Using an Ontology-Based Neural Network and DEA to Discover Deficiencies of Hotel Services

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ABSTRACT

Companies can gain critical real-time insights into customer requirements and service evaluation by mining social media. To acquire the service performance and improve the service deficiencies for hotels, this research proposes a benchmark-based performance evaluation model for hotel service to enable hotel managers to assess the service performance. In the case of non-benchmark service hotels, the identification and improvement model for non-benchmark criteria can recognize and analyze the required quantities of performance improvements for non-benchmark criteria. For understanding the causes of service deficiencies, this research mines the online posts and creates a hierarchical ontology of service deficiencies for hotels. A hierarchical ontology-based neural network is proposed to automatically identify the causes of service deficiencies. This study employs an online forum as a case to achieve the identification accuracy of causes of service deficiencies of 92.68%. The analytical result can demonstrate the significant effectiveness and practical value of the proposed methodology.

KEYWORDS

Back Propagation Neural Network, Hotel Service, Online Customer Review, Ontology, Performance Evaluation

INTRODUCTION

The rapid advancement of the Internet has increased convenience and intangibly altered consumer behavior patterns. Nowadays, more consumers are now sharing information of product or service experiences by posting on online forums, and for companies, such information can understand customers' satisfaction level toward products or services. To investigate product or service deficiencies, online forums have become a major channel used by companies for acquiring feedback from customers who are actually using products or services. Nguyen and Coudounaris (2015) indicated that online hotel reviews not only have a great influence on consumer decision-making but also provide hotel management with valuable insights into consumer service ratings and preferences. According to the

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Nielsen Global Survey of Trust in Advertising Report (2011), 70% of 28,000 online survey respondents from 56 countries stated that online consumer reviews are a trustworthy source of information. Therefore, online posts have a considerable impact on the service industry. Online posts accumulate rapidly because of the exponential growth of the Internet usage population. Nonetheless, many online posts contain unstructured data; that is, text without a consistent format. The currently available software and methods are thus not useful for those wishing to automatically and systematically analyze service ratings and reviews. Hence, how to effectively extract key information from online posts and interpret that information has become the critical competitive advantage. Because of the unstructured nature and large volume of data on online forums, hotel managers must adopt effective and efficient methods to capture the essence of online customer reviews and analyze the data for detecting valuable but hidden information that enables managers to make better business decisions.

To resolve the above-mentioned problems, the present study focuses on the hotel industry and applies a hierarchical ontology-based back-propagation neural network and data envelopment analysis to develop an online customer reviews-based performance evaluation and deficiency discovery methodology for hotel service. First, a criteria framework for performance evaluation of hotel service is established using information from a hotel booking website. According to the evaluation criteria, this study proposes a benchmark-based performance evaluation model for hotel service to understand the service performance of the hotels. Next, this study develops an identification and improvement model for non-benchmark performance criteria to provide non-benchmark hotels with the required quantities of performance improvements for non-benchmark criteria. To gain insight into the causes of non-benchmark service, this study extracts keywords from customers' online posts by using text mining. Moreover, this research aggregates these keywords and then establishes a synonym database to reduce the number of keywords substantially so as to simplify the data analysis. Through using the keyword data, this study proposes a hierarchical ontology for service deficiencies of hotels, which not only clearly shows the classes and causes of service deficiencies but also lists the keywords that characterize the causes of each service deficiency. Subsequently, the back-propagation neural network and the hierarchical ontology for service deficiencies of hotel are integrated to develop a hierarchical ontology-based automatic classification system for detecting the causes of service deficiencies.

The analysis results enable hotel managers to effectively and accurately identify and understand the core issues causing customers to rate hotel service as poor, and by understanding the root causes, concrete improvement plans can be developed to boost a hotel's competitiveness by enhancing its service performance.

LITERATURE REVIEW

Hotel Operations and Service Performance Evaluation

For the new coronavirus disease (COVID-19), no touch service plays an important role to enhance the service performance. Due to the high prices of specialized fingerprint systems, digital cameras can be considered as an alternative source for fingerprints images. Alsmirat et al. (2019) determined the optimum ratio of the fingerprint image compression before storing them to assure the high accuracy of the fingerprint identification system. The result of that research showed that using 20%–30% of the original image size is good to extract enough features with no loss of important information. In order to reduce the mobile devices' overhead, Elgendy et al. (2021) proposed an offloading model for a multi-user mobile edge computing and a new caching concept to substantially minimize the time and energy consumption. In that research, two effective Q-learning and Deep-Q-Network-based algorithms were created to derive the near-optimal solution for this problem to substantially minimize the mobile devices' overhead.

Chen (2009) adopted data envelopment analysis (DEA) to evaluate hotel operational performance in Taiwan and identify hotels with benchmark operational performance. In that study, the input

variables were operational costs and number of rooms, whereas the output variables were room revenue and occupancy rate. To explore the superior ranking of hotels with benchmark operations, Ashrafi et al. (2013) employed superefficient DEA to rank the operational performance of hotels in Singapore. Aside from studies evaluating hotel operational performance, some papers also specifically discuss the performance evaluation of hotel customer service. Zoraghi et al. (2013) established a fuzzy multi-criteria decision-making model (FMCDM) for evaluating and ranking hotel service quality, wherein the evaluation criteria included safety, price, facilities, technology, and responses. In the FMCDM, the decision-maker subjectively and directly assigns weights to the evaluation criteria. The performance evaluation results would have been more objective if relative importance weights determined from pairwise comparison had been used. Hence, Chin and Tsai (2013) used the analytic hierarchy process (AHP) to develop a multi-criteria evaluation framework of international hotel chain service quality based on the PZB model. In the AHP, the pairwise comparison method was employed to determine the relative importance of the evaluation criteria. Among these criteria, Chin and Tsai (2013) discovered that maintenance and cleaning of the environment and facilities, the instant delivery of services, and accurate bills are the most crucial criteria. Chen et al. (2014) employed the Delphi method to collect information and then established a framework for evaluating the performance of spas in international hotels. The fuzzy AHP was employed to evaluate the relative importance of each criterion. Different experts may give different weights of relative importance to evaluation criteria, and this inconsistency may have affected the evaluation results of service performance.

