# The Impact of Textual Reviews on Hotel Satisfaction: A Sentiment Analysis-Based Approach (Postprint)

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## Abstract

### Objective

This study investigates the factors influencing hotel user satisfaction through text analysis of review texts and provides recommendations for hotel managers.

### Method

Word2Vec is utilized for feature extraction and dimensionality reduction on Tripadvisor.com hotel reviews, combined with sentiment analysis techniques to extract the sentiment corresponding to each feature category, and an econometric model is constructed to analyze the relationship between hotel feature evaluations and user satisfaction.

### Results

The research findings indicate: (1) The more positive the sentiment expression in review texts, the higher the satisfaction, but this effect is not linear, instead presenting a 'U-shaped'pattern; (2) The greater the number of feature categories mentioned in user review texts, the more likely that user is to lean toward dissatisfaction; (3) There exist significant differences in consumers' attention to feature categories between luxury hotels and budget hotels, with consumers focusing more on staff service for the former and cleanliness for the latter; (4) For luxury hotels, consumer satisfaction is significantly influenced by the Internet feature dimension, whereas this dimension' s impact is not significant for budget hotels.

## Limitations

The sample selection is not comprehensive enough; future research could scrape data from multiple cities for more comprehensive analysis.

## Conclusion

This study establishes a connection between hotel features and consumer satisfaction from the perspective of review texts, providing a theoretical foundation for research on hotel online reputation.

## Full Text

## The Impacts of Reviews on Hotel Satisfaction: A Sentiment Analysis Method

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### Abstract

**Objective** This study investigates the factors influencing hotel customer satisfaction through textual analysis of online reviews, providing actionable recommendations for hotel management. [**Methods**] We employ Word2Vec to extract and reduce dimensions of hotel reviews from Tripadvisor.com, integrate sentiment analysis techniques to capture the emotional valence associated with each feature category, and construct econometric models to examine the relationship between hotel feature evaluations and user satisfaction. **Results** Our findings reveal: (1) Positive sentiment expression correlates with higher satisfaction, but this relationship follows a U-shaped rather than linear pattern; (2) Reviews mentioning more feature categories tend to indicate lower satisfaction; (3) Consumer attention differs significantly between luxury and budget hotels—staff service is prioritized for luxury hotels while cleanliness is emphasized for budget hotels; (4) Internet connectivity significantly impacts satisfaction for luxury hotels but shows no significant effect for budget hotels. **Limitations** The sample selection lacks comprehensiveness; future research should collect data from multiple cities for more robust analysis. [**Conclusions**] This study establishes a connection between hotel features and consumer satisfaction from a review text perspective, providing a theoretical foundation for online word-of-mouth research in the hospitality industry.

**Keywords:** Review Text, Hotel Features, Sentiment Analysis, Consumer Satisfaction

## 1. Introduction

With the advent of Web 2.0 and the rapid development of e-commerce, User-Generated Content (UGC) on social media platforms has become a primary information source for both consumers and businesses. Online reviews not only assist potential customers in making purchase decisions but also help managers improve product and service quality. Numerous studies have demonstrated that online reviews influence sales and consumer decisions [?], with online movie reviews showing significant correlation with box office revenue and online book reviews positively impacting book sales. Online reviews contain both numerical attributes [?] (e.g., helpfulness votes, star ratings, review counts) and textual attributes [?] (e.g., readability, word count, objectivity, credibility), all of which may affect consumer purchase intentions. However, most scholars have focused on numerical ratings [?], with only a few examining the impact of textual content [?].

Economic and marketing theories [?] establish that products and services have multidimensional attributes, and consumer preferences vary regarding hotel functions and services. When consulting hotel reviews, users selectively focus on certain features based on their preferences. While some studies [?] have considered the impact of multidimensional features on hotel economic performance, and others have attempted to assign different importance weights to product and service features, relying solely on numerical ratings provides an incomplete and imprecise assessment of user-generated content.

