Improving peer-to-peer accommodation service based on text analytics

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Abstract

Purpose – This paper aims to identify key service attributes in peer-to-peer (P2P) accommodation from online reviews and formulate service improvement strategies based on the unsatisfactory service encounters mined from the reviews.

Design/methodology/approach – The methodology involves topic modelling using latent Dirichlet allocation, sentiment analysis, and process analysis based on Process Chain Network (PCN).

Findings – The text analytics results showed that negative P2P accommodation experiences are caused by the lack of hot water for shower, poor sleep quality, and unpleasant check-in.

Research limitations/implications – The PCN analysis shows that the surrogate interactions of the P2P accommodation platform with both the guest and the host impact consumer experiences. This highlights that the key to managing consumer experiences lies in the non-human resources such as information, rather than direct interactions between process entities.

Practical implications – The information on the P2P accommodation platform should be in a more interactive format such as video and 360 degrees camera. Hosts should ensure a good condition of the physical products such as water heaters and beds before guests' arrival. Professional videography and handyperson services should be provided by the platform to help hosts deliver a preferred consumer experience. Flexible and strict check-in polices should also be introduced to smoothen the check-in process.

Originality/value – This study is built on multi-attribute utility theory. It is also one of the first to study P2P accommodation services from an operations management perspective. It demonstrates how text analytics serves as an additional supplement for service improvement.

Keywords: *Peer-to-peer accommodation, Online reviews, Latent Dirichlet allocation, Sentiment analysis, Process chain network, Multi-attribute utility theory*

1. Introduction

The ongoing digitalisation has remarkably changed consumer behaviour toward consumption practices, paving the ways for new business models that connect people to share underutilized assets (Gansky, 2010). A peer-to-peer (P2P) service refers to the sharing of privately-owned products with individuals who are in need of such products temporarily. While P2P service exists in various industries, its impact is more evident in the hospitality industry (Alrawadieh and Alrawadieh, 2018). In the hospitality industry, a P2P service involves a peer (i.e. a host) offering accommodation (e.g. spare bedrooms or unoccupied properties) to another peer (i.e. a guest) for short stay.

In general, people are wary of sleeping in a stranger's home. Therefore, most P2P accommodation platforms, such as Airbnb, facilitate trust by allowing users to share the experience after the stay so that other users can rely on other users' reviews to make accommodation booking decisions. Consumer reviews are generally done in two formats: numeric review ratings (e.g. the number of stars) and textual reviews. With the increase in the number of users in P2P accommodation services, the massive amounts of consumer reviews become a valuable source to understand consumers' expectations of quality accommodation. Researchers have also shown increasing interest in analysing consumer reviews. Many of them use star rating and/or consumer rating as a proxy for

the overall perceived quality of the service (Guo et al., 2017; Öğüt and Onur Taş, 2012). However, this might oversimplify the quality measures by assuming that quality is a unidimensional measure (Archak et al., 2011). According to multi-attribute utility theory (MAUT), products or services have multiple attributes and different attributes can have different levels of importance to consumers. Using consumer ratings as a proxy for the quality may overlook some important attributes that may satisfy or dissatisfy the consumers. To address this drawback, this study focuses on textual reviews as they contain personal narrative of experiences made with a specific product or service (von Helversen et al., 2018), more suitable for identifying the "likes" and "dislikes" of consumers. It uses text analytics to identify key service attributes from the textual reviews and extract the sentiment hidden in the reviews directly. Lawani et al. (2019) used sentiment analysis to derive the quality from the textual reviews and their findings suggested that scores derived from the sentiment analysis are better indicators of quality than single rating scores.

On the other hand, there are prior studies applying text analytics on user-generated content (UGC) in tourism management (Berezina et al., 2016; He et al., 2017; Hu et al., 2019; Xiang et al., 2015). Yet, in the sharing economy context, empirical studies based on UGC such as online reviews remain limited. Most of the studies relied on traditional survey-based approach, to identify the key service attributes of consumer experience. Further, different studies' findings about P2P accommodation may not draw a consistent conclusion. For example, Tussyadiah and Pesonen (2016) found that social interactions motivate people to participate in P2P accommodation. In other studies, however, Tussyadiah (2016) reported that some consumers intentionally avoid social interactions during P2P accommodation. Such contradictory findings may be due to limitations brought by limited samples and different set of measurement items adopted in prior studies. To this end, this study uses text analytics to investigate important service attributes directly from consumer reviews, overcoming the limitations found in prior studies.

Table 1 compares this study with several recent studies that apply text analytics on consumer reviews. Guo et al. (2017), Zhang (2019a) and Lee et al. (2019) used topic modelling to extract important topics from Airbnb or hotel reviews. They did not include sentiment analysis as they focused on the relationship of topics with demographic segments and hotel star-rating (Guo et al., 2017), listing performance (Zhang, 2019a), and time and seasons (Lee et al., 2019). In another study, Zhang (2019b) compared Airbnb topics with the hotel topics identified by Guo et al. (2017) and identified unique topics on Airbnb. Situmorang et al. (2018) and Ju et al. (2019) extracted topics from Airbnb reviews and examined the effect of topics on consumer satisfaction based on sentiment analysis. While most studies conducting sentiment analysis confirmed that Airbnb reviews have positivity bias towards the hosts, Cheng and Jin (2019) identified that topics associated with negative sentiments were noise, floor, shower, parking, and door. Yet, no research effort has been put on integrating Airbnb process improvement with text analytics, indicating a research gap in the literature.

The key aspect that differentiates this study from the existing studies is that this study integrates process analysis with text analytics in P2P accommodation, contributing to the literature on service science and the sharing economy. Nam et al. (2018) and Zuo et al. (2019) are the few studies that integrate process analysis and text analytics. Nam et al. (2018) extracted topics from flight passenger reviews and each topic was considered as service encounters based on passenger experiences. The in-flight service was resigned by mapping the service encounters with a service blueprint framework. Zuo et al. (2019) used sentiment analysis to extract negative comments posted by car-hailing passengers, followed by association analysis to extract frequent co-occurrence words from the negative comments. The frequent co-occurrence words represented service issues in car-hailing that should be improved and were mapped with a process chain network (PCN) framework for

service improvement. PCN is found to be more suitable than service blueprint because it can clearly depict complex interactions among entities (i.e. sharing platform, host, guest in the P2P accommodation service network) (Zuo et al., 2019). Thus, this study aims to mine negative topics and depict them in PCN to identify strategies for service improvement. Accordingly, three research questions will be addressed:

(i) What are the key service dimensions of Airbnb from the perspective of guests?

(ii) Which service dimensions are more associated with negative sentiments?

(iii) How to derive data-driven strategies for improving Airbnb customer satisfaction based on PCN?

The contributions of this study are primarily reflected in its expansion of previous studies examining key service dimensions of P2P accommodation through two areas of integration. First, this study integrates text analytics and MAUT. Unlike prior studies that used statistical information such as average ratings to have an overview of the overall perceived quality of the product or service, this study uses topic modelling to identify multiple attributes and derives sentiment scores as a quantitative measure of customer satisfaction of each attribute. Second, this study integrates sharing economy and operations management. Many research perspectives still come from the marketing field and seek to understand dimensions that influence customer satisfaction in the sharing economy from a consumer behaviour perspective. This study addresses the recent call by Benjaafar and Hu (2020) to explore sharing economy services from an operations management perspective. This study focuses on mining unsatisfactory service encounters and depicting them in PCN to visualise key tangible elements of service delivery. It provides useful insights on the redesign of P2P accommodation services.

The remaining of the paper is organised as follows. Section 2 presents the literature related to this study. Section 3 describes the methodology. Section 4 discusses the result. Section 5 presents the implications and concludes this study.

Table 1. Comparison of this study with prior studies applying text analytics on consumer reviews

Reference	Data used	Topic extraction	Sentiment analysis	Process analysis	Scope
Guo et al. (2017)	266,544 hotel reviews	✓	×	×	Identify topics that are key for hotels and their differences across demographic segments and star-rated hotels
Nam et al. (2018)	64,706 flight passenger reviews	✓	×	✓	Redesign service process based on topics extracted from reviews
Situmorang et al. (2018)	24,911 Airbnb reviews	✓	✓	×	Examine the effect of topics on consumer satisfaction
Cheng and Jin (2019)	170,124 Airbnb reviews	✓	✓	×	Identify key topics that influence Airbnb guests' experiences
Ju et al. (2019)	16,340 Airbnb reviews, online survey (N = 322)	✓	✓	×	Examine the effect of topics on consumer satisfaction
Lee et al. (2019)	169,666 Airbnb reviews	✓	×	×	Demonstrate how Airbnb guests' expectations change over a five-year timespan and in different seasons
Zhang (2019a)	2,766,420 Airbnb reviews	✓	×	×	Identify key topics of consumer reviews and their impacts on Airbnb listings' performance
Zhang (2019b)	1,056,988 Airbnb reviews	✓	✓	×	Compare topics from consumer reviews between Airbnb and hotels
Zuo et al. (2019)	4,331 microblogs posted by car-hailing passengers	×	✓	✓	Mine service issues from negative comments, locate them in PCN and suggest strategies for service improvement
This study	216, 517 Airbnb reviews	✓	✓	✓	Mine negative topics based on sentiment analysis and depict them in PCN to identify strategies for service improvement

2. Literature review

2.1 Sharing economy in hospitality

The rapid growth of the sharing economy has dramatically changed the way consumers travel, which gives ways to successful start-up businesses, such as Airbnb, that offers P2P accommodation. Current literature has highlighted the characteristics that set P2P accommodation apart from traditional hotels. First, authentic local experience is one of the highlights in shared accommodation where the socialization needs of guests are emphasized by many scholars (Cheng, 2016; Habibi et al., 2017). The aim of shared accommodation is to make guests feel at home and bond with the local environment. Such a peer-to-peer contact (Oskam and Boswijk, 2016) differs from ordinary hotel service where social interaction is not expected (Lin et al., 2019). The second distinctive characteristic is the low standardization of shared accommodation. Compared with traditional hotels that reduce risks through standardization, safety regulations and business reputation, sharing economy service is delivered by individual peers who are not as professional as the mainstream providers. As a result, the service is less standardized, and the quality is of low predictability.