Akincilar and Dagdeviren (2014) built a performance evaluation criteria framework for the service quality of hotel websites. The aspects evaluated by the framework included customers, technology, marketing, and safety. The AHP was used to acquire weights of relative importance for each evaluation criterion. They used the preference ranking organization method for enrichment evaluation (PROMETHEE) to rank the website service quality of 16 five-star hotels in Turkey. Using that ranking method, the researcher could only compare the website service performance of two hotels at a time. Because many hotels had to be evaluated, considerable time was required. Benítez et al. (2007) took advantage of fuzzy triangular numbers to let consumers express the performance values of the evaluation criteria for hotel service. Fuzzy semantics were then converted into precise numeric values using defuzzification. Finally, technique for order preference by similarity (TOPSIS) was employed to rank the service quality and performance of Spanish chain hotels. Shirouyehzad et al. (2012) used a Likert scale to evaluate the perceived and expected quality of customers; the key indicators used in their study were reliability, guarantees, service facilities, empathy, and staff responsiveness to customers. DEA was then used to evaluate the service performance of hotels and determine which hotels had benchmark services. Subsequently, TOPSIS was applied to rank these hotels by their service quality performance. Because that research used three-, four-, and five-star hotels as examples, differences in the number of stars may have reduced the objectiveness of service performance evaluation. Furthermore, TOPSIS used the optimal and worst solutions for each criterion to calculate the performance value of each criterion for the evaluated hotels. Their suggestions for non-benchmark hotel service improvements would have been more objective if all criteria can be evaluated simultaneously from a whole viewpoint.

To determine how overall customer satisfaction could be enhanced, Yang et al. (2011) developed an integrative evaluation method of hotel service quality that combines the Kano Model, the importance–satisfaction model, and the improvement indicators. First, the Kano model and the importance–satisfaction model were applied to analyze the importance of each evaluation indicator and the customer satisfaction level. Next, the improvement indicators were employed to identify the crucial criteria for which customer satisfaction was low. Hotel management could use the information in its decision-making related to customer service amelioration. However, that approach is not sufficiently sophisticated to determine key points for service improvement. Moreover, it cannot perform pairwise comparison of performance among hotels. Therefore, this study uses the data envelopment analysis method to develop the benchmark-based performance evaluation model for hotel service.

Text Mining

The data stored on the Internet has increased explosively as a result of lower data storage costs and larger Internet usage populations. The majority of electronic data has an unstructured format. Thus, to improve knowledge extraction in the big data era, numerous researchers are interested in text processing and mining. To reduce the complexity of text mining, text preprocessing is very critical. Preprocessing converts unstructured data into structured data by following certain definitions or rules so as to facilitate subsequent keyword extraction. For English text preprocessing, Rivera et al. (2014) applied symbolization to remove spaces and punctuation. As part of the first step of preprocessing, they also removed stop words such as "the," "for," and "that" by deleting stop words. To decreasing data dimensions, Akçapınar (2015) deleted stop words, changed them to lower case words and then constructed a word-document matrix. In the present study, we also combine the three preprocessing steps to reduce the time of text mining and boost the classification accuracy for causes of customer complaints. At the same time, Software R is employed to segment online posts, delete stop words, perform word stemming, and establish a synonym database for reducing data complexity. Because the posts on the website used in this study belong to short text messages, this research establishes a two-dimensional sentence-keyword matrix to display the text mining results.

After text preprocessing is employed to reduce data complicity, text mining can be performed to identify messages from texts. To classify documents, Chena et al. (2009) used the Naïve Bayesian classifier, which enables users to decide whether a particular feature selection is favorable or poor. To determine which online forum is preferred by Internet users, Li and Wu (2010) performed an online hotspot forecast using 220,053 posts at 31 forums of Sina Sports. K-means clustering and a support vector machine (SVM) were combined to implement unsupervised text mining. Although the forecast result was favorable, the appearance of an outlier abnormality would have strongly affected the classification result because k-means clustering and SVMs are extremely sensitive to abnormal values. Xiang et al. (2015) extracted customer hotel reviews from Expedia.com and explored the associations among review content, review semantic structure, and consumer satisfaction. Text mining was employed to identify the frequency of keywords occurrence, and linear regression was used to validate the association between semantic structure and customer satisfaction. Although their study result is useful, lexical ambiguity had a negative effect on the overall analysis results.

Groth and Muntermann (2011) performed text analysis for financial risk management, and the text analysis results were evaluated using four classification methods, i.e., the Naïve Bayes classifier, the k-nearest neighbors (kNN) algorithm, the support vector machine (SVM), and the neural network. The study results demonstrated that the forecast accuracy of kNN, the SVM, and the neural network were superior to that of the Naïve Bayes classifier. Koteeswaran and Kannan (2013) used an artificial neural network to train a text mining model, and synonyms were defined and classified during the computation process. Their study revealed that a model trained using this method is highly convergent, and the learning result is excellent. Ramasundaram and Victor (2013) compared the performance of the Naïve Bayes classifier, kNN, NGrams, the back-propagation network, the genetic algorithm, and the SVM for text classification. NGrams had the highest speed of convergence, followed by the back-propagation network and the genetic algorithm. Trappey et al. (2006) extracted keywords from patent documents and then used a back-propagation network to train a neural model for patent document classification. Because the back-propagation network can resolve nonlinearity during the learning process, it effectively assists companies in automatic patent document classification and management. To achieve effective automatic classification of document types and enable document retrieval, Chou and Hsing (2010) used a self-organizing map for cluster analysis. High-frequency keywords were then employed for back-propagation network classification. The result demonstrated that this approach was highly accurate for automatic classification and cluster analysis.

This literature reveals that aside from having higher classification accuracy for text mining than other methods, back-propagation neural networks are capable of resolving nonlinear problems.

Therefore, the present study employed a back-propagation neural network for classifying the causes of customer complaints.

Customer Complaint Analysis

In recent years, the rapid advancement of the Internet has altered consumers' decision-making behavior. Blal and Sturman (2014) stated that, because of the prevalence of social media, the reviews posted on online forums have attracted considerable public attention, making online consumer reviews influential significantly. This explains why increasing customers check online product and service reviews before making a purchase or making any consumer decision. Ye et al. (2009) pointed out that online customer reviews have a significant effect on hotel booking. In other words, positive reviews effectively boost hotel bookings. This finding implies that online reviews are a major channel through which customers obtain consumer information. Online reviews also have a considerable impact on hotel revenue. Due to the rapid increase in fake articles on social media, Sahoo and Gupta (2021) used deep learning to introduce the multiple features based automatic fake news detection approach in chrome environment. The approach can detect fake news on Facbook by analyzing user information and shared posts. The proposed deep learning algorithm in that research achieved excellent performance with 99.4% accuracy as compared to machine learning algorithms. Because the acquisition of a large number of annotated datasets spend a lot of labor cost (Ren et al., 2022), deep active learning can be applied in fake news detection. In the case of imbalanced data, Hammad et al. (2021) developed a focal loss function to improve the classification accuracy with . an overall accuracy of 98.84%.

