A PERCEIVED SERVICE QUALITY MODEL IN THE SHARING ECONOMY:

THE CASE OF AIRBNB

MURAT AÇAR

BOĞAZİÇİ UNIVERSITY

2019

A PERCEIVED SERVICE QUALITY MODEL IN THE SHARING ECONOMY:

THE CASE OF AIRBNB

Thesis submitted to the

Institute for Graduate Studies in Social Sciences

in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

in

Management

by

Murat Açar

Boğaziçi University

2019

DECLARATION OF ORIGINALITY

I, Murat Açar, certify that

- I am the sole author of this thesis and that I have fully acknowledged and documented in my thesis all sources of ideas and words, including digital resources, which have been produced or published by another person or institution;
- this thesis contains no material that has been submitted or accepted for a degree or diploma in any other educational institution;
- this is a true copy of the thesis approved by my advisor and thesis committee at Boğaziçi University, including final revisions required by them.

Signature..

Date ....24 May 2019..

ABSTRACT

A Perceived Service Quality Model in the Sharing Economy:

The Case of Airbnb

The shift from ownership to access, the results of endless hyper-consumption, and the change in value mindsets initiated a new phenomenon, which is Sharing Economy (SE). SE has given rise to the humanization of consumer-supplier relationship in tourism and hospitality (TH), and sharing has become a mainstream practice. Airbnb has revolutionized the TH service in a new form of the contractual relationship and gained well-grounded popularity. The customers' willingness to share accommodation with a host in Airbnb as opposed to using a private hotel room has implications for TH in terms of perceived service quality of customers. In this study, a perceived service quality (PSQ) model is researched by text mining on user-generated content in the Airbnb context. We first collect a massive amount of Airbnb guests' textual review data, which is publicly available. Then, we analyze Airbnb guests' Big5 personalities using these personal texts by linguistic analytics and state the psychometric insights. We find that Airbnb guests score high in extraversion and openness dimensions of Big5. Then, using the personality traits of consumers as a basis, we test our PSQ model, which is a combination of the seminal SERVQUAL service quality framework and additional cognitive and attitudinal factors. The findings include that the SERVQUAL model requires adjustment in this context, and it is well-enhanced by cognitive and attitudinal factors, including intimacy, authenticity, privacy, and security. The study also discusses additional exploratory findings on Airbnb guests' textual review data through text mining.

ÖZET

Paylaşım Ekonomisinde Algılanan Hizmet Kalitesi Modeli: Airbnb Örneği

"Sahip olduğun şey sensin" deyimi artık büyük ölçüde "erişebileceğin şey sensin" biçimine dönüştü. Sahiplikten erişime geçiş, sonsuz hiper tüketimin sonuçları ve değer zihniyetindeki değişim, Paylaşım Ekonomisi (PE) adında yeni bir akım başlattı. PE, turizm ve otelcilikte (TO) tüketici-tedarikçi ilişkisinin daha çok insancıllaşmasına yol açmış ve paylaşım temel bir yaklaşım haline gelmiştir. Airbnb, TO hizmetini yeni bir sözleşme ilişkisi biçiminde ortaya atarak devrim yaratmış ve popülerlik kazanmıştır. TO müşterilerinin bir özel otel odası kullanmak yerine, Airbnb ev sahibi ile konaklama paylaşmaya istekli olmaları, algılanan hizmet kalitesi açısından birçok etkiye sahiptir. Bu çalışmada, algılanan hizmet kalitesi (AHK) modeli Airbnb bağlamında doğal dil işleme ile araştırılmıştır. Önce büyük miktarda Airbnb misafirinin yazılı yorum verileri toplanmıştır. Ardından, Airbnb konuklarının kişisel özellikleri bu verileri kullanarak dilbilimsel analizlerle çıkarılmış ve psikometrik bilgileri belirtilmiştir. Bulgular Airbnb kullanıcılarının dışadönüklük ve açıklık boyutlarına yüksek skorlar gösterdiğini içermektedir. Kullanıcıların bu özelliklerini temel alarak, SERVQUAL hizmet kalitesi çerçevesini ve algılanan hizmet kalitesi üzerindeki ek bilişsel ve tutumsal faktörler test edilmektedir. Bulgular, SERVQUAL modelinin bu bağlamda ayarlama gerektirdiğini ve samimiyet, orijinallik, mahremiyet ve güvenlik dahil olmak üzere bilişsel ve davranışsal faktörlerle geliştirildiğini içermektedir. Çalışma ayrıca, Airbnb konuklarına ait metin incelemesi verileri hakkındaki ek bulguları da tartışmaktadır.

CURRICULUM VITAE

NAME: Murat Açar

EDUCATION:

PhD in Management, Boğaziçi University

MSc in Computer Engineering, Bilkent University

BSc in Software Engineering, Atılım University

AREAS OF SPECIAL INTEREST:

Data-driven marketing with artificial intelligence, big data, text analytics, user-generated content, hyper-personalization, sharing economy, emotion economy, service research, systematic literature reviews

PROFESSIONAL EXPERIENCE:

Manager – Consulting Services, Wipro, 2018 - present

Senior Consultant and Project Manager, IBM, 2014 - 2018

Lecturer – Big Data and Analytics, Bahcesehir University, 2015-2017

Research and Teaching Assistant, Bilkent University, 2010-2013

Software Engineer, Milsoft Software Technologies – CMMI 5, 2010

GRANTS:

TUBITAK - PhD Scholarship (Scientific and Technological Research Council of Turkey)

ACKNOWLEDGMENTS

I remember like it was yesterday that I said during the Ph.D. admission examinations: “I want to see the big picture and work in an interdisciplinary manner.” Now, I feel genuinely overjoyed that it has happened. Being a versatile and interdisciplinary academician with a lifelong learner attitude has always been the ultimate objective to me in this ever-changing state-of-the-art.

I want to express my deepest gratitude to my advisor, Prof. Ayşegül Toker, for helping me throughout this research with continuous support. Her immense knowledge, interdisciplinary mindset, and mentorship have genuinely encouraged me to explore more research day-by-day. Prof. Toker’s guidance has made this research possible and pleasing to me.

I am grateful and with heartfelt thanks to Prof. Stefan Koch. From the very first time I talked with him about my willingness to pursue a Ph.D. in Management degree, to till this moment, he has always been supportive and inspiring for me.

I want to thank the rest of my thesis committee, Assoc. Prof. Yavuz Acar, Assist. Prof. Mustafa Hayri Tongarlak and Assist. Prof. Ayşe Meral Dülger Taşkın for taking place and time in reviews. I owe many thanks to the valued people of Boğaziçi University family who have catalyzed this process. The Ph.D. scholarship of TUBITAK is also highly appreciated.

In the end, I am grateful to my wife Merve İpek Açar supporting me spiritually, my mother Bilge Açar, my sisters Mine, Mehtap, Meral, and Meltem along with my young nephews (Barkın, Bartu and Ali) and nieces (Nil and Birsu) for their moral support. Hopefully, I will have them remember and read my words here all the time together in good health and success.

Dedicated to the memory of my father,

Ali Hamdi Açar

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDIX FIGURES

CHAPTER 1

INTRODUCTION

The idiom “you are what you own” has been considerably transformed into “you are what you can get access to.” Sharing Economy (SE) has overgrown and refers to an entirely new business model, socio-economic ecosystem, and context for sharing access to goods and services. SE has revealed new horizons for the service marketing research, which includes the shift from ownership to access, the change in value mindsets, and humanization of consumer-supplier relationship, especially in technology-based service encounters (Acar & Toker, 2018). According to Botsman and Rogers (2011), SE is a result of the linkage between offline and online world, which was triggered by the society to overcome natural resources constraints.

Resources in SE can be tangible (e.g., cars and homes) and intangible (e.g., expert local knowledge and labor). SE allows the sustainable use of idle resources, and it enables sellers to create new and flexible opportunities to market to consumers who experience personalized and even customized products and services at lower prices. In other words, under-used resources are utilized through fee-based sharing, reducing the need for ownership. Collaborative consumption, access-based consumption, and peer-to-peer (P2P) economy are the most commonly used synonyms of SE. It should be noted that SE is multi-disciplined and attributed to several meanings from scholars with different backgrounds. Also, academic research in SE is still in its infancy.

SE opened ways for a considerable number of new players across industries from a supply perspective by broadening the options for supply, which also remedies the response to peak demand. In this manner, SE has given rise to the disruption in tourism and hospitality (TH), and sharing has become a mainstream practice in this context. The recent shift of customers' willingness to share accommodation with a host instead of using a private hotel room has many implications for TH (Lu & Kandampully, 2016).

Airbnb has become one of the most prominent competitors in the hotel industry, and it enables people to lease or rent short-term accommodation including vacation rentals, apartment rentals, homestays, and even experiences via instant booking. From cash-strapped travelers to high-end business travelers, Airbnb has revolutionized the TH service in a new form of the contractual relationship and gained well-grounded popularity. The advent of the SE challenges not only the hotel business but also the theories and models based on the conventional hotel industry (Wang & Nicolau, 2017).

Guttentag and Smith (2017) report that two-thirds of Airbnb guests use the Airbnb service as a hotel substitute, and Airbnb's characteristics are consistent with the concept of disruptive innovation to some extent. Some scholars, on the other hand, argued that SE is a "fundamentally different business model," which could make it a new marketplace instead of a direct competitor in the hotel industry. Richard and Cleveland (2016) argue that hotel firms can oversee the communal sharing and utilize the strength of their brands by extending them to P2P rentals instead of competing against SE. From this point of view, Airbnb does not compete or pose a challenge to traditional TH services but extend the concept of TH (Lu & Kandampully, 2016). Hotel industry has reactively responded to the direct, indirect, and induced effects of Airbnb to economy and Airbnb's impact on hotel industry have recently been researched by several scholars (Mody, Suess, & Lehto, 2017; Priporas, Stylos, Rahimi, & Vedanthachari, 2017; Zervas, Proserpio, & Byers, 2017).

Consumers’ changing attitudes towards utilization and accessibility compared to ownership created an indirect need for an intimate connection between people, namely human connection. Then, social concerns upon services gave rise to mass-customized service expectations of consumers. The goal of Airbnb has turned into increasing the emotional connection and sustaining the high level of satisfaction of its customers. Disruptive innovation theory implies that products or services that offer alternative benefits compared to conventional attributes can transform a market and attain a critical mass, which can be observed in Airbnb’s story (Young, Corsun, & Xie, 2017).

Airbnb is successfully promoting the mottos of “Belong Anywhere” and “Do Not Go There. Live There” to their guests. This point is where Airbnb’s value proposition comes into play. First, it creates not only financial but also personal rewards through a personal concierge and a home-away-from-home experience. Second, Airbnb is not a simple transaction; instead, it is deemed to be a lifetime experience. So guest experience is at the heart of Airbnb’s strategic position.
Pine and Gilmore (2011) predicted the rise of experience in their original study, referring to the experience economy and stating that when services become commoditized, the customer experiences proposed by companies will matter most (further called this as Staging Experiences).

If the hotel industry is to surpass its SE competition in terms of the guest experience, it should leverage an expanded experience economy paradigm that incorporates additional dimensions that touch the emotional connections with the consumers (Mody et al., 2017).

Pine and Gilmore (2011) also proposed the four realms of experience as follows:

- Educational: This is related to the experiences that grab consumers' desire to learn something new
- Esthetics refers to the consumers' interpretation of the physical environment around them
- Entertainment is one of the oldest forms of experience such as entertaining activities
- Escapist means seeking to stay away from daily routines and moving towards a specific place for active involvement in activities worthy of time

Also, there exists evidence in the literature that providers are shifting their focus from service-oriented to the design of quality experiences (Lovelock & Gummesson, 2004). In terms of the glamour of SE in TH, a unique experience is deemed to be second only to better pricing. From the "experience" point of view, SE has also opened new rooms for service research. Service in the context of Airbnb is considered as an experience, rather than a utilitarian relation. Also, service quality has always been a critical factor in highly-competitive service industries like TH.

Service quality perception is multi-faceted, and the studies focusing on it are somewhat limited, especially in TH industry. These studies highlighted the complexities associated with evaluating service quality (e.g., complexity, reliability and validity of measurement instruments) and the contribution of service process delivery on service outcomes, which results in the perception of service quality. Tynan and McKechnie (2009) stressed the importance of customer experiences from a processual view in their original study about experience marketing and suggested the adoption of naturalistic inquiry to understanding the complex interactions in the original contexts fully. In the case of a close interaction between a service provider and a customer, the way the service is performed might be more important than what is delivered. Therefore, perceived service quality can be influenced by different internal processes and interpersonal variables, especially in Airbnb context.

To study service quality perception in Airbnb, the types of settings in this context are to be noted. There are two main types of hosting via Airbnb:

- Remote hospitality, where the host is not physically sharing the home. Here, the guest-host relationship consists of limited face-to-face interactions and is mostly based on instant messages, phone calls, and short encounters. Hosts or some representatives hand over the keys of the apartment to guests and final details are discussed.
- On-site hospitality, where the host is physically sharing the home and present with the guest(s)

Mainly, on-site hospitality is an integral part of the sociability within the host-guest relationship. Priporas et al. (2017) studied service quality in the context of remote hospitality, and we decided to respond to their relevant call for future research on the other type of Airbnb accommodation, which is on-site hospitality referring to "Shared Rooms" and "Private Rooms" in Airbnb's listings. "Shared Rooms" refer to an exact communal experience with the host, and guests sleep in a space that is shared with others and share the entire space with other people. "Private Rooms" refer to privacy, to some extent, in which guests value a local connection, have their private room for sleeping and may share some spaces with others. According to Simmons (2008), postmodern consumers are seeking both individualistic and communal brand experiences. With an analogy, we do expect that human connection and experience gap can be better researched with on-site hospitality existing in "Shared Rooms" and "Private Rooms." This expectation is because hosts design their services to create and build a relationship with their guests, leading to superior guest experiences and the so-called positive moment-of-truth. In addition to the online storytelling on hosts' home pages, the most critical moment-of-truth is created during the guests' stay at the host's place; thus, the host plays a significant role in the customer's perception of service and the subsequent review of the experience (Lu & Kandampully, 2016). Overall, our research motivation is based on the following factors:

i. SE is a new and multi-disciplined field that covers open rooms for research.
ii. Specifically, Airbnb is one of the most prominent businesses in this context, and preliminary analysis showed some promise for *clean* unstructured data collection.
iii. The literature review underlies the infancy of well-grounded studies that thoroughly cover service quality perceptions of customers in Airbnb.

Considering the above-mentioned motivational factors, we focus on the following research questions in Airbnb context:

- What are the personality traits of Airbnb guests?
- How well does the SERVQUAL framework along with cognitive and attitudinal factors suffice for measuring perceived service quality in this context?

This dissertation is structured as follows. Chapter 2 covers the literature review, including SE (especially Airbnb), personality analysis, and perceived service quality. Chapter 3 summarizes the characteristics of the data set. Chapter 4 details our personality analysis research. Chapters 5 and 6 discuss our research model and results, followed by a discussion in Chapter 7 and conclusion in Chapter 8.

CHAPTER 2

LITERATURE REVIEW

2.1 Sharing economy and Airbnb

Cheng (2016) conducted a systematic review of SE by using co-citation and content analysis of papers, and the findings reveal three distinct research areas of SE, namely SE's business models and its impacts, nature of SE, and SE's sustainability development. Moreover, two unique areas, specifically in tourism and hospitality, were identified: SE's impacts on destinations and tourism services, and SE's impacts on tourists. The comparison of both pieces of literature has revealed limited expansion in TH literature even though TH is at the frontier of SE (Cheng, 2016; Huurne, Ronteltap, Corten, & Buskens, 2017; Narasimhan et al., 2017).

SE – in a network of strangers - has changed how services are consumed. The exclusive ownership is being replaced by common usage through this increasingly common form of exchange. SE resides on a triangle of actors: a platform provider (e.g., Airbnb), a peer service provider (e.g., an Airbnb host) and a customer (e.g., an Airbnb guest). The platform provider's primary role is match-making so that a customer can access assets of a peer service provider (Benoit, Baker, Bolton, Gruber, & Kandampully, 2017; Kathan, Matzler, & Veider, 2016; Milanova & Maas, 2017).

Yang and Ahn (2016) studied the loyalty in SE services from a relational benefits perspective and concluded that confidence and social benefits have significant and positive effects on commitment in SE services. Pesonen and Tussyadiah (2017) conducted cluster analysis to identify user profiles corresponding to consumer motivations for using SE accommodation services. They concluded that a consumer group uses SE accommodation services to make their trips more convenient, while another group uses these services mostly for social reasons.

Molz (2014) introduced the term ‘Network Hospitality’ as an extension to ‘Network Sociality’ proposed by Wittel (2001). Network hospitality is relatively new, even though it is rooted in the old traditions of welcoming strangers. Airbnb represents just one of many types of network hospitality, and the online review information becomes the basis for an individual member’s reputation within the network.

Haase and Pick (2015) studied Airbnb from sharing network perspective and proposed a typology, including interaction intensity among guests, hosts, and Airbnb. Mauri, Minazzi, Nieto-García, and Viglia (2018) note that personal reputation is of paramount importance in Airbnb and the presence of storytelling narratives in host profiles increases the popularity of the listings. In the absence of information derived from the face–to–face encounters with people, an individual’s online reputation capital provides a shadow of the future.

The flexibility and openness of Airbnb are reflected in the large variety of types of locations, prices charged, and additional services (e.g., Airbnb experiences) provided by the hosts. Airbnb also added identity verification to its platform, adding more transparency and reducing the fear and friction that can occur when strangers do business. In a P2P marketplace, the verification of user identity increases trust, and thereby, users enhance their online reputations. Moreover, Airbnb has a team that continually reviews suspicious activity and looks for new ways to combat fraud and abuse (Zervas et al., 2017).

The study of Guttentag, Smith, Potwarka, and Havitz (2017) introduces five motivating factors for Airbnb guests, which are interaction, home benefits, novelty, SE ethos, and local authenticity. Guttentag et al. (2017) also reveal a segmentation of Airbnb guests, including money savers, home seekers, collaborative consumers, pragmatic novelty seekers, and interactive novelty seekers. Mao and Lyu (2017) state that different experience expectation, familiarity, and electronic word of mouth impose both direct and indirect influences on repurchase intention in Airbnb context. Mody et al. (2017) utilized the Stimulus-Organism-Response (S-O-R) theory and demonstrated that the importance of dimensions such as serendipity, localness, communitas, and personalization where Airbnb outperform the hotel industry in providing all experience dimensions including extraordinary and memorable experiences:

- Serendipity: unexpected, positive surprises that are above and beyond guests' planned agendas – in creating memorable experiences that surpass the expectations
- Localness: experiences of consuming local food with positive and unforgettable memories for tourists, which subsequently enhance their attachment to local attractions and stimulate favorable behavioral intentions
- Communitas: an evolving feeling of communion with friends, family and, strangers – during extraordinary consumption experiences (e.g., Airbnb recently had an extensive rebranding, moving away from the more pragmatic room-rental positioning towards one that emphasizes community).
- Personalization: ongoing customization based on adaptive learning and knowledge of customer preferences and goals – offers a promising strategic option for managing customer relationships

Möhlmann (2015) explains that the satisfaction and likelihood of choosing Airbnb can be indicated by the determinants that serve guests' self-benefit. Utility, trust, cost savings, and familiarity are found to be essential in Airbnb. The information accumulated on Airbnb's online platform helps both parties to establish their reputation, as well as publicizing their personalities, thereby facilitating the process of finding the best match. Moreover, there are hundreds of people working in Airbnb's customer service, trust, and safety departments who are devoted to ensuring the intimacy provision of trusted services. Airbnb requires all hosts to abide by their "Hospitality Standards," which include expected levels of cleanliness, commitment, and communication. The flexibility, reliability, and consistency of Airbnb's service providers help them to build and maintain the relationship Airbnb enjoys with their guests and hosts (Lu & Kandampully, 2016; Zervas et al., 2017).

