure 4. Dendrogram of the topics

We found a cluster containing “come back,” “highly recommend,” and “homeliness.” Generally speaking, “highly recommend” and “come back” are two semantically-related topics, making it logical that they would form a coherent group. Interestingly, “homeliness” appears to be a peculiar item in the cluster containing these two outcome topics. This shows that “homeliness” strongly impacts guests’ recommendations and intentions to re-visit. If guests feel at home or welcomed during the stay, the likelihood of guest retention increases.

Moreover, we observed that “description accuracy” and “responsiveness” are two logically-unrelated items, but are aggregated at an early stage of the agglomeration process. This shows that guests, who champion description accuracy, are also attentive to whether hosts are responsive to their enquiries during the stay, or vice versa. One reason for this could be that, when guests find that the place is not as described, they will contact the hosts to seek help, or request an explanation or refund. Accordingly, the experience will be improved if the hosts are responsive enough to address the guests’ needs.

5. Discussion and Conclusions

5.1 Conclusion

This study identified four themes ("amenities," "host," "location," and "information") and confirmed their importance in accommodation-sharing. Although the importance of each theme may vary over time, our findings can be an additional supplement for service providers to provide satisfactory stay experiences for customers.

Figure 5 shows the framework based on the methodology, and summarizes how the findings supplement our existing knowledge of customer behavior in accommodation-sharing. Locational benefits have previously been found to be strongly associated with customers' choice to book with accommodation-sharing platforms (Cheng *et al*., 2019; Li and Tsai, 2022; Xu, 2020). Interestingly, while our study underpins the importance of locational benefits in accommodation-sharing, our results show that customers who express intentions to re-visit (behavioral loyalty) and/or recommend the experiences to others (attitudinal loyalty) may not mention such benefits in their reviews. One reason for this could be that, there have been a lot of Airbnb listings available in London, so customers can easily secure a place with locational benefits. As a result, locational benefits become less influential and customers have started considering other factors, such as home benefits (Chi *et al*., 2021), when they decide if they would like to recommend the experiences to others and re-visit in the future.

Regarding hosting behavior, welcoming guests is important as homeliness is strongly associated with attitudinal and behavioral loyalty. It appears that hosts can likely retain customers by making them feel at home during the stay. In the current tourism literature, research on "home" tends to focus on the spatial dimension, without a clear conceptual boundary (Zhu *et al*., 2019). How to construct the feeling of home remains an open question. While our findings are consistent with existing studies arguing that homeliness is subjectively constructed, we also determined that it can be created according to the hosts' presence or absence during the stay. Hosts must strike a balance between fulfilling guests' socialization needs and maintaining a private atmosphere for them. For instance, if the host shares the same space with the guests, they can interact with guests and treat them in a friendly manner during their stay. On the other hand, if guests book an entire property to themselves, hosts should play a more passive role, talking to the guests and suggesting help only when the guests initiate conversations or seek help.

Furthermore, we discovered a new theme: "information." Although this theme has rarely been discussed in the literature, it is an important aspect affecting stay experiences, as information discrepancies result in customer dissatisfaction. Based on our findings, we added new perspectives to the definition of "information" in accommodation-sharing. People are generally wary of sleeping in a stranger's place and easily feel anxious. Anxiety grows when expectation-actuality discrepancy occurs. As information provided by hosts on the online platforms sets customer expectations, information can be seen as a form of indirect interaction to alleviate guests' initial anxieties. Therefore, information in accommodation-sharing not merely refers to clear and comprehensive introductions of check-in processes or the use of appliances. Instead, it is a mean for hosts to shape guests' physiological states, alleviating their anxiety and building trust. Below is a sample of reviews that show information eased a guest's fear.