Heung and Lam (2003) revealed that the reputation of a hotel may be destroyed by customer complaints. To improve customer satisfaction and service quality, analyzing causes of customer complaints is essential. Therefore, how to extract key information from online customer complaints becomes a critical issue for businesses. Cho et al. (2002) considered that online customer satisfaction depends not only on excellent online customer services but also instantaneous response to customer complaints. How to use filtering to extract important complaint posts from numerous online reviews is thus worth research. Mattila and Mount (2003) evaluated the effect of responding to customers' email questions on customer satisfaction and complaint handling. The results demonstrated that how customer complaints are handled and businesses' response time directly affect customer repurchase intention; that is, by using the correct method, responding in a timely manner, and improving response quality, customers' repurchase intention can be increased. Lam and Tang (2004) used statistical hypothesis testing to investigate the characteristics of customer complaints. Questionnaire surveys were employed to collect data on problems encountered by hotel customers, and the collected data were subsequently analyzed. The results revealed that most customers who filed complaints were young people with higher education and high income. Lee and Hu (2004) analyzed customer complaint records from the complaint forum of eComplaint.com. They performed text mining to extract keywords from posts, calculated the frequency of keywords, and used a neural network to classify online complaint posts. Their classification results can assist hotel administrators to understand and to manage the customer dissatisfaction issues.

If Lee and Hu (2004) had employed ontology to construct a framework that analyzed causes of overall customer complaints, the efficacy of the analysis would have been higher. Faed et al. (2014) investigated customer relationship management and customer complaints in the field of harbor transportation. Questionnaire surveys were employed to collect data, and the words were then converted into a numerical format. DEA was used to cluster customers. Lastly, a nonlinear model and fuzzy reasoning were employed to identify how customer loyalty could be improved. Coussement and Poel (2008) proposed an automatic classification system for enhancing the efficiency of recognizing complaint posts. Their empirical results revealed that incorporating language style into a traditional text classification model can effectively save time and improve the performance of classifying forum posts. To handle customer complaint messages automatically, Yalan and Jinlong (2006) used the

ontology web language to construct a customer complaint ontological framework that establishes the relationship between consumer complaint cases with the causes of these complaints. This ontological framework enables users to quickly understand the semantic content and connotations of complaints. Lee et al. (2015) employed an ontology to construct a hierarchical complaint framework that allows business owners to identify the causes of complaints by establishing classes of complaint causes through the effective self-learning function. Although this framework is favorable for identifying causes of complaints, it is slightly too crude. Because these product reviews are too abundant, lengthy and descriptive, Hong and Wang (2021) proposed a deep neural network based framework to summarize customer opinions, including both positive and negative comments, from product reviews. The summaries provide users the valuable opinions on product attributes. Debnath et al. (2022) used the attention-based long short-term memory model to develop an abstractive text summarization system to create sentiment-based summaries of the product reviews.

By more detailed descriptions of the core characteristics of a complaint, the capacity of complaint cause identification of this framework can be improved. If the classes of causes of customer complaints can be effectively and automatically identified, hotel owners will be able to quickly identify the causes of poor service. Chou and Hsing (2010) suggested that applying an ontology to automatic text classification for characteristics extraction can improve the accuracy of document classification. Therefore, the present study uses an ontology to construct a hierarchical ontology-based back-propagation neural network that automatically identifies the causes of service deficiencies of hotels.

METHODOLOGY

Figure 1 illustrates the framework of the online customer reviews-based performance evaluation and deficiency discovery methodology for hotel service. The framework comprises three parts: the benchmark-based performance evaluation for hotel service, text mining of online posts for customer reviews, and hierarchical ontology-based automatic classification of service deficiencies. For the first part, this study proposes a benchmark-based performance evaluation model for hotel service that enables managers to assess the hotels' service performance and to identify hotels with non-benchmark service. Next, the identification and improvement model for non-benchmark performance criteria can recognize poor performance criteria and then analyze the required quantities of performance improvements for non-benchmark criteria. In the second part, this study crawls online posts regarding hotels with non-benchmark service performance. Next, this research segments the sentences in customer posts, removed stop words from the texts, and performed word stemming. To reduce data complexity, a synonym database is established that consolidates the synonyms of each keyword, and keywords from each sentence in each customer post are aggregated and used to construct a two-dimensional keyword-sentence matrix. In the third part, keywords extracted from the second part are used to establish a hierarchical ontology of service deficiencies by using the Web Ontology Language (OWL), and then to develop a hierarchical ontology-based back-propagation neural network for automatically identifying the causes and the classifications of service deficiencies for non-benchmark hotels. The following subsections elaborate on each part of the proposed methodology.

Benchmark-Based Performance Evaluation for Hotel Service

This study uses output-oriented BCC-data envelopment analysis (DEA) (Banker et al., 1984) to develop a benchmark-based performance evaluation model for hotel service as shown in Formulas (1-10). The input variable of the model is the room rate as shown in Formula (8). The output variables can be divided into two classes, i.e., hardware facility and perceived service. Hardware facility comprises the facility function, the hotel location and the Wi-Fi provision as shown in Formulas (2-4), respectively, whereas perceived service is divided into the comfort level, the cleanliness level, and

Figure 1. Framework of the online customer reviews-based performance evaluation and deficiency discovery methodology for hotel service
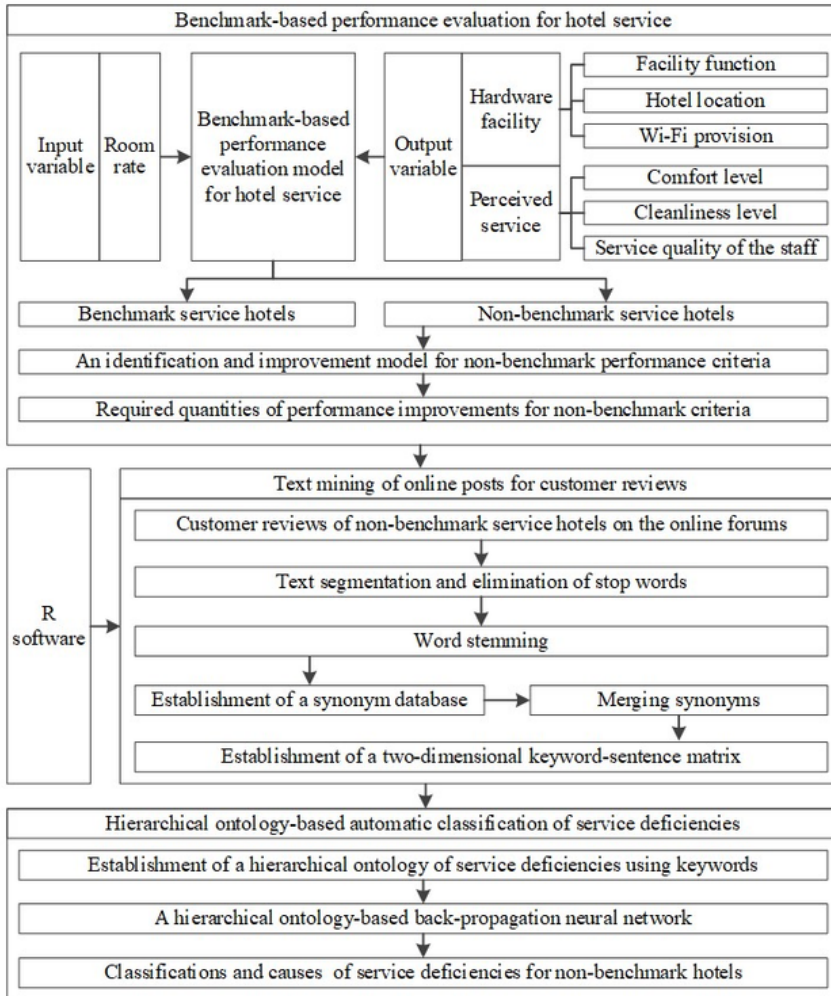
the service quality of the staff as shown in Formulas (5-7), respectively. Performance values of the output variables range from 1 to 10. A higher performance value indicates the higher performance.

