Decision Support Systems 152 (2022) 113634

Contents lists available at ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

How guest-host interactions affect consumer experiences in the sharing economy: New evidence from a configurational analysis based on consumer reviews

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ARTICLE INFO

Keywords:
Sharing economy
Accommodation-sharing
Airbnb
Guest-host interaction
Text analytics
fsQCA

ABSTRACT

This study examines the complexity of consumer experiences in the sharing economy (SE) from the perspective of the level of interaction between consumers and service providers. Consistent with service-dominant logic, the joint efforts of consumers and service providers co-create value. In the context of accommodation-sharing, this means not just the room that guests seek but, rather, the authentic local experience they co-create with their hosts. This study proposes a text-analytics framework to extract important service dimensions directly from consumer reviews. The results indicate that the importance of service dimensions, on which consumers focus in reviews, varies with levels of interaction. To better understand the complex nature of consumer experiences in the SE, the framework integrates text analytics with fuzzy-set Qualitative Comparative Analysis (fsQCA), to shift attention from individual service dimensions to service-dimension configurations. Drawing on complexity theory, this study examines the service-dimension configurations that lead to positive and negative sentiment. The fsQCA results reveal that the causal recipes for sentiment differ for various interaction mechanisms. This is the first study to integrate topic modeling, sentiment analysis, and fsQCA, framing service-provider decision support for responding to consumers' needs.

1. Introduction

Ongoing digitalization has changed consumer behavior toward consumption practices. Instead of owning goods, consumers are more willing to temporarily use goods that others own privately [1]. Such a paradigm change in consumer behavior opens opportunities for new business models, such as the sharing economy (SE), that online platforms facilitate [2], aiming to connect people who share "underutilized assets from spaces to skills to stuff for monetary or non-monetary benefits" [3]. SE service exists in various sectors, but its impact is more evident in the hospitality industry [4]. Distinct from traditional hotel service, accommodation-sharing can result in different consumer expectations [5]. Findings from previous studies focusing on traditional hotels do not sufficiently advance our understanding of consumer expectations for accommodation-sharing, one distinctive aspect of which is its emphasis on interacting with local residents [6]. Yet, various consumers may prefer different levels of interaction. Consumers report frustration when they fail to achieve desired levels of interaction [7]. Different interaction mechanisms result in variable consumer service evaluations [8]. Hence, developing a decision support system (DSS) for accommodation-sharing requires taking account of interaction levels, to effectively capture consumer preferences. Surprisingly, little empirical research investigates the interaction between consumers and service providers [9]. This study uses "types of rooms" to measure the level of interactions between guests and hosts [8]. For example, in a hotel-room or entire-space setting, guests and hosts do not physically share space, limiting their level of interaction [10]. This study uses text analytics to extract important service dimensions directly from consumer reviews across different room types. We establish the first research question: *How does the importance of service dimensions that online reviews describe change with the level of guest-host interactions?*

In addition, various levels of interaction during accommodation-sharing have different service attributes. Guests experiencing certain interaction mechanisms may evaluate attributes differently, resulting in varying levels of consumer satisfaction. For instance, guests who share space with hosts may consider social benefits important; those who book an entire space to avoid physical interaction with hosts may weigh other aspects more heavily. This study applies sentiment analysis to consumers' online reviews and uses those scores as a proxy for consumer satisfaction. Drawing on complexity theory, some service-dimension

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https://doi.org/10.1016/j.dss.2021.113634
Received 8 June 2020; Received in revised form 28 June 2021; Accepted 29 June 2021
Available online 1 July 2021

combinations may lead to satisfactory accommodation experiences. Thus, we establish the second research question: *What service-dimension configurations lead to strong consumer satisfaction with the level of guest-host interaction?*

To address these research questions, we propose a framework that integrates text analytics and fuzzy-set Qualitative Comparative Analysis (fsQCA), to explore how guest-host interactions affect consumer experiences. Most fsQCA studies rely on surveys to identify configurations of service dimensions that sufficiently explain consumer satisfaction. This study identifies configuration patterns from a large number of online reviews, overcoming the limitations of limited samples or inconsistent measurement items and common questions in prior studies. We demonstrate using text analytics to identify service dimensions from online reviews and apply them as fsQCA inputs. Embedding both text analytics and fsQCA is an important feature in an accommodation-sharing DSS because consumers tend to rely on online reviews while making booking decisions [11,12]. This study provides a more holistic picture of consumer experiences in accommodation-sharing by investigating both positive and negative reviews. Despite the effect of negative information on consumer decision-making processes [13], a lack of research focusing on negative reviews hinders insights into improving consumer experiences, with a few exceptions (e.g., [14]). In fact, a deeper look at negative reviews provides additional insights into rectifying maintenance issues or setting realistic expectations [15]. Addressing the call by Tussyadiah and Zach [16], this study narrows the research gap by analyzing both positive and negative reviews.

This paper proceeds as follows. Section 2 summarizes related studies. Section 3 presents this study's methodology and proposed framework. Section 4 presents the results based on real-world data from Airbnb. Section 5 discusses the findings and implications. Section 6 concludes the study, highlighting the future scope of further extending this study.

2. Literature review

2.1. Customer value in the sharing economy

The service-dominant (S—D) logic that Vargo and Lusch [17] propose claims the co-creation of value through joint efforts of consumers and service providers [18], conceptualizing "value" as a process integrating operand and operant resources. As operant resources, consumers actively participate in the design, production, and consumption processes that determine value [19]. Service providers cannot create value; they can only offer value propositions [20]. Linking SE and S—D logic implies that the SE platforms offer a unique value proposition by enabling direct encounters with service providers and providing access to physical resources, all in the presence of consumers, to co-create value [21]. Determining value, which essentially depends on consumer experiences and perceptions, can only occur following a service offer [22]. Zhang et al. [23] develop a Customer Value Proposition model to explore the effects of customer value in the context of the SE, including technical, economic, social, and emotional dimensions. Accommodation-sharing is part of the SE, so this study adopts these four dimensions [23].

Technical value refers to convenience, problem-solving features, and service-provider responsiveness [23]. Service with high technical value can save consumers time and effort, improving satisfaction. Economic value is measurable in terms of the monetary benefits and costs that accompany consuming a service, positive when the monetary benefits exceed the costs. In some cases, accommodation-sharing could be more expensive than hotels, but providing additional benefits unavailable from a hotel implies superior service at a lower cost. Social value relates to the establishment of social connections or seeking like-minded peers [23]. The opportunity to get to know new people and develop friendships stimulates SE participation [24]. Zhang et al. [25] discovered that in accommodation-sharing, guests care more about interaction with the hosts than their jobs or hobbies, suggesting that hosts pay more attention to interaction in their self-description. Emotional value relates to benefits the consumer derives from a product or service that evokes emotions or feelings and generates affective states (e.g., pleasure, joy, surprise). In accommodation-sharing, feeling at home is an important aspect of satisfying guests' emotional needs [26,27]. Guests who choose accommodation-sharing feel that "the production and provision of such homely feelings is something that one can never buy or get in the traditional tourism industry" ([28], p. 353).

