The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/0265-671X.htm

Received 18 January 2022
Revised 10 March 2022
Accepted 18 August 2022

QUALITY PAPER

Quality 4.0: big data analytics to explore service quality attributes and their relation to user sentiment in Airbnb reviews

Natalia Amat-Lefort
Universitat Internacional de Catalunya, Barcelona, Spain and Science Based Business (SBB), Leiden Institute of Advanced Computer Science (LIACS), Leiden University, Leiden, The Netherlands, and
Federico Barravecchia and Luca Mastrogiacomo
Department of Management and Production Engineering (DIGEP), Politecnico di Torino, Turin, Italy

Abstract

Purpose – Quality 4.0 is a new paradigm of quality management, which emphasises the need to adapt to recent technological innovations by updating traditional quality approaches. Amongst the most important factors for adopting Quality 4.0 is the leveraging of big data to collect insights and quality perceptions from clients. Therefore, user reviews have emerged as a valuable source of information, which can be analysed through machine learning procedures to uncover latent quality dimensions.

Design/methodology/approach – This study applies a combination of text mining techniques to analyse Airbnb reviews, identifying service quality attributes and assessing their relation to the users' sentiment. More than two million reviews written by guests in four European cities are analysed. First, topic modelling is applied to find the quality attributes mentioned by reviewers. Then, sentiment analysis is used to assess the positiveness/negativeness of the users' feedback.

Findings – A total of 37 quality attributes are identified. Four of them show a significant positive relation to the guest's sentiment: apartment views, host tips and advice, location and host friendliness. On the other hand, the following attributes are negatively correlated with user sentiment: sleep disturbance, website responsiveness, thermal management and hygiene issues.

Originality/value – This paper provides a practical example of how Quality 4.0 can be implemented, proposing a data-driven methodology to extract service quality attributes from user-generated content. Additionally, several attributes that had not appeared in existing Airbnb studies are identified, which can serve as a reference to extend previous quality assessment scales.

Keywords Quality 4.0, Service quality, Big data analytics, Text mining, Topic modelling, Sentiment analysis

Paper type Research paper

1. Introduction

More than 2 million people stay on Airbnb every night, on average (Airbnb, 2021a). Being one of the most popular sharing economy businesses, Airbnb is an online peer-to-peer platform that allows hosts to offer their spare rooms or properties to guests as an alternative to hotels. In fact, Airbnb has disrupted the hospitality industry (Guttentag, 2015) due to its impact on the market share of traditional accommodation options such as hotels (Zervas *et al.*, 2017). In such a fluctuating industry, service quality is essential to achieve a competitive advantage (Chen and Chen, 2014). Indeed, given that service quality has a strong positive association with customer satisfaction, it is widely acknowledged as a key success factor for businesses (Saha and Theingi, 2009; Shemwell *et al.*, 1998).

International Journal of Quality & Reliability Management
Vol. 40 No. 4, 2023
pp. 990-1008
© Emerald Publishing Limited
0265-671X
DOI 10.1108/IJQRM-01-2022-0024

In order to manage quality in the era of the fourth industrial revolution, it is necessary to adapt to technological innovations and update traditional quality models (Saihi *et al.*, 2021). As a response to these technological challenges and opportunities, a new paradigm of quality management has emerged, known as Quality 4.0 (Dias *et al.*, 2021; Zonnenshain and Kenett, 2020). Amongst the most relevant requirements for implementing Quality 4.0 is understanding how to use big data to collect insights and quality perceptions from customers (Antony *et al.*, 2021c). Thanks to machine learning methods, user reviews have become a valuable source of information for businesses (Barravecchia *et al.*, 2021). More specifically, several studies have shown that user-generated content such as customer reviews can provide valuable insights into service quality attributes (Barravecchia *et al.*, 2020; Brochado *et al.*, 2019; Chakrabarti *et al.*, 2018; Ding *et al.*, 2020; James *et al.*, 2017; Ju *et al.*, 2019; Korfiatis *et al.*, 2019; Mastrogiacomo *et al.*, 2021; Palese and Usai, 2018; Su and Teng, 2018).

In the case of Airbnb, over 250 million reviews have been written by hosts and guests from all over the world (Airbnb, 2021b), creating an extensive source of information. Analysing the large amounts of unstructured text that can be found in online reviews is far beyond manual processing capacity. On the contrary, text mining offers an efficient way to extract actionable insights from large-scale databases of reviews and ratings (Hu and Liu, 2004). Due to their unstructured nature, textual reviews contain much more detailed insights into each guest's personal experience than traditional surveys (Tsao *et al.*, 2020). According to Sparks and Browning (2010), listening to customer feedback from user reviews is essential to understand how service quality can be improved in the hospitality industry.

Considering the advantages of user-generated content as a source of information, a number of studies have used text mining to analyse Airbnb reviews. Existing research on Airbnb reviews has focussed mainly on identifying popular review topics based on the assumption that these topics reflect desirable service attributes (Ju *et al.*, 2019). However, there is very limited literature discussing which attributes have a positive (or negative) relation to the sentiment expressed by the user. Considering that each review contains a narrative of the guest's personal experience (Lee *et al.*, 2019), negative comments are more likely to mention the attributes that did not fulfil their expectations (Zhang *et al.*, 2012). On the other hand, positive reviews with a high sentiment score are more prone to mention the attributes that left the user satisfied. Consequently, by analysing the relationship between the attributes mentioned in each review and its sentiment score, it is possible to infer which attributes should be avoided and which ones should be pursued.

The current work aims to shed light on this issue by identifying positive and negative service attributes in a dataset of 2,735,437 Airbnb reviews. To this end, this study combines two text mining techniques: sentiment analysis and topic modelling. Therefore, the main research objectives of this study are (1) to *identify the main service quality attributes mentioned in Airbnb reviews* and (2) *to determine which attributes have a positive (or negative) correlation with the user's sentiment*. Moreover, this study contributes to Quality 4.0. literature by showing a practical example of how big data analytics can be implemented in quality management. Previous research has focussed mainly on conceptualising this new paradigm of quality, but there is a lack of studies concerning practical implementations of Quality 4.0. Therefore, this study proposes a data-driven approach to analyse user-generated content, using text mining techniques to detect positive and negative service quality attributes.

The rest of the paper is organised as follows. First, the literature review (Section 2) describes the antecedents of service quality assessment in the shared accommodation industry, as well as the existing text mining research on Airbnb reviews. The methodological approach is explained in Section 3, whilst Section 4 presents the results obtained on the analysis of Airbnb data. Finally, Section 5 discusses the most relevant conceptual and practical implications of the study, as well as the limitations and opportunities for future research.

2. Literature review

2.1 Service quality assessment in the shared accommodation sector

From the viewpoint of business administration, service quality can be measured as the discrepancy between the customer's expectations of a service and the actual experience of that service (Parasuraman *et al.*, 1988). Since this concept was introduced, numerous studies have found a positive relationship between service quality and customer satisfaction (Lee *et al.*, 2000; Saha and Theingi, 2009; Spreng and Mackoy, 1996) and loyalty (Bloemer *et al.*, 1999; de Ruyter *et al.*, 1998; Sivadas and Baker-Prewitt, 2000) across different sectors. Moreover, it has been proven that service quality is also linked to the overall profitability of service companies (Chang and Chen, 1998; Zeithaml, 2000). Consequently, service quality is a key to increasing competitive advantage in a business due to its positive impact on relevant success factors for companies.

On the other hand, the rise of shared accommodation platforms has generated a lot of research interest, considering its significant impact on the hotel industry (Zervas *et al.*, 2017). Several studies have analysed the motivations of shared accommodation users (Guttentag *et al.*, 2018; So *et al.*, 2018), as well as other aspects such as the determinants of their trust (Hawlitschek *et al.*, 2016; Mittendorf, 2018; Tussyadiah and Park, 2018), loyalty (Lalicic and Weismayer, 2018), repurchase intentions (Liang *et al.*, 2018), and satisfaction (Möhlmann, 2015; Tussyadiah, 2016).

