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An opinion-driven decision-support framework for benchmarking hotel service ☆

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ABSTRACT

Service-quality is a major determinant of tourists' choice of hotel. Tourists are likely to refer to user-created online reviews on online forums and other social networks comprising critical text data resources that represent the service quality experienced. This study develops a decision-support framework for hotel managers to comprehensively estimate the degree of guest satisfaction (i.e., service-quality measure) together with benchmarking guidelines on service quality improvement. The decision-support framework facilitates the discovery of the most important service attributes from the online reviews of 52 five-star hotels in South Korea (*data preprocessing component*). It clusters the reviews according to the discovered service attributes and conducts sentiment analysis to estimate the magnitude of positive opinions (*sentiment analysis component*). Further, it applies an output-oriented data envelopment analysis to calculate the degree of guest satisfaction and service positioning for each hotel (*benchmarking analysis component*). The framework also investigates how the service quality of each hotel is associated with that of others in terms of each service attribute (*quality association analysis component*). The framework enables managers to comprehensively understand the achievement goals of service quality for the service attributes by means of online review data analytics and modeling.

1. Introduction

Many tourists refer to tourism websites and social networking sites when making travel accommodations, taking reference from other guests' experiences in the form of online reviews and rating scores. These user-created online reviews have become a critical resource and ground for measuring hotel service quality, also serving as a great reference for tourists to choose hotels. Hotel managers are likely to pay attention to these communication channels to improve their hotel service quality based on guest feedback, as they understand that guest satisfaction is a representative barometer reflecting the hotel's service quality.

Guest satisfaction is typically identified, and later improved on, based on guest feedback. According to Sainaghi et al. [70], hotel service quality is addressed through supply determinants, such as service products (e.g., cleanliness, comfort, food and beverage, and room amenities), staff (e.g., reliability, responsiveness, assurance, and empathy), and hotel traits (e.g., facilities, ambience, certification, size, and location), whereas guest satisfaction is addressed from a demand perspective, such as rating scores, review volumes, management responses, and overall value for money. Hotel managers desire to provide great guest satisfaction by identifying service quality related attributes, such as staff courtesy, room service, facility maintenance, meals, etc., even though it is well known that guest satisfaction is naturally based on the perception levels of guest experience, and present subjective and variant features per guest.

Many tourism websites provide quantitative benchmarks for hotels using rating scores on a number of service attributes to rate and summarize, and eventually quantify service quality. These rating scores help hotel managers to easily identify room for service quality improvement; however, it is still highly recommended to look into online guest reviews to understand guest satisfaction considering the polarity of opinions due to its subjective and variant nature.

Recognizing guest satisfaction might be insufficient to improve service quality unless benchmarking information is available to set

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up service-quality references addressing the extent of quality improvement over the service attributes. It would also be informative if the service attributes represent the service quality well, and their inter-dependencies are comparatively estimable for referencing hotels. This study examines the three elements (i.e., guest satisfaction measure, benchmarking strategies, and quality inter-dependency) that have been described as benefitting from online reviews.

This study contributes to the evaluation of hotel service quality and ultimately provides benchmarking strategies to help improve service quality by developing a decision-support framework integrating sentiment analysis with a data envelopment analysis (DEA) model that applies multiple dimensions based on user opinions (i.e., online reviews). The framework discovers a set of key service attributes from the online review collection, clusters the review data according to the key service attributes, and conducts sentiment analysis with each cluster to produce the polarity of opinions. The estimated polarity outcomes are used to evaluate the service quality as well as the relevant benchmarks using the proposed DEA model. Further analysis is conducted to understand the degree of quality association in terms of key service attributes between hotels in a comparative manner.

The remainder of this paper is organized as follows. Section 2 discusses the contributions of this study compared to the literature. Section 3 addresses the decision-support framework and its components. Sections 4 and 6 show the results of the various analyses of real-world data. Section 7 presents the conclusions.

2. Literature review

This section investigates previous studies supporting the theoretical background for evaluating guest satisfaction based on online reviews by means of DEA.