If the value of service performance for the hotel h, i.e., m_h is less than 1, the hotel is a non-benchmark service hotel. Formula (10) expresses the weight of each decision-making unit, and the sum of all decision-making units must be 1. Moreover, all variables of the model have to be higher than 0, whereas θ must be more than or equal to 1 as shown in Formula (10). The slack variable analysis is employed to establish an identification and improvement model for non-benchmark performance criteria as shown in Formulas (11-16). For all criteria, if the value of performance improvement is greater than 0, this criterion is a poor performance criterion. Moreover, the value of performance improvement for such a criterion is the amount by which the value should be increased if the specific hotel is to become a hotel with benchmark service. Table 1 shows the notations of this research:

Table 1. Notations

Variable	Definition
m_h	the value of service performance for the hotel h
f_i	the performance value for the facility functions of the hotel i
l_i	the performance value for the location of the hotel i
w_i	the performance value for the Wi- Fi provision of the hotel i
c_i	the performance value for the comfort level of the hotel i
d_i	the performance value for the cleanliness level of the hotel i
e_i	the performance value for the service quality of the staff of the hotel i
p_i	the room rate of the hotel i
$\frac{1}{\theta_h}$	the approximated value of service performance of the hotel h
sf_h	the slack variable for the performance of the facility function of the hotel h
sl_h	the slack variable for the performance of the location of the hotel h
sw_h	the slack variable for the performance of the Wi-Fi provision of the hotel h
sc_h	the slack variable for the performance of the comfort level of the hotel h
sd_h	the slack variable for the performance of the cleanliness level of the hotel h
se_h	the slack variable for the performance of the service quality of the staff of the hotel h
sp_h	the slack variable for the room rate of the hotel h
λ_i	the weight of the hotel i
if_h	the required increasing amount for the performance of the facility function of the hotel h
il_h	the required increasing amount for the performance of the location of the hotel h
iw_h	the required increasing amount for the performance of the Wi-Fi provision of the hotel h
ic_h	the required increasing amount for the performance of the comfort level of the hotel h
id_h	the required increasing amount for the performance of the cleanliness level of the hotel h
ie_h	the required increasing amount for the performance of the service quality of the staff of the hotel h

$$Min \; \frac{1}{m_h} = \theta_h + \varepsilon \times (sf_h + sl_h + sw_h + sc_h + sd_h + se_h + sp_h) \tag{1}$$

$$s.t \sum_{i=1}^{I} \lambda_i \times (f_i) - \theta_h \times (f_h) - sf_h = 0 \tag{2}$$

$$\sum_{i=1}^{I} \lambda_i \times (l_i) - \theta_h \times (l_h) - sl_h = 0 \tag{3}$$

$$\sum_{i=1}^{I} \lambda_i \times (w_i) - \theta_h \times (w_h) - sw_h = 0 \tag{4}$$

$$\sum_{i=1}^{I} \lambda_i \times (c_i) - \theta_h \times (c_h) - sc_h = 0 \tag{5}$$

$$\sum_{i=1}^{I} \lambda_i \times (d_i) - \theta_h \times (d_h) - sd_h = 0 \tag{6}$$

$$\sum_{i=1}^{I} \lambda_i \times (e_i) - \theta_h \times (e_h) - se_h = 0 \tag{7}$$

$$\sum_{i=1}^{I} \lambda_i \times (p_i) - p_h + sp_h = 0 \tag{8}$$

$$\sum_{i=1}^{I} \lambda_i = 1 \tag{9}$$

$$sf_h, sl_h, sw_h, sc_h, sd_h, se_h, sp_h, \lambda_i \geq 0 ; \theta \geq 1 \tag{10}$$

$$if_h = \left(\theta_h - 1\right) \times \left(f_h\right) + sf_h \tag{11}$$

$$il_h = \left(\theta_h - 1\right) \times \left(l_h\right) + sl_h \tag{12}$$

$$iw_h = \left(\theta_h - 1\right) \times \left(w_h\right) + sw_h \tag{13}$$

$$ic_h = \left(\theta_h - 1\right) \times \left(c_h\right) + sc_h \tag{14}$$

$$id_h = \left(\theta_h - 1\right) \times \left(d_h\right) + sd_h \tag{15}$$

$$ie_h = \left(\theta_h - 1\right) \times \left(e_h\right) + se_h \tag{16}$$

Text Mining of Online Posts for Customer Reviews

To identify the causes of poor service quality in the non-benchmark hotels, this study crawls the customer reviews of non-benchmark service hotels on the online forum. Software R is used to perform text mining of the customer reviews. Software R is a free and open-source application. Additionally, the packages have been written by users worldwide for enhancing the functions of software R. Because the application's source code can be downloaded, the software is useful for software maintenance and development. Therefore, in this study, the tm package of Software R is employed to perform text mining. The function of "removePunctuation" is used to remove punctuation from customer reviews. The function of "removeWords" is employed to segment the sentences and to remove stop words. The function of "stripWhitespace" is utilized to remove spaces; and the function of "content_transformer" is used to convert all letters into lowercase. Next, all data are exported into a text file. Finally, stemming is performed on the keywords in the customer reviews. To simplify the data complexity, this study establishes a synonym database to aggregate all keywords. To analyze customer complaints in detail, this study analyzes each sentence as a unit to identify the cause of a customer complaint. Using the described approach, this study establishes a two-dimensional keyword-sentence matrix.