Customer engagement in TH has been empirically found to enhance customers' service brand evaluation, brand trust, and brand loyalty (So, King, Sparks, & Wang, 2014). Guests attach great importance to motivational drivers, more meaningful beyond-purchase social interactions, and unique experiences in authentic settings, which give rise to customer engagement beyond the service encounter.
In the TH industry, engaged guests spend 46% more money per year than disengaged guests (Pansari & Kumar, 2016).

Engaged guests bring some advantages that are not necessarily monetary ones. Those guests have a secure emotional attachment to the brand and are less price-sensitive than disengaged guests. More importantly, engaged guests can make precise movements and alter their way just for the brand. With that, Airbnb has disrupted the market structure of the TH industry, challenging the status quo of the traditional TH industry that has a non-flexible cost structure (Aznar, Saveras, Segarra, & Claveria, 2018). Family travelers seek for a unique experience the most, and they also pay attention to facilities, online reviews, location, and their friends' recommendations on which Airbnb hosts should better focus (Lin, 2018).

2.2 Personality analysis in marketing

Achrol and Kotler (2011) described how the frontiers of marketing evolved:

- From exchange paradigm to network paradigm
- From satisfaction to consumer experiences
- Human sensory as the fundamental bases of explanation

Human sensory is the main frontier here, and in the last decade, SE opened new horizons for online businesses and radical innovations like Airbnb, wherein among all, technology can be the leading enabler for human sensory. The integration of technological and societal concerns into services has given rise to the quest for mass-customized online and offline service provision to the consumers. For example, the types of service design and delivery, and the expectations of consumers can differ in this evolving service paradigm. To respond these expectations, especially the decrease in the costs of analyzing online data and gathering insights, commonly referred as “Big Data” era, has an impact on SE platforms since Big Data can improve platforms’ perceptions of consumer preferences.

There is a shift from transactional exchange to relationship building in service organizations. Yen (2014) makes a comparison between transactional and relational consumers and states that system quality satisfaction is more significant for transactional customers, but information quality and service quality satisfactions are more critical for relational customers. Behavioral features of services come into play across marketing actions. Airbnb also developed its digital platform in a way to allow service providers and users to connect for mutual benefit.

In addition to technological factors, economic and social changes in society fuel up the growth of SE. From the social point of view, P2P services may have different features compared to their traditional counterparts. This leads to the examination of the individual-level relationship since the act of sharing is between individuals. Personalization is one of the underlying factors in the relationship building process.

Pansari and Kumar (2016) stressed the importance of the paradigm shift where selling itself is moving towards personalized marketing programs that emotionally connect with customers by personalized interactions. The term *personalized* in marketing has become more selective, targeted, relevant, and holistic than ever. Tynan and McKechnie (2009) state that the holistic consumption experience can be better envisaged by ethnographic methods and naturalistic inquiry to show the contextual indicators of the complex interactions fully. Methodologies such as grounded theory, ethnography, and phenomenology should be enhanced by the latest data-driven capabilities that ease to extract postmodern philosophical movements of consumers seeking both personalized and collaborative experiences (Simmons, 2008).

Data-driven marketing has given rise to the search for new data sources to extract valuable insights. Researching consumer behaviors through data of segments like demographics and transactions is now obsolete since the idiom of “you” has become popular in marketing phenomena, especially in SE. “Understanding and knowing consumers themselves” has become more critical than “Predicting and knowing more about consumers” in marketing analytics. The psychology of consumer behavior implicitly precedes the acquisition of consumers’ relevance in multichannel digital marketing.

Psychographic or psychologically personalized marketing that utilizes AI and Big Data might be a game changer in today’s human-centered engagement models and disruptive innovations where experience is at the center. Big data analytics is not only a technological phenomenon or method but has become a critical element for marketing scholars and practitioners to exploit almost any kind of structured or unstructured data resources available in terms of high volume, variability, veracity, and velocity. With that, the focus is moving from computational science to exploratory science upon unstructured data sources. The latest paradigm of scientific discovery emerged is data-intensive; it uses cutting-edge computing power. Service environment has experience at its core, and many experiential elements result in footprints (i.e., data) of interaction.

Like organizations that show their personalities by online textual communication (Pitt & Papania, 2007), consumers' digital footprints such as the words they write and speak are utilized in big data era that has given rise to the accurate prediction of personality traits. Personality is one of the key differentiators in a decision-making process that shape preferences for services (Kosinski, Matz, Gosling, Popov, & Stillwell, 2015). Research in psychology comprehends such natural phenomena through the lens of social phenomena as implied by the social theory (Solis, 2011). Beyond empirical psychological research, the digital form of personality assessment (e.g., automated social language analysis) is a promising approach and a potential game-changer in psychographic marketing.

The level of objectivity and reliability of assessments have diverse impacts on marketing programs, which are better to utilize natural forms of unstructured data analytics, and not subjective interpretation or qualitative analysis (Boyd, 2017; Cheng & Jin, 2019; Matz & Netzer, 2017; Park et al., 2015). Through a roadmap from customers' data to an emotional connection with them, the critical activity is to retrieve personality insights for clustering customers. Lutz and Newlands (2018) studied the consumer segmentation in Airbnb and compared shared room (i.e., on-site hospitality) and entire home (i.e., remote hospitality) consumers who turned out to be different.

In this research context, Airbnb guests' service reviews bring out two lines of effect. First, consumers attach great importance on reviews and ratings of others that affect both the buying behaviors and factors shaping expectation before service encounter (e.g., host's ratings and reviews, host's photos, guest's past accommodation experience and word of mouth). Just like in the e-commerce business, customer reviews are very critical in this context, since existing reviews heavily influence buying decision of new guests in the absence of the actual look and feel of the services to be purchased. Second, from the individual supplier and service provider point of view, hosts and Airbnb itself can, and presumably, do act on the guests' reviews. The quality of reviews is therefore enhanced via the two-sided effect and healthy controls that Airbnb put into effect. Even the available data seems unstructured and hard to manage in nature, Airbnb can use it to improve their services and cascade the insights to individual providers (i.e., hosts in this research) (Hoffen, Hagge, Betzing, & Chasin, 2017).

Wedel and Kannan (2016) reported that the personalization of the marketing mix by using Big Data and AI techniques is a promising field for marketing analytics research, which is one of the baselines of this study. As Park et al. (2015) stated a well-accepted theory of psychology, marketing, and other fields is that human language reflects the personality, thinking style, social connections, and emotional states. Human language and profile are psychologically rich, which underlie many personality traits (Kosinski et al., 2015). Poon and Huang (2017) report that Airbnb users with more allocentric (i.e., collectivist) personality and non-users expressed few differences in their perceived importance of accommodation attributes and the two groups differ in terms of their perception of Airbnb and evaluation of Airbnb compared to hotels (Poon & Huang, 2017). Lee and Kim (2017) studied the brand personality of Airbnb by an application of user involvement and gender differences and found significant differences between that travelers with high and low involvement in terms of the dimensions of sincerity, excitement, competence, and ruggedness, where that level of involvement is higher in female travelers than in male travelers. Lutz and Newlands (2018) indicate that the variety of offerings in Airbnb can create distinct consumer segments based on both demographics and behavioral criteria, and although Airbnb hosts use marketing logic for targeting their listings to specific consumer segments, there is not a strong alignment between consumer segmentation and host-targeting, leading to reduced matching efficiency.

2.3 Perceived service quality

Before going into the literature review for our major research topic PSQ, we adopted the components proposed by Petticrew and Roberts (2012) to perform systematic reviews in social sciences: Population, Intervention, Comparison, Outcomes and, Context. In the proposed research setting, we labeled these components as follows:

- Population: Airbnb on-site hospitality
- Intervention: SERVQUAL
- Comparison: Additional cognitive and attitudinal factors
- Outcomes: Perceived Service Quality
- Context: Airbnb

After finalizing the research setting, we start the elaboration from the concept of service quality itself. A service has four distinct characteristics: intangibility, inseparability, perishability, and variability. Service quality assesses the perceived quality and can be defined as the consumer's judgment of overall distinction and supremacy of the services provided (Ali, Hussain, Konar, & Jeon, 2016). Perceived service quality is defined as the degree of conformance to customer expectations; in other words, a comparison of customer expectations with perceived service performance (Parasuraman, Zeithaml, & Berry, 1988). Service quality can also be defined by differentiating between technical quality (i.e., what is served) and functional quality (i.e., how it is served). Both in Airbnb and the entire TH industry, guest satisfaction and likelihood to reuse are determined by similar factors such as quality and utility of services, trust to the host, and economic value (Barile, Pellicano, & Polese, 2018).

There have been several models for measuring service quality. Examples include the Expectancy-Disconfirmation model (EDM), SERVQUAL (Parasuraman et al., 1988), and SERVPERF (Cronin & Taylor, 1992). Especially, service quality literature received widespread attention after the seminal work by Parasuraman et al. (1988) as they proposed the gap model and developed SERVQUAL (an attribute-based technique) as a tool for measuring service quality. They suggested three underlying themes after reviewing the previous work on services:

- Service quality is more difficult to evaluate than the quality of goods
- Service quality perceptions result from a comparison or *gap* of consumer expectations with actual service performance
- Quality evaluations are not made solely on the outcome of service; they also involve evaluations of the process of service delivery

According to SERVQUAL, service quality consists of five dimensions measured by a total of 22 items. The proposed five service quality dimensions are tangibles, reliability, responsiveness, assurance, and empathy. SERVQUAL requires measures of expectations and performance, and service quality is calculated from subtractions between these two components (i.e., performance [P] - expectations [E]). Similarly, Boulding, Kalra, Staelin, and Zeithaml (1993) measured expectations based on ideal (i.e., "will expectation") and normative (i.e., "should expectation") comparison standards and found discriminant validity between the two measures, thereby undermining the original conceptualization of service quality in SERVQUAL.

Most scholars agree that service quality should be viewed from the consumer perspective by studying consumer perceptions through the lenses of psychometric and predictive evaluations. Perceived service quality impacts the word-of-mouth (WOM) referral intentions and repurchase intentions through positive emotions. Also, perceived service fairness is found to have a significant effect on perceived service quality and directly impacts behavioral intentions, but also indirectly through consumption emotions (Liang, Choi, & Joppe, 2017; Su, Swanson, & Chen, 2015). Service quality has a direct and indirect influence on customers' satisfaction. Also, organizations can integrate service quality, price fairness, and ethical practice in their plans to improve customer satisfaction (Pesonen & Tussyadiah, 2017).

Several scholars stress the importance of intangible aspects of TH service towards perceived service quality of consumers. Regarding service quality in TH, even though guests expect similar core services such as clean rooms and comfortable beds, different attributes support the competitive advantage of hotels and P2P accommodation while conveniences offered by hotels are unparalleled by P2P accommodation, the latter appeal to consumers driven by experiential and social motivations. Customer satisfaction and perceived value are significant factors for customer loyalty. Perceived value, price fairness, service quality-reliability, assurance, and empathy are the significant predictors of customer satisfaction. Perceived service quality is noted as a partial mediator for the effect of the attitude towards using on the intention to reuse (Kallweit, Spreer, & Toporowski, 2014). There is also a chain noted beginning from service quality, to perceived value, to loyalty in the context of e-commerce (Bernardo, Marimon, & Alonso-Almeida, 2012; Yarimoglu, 2015).

Han, Shin, Chung, and Koo (2019) explains Airbnb guests' purchase decision from the lens of Aristotle's appeals on the host-generated information: ethos (i.e., the reasoning the host uses and the logical evidence), pathos (i.e., credibility and trustworthiness), and logos (i.e., words that the host uses to activate emotions). For the ethos, the super host badge (i.e., Airbnb's top-rated and most experienced hosts) and host reviews have positive impacts on the purchase. For the pathos, the positive impact of the use of common words is found to be significant. For the logos, the price, place pictures, and star-ratings have positive impacts on the likelihood of purchase (Han et al., 2019).

Tussyadiah (2016) reveals that the social benefits influence guest satisfaction for guests staying in an Airbnb on-site hospitality which involves staying together with hosts, but it is an insignificant factor for guest satisfaction for guests staying in an Airbnb remote hospitality accommodation. This finding is also a significant input for our research as we study the on-site hospitality and quest for the social factors as well. Liang, Choi, and Joppe (2018) make a distinction between transaction-based satisfaction and experience-based satisfaction, while there is a significant effect of transaction-based satisfaction on experience-based satisfaction, and trust is separated into institution-based trust (i.e., trust in Airbnb) and disposition to trust (i.e., trust in hosts).

Lee and Kim (2018) indicate that Airbnb users' hedonic value has a positive impact on satisfaction and loyalty, while utilitarian value influences only on satisfaction. Lalicic and Weismayer (2018) state that PSQ and the presence of social and authentic experiences are significant antecedents of guests' loyalty toward Airbnb accommodations. In Airbnb context, Stollery and Jun (2017) revealed that the positive influence of monetary saving, hedonic benefit, and novelty on perceived value, and the negative influence of psychological risk on perceived value.

Wang and Jeong (2018) explain that guests' attitudes toward the Airbnb service are determined by perceived usefulness and trust, and their satisfaction with the Airbnb stay is affected by amenities and host-guest relationship. Zaibaf, Taherikia, and Fakharian (2013) studied the effect of perceived service quality on customer satisfaction in the hospitality industry and found that functional quality has a positive and significant impact on the image and perceived quality, and perceived quality has a positive and significant impact on customer satisfaction.

CHAPTER 3

DATA SET

To study the personalities and service quality perceptions of Airbnb guests, we collected the guests' textual and publicly-available online review data from 45 cities all around the globe including 9,982,450 distinct reviews written in 74 distinct languages (Figure 1 shows the major languages and associated counts). English, French, and Spanish reviews are the top three detected languages by the *cld2* package in R studio. In the data set, there are 7,264,026 distinct reviewers (i.e., Airbnb guests) across 417,395 distinct listings.

All the Airbnb listing types are included in the data set: Entire Room (ER), Private Room (PR), and Shared Room (SR). The proportion of reviews for the ER listings is relatively high compared to the other types. We focus primarily on the two classes in this research context for on-site hospitality: PR and SR.

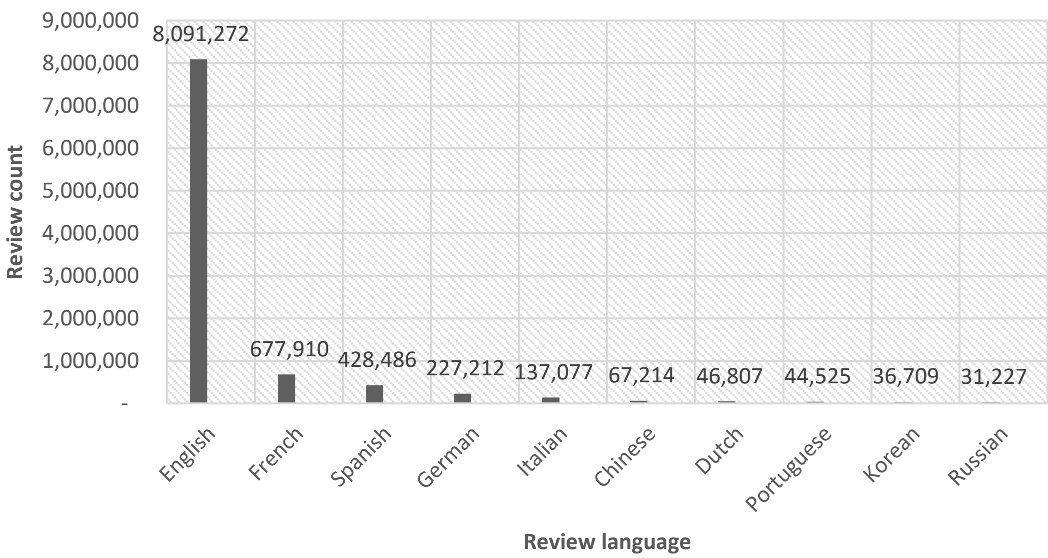


Figure 1. Major review languages in the data set

The collected raw data is further processed for the ease of analysis during the subsequent phases of the research, and we perform comparative analysis with inferential statistics on all kinds of listings. The raw data is divided as per the locations, and we loaded Airbnb location-based data into respective data objects in R studio. Mainly, we elaborated on the referential data integrity based on the data structure first, which means whether listing identifiers, reviewer identifiers, and host identifiers match across the data or not.

We confirmed the data integrity according to the lookup data tables of listings, hosts, and reviewers. Then, we consolidated Airbnb location-based data into one large data table, namely all reviews. Afterward, we subdivided all reviews into language-labeled data tables by the *cld2* R package (e.g., English reviews, French reviews, and Spanish reviews). Finally, we derived the data as per the distinct languages and listing types. Figure 2 depicts the process of data preparation and structuring.

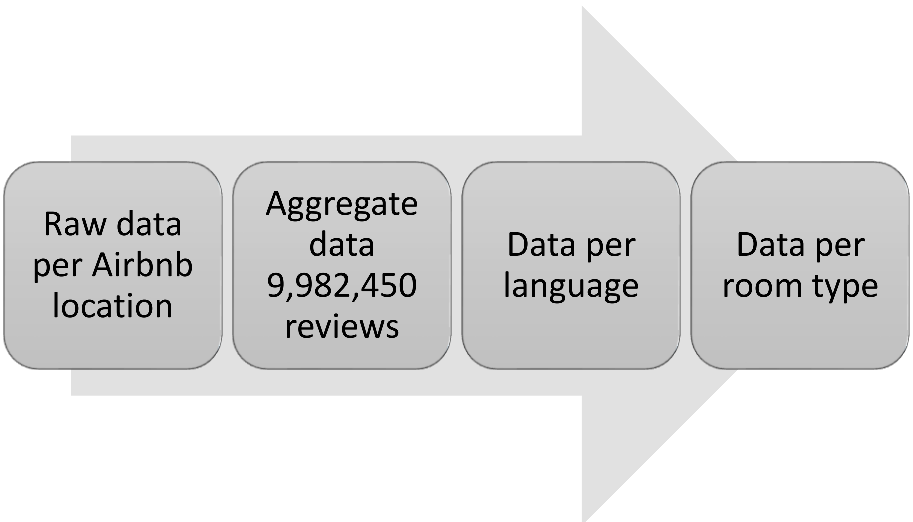


Figure 2. Preparing and structuring the data

Appendix A provides an overview of the entire data set per each of 45 Airbnb locations across the world and listing type. Here are some essential data columns in the data set:

- Listing ID: Unique identifier of the Airbnb listing
- Date: Date time of the review
- Reviewer ID: Unique identifier of the Airbnb guest
- Host ID: Unique identifier of the Airbnb host
- Listing name: The name of Airbnb listing as it appears in Airbnb
- Room Type: One of “Entire home/apt,” “Private room,” or “Shared room.”
- Number of Reviews: The number of reviews that a listing has received.
- Comments: Reviews of guests are limited to 1000 words (recently increased from 500).

CHAPTER 4

PERSONALITY ANALYSIS

The purpose of this section is to demonstrate Airbnb guests' Big5 personalities using their massive amount of personal texts by linguistic analytics and to state those psychometric insights. As was previously mentioned, Airbnb offers a new form of a contractual relationship in tourism and hospitality, and the analysis of its consumers is to be fine-grained by data-driven marketing that uses big data analytics and artificial intelligence (AI) in the era of exploratory science. Psychographic findings including psychological states (variability within consumers over time) and traits (variability across consumers) might be used to attract consumers (Matz & Netzer, 2017). Using IBM Watson Personality Insights (PI) AI service based on linguistic analytics is the key to this research.

PI is a cutting-edge tool for personality analysis by using social media, enterprise data, or other digital communications. From targeted marketing to customer acquisition, PI might have a wide range of use cases. This tool resides on the commonly accepted hypothesis that human language implicitly reveals personality. The language text can include opinions, experiences, attitudes, and sentiments. With a vector representation of the words in the input text, the application employs a machine-learning algorithm (which do not input user demographics) that output a personality profile with the Big5 dimensions.