Given that textual reviews contain more reliable information not reflected in star ratings, and that some features consumers care about may not be included in quantitative rating systems, this study focuses on review text. Through text mining of consumer reviews, we identify dimensions that truly matter to customers, better reflecting authentic opinions about hotels. We combine natural language processing, machine learning, and sentiment analysis to filter and retain the most valuable information from online reviews. Using Word2Vec to train on all hotel review text with skip-gram, we perform clustering analysis on semantic distances of keywords, segment each review into evaluation units, and apply machine learning to classify each unit into thematic features. We then conduct sentiment orientation and intensity analysis [?] to obtain sentiment scores for each feature category. Finally, we aggregate sentiment scores for each feature category mentioned in individual reviews and construct econometric models to analyze the relationship between hotel feature sentiment and consumer satisfaction, enabling identification of feature importance. Additionally, we categorize hotels into luxury and budget segments by star rating to analyze consumer preferences across different hotel tiers.

## 2. Literature Review

**2.1 The Impact of Hotel Features on Consumer Satisfaction** Existing research on how hotel features influence consumer satisfaction based on online reviews primarily employs three methods: expert opinion, syntactic analysis, and model-based analysis.

The most intuitive approach relies on domain experts to identify and evaluate hotel features. However, expert opinions cannot represent the authentic experiences of the broader customer base and are subject to strong subjective biases [?]. Syntactic methods assume that features modified by more adjectives are more important. By analyzing syntactic dependency relationships, researchers count the number of adjectives modifying feature words and cluster them to identify feature importance [?]. Archak et al. [?] used multivariate regression to identify the importance of "feature-opinion pairs" as independent variables with star ratings as the dependent variable, but this approach has limitations since one-star reviews often contain more useful information than five-star reviews [?]. Some studies [?] used econometric models to examine how feature sentiment affects consumer intentions but only considered sentiment polarity without accounting for intensity. Mai [?] improved upon earlier opinion mining paradigms [?] by applying a set of filters to common nouns and using NLP techniques to automatically identify product features and their synonyms. Wang and Wang [?] analyzed the relationship between purchase intention and product feature evaluations for 386 digital cameras on Amazon, combining sentiment analysis with econometric models. This paper adopts a similar approach, integrating hotel feature sentiment with econometric modeling to analyze the relationship between consumer satisfaction and hotel feature evaluations.

**2.2 Sentiment Analysis** As one of the most active research areas in natural language processing [?], sentiment analysis involves determining whether text expresses positive, negative, or neutral sentiment, or identifying user agreement or disagreement. This technique has been widely applied to predict product sales, election outcomes, box office revenue, and stock fluctuations [?]. Sentiment analysis employs various technologies including natural language processing, information extraction, and machine learning. Representative work on feature-level sentiment prediction includes Liu et al. [?], who identified product features in review text, extracted positive and negative sentiment content for each feature, and output feature-sentiment polarity pairs. Li et al. [?] and Blair-Goldensohn et al. [?] built opinion summarization systems for local services like restaurants and hotels, mining service-related features (e.g., Service, Value) through frequent noun methods and aggregating sentiment scores for each feature. This study adopts a lexicon-based approach [?] to calculate sentiment scores for features, providing input for subsequent econometric analysis.

## 3. Methodology

Our research framework includes text corpus preprocessing, Word2Vec, supervised learning-based feature classification, sentiment analysis, and ordered logistic regression models. We use Word2Vec to map words into K-dimensional vector space, where similarity in vector space represents semantic similarity [?].

The process involves: (1) using Word2Vec to categorize review corpora into seven major feature dimensions, (2) feature identification to assign each short clause to a feature category, (3) calculating sentiment scores using sentiment analysis techniques, and (4) aggregation to summarize sentiment scores for each feature category by review ID. In the feature identification stage, we primarily rely on manual labeling of feature words while incorporating domain knowledge. For example, "the food was great" is labeled as "Food" based on feature words, while ambiguous clauses like "I think the room is fairly clean" require hotel domain knowledge to label as "Cleanliness."The research framework is illustrated in [Figure 1: see original paper].

**3.1 Data Collection** On October 1, 2013, we used LocoySpider (http://www.locoy.com) to collect all online hotel reviews for Las Vegas from Tripadvisor.com posted between January 1, 2012, and September 30, 2013. The Tripadvisor.com review detail page is shown in [Figure 2: see original paper]. The collected data includes star ratings across five dimensions (Location, Rooms, Value, Cleanliness, Sleep Quality), review IDs, overall ratings, review titles, and review text. After cleaning, we obtained 217,518 English hotel reviews. We performed Word2Vec analysis on all Las Vegas reviews (217,518 reviews, approximately 40 million words) to generate word vectors. For the econometric model, we randomly selected 5,124 reviews, including 2,625 from luxury hotels and 2,499 from budget hotels.