> "… I was extremely nervous about arriving by myself since this was the first time that I had been to Europe, but all of the information that they provided before my arrival helped to ease my fears…"

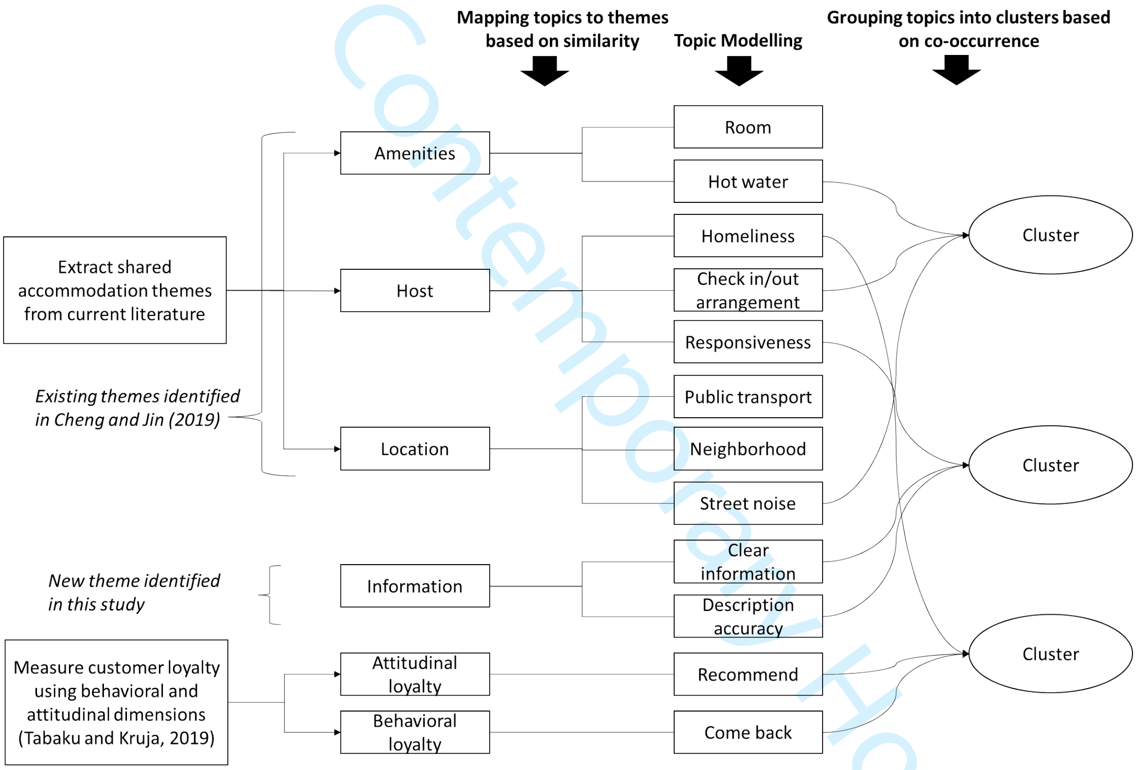

Figure 5. Obtained framework based on the methodology

5.2 Theoretical implications

As a theoretical contribution, the paper advances our knowledge of ECT and customer behavior in accommodation-sharing in three ways. First, we demonstrate ECT's role in examining the relationship between customer evaluation and post-purchase behavior through text-mining rather than surveys. Compared with using measurement items in surveys, extracting customer perceptions and intentions directly from online reviews offers a relatively unified assessment method. For instance, when customers explicitly use such words as "I would like to come back" in a review, this suggests that their satisfaction reached such a high that they fully intend to reuse the service. As such, customers revealing their intentions explicitly—and, significantly, voluntarily—is a strong sign of their true repurchase intentions. This paper provides an alternative for future researchers to extend a research model of ECT by capitalizing on the wealth of online reviews, without the limitations brought by close-ended measures in survey studies.

Second, this study shows that variations in customer-loyalty manifestations in accommodation-sharing can be attributed to customers' situational context. While homeliness is strongly associated with attitudinal and behavioral loyalty, the construction of homely feeling depends on the hosts' presence or absence in the situation. Some guests feel like home when there are no strangers (hosts included) in their stays, while others positively respond to interaction with the hosts in person and feel welcomed. This study reveals the importance of situational context in understanding customer behavior, which is largely ignored in ECT. Future researchers should extend ECT with situational characteristics to provide a more contextualized understanding of customer expectation and behavior, including loyalty.

