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Cross-culture differences in tourists faced with Japanese hospitality: A text mining and natural language processing study of satisfaction and dissatisfaction factors in Chinese and Western cultures

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1 Introduction

Japan has been known historically for its hospitality being the highest grade. The spirit of Japanese hospitality is celebrated around the world in a single Japanese word: *Omotenashi*. With roots in Japanese history and tea ceremony, their hospitality is famous around the world Al-alsheikh and Sato (2015). Therefore it would stand to reason that tourists visiting Japan would have this hospitality as their first and foremost satisfaction factor. However, it is known that customers from different countries and cultures hold different expectations Engel et al. (1990). Thus, it could be theorized that their satisfaction factors should be different. How will different cultures react and perceive hotels and their hospitality in this context? Our study attempts to bring light to this

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with two essential tourist populations that differ in culture to Japan: Chinese and Western tourists.

In the last couple of decades, the Japanese economy has been more and more affected by an increase in inbound international tourism (Jones et al. 2009) with a Year-on-Year Growth Rate of 19.3% in 2017, with a total of 28,691,073 inbound tourists that year (Japan National Tourism Organization 2019). From this total, the tourist population was mostly Asian (86.14%), and approximately a fourth of the total (25.63%) came from China. Western countries, counting English-speaking countries and the whole of Europe, make for 11.4% of the total, with a 7.23% of the total being countries where English is the official or the de facto national language. The effect of Chinese tourists on international economies is increasing. From that, the number of researchers interested in this phenomenon has been increasing as well. (Sun et al. 2017). With these and other multicultural tourist populations, the tourist market is more and more diverse. Diversity in customers' cultural backgrounds means that their expectations when staying at a hotel will also be varied. Hotel management, therefore, needs to cater to these needs and expectations to increase customer satisfaction, maintain a good reputation, and generate positive word-of-mouth.

However, recent studies on social sciences, and thus, on tourist behavior, have been performed using surveys on populations that could be culturally biased for the western world (Nielsen et al. 2017; Jones 2010; Gunaratne 2009; Hogan and Emler 1978). Those that do include Asian populations in their analysis, most commonly study Chinese tourist behavior (e.g. Liu et al. 2019; Chang et al. 2010; Dongyang et al. 2015). The few that compare Asian to western tourist behavior (e.g. Choi and Chu 2000) are commonly survey or interview-based studies with small samples, which, while valid, can have its limitations. This gap in research creates a need for cross-cultural studies for the increasing Asian and Western tourist populations. It could be said that Westerners make for a smaller portion of the tourist population compared to Asians. However, according to Choi and Chu (2000), Westerners are known as "long-haul" customers, spending more than 45% of their budget on hotel lodging. In comparison, their Asian counterparts only spend 25% of their budget on hotels. Therefore, it is essential to study both Asian and Western tourist populations, their differences, and contrast the results with existing literature.

With the advent of Web 2.0 and customer review websites, researchers realized the benefits of online reviews for research, and their importance for sales (Ye et al. 2009; Basuroy et al. 2003), customer consideration (Vermeulen and Seegers 2009) and perception of services and products (Browning et al. 2013), among other effects of online interactions between customers (e.g. Xiang and Gretzel 2010; Ren and Hong 2019). Consequentially, tourism research also began to use information collected online for data mining analysis, such as opinion mining (e.g. Hu et al. 2017), predicting hotel demand from online traffic (Yang et al. 2014), recommender systems (e.g. Loh et al. 2003), and more. Data mining, machine learning, and big data methodologies can increase the number of manageable samples per study. The increase can be from the hundred samples manually analyzed by researchers to the hundreds of thousands that are automatically analyzed by machines. This technology can not only help confirm existing theories but also lead to finding new patterns and to knowledge discovery (Fayyad et al. 1996).

In this study, we take advantage of the availability of enormous amounts of online reviews of Japanese hotels by both Mainland Chinese tourists posting in *Ctrip* and Western English-speaking tourists populations posting in *TripAdvisor*. With this data, we can confirm existing theories about their differences in behavior, as well as perform an exploration of the data to discover factors that could have been overlooked in the past. In order to do this, we use machine learning to automatically classify review sentences as positive or negative opinions of the hotel. We then perform a statistical extraction of the topics that concerns the customers of each population the most.

2 Research objective

This study's objective is to determine the difference in factors driving satisfaction and dissatisfaction between Chinese and English-speaking tourists in the context of high-grade hospitality of Japanese hotels using text-mining techniques. We aim to contrast the satisfaction and dissatisfaction factors of both customer groups across several price ranges using machine learning to classify the sentiment of texts, and natural language processing to study commonly used word pairings. More importantly, we also intend to measure how hard and soft attributes influence much satisfaction and dissatisfaction of both customer groups. We define hard attributes as those that are difficult to change by a hotel management without investing in infrastructure or real estate. In contrast, soft attributes are easily modifiable by improvements in management.

Our proposal includes the use of large scale data from online hotel reviews in Chinese and English to study their differences in a statistical manner. In the past, survey-based studies have provided a theoretical background for a few specific tourist populations of a single culture or that travel with a single purpose. The short scope of those studies means that cultural and language differences often cannot be observed in a single study.

Our study attempts to uncover the difference in satisfaction and dissatisfaction factors between different cultures. These factors can become the focal point for making improvements in the tourism and service industries and increase customer satisfaction. Satisfied customers will then write more positive online reviews that will, in turn, increase sales and attract new customers.

3 Theoretical background and research questions

3.1 Japanese hospitality: *Omotenashi*

The spirit of Japanese hospitality, or *Omotenashi*, has roots in the countries history. However, to this day, it is regarded as the highest standard (Ikeda

2013; Al-alsheikh and Sato 2015). There is even a famous phrase in customer service in Japan: *okyaku-sama wa kami-sama desu*, or translated "The customer is god". Some say that *Omotenashi* originated from the old Japanese art of the tea ceremony in the 16th century. However, other scholars found that its roots come from even earlier, in the form of formal banquets in the 7th century (Aishima et al. 2015). The practice of high standards in hospitality has survived throughout the years. Today, it permeates all business practices in Japan, from the cheapest convenience stores to the most expensive ones. Manners, service, and respect towards the customer are taught to workers in their training, and high standards are always followed as to not fall behind in the competition. In Japanese businesses, hotels included, staff members are trained to speak in *sonkeigo*, or "respectful language", one of the most formal of the Japanese formality syntaxes. They are also trained to bow with different depths depending on the situation, where a light bow could be used to say: "Please, allow me to guide you". Deep bows are also used to apologize for any inconvenience the customer could have, followed by a very respectful apology as well. In fact, despite the word *omotenashi* being translated directly as "hospitality", it includes both the concepts of hospitality and service (Kuboyama 2020).

It stands to reason that this high level of hospitality would be a positive aspect that would be at the top of satisfaction for any customer. However, in Japan, every business has this high level of hospitality, in differing levels of success. A simple convenience shop around the corner could be more hospitable if hotel management falls behind. Businesses have to strive to be the most hospitable, and hotels are not allowed to lag in this competition. Because of this, other factors such as proximity to a convenience store, or transport availability, or perhaps room quality might be more critical to a customer. Customers can always achieve satisfaction from hospitality elsewhere, so hotels need to be competitive in their hospitality.

Therefore we pose a research question for our study:

Research Question 1a: *To what degree are Chinese and Western tourists satisfied with Japanese Omotenashi factors such as staff behavior or service?*

However, Japanese hospitality comes from Japanese culture. Different cultures interacting with it could have a different reaction. While some might be impressed by it, some might consider other factors more important to their stay in a hotel. This point leads us to a derivative of the above research question:

Research Question 1b: *Do Western and Chinese tourists have a different reaction to Japanese Omotenashi factors such as staff behavior or service?*

3.2 Customer satisfaction and dissatisfaction during hotel lodging

Customer satisfaction in tourism has been analyzed since decades past, Hunt (1975) having defining customer satisfaction as the realization or overcoming of expectations towards the service. Oliver (1981) defined it as an emotional response to the provided services in retail and other contexts, and Oh and Parks (1996) reviewed the psychological processes of customer satisfaction for the hospitality industry. It is generally agreed upon that satisfaction and dissatisfaction stem from the individual expectations of the customer. As such, Engel et al. (1990) states that each customer's background, therefore, influences satisfaction and dissatisfaction. Western and Chinese customers can then have very different factors of satisfaction and dissatisfaction since they have different backgrounds and cultures. These varying backgrounds will lead to varying expectations of the hotel services, the experiences they want to have while staying at a hotel, and the level of comfort that they will have. These expectations will be there from the moment that they choose the hotel throughout their stay. These different expectations, in turn, will determine the distinct factors of satisfaction and dissatisfaction for each kind of customer, as well as the order in which they prioritize them.

Because of their different origins, expectations, and cultures, it stands to reason Chinese and Western tourists could have completely different factors to one another. Therefore, it could be that some factors do not appear in the other reviews at all. For example, between different cultures, it can be that a single word can express some concept that would take more words in the other language. So we must measure their differences or similarities at their common ground as well.

Studies on customer satisfaction (e.g. Truong and King 2009; Romão et al. 2014; Wu and Liang 2009) commonly use the Likert scale (Likert 1932) (e.g. 1 to 5 scale from strongly dissatisfied to strongly satisfied) to perform statistical analysis of which factors relate most to satisfaction on the same dimension as dissatisfaction (e.g. Chan et al. 2015; Choi and Chu 2000). The use of the Likert scale leads to correlation analyses where one factor can lead to satisfaction, implying that the lack of it can lead to dissatisfaction. However, a binary distinction (satisfied or dissatisfied) could allow us to analyze the factors that correlate to satisfaction and explore factors that are solely linked to dissatisfaction. There are fewer examples of this approach, but studies have done this in the past (e.g. Zhou et al. 2014). This method can indeed decrease the extent to which we can analyze degrees of satisfaction or dissatisfaction. However, it has the benefit that it can be applied to a large sample of text data via automatic sentiment detection techniques using artificial intelligence.

Previous research has also focused on soft attributes that are controllable by the hotel managers and staff, i.e., hotel services, staff behavior, or facilities (e.g. Shanka and Taylor 2004; Choi and Chu 2001). However, little focus is put on hard factors that are uncontrollable by the hotel staff that can play a part in the customers' choice behavior and satisfaction. Examples of these factors include the surroundings of the hotel, location, language immersion of the country as a whole, or touristic destinations, as well as the integration of the hotel with tours available nearby, among other factors.

This leads to another couple of research questions:

Research Question 2a: *To what degree does satisfaction and dissatisfaction stem from hard and soft attributes of the hotel?*

Research Question 2b: *How differently do Chinese and Western customers perceive hard and soft attributes of the hotel?*

The resulting proportions of hard attributes to soft attributes for each population could serve as a measurement of how much the improvement of management in the hotel can increase future satisfaction in customers.

3.3 Chinese and Western tourist behavior

In the past, tourist behavior analyzed from western samples was wrongly thought to be a representation of universal behavior across all cultures (Nielsen et al. 2017; Jones 2010; Gunaratne 2009; Hogan and Emler 1978). Recently, however, with the rise of Chinese outbound tourism, both academic researchers and businesses have decided to study Chinese tourist behavior (Sun et al. 2017). This increase resulted in several studies focusing on only the behavior of this subset of tourists. To this day, cross-cultural studies and analyses for Asian and Western tourists are scarce. One example is Choi and Chu (2000), where it was found that Western tourists visiting Hong Kong are satisfied more with room quality while Asians are satisfied with value for money. Another is Bauer et al. (1993), where Westerners prefer the hotel health facilities while the Asian tourists were more inclined to enjoy the Karaoke facilities of hotels, and both groups tend to have high expectations about the overall facilities. Another example is Kim and Lee (2000), where American tourists were found to be individualistic and motivated by novelty, while Japanese tourists were found to be collectivist and motivated by prestige and family, with an escape from routine and an increase in knowledge as a common motivator.

One thing to note with the above cross-culture analyses is that they were performed before the year 2000. The current Chinese economy boom is making an increase in the influx of tourists. However, that boom could have created a difference in the expectations of tourists. In turn, that boom could have influenced their satisfaction factors when traveling. Another note is that these studies were performed with questionnaires in places where it would be easy to locate tourists, i.e., airports. However, our study of online reviews takes the data that the hotel customers uploaded themselves.

More recent studies have surfaced as well. A cross-country study Francesco and Roberta (2019) using posts from U.S.A. citizens, Italians and Chinese tourists, determined using a text link analysis that customers from different countries indeed have a different perception and emphasis of a few predefined hotel attributes. According to their results, it appears that U.S.A. customers perceive cleanliness and quietness most positively and that Chinese customers perceive budget and restaurant above other attributes. Another couple of studies Jia (2020); Huang (2017) analyze differences between Chinese and U.S.

tourists using text mining techniques and more massive datasets, although in a restaurant context.

These last three articles focus on U.S.A. culture, while our study focuses on Western culture. Another difference with our study is that of the context of the study. The first study Francesco and Roberta (2019) has the context of tourists from three countries staying in hotels across the world, the second choosing restaurant reviews from the U.S.A. and Chinese tourists eating in three countries in Europe, and the third analyzing reviews of restaurants in Bejing. Our study, on the other hand, focuses on Western culture, instead of a single Western country, and Chinese culture clashing with the hospitality environment in Japan, specifically. The importance of Japan in this analysis comes from the unique environment of high-grade hospitality that the country presents. In this environment, do customers hold their satisfaction to this hospitality regardless of their culture, or are other factors are more important to the customers overall? Our study measures this at a large scale across different hotels in Japan.