The degree of interaction can affect how consumers perceive this value [8]. Accommodation-sharing offers three types of interaction: guest-host, guest-community, and guest-guest [29]. Theoretically, this study explores value co-creation by consumers and service providers, thus considering only guest-host interactions. Eusébio and Carneiro [30] find that levels of tourist-host interaction vary in different environments (e.g., food-and-beverage establishments, bars, nature places). Accordingly, we expect that types of rooms would reflect the level of guest-host interaction. For example, renting an entire apartment without hosts present limits face-to-face interaction. Hosts should differentiate the needs and wants of consumers by levels of interaction and customize their services to improve guest experiences.

2.2. Configurations of service dimensions in the sharing economy

Although previous studies support associating individual service dimensions in SE, they indicate mixed effects of service dimensions on consumer satisfaction and report contradictory results. For example, Tussyadiah and Pesonen [31] find that getting to know and interact with local people motivates participation in accommodation-sharing. However, other studies find some guests reluctant to rent a room in someone's house, intentionally looking for places to avoid social interaction [5]. Such contradictory findings may be due to the use of symmetric methods (e.g., regression analysis, structural equation modeling) that examine each factor individually, failing to address factor interactions [32]. As a result, relying on the relatively simple explanatory model implicit in traditional symmetric methods limits our current understanding of consumer satisfaction in the SE. Drawing from complexity theory, configurational factor analysis is more appropriate than examining the effects of individual factors.

Complexity theory yields deeper insights into combination patterns of causal factors simulating tourism outcome conditions [33]. The nonlinear interaction of components implies that change in one component may insignificantly or hugely impact the entire system. Hence, understanding the system requires examining it as a whole, not its individual components [34]. The essence of complexity theory is its more in-depth explanation of how consumers evaluate services and outcomes [35]. One of its tenets is equifinality, according to which alternative configurations of causal conditions can equally explain the outcome of interest [36]. Another tenet relates to asymmetry, namely, configurations leading to a negative outcome are not the mirror opposites of configurations leading to a positive outcome [37,38]. For instance, consumer satisfaction is not simply the opposite of consumer dissatisfaction. Accordingly, we need two different sets to capture the two qualitatively different outcomes, i.e., consumer satisfaction and dissatisfaction. This study detects sentiment that consumer reviews express, and sentiment scores measure consumer satisfaction. Positive sentiment reflects consumer satisfaction with the service. Similarly, negative sentiment expresses consumer dissatisfaction.

In summary, unlike studies that estimate the net effect of each factor independent of others, this study focuses jointly on multiple factors as a causal model. It shifts attention from individual service dimensions to service-dimension configurations, to develop a better understanding of the complex nature of consumer experiences in the SE.

3. Methodology and proposed framework

Fig. 1 shows the proposed framework starting with the collection of

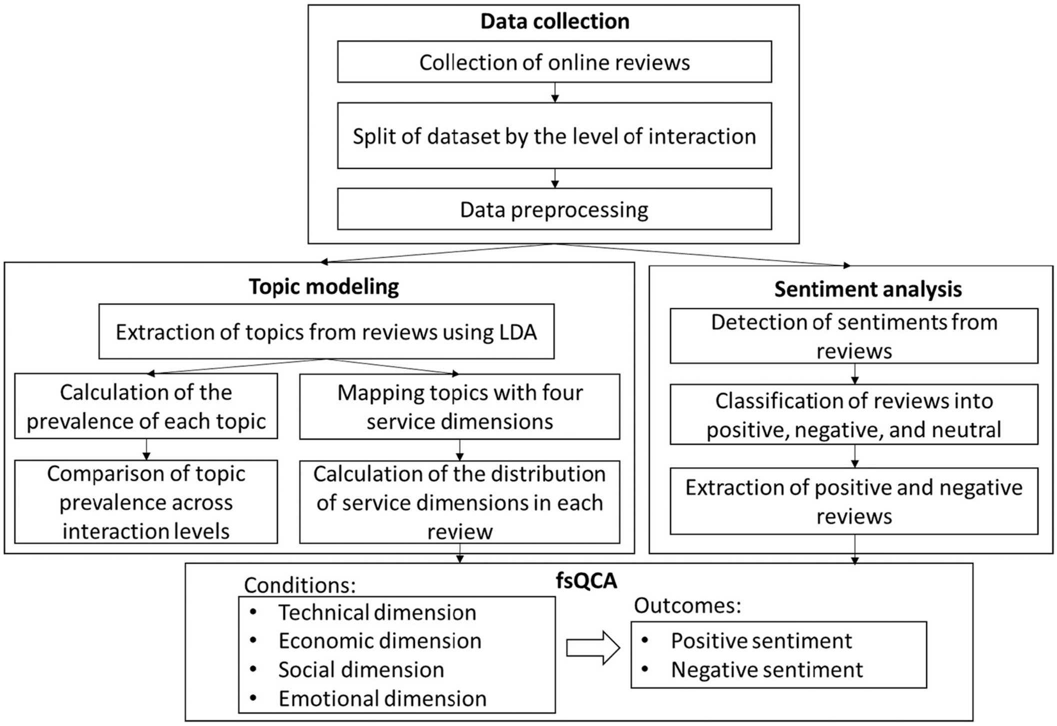

Fig. 1. Proposed framework integrating text analytics and fsQCA.

consumer reviews from SE platforms; topic modeling and sentiment analysis follow. Topic modeling extracts hidden topics from the reviews, and sentiment analysis identifies whether the review is positive, negative, or neutral. The fsQCA uses the results to identify possible configurations of SE dimensions that lead to positive or negative sentiments.

3.1. Data collection

The empirical context of this study is Airbnb, the largest peer-to-peer platform offering accommodation-sharing. The data came from Insideairbnb.com, an independent website that allows access to publicly available information about a city's Airbnb listings. We retrieved 503,071 textual reviews by guests who stayed in London Airbnb listings in 2019. This study only considered English reviews, and omitting non-English reviews reduced the dataset to 431,861 reviews. We removed automated postings due to cancellations, leaving 424,918 reviews.