Third, this study extends previous studies (e.g., Carvalho and Alves, 2022; Xu, 2020) on the importance of interaction that has an influence on customer expectations and value co-creation in accommodation-sharing. We discovered a new textual theme, "information," that includes the host's online description of the accommodation, which can be seen as a form of indirect interaction that shapes customer expectations and subsequent behavior. Before the stay, the interaction is relatively superficial; the hosts present the information through text and photos posted on the online platform. However, we found that people are strangers within the SE, and hence this kind of pre-arrival or even pre-booking interaction can alleviate guests' initial anxieties, thereby enhancing customer satisfaction and behavior. This study demonstrates the important role of information in setting customer expectations beforehand, which should be considered in ECT models, especially for experimental services, such as those related to tourism.

5.3 Practical implications

This study provides important practical implications for both hosts and accommodation-sharing platforms alike. The theme "amenities" is similar to a hotel's "physical environment," except that most Airbnb guests expect amenities similar to those they have at home. As home benefits are unique to accommodation-sharing, hosts can emphasize the significance of home benefits (e.g., kitchens, dining rooms, and appliances) on their listing's page, and maintain their good condition. If hot water is unavailable, hosts can ensure that guests are aware of this issue before accepting the booking. Furthermore, hosts who fail to maintain cleanliness will dissatisfy their guests. To help hosts maintain up-to-standard cleanliness, accommodation-sharing platforms can introduce on-site housekeeping services to hosts upon booking confirmation. If needed, hosts can opt for professional housekeeping services to improve their guests' stay experience. Besides, hosts can provide a more flexible check-in/out schedule. Considering that some hosts rent out their homes when they are out of town, they may not be able to stay responsive all of the time. We suggest that hosts can notify guests that they may be difficult to reach (e.g., when on vacation or business trip). This can help guests better align their expectations with the host's responsiveness. Accommodation-sharing platforms can also send hosts a checklist of suggested methods for ensuring a satisfactory stay experience. Based on our findings, this checklist could include providing a stable hot water supply, home amenities in a good condition, and a clean environment. To construct homely feelings, hosts must strike a balance between fulfilling guests' socialization needs and maintaining a private atmosphere for them.

Regarding the cluster containing "clear information," "description accuracy," and "responsiveness," we would suggest that, in any case where hosts cannot be easily contacted, clear instructions on the self-check-in process and household appliance user manuals be clearly provided. Besides, it is crucial for hosts to regularly update and provide accurate listings' information, including both textual descriptions and pictures. Hosts can invest more on improving the quality of the information they post online. Moreover, accommodation-sharing platforms can include interactive media information (e.g., 360-degree videos) that allow hosts to accurately showcase their listings, or provide guests with a "virtual tour" of the room(s).

Regarding the theme of "location," our findings reveal that customers are dissatisfied when the accommodation is located in noisy areas, which affects the quality of their sleep. Hosts can provide earmuffs or install double-glazed windows in the bedrooms to keep street noise to a minimum. Furthermore, customers measure convenience in terms of public connectivity, as well as the ease of accessing restaurants or shops. If the location is far from transport hubs, restaurants, or shops, hosts can provide bikes or scooters to travel around the neighborhood. Besides, accommodation-sharing platforms can include "quiet area" and "busy area" options in their search filters, thus allowing guests to set their own preferences. This, however, requires a careful division of the listings' locations into "quite area" and "busy area" clusters based on geographic coordinates. Some neighborhood variables, such as the number of nearby pubs, could be used by accommodation-sharing platforms to assess noise levels.

5.4 Limitations and future research

This study has certain limitations, suggesting that further research should be conducted. First, the reviews analyzed in this study are limited to Airbnb reviews from London. We do not have sufficient evidence to affirm the extent of our findings' generalizability. Future research using reviews from different regions and countries could resolve this issue. Second, our study did not take into account the positivity bias in the reviews. Unlike reviews on social media platforms, such as TripAdvisor, reviews on such SE platforms as Airbnb tend to be positive for multiple factors, including sociocultural norms of politeness, established host–guest trust, review and rating reciprocity, and non-anonymous communicative norms (Bridges and Vásquez, 2018). Future studies could conduct further research evaluating the effect of positivity bias on attitudinal and behavioral intentions. Comparative studies on reviews between SE and social media platforms would also be a useful next step. Third, while our research has pinpointed that host–guest interactions are important aspects in shaping customer experience in accommodation-sharing, we acknowledge that social interactions among multiple parties in the SE can transcend traditional trails (i.e., host–guest). On a broader perspective, interactions include additional parties, such as other peers and the community. An in-depth exploration of guest–guest and guest–community interactions may generate additional insights from multiple perspectives.