PI is already pre-trained with thousands of Twitter users to place the ground-truth where the actual personality traits benchmarked the training and testing. We use the *Curl* command line tool and library that have been utilized for transferring text data to the PI application that was customized for this research's needs. Using PI API (Application Programming Interface) key and URL (Uniform Resource Locator) within the Curl commands, JSON outputs have been received. The outputs include the personality findings and significance results for each Big5 dimension and the facets (six per each dimension, a total of thirty) under those five dimensions separately. Table 1 presents an overview of Big5 dimensions and facets.

Table 1. Big5 Dimensions and Facets

Big5 Dimension	Facets
Agreeableness	Altruism, Cooperation, Modesty, Morality, Sympathy, Trust
Conscientiousness	Achievement-striving, Cautiousness, Orderliness, Dutifulness, Discipline, Self-efficacy
Extraversion	Activity-level, Assertiveness, Cheerfulness, Excitement-seeking, Friendliness, Gregariousness
Emotional range	Anger, Anxiety, Depression, Immoderation, Self-consciousness, Vulnerability
Openness	Artistic interests, Adventurousness, Emotionality, Imagination, Intellect, Liberalism

Figure 3 depicts the personality analysis research design, where we followed a four-step analysis process.

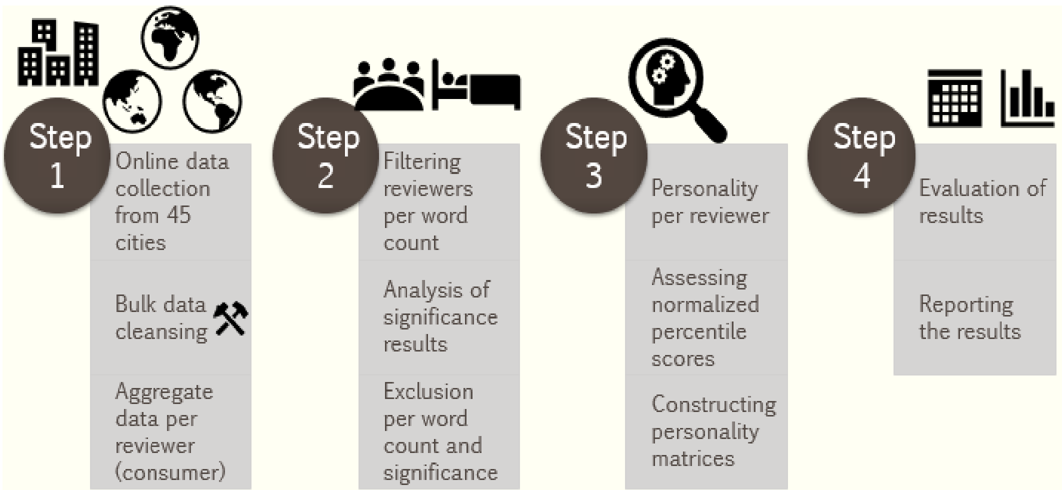


Figure 3. Personality analysis research design

Two top review languages are selected (English and Spanish) based on the MAE (Mean Absolute Error) and average correlation results (see Table 2) reported by the application that compared actual with inferred scores. MAE scores that are closer to zero are better. For correlation, scores higher than 0.2 are acceptable.

Table 2. Precision of Personality Insights for English and Spanish Texts

Language	Big5 dimensions	Big5 facets
English average MAE (Mean Absolute Error)	0.12	0.12
English average correlation	0.33	0.28
Spanish average MAE	0.10	0.12
Spanish average correlation	0.35	0.21

The following open-source tools, especially in data cleansing and preparation, were utilized during the personality analysis process:

- Google language detector 2 and 3 (CLD2 and CLD3) for detecting text languages
- R-Studio packages like textcat for text categorization, hunspell for spell checking, sqldf for SQL-like querying on the dataset, xlsx and openxlsx for individual personality scores, readr for csv operations, qdap for aggregating data by grouping and visualization of text.

After data cleansing on the entire data set presented in the previous chapter, 528 guests are selected, having 1500+ words of review across the Airbnb listings. The word count threshold is set because the PI service requires a certain amount of word count written by the same person. We can catch this by grouping the data as per the reviewer id. Sixteen distinct guests were excluded due to weak significance results reported by the PI service and multi-language reviews that do not sum up to desired word counts per English and Spanish language (i.e., at least 1500 words). These exclusion criteria resulted in our final dataset, which includes 512 guests having 1500+ words across all listings with clear language according to the data quality analysis made by R-Studio. We have cleared out all automated Airbnb responses like “The host canceled this reservation X days before arrival. This is an automated posting.” Also, we run two iterations of personality analysis to observe any potential differences in the sample, where we did not see any significant differences between the personality results of samples, where the first iteration is for 201 guests who have written 2000+ words, and the second and final iteration is for 512 guests who have written 1500+ words. For each request, PI application reports a normalized score as a percentile (as a double in the range of zero to one) for each Big5 personality trait, which is based on the qualities that the application infers from the input text. For all the future results, the following criteria were utilized:

- A percentile score at or above 0.75 is considered as high. Any score above the mean of 0.5 indicates an above average tendency of the sample for a characteristic.
- The reverse statements are true of scores below 0.50 and 0.25, which are considered as below average and low, respectively.

Since the objective is to see how Airbnb guests’ characteristics compare with a large population, the normalized percentile scores were used instead of raw scores. There is no mathematical relationship between the percentiles that are reported for Big5 dimensions and facets, which are calculated independently. With that, even if the facets are sub-descriptors of Big5 dimensions, adding the scores of facets does not necessarily give the results for dimensions. The percentiles for 512 guests were graphed within a histogram for all the personality traits (see Appendix B). Skewness itself yields how the sample set resides for traits. The PI application outputs the significance results per each Big5 dimension and facet. For the sample set, mean, standard deviation, and variance measures were calculated for the normalized scores of application’s outputs. The statistically significant results (see Figure 4) based on the interpretation criteria include that Airbnb guests score high in Altruism (see Appendix B, Figure B1), Cooperation (i.e., Accommodating, see Appendix B, Figure B2), Sympathy (i.e., Empathetic, see Appendix B, Figure B3), Trust (i.e., Trusting of others, see Appendix B, Figure B4), Cautiousness (i.e., Deliberate, see Appendix B, Figure B5), Dutifulness (i.e., Respectful in rules and obligations, see Appendix B, Figure B6), Activity-level (i.e., Energetic, see Appendix B, Figure B7), Extraversion (see Appendix B, Figure B8), Artistic interests (i.e., Appreciative of art, see Appendix B, Figure B9), Intellect (i.e., Philosophical, see Appendix B, Figure B10), Liberalism (i.e., Authority-challenging, see Appendix B, Figure B11), and Openness (i.e., Open to experiencing, see Appendix B, Figure B12).

On the other hand, Airbnb guests score low in Excitement-seeking (i.e., they are calm-seeking, see Appendix B, Figure B13), Gregariousness (i.e., they feel independent, see Appendix B, Figure B14), Anger (i.e., they are mild-tempered, see Appendix B, Figure B15), and Self-consciousness (i.e., they are hard to embarrass, see Appendix B, Figure B16).

Figure 4. The summary of the personality traits of Airbnb guests

In this study, there are pioneering implications for travel marketing and service researchers to show traveler personalities inferred from user-generated content in SE Airbnb service context. Linear combinations of personality scores might be used to come up with distinct organic behaviors of consumers (i.e., associations between separate psychological traits). Matzler, Bidmon, and Grabner-Kräuter (2006) found that extraversion and openness are positively related to the hedonically driven product consumption, which influences brand effect and drives attitudinal loyalty (i.e., those consumers respond stronger to affective stimuli). This implication can be replicated and hypothesized within Airbnb service context since the guests are found to have high extraversion and openness.

As Yoo and Gretzel (2011) reported, the influence of personality on travel-related user-generated content creation can be further researched from this study's point of view. Another line of research is the effect of consumption experiences on consumers to publish 'electronic word of mouth' (*eWoM*). From the consumer side, how Airbnb guests' personalities shape their tendencies to share can be researched as Schreiner, Pick, and Kenning (2018) found that personality characteristics such as materialism, altruism, and interpersonal trust have no direct impact on the willingness to share. From the supplier side, one of the research directions is to elaborate on how positive sentiment of Airbnb hosts in their profile descriptions or photos can enhance the trusted collaboration (Zhang, Yan, & Zhang, 2018). As previously noted also by Matz and Netzer (2017), both scholars and practitioners are expected to expand the understanding of psychological traits and move towards real-time 'tuning' of marketing actions based on these predictions.

CHAPTER 5

PERCEIVED SERVICE QUALITY MODEL

Having discussed the personality traits of Airbnb guests, this chapter aims to identify the antecedents of PSQ of guests' in Airbnb on-site hospitality context. After crosschecking the previously discussed personality insights and the extant literature, we propose a PSQ model in the Airbnb context, which is depicted in Figure 5. SERVQUAL part of the model is the same as proposed by Parasuraman et al. (1988). Identifying and measuring cognitive/attitudinal factors is rather complicated, because they are highly implicit in nature, and guests in Airbnb may not even be aware of them. Thus, they can be hardly measured by conventional measurement instruments like surveys and questionnaires.

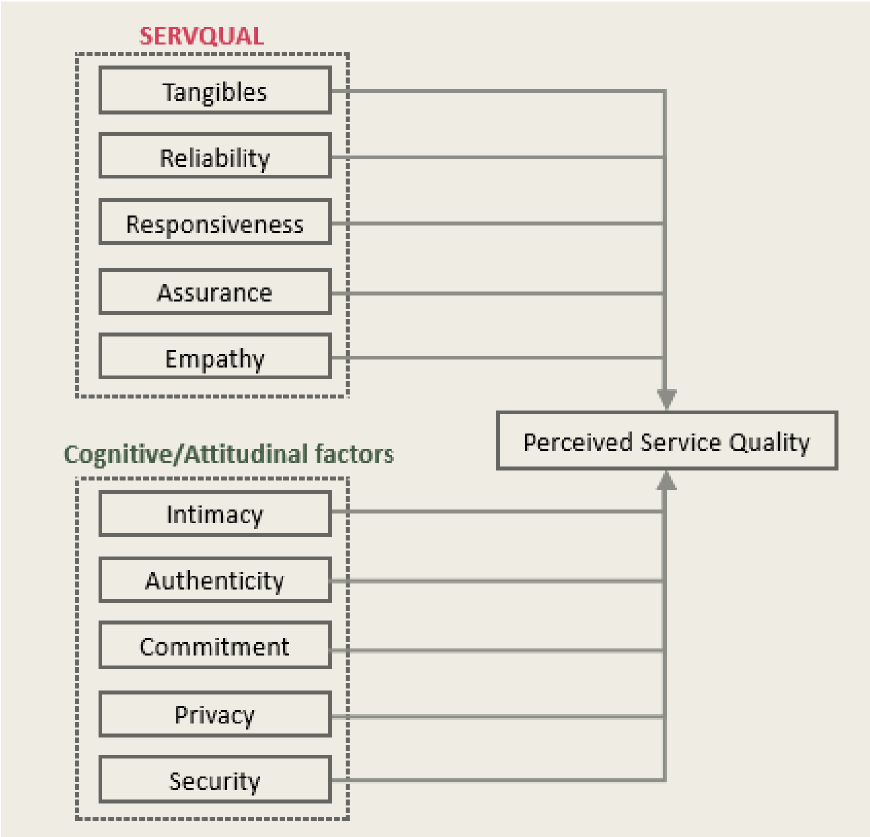


Figure 5. Perceived service quality model: the case of Airbnb

Tangibles are mostly related to the appearance of amenities, facilities, and equipment in the Airbnb listing. Some examples of tangibles are decoration materials, kitchen, and shower. Reliability is the ability of Airbnb and the hosts to serve accurately. In other words, it is about the consistency in reservation items (e.g., timing) and alterations, if any. Responsiveness is the hosts' willingness to help Airbnb guests and provide prompt service, including guests' requests, questions, complaints, and problems. Responsiveness is passed to guests by the length of time they wait for hosts' assistance and answers to questions. Xie and Mao (2019) reveal a trade-off between the host responsiveness and the number of their listings, leading to low responsiveness, and state that the higher the number of listings managed by a host, the lower the performance and responsiveness of the host quality. Therefore, we want to study the responsiveness only in terms of the timing on our context, on-site hospitality.

Assurance is related to the trust and confidence conveyed by the hosts. In Airbnb as a network of strangers, trust and confidence are almost shaped based on peer reviews, host credentials, photos, and profile, not solely on one-to-one interactions. People deal with trust in specific others that arises from the knowledge of the others' good intentions, attained through repeated interactions with those others, and people consider trust and confidence as more than a rational expectation and calculation, which involves social and emotional bases as well. Liang et al. (2018) reveal that trust in Airbnb does not statistically influence trust in hosts, and we only study the trust in hosts. Huurne et al. (2017) show various antecedents of trust in the sharing economy (e.g., reputation, trust in the platform, and interaction experience) related to multiple entities (i.e., seller, buyer, platform, interpersonal, and transaction).

Empathy is one of the essential factors that Airbnb pays attention as well. Airbnb defines three factors for hosts under exceptional hosting to offer guests something unique and surpass their expectations, which are the senses of human connection: empathy, delight, and respect. Empathy means to provide caring and individualized attention to the guests and requires on-the-job cultivation by continually reading and listening to customer feedback. Successful hosts put themselves in their guests' shoes anticipate their guests' needs with small, thoughtful gestures and gestures, and they consider their guests as new friends rather than customers.

People develop trust with strangers at their most valuable possessions and personal experiences, which leads us to the era of Internet-enabled intimacy. The emergence of intimacy as a commercial value in TH industry has been researched. (e.g., How well people know each other? How people occupy space together? How people share private information, such as family pictures and furniture choices?) (Milanova & Maas, 2017; Prager, 1998). Authentic host-guest experiences probably only exist between like-minded and privileged members who possess high cultural capital (Cheng & Jin, 2019). In this regard, Walls et al. (2011) have suggested the need for researchers to identify specific dimensions that exist in both our every day and tourist experiences. Airbnb may eventually address all elements of the accommodation experience, from travel reservations to ticketing for local attractions. More consumers are looking for local authenticity in their travels. Psychological authenticity refers to emotional genuineness, self-attunement, and psychological depth (Lopez, 2013). For example, a person attending a conference at a hotel in London will get the authentic experience of the hotel, but the hotel does not necessarily help the person discover the local culture and people. On the other hand, Airbnb hosts can recommend local attractions and small businesses as well as providing a more authentic experience of the city by opening their own homes to the guests.

Most of the guests choose Airbnb because they want to 'live like a local' as hosts can recommend local businesses to them. Authenticity also brings trust – for guests new to Airbnb and experience, seeing and interacting with real people provides the assurance they need. Authenticity is simply an *aura* that cannot be captured in a reproduction (Benjamin & Underwood, 2008). Authenticity is a statistically significant predictor for satisfaction in Airbnb context (Birinci, Berezina, & Cobanoglu, 2018; Lalicic & Weismayer, 2017), which is a significant input to this research as well. We focus on the existential authenticity (i.e., being one's true self or being true to one's essential nature) from guests' perceptions (e.g., Is Airbnb like 'living the local life'?) (Lalicic and Weismayer, 2018). Liang et al. (2018) reveal that perceived authenticity has a significant effect in reducing Airbnb consumers' perceived risk and positively influencing their perceived value.

Commitment refers to the consistent behavior of Airbnb hosts in terms of the policies and procedures. (e.g., How well hosts abide by Airbnb pricing policies and procedures? Do hosts have ongoing cost-effectiveness of service?) (Lu & Kandampully, 2016). Airbnb keeps track of the Commitment Rate of the hosts, which is the percentage of the number of cancellations over 365 days. Airbnb also has a Community Commitment with a Nondiscrimination Policy, namely Commitment to Inclusion and Respect. Respect is the keyword under commitment dimension that great hosts treat all guests with respect and make them feel included and welcomed in the group. They acknowledge that their guests may come from different places, speak different languages, and have different cultural perspectives.

Privacy can be defined in this context as a safe psychological zone to disclose personal and cultural values. Informational and physical privacy threats are critical in Airbnb context (Lutz, Hoffmann, Bucher, & Fieseler, 2017). There has been a piece of recent staggering news that a guest was staying in an Airbnb and realized some cameras both in the room and the bathroom exit, which is a massive invasion of privacy. Security refers to the state of being free from danger or threat. Voskoboynikov (2017) defines it as a feeling of "I belong here. These are my people, and this is where I want to be." According to Yang and Ahn (2016), security in Airbnb's services is a more critical antecedent of attitude toward Airbnb than critical dimensions of motivation toward SE, such as enjoyment and reputation. With that, we will only elaborate on interpersonal security in Airbnb (i.e., between host and guest, not between guest and Airbnb). Birinci et al. (2018) state that safety and security risk appear to be statistically significant predictors of satisfaction in the Airbnb sample, which we will test in our research model.

CHAPTER 6

METHODOLOGY

The methodology to test the proposed PSQ research model is novel and built upon both text mining and natural language processing (NLP) techniques along with their constituents that we observe in social sciences (e.g., narrative analysis, thematic analysis, quantitative content analysis for shrinking textual data into more manageable bits), linguistics and computer science. The data set is an extensive collection of user-generated textual content that can be used to infer and validate linguistic rules and perform hypothesis testing.

The relevance of data itself sometimes constrains text mining, but here we have the reviews that are written at most fourteen days after the guests' checkout and posted once both the host and guest complete a review. This requirement is the practice of asking guests to rate the service right after it is delivered, and it gives the guest the time and space for more detailed responses, leading to a more holistic overview of the service. Compared to the conventional survey-like multivariate research designs (e.g., longitudinal research and cross-sectional research) and data collections vehicles (e.g., interviews and mail questionnaires), text mining is a superior alternative considering the high degree of control on the research design, short length of data collection (as in our case), low cost of data analysis, and the absence of response rate considerations. Also, the types of data collected in text mining are not limited to the design of our research instruments, such as surveys and mail questionnaires. We do not deal with the pre-testing of the questionnaire, accurate wording of questions and writing multiple-item scale measures (e.g., Likert, semantic-differential, profile analysis) along with the inherent problems in survey instruments (e.g., ambiguous words, leading / loaded words, bogus recalls, implied assumptions, frame of references, complex questions, double-Barreled / compounded questions). The consistency and accuracy of measurement (e.g., reliability over time, across items and different researchers that ensure freeness from random errors and validity including face validity, content validity, criterion validity, and discriminant validity that ensure freeness from systematic errors) is a cumbersome issue. This is because respondent characteristics, situational factors, data collection factors, measuring instrument factors, and data analysis factors usually come into play. Levels of measurement and scale construction can typically be designed using methods lacking in scientific rigor, often relying solely on the researcher's experience and knowledge of the subject matter. Survey respondents who have a negative attitude towards Airbnb may not wish would be admitted to the researcher (or even to themselves) that they have these feelings. Consequently, responses to attitude scales are not always valid.

On the other hand, scaling is the primary consideration of text mining as well since the text-as-narrative is hardly converted into text-as-data and every scale can be adapted to measure almost everything, though the text itself is mostly non-metric and qualitative. Scaling is mostly selected based on information requirements, researcher preferences, and methods, and it impacts the quality of the data collections and its worth. When we overcome those bottlenecks, text mining allows us to make quantitative comparisons and research model testing. Textual data can include the reported behavior, intentions, motivations, attitudes, and even personalities as we performed in this research. The Airbnb reviews are a great source of *voice of the customer* and offer actionable insights into what guests like and dislike about the Airbnb service. Since PSQ and its antecedents need precise definition and exploration in the Airbnb context, text mining is preferred to understand the constituents of PSQ. Text mining can flag up areas where spurious certainty exists, and these are areas where we think we know more than we do, but where in reality there might be little convincing evidence to support our beliefs. Also, guests' reviewing behavior is significantly driven by their experience, and guests' quality expectation towards the Airbnb service can be easily grabbed by analyzing their reviews. Guests' with higher expectations are more likely to share the negative (i.e., lower than expectation) experience by posting unfavorable reviews.