Hierarchical Ontology-Based Automatic Classification of Service Deficiencies for Hotels

Figures 2 and 3 display the hierarchical ontology of service deficiencies for hotels established by this study. The proposed ontology can be divided into two parts, i.e., the hierarchical ontology of service deficiencies for hardware facility of hotels and the hierarchical ontology of service deficiencies for perceived service of hotels. The ontology is based on the performance evaluation framework for hotel service presented in Section 3.1 and has four hierarchical levels, i.e., the dimension layer, the classification layer, the cause layer and the keyword layer for service deficiencies. The first layer and the second layer are the dimensions of performance evaluation for hotel service and the criteria of each dimension, respectively. Through the first and the second layers of this hierarchical ontology,

Figure 2. Hierarchical ontology of service deficiencies for hardware facility of hotels
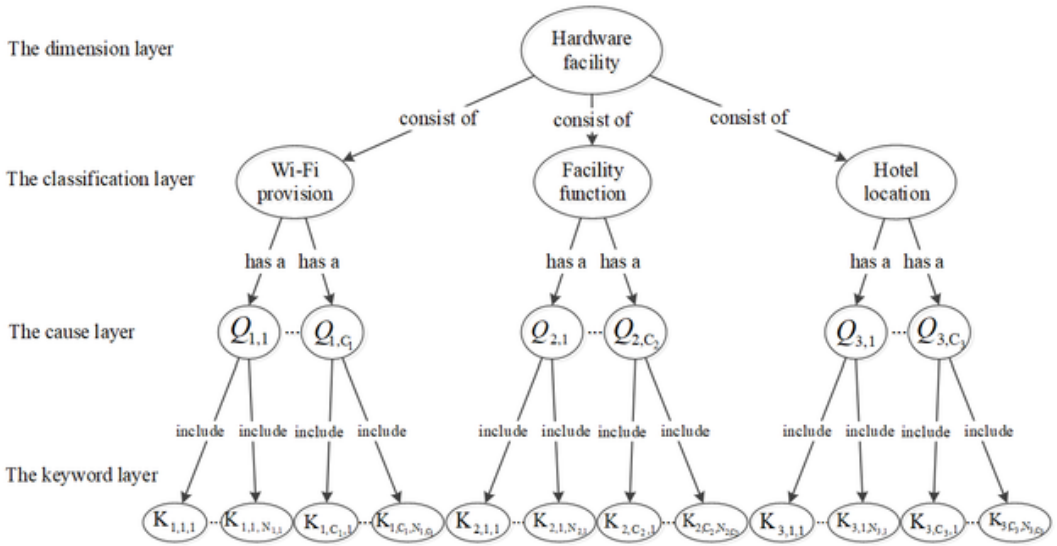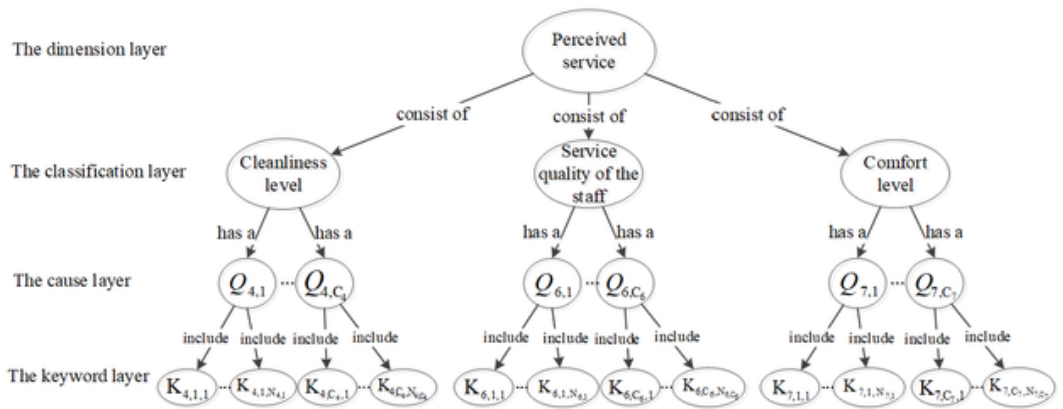

Figure 3. Hierarchical ontology of service deficiencies for perceived service of hotels

the service deficiencies for hotels are systemically classified. Each class comprises several causes. $Q_{i,j}$ denotes the *jth* cause of the *ith* class for service deficiency; C_i denotes the total number of causes in the *ith* class for service deficiency; and $K_{i,j,e}$ denotes the eth keyword of the *jth* cause in the *ith* class for service deficiency. $N_{i,j}$ denotes the total number of keywords of the *jth* cause of the *ith* class for the service deficiency.

Subsequently, this study combines the hierarchical ontology and a back-propagation neural network to develop an automated system for classifying the classification and the causes of service deficiencies for hotels. This system can be divided into the input, hidden, and output layers. The input layer is the numbers of different keywords in each synonym-processed sentence from customer

reviews. Each input value is connected to neurons in the hidden layer; the weight of each connection is assigned by the back-propagation neural network; and the weighted number of keywords is obtained. Next, the activation function is employed to calculate the weight value of each neuron of the hidden layers as shown in Formulas (17) and (18). Each neuron is connected to the output layer, and the connection weight is w_{jr}^o. Using Formula (19), the output value O_r is calculated by the back-propagation neural network. This output value is then used to identify the classification of a service deficiency. Formula (20) is used to calculate the estimated error E of the nodes, and A_r is the actual output value. To enhance the classification accuracy of causes of service deficiencies, Formulas (21) and (22) are applied to correct the neural connection weight Δw_{jr}^o during the training of the back-propagation neural network to reduce the prediction error δ_r^o where η denotes the learning rate:

$$net_j^h = f\left(\sum_i w_{ij}^h \times K_i\right) \tag{17}$$

$$f(x) = f\left(\frac{1}{1 + e^{-x}}\right) \tag{18}$$

$$O_r = g(net_r^o) = g\left(\sum_j w_{jr}^o \times net_j^h\right) \tag{19}$$

$$E = \frac{1}{2}\sum_r (A_r - O_r) \tag{20}$$

$$\Delta w_{jr}^o = \eta \times \delta_r^o \times H_j \tag{21}$$

$$\delta_r^o = \left(A_r - O_r\right) \times g'\left(net_r^o\right) \tag{22}$$

Case Study

Using a hotel booking website, the present study selected 16 three-star hotels in Rome, Italy, for the case analysis. First, the customer reviews given for the double rooms of these 16 hotels based on the room rate and the evaluation values for service were collected for customer stays. Next, the arithmetic mean is used to obtain the value of each evaluation criterion of the benchmark-based performance evaluation model for hotel service as shown in Table 2. Formulas (1-10) were employed to obtain the values of service performance for the 16 hotels as shown in Table 3. Hotel Numbers 2, 7, 9, 13, 14, and 15 were discovered to be hotels with benchmark performance of hotel service, whereas the remainder were the non-benchmark service hotels. To determine the causes of the poor performance of the non-benchmark service hotels, Hotel Number 1 was selected for further analysis. First, the