We used Python to preprocess review data. Tokenization discretized words within a document. Special characters, including punctuation, were removed, and all uppercase characters were converted to lowercase. Then, from the Python natural language toolkit package, "stop words" (e.g., conjunctions, prepositions, and pronouns) conveying no specific meaning were filtered. English is an inflectional language in which a single word (or lemma) may take several inflected forms. Using a set of suffix substitution rules, lemmatization resolved words to their dictionary forms, for which we used the spacy en model in Python. We discarded words with no inherent meaning, keeping only nouns, verbs, adverbs, and adjectives.

3.2. Text analytics (topic modeling and sentiment analysis)

A service dimension can serve as a latent construct distributed over a vocabulary of words that consumers use to describe their experiences, which the literature calls a "topic" [39]. To extract topics from the reviews, this study used latent Dirichlet allocation (LDA) because it makes no assumptions about the structure of grammar properties of the text and efficiently discovers underlying topics from a massive volume of documents [40]. We used the *Gensim* library in Python to construct the LDA model. Topic prevalence indicates the percentage of tokens that the topic covers; the larger the percentage, the greater is the topic prevalence.

A few studies integrate LDA and fsQCA. Wang et al. [41] apply LDA to extracting topics from textual descriptions of crowdfunding projects. Extracted topics became the antecedent conditions for fsQCA, to identify possible condition configurations leading to on-time or late delivery performance. Giordono et al. [42] use LDA to measure two indicators of weather events from newspapers, after which they use fsQCA to identify causal paths for post-event policy change. This study differs from previous studies in two respects. First, those studies use text analytics to identify conditions, but not the fsQCA outcome. How Wang et al. [41] determine outcome memberships is unclear. On the other hand, Giordono et al. [42] provide guidelines for operationalizing and determining outcome membership, but outcome operationalization is specific to the weather-event context. Unlike previous studies, this study uses text analytics to determine the fsQCA conditions and outcomes. As such, all the fsQCA inputs are data-driven, and the methodology can easily apply to other contexts. Second, unlike the datasets in previous studies, this study's dataset is user-generated content containing personal-experience narratives. The researcher should not neglect hidden sentiment, a valuable source of data for understanding the topics. Therefore, in addition to LDA, this study includes sentiment analysis, and the sentiment scores determine the fsQCA outcomes.

Also, in this study, the Python VADER library detected sentiments from the reviews, using its sensitivity to sentiment expression in social media contexts [43]. More importantly, it considers five heuristics for dealing with punctuation, capitalization, degree modifiers, contrastive conjunction, and negation. Sentence structure affects sentiment, so VADER retains a review's original structure and uses the heuristics as cues to change word-set sentiment.

3.3. fsQCA

This study uses fsQCA to obtain a holistic picture of antecedents and complex solutions of accommodation-sharing consumer satisfaction. Before fsQCA, extracting topics in LDA enables mapping to four dimensions that Zhang et al. [23] propose: the technical (*tech*), economic (*econ*), social (*soc*), and emotional (*emo*). Applying fsQCA identifies condition configurations that lead to positive (*pos*) and negative (*neg*) Airbnb sentiments, as Fig. 2 shows.

FsQCA can present as an extension of crisp-set Qualitative Comparative Analysis (csQCA), which "allows a detailed analysis of how causal conditions contribute to a particular result, and draws on a configurational understanding of how a combination of causes leads to the same series of results" ([44], p. 5212). Thus, cases have gradations of their set membership ranging between 0 and 1, involving a more accurate assessment with set theory than csQCA, which can only analyze binary membership [45]. The first step in applying fsQCA is to convert the original values of the variables into fuzzy membership scores. This study adopted the direct method that Ragin [46] suggests, using a logistic function to map the data, based on three qualitative anchors: the thresholds for full membership and full nonmembership and the crossover point. The next step constructs a truth table that provides a list of configurational conditions for outcome prediction. Using frequency and consistency thresholds can reduce truth-table size. The former ensures using only configurations larger than or equal to the threshold value for assessing subset relationships [38]; the latter refers to the extent to which cases sharing a configuration agree on the outcome of interest [46].

The fsQCA 2.5 software program that this study used to generate the results and analyze the configurations provides three solutions: an intermediate, a parsimonious, and a complex solution [47,48]. The study focuses on presenting the complex solution.

4. Results

4.1. Extracting key topics from reviews

While using the perplexity score can assess LDA model quality, recent studies show that optimizing the model using perplexity may result in less semantically meaningful topics [49]. Topic coherence measures may be a better choice [50,51], scoring a single topic by measuring the semantic similarity between high-scoring topic words. Trying values of k starting from 2, we ended at the maximum coherence value. Fig. 3 shows the end of c growth at $k = 20$.

Topic names emerged from the logical connection among the keywords, as Table 1 illustrates, a naming method that scholars utilize (e.g. [14,39,40]). For example, the topic name "host's responsiveness" captures such keywords as "always," "respond," "quickly," "answer," and "question." Having identified a candidate topic name, we further tested

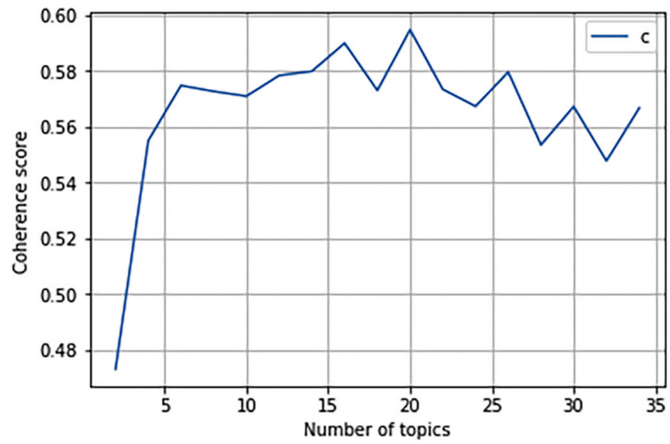

Fig. 3. Coherence scores with different numbers of topics.

it using logical connections with other keywords. When we found the logical connection, we retained the topic name. Otherwise, the naming process started over. This naming method could be subjective, and we used visualization to aid our judgment. Specifically, plotting an intertopic distance map (see Fig. 4) uses the pyLDAvis package in Python, to examine the linkages among topics based on the words assigned to each topic. Each bubble on the map represents a topic, and the size of a bubble represents the prevalence of the topic. A good LDA model will scatter relatively large and non-overlapping bubbles throughout the chart, not clustered in one quadrant. On the other hand, a model with too many topics will typically have many overlapping small-sized bubbles clustered in one region of the map. A significant overlap of bubbles appears among Topics 10 ("Restaurant and shop"), 14 ("Location"), and 19 ("Transport"), meaning that these topics share keywords. These topics relate to the place's neighborhood, so some keywords in common could logically relate to them, justifying the overlap. The model produced a map with few overlapping bubbles and no logical explanation, so we adopted it.