The differentiation between P2P accommodation and traditional hotels indicates the insufficiencies of existing studies from traditional tourism management in understanding tourists' expectations in the sharing economy. While there are prior studies studying the impact of shared accommodation on the hotel industry (Blal et al., 2018; Zervas et al., 2017) and its role as disruptive innovation (Geissinger et al., 2018; Guttentag, 2015), there is a need to devote more research effort regarding the discovery of distinctive service dimensions that contribute to consumer experience in P2P accommodation.

Researchers have shown increasing interest in understanding consumer experience by analysing online reviews. Prior studies confirmed that online reviews had an impact on consumers' purchasing decisions, such as their accommodation booking intention (Gavilan et al., 2018; Lee and Shin, 2014). In view of the fact that consumers will be less inclined to make a booking if the hosts have a lot of negative reviews, Zhang et al. (2019) revealed an interesting finding regarding a trade-off problem faced by the hosts. In order to avoid expectation-actuality discrepancy when the actual property is not as good as what the property images portray, some hosts are hesitant to post high-quality property images as they may create unrealistically high expectations for the guests.

In the literature, there is a lack of investigation of negative reviews. Yet, a closer look at negative reviews is important as this provides an opportunity for hosts to address these areas through rectifying any maintenance issues or setting realistic expectations (Cheng and Jin, 2019). As the scope of this study is to identify unsatisfactory service encounters for service improvement, negative reviews based on sentiment analysis will be investigated.

2.2 Integrating multi-attribute utility theory with text analytics

Multi-Attribute Utility Theory (MAUT) combines a class of psychological measurement models and scaling procedures to evaluate alternatives based on multiple attributes (von Winterfeldt and Fischer, 1975). It provides a comprehensive set of quantitative and qualitative approaches to justify a decision between alternatives (Canada and Sullivan, 1989). It allows decision makers to develop reasonable preference criteria, determine which assumptions, are most appropriate, and assess the resulting utility functions (Lindey, 1985). Therefore, it is widely applied in the broader field of Multi-Criteria Decision Making. While most MAUT applications focuses on selecting an alternative based on multiple

attributes (Collins et al., 2006; Kailiponi, 2010; Minamino et al., 2015), the methodology proposed by this study built on the basis of MAUT and focuses on how consumers evaluate their decisions based on multiple attributes. To achieve this, text analytics is integrated with MAUT.

First, topic modelling can be applied to extract the criteria that customers use when evaluating the services. Each topic mined from the reviews is treated as an important service attribute. Based on MAUT, consumers consider multiple attributes in choosing or evaluating a service. In line with this, we expected that consumers will mention multiple attributes in their reviews. Latent dirichlet allocation (LDA) is particularly chosen for this study because it considers each document (i.e. review in this study) as a mixture of latent topics, each of which is characterised by a distribution over words (Blei et al., 2003). Prior studies have shown that LDA can discover various attributes from Airbnb reviews (Situmorang et al., 2018; Zhang 2019b). According to Zhang (2019a), LDA is particularly suitable for examining Airbnb reviews for two reasons. First, it does not make any assumptions about the structure of grammar properties of the text which make it suitable for mining unstructured online reviews. Second, it is efficient in discovering underlying topics from a massive volume of documents.

In addition, consumers having different preferences on different criteria leads towards the use of MAUT. Accordingly, service evaluation should not be considered as one-dimensional. Yet, while researchers started to understand customer satisfaction by analysing customer reviews, many of them used star rating and/or customer rating as a proxy for the overall perceived quality of the service (e.g. Guo et al., 2017; Öğüt and Onur Taş, 2012). This oversimplified the quality measures by assuming that quality is a unidimensional measure (Archak et al., 2011), and overlooked some important attributes that may satisfy or dissatisfy the consumers. To overcome this limitation, this study uses sentiment analysis to extract sentiment directly from the consumer reviews with respect to each attribute.

Sentiment analysis is a type of natural language processing that can perform classification on sentiments based on published online reviews (Vinodhini and Chandrasekaran, 2012). It allows the discovery of positive, neutral or negative opinions conveyed in any given document, paragraph or sentence. We particularly focus on the negative opinions as they are useful for identifying potential areas for improvement.

2.3 Service improvement

Based on the negative reviews, services that require improvements can be identified. As service improvement starts with a comprehensive understanding of the service processes and components, service blueprinting is one of the methods to visualise the entire service process. It was introduced by Shostack (1982) as a customer-focused approach for service innovation and service improvement (Bitner et al., 2008). Prior studies have used text mining results as an input to service blueprints (Nam et al., 2018; Ryu et al., 2019). Zuo et al. (2019) pointed out that service blueprinting has obvious limitations when applied to analyse the sharing economy service network, due to the complex interaction among various entities. To clearly depict complex interactions among multiple entities in a service network, process chain network (PCN) was proposed by Sampson (2012).

In PCN, activities in the process domain are organized into three types of regions depending to the level of interaction (Sampson, 2012):

- The direct interaction region includes process steps that involve person-to-person interaction between entities;

- The surrogate interaction region includes process steps in which one entity is acting on a non-human resource of another entity; and
- The independent processing region includes process steps that does not involve either direct or surrogate interaction with other entities.

With its emphasis on process regions, PCN has potential to highlight aspects of services involving surrogate interactions that impact customer experience (Kazemzadeh, 2015a). For example, an guest waiting for the host's response, as a surrogate interaction, may negatively influence the customer experience if the wait is long. Kazemzadeh et al. (2015b) compared service blueprinting and PCN, using the hotel stay as examples, and concluded that PCN provides a better insight about the nature of interaction between participant entities involved in a service process.

3. Methodology

The methodology used in this study is shown in Figure 1. It can be used as a practical guideline for researchers to extract key service attributes from UGC using LDA, to classify each attribute into positive, negative or natural using sentiment analysis, and to use PCN for establishing data-driven strategies for service improvement.

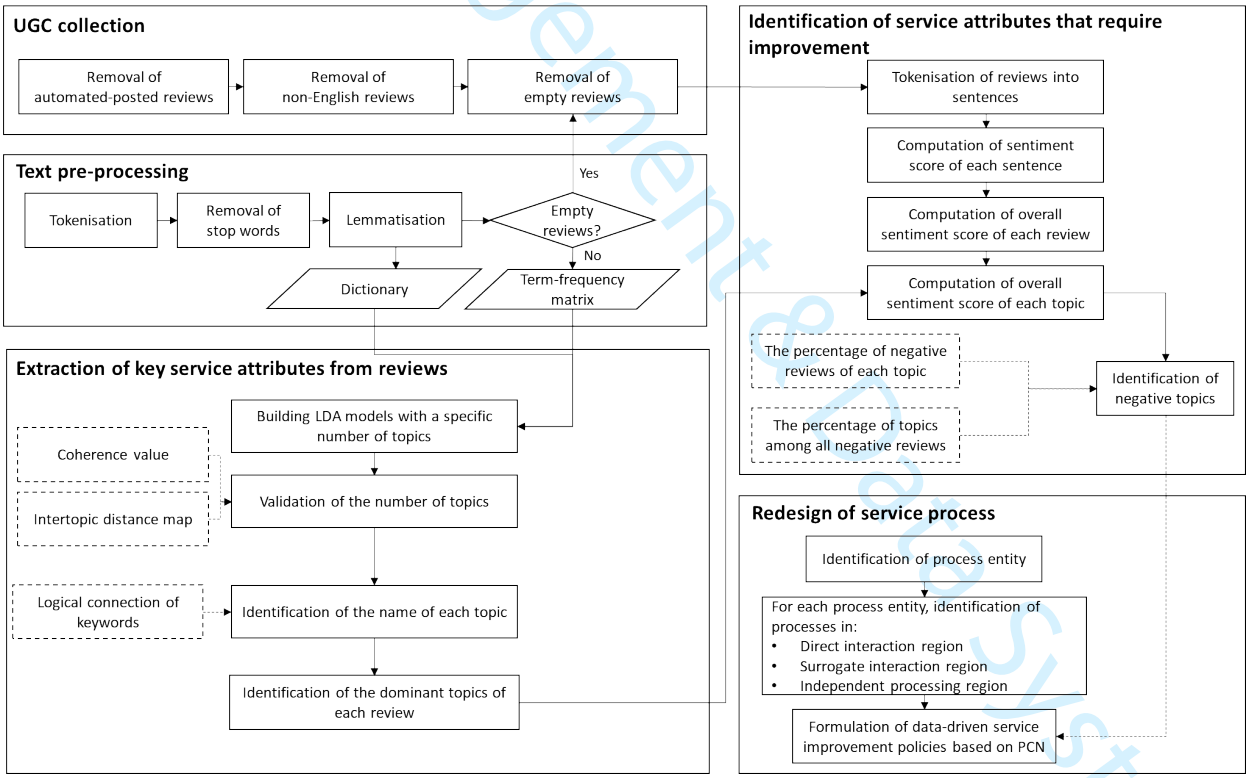


Figure 1. Research methodology

3.1 UGC collection and text pre-processing

In this study, 257,553 reviews posted by guests who used Airbnb services during the stay in London in 2017 are collected. After omitting non-English reviews and automated postings due to cancellation of the booking, the dataset size is reduced to 216,528.