Table 2. Values of performance evaluation for criteria for hotel service

| No. | Input variable | Output variable | | | | | | |
	Room rate	Cleanliness level	Comfort level	Hotel location	Facility function	Service quality of the staff	Price-performance ratio	Wi-Fi provision
1	5068	8.1	7.6	8.6	7.5	7.9	7.7	5.6
2	9469	9.6	9	9.8	8.7	9.4	8.4	8.6
3	11537	8.6	8.3	9.5	8.1	8.3	8	7.9
4	6801	8.2	7.7	9.3	7.5	8.7	8	6.8
5	13739	8.5	7.6	9.1	7.6	9.2	7.9	7.9
6	5905	8.1	7.8	8.8	7.5	7.9	7.8	7.7
7	8696	9.4	8.9	9.6	8.7	9.3	8.5	8.6
8	4787	8.3	7.4	8.7	7.4	8.1	7.9	7.4
9	5970	8.7	8.1	8.9	7.9	9.1	7.9	7.7
10	10579	8.5	7.8	9.7	7.7	8.9	7.9	8.4
11	6061	8.5	7.4	9.3	7.3	8	7.7	7.4
12	7454	8.6	8	9.4	8	8.8	8.2	7.4
13	6616	9	8.7	9	8.4	8.8	8.1	9
14	9406	9.2	8.7	9.8	8.6	9.5	8.7	8.9
15	3828	8.2	8	9	7.9	8.9	8.4	7.8
16	4411	7.3	6.7	8.7	6.7	7.2	7.2	5.6

Table 3. Values of service performance for the 16 hotels

No.	Performance	No.	Performance
1	0.9487	9	1.0000
2	1.0000	10	0.9784
3	0.9497	11	0.9978
4	0.9866	12	0.9874
5	0.9294	13	1.0000
6	0.9464	14	1.0000
7	1.0000	15	1.0000
8	0.9793	16	0.9577

research used the identification and improvement model for non-benchmark performance criteria to determine the required increasing amount for the performance of non-benchmark criteria to make the hotel with benchmark service. Table 4 shows that the performance for service quality of the staff and the Wi-Fi provision require more improvement than other criteria.

In addition, this study crawled customer posts from the online forum of a hotel booking website and use the text mining to understand what caused customers to complain about the hotel's service. Using the above analytical result, this research established the detail hierarchical ontology of service deficiencies for hotels as shown in Figures 4 and 5. From the cause layer for service deficiencies, the causes of service deficiencies regarding the Wi-Fi provision include the unstable connection,

Table 4. Required increasing amounts for the performance of the criteria for Hotel Number 1

Criteria	Required increasing amount
Cleanliness level	0.4380
Comfort level	0.6775
Hotel location	0.4651
Facility functions	0.6052
Service quality of the staff	1.0126
Wi-Fi provision	0.8883

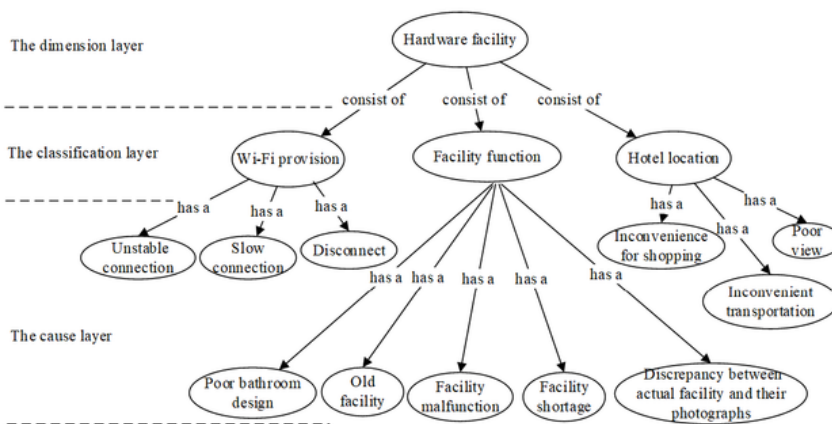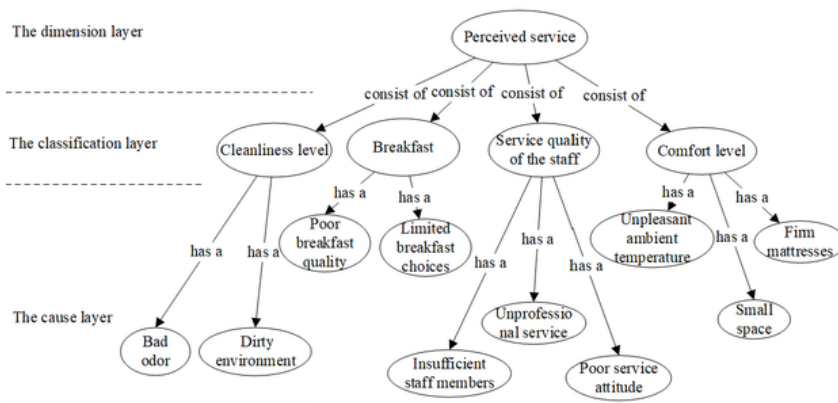Figure 4. Detail hierarchical ontology of service deficiencies for hardware facility of hotels

Figure 5. Detail hierarchical ontology of service deficiencies for perceived service of hotels.

the slow connection and the disconnect. For service deficiencies of the facility function, the causes include poor bathroom design, old facility, facility malfunction, facility shortage, and the discrepancy between the actual facility and their photographs. For service deficiencies of the hotel location, the causes are inconvenience for shopping, inconvenient transportation, and the poor view. The service deficiencies of the cleanliness level are the bad odor and dirty environment. For the service deficiencies of breakfast-related service deficiencies, the causes are poor breakfast quality and limited breakfast choices. The service deficiencies of service quality of the staff are insufficient staff members, unprofessional service and poor service attitude. For the service deficiencies of the comfort level, the causes are unpleasant ambient temperature, small space and firm mattresses. The fourth level is the keyword level which describes the keywords of each cause for service deficiencies.

To establish the keyword layer of the hierarchical ontology of service deficiencies for hotels, complaint posts were crawled from the hotel booking website. Next, Software R was used for performing text mining of the customer posts. The keywords were pooled and a synonym database was constructed to simplify the data analysis and speed up text mining. To analyze customer complaints with favorable precision, this study analyzed customer complaints sentence by sentence. A sentence-keyword matrix was established, and the causes of complaints posted by hotel customers were analyzed.

Due to the performance of service quality of the staff and the Wi-Fi provision for Hotel Number 1 should be enhanced significantly, this research used the two classifications of service deficiencies to establish the keyword layer. Table 5 shows the partial keywords for insufficient staff members, unprofessional service and poor service attitude for service quality of the staff as well as the unstable connection, the slow connection and the disconnect for the Wi-Fi provision. These keywords are used as the input variables of a hierarchical ontology based back-propagation neural network to classify the causes of service deficiencies for hotels.