6.1 Text corpus construction and keyword extraction

Out of 9,982,450 distinct Airbnb reviews written in 74 distinct languages, we proceed with 8,091,272 English reviews (~81% of the entire collection). Considering a review word count consistency and semantically equal distribution of reviewer ideas, we applied a stratified random sampling that resulted in 526,670 distinct reviews (~6.5% of entire English reviews) with an average word count of 65.12 and standard deviation of 50.18, which corresponds to ~34,200,000 words in total. An increase in statistical power is expected with this high sample size. It is known that more stringent significance levels require larger samples to achieve the desired power levels, and smaller effect sizes always require larger sample sizes to achieve the desired power.

To better understand the context-specific language that Airbnb guests are using, we utilized IBM Watson Natural Language Understanding (NLU) application for keyword extraction on the 526,670 distinct reviews and the results are listed in Appendix C. The outputs of Watson NLU service are used within the research model validation and word-map construction for both SERVQUAL and Cognitive/Attitudinal dimensions. Also, NLU allows us to observe the categories of reviews in a five-level hierarchy and the major concepts underlying the reviews, which helped us to deep-dive in the context-specific topics. Table 3 summarizes the major categories.

Table 3. Categories of the Airbnb Reviews

LEVEL 1 Text Category	LEVEL 2 Text Category	LEVEL 3 Text Category
travel	business travel	
travel	specialty travel	adventure travel
travel	specialty travel	ecotourism
travel	tourist facilities	bed and breakfast
travel	traveling with kids	

Table 4 shows the significant concepts that NLU extracted within the Airbnb reviews. Relevance scores are in between 0 and 1, and higher scores indicate greater relevance across the data set.

Table 4. Major Concepts in the Airbnb Reviews

Concept	Relevance
Apartment	0.91
Bedroom	0.76
Kitchen	0.67
Parking lot	0.64
Perfect Place	0.63
Bathroom	0.63
First Time	0.61
Wi-Fi	0.60

We used NLU to uncover the emotions specific to Airbnb guests and observed the word-emotion correspondence. NLU analyzes the emotion (i.e., joy, anger, disgust, sadness, fear) conveyed by specific target phrases or by the reviews, and it extracts the targeted emotion accordingly as follows:

- e.g., Input text: “I liked the kitchen, but I hated the ventilation.”

- Targets: kitchen and ventilation
- Response: kitchen: joy and ventilation: anger

The emotion results per data cluster are depicted in Appendix D. NLU results in the sentiment score (i.e., the sentiment of the text as either negative or positive from -1 to +1, see Table 5 for cluster-wise results) and we will use it as the measurement for the PSQ of Airbnb guests to study the proposed research model. NLU analyzes both the sentiment towards specific target phrases and the sentiment of each review.

Table 5. Overall Sentiment of the Airbnb Guests

Overall Sentiment (between -1 negative to +1 positive) 526,670 distinct reviews within 10 distinct clusters									
Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7	Cluster8	Cluster9	Cluster10
Positive	Positive	Positive	Positive	Positive	Positive	Positive	Positive	Positive	Positive
0.76	0.8	0.79	0.85	0.77	0.7	0.79	0.65	0.69	0.7

6.2 Text annotation, part-of-speech tagging and lemmatization

To go further and identify the roots and types of words in the Airbnb reviews, we used an advanced NLP tool *Udpipe* package within *R* studio for text annotation, which helped as to have all the reviews in the data set as lists of tokens (also known as lemmas including nouns, adjectives, adverbs etc.). We utilized the pre-trained and open-sourced English model in Udpipe package in R-Studio.

Upon the English language model, we performed the text annotation, and the resulting data frame has a column called *upos* which is the Universal Parts of Speech (PoS) tag and a field called *lemma* which is the root form of each token in the text. These two fields give us a broad range of analytical possibilities. Appendix E provides the exhaustive list of PoS tags, and Appendix F depicts the relative proportions of each in the entire review data set. Moreover, Appendix G includes the most occurring nouns, and Appendix H shows the most occurring adjectives. We also looked for the co-occurrences between words which are relevant based on the POS tag (see Appendix I). Where co-occurrences allow seeing how words are used in the same sentence, we examined the correlations between words which are relevant based on the found POS tags. Keyword correlations demonstrate how terms are combined in the same sentence and review across the data set. Co-occurrences elaborate on the frequencies, whereas the correlation of two terms can be high when they appear together even if they exist together a few times.

6.3 Bag of words and word-sense disambiguation

After part of speech tagging and lemmatization, this is the activity of representing each Airbnb review as a bag (multiset) of their words with the frequency counts of discrete words regardless of grammar and contextual meaning. Binary Scoring (present=1, absent=0), counting, and frequency are the key elements of a bag of word (BoW). An example is like the following:

- "I liked the host is extremely accommodating. My wife liked the way the host welcomed us."
- BoW → {"I":1,"liked":2,"the":3,"host":2,"is":1, "extremely":1, "accommodating":1, “my”: 1, “wife”: 1, “way”: 1, “welcomed”: 1, “us”: 1}

Word-sense disambiguation (WSD) refers to the process of identifying the meaning of words in Airbnb context. There are several dictionaries and linguistic models that can be utilized, such as WordNet (Fellbaum, 2000), Harvard IV-4 Psycho-Sociological Dictionary, and Linguistic Category Model (Semin & Fiedler, 1991). These dictionaries are often used by researchers to cross-reference words in text analysis tasks. We have a WSD list with Airbnb specific coding to uncover the real intention of using specific words. For example, the *super host* can mean both an Airbnb term (i.e., part of Airbnb's Super Host program) or just praising the host.

6.4 Explicit semantic analysis and word maps for PSQ dimensions

The meaning of any given-word is represented as a vector of *association weighting* to the PSQ dimensions. Then, we compare the two vectors by cosine similarity and get a numerical value of the semantic relatedness of words to the PSQ dimensions. We propose a novel method for testing the significances of PSQ dimensions in the research model. In practice, probabilistic coherence measures how associated words are to a dimension, but we need to control the statistical independence. For example, here we have a corpus of Airbnb reviews, and a dimension with the words {host, room, reservation} might look suitable at first if we look only at correlations, but these words have very high *tf* (term frequency) in this corpus (i.e., correlated but statistically-independent).

Following questions arise while designing a text mining-based research model testing method in our context:

- How to design a rigorous text mining that maximizes the collection of relevant mentions in the Airbnb reviews regarding the ten dimensions of service quality?
- Is it possible to evaluate a predefined text mining approach with the corresponding word-maps of the ten dimensions of service quality?
- What are the criteria of an affordable and reliable strategy to effectively balance the sensitivity (recall) and precision (effort)?

By the text mining approach, we aim to provide an objective, comprehensive summary of the best evidence within Airbnb guests' reviews (whether it appears in the published literature, or not – and much of it does not). The data we have is in natural language format, and naturally, it is infeasible to note the exact different types of mentions of those PSQ dimensions (i.e., the gold standard and let us assume that in English there are *X*, which converges to infinity, distinct possible ways of expressing PSQ dimensions) in the natural language.

We cannot model and estimate the number and nature of *X*, but we can try to approximate it. With that, the idea behind our word map generation method for PSQ dimensions is as follows. Since we want to know the mentions of the ten specific PSQ dimensions in the Airbnb reviews, we can create a set of reviews for each dimension that we observe their relevancy by manual reading in a narrative analysis manner. Here we define a Quasi-Gold Standard (QGS) approach for identifying the textual ingredients of the ten dimensions proposed in the research model.

As mentioned, grabbing the specific mentions of service quality dimensions is not a straight-forward task, the idea here is to run a priori analysis of reviews to be used as a subset of the QGS per dimension. In this way, the a priori analysis of those reviews can guide the subsequent phases of analysis by providing better keywords that can be used for the construction of more reliable and valid word-maps and boolean search queries. Therefore, for creating word maps and boolean search queries for each of the ten PSQ dimensions (including SERVQUAL, and Cognitive and Attitudinal dimensions, abbreviated to C/A dimensions), we propose our method as depicted in Figure 6, and Appendix J lists down the keywords in the word maps and boolean searches. The sensitivity calculation is, for sure, not based on the *X* number (i.e., gold standard) that we cannot target, but the *x* number (i.e., quasi-gold standard), which means the relevant reviews that we observed during a priori analysis for each dimension. When n=50, a sensitivity of 0.8 means that 40 are captured by the boolean searches that cover the word maps.

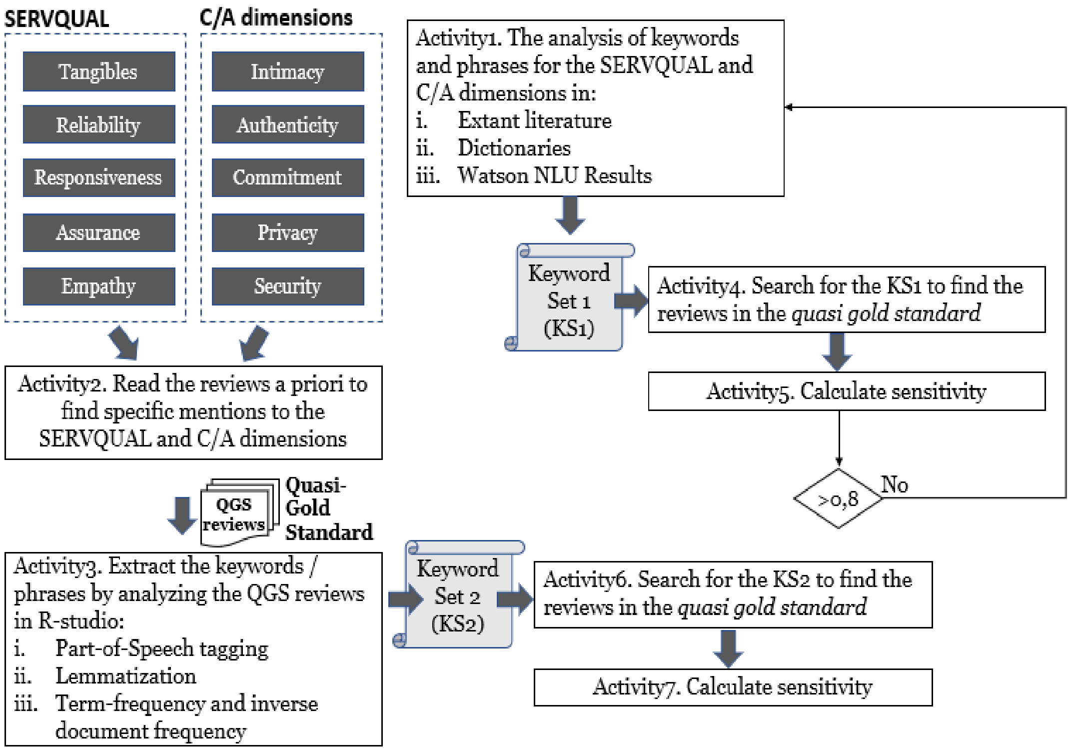


Figure 6. Proposed word map generation method for dimensions

The derivatives of the proposed textual analytics approach are very common especially in medicine and law, where the concept of evidence-based science (i.e., identifying as much relevant content as possible to a feasible extent) is highly popular and imperative, too. There is a very original study by Zhang, Babar, and Tell (2011) where they utilize a similar approach to uncover relevant studies in systematic literature reviews to perform an evidence-based analysis instead of a biased one. We think that the novelty of the approach resides within this interdisciplinary nature, replicability, and generalizability.

Considering the words' importance, we again propose our method Supervised and Altered Latent Dirichlet Allocation for calculating the review-dimension proportion (i.e., to what extent a review corresponds to the ten PSQ dimensions in the research model). Each PSQ dimension represents a set of words and phrases in the Airbnb context. The topic (i.e., PSQ dimension) proportion per review is calculated as per the following function:

$$f\left(PSQdim_{x_i}\right) = f\left(BS_{x_i}\right) \times \sum_{j=1}^{N}(tf(j) \times idf(j) \times ts(j))$$

where:

- *PSQdim* corresponds to Perceived Service Quality score
- *x* refers to one of the PSQ dimensions (Tangibles, Reliability, Responsiveness, Assurance, Empathy, Intimacy, Authenticity, Commitment, Privacy, and Security)
- $f(BS_x)$ refers to the boolean search result on the review as per dimension x 's word map boolean search query (i.e., When we perform a boolean search on Google or a library, we receive a set of outputs. In our case, this will correspond whether a review is in the resulting output set of the boolean search (i.e., zero or one).
- *j* refers to one of the existing terms in the review which is in the resultant set of the boolean search for the dimension (e.g., authentic for Authenticity and kitchen for Tangibles)
- *tf(j)* refers to the term j's frequency (i.e., how frequently the term occurs in the review). Consider a review containing 100 words wherein the word *authentic* appears three times. The term frequency (i.e., tf(authentic) is then 3/100=0,03).

- *idf(j)* refers to the term's inverse-document frequency (i.e., how important a term is within the entire Airbnb review data set)
    - We have 526,670 reviews, and the word *authentic* appears in 36,127 of these. Then, the inverse document frequency (i.e., idf(authentic) is calculated as $\log\frac{526670}{36127}$= 1.163.
- ts(j) refers to the average targeted sentiment of the term j.

We think that this way of PSQ dimension scoring is not fragile for cultural differences and more appropriate for capturing perceived service quality. Surveys generally make use of a number rating from 1 – 10, which lead to a possible ambiguity because cultural differences do matter in how people rate their experiences. People from individualistic cultures can choose the extreme sides of the scale (e.g., amazing, perfect) compared to the people from collectivistic cultures (Furrer, Liu, & Sudharshan, 2000).

When we have the ten dimensions' scores and the dependent PSQ score (i.e., the sentiment of the text as either negative or positive from -1 to +1), we have a matrix of 526670x11, where ten predictor variables are PSQ dimensions and one dependent variable is the PSQ (sentiment) score. For the ten predictor variables, we applied a normalization, which is usually called feature scaling. One possible way to achieve this is the result of the following normalization formula (minimum-maximum normalization) that inputs the calculated PSQ dimensions' scores and returns a normalized score:

$$PSQdim_{x_i} = \frac{PSQdim_{x_i} - PSQdim_{x_{min}}}{PSQdim_{x_{max}} - PSQdim_{x_{min}}}$$

PSQdim corresponds to the calculated value for a specific perceived service quality dimension (Tangibles, Reliability, Responsiveness, Assurance, Empathy, Intimacy, Authenticity, Commitment, Privacy, and Security) and associated minimum and maximum values in the entire matrix for the dimension. Table 6 provides the list of review counts that have resulted in a positive score for a specific PSQ dimension. It is observed that none of the reviews have all ten dimensions' scores as zero (i.e., resulting in a zero array), but naturally, not all the PSQ dimensions are mentioned in all the reviews, and we have an unbalanced set of data for predictor variables.

Table 6. PSQ Dimensions vs. Review Counts

PSQdim	Count of observed reviews (i.e., where dimension score is not equal to zero)
Tangibles	429,112
Reliability	95,618
Responsiveness	171,230
Assurance	196,415
Empathy	211,738
Intimacy	168,316
Authenticity	140,997
Commitment	79,355
Privacy	108,912
Security	81,738

Since all the variables we have are numeric, we can run a multiple regression on the dependent PSQ (sentiment) variable. There are different uses of multiple regression, such as prediction and understanding causes. In our case, the prediction of PSQ through the ten dimensions in the research model is more imperative than observing the inherent, functional relationships. Running linear regression independently and iteratively for each predictor variable (i.e., PSQ dimensions) is a reliable forward selection technique, also known as one of the stepwise procedures.

Two significant assumptions of multiple regression are normality and homoscedasticity. Before we start the analysis, kurtosis and skewness statistics are conducted, and we plot the predictor variables for outlier checks and observe the correlation matrix to see if the predictors are correlated (i.e., any multicollinearity exists or not) and normally distributed. Predictor variables are highly uncorrelated, and we have only 0.32 positive correlation between assurance and empathy, which is at a tolerable level.

We conducted data transformations, and pilot model runs to check whether there are some interactive effects of predictor variables that we may miss. For each *PSQdim*, the difference between the means of high and low PSQ (i.e., sentiment score) is compared with the independent samples t-test. Afterward, all predictors did show a significant difference and are kept in the data set. Also, as most of the popular learning algorithms develop the learning models based on the assumption that the data is balanced as per the predictor(s) and dependent(s), the performance of the learning models might be unsatisfactory when the data set is imbalanced. Therefore, we also constructed a subset including 117,910 reviews, where the observations of each PSQdim are balanced.

In the first iteration, we applied ten-fold cross-validation to mitigate any biased separation of training and test data sets by the algorithm. In the second iteration, we run the least squares with the balanced data because the observed counts of dimensions are unbalanced, which may cause over-fitting in the model. Appendix K demonstrates the multiple regression results of the first and second iterations.

In the third and fourth iterations, we added some control variables and observed whether any explanatory power or significance are changing or not. Again, the regression is run both for the balanced and unbalanced data set. Appendix L depicts the multiple regression results of the third and fourth iterations. The control variables are as follows:

- Listing_Type: “Private room” coded as 0 or “Shared room” coded as 1
- Total_Listing_Reviews: The number of reviews that the listing has received.

When we analyze the results of four distinct iterations (both in Appendix K and Appendix L), the influences of tangibles, assurance, empathy, intimacy, authenticity, privacy, and security on PSQ are confirmed at significant levels; whereas reliability, responsiveness and commitment did not show any significant influence on PSQ. These results indicate that SERVQUAL partially suffice in SE Airbnb context (with only three significant dimensions of it) and well-enhanced with the cognitive and attitudinal (C/A) dimensions, except commitment. Appendix M demonstrates sample reviews that we consume for each dimension.

CHAPTER 7

DISCUSSION

7.1 Discussion on personality results

This study starts with a first-of-a-kind attempt on extracting consumer personalities from user-generated content in SE Airbnb context. Airbnb guests score high in two main dimensions of Big5: extraversion and openness. Matzler, Bidmon, and Grabner-Kräuter (2006) found that extraversion and openness are positively related to the hedonically driven consumption, and consumers who have more of these personality traits respond stronger to affective stimuli. Also, having high scores of altruism, cooperation, and sympathy indicates an inherent tendency to involve in P2P activities. The high scores in trust facet of Big5 provide a harmonious approach of Airbnb guests in trusting of others across P2P interactions.

High cautiousness and dutifulness explain the extent to which Airbnb guests follow the rules and try to avoid mistakes. Activity-level and artistic interests of Airbnb guests are found to be high, which implies that they are not expected to be home-closed (i.e., stay-at-home) individuals and are appreciative of art. The levels of intellectuality and liberalism indicate that Airbnb guests do not avoid philosophical discussions and complex situations.

Excitement-seeking and gregariousness scores get along with each other, which indicate the independence and calm-seeking attitude of Airbnb guests. Since they also score low in self-consciousness and anger, they are hard to be intimidated and embarrassed along with a mild-tempered approach. Linear combinations of these personality scores might be used to come up with distinct organic behaviors of Airbnb guests (i.e., associations between separate psychological traits can be analyzed).

7.2 Discussion on perceived service quality

Since we derive the ten predictors of PSQ through user-generated content, the findings are deemed to keep the research away from spurious certainty. Regarding the SERVQUAL, tangibles are found to be an important antecedent of PSQ as was noted in the extant literature for other types of accommodation settings as well. Tangibles appear as the most mentioned dimension in the Airbnb reviews, and this indicates that Airbnb users attach importance to amenities, facilities, and equipment in the Airbnb listing, which results in the actual performance and expectation comparison upon service encounters.

Reliability and responsiveness are not found to be significant predictors of PSQ, which can be attributed to the different priorities of Airbnb guests compared to the conventional hotel settings. We studied reliability as the consistency in reservation items (e.g., timing) and alterations, and it appeared as the third least referred concern in the Airbnb reviews. Although responsiveness is highly mentioned in the Airbnb reviews as the fourth most referred dimension, its impact on PSQ sentiment score is not significant. The terms of responsiveness do not assert a significant targeted sentiment on the overall PSQ sentiment being uncorrelated in one-to-one tests with the dependent variable and regression results.