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Table 1. Service dimensions in accommodation-sharing in existing literature

Themes	Service dimensions	References
Host	Help from host	Ju *et al*. (2019), Lee *et al*. (2019), Situmorang *et al*. (2018), Zhang (2019a, 2019b), Zhu *et al*. (2019)
	Socialization and interaction	Lalicic and Weismayer (2018), Moon *et al*. (2019), Xu (2020)
	Check-in/out arrangement	Lee (2022), Sutherland and Kiatkawsin (2020), Zhang (2019a, 2019b)
Amenities	Household facilities	Lee *et al*. (2019), Wang and Jeong (2018), Xu (2020), Zhang (2019b)
	Value for money	Lee (2022), Liang *et al*. (2018), Ranjbari *et al*. (2020), Tussyadiah (2016)
	Housekeeping	Lee and Tse (2021), Sutherland and Kiatkawsin (2020), Zhang (2019a, 2019b)
	Pet	Sutherland and Kiatkawsin (2020), Zhu *et al*. (2019)
Location	Neighborhood safety	Ju *et al*. (2019), Sutherland and Kiatkawsin (2020), Zhu *et al*. (2019)
	Transport	Ju *et al*. (2019), Lee and Tse (2021), Zhang (2019a)
	Shops and restaurants	Lee (2022), Zhang (2019a)
	Convenience	Situmorang *et al*. (2018), Zhu *et al*. (2019)

Table 2. Topics extracted from the reviews

Class	**Topic**	**Keywords**
Service dimension	Room	Bathroom; Bed; Bedroom; Clean; Equip; Kitchen; Large; Nice; Room; Well
	Public transport	Away; Bus; Distance; Minute; Public; Station; Stop; Transport; Transportation; Tube; Walk
	Homeliness	Feel; Home; Lovely; Welcome
	Check in/out arrangement	After; Allow; Arrive; Check; Early; Flight; Late; Leave; Luggage; Morning; Out
	Street noise	Night; Noise; Noisy; Sleep; Street; Window
	Hot water	Bed; Coffee; Hot; Shower; Tea; Towel; Water
	Neighborhood	Restaurant; Shop; Pub; Bar; Store; Grocery; Cafe
	Clear information	Clear; Give; Information; Instruction; Provide
	Description accuracy	Describe; Exactly; Photo; Picture; Show
	Responsiveness	Always; Answer; Question; Quickly; Respond
Customer loyalty	Come back	Again; Back; Come; Definitely
	Highly recommend	Anyone; Highly; Recommend

Table 3. Similarities between service dimension topics and themes

	Location	Amenities	Host
Room	0%	29.17%	0%
Public Transport	11.11%	0%	0%
Homeliness	0%	0%	17.64%#
Check in/Out Arrangement	0%	0%	0%
Street Noise	6.06%	3.85%	0%
Hot Water	2.86%	12.0%	0%
Neighborhood	9.09%*	0%	0%
Clear Information	0%	0%	0%
Description Accuracy	0%	0%	0%
Responsiveness	0%	0%	0%

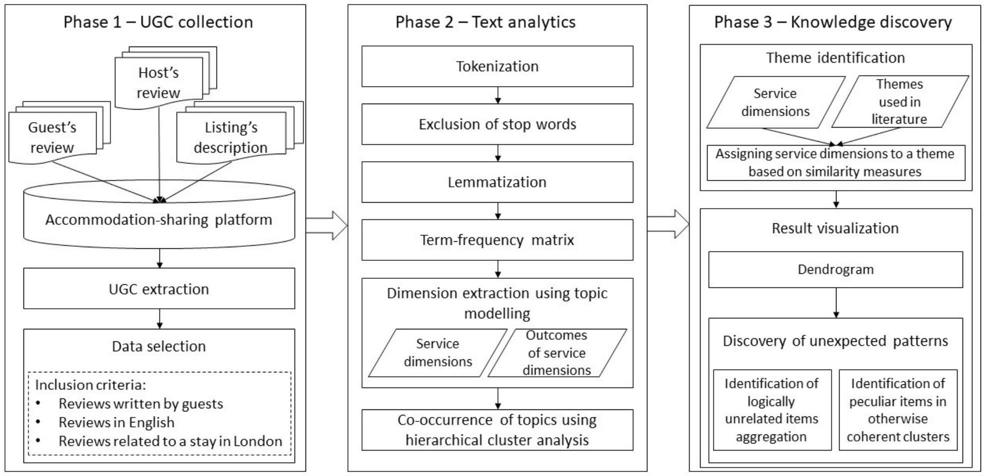
#"welcome" from the topic and "welcoming" from the theme is considered a match