**3.2 Preprocessing** For the English text corpus, we performed the following steps: 1. Word lemmatization and lowercasing 2. Stopword removal (e.g., conjunctions, prepositions, personal pronouns like "and," "in," "you" ) 3. Removal of words unrelated to sentiment or hotel features (e.g., "hotel," "any" )

**3.3 Word2Vec-Based Hotel Feature Word Clustering** Following Duan et al. [?], we extracted frequently occurring nouns as candidate hotel features. Initial analysis of the text corpus revealed high-frequency nouns shown in the word cloud in [Figure 3: see original paper], indicating consumer concerns about breakfast, buffet, cleanliness, wireless, room, value, and location.

To remove noise from high-frequency words, we applied the method from [?], using maximum likelihood ratio tests to calculate relative frequency differences for each identified noun between relevant (hotel reviews) and non-relevant (book reviews) categories. Nouns with low likelihood ratios were considered irrelevant and filtered out. Since the likelihood ratio follows an asymptotic $\chi^2$ distribution, we set a threshold above the p=.05 level to select candidate product features, while manually compiling a set of irrelevant nouns such as named entities ( “hotel,” brand names like “Hilton” ) for removal. This process yielded 55 hotel feature nouns.

We trained Word2Vec on the hotel review corpus (40,953,696 words) with parameters (threads = 3, vectors = 100, window = 12) to obtain word vectors, then extracted vector representations for the 55 hotel feature nouns. Using Euclidean distance between word vectors as similarity measure, we applied K-means clustering.

We evaluated clustering quality using the Silhouette Coefficient to examine cluster separation and compactness. Setting K from 2 to 15 and running 50 iterations each, the results are shown in [Figure 4: see original paper] and [Figure 5: see original paper]. [Figure 4: see original paper] clearly shows a peak at K=7, indicating optimal clustering. We reduced the 100-dimensional data to 2D for visualization, shown in [Figure 6: see original paper].

The clustering analysis identified seven hotel feature categories: Food, Facility, Staff, Cleanliness, Location, Value, and Internet. The clustering results are presented in [Figure 6: see original paper].

**3.4 Machine Learning-Based Feature Classification** Similar studies [**?**, **?**] have segmented reviews into sentences and classified them into dimensions. One study [**?**] used Naive Bayes to classify hotel review sentences into five dimensions with 68% accuracy, while another [**?**] used Support Vector Machine to classify restaurant reviews into six dimensions (food, service, price, ambiance, narrative, and other), achieving highest precision for food (81.43%) and lowest for narrative (49.15%), with an average accuracy of 70.34%.

Following the previous step, we categorized customer concerns into seven categories: Food, Facility, Staff, Cleanliness, Location, Value, and Internet. Adapting the approach from [**?**, **?**], we first segmented each review into short clauses based on punctuation marks ( “,” , “.” , “!” , “?” ), then removed objective clauses without sentiment words (e.g., “we went up to the room” ) and clauses without hotel feature words (e.g., “other complaints are minor” ). This yielded approximately 100,000 opinion units with an average length of 6 words. Example opinion units are shown in .

We employed machine learning to classify each short clause into feature categories. Since the optimal classifier was unknown, we tested both Multinomial Naive Bayes and Support Vector Machines. The results in show that SVM is more suitable for our dataset, achieving higher precision for every category and an average accuracy of 80%, outperforming [**?**, **?**]. We therefore used SVM to classify all opinion units.

**3.5 Lexicon-Based Sentiment Analysis** We calculated sentiment for each short clause using a lexicon-based approach. Sentiment dictionary selection is crucial, as the same sentiment word may have different meanings across contexts [?]. Our sentiment dictionary is derived from [?]. Unlike previous studies that only marked sentiment words and phrases without considering sentiment shifters, we adopt the corpus-based method from Ding et al. [?], incorporating valence shifters [?]—words and phrases that can change sentiment orientation. Typical negation shifters include "not," "never," "none," "nobody," "nowhere," "neither," and "cannot." For example, "the hotel location is great [+1]" becomes "the hotel location is not great [-1]" due to the negation word.