An emerging field of study has focussed on studying the key drivers of service quality in the shared accommodation sector. Priporas *et al.* (2017) investigated the service quality perceptions of Airbnb users in Phuket (Thailand) through a survey based on a measurement tool developed by Akbaba (2006). Their findings pointed out that guests value the convenience of shared accommodation services, as well as the hospitality provided by Airbnb hosts.

Following that line of research, Ju *et al.* (2019) carried out a survey based on Airbnb users in the USA and Canada, aiming to identify the dimensions of service quality attributes in this sector. They initially used text mining to extract service attributes, which were later used to design their survey and propose a service quality assessment instrument for shared accommodation services. The study found that Airbnb's main service quality attributes are associated with the website, host, and facility, and that each one of them can have distinct impacts on customer satisfaction.

One common aspect of the previously mentioned studies is that their conclusions were mainly based on a survey that was completed by Airbnb users. Until recently, there were not many ways to access information about consumer opinions other than questionnaires and interviews. Nevertheless, due to the rise of digital platforms that collect feedback from users, user-generated content has emerged as a new source of information.

2.2 Quality 4.0 and user-generated content

Over the course of history, revolutions have occurred when disruptive technologies and new paradigms initiate a process of profound change in society and the economy. Nowadays, industries worldwide are experiencing a fourth industrial revolution due to the widespread use of digital technologies. This environment presents several challenges and opportunities for quality management, which needs to transform to adapt to the new Quality 4.0 paradigm (Saihi *et al.*, 2021). This new concept of quality emphasises the importance of incorporating technological innovations and data-driven solutions into quality management (Zonnenshain and Kenett, 2020). In fact, research suggests that implementing Quality 4.0 can have a positive impact on several organisational metrics, including the ones related to financial performance (Antony *et al.*, 2021b).

One of the most relevant factors for the successful adoption of Quality 4.0 is understanding how to efficiently handle big data in quality management regardless of the size and type of company (Antony *et al.*, 2021c; Sony *et al.*, 2020). Regarding the practitioners' perspective, a study by Antony *et al.* (2021a, b, c) conducted several interviews with experienced professionals who are currently deploying Quality 4.0 in leading companies across the globe. When the researchers asked them about the key aspects and benefits of

Quality 4.0 for their organisation, "big data tools" was the most frequently mentioned element. Even though these findings confirm that big data analytics can be very useful for organisations, there is a lack of studies showing practical implementations of Quality 4.0. For this reason, the present study aims to provide a practical example of how big data analytics can be implemented in the field of quality management.

One of the many ways big data can have an impact on organisations is by helping them detect quality determinants. Historically, perceived service quality was assessed through interviews and surveys (DeVellis, 2016). Even though these approaches are widely accepted, they are often costly and time consuming (Barravecchia *et al.*, 2021). In this context, one of the opportunities generated by Industry 4.0 is that it has become much easier for consumers to share their opinions about a specific product or service through online review platforms, company websites and social media (Palese and Usai, 2018). This type of user-generated content (ratings and reviews) can be a source of valuable information about consumer satisfaction and perceived service quality (Gu and Ye, 2014; Hargreaves, 2015). Using text mining tools, this content can be analysed to identify quality determinants, noting that critical service features are frequently mentioned in user reviews (Barravecchia *et al.*, 2021). Moreover, as opposed to traditional surveys, user comments and ratings are not affected by laboratory effects (Yacouel and Fleischer, 2012), which makes them an excellent tool to capture the customer's actual thoughts.

2.3 Comparison of text mining methods applied to Airbnb's user-generated content

A recent stream of literature has focussed on exploring Airbnb reviews using text mining approaches in order to get a better understanding of the users' opinions and behaviour. Tussyadiah and Zach (2017) presented one of the first studies in this field, applying term-frequency and word co-occurrence networks in Airbnb reviews to identify the service attributes sought by guests from Portland (Oregon). The results indicated that the most common attributes in user reviews were associated with the listing's location, host (service and hospitality), and property (facilities and atmosphere).

Afterwards, other studies combined similar word-frequency-based techniques with traditional surveys. In particular, Ju *et al.* (2019) used first text mining to find service quality attributes, followed by a survey to examine the effects of these attributes on customer satisfaction. Ranjbari *et al.* (2020) also analysed user reviews to extract the service attributes and conducted a survey to calculate an Importance-Performance Analysis (IPA) matrix. On the other hand, Cheng and Jin (2019) and Güçlü *et al.* (2020) combined term-frequency with sentiment analysis.

Even though term-frequency-based approaches can be useful to extract latent topics from unstructured textual data, they have certain limitations. When word frequency counts are used to extract meaning from texts, they assume that each word has only one meaning (Lee *et al.*, 2010). However, words can have different meanings depending on how they are combined with other words. Additionally, word frequency methods require the definition of each topic by a list of manually selected keywords, making it difficult to analyse the trend of a particular topic (Ding *et al.*, 2020).

In contrast, other text mining methods such as topic modelling and clustering can analyse groups of words together instead of counting them separately (Berry and Castellanos, 2008). In this way, these techniques can consider the variations in each word's meaning across different contexts. In terms of clustering methods, most of the previous studies used techniques based on word co-occurrence networks. For instance, Lee *et al.* (2019) applied hierarchical clustering to assess the evolution over a five-year time span of the attributes that influence Airbnb customer experience in London. They found that certain basic attributes were considered important throughout the years (such as cleanliness and location), but other attributes only appeared in particular years and seasons, such as "Wi-Fi" or "Quietness".

Although conventional clustering methods overcome some of the limitations of term-frequency-based techniques, topic modelling presents several advantages over them. Clustering is based on the idea of classifying documents into different groups based on a specific similarity measure (Berry and Castellanos, 2008). With clustering, every document (reviews, in our case) appears only in one group (such as topics or attributes). In topic modelling, each topic is defined by a group of words and each document is assigned a probability of being associated with a topic (Jelodar *et al.*, 2019). Hence, when applied to the analysis of customer reviews, topic modelling can capture the fact that the same review could mention several different topics.

One of the most widely used topic models is Latent Dirichlet allocation (LDA), which has also been used to analyse Airbnb reviews and compare the extracted topics with hotel reviews (Zhang, 2019). LDA is used as an unsupervised probabilistic topic modelling technique, which assumes that each document (or review) is composed of a set of topics (Blei, 2012). Research has proven that LDA can effectively detect the main topics in social media texts and explore their evolution over time (Wang *et al.*, 2012). Furthermore, LDA does not assume that the documents should have a particular structure or follow any specific grammar rules, which make it particularly appropriate for big data analysis of online reviews (Feldman and Sanger, 2006).

Despite the fact that LDA has many advantages as a text mining technique, it does not offer the possibility of including document metadata into the topic model. However, an extension of LDA known as the structural topic model (STM) can overcome this limitation (Roberts *et al.*, 2019). As opposed to LDA, STM allows researchers to incorporate arbitrary information about each document (such as the date of the review or the nationality of the reviewer) into the model. A study by Ding *et al.* (2020) used STM to extract key service quality attributes from a database of Airbnb reviews posted in Malaysia during a five-year period. They identified 22 topics related to service quality and found certain differences between the perspectives of Malaysian and international users. Their results confirmed the effectiveness of STM as a method to identify service quality attributes from Airbnb user reviews.

After reviewing the features and limitations of each text mining technique, the method selected for this study was STM. Additionally, this study combines topic modelling with sentiment analysis to assess the relation of each service attribute to the user's sentiment. Hence, the current study identifies positive and negative service attributes (in terms of their correlation with sentiment score) from Airbnb reviews in France, Italy, Spain and Portugal. This represents a methodological advance, given that very few studies have analysed both the topics and the sentiment of reviews, particularly in Airbnb services.

Moreover, the literature about European Airbnb users is very scarce, as most of the previous studies focussed on guests from the USA, Australia or Asia (see Table 1). For this reason, this study aims to fulfil the aforementioned gap in the literature. Table 1 presents an overview of the main features and methods applied by previous text mining literature that analysed Airbnb reviews to identify service attributes, also highlighting the main differences amongst the studies.