According to the four dimensions of customer value in the SE, the topic mapping aligns with Zhang et al. [23]. The mapped dimension of each topic appears in the third column of Table 1. The technical dimension topics relate to convenience, problem-solving features, and host responsiveness. In the technical dimension, evaluating convenience in terms of the place's location leads to mapping location-related topics (i.e., "Restaurant and shop", "Location", "Transport"), as well as to the hosts' check-in/out arrangement that mapped three topics, namely, "Check in/out," "Luggage," and "Key and lock." Another topic in the technical dimension, "Host's responsiveness" relates to answering

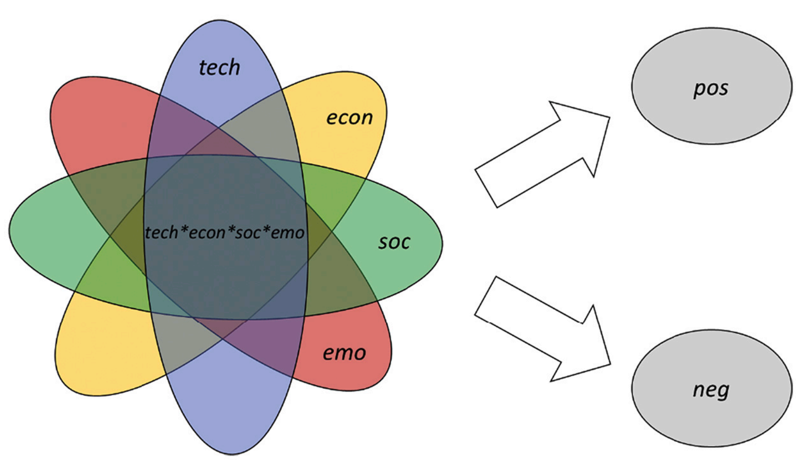

Fig. 2. The configurational model of this study.

Table 1
Topics and keywords extracted by the LDA model.

Topic	Keywords	Dimension
Host's responsiveness	host, always, respond, help, question, quickly, quick, fast, answer, need, reply, available, message, detail, helpful	Technical
Coffee and tea	touch, breakfast, provide, coffee, tea, even, also, morning, thoughtful, towel, fresh, make, extra, fridge, little	
Check in/out	check, host, property, arrive, time, leave, late, day, book, early, let, even, hour, last, get	
Luggage	apartment, floor, stair, luggage, work, top, list, fix, new, building, hotel, break, issue, quality, unit	
Sleep quality	night, room, bit, stay, place, shower, sleep, issue, bed, noise, get, hot, water, bathroom, good	
Restaurant and shop	restaurant, shop, walk, great, close, location, station, apartment, nearby, tube, lot, minute, many, distance, supermarket	
Room	kitchen, bed, flat, bedroom, space, room, bathroom, comfortable, large, well, small, big, spacious, need, area	
Location	well, locate, apartment, flat, clean, quiet, nice, area, neighborhood, equip, comfortable, perfectly, close, explore, spacious	
Key and lock	right, door, next, house, airbnb, look, call, front, give, key, get, go, tell, lock, ready	
Cleanliness	nice, good, room, place, clean, really, stay, location, bathroom, price, big, people, host, small, quite	
Transport	station, walk, close, bus, minute, tube, place, train, stop, great, underground, away, min, easy, location	
Value for money	great, location, place, host, stay, good, value, communication, clean, excellent, apartment, money, flat, thank, lovely	Economic
Communication	easy, check, transport, quick, access, public, communication, response, clean, close, communicate, stay, transportation, super, link	Social
Host's friendliness	clean, host, friendly, comfortable, recommend, stay, helpful, place, super, lovely, room, great, bed, nice, highly	
Travel advice from locals	give, local, tip, lot, area, information, provide, helpful, help, offer, attentive, place, host, incredible, city	
Revisit	back, come, definitely, love, next, stay, time, garden, go, hope, future, return, soon, beautiful, thank	Emotional
Recommendation	recommend, stay, place, perfect, amazing, highly, location, apartment, definitely, host, wonderful, clean, lovely, flat, absolutely	
Enjoyment	really, enjoy, stay, thank, much, worth, real, well, thoroughly, center, position, appreciate, stunning, beautiful, place	
Homeliness	home, feel, make, stay, welcome, lovely, host, comfortable, sure, family, thank, warm, place, house, away	
Pleasant experience	experience, time, good, airbnb, place, stay, want, spend, spot, ever, first, see, day, pleasant, expectation	

questions from or solving problems for guests. In addition, Festila and Müller [52] demonstrate that functional value overlaps with technical value. Therefore, topics that relate to physical amenities, i.e., "Coffee and tea," "Sleep quality," "Room," and "Cleanliness," appear with the technical dimension. Only one topic, "Value for money," concerns the monetary benefits and costs of the Airbnb services, mapped with the economic dimension. The social dimension concerns the building of friendships or social connections between guests and hosts. Interaction-related topics, i.e., "Communication," "Host's friendliness," and "Travel advice from locals," appear with the social dimension. Lastly, "Pleasant experience" and "Enjoyment" reflect guest affective stages and belong with the emotional dimension. Feeling at home is vital in accommodation-sharing for fulfilling guests' emotional needs, so the topic "Homeliness" is mapped with the emotional dimension. Zhu et al. [27] find that reviews about making recommendations or intention to revisit usually show strong personal attachment or belonging. Hence, two affect-related topics, "Revisit" and "Recommendation," are mapped with the emotional dimension. Relative topic importance across room types appears in Fig. 5. The importance of topics reflects topic prevalence, with relative importance differing across the room types.

4.2. Sentiment detection of reviews

When detecting each review's sentiment, VADER provides four measures: positive, negative, neutral, and compound. The compound values, ranging from −1 to +1, classify the reviews as positive, negative, or neutral, as Hutto [53] suggests. When the compound value is greater than or equal to 0.05, the review is positive; less than or equal to −0.05, the review is negative; between −0.05 and 0.05, the review is neutral. Since having many words produces a value likely between −1 and + 1, VADER works best on shorter documents. To make up the deficiencies, we split each review into individual sentences, applying the VADER model at the sentence level, determining the sentiment score of each sentence, and ranking the overall review by the mean of all its sentence sentiment scores.