2.1. Online reviews

Online reviews, whereby one can share information about various products and services with many customers, have a stronger influence on purchasing decisions for consumers than offline information. According to Bhandari and Rodgers [8] and Zhan et al. [85], online reviews are generally considered to be more honest, unbiased, and comprehensive than the information released by sellers, causing them to be viewed as a supplement to official product description, expert comments, and personalized recommendations generated by automated recommendation systems. As a source of information, online reviews are useful for both customers and service providers. Customers can use online reviews to make their purchase decisions, and at the other end, service providers can understand customers' current perceptions and utilize the knowledge of customers' preferences in product improvement, marketing, and customer relationship management [77]. Specifically, according to Gremler et al. [22], Peterson and Merino [63], and Henning et al. [25], positive reviews, such as compliments or explanations of important points, have a positive effect on customer satisfaction, which subsequently leads to purchases, while negative reviews, such as dissatisfaction with the product, have a negative effect on purchases. Sentiment analysis[1] of online reviews has been conducted by several studies for new product development in the cosmetic industry [24] and for measuring quality satisfaction in mobile services [34].

Over time, an increasing number of studies have been conducted on hotel services using data analytical approaches and online reviews, and comprehensive literature reviews [44,45] have been presented on the developmental stages of business intelligence and big data based approaches in the hospitality and tourism sector. Recent studies on utilizing online reviews have been used to develop marketing strategies by identifying the necessary service components. Ahani et al. [3] segmented the customers of spa hotels/resorts based on consumer rating scores and predicted target user preferences in each cluster. Yadav and Roychoudhury [82] considered the types of travelers (i.e., solo, friends, families, couples, and business) to understand the relevance of hotel aspects (e.g., room, staff, food, service, etc.) in terms of the polarity (i.e., positive, negative, and neutral) of customer perceptions. Wang et al. [81] developed a comprehensive decision-support framework that combined the advantages of online reviews and multi-criteria decision-making for selecting hotels for different types of travelers, where the key attributes influencing hotel selection per traveler type were discovered and a picture fuzzy TODIM multi-criteria decision-making approach was used to rank all hotels according to traveler type. Hou et al. [28] conducted a semantic association analysis of online travel reviews, extracted thematic words with frequency distributions, and constructed a visualized semantic association network. Their research explored the potential needs of tourists and discovered connections among them to improve service management and competitive advantages of tourism firms. Vu et al. [80] constructed a travel diary (i.e., a collection of user check-ins arranged temporally) from social media platforms, extracted utility information based on length of visit, number of check-ins, and price range of dining, and applied the utility to a data-mining technique (i.e., high-utility pattern mining) to enrich travel pattern discovery for profitability.

In addition to marketing strategies, the service positioning of hotels has also been identified by examining online reviews. Hu and Trivedi [30] discovered the competitive landscape of hotel brands by analyzing online reviews via statistical approaches. The relative positioning of hotel brands was visualized using multi-dimension graphs, in which the indicators (e.g., factor scores of the detected principal components) were used to measure the normalized Euclidean distance (i.e., association) between hotel brands.

2.2. Customer (guest) satisfaction

Customer satisfaction is defined as "a person's feelings of pleasure or disappointment that results from comparing a product's perceived performance or outcome with his/her expectations" [38]. Customer satisfaction is the leading criterion for determining the quality that is actually delivered to customers through the product/service and by the accompanying service. In short, customer satisfaction is important to all commercial fields because of its influence on repeat purchases and word-of-mouth (WoM) recommendations, both positive and negative [1]. The best known and most widely applied technique is the SERVQUAL method, proposed by Parasuraman et al. [62]. The SERVQUAL method describes customer satisfaction as a function of expectations (i.e., what customers expect from the service) and perceptions (i.e., what customers receive), and defines 5 service-quality dimensions, namely, tangibles, reliability, responsiveness, assurance, and empathy, and 22 items for measuring service quality. SERVQUAL provides an index determined by calculating the difference between perception and expectation rates expressed for the items, weighted as a function of the five service quality dimensions embedded in the items.

