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# A Study to Determine the Elements of Hotel Service Quality based on Online Reviews

Shaowei Guo
School of Xidian University, Shannxi 710000, China
aeolus_guosw@163.com

## Abstract

**Service quality improvement in the hospitality industry has been the focus of academic attention. Online reviews posted by travelers after their stay are of great significance to hotel operators because these reviews represent direct feedback from travelers after their experience. In this paper, an in-depth study on service quality improvement of hotels based on online reviews is done by pre-processing online reviews combined with LDA model to obtain service quality elements; at the same time, an emotion dictionary is established and the final satisfaction rating of travelers is determined by analyzing the emotion words combined with the weight of service quality elements; finally, the correctness of this paper's method is verified through case studies. The method proposed in this paper is important for service quality improvement in the hotel industry and provides reference for hotel operators.**

## Keywords

**Online Reviews; Hotel Service Quality; LDA Model; Sentiment Dictionary.**

## 1. Introduction

With the rapid development of e-commerce and hotel industry in the world, travelers book hotels through the Internet more and more frequently, and according to statistics in 2019 Chinese travelers published reviews on hotel booking websites although there is a small decrease compared to the previous year, still reached 35.83 million [1]. Travelers like to post reviews and share information on hotel booking websites, and this information plays an increasingly important role for managers to make service quality improvements. At the same time, the hotel industry is facing the paradox that travelers' demands are increasing and the management of their own hotels cannot follow up in time. Thus, how to scientifically obtain the service quality of hotels from online reviews and understand the service needs of travelers has become an important research problem.

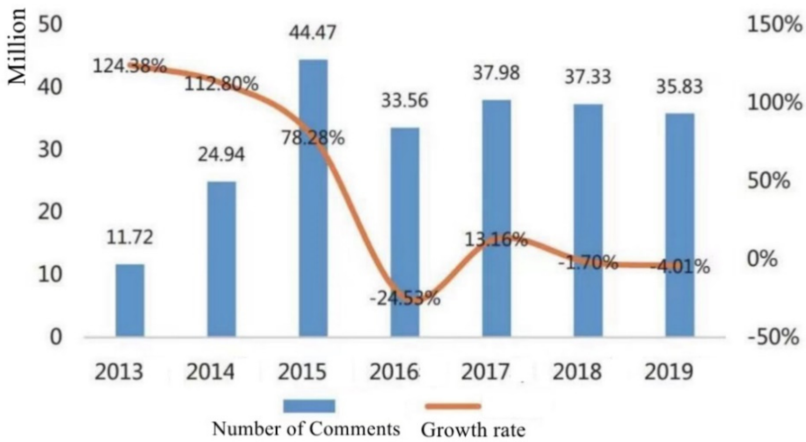


**Figure 1.** Number and growth rate of online hotel reviews, 2013-2019

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Among the existing studies, Sanchez et al. [2] pointed out the need for the subjective perceived willingness of travelers to be considered. Kattara et al.[4] analyzed the results of the questionnaires of travelers and pointed out that travelers opinion is important. Shi and Yue [5] analyzed the results of the questionnaire to find the attributions of the quality factors that affect service quality and provide specific reference for improving service quality. Xu et al. [6] calculated the exploratory and validation factors through questionnaire data, and pointed out the link between passenger satisfaction and service innovation. However, the questionnaire is in a single form and limited, and is not conducive to a comprehensive understanding of travelers' feedback on their stay experience. With the development of big data and the rise of online reviews, it has become a trend for people to actively give reviews after conducting service or product experiences. Bi et al. [7] proposed a dynamic importance performance competitor analysis model by obtaining online reviews in Catwalk and calculating the perceived satisfaction of travelers at different time periods for the hotel importance performance analysis problem. Bi et al. [8] ranked the purchase of digital cameras in Zhongguancun Online based on multi-granularity sentiment intensity analysis and stochastic approximation of ideal points by acquiring data from online reviews. In the modeling and measurement phase, scholars try various methods for service quality improvement. Yu et al. [9] customized tourism service products by calculating the value of each attribute of different tourism products to meet travelers' expectations. The evaluation phase is to measure and evaluate the service quality according to certain criteria, Mascio. [10] proposed the loss function as a service design to evaluate the service quality, Chowdhury et al. [11] established a fuzzy QFD model to consider social factors, environmental factors while performing service design. Tourzani et al. [12] used QFD combined with fuzzy AHP to calculate the weighting of traveler and environmental influences to give a game model between merchants and travelers on environmental issues, and verified the importance of environment in travelers' service experience through example analysis.Wang [13] used QFD to construct a new service quality function to study the collaborative decision problem between logistics services and supply chain.