Using VADER, we discovered that most of the reviews (i.e., 87.37%) are positive, followed by 10.89% neutral, and 1.74% negative. This is not surprising; the literature reports that one aspect of Airbnb reviews is its reciprocal rating system's positivity bias toward hosts [15]. Table 2 shows that this holds true for all room types, for each of which nearly 80% or more of the reviews are positive, and less than 5% are negative. Another sentiment analysis tool—TextBlob—compares the result with VADER as Lee and Tse [14] do. Table 2 shows the proportion of the sentiment classes, using VADER and TextBlob. They differ significantly in that VADER tends to classify more reviews as neutral. This study does not consider neutral reviews for fsQCA; thus, we find the VADER model for detecting positive and negative sentiments effective. Also, its results are similar to those of the other tool.

To further verify the VADER model's reliability, we compared the compound values to the customer ratings, which are unidimensional scores ranging from 0 to 100, posted with the review, and reflecting overall guest satisfaction. Higher ratings imply higher satisfaction levels and, in turn, higher sentiment scores. Fig. 6 shows that reviews with relatively higher ratings have higher sentiment scores. On the other hand, reviews with relatively lower ratings have mostly negative sentiment scores. The verification result shows our VADER model's reliability; reviews with higher ratings generally have higher compound values and vice versa.

4.3. Configurational analysis results

FsQCA identifies service-dimension configurations that explain the presence of positive and negative sentiment. The original values of the causal conditions are the importance of service dimensions of the Airbnb services. A larger value means that consumers mention the dimension more frequently in their reviews; thus, it is more important from the consumers' perspective. The positive reviews were the cases we used to analyze the presence of positive sentiment. Conversely, we used negative reviews to analyze negative sentiment. VADER determined the compound values that became the original outcome values.

One limitation of fsQCA is its reliance on researchers' domain knowledge to calibrate data and produce a truth table to determine possible configurations. While researchers' knowledge and understanding of the domain may lead to a richer analysis, it may introduce subjective bias into the study [54]. Data calibration can use either a direct or indirect method. The indirect method rescales the measurements of variables based on qualitative assessment, while the direct method requires researchers to define three values corresponding to full-set membership, full-set nonmembership, and intermediate-set

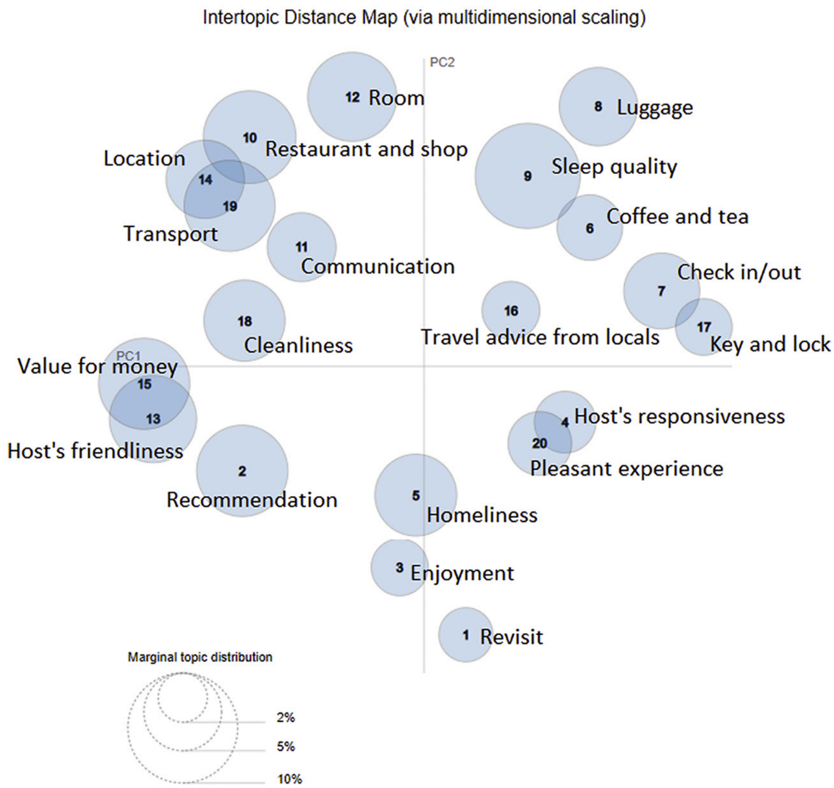

Fig. 4. Intertopic distance map.