A number of both national and international indices based on customer perceptions and expectations have been introduced. Sev-

[1] Sentiment analysis, which is often referred to as opinion mining or emotion analysis, is a data-mining approach of detecting, analyzing, and evaluating subjective consumer content by means of natural-language processing, textual analysis, computational linguistics, and other observations of subjective information [23]. Many applications automatically extract expressed opinions and analyze their subjectivities and emotions to determine cultural trends and marketing development [4,11,18,20,23,36,42,58,65,75,83].

eral satisfaction indices were designed according to the determinants or configuration of the satisfaction index, such as the Swedish Customer Satisfaction Barometer (SCSB), the American Customer Satisfaction Index (ACSI), the Norwegian Customer Satisfaction Barometer (NCSB), and European Customer Satisfaction Index (ECSI) [7]. All the models are based on the same concept, but they differ with regard to the variables considered and the cause-and-effect relationship demonstrated. The models from which these indices are derived can have very complex structures. Indices based on discrete choice models and random utility theory, such as the Service Quality Index (SQI), have also been introduced. SQI is calculated by the utility function of a choice alternative representing a service [26]. For the SQI calculation, the user makes a choice between a habitual service, which is described by the user by assigning a value to each service aspect, and hypothetical services, which are defined through stated preferences (SP) techniques by varying the level of quality of aspects characterizing the service.

Previous measurement methods for customer satisfaction index utilized questionnaire surveys to obtain data on service quality. However, the questionnaire survey-based data collection has two major drawbacks: it is limited in collecting various opinions due to data sampling and pre-defined question contents by the investigator, and it cannot quickly identify the real-time requirements of consumers since it takes a lot of time to gather and analyze the customer's opinions [21]. On the other hand, utilizing online reviews has the advantage of being able to collect and analyze multifaceted information on products from various customers in a short time at a relatively low cost. Above all, online reviews are less distorted with regard to the customer's practical service experience, as they are voluntarily written by them [19].

A few studies have identified the determinants of customer satisfaction or polarity analysis[2] to understand customer satisfaction from online reviews. Hsu [29] proposed an index for online customer satisfaction, which is adapted from the American Customer Satisfaction Index (ACSI). The proposed electronic-CSI model allowed the online retailer to understand the specific factors that significantly influence overall customer satisfaction by reading the causal relationship in the electronic-CSI model and the strategic management map. Ba and Johansson [5] focused on the interface between online buyers and sellers and found that the technological capabilities embedded in the website processes are important factors in determining service quality as the ease of use of the website has a positive effect on customers' perceptions and ultimately online customer satisfaction. Zhao et al. [86] predicted overall customer satisfaction using the technical attributes of online reviews and customers' involvement in the review community. They found that a higher level of subjectivity and readability and a longer length of textual review led to lower overall customer satisfaction and a higher level of diversity, sentiment polarity of textual reviews led to higher overall customer satisfaction, and customers' review involvement positively influenced their overall satisfaction. Ramanathan et al. [68] employed a survey questionnaire method to elicit opinions of retail customer satisfaction based on social media reviews, service operations, and marketing efforts. They found that social media reviews dramatically impact customer satisfaction, and the empirical analysis identified the significant and positive role played by service operations in customer satisfaction levels. Sari et al. [72] analyzed the sentiment of customer satisfaction in online transportation booking in Indonesia using public opinion on Twitter. The Naive Bayes method was used to classify positive, neutral, and negative sentiments from tweets created or posted on Twitter by customers.

Discussions of customer satisfaction in hotel service have also been dependent on analyzing online reviews. Li et al. [41] illustrated the determinants of customer satisfaction in hospitality through an analysis of online reviews. They demonstrated that transportation convenience, food and beverage management, convenience to tourist destinations, and value for money are excellent attributes for customers booking both luxury and budget hotels. Radojevic et al. [66] examined the association between business travel and tourist satisfaction using a rating score of 1–5, rating hotel services via traveler-, hotel-, and national-level variables. Sánchez-Franco et al. [71] applied a supervised classification approach (i.e., naive bayes classifier) to identify relevant features of hospitality to classify ratings of guest satisfaction based on online reviews. Hu et al. [31] aimed to understand customer behaviors that resulted in negative hotel service ratings by analyzing online reviews. According to their findings, customer complaints for high-end hotels were mainly related to intangible service problems and pricing issues, whereas customers of low-end hotels were frequently dissatisfied by tangible services, such as facility-related issues. Padma and Ahn [57] identified the major drivers of satisfaction and dissatisfaction of hotel guests and found that room- and staff-related attributes were the most important determinants of guest satisfaction/dissatisfaction and suggested that luxury hotels should pay more attention to personalizing the guest experience with high room-related qualities.