Therefore, this paper intends to determine the service quality elements of travelers' concerns and travelers' satisfaction ratings based on online reviews. The chapters of this paper are organized as follows: chapter 2 will introduce the determination of service quality elements based on online reviews, chapter 3 will introduce the determination of customer satisfaction ratings based on online reviews, chapter 4 verifies the effectiveness of the method through example analysis, and chapter 5 concludes the contributions and shortcomings.

## 2. Determining Hotel Service Quality Elements based on Online Reviews

### 2.1. Processing of Online Reviews

Nowadays, an extremely large number of traveler groups generate consumption behavior through the Internet every day, and travelers generate corresponding data while conducting consumption experiences. Especially in the hotel industry, such as Ctrip and Trip advisor for booking hotels. At the end of hotel selection, suitable tools are selected to obtain online review data of this object. For the collection of online review information mainly through the program written based on Python 3.8. The online review information is crawled using Python, and the data such as review text, traveler's score, and review time of online reviews are mainly obtained. Since online platforms are mostly data hidden under static chains, the required data cannot be obtained using ordinary crawlers due to IP and browsing limitations, so deep web crawlers are chosen in this paper.

The data obtained through online reviews are classified into review text, traveler type, traveler score, and review time according to categories and saved in an Excel table for backup. The backup online reviews have a large amount of information and complex types, which cannot be used directly. Therefore, the online reviews need to be pre-processed, and the pre-processing includes word separation, lexical annotation and deactivation of words.

The purpose of word separation of the obtained comments is to divide the complete sentences in the comments into a collection of different word sequences according to lexicality, and the word sequences can be used for further analysis after the word separation process. The word separation processing system used in this paper is jieba word separation. jieba word separation is divided into three types: exact mode, full mode and search engine mode [14], and the words after separation are labeled according to different lexicalities based on the Python language, and the words can be aggregated into different sets of lexicalities according to the rules. In this paper, we use NLPIR-ICTCLAS Chinese word separation rules for lexical annotation of online comments, and we can choose either first-level or second-level annotation according to the need, the difference is that first-level annotation only annotates nouns, verbs, etc., and second-level annotation can annotate adjectives containing noun function, verbs containing noun function, proper nouns, etc. In the process of lexical annotation using Jieba, it is necessary to add custom dictionaries if more specialized fields are encountered. Since this paper extracts service quality elements based on online reviews in the service industry, there are not many proper nouns or specialized words, and the element words are mostly used in life, so there is no choice to add custom words using Python.

Deactivated words are words and punctuation marks that appear frequently but lack actual meaning, and are mostly reflected in the online reviews as the tone words of passengers' comments after experiencing the services. For example, "it", "la", "emm", etc. In order to obtain efficient sentiment intensity analysis, the deactivated words in the comments need to be deleted, and the deleted words have the same meaning as the original ones. For example, "look good" and "it look good" express the same emotional feedback from travelers.

The set of words obtained after preprocessing about the $h$ comment of object $A_i$ is denoted as $WS_{ih} = \left\{ W_{ih}^{1}, W_{ih}^{2}, \ldots, W_{ih}^{q_{ih}} \right\}$, where $W_{ih}^{k}$ denotes the $k$ th word in $WS_{ih}$, $q_{ih}$ denotes the total number of words in $WS_{ih}$, and $i = 1,2,\ldots,n$, $h = 1,2,\ldots,q_i$, $k = 1,2,\ldots,q_{ih}$.

