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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 using 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 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 hypothesis development

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 research question:

Research Question 2: *To what degree does satisfaction and dissatisfaction stem from 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 (Kim et al. 2017; Al-Smadi et al. 2018, e.g.).

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

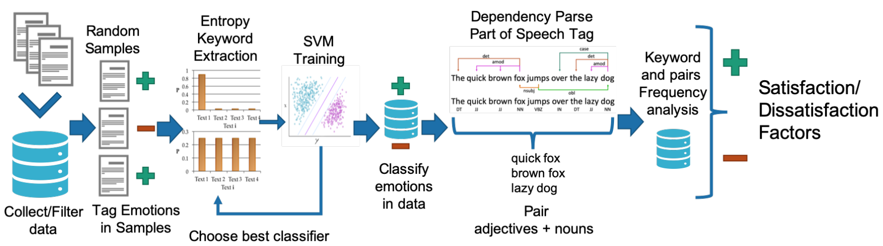


Fig. 1: Overview of the methodology to quantitatively rank satisfaction factors.

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

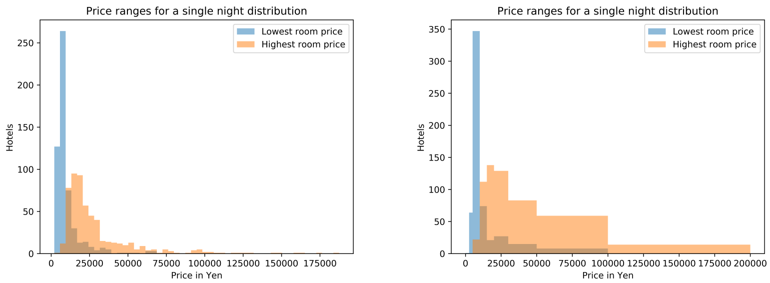
In the *TripAdvisor* data collection, we collected data from 21,380 different hotels. In total, we collected 295,931 reviews, from which 295,503 were detected to be in English. Similarly to the Chinese data, we then separated these English reviews into 2,694,261 sentences using the *gensim* python library.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

4.2 Text processing

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



(a) 50 equal lenght bins (b) manually set 9 price ranges

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

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 in Chen and Manning (2014). A list of dependencies used by this parser is detailed in de Marneffe and Manning (2008). 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 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 in Toutanova and Manning (2000); Toutanova et al. (2003), which uses the Penn Chinese Treebank tags (Xia 2000).

In this study we were interested in identifying combinations of adjectives, some verbs and nouns. We also needed to filter away bad combinations that

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

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.

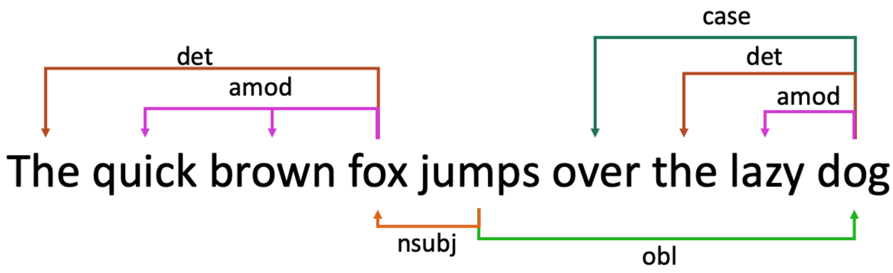


Fig. 3: Example of dependency parsing.

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

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.

4.3 Sentiment analysis

The sentiment analysis was performed using the methodology described in 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 nega-

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

tive 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**

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

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.

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.

$$f(x) = w^\top x + b \tag{1}$$

$$w = \sum_{i=1}^{N} \alpha_i y_i x_i \tag{2}$$

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 **??**. For the negative keywords, we show the results in Table **??**

5.2 Frequently used adjectives and their pairs

Table 8: Top 4 words related to the mainly used adjectives in positive 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	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	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 9: Top 4 words related to the mainly used adjectives in negative 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	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	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 10: Determination of hard and soft attributes for Chinese keywords.

Keyword emotion category	Keyword	Attribute category
Positive Keywords	不错 (not bad)	undefined
	大 (big)	hard
	干净 (clean)	soft
	交通 (traffic)	hard
	早餐 (breakfast)	soft
	近 (near)	hard
	地铁 (subway)	hard
	购物 (shopping)	hard
	推荐 (recommend)	undefined
	环境 (surroundings)	hard
	地铁站 (subway station)	hard
	远 (far)	hard
	周边 (surroundings)	hard
Negative Keywords	价格 (price)	soft
	一般 (general)	undefined
	中文 (Chinese)	soft
	地理 (geography)	hard
	距离 (distance)	hard
	陈旧 (obsolete)	hard
	老 (old)	hard

6 Results

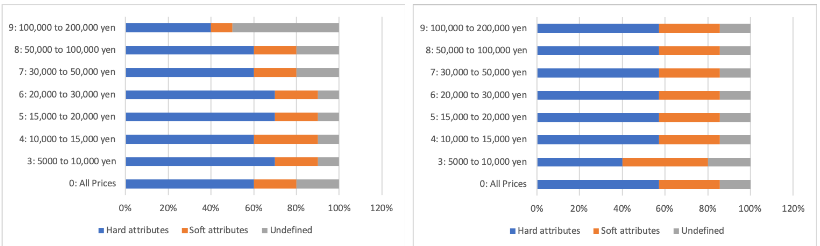
6.1 Experiment results and answering research questions

From the observation of the top-ranking subjects for Chinese tourists, we can assert that keywords relating to service and staff friendliness are not on the top 10 satisfaction factors. Besides, there are complaints about a Chinese friendly environment. This brings insight onto our research question **??**.

We can 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. This is to answer our research question 2

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 and counted the majority of uses in each context. If there is a draw or it is not clear, we declare it undefined. The interpretation of these keywords is shown in the Tables 10 and **??**.

We can see the summarized results for the positive and negative Chinese keywords in Figure 5. For the English keywords, see Figure **??**.



(a) Positive keywords (b) Negative keywords

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

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