2.3. DEA-based customer (guest) satisfaction

DEA models have been used in the literature to measure service quality and customer satisfaction. It is recommended that guest satisfaction be evaluated through multiple dimensions, and DEA is a well-known nonparametric approach for multi-criteria decision-making. The use of DEA requires the setting of a decision-making unit (DMU), preparing inputs and outputs for each DMU, and deriving benchmarking scores of DMUs by identifying the benchmarking frontier.

DEA studies have particularly been performed to measure service quality. In the early stage of hotel efficiency studies, Sigala [76] demonstrated a stepwise approach that combined correlation with DEA analysis for measuring and benchmarking hotel productivity and service quality. Chang [10] investigated the relationship between service quality and customer value and explored the internal composition of this relationship in the hotel industry. Bayraktar et al. [7] used DEA to measure customer satisfaction and loyalty efficiency to attract market share and profitability in Turkey's mobile sector. Comprehensive literature reviews of DEA studies on hotel service for measuring customer satisfaction have been presented by Sellers-Rubio and Casado-Díaz [73] and Sainaghi et al. [70]. It was found that service quality influenced customer satisfaction, while both were positively associated with hotel efficiency.

A series of serial and/or network DEA models have recently contributed to measuring the efficiency of hotel service in a systematic manner with high discriminative power in ranking DMUs (hotels), and to understanding the effect of resources on achieving (in)efficiency. Park et al. [61] proposed a new DEA-based efficiency evaluation model that applies the positive relation between quality improvement and profits provision, and suggested benchmarking information that is separated for quality and quantity improvement. Park et al. [60] presented a two-stage network DEA model

[2] There are three levels of polarity analysis: document, sentence, and entity [42,58]. The document level classifies the emotions expressed by individuals from all text documents into polarity levels (e.g., positive, negative, and neutral) [79]. The sentence level determines the polarity of subjective sentences [36]. Unlike document and sentence levels, the entity level uncovers the entities or objects of emotions and opinions from the text. A challenge of polarity analysis is that sometimes emotions expressed about a particular entity might be negative even though the overall emotion of opinions in a document or sentence might be positive.

employing the relations among costs, service quality, and profit in evaluating performance. This model empirically demonstrated the efficiency of the association between costs and service-quality provision as well as the efficiency of the positive association between perceived service quality and profit generation. Yin et al. [84] developed a novel bi-objective DEA model that addressed the operations-marketing cooperative relationship within a two-stage network structure to investigate how internal cooperative mechanisms among departments affected hotel performance (i.e., efficiency). From an empirical analysis of 68 Taiwanese hotels, the authors showed that the proposed model had great discriminating power when ranking DMUs (i.e., hotels) compared with a hotel operations-only model. The work proposed a theoretical backbone to measure hotel performance by means of interactions of hotel's internal operations and external marketing efforts. Sellers-Rubio and Casado-Díaz [73] proposed a two-stage double bootstrap DEA to examine the effect of environmental variables (i.e., length of stay, number of international tourists, destination quality, and destination location) on regional hotel efficiency. Based on their findings, they recommended that destinations and hotels themselves should collaborate to offer a sufficiently wide range of activities at the destination, as the identification of tourist destination feature is highly associated with hotel efficiency. Lado-Sestayo and Fernández-Castro [39] proposed a four-stage DEA approach to classify efficiency into the aspects attributable to tourist destination (i.e., accessibility, agglomeration, competition, occupancy, demand, and seasonality) and hotel management (i.e., size, market orientation, share, quality management, and centrality). Subsequently, the tourist destination (sub-) efficiency is regressed by the location characteristics, and the estimated managerial (sub-) efficiency is regressed by hotel management aspects. Their findings ratified the propositions of the main hotel location models: accessibility, agglomeration, and market concentration in the tourist destination have a positive impact on revenue-based efficiency. Hwang [32] developed a novel hybrid-network DEA to study tourism supply chains comprising four stages, namely, sourcing (i.e., tourist education), supply (i.e., tourist hotel), delivery (i.e., travel agency), and efficiency (i.e., tourist destination), to simultaneously evaluate integrated efficiency and individual-stage efficiency in a single-DEA implementation. The overall efficiency was resolved into multiple inefficiency indices in order to explore the sources of inefficiency. Through the empirical experiment, the author found that collaboration and integration between divisions in the tourism supply chain appear inadequate and insufficient. Unequal revenue distributions and excess service capacity were found to be the main causes of problems in the integrated performance of the supply chain.