Other studies, perhaps recognizing that samples being comprised of people from Western industrialized countries are not representative, have gone further and studied people from many countries in their samples, and performed a more universal and holistic (not cross-culture) analysis. Choi and Chu (2001), for example, analyzed hotel guest satisfaction determinants in Hong Kong with surveys in English, Chinese and Japanese translations, with people from many countries in their sample. Choi and Chu (2001) found that staff service quality, room quality, and value for money were the top satisfaction determinants. As another example, Uzama (2012) produced a typology for foreigners coming to Japan for tourism, without making distinctions for their culture, but their motivation in traveling in Japan. In another study, Zhou et al. (2014) analyzed hotel satisfaction using English and Mandarin online reviews from guests staying in Hangzhou, China coming from many different countries. The general satisfaction score was noticed to be different in those countries. However, a more in-depth cross-cultural analysis of the satisfaction factors wasn't performed. As a result of their research, Zhou et al. (2014) thus found that customers are universally satisfied by welcome extras, dining environments, and special food services.

Regarding Western tourist behavior, a few examples can tell us what to expect when analyzing our data. Kozak (2002) found that British and German tourists' satisfaction determinants while visiting Spain and Turkey were hygiene and cleanliness, hospitality, the availability of facilities and activities, and accommodation services. Shanka and Taylor (2004) found that English-speaking tourists in Perth, Australia were most satisfied with staff friendliness, the efficiency of check-in and check-out, restaurant and bar facilities, and lobby ambiance.

Regarding outbound Chinese tourists, academic studies about Chinese tourists have increased (Sun et al. 2017). Different researchers have found that Chinese tourist populations have several specific attributes. According to Ryan and Mo (2001) and their study of Chinese tourists in New Zealand, Chinese tourists prefer nature, cleanliness, and scenery in contrast to experiences and activities. Dongyang et al. (2015) studied Chinese tourists in the Kansai region of Japan and found that Chinese tourists are satisfied mostly with exploring the food culture of their destination, cleanliness, and staff. Studying Chinese tourists in Vietnam, Truong and King (2009) found that Chinese tourists are highly concerned with value for money. According to Liu et al. (2019), Chinese tourists tend to have harsher criticism when compared with other international tourists. Moreover, as stated by Gao et al. (2017), who analyzed different generations of Chinese tourists and their connection to nature while traveling, Chinese tourists prefer nature overall. However, the younger generations seem to do so less than their older counterparts.

Although the studies focusing only on Chinese tourists or only on Western tourists have a narrow view, their theoretical contributions are valuable. We can see that depending on the study and the design of questionnaires, as well as the destinations; the results can vary greatly. Not only that, but while there seems to be some overlap in most studies, some factors are completely ignored in one study but not in the other. Since our study uses data mining, the definition of each factor is left for hotel customers to decide en masse via their reviews. This means that the factors will be selected through statistical methods alone, instead of being defined by the questionnaire. Our method allows us to find factors that we would not have contemplated. It also avoids enforcing a factor on the mind of study subjects by presenting them with a question that they did not think of by themselves. This large variety of opinions in a well-sized sample, added to the automatic findings of statistical text analysis methods, gives an advantage to our study compared to others with smaller samples. Besides, this study could help us analyze the satisfaction and dissatisfaction factors cross-culturally and compare them with the existing literature.

Undoubtedly previous literature has examples of other cross-culture studies of tourist behavior and to further highlight our study and its merits. A contrast is shown in Table 1. This table shows that older studies were conducted with surveys and had a different study topic. These are changes in demand Bauer et al. (1993), tourist motivation Kim and Lee (2000), and closer to our study, satisfaction levels Choi and Chu (2000). However, our study topic is not the levels of satisfaction but the factors that drive it, as well as dissatisfaction, which is overlooked in most studies. Newer studies with larger samples and similar methodologies have emerged, although two of these study restaurants instead of hotels Jia (2020); Huang (2017). One important difference is the geographical focus of their studies. While Francesco and Roberta (2019); Jia (2020); Huang (2017) have a multi-national focus, we instead focus on Japan. The focus on Japan is important because of its leading rank in hospitality across all types of businesses. This raises the question: in such an environment, will the customers be universally satisfied with this factor, or will they have differing views within their cultures? Our study brings light to the changes, or lack thereof, in different touristic environments where an attribute can be considered as excellent. The number of samples in other text-mining studies is also smaller to ours in comparison. Apart from that, every study has a different text mining method.

Table 1: Comparison between cross-culture or cross-country previous studies and our study.

	Bauer et.al (1993)	**Choi and Chu (2000)**	**Kim and Lee (2000)**	**Huang (2017)**	**Francesco and Roberta (2019)**	**Jia (2020)**	**Our study**
Comparison objects	Asians vs Westerns	Asians vs Westerners	Anglo-Americans vs Japanese	Chinese vs English-speakers	USA vs China vs Italy	Chinese vs US tourists	Chinese vs Westerners
Study topic	Changes in demand	Satisfaction Levels	Tourist Motivation	Dining experience of Roast Duck	Perception and Emphasis	Motivation and Satisfaction	**Satisfaction and Dissatisfaction**
Geographical focus	Asia Pacific region	Hong Kong	Global	Beijing	Multi-national	Multi-national	**Japan**
Industry	Hotels	Hotels	Tourism	Restaurant (Beijing Roast Duck)	Hotels	Restaurants	Hotels
Study subjects	Hotel managers	Hotel customers	Tourists arriving in airport	Diners online reviews	Hotel customers online reviews	Diners online reviews	Hotel customers online reviews
Sample method	surveys	surveys	survey	text mining	text mining	text mining	text mining
Number of samples	185 surveys	540 surveys	165 Anglo-American 209 Japanese	990 Chinese reviews 398 English reviews	9000 reviews (3000 per country)	2448 reviews (1360 Chinese) (1088 English)	**89,207 reviews (48,070 Chinese) (41,137 English)**
Study method	statistics	VARIMAX	MANOVA	Semantic Network Analysis	Text Link Analysis	Topic modeling (LDA)	**SVM, Dependency Parsing and POS tagging**
Subject nationality	Asians: China, Fiji, Hong Kong, Indonesia, Malaysia, Singapore, Taiwan, Guam, Tahiti, Thailand Westerners: Australia, New Zealand	Asians: China, Taiwan, Japan, South Korea, South-East Asia Westerners: North America, Europe, Australia, New Zealand	USA, Japan	English-speakers: U.K., U.S., Australia, New Zealand, Canada, Ireland Chinese-speakers: China	USA, China, Italy	USA, China	Chinese-speakers: China English-speakers: (U.K., U.S., Australia, New Zealand, Canada, Ireland)

3.4 Data mining, machine learning, knowledge discovery and sentiment analysis

In the current world, data is presented to us in larger and larger quantities. Today's data sizes were commonly only seen in very specialized large laboratories with supercomputers a couple of decades ago. However, they are now standard for market and managerial studies, independent university students, and any scientist that can connect to the Internet. Such quantities of data are available to study now more than ever. Nevertheless, it would be impossible for researchers to parse all of this data by themselves. As Fayyad et al. (1996) summarizes, data by itself is unusable until it goes through a process of selection, preprocessing, transformation, mining, and evaluation. Only then can it be established as knowledge. With the tools available to us in the era of information science, algorithms can be used to detect patterns that would take researchers too long to recognize. These patterns can, later on, be evaluated to generate knowledge. This process is called Knowledge Discovery in Databases.

Now, there are, of course, many sources of numerical data to be explored. However, perhaps what is most available and interesting to managerial purposes is the resource of customers' opinions in text form. Since the introduction of Web 2.0, a never before seen quantity of valuable information is posted to the Internet at a staggering speed. Text mining has then been proposed more than a decade ago to utilize this data (e.g. Rajman and Besançon 1998; Nahm and Mooney 2002). Using Natural Language Processing, one can parse language in a way that translates to numbers so that a computer can analyze it. Since then, text mining techniques have improved over the years. This has been used in the field of hospitality as well for many purposes, including satisfaction analysis from reviews (e.g Berezina et al. 2016; Xu and Li 2016; Xiang et al. 2015; Hargreaves 2015; Balbi et al. 2018), social media's influence on travelers (e.g. Xiang and Gretzel 2010), review summarization (e.g. Hu et al. 2017), perceived value of reviews (e.g Fang et al. 2016), and even predicting hotel demand using web traffic data (e.g Yang et al. 2014).

More than only analyzing patterns within the text, researchers have found how to determine the sentiment behind a statement based on speech patterns, statistical patterns, and other methodologies. This method is called sentiment analysis or opinion mining. A precursor of this method was attempted decades ago (Stone et al. 1966). With sentiment analysis, one could use patterns in the text to determine whether a sentence was being said with a positive opinion, a critical opinion. This methodology could even determine other ranges of emotions, depending on the thoroughness of the algorithm. Examples of sentiment analysis include ranking products through online reviews (e.g Liu et al. 2017; Zhang et al. 2011), predicting political poll results through opinions in Twitter (O'Connor et al. 2010), and so on. In the hospitality field, it has been used to classify reviewers' opinions of hotels in online reviews (e.g. Kim et al. 2017; Al-Smadi et al. 2018).

The algorithm used for sentiment analysis in our study is called a Support Vector Machine. It is a form of supervised machine learning used for binary classification. This means a sample of labeled training data is given to the algorithm to detect patterns in the data and use those patterns to establish a method for classifying other unlabeled data automatically. Machine learning is a general term used for algorithms that, when given data, will automatically use that data to "learn" from its patterns and apply them for improving upon a task. Learning machines can be supervised, as in our study, where the algorithm has manually labeled data to know the correct task result template. Machine learning can also be unsupervised, where without any pre-labeled data. In this latter case, the machine will analyze the structure and patters on the data and perform a task based on its conclusions on its own. Our study calls for a supervised machine since text analysis can be intricate. Many patterns might occur, but we are only interested in satisfaction and dissatisfaction labels. Consequently, we teach the machine through previously labeled text samples.

Machine learning and data mining are two fields with a significant overlap since they can use each other's methods to achieve the task at hand. Machine learning methods focus on the prediction of new data based on known properties and patterns of the given data. Data mining, on the other hand, is discovering new information and new properties of the data. Our machine learning approach will learn the sentiment patterns of our sample texts showing satisfaction and dissatisfaction, and using these to label the rest of the data. We are not exploring new patterns in the sentiment data. However, we are using sentiment predictions for knowledge discovery in our database. Thus our study is a data mining experiment based on machine learning.

Because the methodology for finding patterns in the data is automatic and statistical, it is both reliable and unpredictable. Reliable in that the algorithm will find a pattern by its nature. Unpredictable in that because it has no intervention from the researchers in making questionnaires, it can have different results from anything that the researchers could expect. These qualities determine why, much like actual mining, data mining is mostly exploratory. One can never be sure that one will find a specific something. However, we can make predictions and estimates about where to find knowledge, and what kind of knowledge we can uncover. The exploration of large opinion datasets with these methods is essential. The reason being we can discover knowledge that could be missed by looking at a localized sample rather than a holistic view of every users' opinion. In other words, a machine algorithm can find the needles in a haystack that we did not know were there from taking small bundles of hay at a time.

In this study, we can predict that several things might occur. Our data could show satisfaction and dissatisfaction factors that are universal, and it could also find strictly cultural factors. However, we expect that both of these options will present themselves. We can also assert that we could arrive at very similar results to previous literature if they are correct in their findings. However, we are using a database of several orders of magnitude larger. We can also expect that, because of the lack of questionnaire design and users' freedom to record their pleasures and grievances, we may discover patterns that researchers previously noticed.

4 Methodology

We have extracted a large number of text reviews from a Chinese portal site *Ctrip*, as well as the travel site *TripAdvisor*. We then determined the most commonly used words that would contribute the most to positive and negative opinions in a review. We did this using Shannon's entropy to extract keywords from their vocabulary. These positive and negative keywords allow us to perform a Support Vector Machine (SVM) based emotional classification of the reviews in large quantities, saving time and resources for the researchers. We classified the sentences in the extracted reviews as emotionally positive or negative, using an optimized Support Vector Classifier (SVC). We then applied a dependency parsing to the reviews, as well as a Part of Speech tagging (POS tagging) to observe the relationship between adjective keywords and other nouns used in the reviews. We split the dataset in price ranges to observe the satisfaction factors and their differences between different lower class hotels and higher class hotels. We observed the frequency of the terms in the dataset to extract the most utilized words in either kind of review. We show an overview of this methodology in Figure 1, which is an updated version of the methodology used by Alemán Carreón et al. (2018). Finally, we also observed if the satisfaction factors were soft or hard attributes of the hotel, meaning whether a hotel management can easily change those attributes, or if they are difficult to change without investing in infrastructure or real estate.