*"cafe" from the topic and "cafes" from the theme is considered a match; "shop" from the topic and "shops" from the theme is considered a match

Table 4. Findings of each theme

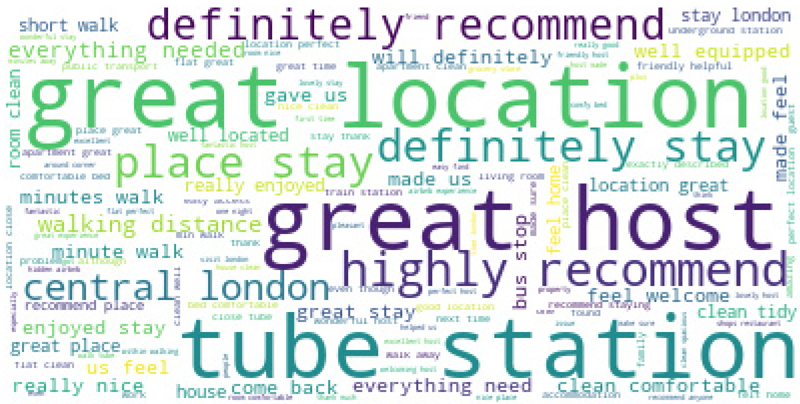
Theme	Findings	Sample reviews
Location	(1) Location convenience is usually measured in terms of public transportation connectivity, and neighborhood amenities, such as cafés, restaurants, and pubs. (2) "Street noise" is generally considered a drawback and is associated with the quality of sleep. It is unfavorable to guests especially when the street noise occurs at night, thus disturbing their sleep.	"Pros: The location of the apartment is really great with restaurants, public transportation and bars just around the corner." "… I can hear the noise on the street and next door whole night. There were young people having party so loud all the night. None of us could sleep that night, although we are so tired after a long trip…"
Amenities	(1) Guests comment on the rooms (kitchen, bedroom, bathroom, or entire apartment) in terms of comfort, cleanliness, and the access to internet and appliances. (2) As guests are charged for the cleaning fee for each booking, they expect up-to-standard cleanliness. (3) Not all the listings in London supply hot water in the bathroom. An unstable supply of hot water is considered a disadvantage to guests.	"We felt so let down by the cleanliness of the flat when we stayed there last week. The smell of mold in the vault area and second bathroom was so strong that we had to hold our breath… Don't forget we were charged a cleaning fee and sadly the service has not been carried out…" "… the worst part is the shower. There is no water pressure and at times we didn't have any warm water at all. So I wouldn't recommend to stay at this place, since the value for money is not given."
Host	(1) Guests are happy when they feel as if they are at home. The construction of homely feelings depends on the room types.	"… My first Airbnb experience was above all expectations. [Host] is an excellent host and made it feel like home. [Host] is genuine,

	(2) Guests expect good responsiveness from the host not only during the stay, but also a few days before arrival. Pre-arrival interaction is part of their service evaluation.	welcoming and accommodating and her knowledge of London and the local area is second to none....” “...The host didn't respond to initial messages/questions written 3 days prior to arrival until the day of arrival, leaving us to question if we actually had a secure reservation or not...”
Information	(1) Guests are unhappy when the facilities are not as described online nor up to a convenient standard. (2) Guests appreciate clear instructions on how to use appliances (e.g., washing machines and dryers) and check-in processes.	“...this is really not up to scratch when you imply in your listing you have wifi, which was not true when listed, and people like us whose work is internet based picked your place because of this...” “...The flat was spotlessly clean and instructions for all the appliances (washing machine, dishwasher, cooktop, oven, etc) were in a kitchen drawer. We did notice that the cooktop had some damage but used it repeatedly without problem...”