Assurance and empathy are found to be important antecedents of PSQ, and Airbnb guests take these dimensions into account in terms of specific review mentions and targeted sentiments as per Watson NLU results. This finding is also aligned with the personality results, which can be the underlying expectation shapers, such as high sympathy, trust, and altruism.

Being one of the cognitive and attitudinal factors, intimacy is a significant predictor of overall PSQ sentiment, being an integral part of human connection. As Airbnb guests score high in cooperation Big5 facet, they expect the same attitude from the hosts, which might be forming their expectation for an intimate stay experience. Also, authenticity is one of the critical dimensions, and this can first be attributed to the personality traits of artistic interests and activity levels. Experience is thought in between host and guest, followed by an expectation to taste the local life.

Commitment dimension is not found to be a significant predictor of PSQ score, being the lowest referred component in the reviews as well. Airbnb strictly follows the hosts' level of alignment with the policies and procedures, and the guests do not assert a significant targeted sentiment regarding commitment terms for the overall PSQ sentiment score.

As one of the most different parts of P2P accommodation compared to the conventional hotels, guests do expect a level of privacy (i.e., safe psychological and physical zone) and security (i.e., being free from danger or threat), which overlay a targeted sentiment towards the overall PSQ sentiment. Also, according to Yang and Ahn (2016), security in Airbnb's services is a more critical antecedent of attitude toward Airbnb than critical dimensions of motivation toward SE, such as enjoyment and reputation. As was previously mentioned, Birinci et al. (2018) state that safety and security risk appear to be statistically significant predictors of satisfaction in Airbnb.

7.3 Limitations

This research has certain limitations. Personality analysis of Airbnb guests is constrained by the word count threshold, which may inhibit the level of cross-cultural findings. Further research can also enlighten the exact differences of personalities between Airbnb users and other accommodation services (e.g., hotel settings). PSQ analysis is only constrained by the context itself because it performs the content analysis and keyword extraction on a massive amount of user reviews. Other antecedents of PSQ can be further explored upon this study's findings to study the unexplained part of adjusted R-squared.

CHAPTER 8

CONCLUSION

SE is a relatively new and multi-disciplined field that covers open rooms for research, and specifically, Airbnb is one of the most prominent businesses in this context. The literature review presented underlies the infancy of well-grounded studies covering service quality perceptions of customers in SE. Seeking additional dimensions from Airbnb guests' reviews is a novel research approach in studying customer engagement, and those dimensions are included in the research model.

Tech-savvy marketing researcher is a new phenomenon that requires an interdisciplinary mindset. The emotional connections of consumers with services are neither uniform nor constant, and they can vary by industry, brand, touchpoint of the service encounter, and the consumers' position in the decision journey. The resultant emotions in the Airbnb reviews are highly joy in the texts, and the sentiment is more often positive across the reviews. Referring to the customer engagement matrix of Pansari and Kumar (2016), with the sentiment and emotion scores, we can also say that Airbnb in its "True Love" stage with high positive emotions (i.e., joy) and highly positive sentiment reported in the reviews.

Grabbing the specific mentions of service quality dimensions is not a straight-forward task, and the methodology proposed here is to run a priori analysis of reviews to be used as a subset of the quasi-gold standard per dimension. In this way, a priori analysis of those reviews guided the subsequent phases of analysis by providing better keywords that were used for the construction of more reliable and valid word-maps and boolean search queries. Therefore, for creating word maps and boolean search queries for each of the ten PSQ dimensions (including SERVQUAL, and Cognitive and Attitudinal dimensions, abbreviated to C/A dimensions), we base our method on a sound, scientific approach.

In this study, there are pioneering implications for marketing and service researchers to show traveler personalities inferred from user-generated content in the sharing economy Airbnb service context. We find that Airbnb guests score high in extraversion and openness dimensions of Big5. Linear combinations of personality scores might be used to come up with distinct organic behaviors of consumers (i.e., associations between separate psychological traits). Matzler et al. (2006) found that extraversion and openness are positively related to the hedonically driven product consumption, which influences brand effect and drives purchase loyalty (i.e., those consumers respond stronger to affective stimuli). This implication can be replicated and hypothesized within Airbnb service context since the guests are found to have high extraversion and openness.

The essential categories of Airbnb reviews that have been identified are business travel, specialty travel, and traveling with kids. The high-level concepts underlie the critical items referred to in reviews, and those are mostly related to the tangibles, amenities, facilities, and location. Three distinct groups of word-clouds appear as per the co-occurrences: location-related, amenities and facilities related, and host interaction and experience related. Using the personality traits of consumers as a basis, we test our PSQ model, which is a combination of the seminal SERVQUAL service quality framework and additional cognitive and attitudinal factors. The findings include that the SERVQUAL model requires adjustment in this context, and it is well-enhanced by cognitive and attitudinal factors, including intimacy, authenticity, privacy, and security.

APPENDIX A

AIRBNB LOCATIONS IN THE DATA SET

Locations in Airbnb Data	Number of reviews	Number of distinct reviewers	Number of distinct listings	ER %	PR %	SR %	Average word count per review	Standard deviation of word count
Amsterdam, The Netherlands	337816	323133	16157	80.1	19.7	0.2	56.45886	47.39348
Antwerp, Belgium	26644	25112	1024	71	27.9	1.1	48.50977	39.43244
Asheville, United States	27721	25669	742	61.5	37.9	0.6	67.5114	50.00364
Athens, Greece	124377	112047	3927	83.2	15.8	1	63.55369	52.37973
Austin, Texas, United States	134550	117591	6007	69.4	28.3	2.3	57.46183	47.94543
Barcelona, Spain	500413	473204	14838	40.1	58.9	1	55.13578	50.45597
Berlin, Berlin, Germany	266555	245576	16180	52.2	46.5	1.3	50.93166	42.95077
Boston, Massachusetts, US	120787	112540	3986	62.2	36.6	1.2	53.42348	50.01038
Brussels, Belgium	112060	103056	4904	64.5	34.2	1.3	48.21616	41.57828
Chicago, Illinois, United States	132353	121572	4497	59.7	37.2	3.1	57.75287	51.369
Copenhagen, Denmark	221047	206585	16445	80.9	18.7	0.5	56.17079	44.86127
Denver, Colorado, US	128834	116788	3406	68.1	30.1	1.8	48.27096	43.61672
Dublin, Leinster, Ireland	141152	130051	5361	47.3	50.1	2.6	59.24268	47.81057
Edinburgh, Scotland	259295	239798	8557	57.2	42.5	0.3	52.86119	43.70517
Geneva, Switzerland	46583	40780	2359	66.1	33	0.9	43.57983	41.27622
Hong Kong, China	82394	73759	4617	50.1	44.7	5.2	54.88736	61.3998
London, England	672760	571730	37438	51.5	47.1	1.4	58.641	51.35805
Los Angeles, California, US	651938	529730	24030	63	32.9	4.1	54.56894	51.44898
Madrid, Spain	444774	399996	13261	64.1	34.8	1.1	48.5384	45.02056
Malaga, Spain	98114	91698	3834	79.1	20.2	0.7	50.81432	45.93124
Mallorca, Spain	109662	97733	8407	87.9	12	0.1	66.89309	56.74921
Manchester, England	14880	13717	676	42	56.6	1.4	54.7132	43.69469
Melbourne, Australia	231550	193179	11223	61.3	37.2	1.5	50.63239	43.66092
Montreal, Canada	97208	86871	7028	60.7	38	1.3	61.55244	50.13677
Nashville, Tennessee, US	170343	154694	4570	76.5	22.5	1	52.25317	44.8812
New Orleans, Louisiana, US	188329	174798	4723	83.1	16.3	0.6	62.0787	55.3435
New York City, New York, US	896208	781742	37916	51	46.9	2.1	57.15083	53.04253
Northern Rivers, Australia	24951	22630	1726	77.1	22.7	0.2	62.58451	47.47128
Oakland, California, US	26736	23346	1311	56.1	40.5	3.4	66.50814	53.94048
Paris, France	969581	854834	45797	87.3	12	0.7	53.2519	51.12878
Portland, Oregon, US	224755	196178	4204	68.1	30.6	1.3	55.31222	46.70338
Quebec City, Canada	50396	47884	1963	63.7	35.2	1.1	47.32303	42.77186
Rome, Italy	572969	540706	18758	60.3	39	0.7	66.21876	55.64346
San Diego, California, US	92862	85263	4590	66.1	31.1	2.8	67.04618	55.21456
San Francisco, California, US	256635	230331	7123	57.6	40.4	2	57.94606	50.78153
Santa Cruz, California, US	22121	20455	702	65.5	33.1	1.4	69.98422	54.60817
Seattle, Washington, US	84849	75730	3191	66.8	30.2	3	68.49241	54.06384
Sydney, Australia	335036	277825	22685	60.7	37.6	1.7	46.92218	44.10497
Tasmania, Australia	138532	97564	3909	76.5	22.9	0.6	45.95982	39.0521
Toronto, Ontario, Canada	203887	170733	9895	65.1	33.2	1.7	50.43339	46.34209
Vancouver, Canada	149595	135048	5660	69	30.1	0.9	52.92683	46.33905
Venice, Italy	216305	210898	5243	77.2	21.9	0.9	65.64307	55.45585
Victoria, Canada	31243	28226	1441	76.3	23	0.7	64.94363	49.11254
Vienna, Austria	191102	180407	7424	72.1	26.9	1	51.62907	44.55493
Washington, D.C., US	152548	139705	5660	68.7	28.8	2.5	58.26675	51.48371