4.1 Data collection

In the data collection stage for Chinese reviews in *Ctrip*, a total of 5774 review pages of hotels in Japan were collected. From these pages, we extracted a total of 245,919 reviews, from which 211,932 were detected to be standard Mandarin Chinese from mainland China. Since a single review can have sentences with

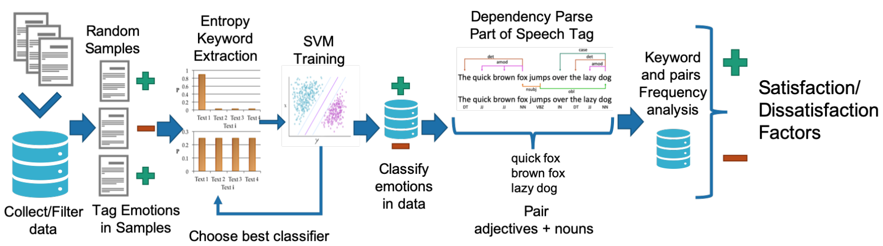


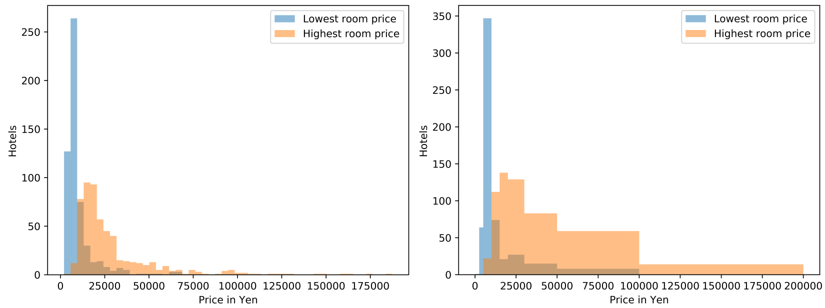
Fig. 1: Overview of the methodology to quantitatively rank satisfaction factors.

different sentiments, we separated sentences using punctuation marks. The Chinese reviews were comprised of 187,348 separate sentences.

In the *TripAdvisor* data collection, we collected data from 21,380 different hotels. In total, we collected 295,931 reviews, from which 295,503 were detected to be in English. Similarly to the Chinese data, we then separated these English reviews into 2,694,261 sentences using the *gensim* python library. For the language detection in both cases we used the *langdetect* python library.

However, we needed to make the data and comparisons we draw from each of these datasets fair. For that purpose, we filtered both databases only to contain reviews from hotels in both datasets, using their English names to do a search match. We also filtered them to be in the same date range and cut off reviews outside of each other's date ranges. In addition, we selected only the hotels that had a pricing information available. We extracted the lowest price possible for a room or bed for one night, and the highest price possible for one night as well. The difference in pricing can be from better room settings, such as double or twin rooms, or suites of several classes depending on the hotel. Regardless of the reason, the highest priced room can be an indicator of the class of hotel indirectly, which can give us an insight into the kind of service that is offered. After filtering, we found that the number of hotels in common in the data collected was 557. The overlapping date range for reviews was from July 2014 to July 2017. Within these hotels, from *Ctrip* there was 48,070 reviews comprised of 101,963 sentences, and from *TripAdvisor* there was 41,137 reviews comprised of 348,039 sentences. We found that after filtering the data, the number of reviews was similar for both English and Chinese reviews, but that English reviews tend to be longer in general.

The price for a night in these hotels ranges from low priced capsule hotels at 2000 yen per night, to high-end hotels 188,000 yen a night as the far ends of the bell curve. Customers' expectations can vary greatly depending on the pricing of the hotel room they stay at. We therefore made observations on the distribution of pricing in the hotels of our database and binned the data by price ranges, decided by consideration of objective of stay. We show these distributions in Figure 2. The structure of the data after division by price is shown in Table 2, which also includes the results of emotional classification after application of our SVC, as explained in 4.3. The first three price ranges (0 to 2500 yen, 2500 to 5000 yen, 5000 to 10,000 yen) would correspond to low class hotels or even hostels on the lower end, and cheap business hotels on the higher end. Further on there are business hotels in the next range (10,000 to 15,000 yen), and after that the stays could be at Japanese style *ryokan* when traveling in groups, high class business hotels, luxury love hotels, or higher class hotels (15,000 to 20,000 yen, 20,000 to 30,000 yen). Further than that is more likely to be *ryokan* or high class resorts or five-star hotels (30,000 to 50,000 yen, 50,000 to 100,000 yen, 100,000 to 200,000 yen). Note that because of choosing the highest price per one night in each hotel, the cheapest two price ranges (0 to 2500 yen, 2500 to 5000 yen) are empty, despite some rooms being priced at 2000 yen per night. Because of this, other tables will omit these two price ranges.



(a) 50 equal lenght bins

(b) manually set 9 price ranges

Fig. 2: Price for one night distribution, blue: lowest price, orange: highest price.

4.2 Text processing: Dependency parsing and Part of Speech tagging

Chinese text, unlike English, does not have spaces between each word to separate them. In addition, we also needed to analyze the grammatical relationship between words, be it English or Chinese, in order to understand connections between adjectives and the noun they refer to. For all these processes we used the Stanford CoreNLP pipeline developed by the Natural Language Processing Group at Stanford University (Manning et al. 2014). In order to separate Chinese words for analysis, we used the Stanford Word Segmenter (Chang et al. 2008). In the case of texts in English, however, only using spaces is not enough to correctly collect concepts. The English language is full of variations and conjugations of words depending on the context and tense. Thus, a better segmentation is achieved by using lemmatization, which returns the dictionary form of each word. For this purpose, we used the *gensim* library with the English texts.

A dependency parser analyzes the grammatical structure of a sentence, detecting connections between words and describing the action and direction of those connections. We show an example of these dependencies in Figure 3. In this study we use the Stanford NLP Dependency Parser, as described by Chen and Manning (2014). A list of dependencies used by this parser is detailed by de Marneffe and Manning (2008). In more recent versions, they use an updated dependency tag list from Universal Dependencies (Zeman et al. 2018). In our study, this step was necessary to extract adjective modifiers and their subject. We did that by parsing the entire database, and extracting instances of a few determined dependency codes. One of these dependency codes is “amod”, which stands for adjectival modifier, where an adjective modifies a noun directly (e.g. A big apple). The other dependency code we used was “nsubj”, or nominal subject, which is the syntactic subject of a class. We used this one for cases where the adjective is modifying the noun indirectly through other words (e.g. The apple is big). This dependency does not necessarily only include a combination of adjectives and nouns, but it can also be connected

Table 2: Collected data and structure after price range categorizing.

Price range	Data collected	Ctrip database	Tripadvisor database
0: All Prices	Hotels	557	557
	Reviews	48,070	41,137
	Sentences	101,963	348,039
	Positive sentences	88,543	165,308
	Negative sentences	13,420	182,731
1: 0 to 2500 yen	Hotels	0	0
	Reviews	0	0
2: 2500 to 5000 yen	Hotels	0	0
	Reviews	0	0
3: 5000 to 10,000 yen	Hotels	22	22
	Reviews	452	459
	Sentences	1,108	3,988
	Positive sentences	924	1,875
	Negative sentences	184	2,113
4: 10,000 to 15,000 yen	Hotels	112	112
	Reviews	2,176	2,865
	Sentences	4,240	24,107
	Positive sentences	3,566	11,619
	Negative sentences	674	12,488
5: 15,000 to 20,000 yen	Hotels	138	138
	Reviews	7,043	4,384
	Sentences	14,726	37,342
	Positive sentences	12,775	17,449
	Negative sentences	1,951	19,893
6: 20,000 to 30,000 yen	Hotels	129	129
	Reviews	11,845	13,772
	Sentences	24,413	115,830
	Positive sentences	21,068	55,381
	Negative sentences	3,345	60,449
7: 30,000 to 50,000 yen	Hotels	83	83
	Reviews	8,283	7,001
	Sentences	17,939	58,409
	Positive sentences	15,642	28,493
	Negative sentences	2,297	29,916
8: 50,000 to 100,000 yen	Hotels	59	59
	Reviews	16,670	9,646
	Sentences	36,255	81,940
	Positive sentences	31,638	38,217
	Negative sentences	4,617	43,723
9: 100,000 to 200,000 yen	Hotels	14	14
	Reviews	1,601	3,010
	Sentences	3,282	26,423
	Positive sentences	2,930	12,274
	Negative sentences	352	14,149

with copular verbs, nouns, or other adjectives. For this reason we saw necessary to also perform a Part of Speech (POS) tagging of these clauses.

A Part of Speech (POS) tagger is a program that assigns word tokens with tags identifying the part of speech. An example is shown in Figure 4. A Part of Speech is a category of lexical items that serve similar grammatical purposes; for example, nouns, adjectives, verbs, conjunctions, and so on. In our study, we used the Stanford NLP POS tagger software, described by Toutanova and Manning (2000); Toutanova et al. (2003), which uses the Penn Chinese Treebank tags (Xia 2000).

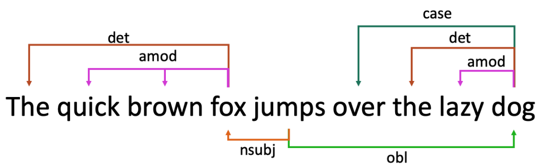


Fig. 3: Example of dependency parsing.

Fig. 4: Example of POS tagging with the Penn Treebank tags.

In this study we were interested in identifying combinations of adjectives, some verbs and nouns. We also needed to filter away bad combinations that were brought by the versatility of nominal subject dependencies. For this purpose, we identified the tags for nouns, verbs, and adjectives in Chinese and English, with the English tags being a bit more varied. What would be called adjectives in English corresponds more to stative verbs in Chinese, so we needed to extract those as well. We show a detailed description of the chosen tags in Table 3. We also show a detailed description of the tags we needed to filter, which we selected heuristically by observing commonly found undesired pairs, in Table 4.

Table 3: Target Parts of Speech for extraction and pairing.

Language	POS Tag	Part of Speech	Examples
Chinese target tags	NN	Noun (general)	酒店 (hotel)
	VA	Predicative Adjective (verb)	干净 的 (clean)
	JJ	Noun modifier (adjectives)	干净 (clean)
	VV	Verb (general)	推荐 (recommend)
English target tags	NN	Noun (general)	room
	NNS	Noun (plural)	beds
	JJ	Adjective	big
	JJS	Adjective (superlative)	best
	JJR	Adjective (comparative)	larger
	VB	Verb (base form)	take
	VBP	Verb (single present)	take
	VBN	Verb (past participle)	taken
	VBG	Verb (gerund / present participle)	taking

Once we had these adjective + noun or verb + noun pairs, we could determine what the customers are referring to in their reviews, and with what frequency they use those pairings positively or negatively.

Table 4: Filtered out Parts of Speech to aid pairing.

Language	POS Tag	Part of Speech	Examples
Commonly filtered tags	DT	Determiner	a, an
	PN	Pronoun	I, you, they
	CD	Cardinal Number	1, 2, 3, 4, 5
	PU	Punctuation	.!?
Chinese filtered tags	DEV	Particle	地 (Japan) (adverbial particle)
	NR	Noun (proper noun)	日本 (Japan)
	M	Measure word	个 (general classifier), 公里 (kilometer)
	SP	Sentence-final particle	他 (he), 好 (good)
	IJ	Interjection	啊 (ah)
English target tags	NNP	Noun (proper noun)	Japan
	PRP$	Possessive Pronoun	My, your, her, his
	WP	Wh-pronoun	What, who

4.3 Sentiment analysis using a Support Vector Classifier

The sentiment analysis was performed using the methodology described by Alemán Carreón et al. (2018). Keywords are determined by a comparison of Shannon's entropy (Shannon 1948) between two classes by a factor of α for one class and α' for the other, and then they are used in an SVM (Cortes and Vapnik 1995), optimizing keywords to select the best performing classifier using the F_1-measure Powers (2011). The selected SVM keywords would then clearly represent the user driving factors leading to positive and negative emotions. We also performed experiments to choose the best value of the parameter C used in the SVM. C is a constant that affects the optimization process when minimizing the error of the separating hyperplane. Low values of C give some freedom of error, which minimizes false positives. However, depending on the data, it can increase false negatives. Inversely, high values of C will likely result in minimal false negatives, but a possibility of false positives. SVM performance results are displayed in Tables 5 and 6. Examples of tagged sentences are shown in Table 7.

Table 5: Best performing SVC 5-fold cross-validation Chinese text classifiers.

Keyword List	**Classifier emotion**	**C**	F_1 μ	F_1 σ
Satisfaction keywords ($\alpha = 2.75$)	Satisfaction	2.5	0.91	0.01
Negative keywords ($\alpha' = 3.75$)	Dissatisfaction	0.5	0.67	0.11
Combined ($\alpha = 2.75$, $\alpha' = 3.75$)	**Satisfaction**	**0.5**	**0.95**	**0.01**

Shannon's entropy can be used to observe the probability distribution of each word inside the corpus. A word that is included in many documents will have a high entropy value for that set of documents. Opposite to this, a word appearing in only one document will have an entropy value of zero.

Table 6: Best performing SVC 10-fold cross-validation English text classifiers.

Keyword List	**Classifier emotion**	**C**	F_1 μ	F_1 σ
Satisfaction keywords ($\alpha = 1.5$)	Satisfaction	1.75	0.82	0.02
Dissatisfaction keywords ($\alpha' = 4.25$)	Dissatisfaction	3	0.80	0.03
Combined ($\alpha = 1.5$, $\alpha' = 4.25$)	**Satisfaction**	**2**	**0.83**	**0.02**

Table 7: Examples of positive and negative sentences used for training SVM.

Language	**Emotion**	**Sentences**
Chinese	Positive	酒店 的 服务 很 好 和 我 住 过 的 所有 日本 酒店 一样 各 种 隐形 服务 非常 厉害 (translated as: "The service of the hotel is very good. All the services of the Japanese hotels I have stayed in are extremely good.")
		有 一 个 后门 到 地铁站 非常 近 周边 也 算 方便 酒店 服务 和 卫生 都 很 好 (translated as: "There is a back door to the subway station very close to it. The surrounding area is also convenient hotel service and health are very good")
	Negative	酒店 旁边 很 荒凉 连个 便利 店 都 要 走 很远 (translated as: "The hotel is very bleak, and you have to go very far to go to the nearest convenience store.")
		唯一 不 足 是 价格 太高 (translated as: "The only negative is that the price is too high.")
English	Positive	It was extremely clean, peaceful and the hotel Hosts made us feel super welcome
		Location is very good, close to a main road with a subway station, a bakery, a 7 eleven and a nice restaurant that is not too expensive but serves good food
	Negative	The only downside. Our room was labeled 'non-smoking' but our duvet reeked of smoke.
		A bit pricey though

An SVM is trained to classify data based on previously labeled data, generalizing features of the data by defining a separating (p-1)-dimensional hyperplane in a p-dimensional space in which each dimension is a feature of the data. The separating hyperplane, along with the support vectors, divides the multi-dimensional space and minimizes the error of classification.