## 2.2. Determining Hotel Service Quality Elements based on LDA Model

LDA (Latent Dirichlet Allocation), also known as document topic generation model, is a three-level Bayesian probabilistic model, which contains two levels of relationships while having three levels of structure, two levels of structure refers to the relationship between documents and topics, and the relationship between topics and words. The three-layer structure refers to documents, topics and words, and both documents and topics and topics and words obey the Dirichlet prior distribution [15]. LDA applied to service quality element identification can consider each online review as a bag of words and consider each service quality element in the bag of words as generated by a uniform process with a certain probability to select a certain topic and a certain probability to select a certain service quality in that topic element, the LDA principle is shown in Figure 2:

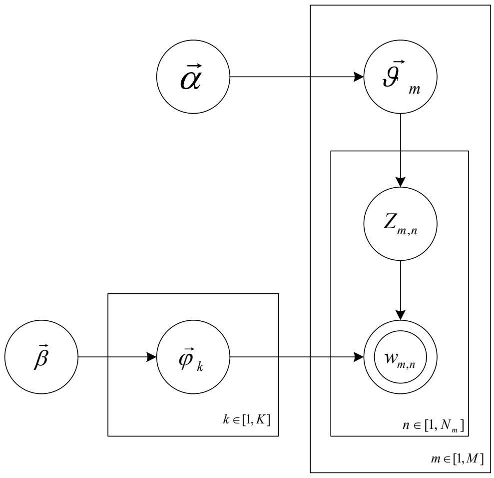


**Figure 2.** LDA model

This full probability diagram can be decomposed into two main service quality element extraction processes, First is $\vec{\alpha} \to \vec{\theta}_m \to Z_{m,n}$ , the process of generating the topic number corresponding to each potential service quality element in the online reviews. This process represents the generation of the topic number of the nth online review by a polynomial distribution function $\vec{\theta}_m$ at the time of generating the *m* th online review $Z_{m,n}$ .The topic number of the nth online review is randomly generated, where α is the hyperparameter of the Dirichlet prior distribution obeyed by the topic vector $\theta$, which reflects the concentration of the topic distribution in the online review. Next by $\vec{\beta} \to \vec{\varphi}_k \to w_{m,n} | k = Z_{m,n}$ , the process of generating service quality elements with the premise that the topic number of each service quality element in the online reviews is known. That is, the service quality elements are randomly generated by the polynomial distribution function $\vec{\varphi}_k$ in the bag of words labeled $Z_{m,n}$ , where $\beta$ is the hyperparameter of the Dirichlet distribution of the prior distribution of the service quality elements of each topic, reflecting the concentration of the distribution of the service quality elements in the topic. α and β are the hyperparameters of the Dirichlet prior distribution, w is the visible variable, and $\theta$、$\varphi$、$Z$ is the hidden variable. The purpose of the model is to estimate the hidden variables based on *w*, *α*, and *β*. The model fits best when α = 50/k and β = 0.01, when the service quality elements identified are most accurate.

Blei [15] proposed the use of the perplexity approach to determine the optimal number of topics, which was first used initially in language models,The perplexity-based approach is the most common approach used in LDA for topic estimation. In this paper, the confusion degree will also be used to estimate the optimal number of topics. A common understanding of perplexity can be how uncertain the model generated by LDA is about which topic an online review d belongs to, for an online review d. This degree of uncertainty is the perplexity. Other things being fixed, the higher the number of topics, the smaller the degree of confusion. It is calculated as shown in Equation 1.

$$P(w|M) = \exp - \frac{\sum_{m=1}^{M} \log p(w_m|M)}{\sum_{m=1}^{M} N_m} \tag{1}$$

In Equation 1, $M$ is the number of online reviews in the online review set, $N_m$ is the number of quality of service elements in the mth online review, and $p(w_m|M)$ is the probability that the LDA model produces the *m* th online review.The essence of the LDA topic consistency measure is the calculation of the semantic similarity of the maximum number-n quality of service

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element words assigned to the topic . The principle is to measure the relatedness of two texts, as shown in Equation 2.