Text pre-processing is performed on the reviews. Tokenization is used to discretize words within a review. Stop words that do not convey specific meaning are filtered. Lemmatisation is conducted to aggregate inflected forms of the same noun or verb into a common lemma. In addition, only nouns, verbs, adverbs, and adjectives are kept. After removing the null reviews, there are 216,517 reviews remaining for this study, and a list of 29,965 words is generated. A dictionary is created to map a unique ID to each word. The frequency of each word is computed to create a term-frequency matrix. The dictionary and the term-frequency matrix are the two main inputs to LDA. A word cloud, as shown in Figure 2, is generated to understand the keywords that are frequently mentioned by customers.

Figure 2. Word cloud diagram

3.2 Extraction of key service attributes from reviews

This study used *Gensim* library in Python to build the LDA model. One of the critical tasks in building an LDA model is to determine the number of topics. Topic coherence is chosen for mode evaluation (Nikolenko et al., 2017). Topic coherence measures score a single topic by measuring the degree of semantic similarity between high scoring words in the topic. They help distinguish between topics that are semantically interpretable topics and topics that are artefacts of statistical inference, hence suitable for this study.

Before adopting the model, additional work is done to check whether the topics are meaningful and interpretable and clean. While some researchers performed this subjectively (Zhang, 2019a), we use visualisation to aid our subjective judgement. Specifically, an intertopic distance map is plotted using the *pyLDAvis* package to examine the overlap of topics. In general, a good model will have distinct and thus non-overlapping topics.

3.3 Identification of service attributes that require improvement

Lexicons that have been widely used for sentiment analysis include LIWC and VADER. In this study, VADER is chosen because it is more sensitive to sentiment expression in social media contexts such as

Airbnb reviews (Alsudais and Teubner, 2019; Hutto and Gilbert, 2014). It incorporates a well-established lexicon set that includes social media terms, such as Western-style emoticons (e.g. :-)), sentiment-related acronyms and initialisms (e.g. LOL), and commonly used slang with sentiment value (e.g. nah, giggly). More importantly, it is suitable for analysing social media content because it takes into account five heuristics for dealing with punctuation, capitalisation, degree modifiers, contrastive conjunction, and negation (Hutto and Gilbert, 2014).

VADER returns a sentiment score in the range of -1 to +1, from most negative to most positive. If there are a lot of words in the document, the score will be close to -1 to +1. Thus, VADER works best on short documents. In view of this, each review is split into individual sentences. The overall sentiment of the review is the mean of the sentiment scores of all its sentences.

3.4 Redesign of service process

Taking Airbnb platform as an example, the service process of P2P accommodation can be divided into five sub-processes as follows:

(i) The guest registered an account on the platform. Based on his/her search criteria, the platform provides a list of available listing. To show intention to book a listing, he/she inputs the payment details and sends a booking request. If the request is declined, this sub-process will start again.
(ii) The platform forwards the booking request to the host.
(iii) The host receives a request from the guest. He/She has the choice to accept or reject the request.
(iv) If the request is accepted by the host, the platform processes the payment. The guest checks in to the place. The platform holds the payment until 24 hours after guest's check-in.
(v) After the stay, both the guest and the host post a review about their experience on platform.

Based on these sub-processes, a PCN diagram is produced as shown in Figure 3. Unsatisfactory service encounters mined from text analytics can be mapped to the PCN to identify ideas for improvement.

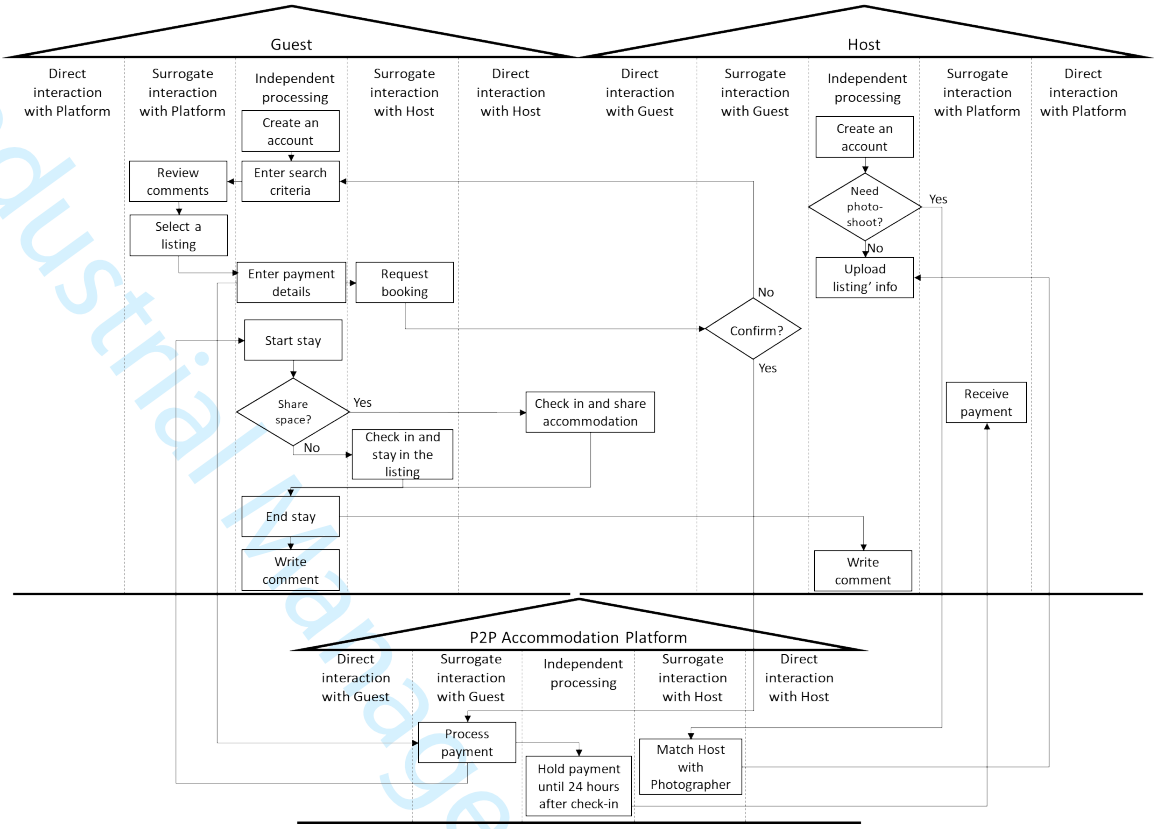


Figure 3. PCN diagram of P2P accommodation services

4. Results and discussion

4.1 Extracted service attributes from Airbnb reviews

The approach to finding the optimal number of topics is to have various LDA models with different numbers of topics (k) and pick the one that gives the highest coherence value (c). Our selection criterion is to choose a "k" that marks the end of a rapid growth of topic coherence. According to the result as shown in Figure 4, the value of 10 is chosen. Choosing a value larger than 10 may provide more granular sub-topics.

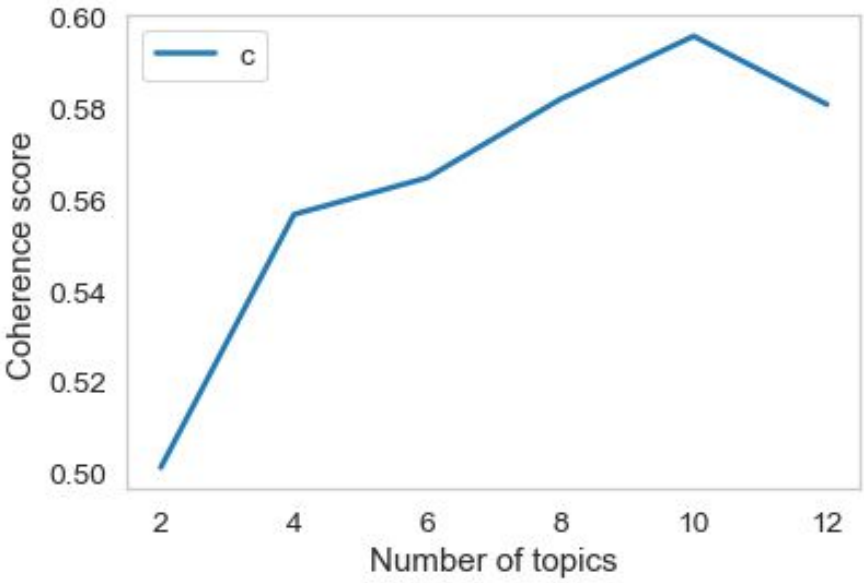


Figure 4. Coherence scores with different numbers of topics

We give a name to each topic based on the frequently-mentioned keywords returned by the model as shown in Table 2. A topic name is proposed based on the logical connection among the keywords (Guo et al., 2017; Zhang, 2019a; Zhang, 2019b). The topic name was retained when the logical connection was found. Otherwise, the naming process started all over again.