3. Methodology

In order to identify the service quality attributes of Airbnb and gather the necessary data to estimate their correlation with sentiment score, this study has applied a seven-step methodology: (1) dataset extraction, (2) data pre-processing, (3) sentiment analysis, (4) identification of the optimal number of topics, (5) topic extraction, (6) mapping topics onto service quality attributes and (7) labelling. Figure 1 shows an overview of the methodology applied.

Therefore, this study combines two text mining techniques: sentiment analysis and topic modelling. More specifically, a rule-based model known as Valence Aware Dictionary for

Study	N. of reviews	Time span	Geographical scope	Survey	Text mining techniques Word frequency/ co-occurrence	Topic modelling	Sentiment analysis
Tussyadiah and Zach (2017)	41,560	5 years	USA		X		
Ju *et al.* (2019)	16,430	3 days	USA	X	X		
Lee *et al.* (2019)	169,666	5 years	UK		X		
Zhang (2019)	1,026,988	6 years	USA		X	X	
Cheng and Jin (2019)	181,263	N/A*	Australia		X		X
Ranjbari *et al.* (2020)	112,138	1 year	Australia	X	X		
Ding *et al.* (2020)	242,020	5 years	Malaysia			X	
This study	2,735,437	10 years	France, Italy, Spain and Portugal			X	X

Note(s): *N/A: Not available, unspecified

Table 1. Main features of previous text mining literature that analysed Airbnb reviews to identify service attributes

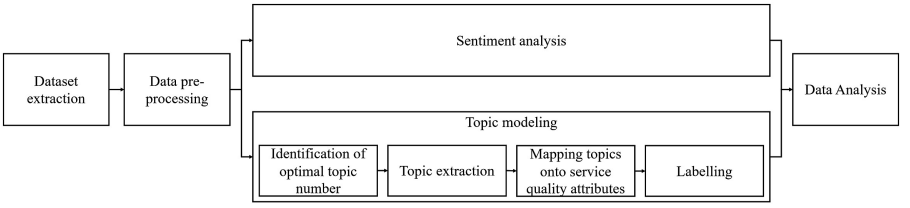

Figure 1. Overview of the methodology

Sentiment Reasoning (VADER) is used to assign a sentiment score to each review. The score calculated by the model indicates both the polarity (positive or negative) and the intensity (strength) of the emotions in each review. Once the sentiment analysis has been performed, the service attributes mentioned in each review are identified by applying the STM, which is a variant of the LDA technique. This topic modelling method identifies the underlying topics and calculates an estimation of each topic's weight in each review. Finally, by estimating the correlation of each attribute with the sentiment score, we can infer which ones are positive or negative, i.e. (desirable or undesirable service quality attributes).

3.1 Dataset extraction

The dataset for this study was extracted from the InsideAirbnb website, which is an independent, non-commercial initiative that provides public access to Airbnb data (InsideAirbnb, 2021), including the reviews for each listing.

In terms of the study's geographical scope, reviews from four European countries were included: France, Italy, Spain and Portugal. According to the Global Leadership and Organisational Behaviour Effectiveness (GLOBE) project, these countries belong to the "Latin Europe" cluster. A study by Gupta *et al.* (2002) validated these clusters. Even though these countries are highly ranked amongst the most popular tourist destinations in the world

(World Tourism Organization, 2020), previous Airbnb research has not analysed them. According to data published by Airbnb (2019), the European countries where Airbnb had the highest direct economic impact were France ($10.8 billion), Spain ($6.9 billion), Italy ($6.4 billion), the UK ($5.6 billion), and Portugal ($2.3 billion). Thus, this study focusses on Airbnb in these Latin European countries, with the aim of generate cross-regional insights into peer-to-peer accommodation services.

In total, 2,735,437 reviews were collected from 100,454 listings in Paris, Rome, Barcelona and Lisbon as of July 2020 (review dates ranged from 2010 to 2020). These cities were selected because they are the most popular tourist destinations (Euromonitor, 2019) in the countries defined in the geographical scope.

3.2 Data pre-processing

In order to prepare the data for the text mining process, it is necessary to conduct several pre-processing procedures (Feinerer *et al.*, 2008). First, reviews were filtered by language using the Textcat package in *R* (Hornik *et al.*, 2013) in order to exclude non-English reviews. Afterwards, the following processes were carried out, following the approaches recommended in previous studies (Barravecchia *et al.*, 2020; Ding *et al.*, 2020; Mastrogiacomo *et al.*, 2021): (1) Text normalisation (conversion of all text into lowercase letters to reduce ambiguity), (2) Text tokenization (separating each sentence into words), (3) Text stemming to remove word inflections or derivations, leaving only the word's stem (e.g. The words "visited" and "visiting" are reduced to their stem "visit"), (4) Removal of the punctuation, numbers and common English stop words (e.g. "and", "the"), (5) Removal of the words shorter than 2 or longer than 15 characters, as well as the reviews with less than 10 words; (6) Removal of words with an extremely low frequency (appearing in less than 20 documents) which would not be representative for the analysis, (7) Removal of the words generally not significant to identify topical content (such as: "another", "review", "made", "did", "done", etc.) and (8) N-gram analysis to find frequently co-occurring words and transform them into unigrams (e.g. "customer service" to "customerservice").

3.3 Sentiment analysis

Sentiment analysis is defined as "the computational study of people's opinions, attitudes and emotions toward an entity" (Medhat *et al.*, 2014, p. 1093). In the case of customer reviews, sentiment analysis can be used to classify, measure and monitor the user's emotions towards a particular product or service.

There is a wide variety of tools that can be used to perform sentiment analysis, each one of them presenting particular characteristics. In order to compare these tools, Ribeiro *et al.* (2016) developed a benchmark named SentiBench. One of the tools that appeared as a highly ranked sentiment analysis model was VADER.

For the current study, VADER was applied to calculate the sentiment score of each review on a scale of -1 (most negative) to $+1$ (most positive). VADER is a rule-based model for sentiment analysis, which has been specifically adapted to provide a highly accurate sentiment assessment in social media texts. In fact, it has been proven that VADER can even outperform individual human raters (F1 Classification Accuracy = 0.96, as opposed to 0.84 from humans) when analysing social media content (Hutto and Gilbert, 2014).

Another sentiment analysis tool known as Linguistic Inquiry and Word Count (LIWC) is also amongst the few that have been validated by humans, but VADER presents certain advantages over it. In particular, VADER is more accurate in social media contexts because it takes into account the characteristics of the text that can affect the perceived sentiment intensity (Hutto and Gilbert, 2014). For instance, it can capture the sentiment expressed by emoticons, punctuation (such as exclamation points), capitalisation (i.e. ALL-CAPS to emphasise sentiment), acronyms, slang, etc.

Considering these advantages, VADER was selected to conduct the sentiment analysis, assigning a score between −1 and +1 to each review.

3.4 Identification of the optimal number of topics and topic extraction

In the context of natural language processing, topic models are probabilistic models used to discover latent topics in a collection of documents (Blei and Lafferty, 2006). Aside from identifying the underlying topics in a text corpus, topic modelling associates a set of keywords to each topic and estimates the distribution of topic weights for each document (Blei, 2012).

For the current study, the STM was used to extract the latent topics from a dataset of Airbnb customer reviews. STM is an extended version of previous widely accepted probabilistic topic models such as LDA (Blei, 2012). The main difference between STM and previous models is that it can incorporate document-level covariate information into the topic model. Including these covariates can improve the model's inference and interpretability, and they can have an impact on the topics' content and/or prevalence (Roberts *et al.*, 2019).

The optimal number of topics (T) is an essential parameter for topic modelling techniques. One of the methods that can be used to identify T is by applying the topic modelling algorithm iteratively (with different numbers of topics) to find the iteration with the best performance (Wallach *et al.*, 2009). In order to evaluate the performance of each iteration, several metrics can be analysed, such as the semantic coherence, held-out likelihood or exclusivity (Roberts *et al.*, 2019). The current study used held-out likelihood, which refers to the probability of unseen held-out documents given a trained model (Wallach *et al.*, 2009). On average, better models will be associated with a higher held-out likelihood.