$$PMI(x,y)=\log p(x,y)p(x)p(y)=\log p(x|y)p(x)=\log p(y|x)p(y) \tag{2}$$

In probability theory, if *x* is not correlated with *y*, then $p(x|y)$ = $p(x)$ $p(y)$. If *x* is correlated with *y*, then $p(x|y)$ is greater than $p(x)$ $p(y)$, and the greater the correlation, the greater the difference between the two. $\log p(y|x)p(y)$ means that the conditional probability $p(x)$ of *x* occurring in the presence of y is divided by the probability $p(x|y)$ of x itself occurring, indicating the degree of correlation between x and y. The log here can be simply understood as the value of log taken for $p(x)$ can convert a probability value into an information quantity (to be multiplied by -1 again to make it positive), and with a base of 2 can be simply understood as the number of service quality elements that can be used to represent this variable.

## 3. Determining Passenger Satisfaction Ratings based on Online Reviews

### 3.1. Establishment of Sentiment Dictionary

Sentiment dictionaries are built on the basis of positive and negative binary dictionaries, and the current representative Chinese sentiment dictionaries are NTUSD, a sentiment dictionary from Taiwan University, Li Jun Chinese positive and negative dictionaries from Tsinghua University and HowNet sentiment dictionary from KnowNet [16]. In this paper, the HowNet sentiment dictionary of Zhiwang is used, and the specific steps are to merge the positive sentiment words in HowNet with related evaluation words to form a positive base sentiment dictionary, and to merge the negative sentiment words in HowNet with related evaluation words to form a negative base sentiment dictionary. Firstly, all sentiment words are assembled and duplicate semantics are removed. The Python language based on HowNet can determine the sentiment level of a sentiment word by calculating the intersection of the sentiment level enhancement set and the sentiment intensity reduction set when implementing sentiment analysis. A sentiment dictionary can be built to help explain the affirmative/negative/degree adverb grading of sentiment words, and HowNet grades degree adverbs according to four dimensions: 0.5, 1.0, 1.5, and 2.0. The details are shown in Table 1

**Table 1.** Grading table of degree adverbs based on HowNet version 07

| | | |
|---|---|---|
| Negative words | 1.0 | No, don't need, never, can't, rarely, etc. |
| Affirmative words | 1.0 | well, need, greatly, can, etc. |
| Adverbs of degree | 2.0 | most, extremely, completely, absolutely, super |
| | 1.5 | especially, very, very, really, more |
| | 1.0 | compare, more, more, more and more, also, also |
| | 0.5 | Slightly, slightly, somewhat, somewhat, slightly, quite |

### 3.2. Determination of Customer Satisfaction Ratings

After determining the sentiment lexicon, the passenger satisfaction rating can be determined. Defining $AV$ denotes the sentiment value of different dimensions (elements of this service quality), $f^{pos}$ denotes positive sentiment, $f^{neg}$ denotes negative sentiment, $m$ denotes the number of adverbs, $Adv_i$ denotes the intensity value of degree adverbs, $n$ denotes the number of negatives, $w(\Pr i_j)$ denotes the negatives weight function, and the calculation formula is

$$\prod_{j=1}^{n} w(\Pr i_j)=\begin{cases}1, & j \text{ is an even number} \\ -1, & j \text{ is an odd number}\end{cases} \tag{3}$$

According to the calculation formula for unmentioned feature words, feature words + and cumulative emotion words, feature words + negative emotion words feature words + adverbs + positive emotion words, feature words + negative words + positive emotion words, feature words + negative words + adverbs + positive emotion words, feature words + adverbs + negative emotion words, feature words + negative words + negative emotion words, feature words + negative words + adverbs + negative emotion words. If the score of a dimension is expressed as $AV_{ij}^{pos}=1.5$, $AV_{ij}^{neg}=0$ then it means that the $i$rd comment mentions attribute $j$ and the sentiment for service quality element feature $j$ is positive and optimistic and scores 1.5; if the score of a dimension is expressed as $AV_{ij}^{pos}=0, AV_{ij}^{neg}=1$ then it means that the $i$th comment mentions service quality element $j$ and the sentiment for service quality element feature is negative and pessimistic and scores 1; if $AV_{ij}^{pos}=0, AV_{ij}^{neg}=0$ it means that the $i$th comment does not mention the service quality element $j$. So the satisfaction score is calculated by the formula

$$\text{per}^j=\sum_{i=1}^{i=n} AV_{ij}^{pos}+[-1*(\sum_{i=1}^{i=n} AV_{ij}^{neg})] \tag{4}$$