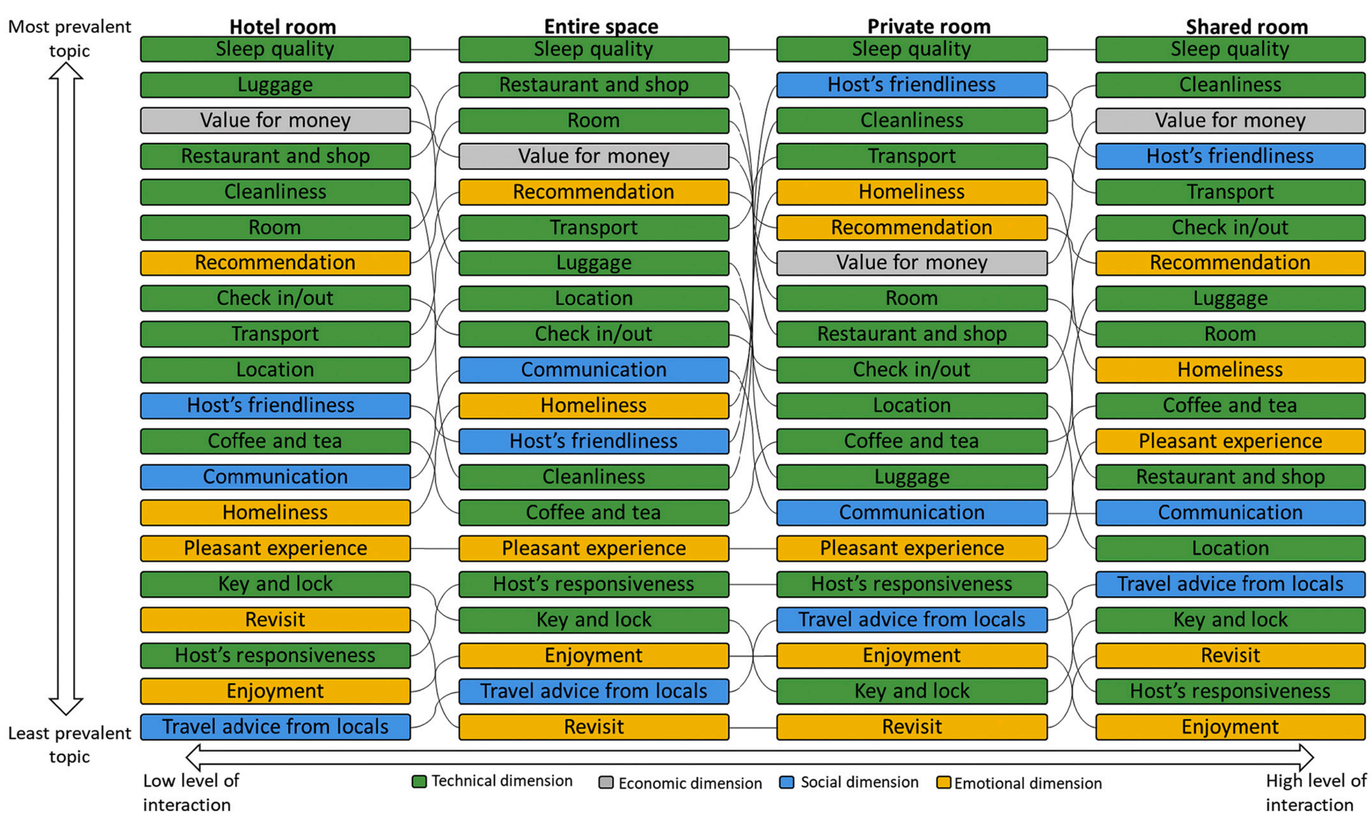

Fig. 5. The relative importance of topics across the room types.

Table 2
Comparison of sentiments across the room types.

Class	Tool	Hotel	Entire space	Private room	Shared room
Positive review (%)	VADER	79.18	87.55	87.55	79.11
	TextBlob	83.48	90.09	89.50	82.59
Neutral review (%)	VADER	17.21	10.33	11.09	18.21
	TextBlob	12.96	7.76	8.95	14.60
Negative reviews (%)	VADER	3.61	2.13	1.36	2.68
	TextBlob	3.55	2.15	1.55	2.80

membership. This study adopted the direct method because it more easily enables replicability and more clearly explains the threshold choices. We followed the guidelines [46] to make references to descriptive statistics for calibration. As Veríssimo [55] reports, the original value that covers 5%, 50%, and 95% of the data values was the point of full nonmembership, the crossover point, and the point of full membership, respectively. Once the calibration is complete, a truth table displays each possible configuration. The truth table requires preliminary refinement based on frequency and consistency. The frequency threshold ensures that at least 80% of the cases in the sample are part of the analyses for the outcome, as Ragin [46] suggests. To analyze positive sentiment, the consistency threshold is set at 0.8. For the negative sentiment, the consistency threshold is set at 0.7, to generate at least one configuration solution.

Table 3 summarizes the fsQCA results. A black circle (●) indicates the presence of a condition while a crossed-out circle (⊗) indicates the absence of a condition. A blank circle (○) is used to represent a do-not-care condition, meaning that the condition might be present or absent. The results show that the configurations of causal conditions that explain the presence of the two outcomes are different when the room types are different. We examine the overall solution coverage that indicates the extent to which the configurations determine positive or negative sentiment. All the solution coverages are at least 0.79, suggesting that the solutions cover a considerable proportion of the outcome. Thus, we adopt the solutions. Significantly, while fsQCA provides increased flexibility for data analysis, and the thresholds in this study may serve as a reference for similar studies, researchers should not employ them mechanically. Researchers may adjust the thresholds until they find the solutions informative.

5. Discussion and implications

5.1. Change in consumers' focus in reviews across room types

Fig. 5 shows that consumers' online reviews focus differently according to the type of rooms in which they stay, on several topics of significantly varying importance. First, the importance of homeliness follows an inverted-U shape when the level of host-guest interactions increases. Guests reasonably mention homeliness least when evaluating the experience of staying in a hotel room that does not offer many home benefits. The importance of homeliness increases significantly from evaluations of the entire space to private rooms. The main difference between these room settings lies in the presence of the hosts. In the entire-space setting, the guests stay without hosts present. In the private-room setting, the guests and the hosts share some space. When hosts and the guests have more in-person interaction in a private-room setting, guests care more about homeliness. Feeling at home can emerge when the hosts interact with guests in a way that makes them feel welcome. Yet, while the level of interaction increases from the private room to the shared room, the importance of homeliness drops. A possible reason is that other strangers (e.g., other guests) could occupy a shared-room setting. The construct of feeling at home is not easy to achieve when strangers are around. Zhu et al. [27] support this, confirming that private space is a vital feature of being home. Accordingly, we suggest that while the guest-host interactions play an important role in homeliness, hosts should maintain a private atmosphere for the guests to make them feel at home.

Second, guests at a higher interaction level (i.e., private room and shared room) care more about social value, particularly in terms of a host's friendliness and local travel advice, than consumers at a lower interaction level (i.e., hotel room and entire space). In hotel-room and entire-space settings, guests focus less on the host's friendliness. In contrast, by staying in a private room or a shared room, the guests and hosts can spend more time together, and thus, guests take account of hosts' friendliness in the service evaluation in reviews. Another interesting finding concerns travel advice from locals, the importance of which increases with the level of interaction; consumers at a higher interaction level value local connections more.

Regardless of room type, guests focus most on sleep quality. This is in line with Hon and Fung [56], who show that offering the appropriate sleep environment can enhance guests' satisfaction and revisit intention. In fact, various factors, such as room temperature, smell, and bed