APPENDIX B

PERSONALITY FINDINGS

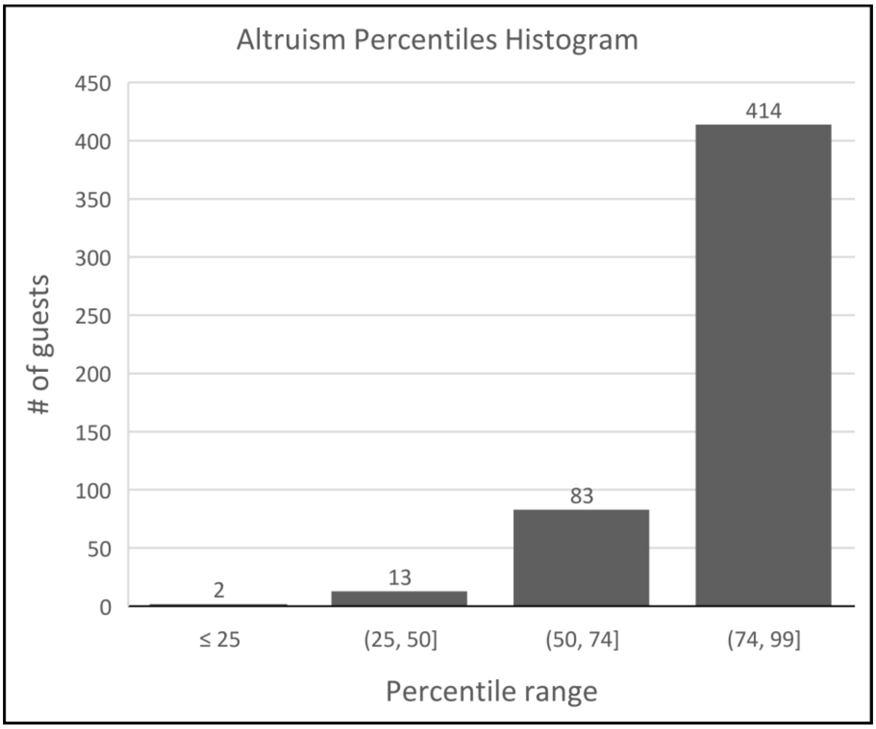


Figure B1. Big5 agreeableness dimension - altruism results

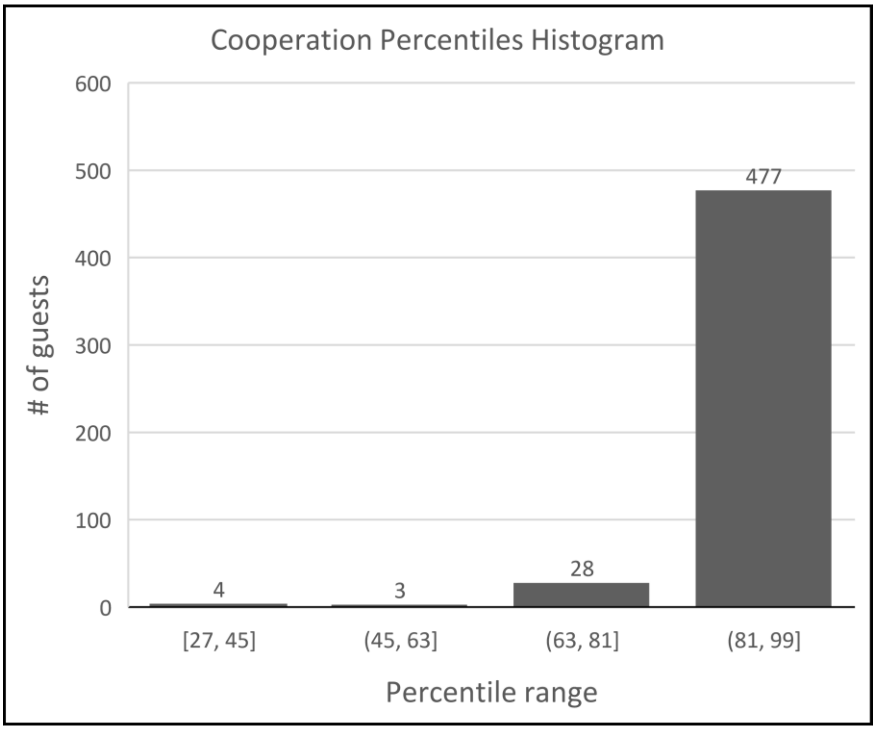


Figure B2. Big5 agreeableness dimension - cooperation results

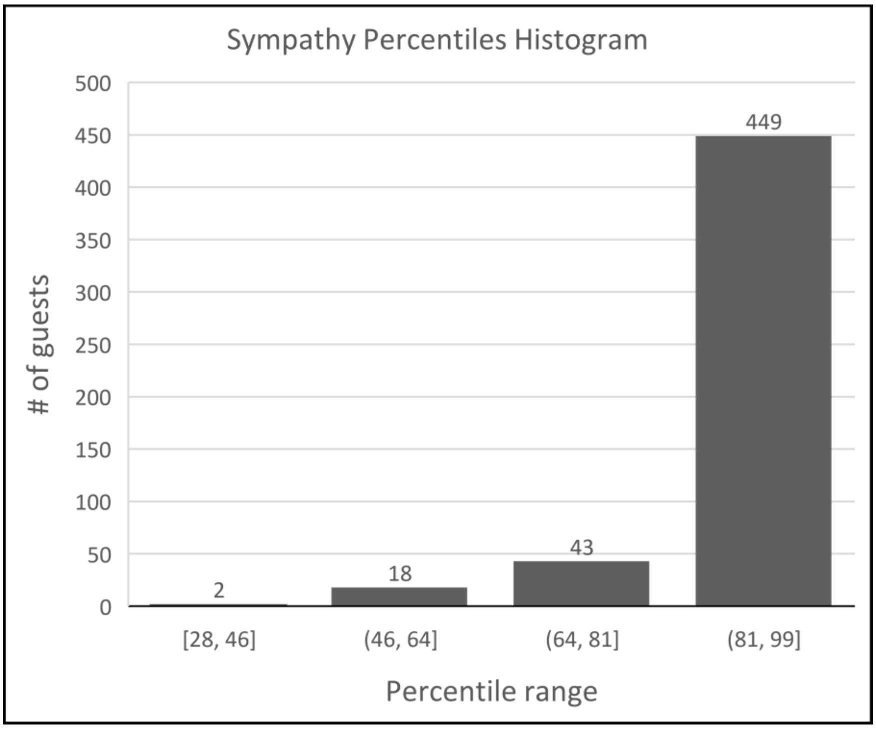


Figure B3. Big5 agreeableness dimension - sympathy results

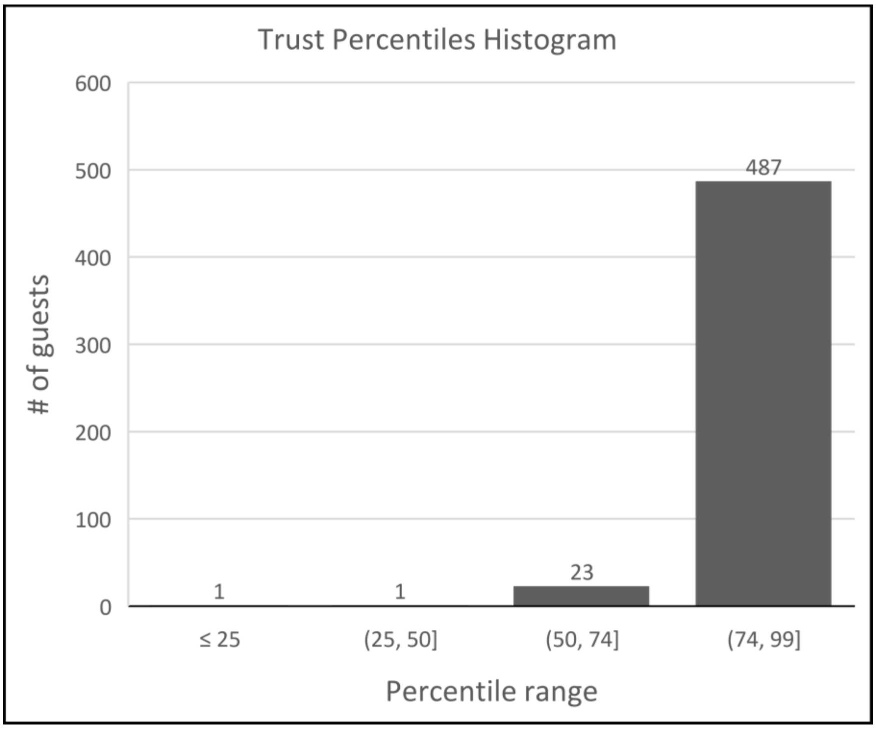


Figure B4. Big5 agreeableness dimension - trust results

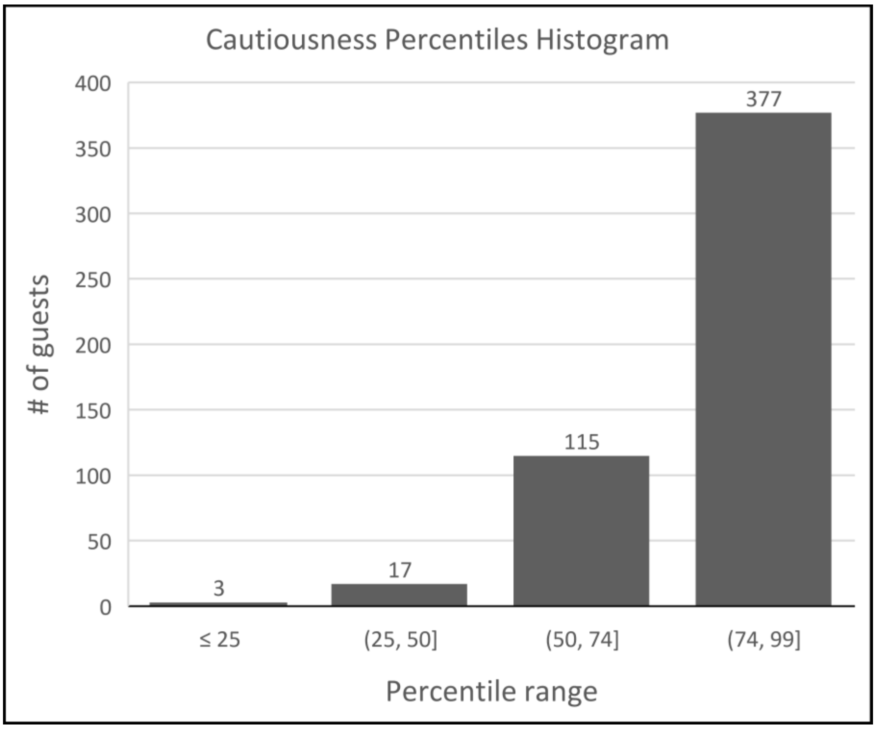


Figure B5. Big5 conscientiousness dimension - cautiousness results

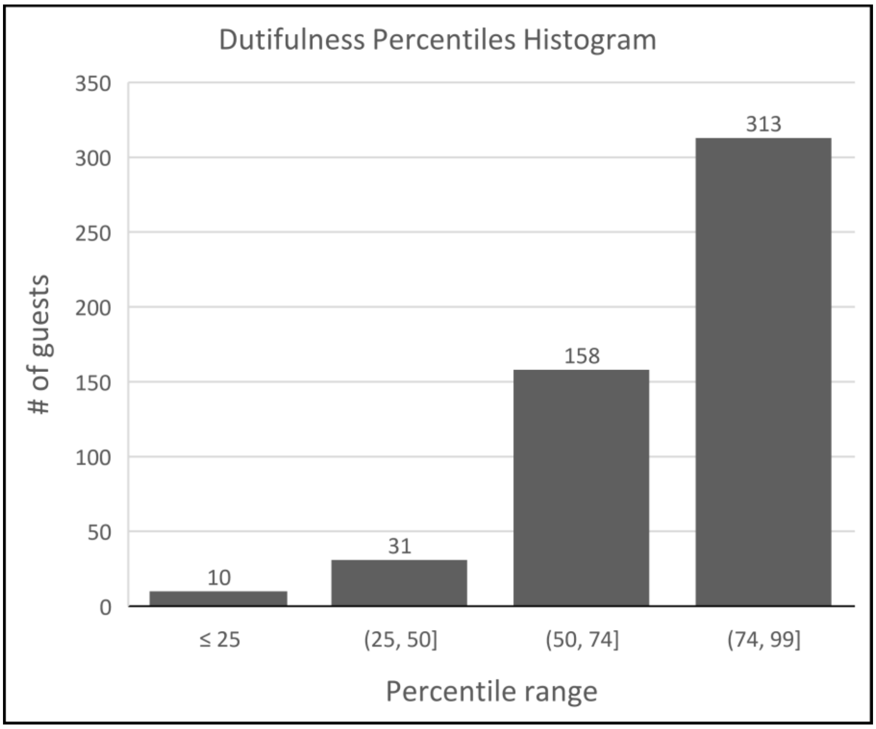


Figure B6. Big5 conscientiousness dimension - dutifulness results

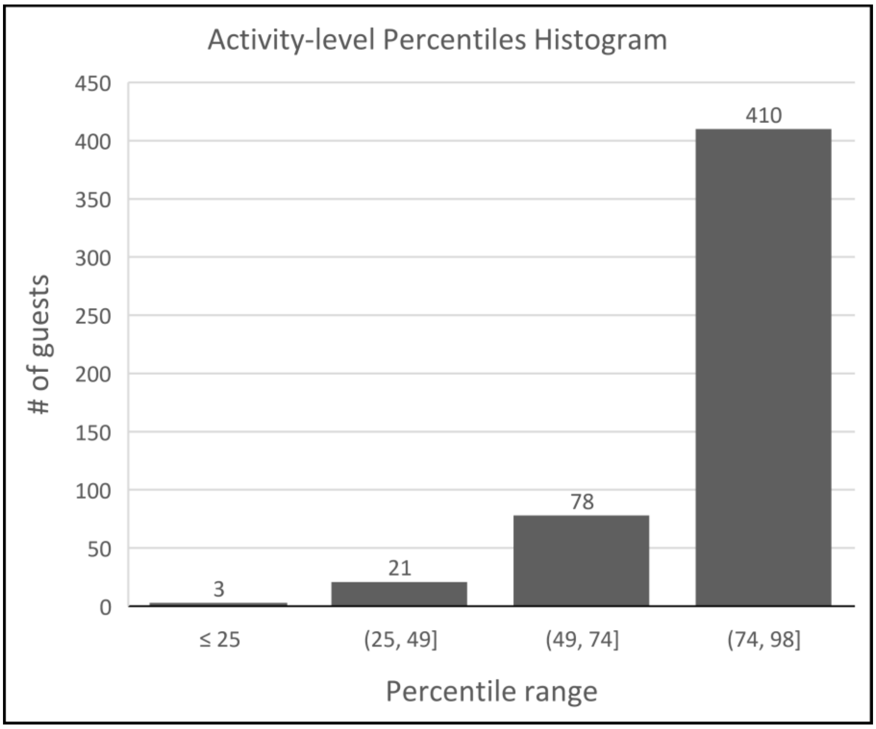


Figure B7. Big5 extraversion dimension – activity-level results

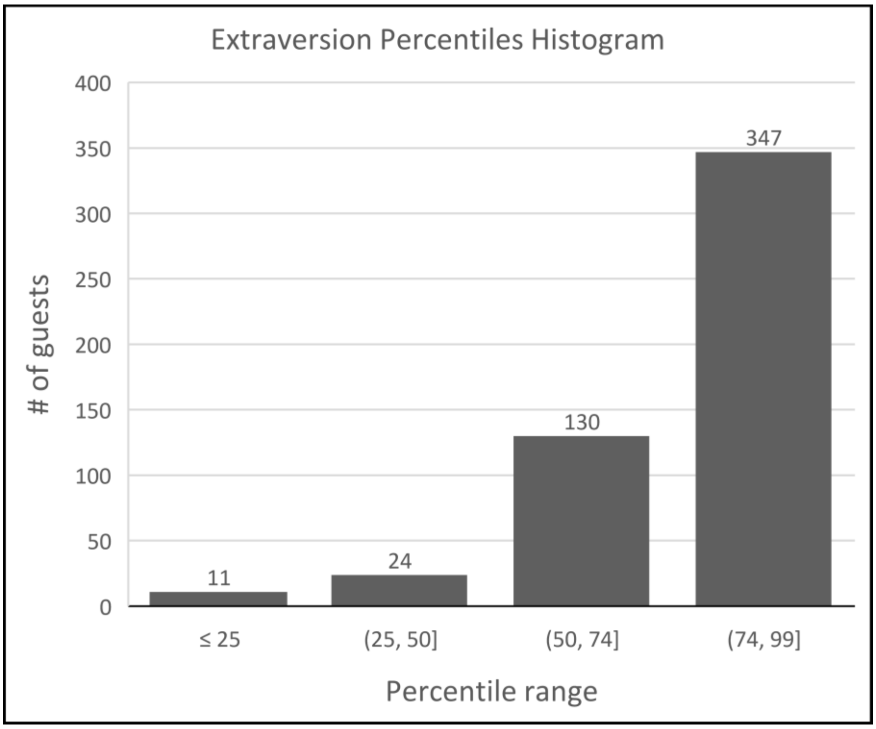


Figure B8. Big5 extraversion dimension results

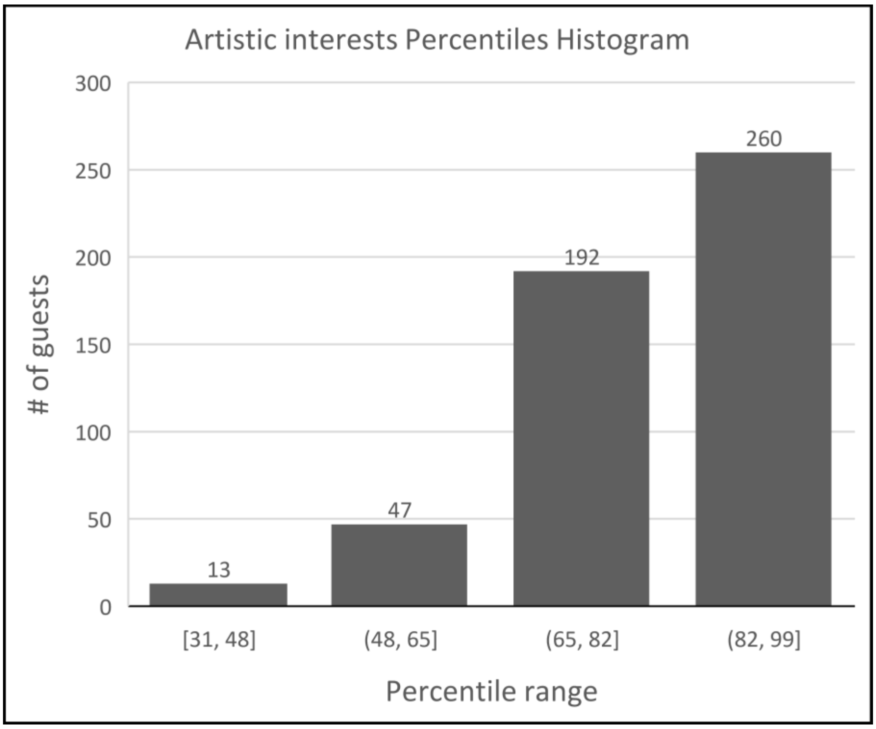


Figure B9. Big5 openness dimension – artistic-interests results

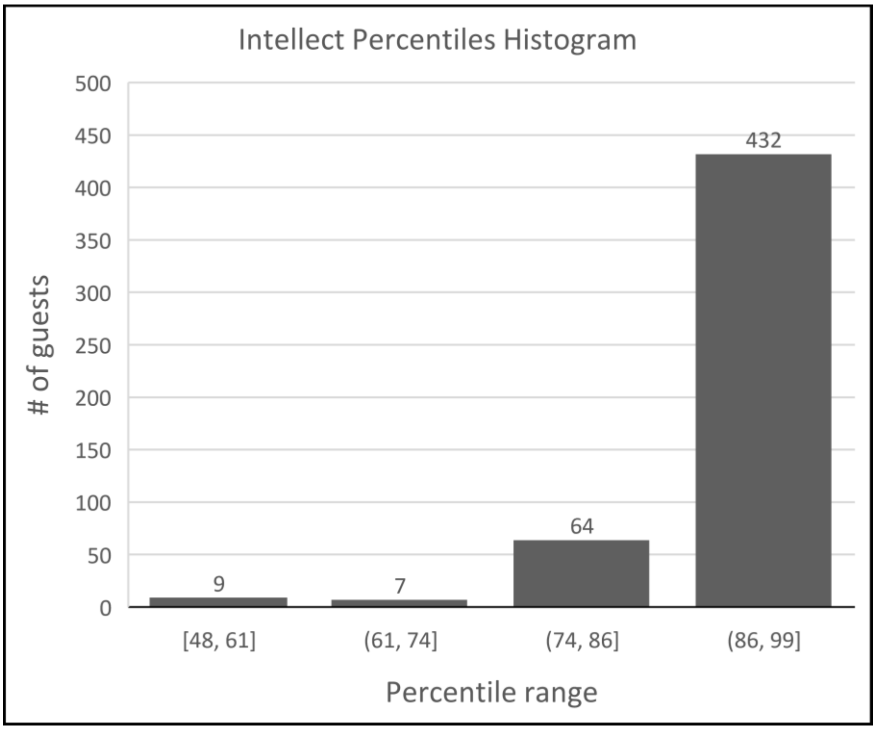


Figure B10. Big5 openness dimension – intellect results

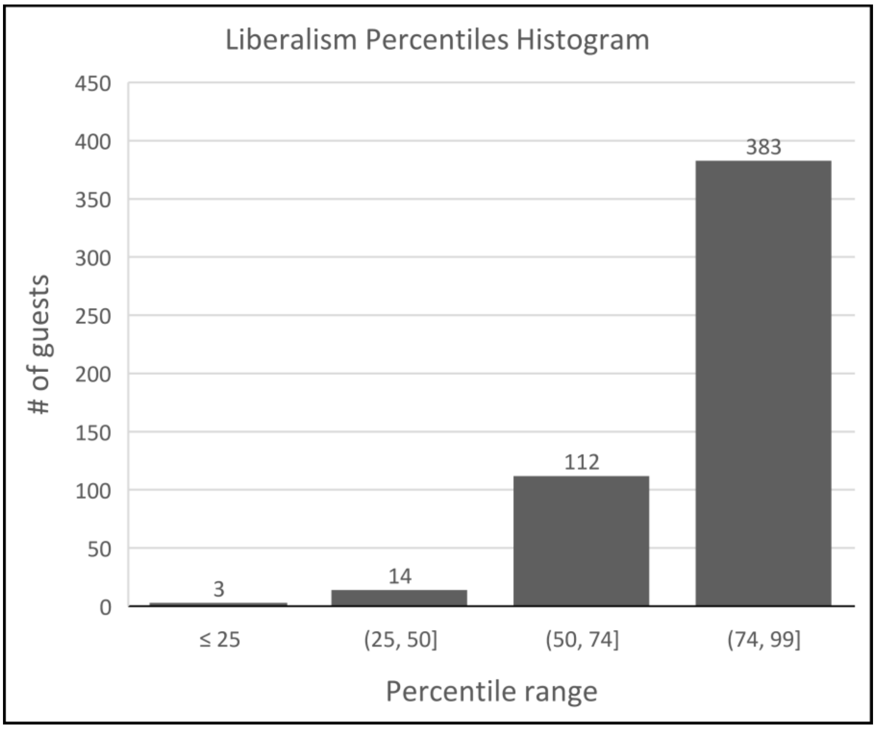


Figure B11. Big5 openness dimension – liberalism results

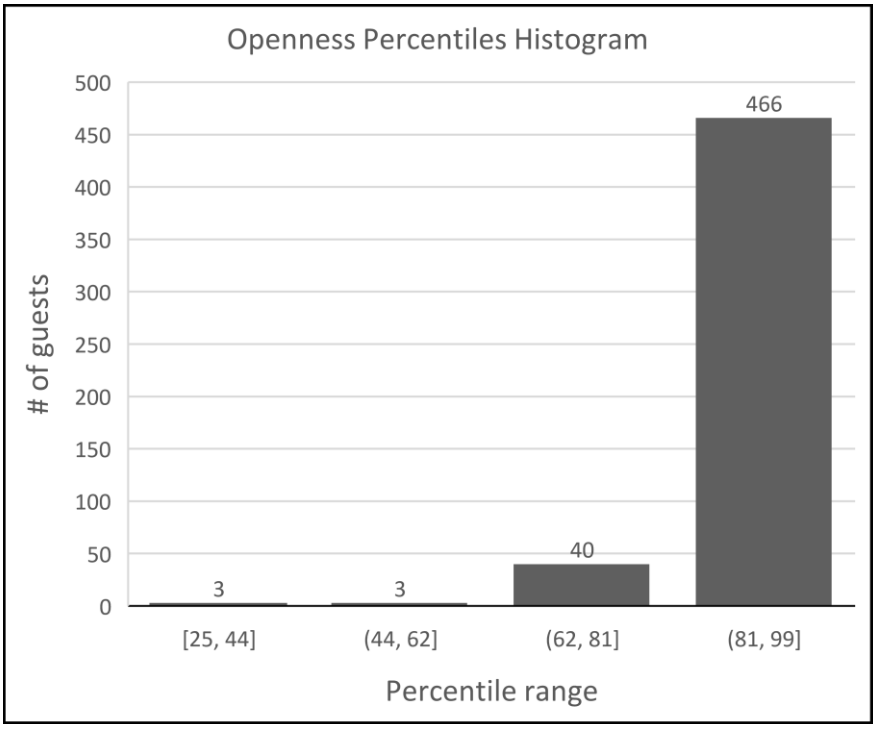


Figure B12. Big5 openness dimension results

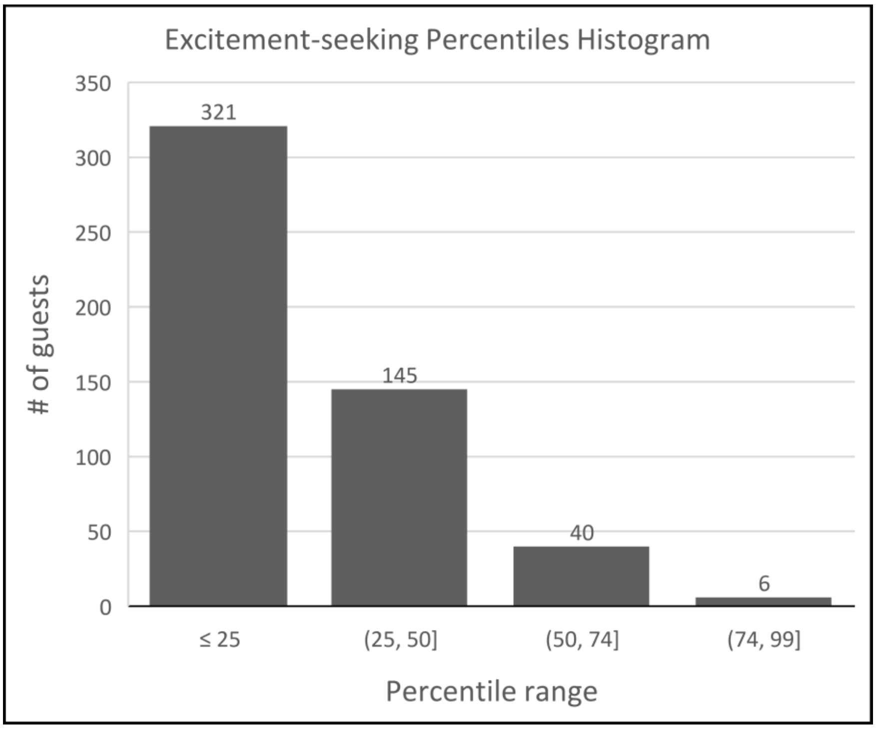


Figure B13. Big5 extraversion dimension – excitement-seeking results

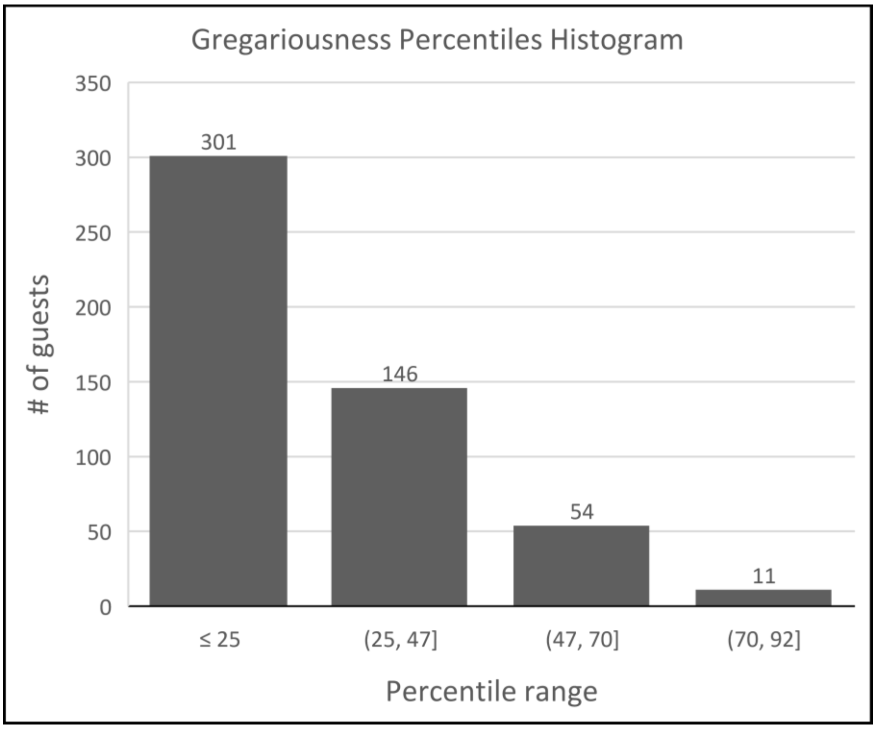


Figure B14. Big5 extraversion dimension – gregariousness results

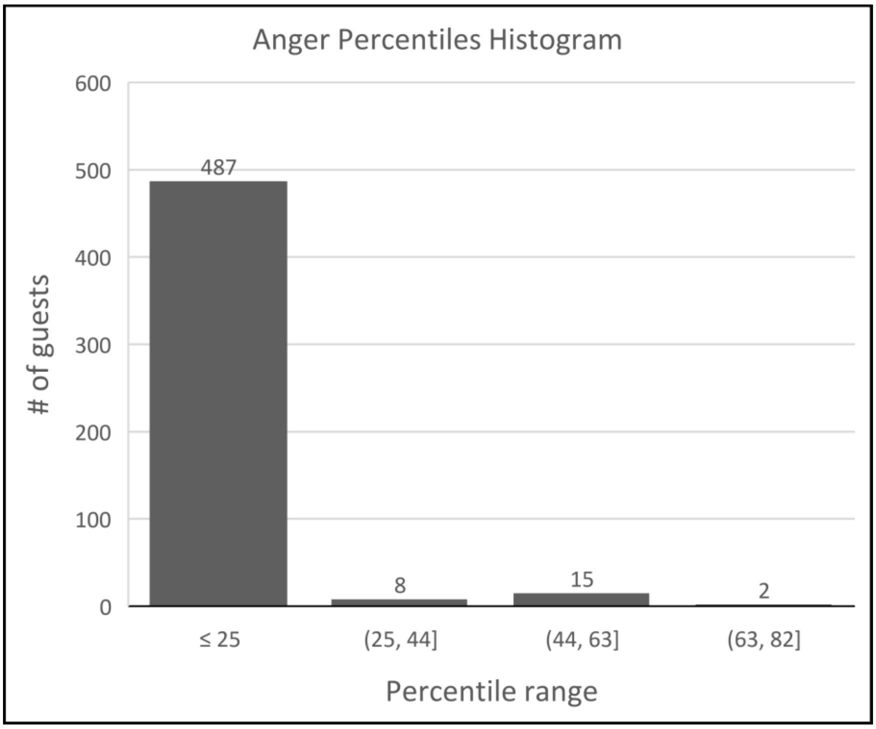


Figure B15. Big5 emotional range dimension – anger results

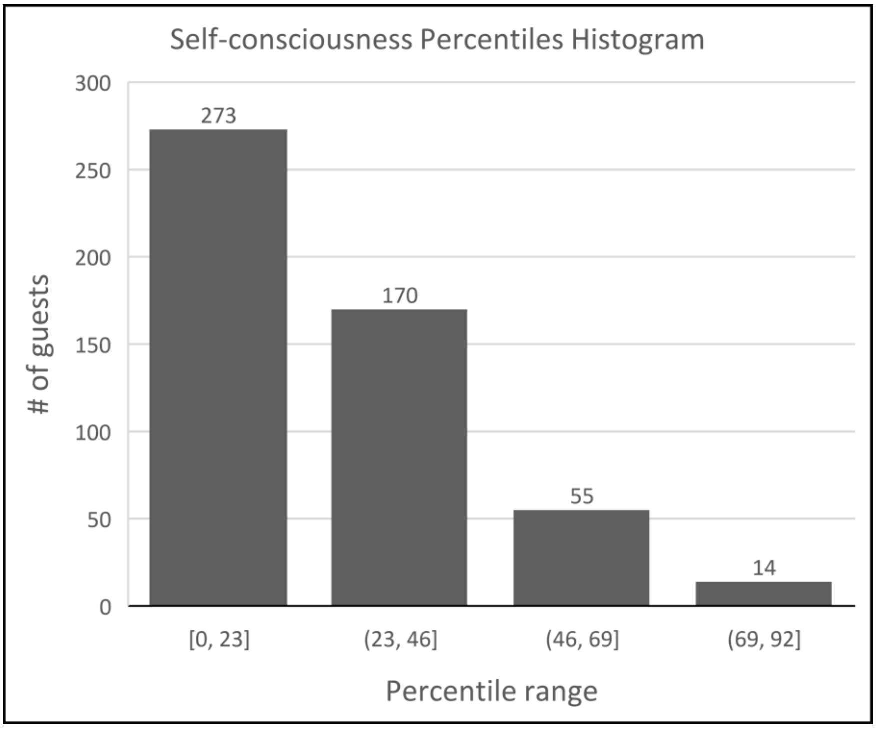


Figure B16. Big5 emotional range dimension – self-consciousness results

APPENDIX C

KEYWORDS IN THE AIRBNB REVIEWS

Keywords with high relevance (i.e. between 0.51 and 1)				
great experience	quiet street	kitchen appliances	19th century feel	touristic places
amazing host	Perfect location	fast internet	private shelf	only major thing
comfortable bed	good-natured guy	helpful tips	nice details	clear directions
apartment feel	flexible check-out	second stay	comfortable decor	future visit
short stay	easy access	classic old neighborhood	wonderful design	new people
Great artwork	art work	great Airbnb experience	own bathroom	minute walk of train stations
large kitchen	clean bathroom	wonderful hosts	only complaint	beautiful details
attentive host	warm welcome	great view	reliable host	comfortable kitchen
smallest details	second time	safe neighborhood	cool experience	Easy check-in
good design	joyful trip	friendly guy	great balcony	parking lots
spacious bedroom	convenient location	lovely amenity	wonderful view	unique experience
lovely bath towels	plenty of privacy	gracious host	brief stay	great host
quiet residential area	feel of a private unit	warm host	fantastic hosts	great proportions
worldly feel	cozy comforter	welcoming host	cozy little	restful space
good heating	welcoming feel	shelf space	own private space	little touches
great communicator	older home	much privacy	fabulous hosts	closest underground station

APPENDIX D

EMOTIONS OF THE AIRBNB GUESTS

Overall Emotion - 526.670 distinct reviews

Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7	Cluster8	Cluster9	Cluster10
Joy	Joy	Joy	Joy	Joy	Joy	Joy	Joy	Joy	Joy
0.7	0.68	0.69	0.69	0.68	0.72	0.72	0.65	0.68	0.7
Anger	Anger	Anger	Anger	Anger	Anger	Anger	Anger	Anger	Anger
0.07	0.1	0.09	0.07	0.08	0.08	0.07	0.1	0.08	0.08
Disgust	Disgust	Disgust	Disgust	Disgust	Disgust	Disgust	Disgust	Disgust	Disgust
0.07	0.07	0.07	0.07	0.06	0.06	0.07	0.1	0.07	0.06
Sadness	Sadness	Sadness	Sadness	Sadness	Sadness	Sadness	Sadness	Sadness	Sadness
0.12	0.16	0.15	0.15	0.51	0.43	0.14	0.18	0.43	0.15
Fear	Fear	Fear	Fear	Fear	Fear	Fear	Fear	Fear	Fear
0.09	0.09	0.07	0.08	0.09	0.08	0.05	0.12	0.07	0.09

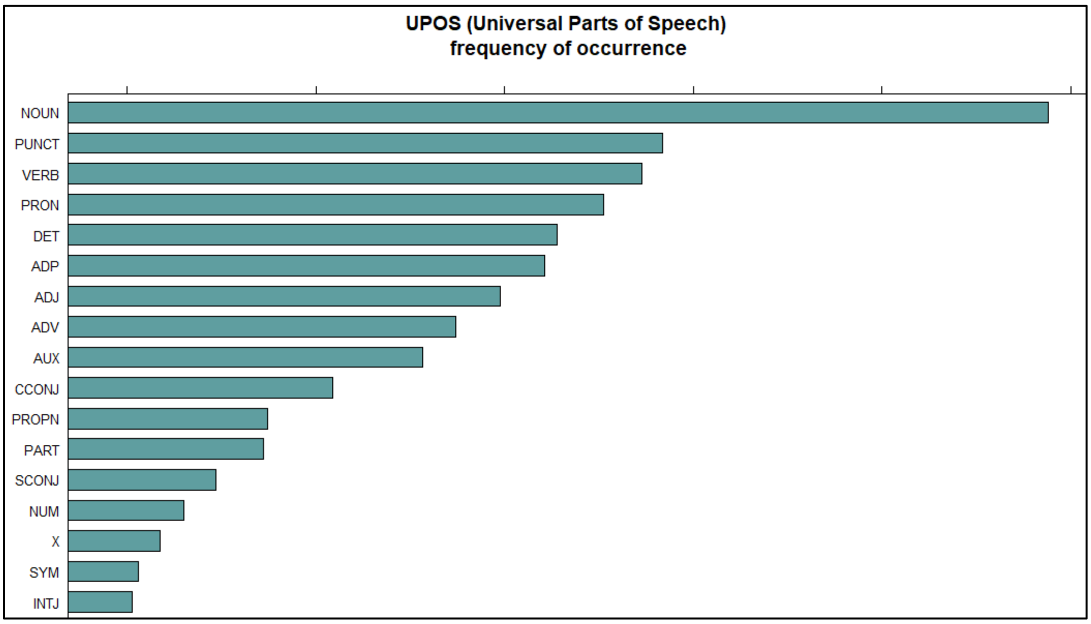
APPENDIX E

UNIVERSAL PARTS OF SPEECH TAGS

PoS tag	Description
ADJ	adjective (e.g., big, old, green, cozy)
ADP	ad-position (e.g., in, to, during)
ADV	adverb (e.g., very, well, exactly)
AUX	auxiliary (e.g., has, is, was, should)
CCONJ	coordinating conjunction (e.g., and, or, but)
DET	determiner (e.g., a, an, the, my, his/her, which)
INTJ	interjection (e.g., ouch, bravo, hello)
NOUN	noun (e.g., girl, cat, sofa, bed, kitchen)
NUM	numeral (e.g., one, IV, 3)
PART	particle (e.g., ‘s, not)
PRON	pronoun (e.g., you, she, everything)
PROPN	proper noun (e.g., Mary, London, Airbnb)
PUNCT	punctuation (e.g., (), . ,)
SCONJ	subordinating conjunction (e.g., that, if, while)
SYM	symbol (e.g., $, %, §, ©)
VERB	verb (e.g., run, ate, eating)
X	other (used for words that for some reason cannot be assigned a real part-of-speech category.)

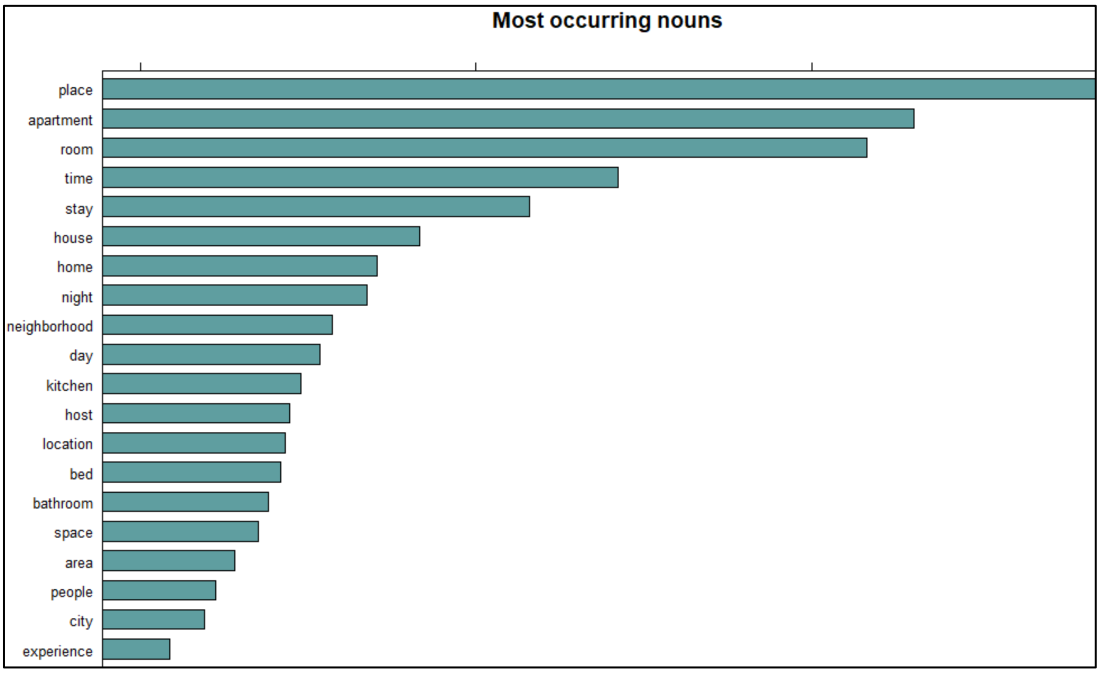
APPENDIX F

UNIVERSAL PARTS OF SPEECH PROPORTIONS