An intertopic distance map, as shown in Figure 5, is used to visualise the topics and the keywords. Each bubble on map represents a topic. The larger the bubble, the more prevalent the topic. A significant overlap of bubbles appears between Topic 2 ("Transport") and Topic 4 ("Restaurant and shop"). It means that there are common keywords associated with both topics. This can be justified as these topics are about the neighbourhood of the place and common keywords such as "walk", "minute" and "tube" are logically related to both topics. Since the map does not have a lot of overlapping bubbles that cannot be logically explained, the model is adopted.

Table 2. Topics extracted from the LDA model

Topic No.	Topic	10 Keywords	Definition
1	Homeliness	stay, home, feel, make, host, welcome, time, back, thank, come	The construction or provision of a feeling of home away from home while staying at the property
2	Transport	station, close, bus, walk, tube, minute, place, nice, stop, easy	The convenience of the location of the property in terms of public transport connectivity
3	General stay experience and recommendation of the host	great, location, stay, host, place, recommend, perfect, lovely, flat, highly	A general review summarising the stay experience and if the guest would recommend the host to others
4	Restaurant and shop	walk, restaurant, flat, shop, minute, great, area, away, street, tube	The convenience of the location of the property in terms of restaurants and shops in the neighbourhood
5	General recommendation of the property	stay, apartment, well, easy, clean, great, recommend, flat, transport, close	A general review summarising if the guest would recommend the property to others
6	Check-in/out	check, day, get, time, even, arrive, place, night, also, give	The efficiency and flexibility of the check-in and check-out arrangement
7	Cleanliness	good, nice, place, really, stay, clean, host, room, recommend, friendly	The standard of keeping the property nice and clean before the guest's arrival
8	Bed and sleep at night	good, apartment, location, work, small, bit, bed, night, well, flat	The quality of bed that affects sleep quality of the guest at night
9	Physical amenities	room, bathroom, bed, clean, comfortable, nice, kitchen, bedroom, big, private	The quality of physical environment including the facilities of the place and room
10	Hot water and host's responsiveness	water, question, quickly, cold, respond, issue, answer, problem, hot, shower	The availability of hot water supply in the property and the responsiveness of hosts for problem-solving

While Topic 3 and Topic 5 appeared as key topics mentioned by consumers, they are not regarded as service attributes but outcomes of other topics (Cheng and Jin, 2019). Since the scope of this study is to identify service attributes, Topic 3 and Topic 5 were excluded in the sentiment analysis.

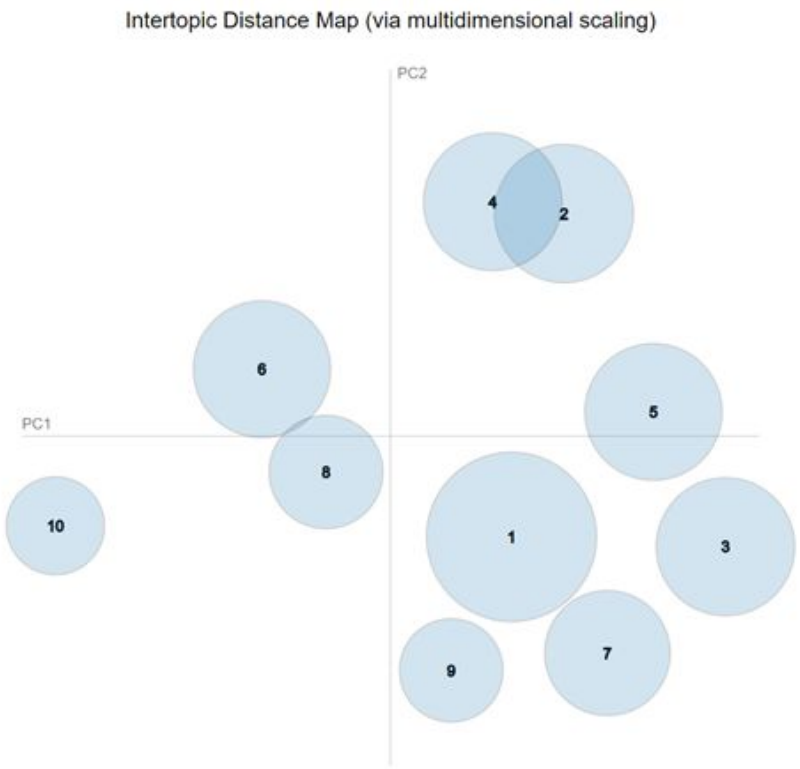


Figure 5. Map analysis

4.2 Identification of unsatisfactory service encounters based on sentiment analysis

To assign a sentiment score to each review, the original structure of the reviews is used and fed into the VADER model. VADER provides four measures: positive, negative, neutral and compound. In this study, the compound values ranged from -1 to +1 are used to classify the reviews into positive, negative or neutral reviews, as suggested by Hutto (2014). When the compound value is larger than or equal to 0.05, the review is positive. When the compound value is smaller than or equal to -0.05, the review is negative. When the compound value is between -0.05 and 0.05, the review is neutral. As we aim to identify negative topics, each review is assigned to its dominant topic based on the LDA result. Our results showed that "Hot water and host's responsiveness" contains the largest portion of negative reviews (18.31%), followed by "bed" (4.88%), which are followed by "check-in/out" (2.64%).

To verify the reliability of the model, another sentiment analysis tool called TextBlob is used for comparison. Table 3 shows the proportion of the sentiment classes of each topic using VADER and TextBlob. It is observed that a main difference between VADER and TextBlob is that VADER tend to classify more reviews as neutral, rather than positive. Overall, the performances of VADER and TextBlob are similar in classifying the reviews as negative. As the key focus of this study is to focus on the negative reviews for identifying areas for improvement, we believe the VADER model is reliable in detecting negative sentiment as it gives similar results compared with another tool.

Among all the negative reviews classified by VADER, we further break them down into various topics as shown in Figure 6. It is found that more than half (74.53%) of the negative reviews are associated with topics "Hot water and host's responsiveness", "bed and sleep at night" and "check-in/out".

Table 3. Sentiment classification

Topic	Tool	Positive sentiment	Neutral sentiment	Negative sentiment
Homeliness	VADER	95.55	4.10	0.35
	TextBlob	96.34	3.15	0.51
Transport	VADER	93.26	6.14	0.59
	TextBlob	95.61	3.59	0.80
Restaurant and shop	VADER	95.95	3.58	0.47
	TextBlob	97.23	2.12	0.65
Check in/out	VADER	91.07	6.29	2.64
	TextBlob	94.79	2.99	2.22
Cleanliness	VADER	87.29	12.40	0.30
	TextBlob	88.01	11.62	0.36
Bed and sleep at night	VADER	82.29	12.83	4.88
	TextBlob	88.65	6.29	5.06
Physical amenities	VADER	80.91	17.94	1.15
	TextBlob	83.89	14.61	1.50
Hot water and host's responsiveness	VADER	62.84	18.84	18.31
	TextBlob	78.17	5.42	16.41

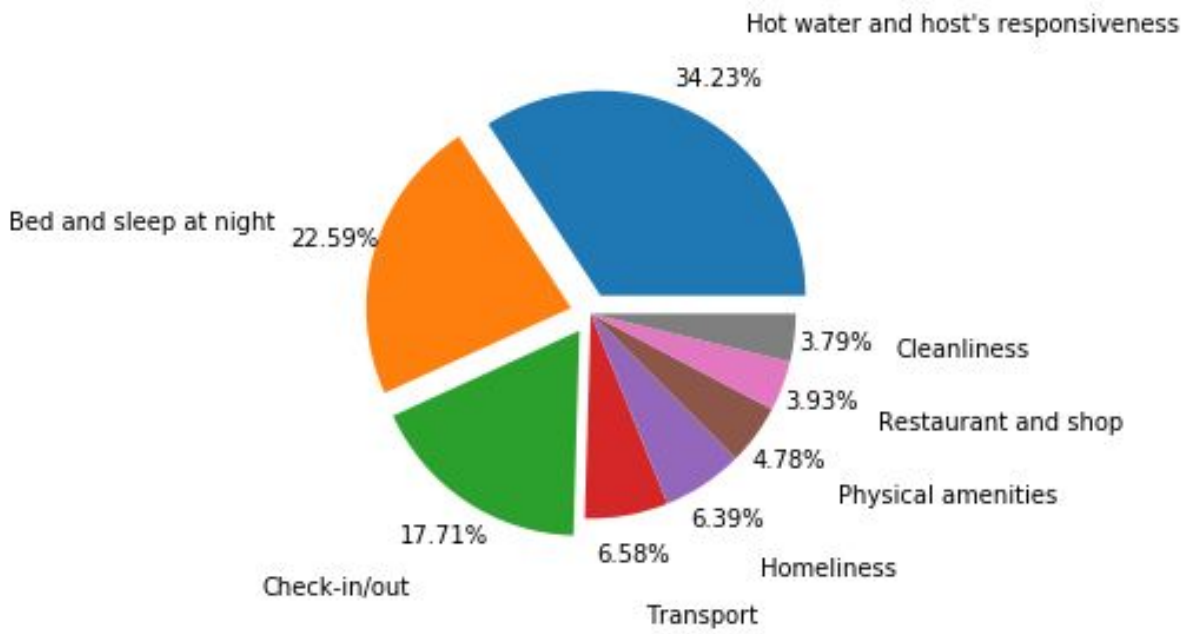


Figure 6. Distribution of topics in negative reviews

After a careful examination of the negative reviews with topic membership larger than 0.9, it is found that the negative P2P accommodation experiences are caused by three problems: (i) the lack of hot water for shower, (ii) poor sleep quality, and (iii) unpleasant check-in.