With these data, a back-propagation neural network was trained to establish the automatic classification system. First, the neuralnet package of Software R was employed to train the back-propagation neural network model. The raret package of Software R is used to randomly sample 70% of the data to be used as the training data; the remaining 30% is used for testing data. The accuracy for the cause of service deficiencies for service quality of the staff and the Wi-Fi provision is 92.68%. Table 6 shows the comparison of performance results with other methods. The proposed approach in this research outperforms other methods. In addition, other methods only classify the categories of customer complaints. They cannot further decide the cause of each customer complaint due to without the hierarchical ontology.

After the hierarchical ontology-based back-propagation neural network is created, the system can be used to analyze the causes of customer complaints regarding service deficiencies of the non-benchmark hotels. The analysis discovered that service deficiencies of Hotel Number 1 were unprofessional service for service quality of the staff and the unstable connection for the Wi-Fi provision with the most customer complaints. The results given by this study would be useful to the

Table 5. The partial keywords for service quality of the staff and the Wi-Fi provision

	Cause	Keywords
Wi-Fi provision	Unstable connection	Unreliable, unstable, weak, wi-fi
	Slow connection	Slow, speed, wi-fi
	Disconnect	Disconnect, wi-fi, not work
Service quality of the staff	Insufficient staff members	Wait, understaffed, nobody
	Unprofessional service	Unknown, wrong information, unprofessional
	Poor service attitude	Grumpy, impolite, unfriendly

Table 6. Comparative analysis of the proposed approach with other methods

Authors/year	Method	Accuracy (%)
Bozyiğit et al., 2022	Extreme Gradient Boosting with Term Frequency-Inverse Document Frequency	84
Chen et al., 2021	Least Absolute Shrinkage and Selection Operator and Decision Trees	88.70
Leem and Eum, 2021	Naïve Bayes	86.4
HaCohen-Kerner et al., 2019	Simple Logistic	81.59
Our proposed approach	Hierarchical Ontology-Based Neural Network	92.68

management of Hotel Number 1 in effectively determining the principal causes of service deficiencies and significantly enhancing its overall service performance.

CONCLUSION

The flourishing of electronic commerce has intangibly altered consumer behavior patterns. In addition, increasing numbers of consumers share their service experience with other members of the public on online forums. For companies interested in understanding the satisfaction levels and customer complaints, online reviews enable them to collect valuable real time information. However, to handle and analyze a large volume of customer service evaluation, hotel managers require an efficient and effective method. As a result, this study develops the online customer reviews-based performance evaluation and deficiency discovery methodology for hotel service. By using the benchmark-based performance evaluation model for hotel service, the non-benchmark hotels can be recognized and then the identification and improvement model for non-benchmark performance criteria can ascertain the non-benchmark performance criteria and provide the managers with the concrete improvement amounts for the non-benchmark performance criteria. Through the above information, the non-benchmark hotels can obtain the improvement directions, i.e., which performance criteria are the high priorities to be ameliorated. To explore the main causes of poor service performance for the non-benchmark performance criteria, this study crawled online posts and performed text mining to construct the hierarchical ontology of service deficiencies for hotels and to develop the hierarchical ontology-based back-propagation neural network for automatic classification of the causes of service deficiencies for non-benchmark hotels. The developed system can help the managers of non-benchmark hotels to quickly, precisely, and comprehensively analyze the causes of online customer complaints. The analysis results enable the hotel managers, at low cost, to gain deep insight into the core reasons behind their hotel's poor service performance so that they can propose the corresponding improvement alternatives that can enhance the hotel service. This study selected 16 three-star hotels in Italy as research subjects to illustrate and validate the feasibility and exhibit the effect of this methodology.

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CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

REFERENCES

Akçapınar, G. (2015). How automated feedback through text mining changes plagiaristic behavior in online assignments. *Computers & Education*, *87*, 123–130. doi:10.1016/j.compedu.2015.04.007

Akincilar, A., & Dagdeviren, M. (2014). A hybrid multi-criteria decision making model to evaluate hotel websites. *International Journal of Hospitality Management*, *36*, 263–271. doi:10.1016/j.ijhm.2013.10.002

Alsmirat, M. A., Al-Alem, F., Al-Ayyoub, M., Jararweh, Y., & Gupta, B. (2019). Impact of digital fingerprint image quality on the fingerprint recognition accuracy. *Multimedia Tools and Applications*, *78*(3), 3649–3688. doi:10.1007/s11042-017-5537-5

Ashrafi, A., Seow, H.-V., Lee, L. S., & Lee, C. G. (2013). The efðciency of the hotel industry in Singapore. *Tourism Management*, *37*, 31–34. doi:10.1016/j.tourman.2012.12.003

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, *30*(9), 1078–1092. doi:10.1287/mnsc.30.9.1078

Benı'tez, J. M., Martı'n, J. C., & Román, C. (2007). Using fuzzy number for measuring quality of service in the hotel industry. *Tourism Management*, *28*(2), 544–555. doi:10.1016/j.tourman.2006.04.018

Blal, I., & Sturman, M. C. (2014). The differential effects of the quality and quantity of online reviews on hotel room sales. *Cornell Hospitality Quarterly*, *55*(4), 365–375. doi:10.1177/1938965514533419

Bozyiğit, F., Dogan, O., & Kilinç, D. (2022). Categorization of customer complaints in food industry using machine learning approaches. *Journal of Intelligent Systems Theory and Applications*, *5*(1), 85–91. doi:10.38016/jista.954098

Chen, J., Huang, H., Tian, S., & Qu, Y. (2009). Feature selection for text classification with Naïve Bayes. *Expert Systems with Applications*, *36*(3), 5432–5435. doi:10.1016/j.eswa.2008.06.054

Chen, T.-H. (2009). Performance measurement of an enterprise and business units with an application to a Taiwanese hotel chain. *International Journal of Hospitality Management*, *28*(3), 415–422. doi:10.1016/j.ijhm.2008.10.010

Chen, W.-K., Riantama, D., & Chen, L.-S. (2021). Using a text mining approach to hear voices of customers from social media toward the fast-food restaurant industry. *Sustainability*, *13*(1), 268. doi:10.3390/su13010268

Chen, Y.-C., Yu, T.-H., Tsui, P.-L., & Lee, C.-S. (2014). A fuzzy AHP approach to construct international hotel spa atmosphere evaluation model. *Quality & Quantity*, *48*(2), 645–657. doi:10.1007/s11135-012-9792-2

Chin, J.-B., & Tsai, C.-H. (2013). Developing a service quality evaluation model for luxurious restaurants in international hotel chains. *Total Quality Management & Business Excellence*, *24*(9-10), 1160–1173. doi:10.1080/14783363.2012.661132

Cho, Y., Im, I., Hiltz, R., & Fjermestad, J. (2002). An analysis of online customer complaints: implications for Web complaint management. *Proceedings of the 35th Hawaii International Conference on System Sciences*, 2308-2317.