Figure 2 presents the values obtained when calculating the held-out likelihood as a function of T (from 7 to 100). Taking into account the held-out likelihood calculation, the current study selected the number of topics that resulted in the best overall performance. This approach is similar to the one applied in previous topic modelling studies (Ding *et al.*, 2020; Korfiatis *et al.*, 2019). As can be observed in Figure 2, the highest held-out likelihood was obtained when the value of T was 65. Therefore, 65 was identified as the optimal number of topics.

However, not all of the topics identified in the corpus corresponded to service quality attributes. For this reason, it was necessary to define a criterion to map these topics to service quality attributes. The next section describes how the mapping was conducted.

3.5 Mapping topics onto service quality attributes

As a result of applying STM to the pre-processed text corpus, the topics were successfully extracted. In order to identify the topics related to service quality attributes, the results were compared with the Airbnb service quality dimensions defined by Ju *et al.* (2019). Their scale was selected as a reference because it was the first survey-based approach specifically designed to assess service quality in Airbnb. Table 2 shows the mapping of topics onto their corresponding service quality attributes.

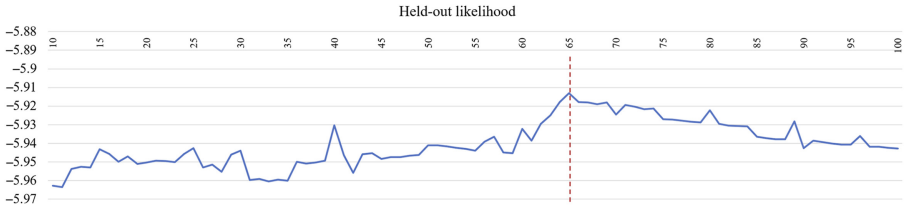

Figure 2.
Held-out likelihood for varying numbers of topics

Dimensions (Ju *et al.*, 2019)	Id	Service attributes identified	Topic label source	Relevant keywords (stemmed for text pre-processing purposes)
Host service quality	1	Host tips and advice	Adapted from Ju *et al.* (2019)	Visit, place, see, tip and short
	2	Host welcome	Adapted from Tussyadiah and Zach (2017)	Welcom, inform, warm, met and gave
	3	Host friendliness	Adapted from Ranjbari *et al.* (2020)	Help, friend, kind, pleasant and thought
	4	Host kindness	Adapted from Ju *et al.* (2019)	Host, autom, accommod, offer and wonder
	5	Feeling at home	Adapted from Zhang (2019)	Home, made, make, feel and trip
	6	Communication with host	Adapted from Kiatkawsin *et al.* (2020)	Easi, communic, get, check and checkin
	7	Host responsiveness	Zhang (2019)	Quick, response, always, question and respond
	8	Late check-in	Adapted from Zhang (2019)	Late, wait, reserv, flight and delay
	9	Check-in/check-out flexibility	Ranjbari *et al.* (2020)	Check, even, earli, leav and accommod
Web responsiveness quality	10	Website responsiveness	Parasuraman *et al.* (1988)	Person, guest, ask, detail and care
Web efficiency quality	11	Accuracy of apartment description	Adapted from Ranjbari *et al.* (2020)	Expect, photo, descript, accur and smaller
	12	Accuracy of apartment pictures	Labelled by authors	Just, look, pictur, exact and describ
Facility service quality		*Apartment features*		
	13	Apartment safety	Ranjbari *et al.* (2020)	Build, door, safe, felt and outsid
	14	Room aesthetics	Cheng and Jin (2019)	Room, bathroom, bedroom, kitchen and live
	15	Cleanliness	Ranjbari *et al.* (2020)	Clean, good, flat, hous and near
	16	Bed comfort	Adapted from Zhang (2019)	Comfort, bed, slept, pillow and soft
	17	Apartment dimensions	Labelled by authors	Small, size, unit, shower and cloth
	18	Sleeping capacity	Kiatkawsin *et al.* (2020)	Space, access, plenti, spot and coupl
	19	Views	Ranjbari *et al.* (2020)	Beauti, amaz, stay, view and absolut
	20	Relax/unwind areas in apartment	Adapted from Kiatkawsin *et al.* (2020)	Day, long, relax, sightse and end
	21	Ease of access (stairs)	Labelled by authors	Floor, stair, top, elev and luggag
	22	Food and drinks	Adapted from Zhang (2019)	Breakfast, food, coffe, even and wine
	23	Thermal management (water/heating issues)	Kiatkawsin *et al.* (2020)	Work, problem, shower, water and hot
	24	Hygiene issues (uncleanliness)	Labelled by authors	Toilet, bad, smell, unfortun and seem
		Equipment		
	25	Room equipment	Adapted from Zhang (2019)	Provid, use, kitchen, includ and cook
	26	Internet connection	Adapted from Lee *et al.* (2019)	Wifi, connect, Internet, watch and view
	27	Apartment furniture	Ranjbari *et al.* (2020)	Well, quiet, spacious, equip and decor
		Location characteristics		
	28	Location (overall)	Tussyadiah and Zach (2017)	Locat, apart, stay, recommend and love
	29	Neighbourhood features	Lawani *et al.* (2019)	Neighbourhood, huge, plus, far and favorit
	30	Accessibility	Kiatkawsin *et al.* (2020)	Also, apart, around, near and easy
	31	Proximity to attractions	Ranjbari *et al.* (2020)	Street, away, step, market and block
	32	Distance from city centre	Labelled by authors	Citi, can, center, centr and park
	33	Proximity to public transports	Adapted from Ranjbari *et al.* (2020)	Close, metro, station, conveni and nearbi
	34	Proximity to restaurants	Adapted from Zhang (2019)	Restaur, area, lot, shop and bar
	35	Reachability from the airport	Labelled by authors	Airport, bus, train, take and stop
	36	Sleep disturbance (night noise)	Kiatkawsin *et al.* (2020)	Night, bit, window, sleep and nois
		Other attributes		
	37	Family friendliness	Kiatkawsin *et al.* (2020)	Famil, kid, adult, children and apart

Table 2.
Mapping and labelling of identified topics onto service quality attributes

The topics that could not be assigned to these categories were not considered as service quality attributes. More specifically, the following topics could not be matched with any service quality dimensions: Price, Suggestions to other users, References to other reviews, Length of stay. Furthermore, other topics only reflected the user's overall satisfaction with the service but did not specify any particular service attribute (e.g. "Great stay! We had a good time, will come back soon"). These topics were also not retained for the analysis. Similarly, topics that referred to automated or null reviews were not taken into account. Finally, several topics related to reviews that were written in more than one language (aside from English) were also discarded. As a result, out of the 65 topics identified in the corpus, 37 were mapped onto service quality attributes.

3.6 Labelling

Through topic modelling, each review was assigned a set of probabilities (topic weights) of being associated with each one of the topics identified in the corpus, with values between 0 and 1. Therefore, topic modelling can capture the fact that the same review could mention several different topics, and it can also reflect the relevance of each topic in a particular review. A high topic weight of "Topic X" reflects a greater probability that a particular review is related to "Topic X". In a hypothetical example, the following review (with keywords marked in bold) obtains a topic weight of 55% for the "Proximity to restaurants" attribute, 17% for "Cleanliness", 28% for "Host friendliness" and 0% for "Proximity to public transports" (assuming these were the only topics in the model):

> The apartment was absolutely beautiful and very *clean*! It was close to lots of *restaurants*, so there were many options to enjoy delicious *local cuisine* nearby. There was a nice pizza *restaurant* across the street. Our *host* was very *friendly* and *helpful* before and during our stay. We highly recommend this apartment!

However, topic labels are not provided by the STM. The process of assigning appropriate labels to each topic derived from the model is known as topic labelling. In order to provide a label for each attribute identified through the topic modelling process, the reviews with the highest topic weight for each attribute were used as a reference. Additionally, the most relevant keywords associated with each attribute were also used as a reference for the labelling process. Table 2 shows the top 5 keywords for each attribute, which are the words with the highest probability within each topic. Highest probability words are very useful to select an appropriate label for each topic (Roberts *et al.*, 2019).