Regarding the hot water supply, consumers have negative emotions when they cannot enjoy hot shower. Some reviews reflect that consumers tried to contact the host because of the water supply problem. However, their negative sentiment became more intense if the host does not respond, or is rude when being contacted.

Regarding poor sleep quality, consumers cannot sleep well due to uncomfortable or small bed, or noise at night. Whether a bed is comfortable could be very subjective. It is difficult for consumers to determine this unless they try on it during the stay. Besides, one of the possible reasons for consumers to complain about the size of the bed is that the bed looks bigger in the pictures, causing an expectation-actuality discrepancy when the actual property is not as good as what the pictures portray (Zhang et al., 2019). This shows that more information related to the bedroom, such as the layout of the bedroom and the dimension of bed, should be provided.

Regarding the unpleasant check-in, it is discovered that consumers have negative experiences when the room is not ready, or the reservation is cancelled upon arrival. It is found that the negative experiences occur mainly in the case of host-led check-in. Currently, hosts can specify their check-in time that are suitable for their schedule. However, if guests prefer a different check-in time, it is up to them to resolve the issue. Most P2P accommodation sharing platforms do not hold any information about their agreed check-in time. On one hand, it could be flexible for both parties on the coordination of check-in details. On the other hand, if there is any miscommunication, issues such as a long waiting time for check-in occur.

Another check-in problem is the sudden cancellation of the reservation by the host. When this happens, guests can receive a full refund. Nevertheless, guests are not satisfied with this solution especially if the reservation is cancelled at this last minute. This is because travelling plans could be

affected by the change of accommodation, there could be little choice of alternatives available or the alternatives could be more expensive.

4.3 Areas for service improvement

It is observed that the unsatisfactory service encounters related to hot water supply and poor sleep quality cannot be solved if the hosts are unwilling to solve the problems. Thus, the improvement should be mapped with the independent processing of the host (e.g. ensuring a stable supply of hot water and a good condition of the bed, and installing double-gazed windows to keep the place quieter at night). Moreover, the online platform can be more active to provide support to the host (e.g. providing handyman services) to solve the problems because the profitability of the platform will also be affected if the problems remain unfixed. In addition, another unsatisfactory service encounter in the check-in process occurs when there is miscommunication between the host and the guest. In order to address this issue, the platform, as a matchmaker between the host and the guest, plays an important role. Thus, the improvement should be mapped with the platform's surrogate interactions with the guest and the host. On one hand, the platform can allow the guest to clearly specify the preferred check-in time. By doing so, the platform can filter out some listings that fail to meet the guest's preferences. On the other hand, the platform can remind the host to be punctual in the case of host-led check-in and design penalties to minimize last-minute cancellation of a booking.

Based on the findings, three service improvement strategies for both the P2P accommodation platform and hosts are suggested and Figure 7 depicts the improved service delivery process. The new sub-processes introduced are shaded. It can be seen that the suggested strategies affect the platform's surrogate interaction with the guest and the host. This shows that the key to managing consumer experiences lies in the non-human resources such as information, rather than direct interactions between process entities.

4.3.1 Supplementing website information with interactive media information

Using interactive media information is an effective way for the host to leverage relationship and create emotional connection with their potential guests. Information about the properties is not only in the form of text and images, but in a more interactive format such as video and 360 degrees camera. Platforms can allow the hosts to upload video introducing themselves, showcasing the place, as well as the neighbourhood. They can introduce themselves and impress guests by revealing their positive personality which cannot be easily reflected from textual information. From the perspective of guests, video allows them to grasp a better idea on how the room looks like (e.g. whether the bedroom is too small), the personality of the host (e.g. whether he/she is humorous), or whether the neighbourhood is too noisy for sleep (e.g. whether there are many bars and pubs open lately at night). This can help them engage and align their expectations with the accommodation services. Currently, some P2P accommodation platforms, such as Airbnb, provide professional photography services upon request. We suggest that the option of professional video shooting can be added. Considering that guests have negative experiences when the hosts are unavailable to respond to their problems, it is also suggested hosts making a video to explain how to do the self-check-in or use several appliances such as water heaters. This can be useful especially when the guests have difficulties in getting into the property or using any appliances when the hosts are not around to help.

4.3.2 Growing a network of handypersons

After a reservation is booked, P2P accommodation platforms can send an email to the hosts reminding them to get the property ready, suggesting activities to do and qualities to achieve in order to deliver a pleasant guest experience. Based on the findings, suggested activities include ensuring a stable supply of hot water and a good condition of the bed and replacing windows with double-gazed windows to keep the place quieter. In order to make it easier for the hosts to perform the suggested activities, the platforms can grow a network of handypersons and matches hosts with nearby available handypersons. There is a benefit for the hosts to choose a handyperson service from a accommodation platform. By doing so, the platform can verify and include the information on the host's page after the service is completed. Then, the guests can have more information to judge the overall condition of the place. This can be useful for hosts who were complained by previous guests about the condition of their properties such as a broken shower or weak toilet flush. A verified handyperson service from the platform can let their future potential guests recognise that previous problems have been fixed, increasing the chance of their listings to be booked.

4.3.3 Introducing flexible and strict check-in policies

It is suggested that the platform can introduce two types of check-in policies: flexible check-in, and strict check-in. If guests choose the "flexible" check-in policy while searching a listing, the platform will return a list of available spaces regardless the check-in time specified by the guests and the hosts. It would be up to them to coordinate the check-in details. On one hand, this policy is more flexible, so it is suitable for hosts who have flexible schedule and guests who are not sure about their arrival time. On the other hand, this policy requires more effective communication between the hosts and the guests to work out the details for checking in. If the guests choose the "strict" check-in policy, the platform will only return listings that match with the guests' selected check-in period. This policy would mean that both parties have to follow the agreed check-in schedule. This policy will be favourable to guests who have concerns about having nowhere to go or store their luggage if they cannot check in as planned. A refund should be given to guests if the hosts do not show up at the specified time. This policy will also impose penalty on hosts if they cancel the booking after the allowable time period, e.g. 72 hours before the guest's arrival.