In our study, we used the linear kernel of the SVM classification process, defined by the formula (1) below. Each training sentence is a point of data, a row in the vector x. Each column represents a feature; in our case, the quantities of each of the keywords in that particular sentence. The labels of previously known classifications (1 for positive, 0 for negative) for each sentence comprise the $f(x)$ vector. The Weight Vector w is comprised of the influences each point has had in the training process to define the angle of the hyperplane. The bias coefficient b determines its position.

During the SVM learning algorithm, each data point that is classified incorrectly causes a change in the weight vector to classify new data correctly. These changes to the weight vector are greater for features close to the separating hyperplane. These features have stronger changes because they needed to be taken into account to classify with a minimal error. Sequentially, the weight vector can be interpreted as a numerical representation of each feature's effect on each class in the classification process. Below we show the formula for the weight vector w (2), where x is the training data and each vectorized sentence

x_i in the data is labeled y_i. Each cycle of the algorithm alters the value of w by α to reduce the number of wrong classifications. This equation shows the last value of α after the end of the cycle.

$$f(x) = w^\top x + b \quad (1)$$

$$w = \sum_{i=1}^{N} \alpha_i y_i x_i \quad (2)$$

We tagged 159 Chinese sentences and 2357 English sentences as positive or negative for our training data. The entropy comparison factors α and α' were tested from 1.25 to 6 in intervals of 0.25. We applied this SVC to classify the rest of our data collected. Subsequently, the positive and negative sentences counts shown in Table 2 are the result of applying our SVC for classification.

5 Data Analysis

5.1 Frequent keywords in differently priced hotels

To understand the satisfaction and dissatisfaction factors of Chinese tourists and English-speaking tourists when lodging in Japan, we study both the frequency of the words they use. Following that, to know the relevance of a keyword as a preference for each group, we observed the frequencies of each entropy-based keyword in our complete data set and in each price range subsequently. The frequency of the keywords in the database shows the level of priority it has for customers.

We observed the top 10 words with the highest frequencies for keywords that were linked by entropy to satisfaction and dissatisfaction in emotionally positive and negative statements to study. The keywords are the quantitative rank of the needs of Chinese and English speaking customers. We show the top 10 positive keywords for each price range comparing English and Chinese in Table 8. For the negative keywords, we show the results in Table 9.

We can observe that the most used keywords for most price ranges in the same language are similar to each other, with a few changes in priority for the keywords involved. For example, in Chinese, we can see that the customers praise cleanliness first in cheaper hotels, whereas the size of the room or bed is praised more in hotels of higher class. Another example is that in negative English reviews, complaints about price appear only after 10,000 yen hotels, and it climbs in importance following the increase in price of the hotel.

5.2 Frequently used adjectives and their pairs

Some keywords in these lists are adjectives, such as the word “big” mentioned before. In order to understand those, we performed the dependency parsing

Table 8: English and Chinese comparison of the top 10 positive keywords per price range.

Price range	Chinese keyword	Counts in Ctrip	English keyword	Counts in Tripadvisor
0: All Prices	不错 (not bad)	12892	good	19148
	大 (big)	9844	staff	16289
	干净 (clean)	6665	great	16127
	交通 (traffic)	6560	location	11838
	早餐 (breakfast)	5605	nice	11615
	近 (near)	5181	clean	9064
	地铁 (subway)	4321	helpful	5846
	购物 (shopping)	4101	excellent	5661
	推荐 (recommend)	3281	comfortable	5625
	环境 (surroundings)	3258	friendly	5606
3: 5000 to 10,000 yen	不错 (not bad)	139	good	206
	干净 (clean)	114	staff	181
	早餐 (breakfast)	112	clean	174
	大 (big)	76	nice	166
	交通 (traffic)	72	great	143
	地铁 (subway)	66	location	91
	近 (near)	55	comfortable	79
	地铁站 (subway station)	51	helpful	70
	远 (far)	41	friendly	64
	附近 (nearby)	34	recommend	59
4: 10,000 to 15,000 yen	不错 (not bad)	601	good	1399
	干净 (clean)	455	staff	1165
	大 (big)	348	great	961
	近 (near)	323	nice	808
	早餐 (breakfast)	270	location	800
	卫生 (health)	201	clean	656
	交通 (traffic)	196	excellent	412
	地铁 (subway)	164	friendly	400
	远 (far)	158	helpful	393
	附近 (nearby)	150	comfortable	391
5: 15,000 to 20,000 yen	不错 (not bad)	1925	good	2242
	干净 (clean)	1348	staff	1674
	大 (big)	1277	great	1414
	交通 (traffic)	1058	clean	1204
	近 (near)	1016	nice	1175
	地铁 (subway)	801	location	1109
	早餐 (breakfast)	777	comfortable	621
	地铁站 (subway station)	639	friendly	615
	附近 (nearby)	572	free	581
	购物 (shopping)	516	helpful	552
6: 20,000 to 30,000 yen	不错 (not bad)	3110	good	6550
	大 (big)	2245	staff	5348
	交通 (traffic)	1990	great	5074
	干净 (clean)	1940	location	4414
	近 (near)	1433	nice	3451
	地铁 (subway)	1073	clean	3364
	早餐 (breakfast)	1007	shopping	1992
	购物 (shopping)	979	helpful	1970
	周边 (surroundings)	837	comfortable	1941
	附近 (nearby)	825	friendly	1915
7: 30,000 to 50,000 yen	不错 (not bad)	2291	good	3407
	大 (big)	1913	staff	2867
	干净 (clean)	1159	great	2620
	交通 (traffic)	1105	location	2186
	近 (near)	935	nice	2160
	早餐 (breakfast)	846	clean	1750
	推荐 (recommend)	638	helpful	1147
	购物 (shopping)	636	train	1040
	周边 (surroundings)	552	subway	1034
	环境 (surroundings)	541	friendly	1001
8: 50,000 to 100,000 yen	不错 (not bad)	4451	great	4425
	大 (big)	3670	good	4350
	早餐 (breakfast)	2422	staff	3777
	交通 (traffic)	2012	nice	2991
	购物 (shopping)	1764	location	2439
	新 (new)	1634	clean	1655
	棒 (great)	1626	excellent	1555
	地铁 (subway)	1604	helpful	1313
	干净 (clean)	1577	comfortable	1246
	近 (near)	1354	friendly	1238
9: 100,000 to 200,000 yen	不错 (not bad)	375	great	1488
	大 (big)	315	staff	1277
	棒 (great)	189	good	994
	早餐 (breakfast)	171	nice	864
	环境 (surroundings)	157	location	799
	交通 (traffic)	127	excellent	631
	选择 (select)	112	beautiful	455
	推荐 (recommend)	109	large	404
	赞 (awesome)	101	helpful	401
	购物 (shopping)	98	wonderful	372

Table 9: English and Chinese comparison of the top 10 negative keywords per price range.

Price range	Chinese keyword	Counts in Ctrip	English keyword	Counts in Tripadvisor
0: All Prices	价格 (price)	1838	pricey	462
	一般 (general)	1713	poor	460
	中文 (Chinese)	733	dated	431
	地理 (geography)	691	disappointing	376
	距离 (distance)	434	worst	327
	陈旧 (obsolete)	319	minor	258
	老 (old)	297	uncomfortable	253
	华人 (Chinese person)	15	carpet	240
			annoying	220
			sense	220
3: 5000 to 10,000 yen	价格 (price)	31	worst	6
	一般 (general)	28	walkway	5
	距离 (distance)	11	unable	4
	地理 (geography)	10	worse	4
	中文 (Chinese)	9	annoying	3
			dirty	3
			funny smell	3
			poor	3
			renovation	3
			carpet	2
4: 10,000 to 15,000 yen	价格 (price)	98	dated	40
	一般 (general)	91	poor	29
	距离 (distance)	43	disappointing	26
	陈旧 (obsolete)	34	worst	24
	地理 (geography)	31	uncomfortable	23
	老 (old)	30	cigarette	22
	中文 (Chinese)	26	pricey	22
			minor	21
			paper	19
			unable	19
5: 15,000 to 20,000 yen	价格 (price)	296	poor	57
	一般 (general)	218	dated	41
	地理 (geography)	125	disappointing	38
	中文 (Chinese)	93	annoying	36
	距离 (distance)	84	worst	36
	陈旧 (obsolete)	43	cigarette	31
	老 (old)	26	rude	28
	华人 (Chinese person)	3	uncomfortable	26
			paper	25
			pricey	24
6: 20,000 to 30,000 yen	一般 (general)	504	poor	136
	价格 (price)	472	dated	131
	地理 (geography)	164	pricey	120
	中文 (Chinese)	155	disappointing	112
	距离 (distance)	116	uncomfortable	103
	陈旧 (obsolete)	75	minor	93
	老 (old)	55	smallest	88
	华人 (Chinese person)	2	worst	86
			cigarette	79
			annoying	70
7: 30,000 to 50,000 yen	价格 (price)	326	poor	92
	一般 (general)	311	pricey	92
	地理 (geography)	110	dated	65
	中文 (Chinese)	94	worst	64
	陈旧 (obsolete)	71	carpet	55
	距离 (distance)	68	uncomfortable	55
	老 (old)	45	dirty	51
	华人 (Chinese person)	2	disappointing	50
			cigarette	46
			unable	43
8: 50,000 to 100,000 yen	价格 (price)	561	pricey	163
	一般 (general)	510	dated	150
	中文 (Chinese)	337	disappointing	129
	地理 (geography)	239	poor	124
	老 (old)	134	worst	98
	距离 (distance)	97	walkway	82
	陈旧 (obsolete)	90	carpet	71
	华人 (Chinese person)	8	minor	63
			sense	63
			outdated	58
9: 100,000 to 200,000 yen	价格 (price)	54	pricey	40
	一般 (general)	51	sense	34
	中文 (Chinese)	19	minor	33
	距离 (distance)	15	lighting	20
	地理 (geography)	12	disappointing	19
	陈旧 (obsolete)	6	poor	19
	老 (old)	5	annoying	16
			mixed	15
			disappointment	14
			paper	14

and part of speech tagging explained in section 4.2. While there were many of these connections, we only considered the top 4 used keyword connections per adjective per price range. We show the most used Chinese adjectives in positive keywords in Table 10, and for negative Chinese adjective keywords in Table 11. Similarly, for English adjectives used in positive sentences we show the most common examples in Table 12, and for adjectives used in negative sentences in Table 13.

Table 10: Top 4 words related to the mainly used adjectives in positive Chinese texts.