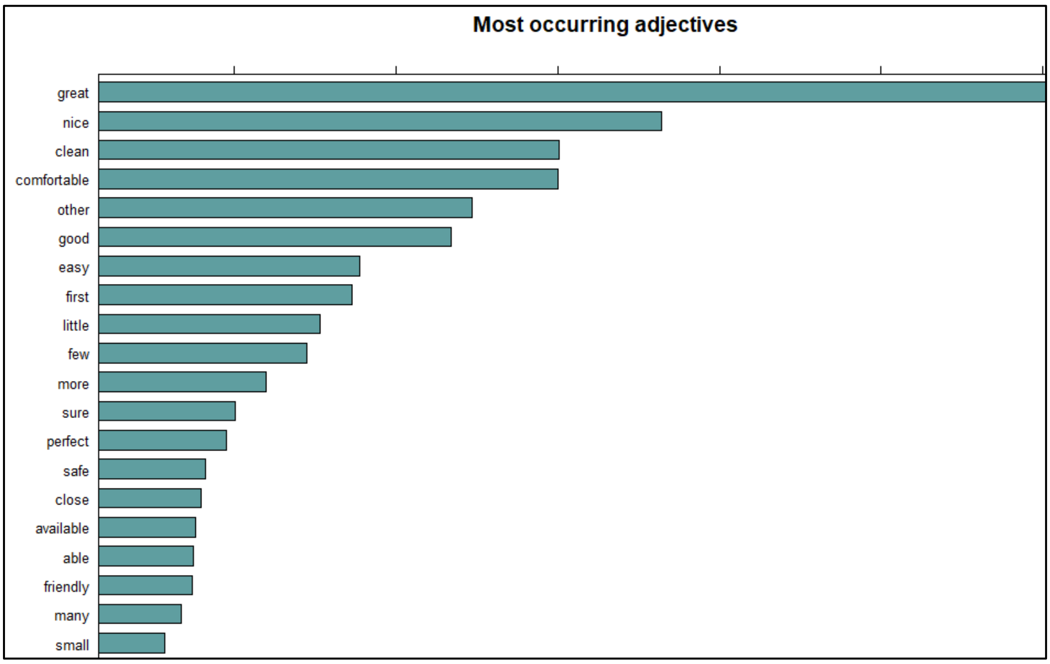
APPENDIX G

MOST OCCURRING NOUNS IN THE DATA SET



APPENDIX H

MOST OCCURRING ADJECTIVES IN THE DATA SET



APPENDIX I

WORD CO-OCCURRENCES IN THE AIRBNB REVIEWS

APPENDIX J

PERCEIVED SERVICE QUALITY DIMENSIONS

Dimension	Most frequent words (combined with the roots and combinations)	Additional sources (refers to Activity1-Figure 6)
Tangibles	bath, water, room, house, home, apartment, shower, kitchen, bed, floor, facility, equipment, material, door, coffee, breakfast, linen, comfort, garden, beach, restaurant, food, bath, flat, clean, beverage, atmosphere, capacity, location, decoration, amenity, appearance, environment, wi-fi, air conditioner, space, clean, shower, refrigerator, dryer, washer, park, transport, nearby, noise, ventilation, location	Tussyadiah and Zach (2016) Cheng and Jin (2018) SERVQUAL (Parasuraman et al., 1988) LODGSERV (Knutson et al., 1990) HOLSERV (Mei et al., 1999) LQI (Getty and Getty, 2003)
Reliability	host, promise, hour, consistent, reliable, reservation, change, dependable, responsible, steady, loyal, tolerate, convenient, support, time, open	
Responsiveness	host, respond, quick, available, prompt, resolve, timely, check-in, check-out, willing, request, communicate, demand, quest, receptive, answer, sympathy, compassionate, complaint, conscious, understand, react, assist, short, expeditious, immediate, instant, punctual, speed, rapid	
Assurance	host, trust, confidence, guide, courteous, polite, attitude, welcome, impartial, guarantee, ensure, insure, certain, sure, assure	
Empathy	host, flexible, assist, individualized, small details, specific need, attention, understanding, mercy, feedback, favor, empathy, grace, gesture, sense, respect, thoughtful, touch	
Intimacy	host, sincere, gracious, intimate, accommodating, family, affinity, compassion, warmth, gentle, soft, love, care, soul, affection, friend, close, devote, cordial, mutual, together, relation, attentive	Milanova & Maas (2017) Prager (1998) Regan & Choe (2017)
Authenticity	genuine, original, authentic, bona fide, fake, genuine, honest, real, rightful, sure, true, painstaking, faithful, legitimacy, fidelity, historic, unique, local, experience, fantastic, tourist, art, cozy, feel	Birinci et al. (2018) Benjamin & Underwood (1998) Lalicic and Weismayer (2017)
Commitment	host, policy, culture, rule, insurance, legal, price, cost, discriminate, respect, consistent, effective, expensive, religion, race, procedure, ethnic, language	Guttentag et al. (2017) Liang et al. (2018) Regan & Choe (2017)
Privacy	private, seclude, peace, quiet, invade, secrecy, anonym, aloneness, alone, insulation, isolate, seclusion, zone, segregate, separate, solitude, confidential, rest	Lutz et al. (2017) Voskoboynikov (2017)
Security	safe, secure, damage, guarantee, neighbor, preserve, danger, free, threat, guard, risk, vulnerable, protect, guard, hazard, afraid	Birinci et al. (2018) Lopez (2013) Yang and Ahn (2016)

APPENDIX K

REGRESSION RESULTS

	Unbalanced data with 10-fold cross validation 1st iteration (N = 526,670)		Under sampled (balanced) data with 10-fold cross validation 2nd iteration (N = 117,910)	
	t-value	Significance	t-value	Significance
(Intercept)	98.697	< 2e-16***	24.119	< 2e-16***
Tangibles	2.001	0.045*	10.356	0.010**
Reliability	-0.669	0.503-	3.613	0.692-
Responsiveness	-0.688	0.491-	-11.911	0.301-
Assurance	1.672	0.044*	-8.08	0.041*
Empathy	3.297	0.001***	4.238	0.009**
Intimacy	5.537	3.08e-8***	3.168	< 2e-16***
Authenticity	3.756	0.001***	1.056	< 2e-16***
Commitment	0.690	0.49-	-0.992	0.37
Privacy	2.371	0.019*	5.391	0.049*
Security	2.906	0.003**	7.198	0.017*
Adj. R-squared	0.71		0.69	

Significance codes: 0.001: ***, 0.01: **, 0.05: *, not significant: –

Notes: The dependent variable is PSQ sentiment score.

APPENDIX L

REGRESSION RESULTS WITH CONTROL VARIABLES

	Unbalanced data with 10-fold cross validation 3rd iteration (N=526,670)		Under sampled (balanced) data with 10-fold cross validation 4th iteration (N=117,910)	
	t-value	Significance	t-value	Significance
(Intercept)	65.43	< 2e-16***	33.1	< 2e-16***
C1_Listing_Type	1.87	0.61-	1.14	0.29^{-}
C2_Total_Listing_Reviews	1.09	0.37-	3.02	0.42^{-}
Tangibles	1.17	0.030*	3.1	0.019*
Reliability	-0.49	0.182^{-}	-3.72	0.382^{-}
Responsiveness	-1.2	0.194^{-}	-4.19	0.094^{-}
Assurance	4.3	0.046*	1.99	0.006**
Empathy	2.09	0.009**	1.07	0.010**
Intimacy	12.13	0.000***	5.96	< 2e-16***
Authenticity	3.18	0.001***	2.68	0.001***
Commitment	3.30	0.098^{-}	1.90	0.153-
Privacy	0.89	0.007**	1.27	0.005**
Security	1.16	0.004**	1.64	0.002**
Adj. R-squared	0.67		0.69	
Significance codes: 0.001: ***, 0.01: **, 0.05: *, not significant: – Notes: The dependent variable is PSQ sentiment score.				