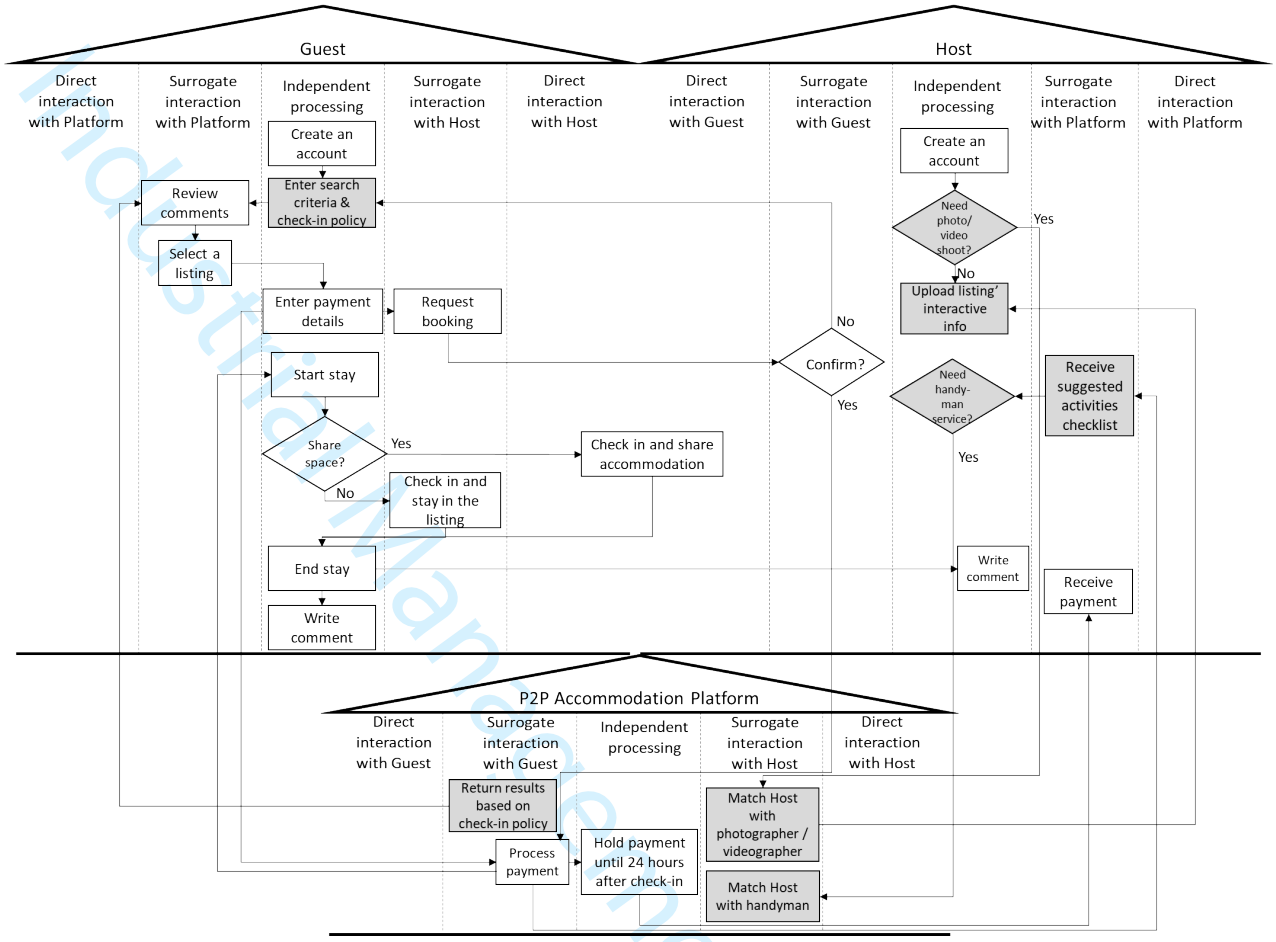


Figure 7. PCN diagram of improved P2P accommodation services

5. Conclusion

This study identifies key service attributes of P2P accommodation from consumer reviews and maps them with the service process to identify areas for improvement. The results suggest that negative P2P accommodation experiences are caused by the lack of hot water for shower, poor sleep quality, and unpleasant check-in process.

The theoretical contributions of this study mainly lie in the extension of MAUT and previous studies examining key service dimensions of P2P accommodation. First, this study integrates text analytics and MAUT. It adds to the literature by building a data-driven mechanism to advance our understanding of customer satisfaction regarding different attributes in P2P accommodation. It starts with topic modelling to identify multiple attributes that are important in P2P accommodation and then derives sentiment scores from the reviews directly as a quantitative measure of customer satisfaction of each attribute. This overcomes the limitations found in prior studies that treated customer satisfaction as a unidimensional measure and used statistical information such as average ratings to have an overview of the overall perceived quality of the product or service.

Second, this study extends previous studies by linking text analytics with service improvement. Prior studies applied text analytics merely for understanding consumers' good mindset of good quality of accommodation (Cheng and Lin, 2019; Ju et al., 2019; Lee et al., 2019) and the relationships between consumer sentiments and listings' attributes (Lawani et al., 2019; Zhang,

2019a). The applications have not been linked with service improvement that can secure consumers in a longer term, with some exceptions (e.g. Nam et al., 2018; Zuo et al., 2019). Despite the fact that there is a lack of investigation of negative reviews in the literature, this study takes a closer look at negative reviews as this provides an opportunity for service providers to address these areas through rectifying any maintenance issues or setting realistic expectations (Cheng and Jin, 2019). This study focuses on mining negative topics and depicting them in PCN to visualise key tangible elements of service delivery.

Third, this study integrates sharing economy and operations improvement. Many research perspectives still come from the marketing field and seek to understand dimensions that influence customer satisfaction in the sharing economy from a consumer behaviour perspective. However, few studies have been conducted from an operations improvement perspective. We analyse the online reviews and establish data-driven practice for improving the P2P accommodation service process, addressing the recent call by Benjaafar and Hu (2020) to explore sharing economy services from an operations management perspective.

This study has two limitations that open up future research avenues. First, this study only considered the reviews posted by the guests. The strategies formulated without listening to the "voice" of hosts could be unfair to the hosts. Future work can include analysing reviews from the hosts and/or having focus groups with hosts so as to draw additional insights on improving the service delivery processes holistically. Second, this study only classified the sentiment into positive, negative and neutral. However, it will be useful if future work can detect the type of emotions such as joy, anger and sadness, from the reviews. Having a better understanding of the relationship between service attributes and emotions can help formulate more effective strategies to improve consumer experiences.

References

Alrawadieh, Z. and Alrawadieh, Z. (2018), "Exploring entrepreneurship in the sharing accommodation sector: empirical evidence from a developing country", *Tourism Management Perspectives*, Vol. 28, pp.179-188.

Alsudais, A., and Teubner, T. (2019), "Large-scale sentiment analysis on Airbnb reviews from 15 cities", In Proceedings of *Twenty-fifth Americas Conference on Information Systems*, Cancun, Mexico.

Archak, N., Ghose, A., and Ipeirotis, P. G. (2011), "Deriving the pricing power of product features by mining consumer reviews", *Management Science,* Vol. 57 No. 8, pp.1485-1509.

Benjaafar, S. and Hu, M. (2020), "Operations management in the age of the sharing economy: what is old and what is new?", *Manufacturing & Service Operations Management,* Vol. 22 No. 1, pp.93-101.

Berezina, K., Bilgihan, A., Cobanoglu, C. and Okumus, F. (2016), "Understanding satisfied and dissatisfied hotel customers: text mining of online hotel reviews", *Journal of Hospitality Marketing & Management*, Vol. 25 No. 1, pp.1-24.

Bitner, M., Ostrom, A.L. and Morgan, F.N. (2008), "Service blueprinting: a practical technique for service innovation", *California Management Review*, Vol. 50 No. 3, pp.66-94.

Blal, I., Singal, M. and Templin, J. (2018), "Airbnb's effect on hotel sales growth", *International Journal of Hospitality Management*, Vol. 73, pp.85-92.

Blei, D.M., Ng, A.Y. and Jordan, M.I. (2003), "Latent dirichlet allocation", *Journal of Machine Learning Research*, Vol. 3, pp.993-1022.

Canada, J.R. and Sullivan, W.G. (1989), *Economic and Multi-attribute Evaluation of Advanced Manufacturing Systems*. Prentice-Hall, New York, NY.

Cheng (2016), "Sharing economy: a review and agenda for future research", *International Journal of Hospitality Management*, Vol. 57, pp.60-70.

Cheng, M. and Jin, X. (2019), "What do Airbnb users care about? An analysis of online review comments", *International Journal of Hospitality Management,* Vol. 76(Part A), pp.58-70.

Collins, T. R., Rossetti, M.D., Nachtmann, H.L. and Oldham, J.R. (2006), "The use of multi-attribute utility theory to determine the overall best-in-class performer in a benchmarking study", *Benchmarking: An International Journal*, Vol. 13 No. 4, pp.431-446.

Gansky, L. (2010). *The mesh: Why the future of business is sharing*. New York: Penguin.

Gavilan, D., Avello, M. and Martinez-Navarro, G. (2018), "The influence of online ratings and reviews on hotel booking consideration", *Tourism Management,* Vol. 66, pp.53-61.

Geissinger, A., Laurell, C. and Sandström, C. (2018), "Digital Disruption beyond Uber and Airbnb – tracking the long trail of the sharing economy", *Technological Forecasting & Social Change*. https://doi.org/10.1016/j.techfore.2018.06.012.

Guo, Y., Barnes, S.J. and Jia, Q. (2017), "Mining meaning from online ratings and reviews: tourist satisfaction analysis using latent dirichlet allocation", *Tourism Management,* Vol. 59, pp.467-483.

Guttentag, D. (2015), "Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector", *Current Issues in Tourism*, Vol. 18 No. 12, pp.1192-1217.

Habibi, M. R., Davidson, A. and Laroche, M. (2017), "What managers should know about the sharing economy", *Business Horizons*, Vol. 60, pp.113-121.

He, W., Tian, X., Tao, R., Zhang W., Yan, G. and Akula, V. (2017), "Application of social media analytics: a case of analysing online hotel reviews", *Online Information Review*, Vol. 41 No. 7, pp.921-935.

Hu, N., Zhang, T., Gao, B. and Bose, I. (2019), "What do hotel customers complain about? Text analysis using structural topic model", *Tourism Management*, Vol. 72, pp.417-426.

Hutto, C. J., and Gilbert, E. (2014), "VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text", in *Proceedings of the Eighth International AAAI Conference on Weblogs and Social Media (ICWSM-14)*, Ann Arbor, MI, pp.216–225.

Hutto, C.J. (2014), *VADER-Sentiment-Analysis*. Github. Available at: https://github.com/cjhutto/vaderSentiment (Accessed 11 December 2019).

Ju, Y., Back, K.-J., Choi, Y. and Lee, J.-S. (2019), "Exploring Airbnb service quality attributes and their asymmetric effects on customer satisfaction", *International Journal of Hospitality Management*, Vol. 77, pp.342-352.