Price range	不错 (not bad)	大 (big)	干净 (clean)	近 (near)	新 (new)
0: All Prices	不错 (not bad) : 12892 不错 酒店 (nice hotel) : 1462 不错 位置 (nice location) : 1426 不错 服务 (nice service) : 869 不错 环境 (nice environment) : 714	大 (big) : 9844 大 房间 (big room) : 3197 大 床 (big bed) : 772 大 酒店 (big hotel) : 379 大 超市 (big supermarket) : 232	干净 (clean) : 6665 干净 房间 (clean room) : 1224 干净 酒店 (clean hotel) : 737 干净 卫生 (clean and hygienic) : 464 干净 环境 (clean environment) : 61	近 (near) : 5181 近 酒店 (near hotel) : 453 近 桥 (near bridge) : 144 近 地铁站 (near subway station) : 122 近 站 (near station) : 108	新 (new) : 2775 新 设施 (new facility) : 363 新 酒店 (new hotel) : 246 新 装修 (new decoration) : 116 新 房间 (new room) : 53
3: 5000 to 10,000 yen	不错 (not bad) : 139 不错 酒店 (nice hotel) : 17 不错 位置 (nice location) : 16 不错 早餐 (nice breakfast) : 12 不错 服务 (nice service) : 8	大 (big) : 76 大 房间 (big room) : 11 大 床 (big bed) : 10 大 超市 (big supermarket) : 5 大 商场 (big market) : 3	干净 (clean) : 114 干净 房间 (clean room) : 21 干净 酒店 (clean hotel) : 10 干净 卫生 (clean and hygienic) : 6 干净 总体 (clean overall) : 4	近 (near) : 55 近 酒店 (near hotel) : 4 近 地铁 (near subway) : 2 不错 附近 (not bad nearby) : 0 便利 附 近 (convenient nearby) : 0	
4: 10,000 to 15,000 yen	不错 (not bad) : 601 不错 位置 (nice location) : 72 不错 酒店 (nice hotel) : 37 不错 服务 (nice service) : 34 不错 早餐 (nice breakfast) : 26	大 (big) : 348 大 房间 (big room) : 76 大 床 (big bed) : 30 大 社 (big club) : 26 大 空间 (big space) : 16	干净 (clean) : 455 干净 房间 (clean room) : 66 干净 卫生 (clean and hygienic) : 52 干净 酒店 (clean hotel) : 48 干净 打扫 (clean up) : 9	近 (near) : 323 近 酒店 (near hotel) : 27 近 站 (near station) : 14 近 地铁 (near subway) : 12 近 车站 (near the station) : 10	新 (new) : 37 新 设施 (new facility) : 9 新 装修 (new decoration) : 2 新 酒店 (new hotel) : 2
5: 15,000 to 20,000 yen	不错 (not bad) : 1925 不错 位置 (nice location) : 207 不错 酒店 (nice hotel) : 168 不错 服务 (nice service) : 131 不错 早餐 (nice breakfast) : 109	大 (big) : 1277 大 房间 (big room) : 316 大 床 (big bed) : 140 大 超市 (big supermarket) : 73 大 酒店 (big hotel) : 49	干净 (clean) : 1348 干净 房间 (clean room) : 234 干净 酒店 (clean hotel) : 161 干净 卫生 (clean and hygienic) : 92 干净 设施 (clean facilities) : 19	近 (near) : 1016 近 酒店 (near hotel) : 82 近 站 (near station) : 35 近 地铁站 (near subway station) : 34 近 桥 (near bridge) : 29	新 (new) : 234 新 设施 (new facility) : 47 新 酒店 (new hotel) : 25 新 装修 (new decoration) : 15 新 房间 (new room) : 10
6: 20,000 to 30,000 yen	不错 (not bad) : 3110 不错 位置 (nice location) : 409 不错 酒店 (nice hotel) : 326 不错 服务 (nice service) : 206 不错 环境 (nice environment) : 183	大 (big) : 2245 大 房间 (big room) : 680 大 床 (big bed) : 198 大 酒店 (big hotel) : 102 大 空间 (big space) : 64	干净 (clean) : 1940 干净 房间 (clean room) : 360 干净 酒店 (clean hotel) : 203 干净 卫生 (clean and hygienic) : 137 干净 环境 (clean environment) : 21	近 (near) : 1433 近 酒店 (near hotel) : 164 近 地铁 (near subway) : 34 近 地铁站 (near subway station) : 31 近 车站 (near the station) : 27	新 (new) : 517 新 设施 (new facility) : 89 新 酒店 (new hotel) : 51 新 装修 (new decoration) : 24 新 房间 (new room) : 10
7: 30,000 to 50,000 yen	不错 (not bad) : 2291 不错 位置 (nice location) : 277 不错 酒店 (nice hotel) : 274 不错 服务 (nice service) : 140 不错 环境 (nice environment) : 140	大 (big) : 1913 大 房间 (big room) : 643 大 床 (big bed) : 141 大 超市 (big supermarket) : 74 大 酒店 (big hotel) : 66	干净 (clean) : 1159 干净 房间 (clean room) : 224 干净 酒店 (clean hotel) : 146 干净 卫生 (clean and hygienic) : 71 干净 环境 (clean environment) : 16	近 (near) : 935 近 酒店 (near hotel) : 80 近 站 (near station) : 24 近 桥 (near bridge) : 20 近 山 (near mountain) : 12	新 (new) : 260 新 设施 (new facility) : 63 新 酒店 (new hotel) : 25 新 装修 (new decoration) : 15 新 房间 (new room) : 11
8: 50,000 to 100,000 yen	不错 (not bad) : 4451 不错 酒店 (nice hotel) : 587 不错 位置 (nice location) : 415 不错 服务 (nice service) : 328 不错 早餐 (nice breakfast) : 251	大 (big) : 3670 大 房间 (big room) : 1340 大 床 (big bed) : 238 大 酒店 (big hotel) : 144 大 商场 (big market) : 88	干净 (clean) : 1577 干净 房间 (clean room) : 310 干净 酒店 (clean hotel) : 161 干净 卫生 (clean and hygienic) : 101 干净 服务 (clean service) : 13	近 (near) : 1354 近 酒店 (near hotel) : 88 近 桥 (near bridge) : 76 近 地铁站 (near subway station) : 35 近 铁 (Kintetsu) : 24	新 (new) : 1634 新 设施 (new facility) : 141 新 酒店 (new hotel) : 123 新 装修 (new decoration) : 57 新 斋 (new) : 22
9: 100,000 to 200,000 yen	不错 (not bad) : 375 不错 酒店 (nice hotel) : 53 不错 位置 (nice location) : 30 不错 环境 (nice environment) : 27 不错 服务 (nice service) : 22	大 (big) : 315 大 房间 (big room) : 131 大 面积 (large area) : 19 大 床 (big bed) : 15 大 卫生间 (big toilet) : 13	干净 (clean) : 72 干净 房间 (clean room) : 9 干净 酒店 (clean hotel) : 8 干净 卫生 (clean and hygienic) : 5 干净 一如既往 (clean as always) : 0	近 (near) : 65 近 酒店 (near hotel) : 8 近 地铁站 (near subway station) : 3 近 市场 (near market) : 3 不错 附近 (not bad nearby) : 0	新 (new) : 77 新 酒店 (new hotel) : 19 新 设施 (new facility) : 13 新 装修 (new decoration) : 3 新 位置 (new location) : 2

Table 11: Top 4 words related to the mainly used adjectives in negative Chinese texts.

Price range	一般 (general)	陈旧 (obsolete)	老 (old)
0: All Prices	一般 (general) : 1713 一般 设施 (general facilities) : 137 一般 服务 (general service) : 115 一般 酒店 (average hotel) : 106 一般 早餐 (average breakfast) : 97	陈旧 (obsolete) : 319 陈旧 设施 (obsolete facilities) : 184 陈旧 设备 (obsolete equipment) : 18 陈旧 房间 (outdated room) : 10 陈旧 酒店 (outdated hotel) : 10	老 (old) : 297 老 酒店 (old hotel) : 74 老 设施 (old facility) : 58 老 店 (old shop) : 15 老 装修 (old decoration) : 11
3: 5000 to 10,000 yen	一般 (general) : 28 一般 设施 (general facilities) : 5 一般 早餐 (average breakfast) : 3 一般 味道 (general taste) : 2 一般 效果 (general effect) : 2		老 (old) : 2
4: 10,000 to 15,000 yen	一般 (general) : 91 一般 设施 (general facilities) : 10 一般 位置 (general location) : 8 一般 酒店 (average hotel) : 6 一般 早餐 (average breakfast) : 5	陈旧 (obsolete) : 34 陈旧 设施 (obsolete facilities) : 17 陈旧 家具 (obsolete furniture) : 2 陈旧 设备 (obsolete equipment) : 2	老 (old) : 30 老 酒店 (old hotel) : 8 老 设施 (old facility) : 7 老 建筑 (old building) : 3
5: 15,000 to 20,000 yen	一般 (general) : 218 一般 设施 (general facilities) : 23 一般 酒店 (average hotel) : 21 一般 早餐 (average breakfast) : 14 一般 卫生 (general hygiene) : 8	陈旧 (obsolete) : 43 陈旧 设施 (obsolete facilities) : 25 陈旧 设备 (obsolete equipment) : 3 陈旧 酒店 (outdated hotel) : 2	老 (old) : 26 老 酒店 (old hotel) : 11 老 设施 (old facility) : 7 老 外观 (old appearance) : 2
6: 20,000 to 30,000 yen	一般 (general) : 504 一般 设施 (general facilities) : 42 一般 酒店 (average hotel) : 37 一般 服务 (general service) : 34 一般 早餐 (average breakfast) : 21	陈旧 (obsolete) : 75 陈旧 设施 (obsolete facilities) : 42 陈旧 设备 (obsolete equipment) : 7 陈旧 装修 (old decoration) : 3 陈旧 酒店 (outdated hotel) : 2	老 (old) : 55 老 酒店 (old hotel) : 9 老 设施 (old facility) : 8 老 店 (old shop) : 3 老 房间 (old room) : 3
7: 30,000 to 50,000 yen	一般 (general) : 311 一般 设施 (general facilities) : 23 一般 服务 (general service) : 22 一般 早餐 (average breakfast) : 19 一般 酒店 (average hotel) : 15	陈旧 (obsolete) : 71 陈旧 设施 (obsolete facilities) : 43 陈旧 设备 (obsolete equipment) : 5 陈旧 房间 (outdated room) : 3	老 (old) : 45 老 酒店 (old hotel) : 11 老 设施 (old facility) : 7 老 店 (old shop) : 3 老 房间 (old room) : 2
8: 50,000 to 100,000 yen	一般 (general) : 510 一般 服务 (general service) : 39 一般 设施 (general facilities) : 32 一般 早餐 (average breakfast) : 30 一般 酒店 (average hotel) : 25	陈旧 (obsolete) : 90 陈旧 设施 (obsolete facilities) : 53 陈旧 房间 (outdated room) : 5 陈旧 感觉 (Stale feeling) : 2	老 (old) : 134 老 酒店 (old hotel) : 34 老 设施 (old facility) : 26 老 装修 (old decoration) : 9 老 店 (old shop) : 7
9: 100,000 to 200,000 yen	一般 (general) : 51 一般 服务 (general service) : 7 一般 早餐 (average breakfast) : 5 一般 位置 (general location) : 2 一般 房间 (average room) : 2	陈旧 (obsolete) : 6 陈旧 设施 (obsolete facilities) : 4	老 (old) : 5 老 设施 (old facility) : 2

Table 12: Top 4 words related to the mainly used adjectives in positive English texts.

Price range	good	clean	comfortable	helpful	free	large
0: All Prices	good : 19148 good location : 1985 good service : 1042 good breakfast : 942 good hotel : 874	clean : 9064 clean room : 3596 clean hotel : 969 clean bathroom : 282 clean everything : 200	comfortable : 5625 comfortable bed : 1919 comfortable room : 1098 comfortable stay : 272 comfortable hotel : 238	helpful : 5846 helpful staff : 2927 helpful concierge : 304 helpful desk : 110 helpful service : 74	free : 4318 free wifi : 773 free shuttle : 286 free drink : 234 free bus : 225	large : 4104 large room : 1256 large hotel : 268 large bathroom : 202 larger room : 192
3: 5000 to 10,000 yen	good : 206 good location : 30 good value : 19 good english : 10 good place : 7	clean : 174 clean room : 55 clean bathroom : 14 clean place : 12 clean hotel : 6	comfortable : 79 comfortable bed : 21 comfortable room : 9 comfortable futon : 8 comfortable stay : 3	helpful : 70 helpful staff : 36	free : 35 free wifi : 10 free tea : 4 free raman : 2 free toothbrush : 2	large : 31 large room : 7 large area : 2 large size : 2
4: 10,000 to 15,000 yen	good : 1399 good location : 159 good breakfast : 87 good hotel : 71 good service : 67	clean : 656 clean room : 247 clean hotel : 74 clean bathroom : 20 clean everything : 14	comfortable : 391 comfortable bed : 123 comfortable room : 90 comfortable hotel : 26 comfortable stay : 20	helpful : 393 helpful staff : 206 helpful concierge : 20 helpful desk : 10 helpful service : 4	free : 271 free wifi : 53 free breakfast : 15 free service : 12 free drink : 11	large : 250 large room : 84 large bathroom : 20 larger room : 12 large hotel : 10
5: 15,000 to 20,000 yen	good : 2242 good location : 242 good hotel : 116 good breakfast : 113 good service : 108	clean : 1204 clean room : 440 clean hotel : 133 clean bathroom : 38 clean everything : 26	comfortable : 621 comfortable bed : 219 comfortable room : 99 comfortable stay : 30 comfortable hotel : 20	helpful : 552 helpful staff : 301 helpful desk : 11 helpful concierge : 9 helpful reception : 5	free : 581 free wifi : 109 free shuttle : 35 free bus : 30 free breakfast : 27	large : 349 large room : 85 large suitcase : 18 larger room : 18 large hotel : 17
6: 20,000 to 30,000 yen	good : 6550 good location : 703 good service : 331 good english : 304 good breakfast : 303	clean : 3364 clean room : 1379 clean hotel : 379 clean bathroom : 95 clean everything : 77	comfortable : 1941 comfortable bed : 658 comfortable room : 359 comfortable stay : 100 comfortable hotel : 82	helpful : 1970 helpful staff : 1019 helpful concierge : 79 helpful desk : 42 helpful receptionist : 17	free : 1186 free wifi : 269 free breakfast : 68 free coffee : 57 free drink : 38	large : 1257 large room : 329 large hotel : 87 larger room : 81 large bed : 43
7: 30,000 to 50,000 yen	good : 3407 good location : 380 good breakfast : 191 good service : 182 good english : 155	clean : 1750 clean room : 725 clean hotel : 197 clean bathroom : 61 clean everything : 36	comfortable : 1000 comfortable bed : 345 comfortable room : 193 comfortable hotel : 49 comfortable stay : 47	helpful : 1147 helpful staff : 607 helpful concierge : 53 helpful service : 20 helpful desk : 17	free : 933 free drink : 145 free wifi : 129 free coffee : 45 free bus : 38	large : 580 large room : 174 larger room : 32 large hotel : 30 large bed : 28
8: 50,000 to 100,000 yen	good : 4350 good location : 406 good service : 296 good hotel : 196 good breakfast : 191	clean : 1655 clean room : 648 clean hotel : 156 clean bathroom : 48 cleanliness : 40	comfortable : 1246 comfortable bed : 425 comfortable room : 266 comfortable stay : 56 comfortable hotel : 51	helpful : 1313 helpful staff : 589 helpful concierge : 108 helpful service : 28 helpful desk : 26	free : 1072 free shuttle : 181 free wifi : 172 free bus : 127 free service : 65	large : 1233 large room : 442 large hotel : 109 large bathroom : 58 larger room : 38
9: 100,000 to 200,000 yen	good : 994 good location : 65 good service : 56 good breakfast : 53 good hotel : 40	clean : 261 clean room : 102 clean hotel : 24 cleanliness : 8 clean place : 7	comfortable : 347 comfortable bed : 128 comfortable room : 82 comfortable stay : 16 comfortable hotel : 10	helpful : 401 helpful staff : 169 helpful concierge : 35 helpful everyone : 7 helpful team : 5	free : 240 free wifi : 31 free breakfast : 19 free drink : 16 free bus : 14	large : 404 large room : 135 large bathroom : 38 large hotel : 15 large bed : 12

Table 13: Top 4 words related to the mainly used adjectives in negative English texts.