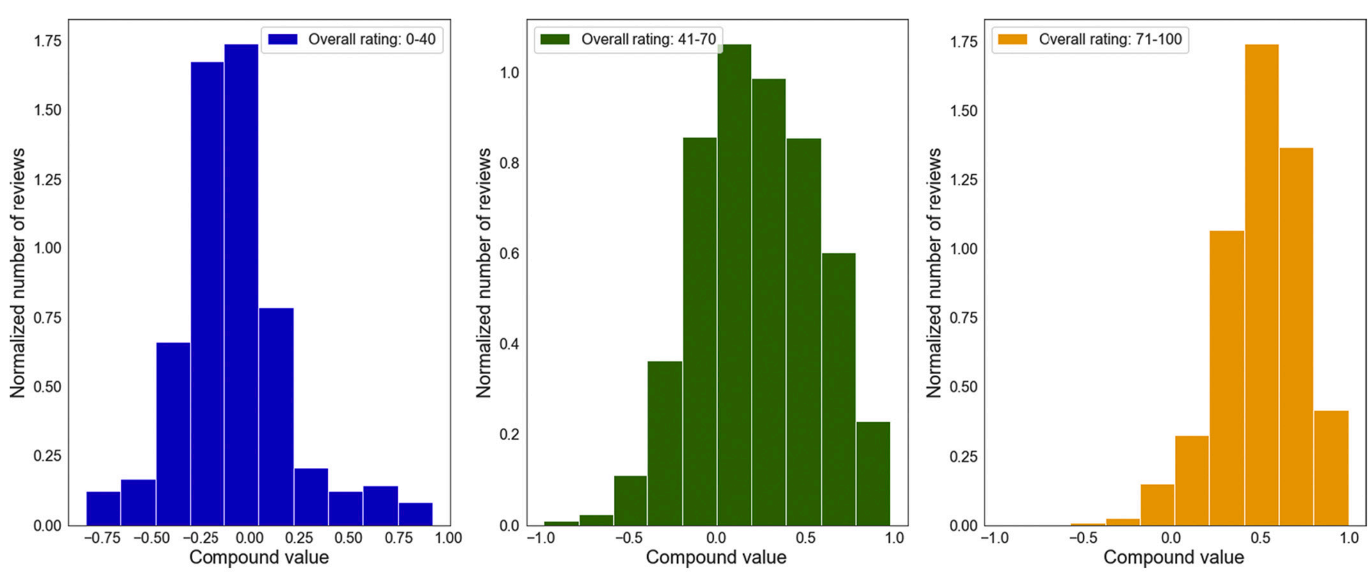

Fig. 6. Sentiment scores and overall ratings of the reviews.

Table 3
Configurations for the presence of positive and negative sentiments.

		Outcome: positive sentiment						Outcome: negative sentiment				
Hotel room	Configuration	HP1	HP2	HP3	HP4			HN1	HN2	HN3	HN4	
	Technical	⊗	○	○	○			⊗	○	○	○	
	Economic	●	⊗	●	●			○	○	⊗	●	
	Social	○	●	⊗	●			○	●	○	○	
	Emotional	○	●	●	⊗			○	○	●	⊗	
	Raw coverage	0.541	0.311	0.330	0.312			0.658	0.624	0.481	0.297	
	Unique coverage	0.104	0.112	0.020	0.027			0.098	0.054	0.043	0.013	
	Consistency	0.790	0.799	0.829	0.830			0.640	0.677	0.646	0.714	
	Solution coverage	0.709						0.875				
	Solution consistency	0.749						0.586				
Entire space	Configuration	EP1	EP2	EP3	EP4	EP5	EP6	EN1	EN2	EN3	EN4	
	Technical	⊗	⊗	⊗	○	○	○	⊗	○	○	○	
	Economic	○	○	●	⊗	●	●	○	○	⊗	●	
	Social	○	●	○	●	⊗	●	○	○	●	⊗	
	Emotional	●	○	○	●	●	⊗	○	●	○	○	
	Raw coverage	0.530	0.467	0.521	0.310	0.313	0.287	0.681	0.597	0.498	0.298	
	Unique coverage	0.062	0.031	0.073	0.020	0.017	0.021	0.089	0.066	0.045	0.012	
	Consistency	0.769	0.768	0.793	0.809	0.848	0.823	0.622	0.628	0.646	0.715	
	Solution coverage	0.793						0.875				
	Solution consistency	0.714						0.569				

Private	Configuration	PP1	PP2	PP3	PP4	PP5	PP6	PN1	PN2	PN3		
room	Technical	⊗	⊗	⊗	○	○	○	⊗	○	○		
	Economic	○	○	●	○	●	●	○	○	⊗		
	Social	○	●	○	●	○	●	○	●	○		
	Emotional	●	○	○	●	●	○	○	○	●		
	Raw coverage	0.521	0.486	0.481	0.369	0.358	0.333	0.684	0.609	0.524		
	Unique coverage	0.061	0.051	0.059	0.019	0.022	0.021	0.105	0.078	0.044		
	Consistency	0.755	0.771	0.796	0.804	0.820	0.824	0.613	0.623	0.659		
	Solution coverage	0.793						0.862				
	Solution consistency	0.709						0.574				
Shared	Configuration	SP1	SP2	SP3	SP4			SN1	SN2	SN3	SN4	SN5
room	Technical	⊗	○	○	○			○	⊗	○	⊗	⊗
	Economic	○	○	●	●			⊗	○	●	⊗	○
	Social	○	●	○	●			○	●	⊗	○	○
	Emotional	○	●	●	○			●	○	⊗	○	⊗
	Raw coverage	0.712	0.379	0.397	0.366			0.511	0.488	0.265	0.531	0.486
	Unique coverage	0.159	0.018	0.025	0.026			0.065	0.024	0.040	0.010	0.021
	Consistency	0.698	0.795	0.815	0.818			0.686	0.777	0.778	0.698	0.754
	Solution coverage	0.794						0.800				
	Solution consistency	0.682						0.662				

amenities, can affect sleep quality. Based on the keywords associated with the topic "Sleep quality," noise is one of the key related aspects. This finding is in line with Lee et al. [57], who report that guests have negative experiences due to noises that construction work, traffic, and bars can cause. Accordingly, hosts should provide an optimal environment for guests to manage their sleep. For example, double-glazed windows keep the place quieter. In shared space, they can set house rules for noise control.

5.2. Configurations of causal conditions for positive and negative sentiments

Strong positive sentiment occurs when the configurations reflect combinations of service-dimension presence and absence. Generating a strong positive sentiment in a hotel-room setting results from the combined presence of the economic dimension and absence of the technical dimension (configuration HP1), the presence of the emotional dimension and the absence of the social dimension (configuration HP3), or the presence of the social dimension and the absence of the emotional dimension (configuration HP4). On the other hand, in the absence of the economic dimension, strong positive sentiment can emerge with the presence of both emotional and social dimensions (configuration HP2). Interestingly, all the configurations for strong positive sentiments in a hotel-room setting also apply in an entire-space setting (configurations EP3–6). This shows that when consumers choose to stay in a place where in-person host-guest interactions are avoidable, their service evaluation could be similar. In addition, absent the technical dimension, the causal configurations in an entire-room setting (configurations EP1–3) are the same as those in a private-room setting (configurations PP1–3), achieving strong positive sentiment with the presence of at least one of the other three dimensions when the technical dimension is absent. In a private-room setting, the same outcome results when two out of the three dimensions—emotional, social, and economic—are present (configurations PP4–6). Moreover, in a shared-room setting, configurations leading to positive sentiment include the absence of the technical dimension (configuration SP1) and the presence of two dimensions other than the technical dimension (configurations SP2–4). Configurations SP2–4 are the same as configurations PP4–6. This indicates that when people share space, the technical dimension plays a minor role in the outcome. One possible reason is that when guests occupy the space alone, their sense of ownership is less, and in turn, guests weigh the technical dimension, such as physical amenities, less heavily.