Kailiponi, P. (2010), "Analyzing evacuation decisions using multi-attribute utility theory", *Procedia Engineering*, Vol. 3, pp.163-174.

Kazemzadeh, Y., Milton, S.K. and Johnson, L.W. (2015a), "Service blueprinting and process-chain-network: an ontological comparison", *International Journal of Qualitative Research in Services*, Vol. 2 No. 1, pp.1-12.

Kazemzadeh, Y., Milton, S.K. and Johnson, L.W. (2015b), "A comparison of concepts in service blueprinting and process-chain-network", *International Journal of Business and Management,* Vol. 10 No. 4, pp.13-25.

Lawani, A., Reed, M.R., Mark, T. and Zheng, Y. (2019), "Reviews and price on online platforms: evidence from sentiment analysis of Airbnb reviews in Boston", *Regional Science and Urban Economics*, Vol. 75, pp.22-34.

Lee, C.K.H., Tse, Y.K., Zhang, M. and Ma, J. (2019), "Analysing online reviews to investigate customer behaviour in the sharing economy: the case of Airbnb", *Information Technology & People*. DOI 10.1108/ITP-10-2018-0475

Lee, E.-J. and Shin, S.Y. (2014), "When do consumers buy online product reviews? Effects of review quality, product type, and reviewer's photo", *Computers in Human Behavior*, Vol. 31, pp.356-366.

Lin, P.M.C., Fan, D.X.F., Zhang, H.Q. and Lau, C. (2019), "Spend less and experience more: understanding tourists' social contact in the Airbnb context", *International Journal of Hospitality Management*, Vol. 83, pp.65-73.

Lindey, D.V. (1985). *Making Decisions*. Wiley, New York, NY.

Minamino, Y., Inoue, S. and Yamada, S. (2015), "Multi-attribute utility theory for estimation of optimal release time and change-point", *International Journal of Reliability, Quality and Safety Engineering*, Vol. 22 No. 4, 1550019.

Nam, S., Ha, C. and Lee, H.C. (2018), "Redesigning in-flight service with service blueprint based on text analysis", *Sustainability*, Vol. 10 No. 12, 4492. https://doi.org/10.3390/su10124492

Nikolenko, S.I., Kotcov, S. and Kotsova, O. (2017), "Topic modelling for qualitative studies", *Journal of Information Science*, Vol. 42 No. 1, pp.88-102.

Öğüt, H. and Onur Taş, B. K. (2012), "The influence of internet customer reviews on the online sales and prices in hotel industry", *The Service Industries Journal*, Vol. 32 No. 2, pp.197-214.

Oskam, J. and Boswijk, A. (2016), "Airbnb: the future of networked hospitality businesses", *Journal of Tourism Futures*, Vol. 2 No. 1, pp.22-42.

Ryu, D.-H., Lim, C and Kim, K.-J. (2019), "Development of a service blueprint for the online-to-offline integration in service", *Journal of Retailing and Consumer Services.* https://doi.org/10.1016/j.jretconser.2019.101944

Sampson, S.E. (2012), "Visualizing service operations", *Journal of Service Research*, Vol. 15 No. 2, pp.182-198.

Shostack, G. L. (1982), "How to design a service", *European Journal of Marketing*, Vol. 16 No. 1, pp.49-63.

Situmorang, K.M., Hidayanto, A.N., Wicaksono, A.F. and Yuliawati, A. (2018), "Analysis on customer satisfaction dimensions in peer-to-peer accommodation using latent dirichlet allocation: a case

study of Airbnb", In Proceedings of *Electrical Engineering Computer Science and Informatics*, Malang, Indonesia, pp.542-547.

Tussyadiah, I.P. (2016), "Factors of satisfaction and intention to use peer-to-peer accommodation", *International Journal of Hospitality Management*, Vol. *55*, pp.70-80.

Tussyadiah, I.P. and Pesonen, J. (2016), "Impacts of peer-to-peer accommodation use on travel patterns", *Journal of Travel Research*, Vol. 55 No. 8, pp.1022-1040.

von Helversen, B., Abramczuk, K., Kopeć, W. and Nielek, R. (2018), "Influence of consumer reviews on online purchasing decisions in older and younger adults", *Decision Support Systems,* Vo. 113, pp.1-10.

von Winterfeldt, D. and Fischer, G. W. (1975), "Multi-attribute utility theory: models and assessment procedures", *Utility, probability, and human decision making*. Springer, Dordrecht, pp.47-85.

Xiang, Z., Schwartz, Z., Gerdes Jr., J.H. and Uysal, M. (2015), "What can big data and text analytics tell us about hotel guest experience and satisfaction?", *International Journal of Hospitality Management*, Vol. 44, pp.120-130.

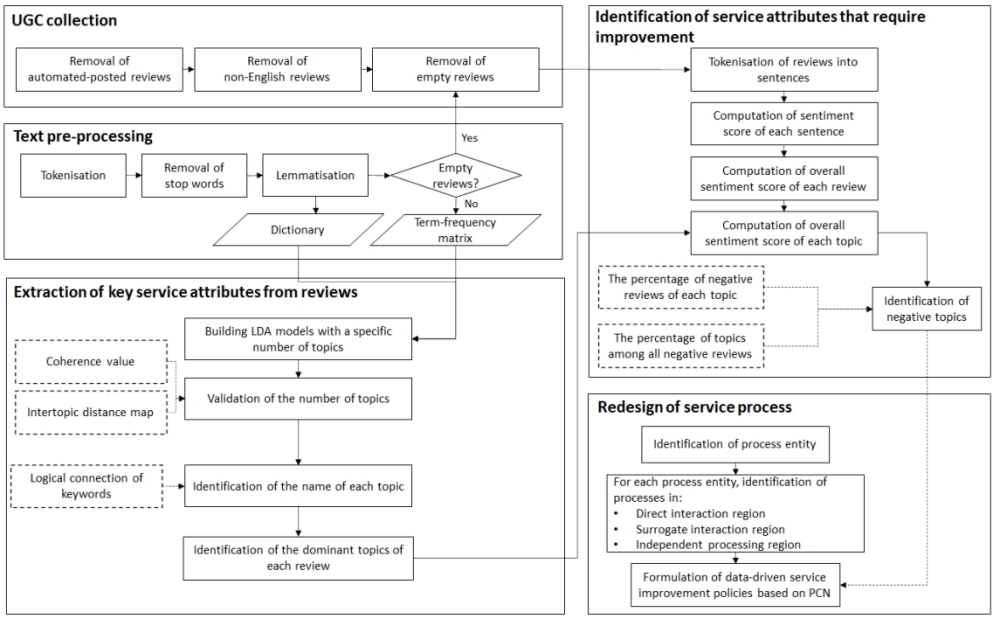
Zervas, G., Proserpio, D. and Byers, J.W. (2017), "The rise of the sharing economy: estimating the impact of Airbnb on the hotel industry", *Journal of Marketing Research*, Vol. 54 No. 5, pp.687-705.

Zhang, J. (2019a), "Listening to the consumer: exploring review topics on Airbnb and their impact on listing performance", *Journal of Marketing Theory and Practice*, Vol. 27 No. 4, pp.371-389.

Zhang, J. (2019b), "What's yours is mine: exploring customer voice on Airbnb using text-mining approaches", *Journal of Consumer Marketing*, Vol. 36 No. 5, pp.655-665.

Zhang, S., Mehta, N., Singh, P.V., and Srinivasan, K. (2019), "Do lower-quality images lead to greater demand on Airbnb?", Working Paper, Carnegie Mellon University.

Zuo, W., Zhu, W., Chen, S. and He, X. (2019), "Service quality management of online car-hailing based on PCN in the sharing economy", *Electronic Commerce Research and Applications*, Vol. 34, 100827.