Price range	poor	dated	worst	dirty	uncomfortable
0: All Prices	poor : 460 poor service : 55 poor breakfast : 41 poor quality : 27 poor english : 24	dated : 431 outdated : 128 outdated room : 20 outdated hotel : 10 outdated bathroom : 7	worst : 327 worst hotel : 43 worst experience : 18 worst part : 15 worst service : 10	dirty : 188 dirty carpet : 34 dirty room : 23 not dirty : 7 dirty bathroom : 6	uncomfortable : 253 uncomfortable bed : 63 uncomfortable pillow : 20 uncomfortable mattress : 8 uncomfortable night : 8
3: 5000 to 10,000 yen	poor : 3		worst : 6 worst room : 2	dirty : 3	uncomfortable : 2
4: 10,000 to 15,000 yen	poor : 29 poor breakfast : 3 poor service : 3 poor conditioning : 2 poor view : 2	dated : 40 outdated : 11 outdated decor : 2 outdated room : 2	worst : 24 worst hotel : 4 worst experience : 2	dirty : 11 dirty floor : 2	uncomfortable : 23 uncomfortable bed : 4 not uncomfortable : 2 uncomfortable night : 2 uncomfortable pillow : 2
5: 15,000 to 20,000 yen	poor : 57 poor service : 10 poor breakfast : 6 poor hotel : 5 poor experience : 3	dated : 41 outdated : 8	worst : 36 worst hotel : 8 worst experience : 3 worst part : 2 worst service : 2	dirty : 14 dirty room : 2	uncomfortable : 26 uncomfortable bed : 7 uncomfortable pillow : 2
6: 20,000 to 30,000 yen	poor : 136 poor breakfast : 15 poor service : 14 poor english : 9 poor quality : 9	dated : 131 outdated : 31 outdated room : 6 outdated hotel : 2	worst : 86 worst hotel : 11 worst part : 7 worst breakfast : 5 worst experience : 5	dirty : 67 dirty room : 10 dirty carpet : 8 dirty bathroom : 3 dirty chair : 2	uncomfortable : 103 uncomfortable bed : 24 uncomfortable pillow : 11 uncomfortable night : 4 uncomfortable experience : 3
7: 30,000 to 50,000 yen	poor : 92 poor service : 8 poor breakfast : 7 poor english : 7 poor connection : 5	dated : 65 outdated : 17 outdated hotel : 4 outdated bathroom : 2 outdated decor : 2	worst : 64 worst hotel : 10 worst room : 3 worst service : 3 worst part : 2	dirty : 51 dirty carpet : 11 dirty room : 7 dirty clothe : 2 dirty luggage : 2	uncomfortable : 55 uncomfortable bed : 20 uncomfortable mattress : 6 uncomfortable pillow : 5 uncomfortable room : 5
8: 50,000 to 100,000 yen	poor : 124 poor service : 16 poor breakfast : 9 poor quality : 9 poor english : 6	dated : 150 outdated : 58 outdated room : 9 outdated furniture : 6 outdated hotel : 4	worst : 98 worst hotel : 9 worst experience : 5 worst part : 3	dirty : 36 dirty carpet : 12 dirty room : 3 dirty cup : 2 dirty rug : 2	uncomfortable : 33 uncomfortable bed : 7
9: 100,000 to 200,000 yen	poor : 19 poor service : 4 poor choice : 2 poor experience : 2	dated : 3 outdated : 2	worst : 12 worst experience : 2	dirty : 6	uncomfortable : 8 little uncomfortable : 2

5.3 Determining hard and soft attribute usage

In order to further understand the differences in satisfaction and dissatisfaction in Chinese and Western customers of Japanese hotels, we classified these factors as either hard or soft attributes of a hotel. We define these by the feasibility with which a hotel management might make an improvement on this end to satisfy the customer further. We define hard attributes as matters that would be impossible for the hotel to change, such as the surroundings and location of the hotel, or impractical and expensive to change, such as matters requiring construction costs, which are possible but of high investment and risk. Soft attributes, on the other hand, are attributes of the hotel which are easily changeable if small investments are made. For example, an improvement in the services of the hotel or the cleanliness of the rooms is a soft attribute.

We can thus observe the top 10 satisfaction and dissatisfaction keywords and determine whether they are soft attributes that the hotel management can easily change, or hard attributes that the hotel management cannot change without changing infrastructure or location.

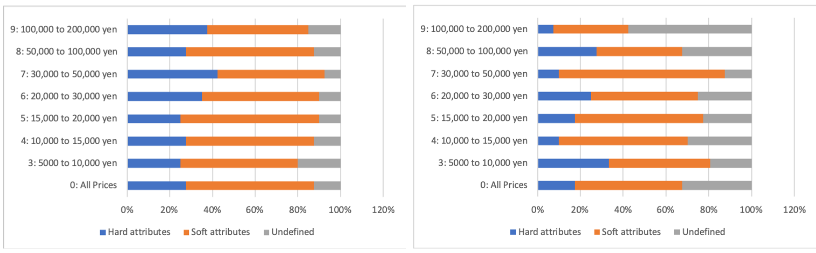
We manually labeled the top keywords of each language into either hard or soft by considering how the word would be used when writing a review. If the word is describing factors that are unchangeable by the staff or management, we consider them hard. If the word implies an issue that could be solved or managed by the hotel staff or management, we consider it soft. For adjectives, we looked at the top 4 adjective and noun pairings used in the entire dataset, and counted the percentage of usage in each context. If it is not clear from the word or the pairing alone, we declare it undefined. Then, we added the counts of these words in each category, where a single word with no pairing is always 100% in the category it corresponds to, and we add the partial percentages for each category when an adjective includes various contexts. The interpretation of these keywords is shown in the Tables 14 and 15. We can see the summarized results for the hard and soft percentages of positive and negative Chinese keywords in Figure 5. For the English keywords, see Figure 6.

(a) Positive keywords (b) Negative keywords

Fig. 5: Percentages of hard and soft attributes of the top Chinese keywords for all price ranges

Table 14: Determination of hard and soft attributes for Chinese keywords.

Keyword emotion category	**Keyword**	**Attribute category**
Positive Keywords	不错 (not bad)	75% hard, 25% soft
	大 (big)	100% hard
	干净 (clean)	25% hard, 75% soft
	早餐 (breakfast)	soft
	交通 (traffic)	hard
	棒 (great)	25% hard, 50% soft, 25% undefined
	近 (near)	100% hard
	购物 (shopping)	hard
	环境 (surroundings)	hard
	地铁 (subway)	hard
	卫生 (health)	soft
	新 (new)	50% hard, 25% soft, 25% undefined
	推荐 (recommend)	undefined
	选择 (select)	undefined
	地铁站 (subway station)	hard
	远 (far)	100% hard
	附近 (nearby)	100% hard
	周边 (surroundings)	hard
	赞 (awesome)	undefined
Negative Keywords	价格 (price)	soft
	一般 (general)	50% hard, 50% soft
	中文 (Chinese)	soft
	距离 (distance)	hard
	地理 (geography)	hard
	陈旧 (obsolete)	100% hard
	老 (old)	75% hard, 25% soft
	华人 (Chinese person)	soft



(a) Positive keywords (b) Negative keywords

Fig. 6: Percentages of hard and soft attributes of the top English keywords for all price ranges

6 Results

6.1 Experiment results and answering research questions

650 Our research questions were about two things. In research questions 1a and 1b, we decide as the objective of this study to determine how Chinese and Western tourists interact with the service and hospitality in Japan, *omotenashi*, and

Table 15: Determination of hard and soft attributes for English keywords.

Keyword emotion category	Keyword	Attribute category
Positive Keywords	good	25% hard, 50% soft, 25% undefined
	great	50% hard, 25% soft, 25% undefined
	staff	soft
	clean	100% soft
	location	hard
	nice	50% hard, 25% soft, 25% undefined
	excellent	25% hard, 50% soft, 25% undefined
	helpful	100% soft
	comfortable	25% hard, 50% soft, 25% undefined
	shopping	hard
	beautiful	25% hard, 75% soft
	friendly	100% soft
	train	hard
	large	100% hard
	free	100% soft
	subway	hard
	recommend	undefined
	wonderful	50% soft, 50% undefined
Negative Keywords	pricey	100% soft
	worst	25% hard, 50% soft, 25% undefined
	dated	75% hard, 25% undefined
	poor	100% soft
	walkway	hard
	sense	undefined
	unable	100% soft
	disappointing	50% soft, 50% undefined
	minor	100% undefined
	worse	100% undefined
	annoying	75% hard, 25% undefined
	lighting	soft
	uncomfortable	100% soft
	carpet	soft
	dirty	75% soft, 25% undefined
	cigarette	soft
	funny smell	soft
	rude	100% soft
	smallest	75% hard, 25% undefined
	mixed	100% undefined
	renovation	hard
	paper	undefined
	disappointment	undefined
	outdated	75% hard, 25% undefined

how are they different in their perceptions in this matter. From the observation of the top-ranking positive factors for Chinese tourists across different price ranges in Table 8, and specifically the word “不错 (not bad)” and its pairings in Table 10, that while service, cleanliness and breakfast are praised in most hotels, location is usually placed above it in importance on the pairings. When we see the rest of the factors lower on the list, we see that across different price ranges, the list is more populated with hard attributes like location and transportation availability. From the negative keyword usages in Table 9, there are complaints about lack of a Chinese friendly environment, although most complaints are also about hard attributes such as the age of the building and the distance from other convenient spots. The most complained about aspect, however, is the price of the hotel. It is surprising to note that all of the price ranges have this negative keyword at the top of the list, suggesting that it is a main concern to Chinese customers with different purposes of travel.

On the other hand, the word “staff” is the second or third in the lists of satisfaction factors in English-written reviews in all the price ranges, followed by a few other keywords lower in the top 10 list, such as “helpful” or “friendly”. When we look at the adjectival pairing of the top-ranked keyword “good” in Table 12, we find that mostly, they praise either the location, the service, breakfast, or English availability. When we look at the negative keyword ‘poor’ and its pairings in Table 13, we see that it is also service related concepts that the Western tourists are disappointed with when they react negatively.

With these results, we can observe that both Chinese and English-speaking tourists in Japan have different priorities. However, both populations consider the location of the hotel and the availability of transport (subways and trains) nearby, as secondary but still essential points in their satisfaction with a hotel. The Chinese customers are primarily satisfied with the room quality in spaciousness and cleanliness, as well as the service of breakfast. In contrast, the English-speaking customers are easily upset by any lack of cleanliness and smoke smell from cigarettes. It is surprising that the cigarette smell is an issue even in middle to high class hotels above 30,000 yen per night, although above 50,000 yen per night this problem seems to disappear from the list of top 10 concerns. Old and dated buildings seem to be a concern for both populations. On the positive side, for all price ranges considered, English-speaking tourists value staff friendliness over room quality when considering their satisfaction, while Chinese tourists consider location and transportation more often.

We also can observe some keywords that are not considered by their counterparts. For example, English-speaking customers mentioned tobacco smell in many reviews, while it wasn’t statistically identified as a problem at all for their Chinese counterparts. On the other hand, while it appears in both English and Chinese lists, references to “shopping” are more common in the Chinese lists across hotels of 15,000 yen to 200,000 yen per night. Meanwhile, the term ‘shopping’ only appears in the 20,000 to 30,000 yen per night top 10 positive keywords list for English-speakers.

In our research questions 2a and 2b, we ponder how customers of both cultural backgrounds react to hard and soft attributes of the hotel, and how they differ in those reactions. Here we define hard attributes as those that are impossible or impractical to change for the hotel management, for example matters like the surroundings, view or location convenience. On the other hand, soft attributes are those that the hotel could easily and practically change without much limitations except for small financial investments, for example, improvement on the services of the hotel via training or hiring specialized staff. In our study, we find that that mostly Chinese tourists are positively reacting more to hard attributes of the hotel, and in negative sentences, there is a slightly hard leaning (53%) concern with hard attributes, albeit it is more uniform in this instance. English-speaking tourists on the other hand, are both positively and negatively more responsive to soft attributes, and in the case of negative keywords, tourists are overwhelmingly more concerned with soft attributes of the hotel dissatisfying them somehow.

One factor that both populations have in common is, when perceiving the hotel negatively, "old" or "outdated", or "obsolete" aspects of the room or the hotel are being criticized across, surprisingly, most price ranges. This is, however, a hard attribute, and is unlikely to change for most hotels.

6.2 Chinese tourists - A big and clean space, and a good breakfast

We found that mainland Chinese tourists are satisfied mostly by a big and clean space provided by the Japanese hotels. From the adjectival pairings that we extracted with dependency parsing and POS tagging in Table 10, we can observe that mostly they mean big and clean rooms. Other mentions are also big markets nearby, or a big bed. We can observe that across different price ranges, the usage of the word "big" increases as the hotel increases in price, but that still they react positively in a significant manner in cheaper hotels. Inspecting closer by taking random samples of the pairs of "big space" or "large area", we can see that there are also many references to the public bathing facilities in the hotel. In Japan, there is what is called *sentō*, which are artificially made public bathing facilities, on occasions including saunas and baths with unique qualities. On the other hand, there are natural hot springs, called *onsen*. They can either be bathing in the natural source of the water or using the hot springs in artificially made bath facilities. It is a Japanese custom and culture that all customers use the facilities after cleaning themselves in a shower and go into the baths without any clothes. It can be a cultural shock for many tourists, but this is a fundamental attraction for many.