We calculated sentiment scores for each short clause using an aggregation function. Assuming a sentence $s$ contains a series of sentiment shifters $W_1, W_2, \ldots, W_{ij}$ and sentiment polarity words, the sentiment score $Senti(s)$ is determined by an additive function. Following [?, ?], since each opinion unit is very short, the resulting sentiment score represents the consumer' s opinion about the corresponding hotel feature.

Finally, we aggregated sentiment scores by review ID to create a review-feature sentiment matrix, obtaining sentiment scores for each review across the seven dimensions: Food, Facility, Staff, Cleanliness, Location, Value, and Internet.

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## 4. Experiments and Results Analysis

This study focuses on review text rather than numerical star ratings because textual content contains more reliable information not captured in rating systems, and some features consumers care about may not be included in quantitative rating frameworks. Since our dependent variable is ordinal (satisfaction levels from 1 to 5, representing increasing satisfaction), we employ Ordered Logistic Regression [?].

**4.1 Descriptive Statistical Analysis of Model Variables** presents descriptive statistics. Under the new dimensions, customer sentiment expressions are both positive and negative. The Facility dimension shows the strongest sentiment intensity, with a minimum of -4.65 and maximum of 11.1—having the largest absolute values for both negative and positive sentiment among all seven dimensions. The Staff dimension ranks second, with values ranging from -4.02 to 8.17. In contrast, the original dimensions (Location, Rooms, Value, Cleanliness, Sleep Quality) have ratings from 1 to 5 with similar averages, suggesting strong inter-dimension correlations and incomplete data due to missing values.

**4.2 Comparison of Correlation Coefficients Between Original and Regenerated Hotel Feature Dimensions** We conducted sentiment analysis on 5,124 selected reviews and examined correlations among the newly generated dimensions in . shows that the original five dimensions have significant correlations, with coefficients ranging from 0.43 to 0.73. This high correlation indicates problems with the dimension classification, as it cannot accurately reflect customers' true attitudes toward specific hotel aspects. In contrast, correlations between new dimensions are much lower, with a maximum of 0.22. Except for the negative correlation between Internet and Location, all other inter-dimension correlations are positive, suggesting that consumer perceptions of one dimension are positively influenced by others. Therefore, using the new dimension data is appropriate for studying how different features affect overall hotel satisfaction.

**4.3 Impact of Hotel Feature Sentiment on Satisfaction** Numerous studies have examined hotel features, though classic models like SERVQUAL [**?**] often contain too many items and are overly theoretical. With the rise of review platforms, traditional questionnaires are no longer the only data source. Researchers have studied various dimensions including cleanliness, location, rooms, service, sleep quality, and value [**?**], while others have examined how factors like rooms, internet, food, and location affect overall satisfaction [**?**]. Some studies [**?**] identify value, rooms, and service as most important, while others [**?**] note that consumer preferences differ by hotel tier—luxury hotel guests have strict internet requirements, while budget hotel guests prioritize basic amenities like toothpaste and toothbrushes. While hotel satisfaction research is extensive, most data comes from surveys or numerical ratings rather than mining actual consumer opinions from text. Our study addresses this gap by analyzing professional travel review website comments to identify consumer preferences and their impact on satisfaction.

In our econometric model, Model (1) uses overall customer satisfaction as the dependent variable, with staff_{senti}, food_{senti}, cleanliness_{senti}, facility_{senti}, location_{senti}, and value_{senti} as independent variables, controlling for hotel fixed effects.

Research shows that customer experiences and preferences differ across hotel tiers [**?**]. To examine how customers focus on different dimensions across hotel types, we categorized hotels into luxury ($ 4*stars*)*andbudget*( $3 stars). Models (2) and (3) separately analyze luxury and budget hotel data.