In the case of attributes identified in previous Airbnb studies, the label source indicates the study from which the name of the attribute was extracted. Six of the attributes were labelled manually by the authors through group discussion and evaluation, given that they could not be found in previous literature. Lastly, the reviews with the highest weight for each topic were analysed to confirm the adequacy of their respective labels.

Figure 3 illustrates (with examples) the process of extracting topics, labelling them and mapping them onto service quality dimensions in order to identify service quality attributes.

4. Results

4.1 Airbnb service quality attributes

As a result of mapping the topic modelling outcome onto the Airbnb service quality dimensions specified by Ju *et al.* (2019), several quality attributes were identified. Table 2 shows the service quality attributes found in the dataset of Airbnb reviews that were analysed. Each one of these attributes was related to one of the following dimensions: Host service quality, Web responsiveness quality, Web efficiency quality and Facility service quality.

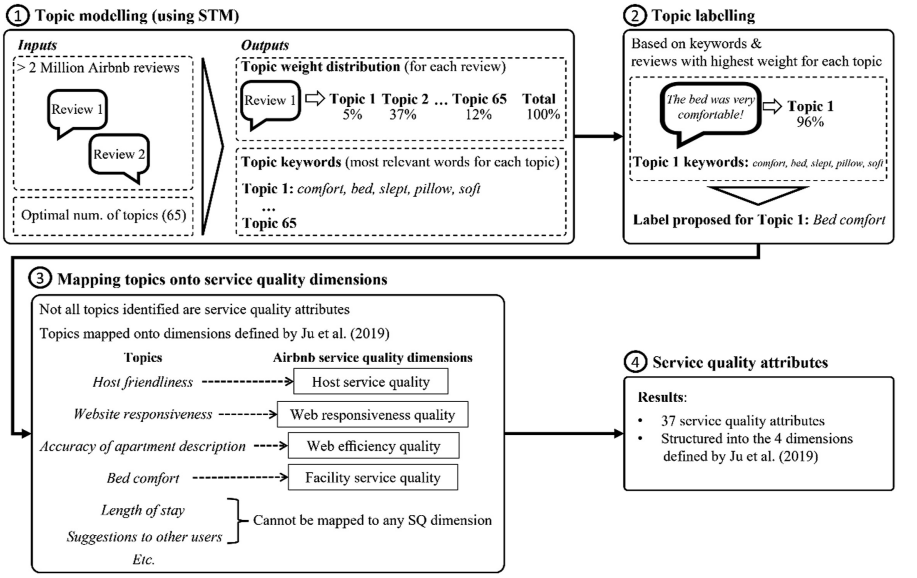

Figure 3.
Process to identify service quality attributes from topic modelling results

Host service quality refers to the quality of the interaction between the host and the guest. Within this dimension, several topics were identified as service attributes, including Host friendliness, Host tips and advice, Host responsiveness and Check-in/Check-out flexibility.

Web responsiveness quality indicates the platform's ability to respond to the user's enquiries, as well as to compensate guests when there is a problem. One of the topics (which was associated with keywords such as "person", "guest", "ask", "detail", "care", and "contact) was matched with this dimension. Therefore, the service attribute linked to this topic was labelled "Website responsiveness".

The dimension of Web efficiency measures the quality of the website's information and its organisation. Two of the topics identified were mapped onto this dimension, considering that they were related to the accuracy of the information found on the website (such as the apartment's description and pictures).

Finally, Facility service quality refers to the quality of the place where the service is provided: the apartment, the room, the neighbourhood, etc. This dimension was the one that was matched with the highest number of topics, which were divided into four categories: apartment features (i.e. cleanliness and bed comfort), equipment (i.e. apartment furniture and internet connection), location (i.e. proximity to restaurants and distance from city centre) and other attributes (family friendliness).

4.2 Correlation of service attributes with user sentiment

Identifying Airbnb's service quality attributes was the first research objective of the current study, together with defining which attributes have a positive (or negative) correlation with the user's sentiment.

In order to estimate the relation of each quality attribute to user sentiment, the Pearson's correlations between each review's sentiment score and the weights of each topic for that particular review were calculated. This was possible because STM provided a distribution of topic weights for each review, and the sentiment analysis assigned a sentiment score to each review. With the purpose of determining which correlations were statistically significant,

their p-values and the levels of significance specified in the Table of critical values were considered (Weathington *et al.*, 2012).

Out of the 37 service attributes detected through topic modelling, eight of them presented a statistically significant correlation with the sentiment score. Their returned p-values were <0.001, confirming their significance. As can be observed in the correlation matrix (Figure 4), half of these attributes were positively correlated with the sentiment score (Views, Host tips and advice, Location, Host friendliness). However, the other attributes showed a negative correlation with the sentiment (Sleep disturbance, Website responsiveness, Thermal management, Hygiene issues). The attribute with the greatest negative correlation with sentiment score was Hygiene issues ($r = -0.58$), followed by Thermal management (water and heating issues, $r = -0.29$). On the contrary, Views was the attribute with the most significant positive correlation with sentiment score ($r = 0.27$), followed by Host tips and advice ($r = 0.25$).

Figure 5 shows (graphically, in the form of scatter plots) the relationship between these service attributes and the sentiment score.

The vertical axis in the scatter plots represents the topic weight (which reflects the importance of an attribute in a particular review), whereas the horizontal axis represents the sentiment score assigned to each review (ranging from −1 to 1). As can be observed in the first row of Figure 5, in the four topics identified as positive service attributes, higher topic weights are related to higher sentiment scores. On the contrary, in the case of negative service attributes (second row of Figure 5), higher topic weights are associated with lower sentiment scores. However, the trend in negative attributes is not as strong as in the positive ones, given that the dataset presented a majority of positive reviews, as is often the case in user-generated content (Ju *et al.*, 2019).