However, size of the room or the bed is a hard attribute, and without considering rebuilding the hotel, is quite difficult to improve on. Cleanliness, on the other hand, is mostly relating to soft attributes when we observe its adjectival pairings. We can observe pairs such as "clean room" at the top rank of all price ranges, and then variably "clean hotel", "clean overall", "clean environment", and "clean facilities", among other examples. In negative reviews, there is a mention of criticizing the "general hygiene" of the hotel, although it's an uncommon pair. We can therefore assert that cleanliness is an important soft attribute for Chinese customers, and that they are mostly pleased, with their expectations being met.

One key component we found in Chinese customer satisfaction soft factors is the inclusion of breakfast within the hotel. While other food-related words were extracted, most of them were general, like "food" or "eating," and in a lower ranking. In contrast, the word "breakfast" refers possibly to its inclusion in the hotel commodities, was frequently used in positive texts compared to other food-related words. The word "breakfast" is also observed across all price ranges, although at different priorities in each of them. However we assert that it is an important factor. Observing word pairs from the positive Chinese keywords in Table 10, we can also see that "not bad" is paired with "breakfast" in four of the seven price ranges that had reviews available as part of the top 4 pairings, and only slightly lower on other categories, although it is not shown on the table. Thus we consider that a recommended strategy for hotel management is to invest in the inclusion or betterment of hotel breakfast as a strategy to increase good reviews.

6.3 Western tourists - A friendly face, and absolutely clean

From the satisfaction factors of English-speaking tourists, we can see that at least three words relate directly to staff friendliness and services, being "staff","helpful" and "friendliness" in the general database. The word "staff" is the second most frequently used word for satisfied customers across most price ranges, and only third in one of them. Adding to that, "helpful" and "friendly" follow it lower in the list in most price ranges. The word "good" is mostly about the location, the service, breakfast, or English availability in Table 12. Similar to Chinese customers, Western customers also seem to be enjoying the included breakfasts when it comes to their satisfaction keyword pairings, although the word doesn't appear directly in the top 10 list as in their Chinese counterparts. The words "helpful" and "friendly" are mostly paired with "staff", "concierge", "desk", and "service". When we look at the negative keyword 'poor' and its pairings in Table 13, we see that it is also service related concepts that the Western tourists are disappointed with when they react negatively. The word "great", which is also high in most price ranges, and the top keyword in the highest priced hotels, is also accompanied by mostly soft attributes, in pairings such as "great location : 2313", "great view : 1099" and "great service : 841", if we include the counts from all the price ranges together. Japanese high standards in hospitality very likely influenced this result.

Another soft attribute that is high on the list for most of the price ranges is the word "clean". Since it is an adjective, we have explored the word pairings as well. Customers are mostly praising "clean rooms" and "clean bathrooms", while also just referring to the hotel in general. It seems as well that when observing the negative keyword frequencies for English-speakers, we can find words such as "dirty", "carpet", and from the word pairings "dirty carpet", "dirty room", and "dirty bathroom". Along with complaints about off-putting smells, we can conclude that Western tourists have high expectations about cleanliness when traveling in Japan.

An interesting detail of the keyword ranking is that the word "comfortable" is high on the list of satisfaction factors and "uncomfortable" high on the dissatisfaction factors. The words are paired with nouns like "bed", or "room", "pillow" or "mattress", generally referring to their sleep conditions in the hotel.

It seems that in general, western tourists are highly sensitive to comfort levels in the hotels and whether it reaches their expectations. The ranking for the negative keyword “uncomfortable” is similar across most price ranges, except the two most expensive ones, where this keyword disappears from the top 10 list.

While less high in priority, the price range of 15,000 to 20,000 yen hotels also mention “free” as one of the top 10 positive keywords, which is paired mostly with “wifi”. This price range is mostly for business hotels, which can be where users would be expecting this feature the most.

6.4 Tobacco, what’s that smell?

A concern for Western tourists was the smell of tobacco in their room. This can be considered a soft attribute. Not only as a standalone word of “cigarette”, but also confirming with word pairs in Table 13, we can find other related word pairs such as “funny smell”. Upon manual inspection of a sample of reviews with this keyword, we found that the room was often advertised as non-smoking, yet, the smell permeated the room and curtains. Another common complaint was that there were no non-smoking facilities available at all in the first place. The smell of smoke can completely ruin some customers’ stay and give a bad impression to review writers, which can lower the number of future customers.

However, in comparison, Chinese customers seem not to be bothered by this at all. We consulted studies involving the use of tobacco in different countries. Previous research states that 49 - 60% of Chinese men (and 2.0 - 2.8% of women) currently smoke or have smoked before, taken from a sample of 170,000 Chinese adults in 2013-2014, which is high compared to many English-speaking countries (Zhang et al. 2019; World Health Organization 2015).

Japan itself has a polarized view on smoking, and despite being one of the world’s largest tobacco markets, its use has been decreasing in recent years. Smoking in public spaces is prohibited in some wards of Tokyo (namely Chiyoda, Shinjuku, and Shibuya). However, it is generally only urged and not mandatory to have smoking restrictions in restaurants, bars, hotels, and public areas. However, there are many places where “smoking rooms” are available to keep the smoke to an enclosed area and avoid bothering others. Despite this, businesses, especially those who cater to certain kinds of customers, will generally be discouraged from having smoking restrictions if they want to keep their clientele. If Japanese hotels want to cater to all kinds of customers, Western and Asian alike, they must provide spaces without tobacco smell. After all, even if it does not bother a few customers, the lack of smell would make it an appropriate space for all kinds of customers.

6.5 Location, location, location

The location of the hotel, closeness to the subway and public transport, and availability of nearby shops were observed to be of importance to both Chinese and English-speaking tourists. In positive word pairings Tables 10 and 12, we can find pairs such as "nice location", "near subway station", "near subway" in Chinese texts and "good location", "great location", and "great view", as well as single keywords "location" and "shopping" for Enlgish-speakers, and "traffic", "shopping", "subway", and "surroundings" for Chinese speakers. All of these keywords, as well as their location in the priorities of each population across the price ranges, signal that while it was not the priority for either of them, the hotel's location is a secondary but still important point in the hotel's satisfaction. However, since this is a hard attribute, unchangeable to the management of the hotel, it is not often considered in the literature. Upon inspection of examples from the data, we found that most customers were satisfied if the hotel was near to at least two other subjects: subway, train, and convenience stores.

Japan is a country with a peculiar public transport system. The rush hour makes for a subway filled to the brim with people in suits making their commute, and trains and subway stations in Tokyo create a confusing public transport map for a visitor. Buses are also available, although less used than the rail systems in the big cities. These three are unusually affordable in price. Then there are the more expensive transports, such as the bullet train *shinkansen* for traveling across the country, and taxis. Taxis in Japan are a luxury compared to other countries. Where in less developed countries the taxi is the cheap method of transport of choice, in Japan, taxis are made to provide a high-quality experience, with a matching price. This means that for tourists, subway availability and maps or GPS applications, as well as a plan to travel the city, are of utmost necessity.

Japanese convenience stores, on the other hand, are also famous worldwide. Japanese convenience stores are a haven for the traveler in need. It offers anything, from drinks and snacks to full meals, copy and scanning machines, alcohol, cleaning supplies, personal hygiene items, underwear, towels, international ATMs, and so on. If some trouble occurred, or a traveler forgot to pack a particular item, it is almost sure that they can find it.

Therefore, considering that both transport systems and nearby shops are points of interest for Chinese and Western tourists, Japanese hotels have to carefully choose their location from the moment they are constructed. While not a top priority, this is a universal factor for both customer groups, and it can be an instant way to generate positive reviews.

7 Discussion

8 Limitations and Future Work

This paper is not without its limitations. We analyzed keywords of satisfaction and dissatisfaction statistically based on whether they appeared on satisfied reviews or dissatisfied ones. Following that, we attempted to understand the context that these words were being used in by using a dependency parser and observing the related nouns. However, the study is limited in that it only analyzes the words directly related to each keyword, and doesn't follow the upstream or downstream path down further connections. This means that if the words are used in combination with other keywords we did not trace the effects of multiple contradicting statements. For example, in the sentence "The room is good but the food is lacking", we would extract "good food" and "lacking food", but do not consider the fact that both occurred in the same sentence.

In this study, we analyzed the differences in customers expectations at different levels of *Omotenashi* by dividing our data into price ranges. However, in the same price range, say the high expenses ones, we can find both a western style five stars resort as well as a high end Japanese style *ryokan*. Services offered in these hotels are very high quality, although very different in nature. However, most of our database is focused on the middle range priced hotels, which is comparably less varied in service, although still there is a divide between western and Japanese style hotels.

Another limitation is that a large portion of the Asian tourists coming to Japan is Taiwanese and Korean. We could not analyze these populations because our team members do not know those languages. Aside from that, because of the nature of the data collected, further typology analysis could not be made (for example, Chinese men and women of different ages or their Westerner counterparts).

In future work, we plan to investigate further into this topic. We plan to extend our data to research for different trends for different regions of Japan and in different kinds of hotels, as well as between customers traveling alone or in groups, for fun or work. Another point of interest in the future of this study is to use word clusters with similar meanings instead of single words.

9 Conclusion

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References

Aishima T, Sato Y, et al. (2015) The origin of japanese omotenashi in man-yo-shu. Business & accounting review (16):103–122

Al-alsheikh A, Sato Y (2015) Characteristics of the hospitality, omotenashi in the traditional japanese inn: A case study of kagaya. Business & accounting review (16):123–142

Al-Smadi M, Al-Ayyoub M, Jararweh Y, Qawasmeh O (2018) Enhancing aspect-based sentiment analysis of Arabic hotels' reviews using morphological, syntactic and semantic features. Information Processing & Management 56(2), DOI 10.1016/j.ipm.2018.01.006

Alemán Carreón EC, Nonaka H, Hiraoka T, Kumano M, Ito T, Hirota M (2018) Emotional contribution analysis of online reviews. In: Proceedings of The 2018 International Conference on Artificial Life and Robotics (ICAROB2018), Beppu, Japan, vol 23, pp 359–362, DOI 10.5954/ICAROB.2018.OS5-3

Balbi S, Misuraca M, Scepi G (2018) Combining different evaluation systems on social media for measuring user satisfaction. Information Processing & Management 54(4):674–685, DOI 10.1016/j.ipm.2018.04.009

Basuroy S, Chatterjee S, Ravid S (2003) How critical are critical reviews? the box office effects of film critics, star power, and budgets. Journal Of Marketing 67(4):103–117, DOI 10.1509/jmkg.67.4.103.18692

Bauer T, Jago L, Wise B (1993) The changing demand for hotel facilities in the asia pacific region. International Journal of Hospitality Management 12(4):313–322, DOI 10.1016/0278-4319(93)90048-E

Berezina K, Bilgihan A, Cobanoglu C, Okumus F (2016) Understanding satisfied and dissatisfied hotel customers: Text mining of online hotel reviews. Journal of Hospitality Marketing & Management 25(1):1–24, DOI 10.1080/19368623.2015.983631

Browning V, So KKF, Sparks B (2013) The influence of online reviews on consumers' attributions of service quality and control for service standards in hotels. Journal of Travel & Tourism Marketing 30(1-2):23–40, DOI 10.1080/10548408.2013.750971

Chan A, Hsu CH, Baum T (2015) The impact of tour service performance on tourist satisfaction and behavioral intentions: A study of Chinese tourists in Hong Kong. Journal of Travel & Tourism Marketing 32(1-2):18–33, DOI 10.1080/10548408.2014.986010

Chang P, Galley M, Manning C (2008) Optimizing Chinese word segmentation for machine translation performance. In: Proceedings of the Third Workshop On Statistical Machine (Statmt '08), Columbus,Ohio,USA, pp 224–232, URL `http://nlp.stanford.edu/pubs/acl-wmt08-cws.pdf`

Chang R, Kivela J, Mak A (2010) Food preferences of Chinese tourists. Annals Of Tourism Research 37(4):989–1011, DOI 10.1016/j.annals.2010.03.007

Chen D, Manning CD (2014) A fast and accurate dependency parser using neural networks. In: Proceedings of the 2014 conference on Empirical Methods in Natural Language Processing (EMNLP), pp 740–750

Choi TY, Chu R (2000) Levels of satisfaction among asian and western travellers. International Journal of Quality & Reliability Management 17(2):116–132, DOI 10.1108/02656710010304537

Choi TY, Chu R (2001) Determinants of hotel guests' satisfaction and repeat patronage in the hong kong hotel industry. International Journal of Hospitality Management 20(3):277–297, DOI 10.1016/S0278-4319(01)00006-8, URL `http://www.sciencedirect.com/science/article/pii/S0278431901000068`

Cortes C, Vapnik V (1995) Support-vector networks. Machine Learning 20(3):273–297, DOI 10.1007/bf00994018

Dongyang Z, Mori T, Hayashi K, et al. (2015) A study on preferences and behavioral patterns of Chinese tourists in Kansai region, Japan. Konan Economic Papers 55(1-2):31–46, DOI 10.14990/00001507

Engel J, Blackwell R, Miniard P (1990) Consumer Behavior (6th edition). Dryden Press, Hinsdale, Illinois, USA