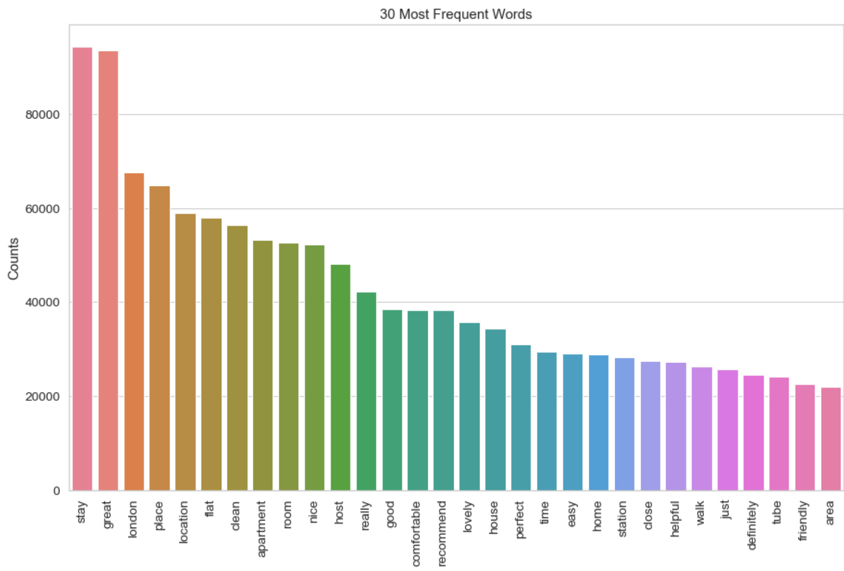
Research methodology

338x190mm (96 x 96 DPI)



Word cloud

141x70mm (72 x 72 DPI)

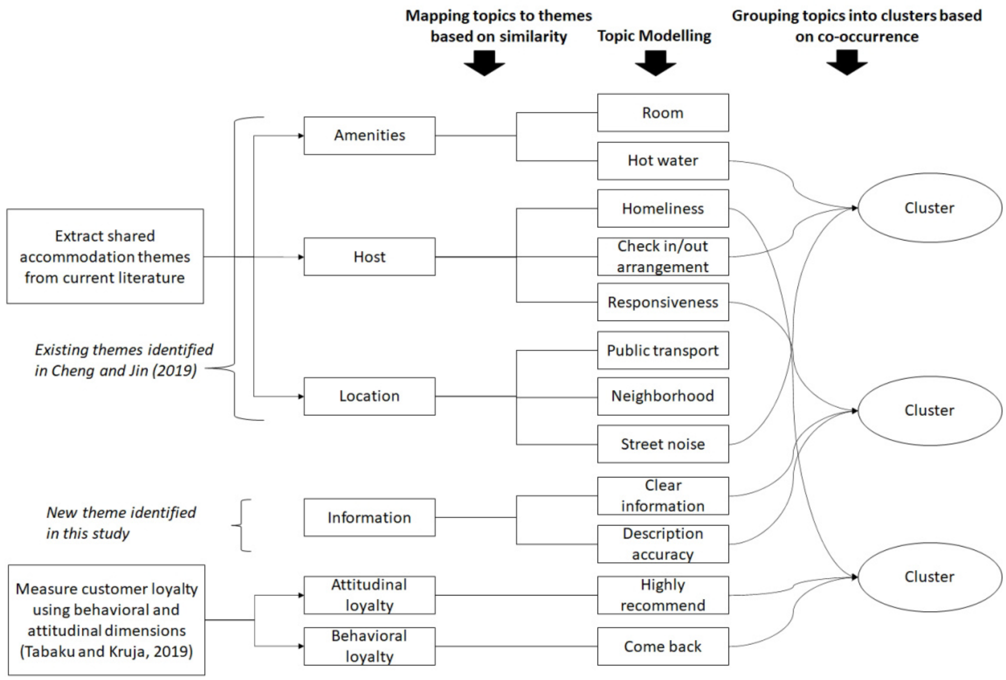


The top 30 frequent words in the reviews

979x605mm (28 x 28 DPI)

Dendrogram of the topics

548x326mm (72 x 72 DPI)



Obtained framework based on the methodology

749x509mm (47 x 47 DPI)