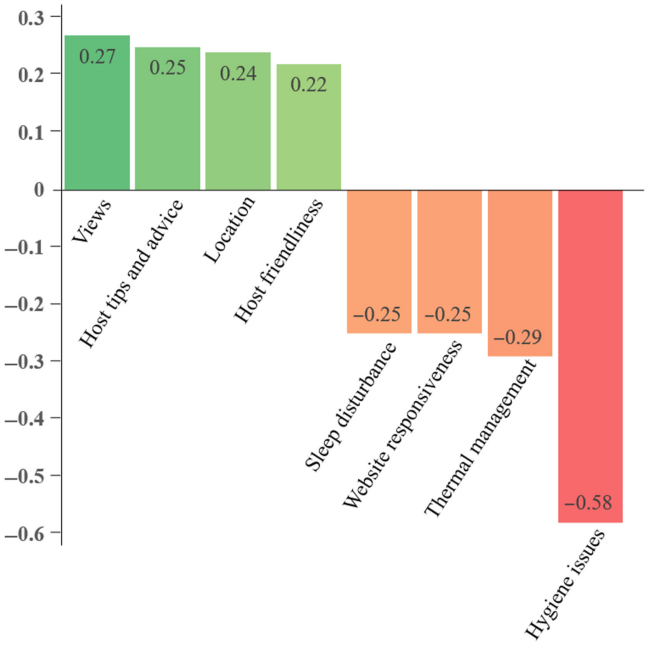

Figure 4.
Pearson's correlations between service attributes and sentiment score

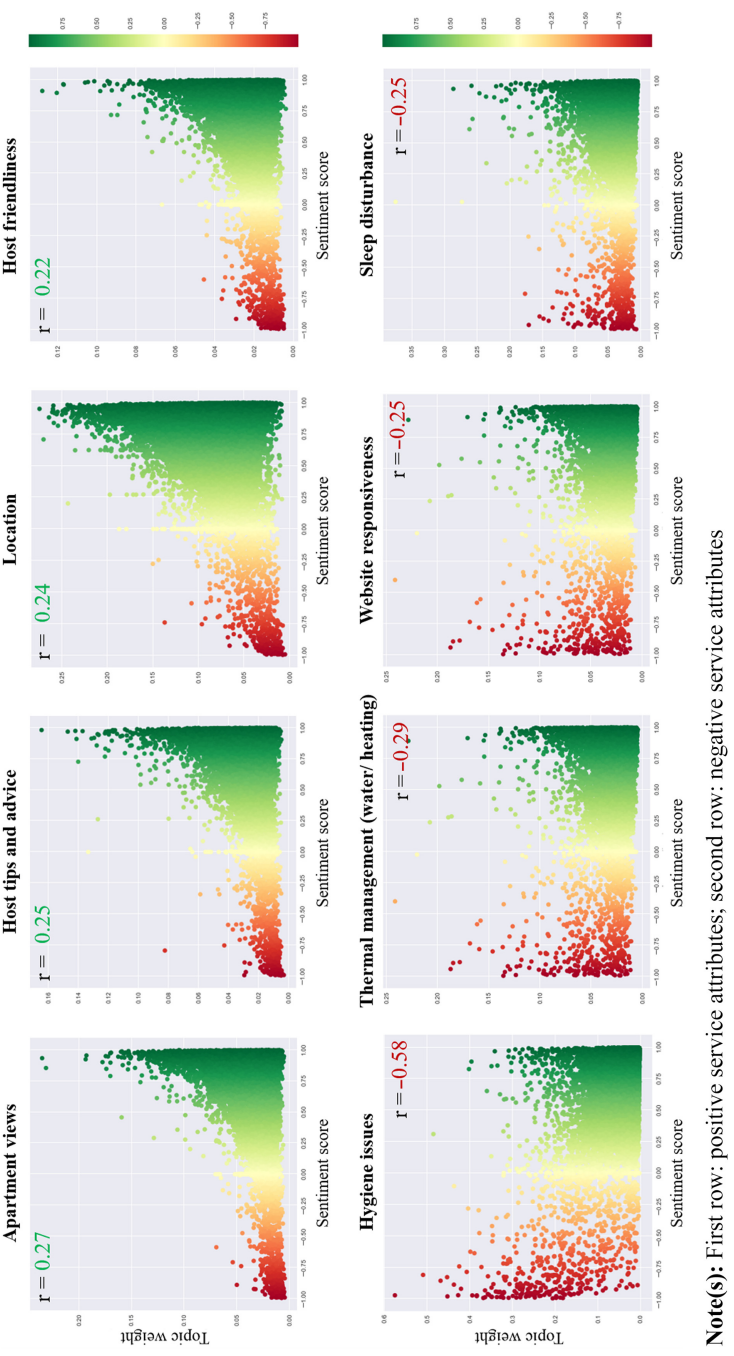

Figure 5.
Scatter plots showing the relationship between service attributes and sentiment score

5. Conclusions and discussion

5.1 Theoretical and practical implications

The current study used a data-driven approach (combining topic modelling and sentiment analysis) to identify Airbnb service quality attributes, based on reviews written by users in four European countries. As a result, 37 attributes related to service quality were identified (see Table 2), 6 of which had not been detected in previous Airbnb studies. These insights provide a better understanding of the needs and quality perceptions of digital home-sharing platform users.

From a theoretical perspective, this study provides evidence to support previous conceptual research that pointed to big data analytics as a key element in Quality 4.0. More specifically, it exemplifies how quality management can benefit from analysing customer feedback using text mining techniques. According to Saihi *et al.* (2021), most of the existing Quality 4.0 literature focusses on describing its potential benefits but requires further detail in terms of real applications through practical examples and case studies. For instance, a study by Antony *et al.* (2021a, b, c) analysed previous research and found that implementing Quality 4.0 can have a positive impact on several business performance metrics. Other researchers indicate that handling big data analytics is one of the key factors to achieve successful deployment of Quality 4.0 (Antony *et al.*, 2021c; Sony *et al.*, 2020). On the other hand, Saihi *et al.* (2021) noted that the majority of studies emphasised the potential advantages of using advanced technology for quality control, whilst very few focussed on other quality management tools and methodologies. This study responds to previous research in two ways. First, it confirms that big data analytics are an essential part of Quality 4.0, as they can provide valuable information for quality management. Second, it proposes a practical example of how this new approach to quality management can be implemented in a real business. Therefore, the current study aims to contribute to rethinking how quality research can adapt to the digital era and leverage technology to obtain customer insights.

From a practical point of view, the results of this study can be used to extend existing Airbnb service quality assessment tools. More specifically, 4 of the attributes that were identified within the Host service quality dimensions had not been included in the scale by Ju *et al.* (2019), such as "Check-in/check-out flexibility". Regarding the Facility service quality dimension, 19 new attributes were detected, such as "Internet connection" or "Room equipment". Additionally, the current work presents a data-driven approach to analyse user-generated content by combining STM and sentiment analysis to detect positive and negative service quality attributes. This verifies the adequacy of STM as a technique to obtain insights from user-generated content. It also confirms that STM is a technique that can be used to perform service quality research, which has also been applied successfully in previous Airbnb studies (Ding *et al.*, 2020). Finally, this research also contributes to the literature of service quality in peer-to-peer accommodation services by identifying the quality attributes perceived by European users of Airbnb. The results provide valuable insights regarding the preferences of Airbnb users in Europe, given that most of the previous studies had focussed on users from the US, Australia and Southeast Asia. Therefore, the results obtained in the current work can serve as a reference for future comparative studies amongst Airbnb users at different tourist destinations.

5.2 Limitations and future research

This study comes with certain limitations, which at the same time present several opportunities for future research. First, the focus of this article was Airbnb, which is the most relevant platform in the home-sharing sector, but there are many other platforms that could also be examined in different industries. Second, although the dataset included reviews from users in different countries, this study did not assess the potential differences amongst guest preferences regarding service attributes in these countries. Third, due to space limitations, the current study did not analyse the evolution in time of the service attributes that were identified.

References

Airbnb (2019), "Airbnb estimated direct economic impact exceeds $100 billion in one year", available at: https://news.airbnb.com/airbnb-estimated-direct-economic-impact-exceeds-100-billion-in-one-year.

Airbnb (2021a), "Airbnb Trust and Safety - your safety is our priority", available at: https://www.airbnb.com/trust (accessed 5 February 2021).

Airbnb (2021b), "New data: the Airbnb advantage", available at: https://news.airbnb.com/new-data-the-airbnb-advantage/(accessed 6 February 2021).

Akbaba, A. (2006), "Measuring service quality in the hotel industry: a study in a business hotel in Turkey", *International Journal of Hospitality Management*, Vol. 25 No. 2, pp. 170-192, Pergamon.

Antony, J., McDermott, O. and Sony, M. (2021a), "Quality 4.0 conceptualisation and theoretical understanding: a global exploratory qualitative study", *TQM Journal*, August, doi: 10.1108/TQM-07-2021-0215.

Antony, J., Sony, M., Furterer, S., McDermott, O. and Pepper, M. (2021b), "Quality 4.0 and its impact on organizational performance: an integrative viewpoint", *TQM Journal*, December, doi: 10.1108/TQM-08-2021-0242.

Antony, J., Sony, M., McDermott, O., Jayaraman, R. and Flynn, D. (2021c), "An exploration of organizational readiness factors for Quality 4.0: an intercontinental study and future research directions", *International Journal of Quality and Reliability Management*, Emerald Publishing, Vol. ahead-of-print No. ahead-of-print, Issue: December 2021, doi: 10.1108/IJQRM-10-2021-0357.

Barravecchia, F., Mastrogiacomo, L. and Franceschini, F. (2020), "Categorizing quality determinants in mining user-generated contents", *Sustainability*, MDPI AG, Vol. 12 No. 23, p. 9944.

Barravecchia, F., Mastrogiacomo, L. and Franceschini, F. (2021), "Digital voice-of-customer processing by topic modelling algorithms: insights to validate empirical results", *International Journal of Quality and Reliability Management*, Emerald Group Holdings, Vol. 39 No. 6, pp. 1453-1470, doi: 10.1108/IJQRM-07-2021-0217/FULL/XML.

Berry, M.W. and Castellanos, M. (2008), *Survey of Text Mining II: Clustering, Classification, and Retrieval*, 1st ed., Springer, London, ISBN: 978-1-84800-045-2, doi: 10.1007/978-1-84800-046-9.