Fang B, Ye Q, Kucukusta D, Law R (2016) Analysis of the perceived value of online tourism reviews: Influence of readability and reviewer characteristics. Tourism Management 52:498–506, DOI 10.1016/j.tourman.2015.07.018

Fayyad U, Piatetsky-Shapiro G, Smyth P (1996) From data mining to knowledge discovery in databases. AI magazine 17(3):37–37, DOI 10.1609/aimag.v17i3.1230, URL `https://wvvw.aaai.org/ojs/index.php/aimagazine/article/download/1230/1131`

Francesco G, Roberta G (2019) Cross-country analysis of perception and emphasis of hotel attributes. Tourism Management 74:24 – 42, DOI https://doi.org/10.1016/j.tourman.2019.02.011, URL `http://www.sciencedirect.com/science/article/pii/S0261517719300408`

Gao J, Zhang C, Huang Z (2017) Chinese tourists' views of nature and natural landscape interpretation: a generational perspective. Journal of Sustainable Tourism 26(4):668–684, DOI 10.1080/09669582.2017.1377722

Gunaratne SA (2009) Globalization: A Non-Western Perspective: The Bias of Social Science/Communication Oligopoly. Communication, Culture and Critique 2(1):60–82, DOI 10.1111/j.1753-9137.2008.01029.x, `http://oup.prod.sis.lan/ccc/article-pdf/2/1/60/21366916/jcccrit0060.pdf`

Hargreaves C (2015) Analysis of hotel guest satisfaction ratings and reviews: An application in Singapore. American Journal Of Marketing Research 1(4):208–214

Hogan RT, Emler NP (1978) The biases in contemporary social psychology. Social Research pp 478–534

Hu YH, Chen YL, Chou HL (2017) Opinion mining from online hotel reviews – a text summarization approach. Information Processing & Management 53(2):436–449, DOI 10.1016/j.ipm.2016.12.002

Huang J (2017) The dining experience of beijing roast duck: A comparative study of the chinese and english online consumer reviews. International Journal of Hospitality Management 66:117 – 129, DOI https://doi.org/10.1016/j.ijhm.2017.07.003, URL `http://www.sciencedirect.com/science/article/pii/S0278431917301251`

Hunt JD (1975) Image as a factor in tourism development. Journal of travel research 13(3):1–7

Ikeda N (2013) Omotenashi: Japanese hospitality as the global standard. In: Management of service businesses in Japan, pp 145–154

Japan National Tourism Organization (2019) Nationality / monthly foreign visitors to japan (2003-2019). Tech. rep., Japan National Tourism Organization, URL `https://www.jnto.go.jp/jpn/statistics/since2003_visitor_arrivals.pdf`, (in Japanese)

Jia SS (2020) Motivation and satisfaction of chinese and u.s. tourists in restaurants: A cross-cultural text mining of online reviews. Tourism Management 78:104071, DOI https://doi.org/10.1016/j.tourman.2019.104071, URL `http://www.sciencedirect.com/science/article/pii/S0261517719302687`

Jones D (2010) A weird view of human nature skews psychologists' studies. Science 328(5986):1627–1627, DOI 10.1126/science.328.5986.1627, URL `https://science.sciencemag.org/content/328/5986/1627`, `https://science.sciencemag.org/content/328/5986/1627.full.pdf`

Jones T, Nagata S, Nakajima M, Masuyama K (2009) Prefectural branding in Japan – tourism, national parks and the Shinshu brand. Place Branding and Public Diplomacy 5(3):192–201, DOI 10.1057/pb.2009.13

Kim C, Lee S (2000) Understanding the cultural differences in tourist motivation between anglo-american and japanese tourists. Journal of Travel & Tourism Marketing 9(1-2):153–170, DOI 10.1300/J073v09n01_09

Kim K, joung Park O, Yun S, Yun H (2017) What makes tourists feel negatively about tourism destinations? application of hybrid text mining methodology to smart destination management. Technological Forecasting and Social Change 123:362–369, DOI 10.1016/j.techfore.2017.01.001

Kozak M (2002) Measuring tourist satisfaction with multiple destination attributes. Tourism Analysis 7(3-4):229–240(12), DOI 10.3727/108354203108750076

Kuboyama T (2020) “omotenashi” must comprise hospitality and service. In: Serviceology for Services, Springer Singapore, pp 34–53, DOI 10.1007/978-981-15-3118-7_3, URL https://doi.org/10.1007/978-981-15-3118-7_3

Likert R (1932) A technique for the measurement of attitudes. Archives of psychology

Liu Y, Bi JW, Fan ZP (2017) Ranking products through online reviews: A method based on sentiment analysis technique and intuitionistic fuzzy set theory. Information Fusion 36:149–161, DOI 10.1016/j.inffus.2016.11.012

Liu Y, Huang K, Bao J, Chen K (2019) Listen to the voices from home: An analysis of Chinese tourists’ sentiments regarding Australian destinations. Tourism Management 71:337 – 347, DOI 10.1016/j.tourman.2018.10.004, URL http://www.sciencedirect.com/science/article/pii/S0261517718302395

Loh S, Lorenzi F, Saldaña R, Licthnow D (2003) A tourism recommender system based on collaboration and text analysis. Information Technology & Tourism 6(3):157–165, DOI 10.3727/1098305031436980

Manning CD, Surdeanu M, Bauer J, Finkel J, Bethard SJ, McClosky D (2014) The Stanford CoreNLP natural language processing toolkit. In: Proceedings of the Association for Computational Linguistics (ACL) System Demonstrations, pp 55–60, URL http://www.aclweb.org/anthology/P/P14/P14-5010

de Marneffe MC, Manning CD (2008) Stanford typed dependencies manual. Tech. rep., URL https://nlp.stanford.edu/software/dependencies_manual.pdf

Nahm UY, Mooney RJ (2002) Text mining with information extraction. In: Proceedings of the AAAI 2002 Spring Symposium on Mining Answers from Texts and Knowledge Bases, Stanford CA, pp 60–67

Nielsen M, Haun D, Kärtner J, Legare CH (2017) The persistent sampling bias in developmental psychology: A call to action. Journal of Experimental Child Psychology 162:31 – 38, DOI 10.1016/j.jecp.2017.04.017, URL http://www.sciencedirect.com/science/article/pii/S0022096517300346

O’Connor B, Balasubramanyan R, Routledge B, Smith N (2010) From tweets to polls: Linking text sentiment to public opinion time series. In: Proceedings of the Fourth International AAAI Conference On Weblogs And Social Media, 11(1-2), p 122–129

Oh H, Parks SC (1996) Customer satisfaction and service quality: a critical review of the literature and research implications for the hospitality industry. Hospitality Research Journal 20(3):35–64

Oliver RL (1981) Measurement and evaluation of satisfaction processes in retail settings. Journal of retailing

Powers D (2011) Evaluation: From precision, recall and f-measure to roc, informedness, markedness & correlation. Journal Of Machine Learning Technologies 2(1):37–63, URL http://www.flinders.edu.au/science_engineering/fms/School-CSEM/publications/tech_reps-research_artfcts/TRRA_2007.pdf

Rajman M, Besançon R (1998) Text mining-knowledge extraction from unstructured textual data. In: Advances in data science and classification, Springer, pp 473–480

Ren G, Hong T (2019) Examining the relationship between specific negative emotions and the perceived helpfulness of online reviews. Information Processing & Management 56(4):1425–1438, DOI 10.1016/j.ipm.2018.04.003

Romão J, Neuts B, Nijkamp P, Shikida A (2014) Determinants of trip choice, satisfaction and loyalty in an eco-tourism destination: a modelling study on the Shiretoko Peninsula, Japan. Ecological Economics 107:195–205, DOI 10.1016/j.ecolecon.2014.07.019

Ryan C, Mo X (2001) Chinese visitors to New Zealand - demographics and perceptions. Journal Of Vacation Marketing 8(1):13–27, DOI 10.1177/135676670200800103

Shanka T, Taylor R (2004) An investigation into the perceived importance of service and facility attributes to hotel satisfaction. Journal of Quality Assurance in Hospitality & Tourism 4(3-4):119–134, DOI 10.1300/J162v04n03_08

Shannon C (1948) A mathematical theory of communication. Bell System Technical Journal 27(3):279–423, DOI 10.1002/j.1538-7305.1948.tb01338.x

Stone PJ, Dunphy DC, Smith MS (1966) The general inquirer: A computer approach to content analysis. MIT press

Sun Y, Wei Y, Zhang L (2017) International academic impact of Chinese tourism research: a review based on the analysis of SSCI tourism articles from 2001 to 2012. Tourism

Management 58:245–252, DOI 10.1016/j.tourman.2016.03.008

Toutanova K, Manning C (2000) Enriching the knowledge sources used in a maximum entropy part-of-speech tagger. In: Proceedings of the 2000 Joint SIGDAT Conference EMNLP/VLC, 63-71, 2000

Toutanova K, Klein D, Manning CD, Singer Y (2003) Feature-rich part-of-speech tagging with a cyclic dependency network. In: Proceedings of the 2003 conference of the North American chapter of the association for computational linguistics on human language technology-volume 1, Association for Computational Linguistics, pp 173–180

Truong T, King B (2009) An evaluation of satisfaction levels among Chinese tourists in Vietnam. International Journal Of Tourism Research 11(6):521–535, DOI 10.1002/jtr.726, URL https://onlinelibrary.wiley.com/doi/pdf/10.1002/jtr.726

Uzama A (2012) Yokoso! japan: Classifying foreign tourists to japan for market segmentation. Journal of Hospitality Marketing & Management 21(2):132–154, DOI 10.1080/19368623.2011.615016

Vermeulen I, Seegers D (2009) Tried and tested: The impact of online hotel reviews on consumer consideration. Tourism Management 30:123–127, DOI 10.1016/j.tourman.2008.04.008

World Health Organization (2015) Who global report on trends in prevalence of tobacco smoking 2015. URL https://apps.who.int/iris/bitstream/handle/10665/156262/9789241564922_eng.pdf, ISBN: 978-9241564922

Wu CHJ, Liang RD (2009) Effect of experiential value on customer satisfaction with service encounters in luxury-hotel restaurants. International Journal of Hospitality Management 28(4):586–593, DOI 10.1016/j.ijhm.2009.03.008

Xia F (2000) The part-of-speech tagging guidelines for the penn chinese treebank (3.0). Tech. Rep. IRCS Technical Reports Series. 38, Institute for Research in Cognitive Science, University of Pennsylvania, URL http://repository.upenn.edu/ircs_reports/38

Xiang Z, Gretzel U (2010) Role of social media in online travel information search. Tourism Management 31(2):179–188, DOI 10.1016/j.tourman.2009.02.016

Xiang Z, Schwartz Z, Gerdes JH, Uysal M (2015) What can big data and text analytics tell us about hotel guest experience and satisfaction? International Journal of Hospitality Management 44:120–130, DOI 10.1016/j.ijhm.2014.10.013

Xu X, Li Y (2016) The antecedents of customer satisfaction and dissatisfaction toward various types of hotels: A text mining approach. International journal of hospitality management 55:57–69, DOI 10.1016/j.ijhm.2016.03.003

Yang Y, Pan B, Song H (2014) Predicting hotel demand using destination marketing organization's web traffic data. Journal of Travel Research 53(4):433–447, DOI 10.1177/0047287513500391

Ye Q, Law R, Gu B (2009) The impact of online user reviews on hotel room sales. International Journal of Hospitality Management 28(1):180–182, DOI 10.1016/j.ijhm.2008.06.011

Zeman D, Popel M, Straka M, Hajič J, Nivre J, Ginter F, Luotolahti J, Pyysalo S, Petrov S, Potthast M, Tyers F, Badmaeva E, Gökırmak M, Nedoluzhko A, Cinková S, jr JH, Hlaváčová J, Kettnerová V, Urešová Z, Kanerva J, Ojala S, Missilä A, Manning C, Schuster S, Reddy S, Taji D, Habash N, Leung H, de Marneffe MC, Sanguinetti M, Simi M, Kanayama H, de Paiva V, Droganova K, Alonso HM, Çağrı Çöltekin, Sulubacak U, Uszkoreit H, Macketanz V, Burchardt A, Harris K, Marheinecke K, Rehm G, Kayadelen T, Attia M, Elkahky A, Yu Z, Pitler E, Lertpradit S, Mandl M, Kirchner J, Alcalde HF, Strnadová J, Banerjee E, Manurung R, Stella A, Shimada A, Kwak S, Mendonça G, Lando T, Nitisaroj R, Li J (2018) Conll 2018 shared task: Multilingual parsing from raw text to universal dependencies. In: Proceedings of the CoNLL 2018 Shared Task: Multilingual parsing from raw text to universal dependencies, pp 1–21

Zhang H, Yu Z, Xu M, Shi Y (2011) Feature-level sentiment analysis for Chinese product reviews. In: Proceedings of the 2011 3Rd International Conference On Computer Research And Development, vol 2, pp 135–140, DOI 10.1109/iccrd.2011.5764099

Zhang M, Liu S, Yang L, Jiang Y, Huang Z, Zhao Z, Deng Q, Li Y, Zhou M, Wang L, et al. (2019) Prevalence of smoking and knowledge about the smoking hazards among 170,000 Chinese adults: a nationally representative survey in 2013-2014. Nicotine & tobacco research: official journal of the Society for Research on Nicotine and Tobacco

ntz020, DOI 10.1093/ntr/ntz020
Zhou L, Ye S, Pearce PL, Wu MY (2014) Refreshing hotel satisfaction studies by reconfiguring customer review data. International Journal of Hospitality Management 38:1–10, DOI 10.1016/j.ijhm.2013.12.004