Model (4) examines the number of feature categories mentioned and overall sentiment expression, using overall satisfaction as the dependent variable with Num_{{{of}}*{{feature}}}, ave*{sentiment}, and sentiment^2 as independent variables. Regression results are shown in .

shows that Model (1) indicates consumer satisfaction is positively affected by sentiment across Facility, Staff, Location, Cleanliness, Food, and Value dimensions. The Staff dimension has a coefficient of (0.7608, $p<0.01$) with an odds ratio (OR) of 2.14, while Facility has a coefficient of (0.6049, $p<0.01$) with OR=1.83. The odds ratios indicate the impact magnitude of each one-unit increase in the independent variable. Staff service shows the largest odds ratio, suggesting it has the greatest impact on ratings, followed by Facility. Internet shows no significant effect, possibly because this dimension is relatively new and less consciously evaluated by consumers.

Comparing Models (2) and (3), for luxury hotels, Staff has the greatest impact (coefficient=0.8931, $p<0.01$, OR=2.44), while for budget hotels, Staff is also important but with a smaller effect (coefficient=0.7486, $p<0.01$, OR=2.11). For budget hotels, Cleanliness has the strongest impact on satisfaction—the cleaner the budget hotel, the more satisfied the customer. Internet connectivity differently affects satisfaction across tiers: for luxury hotels, network coverage and ease of use positively impact satisfaction, likely because luxury hotel guests are often business travelers with work-related needs. For budget hotels, Internet shows no significant effect.

Model (4) reveals that extreme satisfaction or dissatisfaction is reflected in review text, making content analysis crucial. Sentiment expression aligns with satisfaction perception—more positive sentiment yields higher satisfaction, but the effect of sentiment intensity is non-linear. Additionally, mentioning more feature categories correlates with lower satisfaction, suggesting that reviews focusing on fewer dimensions indicate higher satisfaction.

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## 5. Conclusion

Analysis of Tripadvisor.com' s original rating system reveals high correlations among its "Location, Rooms, Value, Sleep Quality, Cleanliness" dimensions, suggesting the classification is problematic. Consumers may be uncertain which dimension to rate for certain experiences, and desired features may lack corresponding rating categories, indicating that quantitative star ratings can be inauthentic, incomplete, and inaccurate.

Through macro and micro textual analysis combined with sentiment analysis and ordered logistic regression, we find that Facility (e.g., room size, bedroom comfort, balcony layout, swimming pool) has the greatest impact on overall satisfaction, followed by Staff service. For luxury hotels, satisfaction is significantly affected by Internet connectivity—WiFi and Internet accessibility substantially impact ratings. Luxury hotel guests prioritize staff service, while budget hotel guests are most influenced by cleanliness. These findings help managers maximize satisfaction with minimal investment: focus on Facility and Staff to create strong first and last impressions; luxury hotels should prioritize Internet quality, while budget hotels must maintain cleanliness standards. Textual analysis of hotel reviews enables managers across different hotel types to achieve better returns with less investment, which is strategically significant for long-term development.

**Limitations:** The sample lacks comprehensiveness, focusing on only one city. Research indicates that customer concerns vary by city—for example, "Bug" may be a high-frequency term in London hotel cleanliness reviews but rarely appears in our Las Vegas corpus. Due to specific geographic and climatic conditions, factors influencing satisfaction perception differ across locations. Future research should collect samples from multiple cities for comprehensive comparative analysis.

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## Author Contributions

**Wu Weifang:** Designed the research, performed data analysis, wrote and revised the manuscript.
**Gao Baojun:** Conceived the research idea, collected and cleaned data, provided revision suggestions.
**Yang Haixia:** Analyzed data, provided revision suggestions.
**Sun Hanlin:** Collected and cleaned data.

## Conflict of Interest Statement

All authors declare no conflict of interest.

**Supporting Data**

The supporting data is self-archived by the authors and available upon request at weifang@whu.edu.cn: [1] Wu Weifang, Gao Baojun, Sun Hanlin. LasVegas.csv. Las Vegas hotel review data.
[2] Wu Weifang, Gao Baojun, Yang Haixia. HotelText_{word2vec}.bin. Word vector representations of review corpus.
[3] Wu Weifang, Gao Baojun, Yang Haixia. aspect-sentimentsumscore.RData. Review feature sentiment matrix data.

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*Note: Figure translations are in progress. See original paper for figures.*