APPENDIX M

SAMPLE GUEST REVIEWS

Dimension	Sample Airbnb guest review
Tangibles	“Her home is filled with loads of creative books and decor and has a very lived-in feeling to it. This house is great for families that need a large kitchen, or for creatives that want an inspiring home away from home.”
Reliability	“Sarah is also incredibly accommodating and very reliable at replying if you have an issue.”
Responsiveness	“Checking me in remotely she was very responsive, and she was extremely accommodating with regards to the time of check-in and check-out for me.”
Assurance	“You can rest assured that you will be comfortable when you decide to stay at Lindsay's rental.”
Empathy	“It is that community feeling that makes this platform so amazing, and unfortunately Hector lacked that empathy. I hope that he seriously reconsiders his interactions with his guests and strives to make his hosting less transactional.”
Intimacy	“A beautiful, comfortable flat in a great location. This place offers all the amenities and benefits of a hotel, but the intimacy of staying in a home.”
Authenticity	“Very nice to find a hand-written note waiting for me on arrival. The description and photos are very accurate, and the multitude of rave reviews are a testament to the authenticity of David's listing.”
Commitment	“We sat around drinking and talking about religion/spirituality/ and politics most of the night she held her ground with her understanding of world religions.”
Privacy	“With an active construction site across the street, it was impossible to obtain privacy (especially at night), and keep the unit cool during the day. The curtains were also falling off the rod in several places.”
Security	“There are lots of dilapidated dwellings with the kind of welded-bar screen doors you would expect to see in places where people are concerned about the safety of their persons or property. Caroline's place has a door like this.”

REFERENCES

Acar, M., & Toker, A. (2018, July). A perceived service quality model in sharing economy: The case of Airbnb. Paper presented at Global Marketing Conference, Tokyo (pp. 1179-1185).

Achrol, R. S., & Kotler, P. (2011). Frontiers of the marketing paradigm in the third millennium. *Journal of the Academy of Marketing Science,40*(1), 35-52. doi:10.1007/s11747-011-0255-4

Ali, F., Hussain, K., Konar, R., & Jeon, H. (2016). The effect of technical and functional quality on guests' perceived hotel service quality and satisfaction: A SEM-PLS analysis. *Journal of Quality Assurance in Hospitality & Tourism,18*(3), 354-378. doi:10.1080/1528008x.2016.1230037

Aznar, P., Sayeras, J. M., Segarra, G., & Claveria, J. (2018). Airbnb competition and hotels' response: The importance of online reputation. *Athens Journal of Tourism,5*(1), 7-20. doi:10.30958/ajt.5.1.1

Barile, S., Pellicano, M., & Polese, F. (2018). *Social dynamics in a systems perspective*. Cham, Switzerland: Springer.

Benjamin, W., & Underwood, J. A. (2008). *The work of art in the age of mechanical reproduction*. London: Penguin Books.

Benoit, S., Baker, T. L., Bolton, R. N., Gruber, T., & Kandampully, J. (2017). A triadic framework for collaborative consumption (CC): Motives, activities and resources & capabilities of actors. *Journal of Business Research,79*, 219-227. doi:10.1016/j.jbusres.2017.05.004

Bernardo, M., Marimon, F., & Alonso-Almeida, M. D. (2012). Functional quality and hedonic quality: A study of the dimensions of e-service quality in online travel agencies. *Information & Management,49*(7-8), 342-347. doi:10.1016/j.im.2012.06.005

Birinci, H., Berezina, K., & Cobanoglu, C. (2018). Comparing customer perceptions of hotel and peer-to-peer accommodation advantages and disadvantages. *International Journal of Contemporary Hospitality Management,30*(2), 1190-1210. doi:10.1108/ijchm-09-2016-0506

Botsman, R., & Rogers, R. (2011). *What's mine is yours: How collaborative consumption is changing the way we live*. London: HarperCollins.

Boulding, W., Kalra, A., Staelin, R., & Zeithaml, V. A. (1993). A dynamic process model of service quality: From expectations to behavioral intentions. *Journal of Marketing Research,30*(1), 7. doi:10.2307/3172510

Boyd, R. L. (2017). Psychological text analysis in the digital humanities. *Data Analytics in Digital Humanities*,161-189. doi:10.1007/978-3-319-54499-1_7

Cheng, M. (2016). Sharing economy: A review and agenda for future research. *International Journal of Hospitality Management,57*, 60-70. doi:10.1016/j.ijhm.2016.06.003

Cheng, M., & Jin, X. (2019). What do Airbnb users care about? An analysis of online review comments. *International Journal of Hospitality Management,76*, 58-70. doi:10.1016/j.ijhm.2018.04.004

Cronin, J. J., & Taylor, S. A. (1992). Measuring service quality: A reexamination and extension. *Journal of Marketing,56*(3), 55. doi:10.2307/1252296

Fellbaum, C. (2000). *WordNet: An electronic lexical database*. Cambridge, MA: MIT Press.

Furrer, O., Liu, B. S., & Sudharshan, D. (2000). The relationships between culture and service quality perceptions. *Journal of Service Research,2*(4), 355-371. doi:10.1177/109467050024004

Guttentag, D. A., & Smith, S. L. (2017). Assessing Airbnb as a disruptive innovation relative to hotels: Substitution and comparative performance expectations. *International Journal of Hospitality Management,64*, 1-10. doi:10.1016/j.ijhm.2017.02.003

Guttentag, D. A., Smith, S., Potwarka, L., & Havitz, M. (2017). Why tourists choose Airbnb: A motivation-based segmentation study. *Journal of Travel Research,57*(3), 342-359. doi:10.1177/0047287517696980

Haase, M., & Pick, D. (2015). Value creation in sharing networks: Towards a typology of sharing networks. *Interaktive Wertschöpfung Durch Dienstleistungen,*439-468. doi:10.1007/978-3-658-08518-6_20

Han, H., Shin, S., Chung, N., & Koo, C. (2019). Which appeals (ethos, pathos, logos) are the most important for Airbnb users to booking? *International Journal of Contemporary Hospitality Management,31*(3), 1205-1223. doi:10.1108/ijchm-12-2017-0784

Hoffen, M. V., Hagge, M., Betzing, J. H., & Chasin, F. (2017). Leveraging social media to gain insights into service delivery: A study on Airbnb. *Information Systems and E-Business Management,16*(2), 247-269. doi:10.1007/s10257-017-0358-7

Huurne, M. T., Ronteltap, A., Corten, R., & Buskens, V. (2017). Antecedents of trust in the sharing economy: A systematic review. *Journal of Consumer Behaviour,16*(6), 485-498. doi:10.1002/cb.1667

Kallweit, K., Spreer, P., & Toporowski, W. (2014). Why do customers use self-service information technologies in retail? The mediating effect of perceived service quality. *Journal of Retailing and Consumer Services,21*(3), 268-276. doi:10.1016/j.jretconser.2014.02.002

Kathan, W., Matzler, K., & Veider, V. (2016). The sharing economy: Your business models' friend or foe? *Business Horizons*,*59*(6), 663-672. doi:10.1016/j.bushor.2016.06.006

Kosinski, M., Matz, S. C., Gosling, S. D., Popov, V., & Stillwell, D. (2015). Facebook as a research tool for the social sciences: Opportunities, challenges, ethical considerations, and practical guidelines. *American Psychologist*,*70*(6), 543-556. doi:10.1037/a0039210

Lalicic, L., & Weismayer, C. (2017). The role of authenticity in Airbnb experiences. *Information and Communication Technologies in Tourism 2017*,781-794. doi:10.1007/978-3-319-51168-9_56

Lalicic, L., & Weismayer, C. (2018). A model of tourists' loyalty: The case of Airbnb. *Journal of Hospitality and Tourism Technology*,*9*(1), 80-93. doi:10.1108/jhtt-02-2017-0020

Lee, S., & Kim, D. (2017). Brand personality of Airbnb: Application of user involvement and gender differences. *Journal of Travel & Tourism Marketing*,*35*(1), 32-45. doi:10.1080/10548408.2017.1284030

Lee, S., & Kim, D. (2018). The effect of hedonic and utilitarian values on satisfaction and loyalty of Airbnb users. *International Journal of Contemporary Hospitality Management*,*30*(3), 1332-1351. doi:10.1108/ijchm-09-2016-0504

Liang, L. J., Choi, H. C., & Joppe, M. (2017). Understanding repurchase intention of Airbnb consumers: Perceived authenticity, electronic word-of-mouth, and price sensitivity. *Journal of Travel & Tourism Marketing*,*35*(1), 73-89. doi:10.1080/10548408.2016.1224750

Liang, L. J., Choi, H. C., & Joppe, M. (2018). Exploring the relationship between satisfaction, trust and switching intention, repurchase intention in the context of Airbnb. *International Journal of Hospitality Management*,*69*, 41-48. doi:10.1016/j.ijhm.2017.10.015

Lin, P. M. (2018). Is Airbnb a good choice for family travel? *Journal of China Tourism Research*,1-18. doi:10.1080/19388160.2018.1551167

Lopez, S. J. (2013). *The encyclopedia of positive psychology*. Chichester, West Sussex, UK: Wiley-Blackwell.

Lovelock, C., & Gummesson, E. (2004). Whither services marketing? *Journal of Service Research*,*7*(1), 20-41. doi:10.1177/1094670504266131

Lu, C., & Kandampully, J. (2016). What drives customers to use access-based sharing options in the hospitality industry? *Research in Hospitality Management*,*6*(2), 119-126. doi:10.1080/22243534.2016.1253276

Lutz, C., Hoffmann, C. P., Bucher, E., & Fieseler, C. (2017). The role of privacy concerns in the sharing economy. *Information, Communication & Society*,*21*(10), 1472-1492. doi:10.1080/1369118x.2017.1339726

Lutz, C., & Newlands, G. (2018). Consumer segmentation within the sharing economy: The case of Airbnb. *Journal of Business Research,88*, 187-196. doi:10.1016/j.jbusres.2018.03.019

Mao, Z., & Lyu, J. (2017). Why travelers use Airbnb again? *International Journal of Contemporary Hospitality Management,29*(9), 2464-2482. doi:10.1108/ijchm-08-2016-0439

Matz, S. C., & Netzer, O. (2017). Using big data as a window into consumers' psychology. *Current Opinion in Behavioral Sciences,18*, 7-12. doi:10.1016/j.cobeha.2017.05.009

Matzler, K., Bidmon, S., & Grabner-Kräuter, S. (2006). Individual determinants of brand affect: The role of the personality traits of extraversion and openness to experience. *Journal of Product & Brand Management,15*(7), 427-434. doi:10.1108/10610420610712801

Mauri, A. G., Minazzi, R., Nieto-García, M., & Viglia, G. (2018). Humanize your business. The role of personal reputation in the sharing economy. *International Journal of Hospitality Management,73*, 36-43. doi:10.1016/j.ijhm.2018.01.017

Milanova, V., & Maas, P. (2017). Sharing intangibles: Uncovering individual motives for engagement in a sharing service setting. *Journal of Business Research,75*, 159-171. doi:10.1016/j.jbusres.2017.02.002

Mody, M. A., Suess, C., & Lehto, X. (2017). The accommodation experiencescape: A comparative assessment of hotels and Airbnb. *International Journal of Contemporary Hospitality Management,29*(9), 2377-2404. doi:10.1108/ijchm-09-2016-0501

Molz, J. G. (2014). Toward a network hospitality. *First Monday,19*(3). doi:10.5210/fm.v19i3.4824

Möhlmann, M. (2015). Collaborative consumption: Determinants of satisfaction and the likelihood of using a sharing economy option again. *Journal of Consumer Behaviour,14*(3), 193-207. doi:10.1002/cb.1512

Narasimhan, C., Papatla, P., Jiang, B., Kopalle, P. K., Messinger, P. R., Moorthy, S., . . . Zhu, T. (2017). Sharing economy: Review of current research and future directions. *Customer Needs and Solutions,5*(1-2), 93-106. doi:10.1007/s40547-017-0079-6

Pansari, A., & Kumar, V. (2016). Customer engagement: The construct, antecedents, and consequences. *Journal of the Academy of Marketing Science,45*(3), 294-311. doi:10.1007/s11747-016-0485-6

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). *Servqual: A multiple item scale for measuring consumer perceptions of service quality*. Cambridge, MA.: Marketing Science Institute.

Park, G., Schwartz, H. A., Eichstaedt, J. C., Kern, M. L., Kosinski, M., Stillwell, D. J., . . . Seligman, M. E. (2015). Automatic personality assessment through social media language. *Journal of Personality and Social Psychology,108*(6), 934-952. doi:10.1037/pspp0000020

Pesonen, J., & Tussyadiah, I. (2017). Peer-to-peer accommodation: Drivers and user profiles. *Collaborative Economy and Tourism on the Verge,*285-303. doi:10.1007/978-3-319-51799-5_17

Petticrew, M., & Roberts, H. (2012). *Systematic reviews in the social sciences: A practical guide*. Malden, MA: Blackwell.

Pine, B. J., & Gilmore, J. H. (2011). *The experience economy*. Boston: Harvard Business Review Press.

Pitt, L. F., & Papania, L. (2007). In the words: Managerial approaches to exploring corporate intended image through content analysis. *Journal of General Management,32*(4), 1-16. doi:10.1177/030630700703200401

Poon, K. Y., & Huang, W. (2017). Past experience, traveler personality and tripographics on intention to use Airbnb. *International Journal of Contemporary Hospitality Management,29*(9), 2425-2443. doi:10.1108/ijchm-10-2016-059

Prager, K. J. (1998). *The psychology of intimacy*. New York: Guilford.

Priporas, C., Stylos, N., Rahimi, R., & Vedanthachari, L. N. (2017). Unraveling the diverse nature of service quality in a sharing economy. *International Journal of Contemporary Hospitality Management,29*(9), 2279-2301. doi:10.1108/ijchm-08-2016-0420

Regan, M. O., & Choe, J. (2017). Airbnb and cultural capitalism: Enclosure and control within the sharing economy. *Anatolia,28*(2), 163-172. doi:10.1080/13032917.2017.1283634

Richard, B., & Cleveland, S. (2016). The future of hotel chains. *Journal of Vacation Marketing,22*(3), 239-248. doi:10.1177/1356766715623827

Schreiner, N., Pick, D., & Kenning, P. (2018). To share or not to share? Explaining willingness to share in the context of social distance. *Journal of Consumer Behaviour,17*(4), 366-378. doi:10.1002/cb.1717

Semin, G. R., & Fiedler, K. (1991). The linguistic category model, its bases, applications and range. *European Review of Social Psychology,2*(1), 1-30. doi:10.1080/14792779143000006

Simmons, G. (2008). Marketing to postmodern consumers: Introducing the internet chameleon. *European Journal of Marketing,42*(3/4), 299-310. doi:10.1108/03090560810852940

So, K. K., King, C., Sparks, B. A., & Wang, Y. (2014). The role of customer engagement in building consumer loyalty to tourism brands. *Journal of Travel Research,55*(1), 64-78. doi:10.1177/0047287514541008

Solis, B. (2011). *Engage: The complete guide for brands and businesses to build, cultivate, and measure success in the new web*. Hoboken, NJ: Wiley.

Stollery, A., & Jun, S. H. (2017). The antecedents of perceived value in the Airbnb context. *Asia Pacific Journal of Innovation and Entrepreneurship,11*(3), 391-404. doi:10.1108/apjie-12-2017-040

Su, L., Swanson, S. R., & Chen, X. (2015). The impact of perceived service fairness and quality on the behavioral intentions of chinese hotel guests: The mediating role of consumption emotions. *Journal of Travel & Tourism Marketing,33*(Sup1), 88-102. doi:10.1080/10548408.2015.1008668

Tussyadiah, I. P. (2016). Factors of satisfaction and intention to use peer-to-peer accommodation. *International Journal of Hospitality Management,55*, 70-80. doi:10.1016/j.ijhm.2016.03.005

Tussyadiah, I. P., & Zach, F. (2016). Identifying salient attributes of peer-to-peer accommodation experience. *Journal of Travel & Tourism Marketing,34*(5), 636-652. doi:10.1080/10548408.2016.1209153

Tynan, C., & Mckechnie, S. (2009). Experience marketing: A review and reassessment. *Journal of Marketing Management,25*(5-6), 501-517. doi:10.1362/026725709x461821

Voskoboynikov, F. (2017). *The psychology of effective management: Strategies for relationship building*. New York: Routledge.

Walls, A. R., Okumus, F., Wang, Y. (., & Kwun, D. J. (2011). An epistemological view of consumer experiences. *International Journal of Hospitality Management,30*(1), 10-21. doi:10.1016/j.ijhm.2010.03.008

Wang, C., & Jeong, M. (2018). What makes you choose Airbnb again? An examination of users' perceptions toward the website and their stay. *International Journal of Hospitality Management,74*, 162-170. doi:10.1016/j.ijhm.2018.04.006

Wang, D., & Nicolau, J. L. (2017). Price determinants of sharing economy based accommodation rental: A study of listings from 33 cities on Airbnb.com. *International Journal of Hospitality Management,62*, 120-131. doi:10.1016/j.ijhm.2016.12.007

Wedel, M., & Kannan, P. (2016). Marketing analytics for data-rich environments. *Journal of Marketing,80*(6), 97-121. doi:10.1509/jm.15.0413

Wittel, A. (2001). Toward a network sociality. *Theory, Culture & Society,18*(6), 51-76. doi:10.1177/02632760122052048

Xie, K., & Mao, Z. (2019). Locational strategy of professional hosts: Effect on perceived quality and revenue performance of Airbnb listings. *Journal of Hospitality & Tourism Research,*109634801983627. doi:10.1177/1096348019836277

Yang, S., & Ahn, S. (2016). Impact of motivation in the sharing economy and perceived security in attitude and loyalty toward Airbnb. doi:10.14257/astl.2016.129.36

Yarimoglu, E. K. (2015). A review of service and e-service quality measurements: Previous literature and extension. *Journal of Economic and Social Studies,5*(1). doi:10.14706/jecoss115110

Yen, Y. (2014). A comparison of quality satisfaction between transactional and relational customers in e-commerce. *The TQM Journal,26*(6), 577-593. doi:10.1108/tqm-11-2012-0089

Yoo, K., & Gretzel, U. (2011). Influence of personality on travel-related consumer-generated media creation. *Computers in Human Behavior,27*(2), 609-621. doi:10.1016/j.chb.2010.05.002

Young, C. A., Corsun, D. L., & Xie, K. L. (2017). Travelers' preferences for peer-to-peer (P2P) accommodations and hotels. *International Journal of Culture, Tourism and Hospitality Research,11*(4), 465-482. doi:10.1108/ijcthr-09-2016-0093

Zaibaf, M., Taherikia, F., & Fakharian, M. (2013). Effect of perceived service quality on customer satisfaction in hospitality industry: Gronroos' service quality model development. *Journal of Hospitality Marketing & Management,22*(5), 490-504. doi:10.1080/19368623.2012.670893

Zervas, G., Proserpio, D., & Byers, J. W. (2017). The rise of the sharing economy: Estimating the impact of Airbnb on the hotel industry. *Journal of Marketing Research,54*(5), 687-705. doi:10.1509/jmr.15.0204

Zhang, H., Babar, M. A., & Tell, P. (2011). Identifying relevant studies in software engineering. *Information and Software Technology,53*(6), 625-637. doi:10.1016/j.infsof.2010.12.010

Zhang, L., Yan, Q., & Zhang, L. (2018). A computational framework for understanding antecedents of guests perceived trust towards hosts on Airbnb. *Decision Support Systems,115*, 105-116. doi:10.1016/j.dss.2018.10.002