## 3.3. Analysis of the Example

In this paper, the object of study is set as H-brand fast hotel chain, and Python 3.8 is used to write a crawler application to collect the required data from the Ctrip.com website. The language of the specific program is shown in the Appendix.

The online review text obtained through the web contains a large amount of raw data. Firstly, this information that is not related to the review text is eliminated, and secondly, some information that is not the object of the study is removed from the crawl results. The data involved in the valid reviews obtained include: basic information of the hotel (such as opening time, distance to the nearest metro station, price, sales, number of collections, distinctive features, promotions, etc.) and basic information of the online reviews (such as number of reviews, review text, etc.). A total of 585 reviews were crawled using the crawler, and 33 invalid reviews were excluded.

The collected data were pre-processed using jieba word splitting based on Python version 3.8. First, the original set of comments was split into several words to be processed. Then, the words to be processed are lexically labeled based on the ICTCLAS lexical labeling specification table, and each of the words to be processed is lexically labeled.

The extracted hotel service quality elements are extracted using the LDA bag-of-words model based on Equations 1 and 2, and the confusion degree and semantic similarity are firstly calculated to obtain the representative words as shown in Table 2. In order to visually show the weight of the representative words in the document, this paper generates a word cloud based on Python as shown in Figure 3.

After determining the quality of service elements, the online review sentiment words are processed based on the How Net sentiment dictionary and Equation 3,4, and a sentiment dictionary based on HowNet version 07 is built using Python to extract sentiment adverbs. The positive and negative sentiment of each comment is determined.

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**Table 2.** Word frequencies of service quality elements of Hotel H

| Service quality elements | Representative words | Word frequency |
|---|---|---|
| Facilities | Air conditioning, sofa | 231 |
| Services | Attitude, Service | 133 |
| Brands | Hanting, brand | 101 |
| Location | Traffic, train station | 80 |
| Hygiene | Cleaning, hygiene | 66 |
| Dining | Breakfast, breakfast | 65 |
| Price | Price | 41 |
| Bedding | Mattress, pillow | 23 |


**Figure 3.** H Hotel service quality elements word cloud

**Table 3.** Customer satisfaction rating of Hotel H

| Elements | Facility | Service | Brand | Location | Hygiene | Dining | Price | Bedding |
|---|---|---|---|---|---|---|---|---|
| Weighting | 0.312 | 0.180 | 0.136 | 0.108 | 0.089 | 0.088 | 0.055 | 0.031 |
| Satisfaction rating | 4.82 | 4.54 | 4.77 | 4.9 | 3.98 | 4.11 | 4.78 | 4.65 |

## 4. Summary

Based on the theoretical research related to service quality improvement, this paper has conducted an in-depth study on the extraction of service quality elements and the classification of service quality elements and service quality improvement strategies. By summarizing the research work of this paper, the service quality element extraction system is established. The service quality elements and their weights were determined through online review mining and sentiment analysis. The determination of service quality elements provides the strategy and direction of service quality elements for the measurement and improvement of operators' service quality. The weighting of service quality elements is determined to lay the theoretical foundation for the subsequent research. Research on service quality improvement is currently flourishing. This paper only discusses several issues in the service quality problem, and although certain research results have been achieved, there are still some issues to be further discussed and studied, such as the analysis of the traveler evaluation information mined through the form of sentiment analysis, there may be some situations where the sentiment analysis methods cannot fully understand the semantics of online reviews, so that the results obtained may not always be completely accurate and will There are certain influencing factors, and thus the results of service quality elements extraction may have a slight bias, and future research can further explore in this aspect.

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