Chou, S., & Hsing, T.-P. (2010). Text mining technique for Chinese written judgment of criminal case. *Pacific-Asia Workshop on Intelligence and Security Informatics, 6122*, 113-125.

Coussement, K., & Poel, D. V. D. (2008). Improving customer complaint management by automatic email classification using linguistic style features as predictors. *Decision Support Systems*, *44*(4), 870–882. doi:10.1016/j.dss.2007.10.010

Debnath, D., Das, R., & Rafi, S. (2022). Sentiment-based abstractive text summarization using attention oriented LSTM model. *Intelligent Data Engineering and Analytics*, *266*, 199–208. doi:10.1007/978-981-16-6624-7_20

Elgendy, I. A., Zhang, W. Z., He, H., Gupta, B. B., & Abd El-Latif, A. A. (2021). Joint computation offloading and task caching for multi-user and multi-task MEC systems: Reinforcement learning-based algorithms. *Wireless Networks*, *27*(3), 2023–2038. doi:10.1007/s11276-021-02554-w

Faed, A., Hussain, O. K., & Chang, E. (2014). A methodology to map customer complaints and measure customer satisfaction and loyalty. *Service Oriented Computing and Applications*, *8*(1), 33–53. doi:10.1007/s11761-013-0142-6

Groth, S. S., & Muntermann, J. (2011). An intraday market risk management approach based on textual analysis. *Decision Support Systems*, *50*(4), 680–691. doi:10.1016/j.dss.2010.08.019

HaCohen-Kerner, Y., Dilmon, R., Hone, M., & Ben-Basan, M. A. (2019). Automatic classification of complaint letters according to service provider categories. *Information Processing & Management*, *56*(6), 102102. doi:10.1016/j.ipm.2019.102102

Hammad, M., Alkinani, M. H., Gupta, B. B., & Abd El-Latif, A. A. (2021). Myocardial infarction detection based on deep neural network on imbalanced data. *Multimedia Systems*. Advance online publication. doi:10.1007/s00530-020-00728-8

Heung, V. C. S., & Lam, T. (2003). Customer complaint behaviour towards hotel restaurant services. *International Journal of Contemporary Hospitality Management*, *15*(5), 283–289. doi:10.1108/09596110310482209

Hong, M., & Wang, H. (2021). Research on customer opinion summarization using topic mining and deep neural network. *Mathematics and Computers in Simulation*, *185*, 88–114. doi:10.1016/j.matcom.2020.12.009

Koteeswara, S., & Kannan, E. (2013). Analysis of bilateral intelligence (ABI) for textual pattern learning. *Information Technology Journal*, *12*(4), 867–870. doi:10.3923/itj.2013.867.870

Lam, T., & Tang, V. (2003). Recognizing customer complaint behavior. *Journal of Travel & Tourism Marketing*, *14*(1), 69–86. doi:10.1300/J073v14n01_05

Lee, C. C., & Hu, C. (2004). Analyzing hotel customers' e-complaints from an internet complaint forum. *Journal of Travel & Tourism Marketing*, *17*(2-3), 167–181. doi:10.1300/J073v17n02_13

Lee, C.-H., Wang, Y.-H., & Trappey, A. J. C. (2015). Ontology-based reasoning for the intelligent handling of customer complaints. *Computers & Industrial Engineering*, *84*, 144–155. doi:10.1016/j.cie.2014.11.019

Leem, B.-H., & Eum, S.-W. (2021). Using text mining to measure mobile banking service quality. *Industrial Management & Data Systems*, *121*(5), 993–1007. doi:10.1108/IMDS-09-2020-0545

Li, N., & Wu, D. D. (2010). Using text mining and sentiment analysis for online forums hotspot detection and forecast. *Decision Support Systems*, *48*(2), 354–368. doi:10.1016/j.dss.2009.09.003

Mattila, A. S., & Mount, D. J. (2003). The impact of selected customer characteristics and response time on e-complaint satisfaction and return intent. *International Journal of Hospitality Management*, *22*(2), 135–145. doi:10.1016/S0278-4319(03)00014-8

Nguyen, K. A., & Coudounaris, D. N. (2015). The mechanism of online review management: A qualitative study. *Tourism Management Perspectives*, *16*, 163–175. doi:10.1016/j.tmp.2015.08.002

Ramasundaram, S., & Victor, S. P. (2013). Algorithms for text categorization: A comparative study. *World Applied Sciences Journal*, *22*(9), 1232–1240.

Ren, P., Xiao, Y., Chang, X., Huang, P.-Y., Li, Z., Gupta, B. B., Chen, X., & Wang, X. (2022). A survey of deep active learning. *ACM Computing Surveys*, *54*(9), 1–40. doi:10.1145/3472291

Rivera, S. J., Minsker, B. S., Work, D. B., & Roth, D. (2014). A text mining framework for advancing sustainability indicators. *Environmental Modelling & Software*, *62*, 128–138. doi:10.1016/j.envsoft.2014.08.016

Sahoo, S. R., & Gupta, B. B. (2021). Multiple features based approach for automatic fake news detection on social networks using deep learning. *Applied Soft Computing*, *100*, 106983. doi:10.1016/j.asoc.2020.106983

Shirouyehzad, H., Lotfi, F. H., Shahin, A., Aryanezhad, M. B., & Dabestani, R. (2012). Performance evaluation of hotels by data envelopment analysis based on customers' perception and gap analysis. *International Journal of Services and Operations Management*, *12*(4), 447–467. doi:10.1504/IJSOM.2012.047953

The Nielsen Company. (n.d.). *Nielsen Global Survey of Trust in Advertising Report*. http://www.nielsen.com

Trappey, A. J. C., Hsu, F.-C., Trappey, C. V., & Lin, C.-I. (2006). Development of a patent document classification and search platform using a back-propagation network. *Expert Systems with Applications*, *31*(4), 755–765. doi:10.1016/j.eswa.2006.01.013

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

Yang, C.-C., Jou, Y.-T., & Cheng, L.-Y. (2011). Using integrated quality assessment for hotel service quality. *Quality & Quantity*, *45*(2), 349–364. doi:10.1007/s11135-009-9301-4

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

Zoraghi, N., Amiri, M., Talebi, G., & Zowghi, M. (2013). A fuzzy MCDM model with objective and subjective weights for evaluating service quality in hotel industries. *Journal of Industrial Engineering International*, *9*(38), 1–13. doi:10.1186/2251-712X-9-38

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