Blei, D.M. (2012), "Probabilistic topic models", *Communications of the ACM*, Vol. 55 No. 4, pp. 77-84, ACM PUB27 New York, NY.

Blei, D.M. and Lafferty, J.D. (2006), "Dynamic topic models", in *Proceedings of the 23rd International Conference on Machine Learning*, June, pp. 113-120.

Bloemer, J., de Ruyter, K. and Wetzels, M. (1999), "Linking perceived service quality and service loyalty: a multi-dimensional perspective", *European Journal of Marketing*, Emerald, Vol. 33 Nos 11/12, pp. 1082-1106.

Brochado, A., Rita, P., Oliveira, C. and Oliveira, F. (2019), "Airline passengers' perceptions of service quality: themes in online reviews", *International Journal of Contemporary Hospitality Management*, Emerald Group Publishing, Vol. 31 No. 2, pp. 855-873.

Chakrabarti, S., Trehan, D. and Makhija, M. (2018), "Assessment of service quality using text mining – evidence from private sector banks in India", *International Journal of Bank Marketing*, Emerald Group Publishing, Vol. 36 No. 4, pp. 594-615.

Chang, T.Z. and Chen, S.J. (1998), "Market orientation, service quality and business profitability: a conceptual model and empirical evidence", *Journal of Services Marketing*, MCB UP, Vol. 12 No. 4, pp. 246-264.

Chen, W.J. and Chen, M.L. (2014), "Factors affecting the hotel's service quality: relationship marketing and corporate image", *Journal of Hospitality Marketing and Management*, Routledge, Vol. 23 No. 1, pp. 77-96.

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

de Ruyter, K., Wetzels, M. and Bloemer, J. (1998), "On the relationship between perceived service quality, service loyalty and switching costs", *International Journal of Service Industry Management*, Emerald Group Publishing, Vol. 9 No. 5, pp. 436-453.

DeVellis, R.F. (2016), *Scale Development Theory and Applications*, 4th ed., SAGE Publication, Thousand Oaks, California.

Dias, A.M., Carvalho, A.M. and Sampaio, P. (2021), "Quality 4.0: literature review analysis, definition and impacts of the digital transformation process on quality", *International Journal of Quality and Reliability Management*, Emerald Group Holdings, Vol. 39 No. 6, doi: 10.1108/IJQRM-07-2021-0247/FULL/XML.

Ding, K., Choo, W.C., Ng, K.Y. and Ng, S.I. (2020), "Employing structural topic modelling to explore perceived service quality attributes in Airbnb accommodation", *International Journal of Hospitality Management*, Elsevier, Vol. 91 August, 102676.

Euromonitor (2019), "Top 100 city destinations: 2019 edition | Euromonitor", available at: https://go.euromonitor.com/white-paper-travel-2019-100-cities.html (accessed 6 February 2021).

Feinerer, I., Hornik, K. and Meyer, D. (2008), "Text mining infrastructure in R", *Journal of Statistical Software*, American Statistical Association, Vol. 25 No. 5, pp. 1-54.

Feldman, R. and Sanger, J. (2006), *The Text Mining Handbook, the Text Mining Handbook*, Cambridge University Press, Cambridge.

Gu, B. and Ye, Q. (2014), "First step in social media: measuring the influence of online management responses on customer satisfaction", *Production and Operations Management*, Wiley-Blackwell, Vol. 23 No. 4, pp. 570-582.

Güçlü, B., Roche, D. and Marimon, F. (2020), "City characteristics that attract Airbnb travellers: evidence from Europe", *International Journal for Quality Research*, Vol. 14 No. 1, doi: 10.24874/IJQR14.01-17.

Gupta, V., Hanges, P.J. and Dorfman, P. (2002), "Cultural clusters: methodology and findings", *Journal of World Business*, JAI, Vol. 37 No. 1, pp. 11-15.

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

Guttentag, D., Smith, S., Potwarka, L. and Havitz, M. (2018), "Why tourists choose Airbnb: a motivation-based segmentation study", *Journal of Travel Research*, SAGE Publications, Vol. 57 No. 3, pp. 342-359.

Hargreaves, C.A. (2015), "Analysis of hotel guest satisfaction ratings and reviews: an application in Singapore", *American Journal of Marketing Research*, Vol. 1, available at: http://www.aiscience.org/journal/ajmrhttp://creativecommons.org/licenses/by-nc/4.0/(accessed 6 February 2021).

Hawlitschek, F., Teubner, T. and Weinhardt, C. (2016), "Trust in the sharing economy", *Die Unternehmung*, Nomos Verlag, Vol. 70 No. 1, pp. 26-44.

Hornik, K., Mair, P., Rauch, J., Geiger, W., Buchta, C. and Feinerer, I. (2013), "The textcat package for n-gram based text categorization in R", *Journal of Statistical Software*, Vol. 52 No. 6, doi: 10.18637/jss.v052.i06.

Hu, M. and Liu, B. (2004), "Mining opinion features in customer reviews", *Proceedings of the National Conference on Artificial Intelligence*, pp. 755-760.

Hutto, C.J. and Gilbert, E. (2014), "VADER: a parsimonious rule-based model for sentiment analysis of social media text", *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 8, available at: http://sentic.net/ (accessed 7 February 2021).

InsideAirbnb (2021), "Inside Airbnb. Adding data to the debate", available at: http://insideairbnb.com/ (accessed 6 February 2021).

James, T.L., Villacis Calderon, E.D. and Cook, D.F. (2017), "Exploring patient perceptions of healthcare service quality through analysis of unstructured feedback", *Expert Systems with Applications*, Elsevier, Vol. 71, pp. 479-492.

Jelodar, H., Wang, Y., Yuan, C., Feng, X., Jiang, X., Li, Y. and Zhao, L. (2019), "Latent Dirichlet allocation (LDA) and topic modeling: models, applications, a survey", *Multimedia Tools and Applications*, Springer New York LLC, Vol. 78 No. 11, pp. 15169-15211.

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*, Elsevier, Vol. 77, pp. 342-352.

Kiatkawsin, K., Sutherland, I. and Kim, J.Y. (2020), "A comparative automated text analysis of airbnb reviews in Hong Kong and Singapore using latent dirichlet allocation", *Sustainability*, Vol. 12 No. 16, p. 6673.

Korfiatis, N., Stamolampros, P., Kourouthanassis, P. and Sagiadinos, V. (2019), "Measuring service quality from unstructured data: a topic modeling application on airline passengers' online reviews", *Expert Systems with Applications*, Elsevier, Vol. 116, pp. 472-486.

Lalicic, L. and Weismayer, C. (2018), "A model of tourists' loyalty: the case of Airbnb", *Journal of Hospitality and Tourism Technology*, Emerald Group Publishing, Vol. 9 No. 1, pp. 78-90.

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, H., Lee, Y. and Yoo, D. (2000), "The determinants of perceived service quality and its relationship with satisfaction", *Journal of Services Marketing*, Emerald Group Publishing, Vol. 14 No. 3, pp. 217-231, doi: 10.1108/08876040010327220.

Lee, S., Song, J. and Kim, Y. (2010), "An empirical comparison of four text mining methods", *Journal of Computer Information Systems*, Vol. 51 No. 1, pp. 1-10.

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 and People*, Emerald Group Publishing, Vol. 33 No. 3, pp. 945-961.

Liang, L.J., Choi, H.C. and Joppe, M. (2018), "Exploring the relationship between satisfaction, trust and switching intention, repurchase intention in the context of Airbnb", *International Journal of Hospitality Management*, Elsevier, Vol. 69, pp. 41-48.

Mastrogiacomo, L., Barravecchia, F., Franceschini, F. and Marimon, F. (2021), "Mining quality determinants of product-service systems from user-generated contents", *Quality Engineering*.

Medhat, W., Hassan, A. and Korashy, H. (2014), "Sentiment analysis algorithms and applications: a survey", *Ain Shams Engineering Journal*, Ain Shams University, Vol. 5 No. 4, pp. 1093-1113.