The configurations leading to strong negative sentiment differ from those leading to strong positive sentiment. The configurations for negative sentiment involve the absence of conditions more than presence. Yet, the absence of a condition may not be sufficient to explain the presence of strong negative sentiment, depending on how it combines with the presence and absence of other conditions. First, in a hotel-room setting, a strong negative sentiment results when the technical dimension is absent (configuration HN1) or the social dimension is present (configuration HN2). It can also result from the combination of the presence of the emotional dimension and the absence of the economic dimension (configuration HN3) or the presence of the economic dimension with the absence of the emotional dimension (configuration HN4). In an entire-space setting, a strong negative sentiment can occur in the absence of the technical dimension (configuration EN1) or in the presence of the emotional dimension (configuration EN2). Regardless of the importance of technical and emotional dimensions, social and economic dimensions cannot both be present and result in strong negative sentiment. Only one present and the other absent achieves strong negative sentiments (configurations EN3–4). Surprisingly, the configurations for strong negative sentiment in a private-room setting (configurations PN1–3) also occur in the hotel-room setting. This shows that when their stay in a hotel room or a private room dissatisfies consumers, they could focus in their reviews on a similar combination of dimensions—unexpected because hotel rooms and private rooms offer different product and service attributes that could lead to different service evaluations. Yet, the content of the reviews might better explain this result. For instance, when hotel guests consider their stay negative, they may emphasize the social dimension in their reviews by saying that they had too much interaction with the hosts. Conversely, when private-room guests consider their stay negative, they may emphasize social dimensions in their reviews by indicating too little interaction with the hosts. Therefore, by looking solely at the configurations that fsQCA determines, we can only tell the combination of service-dimension patterns leading to strong sentiments; the detailed description of each service dimension does not appear. Finally, a strong negative sentiment in a shared-room setting occurs in the absence of the technical dimension combined with the presence of the social dimension (configuration SN2), the absence of the economic dimension (configuration SN4), or the absence of the emotional dimension (configuration SN5). Further, the same outcome results by combining the absence of the economic dimension with the presence of the emotional dimension (configuration SN1) or the presence of the economic dimension with the co-absence of both emotional and social dimensions.

5.3. Theoretical and practical implications

In the current literature, fsQCA remains a relatively new method for DSS. It is more commonly used in social sciences, marketing, operations, and supply chain management, where many sources and types of data for the causal conditions and outcomes come from interviews (e.g., [58]), surveys (e.g., [59]) and vignette-based experiments (e.g., [60]). Secondary data are increasingly available for exploring real-world phenomena, and more researchers use secondary data as the source for fsQCA (e.g., [61]). Most are structured data, and we knew little about how unstructured data, such as online consumer reviews, could support fsQCA. Our study fills this gap, integrating two methodological approaches (text analytics and fsQCA), to directly extract important service dimensions from online reviews, and shift attention from individual service dimensions to configurations of service dimensions, to develop a fine-grained understanding of consumer satisfaction in the SE. Specifically, by leveraging the methodological advantages of fsQCA and complementing the results with text analytics (LDA and sentiment analysis), this study reveals that the causal recipes for consumer satisfaction differ across room types. This finding significantly contributes to the debate on consumer behavior by expanding the perspective of previous studies that consider SE services a single service, regardless of the level of face-to-face interaction.

This study's results take the form of prescriptive causal recipes that contrast with the types of insights one can gather by relying only on the traditional econometric approaches, focusing on the effect of just one or two causal variables and how a unit change may affect a certain performance outcome [62]. Our data-driven prescriptive configurational recipes also usefully complement the insights that one might gather from complexity approaches that rely on simulations to understanding a phenomenon but not necessarily provide causal recipes of the type that a configurational approach delivers [62].

The key takeaway from this study is twofold. First, a DSS should adopt text-mining approaches to uncovering important knowledge for managing consumer behavior. While many systems extract star or customer ratings as a proxy for overall service quality, they may oversimplify the quality measures by assuming that quality is unidimensional. User-generated content, such as online reviews that contain personal narratives of experiences with a specific product or service, better suits the identification of consumer likes and dislikes. Second, consumer behavior is a complex system that examining its individual components cannot sufficiently explain. Therefore, a DSS supporting decisions to enhance consumer satisfaction should attend to service-dimension configurations, rather than individual service dimensions.

From a practical perspective, embedding fsQCA in DSS is useful for analyzing consumer experiences as a complex system. The proposed methodology enables service providers to make better decisions by targeting consumer segments with different interaction levels and identifying the configurations of factors that explain consumer experiences, to improve decisions regarding the design and functional aspects of an online platform in the SE. In practice, to reduce information search and acquisition costs, many online platforms use a standardized design to list the product/service descriptions. Our results suggest tailoring the platform design to specific consumer segments with different interaction levels, by highlighting the more important attributes to assist consumers in making better decisions. From the functional perspective of an online platform, introducing structured comment forms could lead consumers to comment on specific dimensions. Analyzing collected data to ensure better decision-making calls for more effective system design to rate service-provider performance.

6. Conclusion

This study proposes a framework that integrates text analytics and fsQCA, to examine the complexity of consumer experiences in the SE according to the level of interaction between consumers and service providers. Methodologically, it contributes by integrating LDA, sentiment analysis, and fsQCA. It identifies 20 topics that Airbnb guests usually mention. Results show that guests weigh service dimensions differently when they experience different levels of interaction with the hosts. The study further classifies topics by technical, economic, social, and emotional dimensions, identifying dimensional configurations sufficient to indicate strong positive and strong negative sentiments in the reviews.

Future research directions are threefold. First, we analyzed reviews from London due to the current and potential importance of London tourism and Airbnb developments. We lack enough evidence to affirm the degree of generalizability of the findings. Future research that includes reviews from other cities and countries could resolve that issue. Second, various types of guests (e.g., business travelers, leisure travelers) may evaluate service attributes differently. Future research could compare the importance of service dimensions across types of guests under various interaction mechanisms. Third, future studies could apply our methodology, which only examines guest-host interactions, to analyzing consumer reviews that address other types of interaction (e.g., guest-community, guest-guest), to compare results.

Credit author statement

Carmen Kar Hang Lee: the sole authorship.

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