Research methodology

Word cloud diagram

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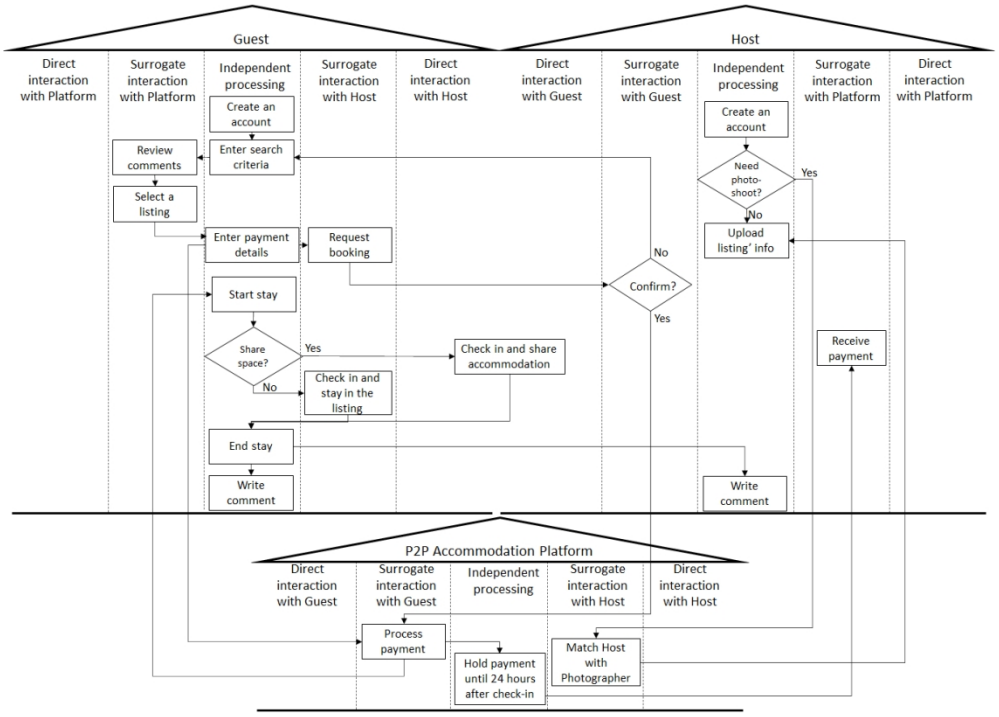
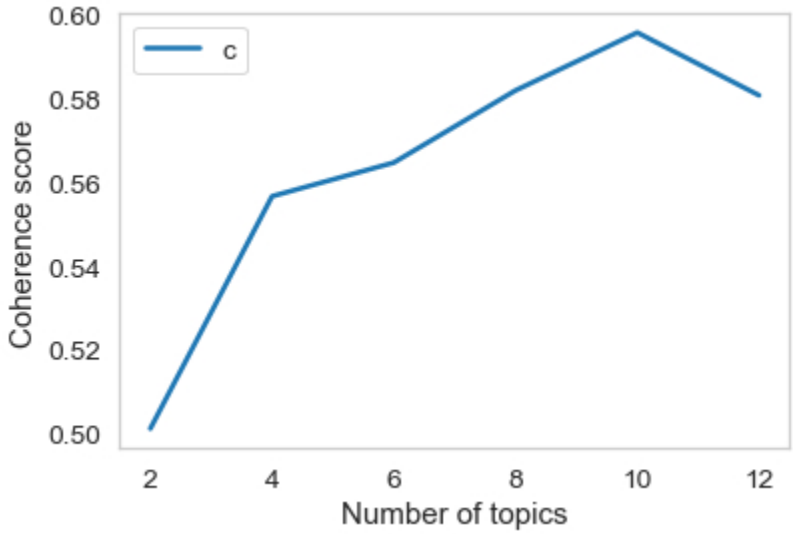
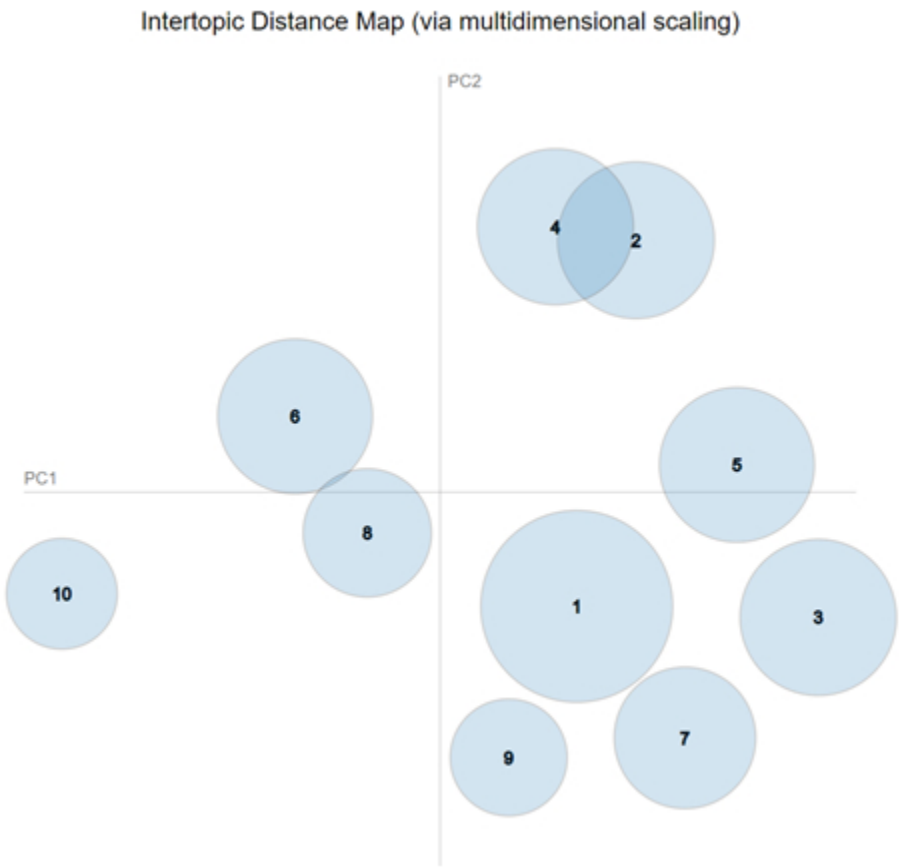


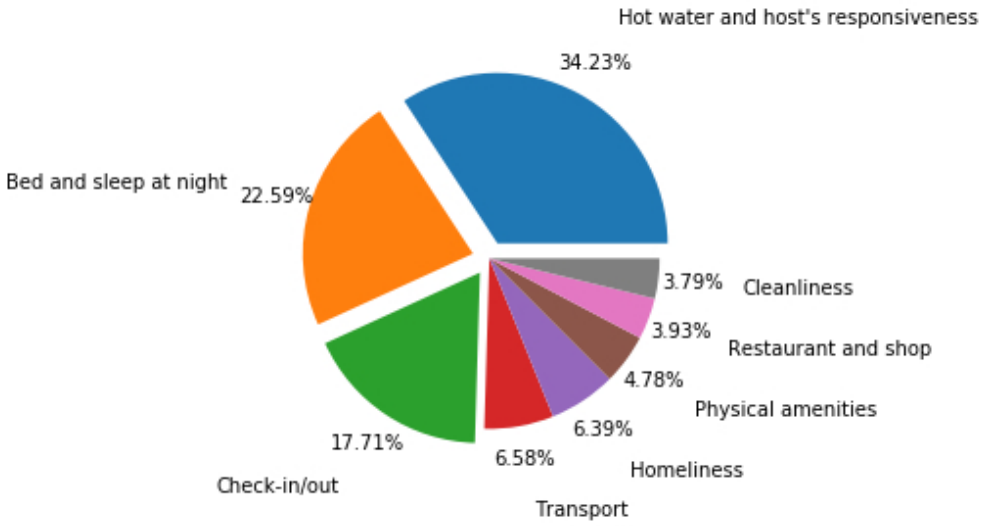
PCN diagram of P2P accommodation services



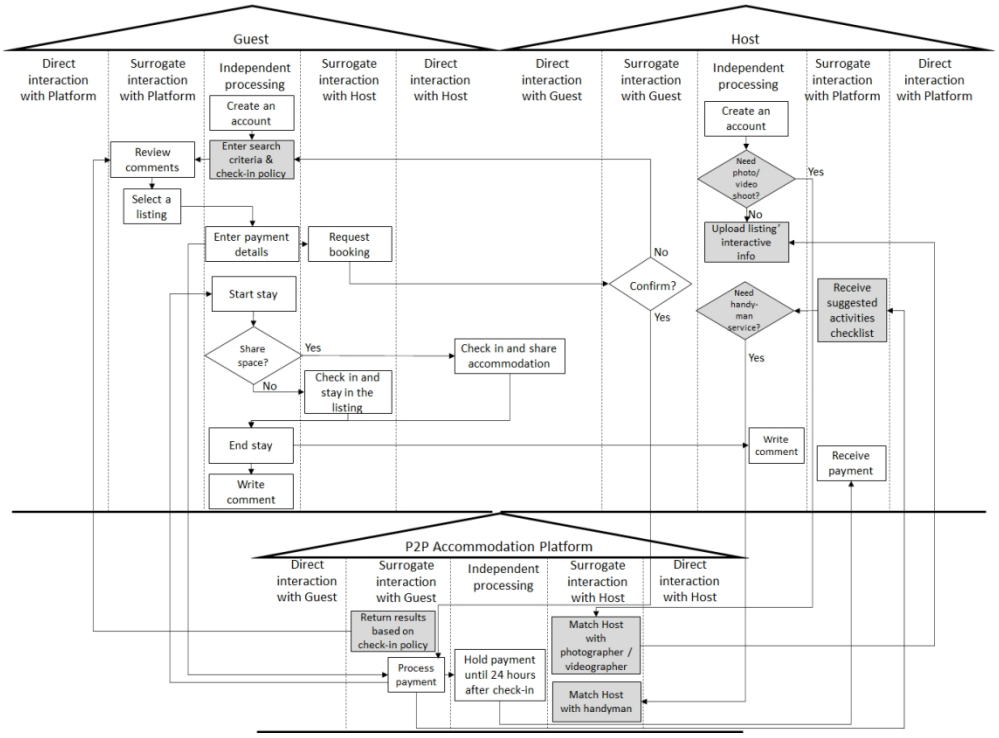
Coherence scores with different numbers of topics



Map analysis



Distribution of topics in negative reviews



PCN diagram of improved P2P accommodation services