Mittendorf, C. (2018), "Collaborative consumption: the role of familiarity and trust among Millennials", *Journal of Consumer Marketing*, Emerald Group Publishing, Vol. 35 No. 4, pp. 377-391.

Möhlmann, M. (2015), "Collaborative consumption: determinants of satisfaction and the likelihood of using a sharing economy option again", *Journal of Consumer Behaviour*, John Wiley and Sons, Vol. 14 No. 3, pp. 193-207.

Palese, B. and Usai, A. (2018), "The relative importance of service quality dimensions in E-commerce experiences", *International Journal of Information Management*, Elsevier, Vol. 40, pp. 132-140.

Parasuraman, A., Zeithaml, V.A. and Berry, L.L. (1988), "Servqual: a multiple-item scale for measuring consumer perceptions", *Journal of Retailing*, Vol. 64 No. 1, pp. 12-40.

Priporas, C.V., Stylos, N., Vedanthachari, L.N. and Santiwatana, P. (2017), "Service quality, satisfaction, and customer loyalty in Airbnb accommodation in Thailand", *International Journal of Tourism Research*, John Wiley and Sons, Vol. 19 No. 6, pp. 693-704.

Ranjbari, M., Shams Esfandabadi, Z. and Scagnelli, S.D. (2020), "A big data approach to map the service quality of short-stay accommodation sharing", *International Journal of Contemporary Hospitality Management*, Emerald Group Publishing, Vol. 32 No. 8, pp. 2575-2592.

Ribeiro, F.N., Araújo, M., Gonçalves, P., André Gonçalves, M. and Benevenuto, F. (2016), "SentiBench - a benchmark comparison of state-of-the-practice sentiment analysis methods", *EPJ Data Science*, Vol. 5 No. 1, pp. 1-29.

Roberts, M.E., Stewart, B.M. and Tingley, D. (2019), "Stm: an R package for structural topic models", *Journal of Statistical Software*, American Statistical Association, Vol. 91 No. 1, pp. 1-40.

Saha, G.C. and Theingi (2009), "Service quality, satisfaction, and behavioural intentions: a study of low-cost airline carriers in Thailand", *Managing Service Quality*, Emerald Group Publishing, Vol. 19 No. 3, pp. 350-372.

Saihi, A., Awad, M. and Ben-Daya, M. (2021), "Quality 4.0: leveraging Industry 4.0 technologies to improve quality management practices – a systematic review", *International Journal of Quality and Reliability Management*, Emerald Publishing, Vol. ahead-of-print No. ahead-of-print, doi: 10.1108/IJQRM-09-2021-0305.

Shemwell, D.J., Yavas, U. and Bilgin, Z. (1998), "Customer-service provider relationships: an empirical test of a model of service quality, satisfaction and relationship-oriented outcomes", *International Journal of Service Industry Management*, Emerald Group Publishing, Vol. 9 No. 2, pp. 155-168.

Sivadas, E. and Baker-Prewitt, J.L. (2000), "An examination of the relationship between service quality, customer satisfaction, and store loyalty", *International Journal of Retail and Distribution Management*, Vol. 28 No. 2, pp. 73-82, doi: 10.1108/09590550010315223.

So, K.K.F., Oh, H. and Min, S. (2018), "Motivations and constraints of Airbnb consumers: findings from a mixed-methods approach", *Tourism Management*, Elsevier, Vol. 67, pp. 224-236.

Sony, M., Antony, J. and Douglas, J.A. (2020), "Essential ingredients for the implementation of Quality 4.0: a narrative review of literature and future directions for research", *TQM Journal*, Vol. 32 No. 4, doi: 10.1108/TQM-12-2019-0275.

Sparks, B.A. and Browning, V. (2010), "Complaining in cyberspace: the motives and forms of hotel guests' complaints online", *Journal of Hospitality Marketing and Management*, Taylor & Francis Group, Vol. 19 No. 7, pp. 797-818.

Spreng, R.A. and Mackoy, R.D. (1996), "An empirical examination of a model of perceived service quality and satisfaction", *Journal of Retailing*, JAI, Vol. 72 No. 2, pp. 201-214.

Su, Y. and Teng, W. (2018), "Contemplating museums' service failure: extracting the service quality dimensions of museums from negative on-line reviews", *Tourism Management*, Elsevier, Vol. 69, pp. 214-222.

Tsao, H.Y., Chen, M.Y., Campbell, C. and Sands, S. (2020), "Estimating numerical scale ratings from text-based service reviews", *Journal of Service Management*, Vol. 31 No. 2, pp. 187-202.

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

Tussyadiah, I.P. and Park, S. (2018), "When guests trust hosts for their words: host description and trust in sharing economy", *Tourism Management*, Elsevier, Vol. 67, pp. 261-272.

Tussyadiah, I.P. and Zach, F. (2017), "Identifying salient attributes of peer-to-peer accommodation experience", *Journal of Travel and Tourism Marketing*, Routledge, Vol. 34 No. 5, pp. 636-652.

Wallach, H.M., Murray, I., Salakhutdinov, R. and Mimno, D. (2009), "Evaluation methods for topic models", *Proceedings of the 26th International Conference On Machine Learning, ICML*, Vol. 2009 No. 4, pp. 1105-1112.

Wang, Y., Agichtein, E. and Benzi, M. (2012), "TM-LDA: efficient online modeling of latent topic transitions in social media", *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, New York, New York, USA, ACM Press, pp. 123-131.

Weathington, B.L., Cunningham, C.J.L. and Pittenger, D.J. (2012), "Appendix B: statistical tables", *Understanding Business Research*, Wiley, pp. 435-483.

World Tourism Organization (2020), "UNWTO world tourism barometer and statistical annex", *UNWTO World Tourism Barometer*, Vol. 18 December 2020, World Tourism Organization (UNWTO), doi: 10.18111/wtobarometereng.2020.18.1.7.

Yacouel, N. and Fleischer, A. (2012), "The role of cybermediaries in reputation building and Price premiums in the online hotel market", *Journal of Travel Research*, SAGE Publications, Vol. 51 No. 2, pp. 219-226.

Zeithaml, V.A. (2000), "Service quality, profitability, and the economic worth of customers: what we know and what we need to learn", *Journal of the Academy of Marketing Science*, SAGE Publications, Vol. 28 No. 1, pp. 67-85.

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*, American Marketing Association, Vol. 54 No. 5, pp. 687-705.

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

Zhang, W., Xu, H. and Wan, W. (2012), "Weakness Finder: find product weakness from Chinese reviews by using aspects based sentiment analysis", *Expert Systems with Applications*, Vol. 39 No. 11, pp. 10283-10291, Pergamon.

Zonnenshain, A. and Kenett, R.S. (2020), "Quality 4.0—the challenging future of quality engineering", *Taylor and Francis*, Vol. 32 No. 4, pp. 614-626, doi: 10.1080/08982112.2019.1706744.

About the authors

Natalia Amat-Lefort is Lecturer at Leiden University (Leiden, Netherlands) and PhD researcher at the International University of Catalonia (Barcelona, Spain), with previous experience in Strategy and Operations consulting at KPMG and Ernst and Young. Her research focusses on the assessment of quality and consumer experience in digital platform services. Natalia Amat-Lefort is the corresponding author and can be contacted at: n.amat.lefort@liacs.leidenuniv.nl

Federico Barravecchia is Assistant Professor at the Department of Management and Production Engineering at Politecnico di Torino. His main scientific interests currently concern the areas of quality engineering and manufacturing servitization.

Luca Mastrogiacomo is Associate Professor of Manufacturing Technologies and Systems at Politecnico di Torino, currently teaching "Production systems", "Industrial quality management" and "Service quality". He is the co-author of 3 books, 2 patents and more than 100 papers on journals and/or national and international conferences. His research focusses on manufacturing technology, quality engineering and industry metrology. He is Vice-Coordinator of the Programme of Management Engineering at Politecnico di Torino.

For instructions on how to order reprints of this article, please visit our website:
www.emeraldgrouppublishing.com/licensing/reprints.htm
Or contact us for further details: **permissions@emeraldinsight.com**