Lee and Kim [40] proposed a pure output-oriented Banker–Charnes–Cooper (BCC) approach [13] for measuring and benchmarking service quality through five dimensions (i.e., tangibles, reliability, responsiveness, assurance, and empathy) by leveraging established service performance criteria [14,15]. The authors provided service-provider DMUs to determine whom to benchmark and to what degree service quality should be improved. Mariani and Visani [52] introduced a pioneering study that examined the significance of online customer satisfaction rating scores to measure efficiency scores and improve the discriminative power among DMUs (hotels) on hotel performance. They aimed to bridge the gap between online rating scores and hotel performance by applying a classical input-oriented BCC-DEA model with three input variables (i.e., rooms, employees, and net operating expenses) and two output variables (i.e., revenue and online rating scores) for a sample of various Italian hotel categories.

Whereas Lee and Kim [40] applied survey data to measure service quality, the present study measured hotel service quality based on online guest feedback and provided a way to interpret the benchmarking results into the achievement goals of service quality. As described in Subsection 2.2, online reviews are generally preferable [8,85] because the questionnaire survey has drawbacks [19,21]. The present study used online reviews (opinions) instead of rating scores [52,73] to measure efficiency scores of the DEA model, as the usefulness of rating scores has been questioned in past studies [43,54–56]. The present study does not only measures service quality but also provides achievement goals by estimating the required improvement in positive feedback for service attributes, where the polarity of guest opinions for each service attribute is carefully designed as a statistical ratio indicator [2] without violating the convexity of DEA modeling [17,27]. Recent data analytics studies [28,30,80–82] discovered and analyzed various service attributes from online reviews for tourism decision analysis on marketing strategies and service positioning. Since the DEA studies discussed in subsections 2.2–2.3 used unclear processes to choose the inputs and outputs for DMUs despite modeling sophistication, this study refers to data analytics studies to discover the key service attributes representing service quality and use them to comprehensively measure guest satisfaction.

Therefore, this study aims to propose a systematic process of measuring guest satisfaction, comprehensively representing service quality stemming from online guest reviews to recognize the positioning of hotels and estimate the achievement goals of service quality in terms of key service attributes. The comprehensiveness is characterized by aggregating well-discovered service attributes from online reviews. Through a statistical design of quantifying service attributes, the positioning is addressed by the DEA benchmarking analysis, and the achievement goal is provided by estimating the service quality improvement requirement by referring to benchmarks and guided service standards. This study represents an extension of the emerging research stream of DEA studies that have used electronic-WoM to comparatively assess firm efficiency (i.e., [52]) by integrating sentiment analysis.

3. Decision-support framework

This study introduces a comprehensive decision-support framework to determine the degrees of guest satisfaction of hotels stemming from online reviews, explain the service positioning of hotels that represent guest satisfaction, and assess the comparative quality association of guest satisfaction between pairs of hotels.

The decision support framework consists of four components, namely data preprocessing, sentiment analysis, benchmarking analysis, and quality association analysis, as shown in Fig. 1. The fundamental roles of each module are described below and discussed in greater detail in the subsequent subsections.

- ***Data preprocessing***: The framework crawls online reviews from a travel community website and discovers key service attributes, representing hotel service quality elements, based on the content of crawled online reviews.
- ***Sentiment analysis***: The framework clusters well-cleaned online review sentences into the predetermined clusters for a hotel. Note that each cluster corresponds to a key service attribute. Polarity analysis is conducted to identify the types of opinions (i.e., positive, neutral, and negative) and estimate the magnitude of positive opinions per cluster for a hotel.
- ***Benchmarking analysis***: The framework evaluates hotel guest satisfaction by means of an output-oriented DEA-CCR model, where the outputs of a DMU (i.e., a hotel) are the estimated magnitude of positive opinions. The results provide the hotel positioning for each cluster (i.e., key service attribute), for which guest satisfaction is measured by the DEA model, to determine the extent by which hotel managers need to improve the relevant key service attributes.

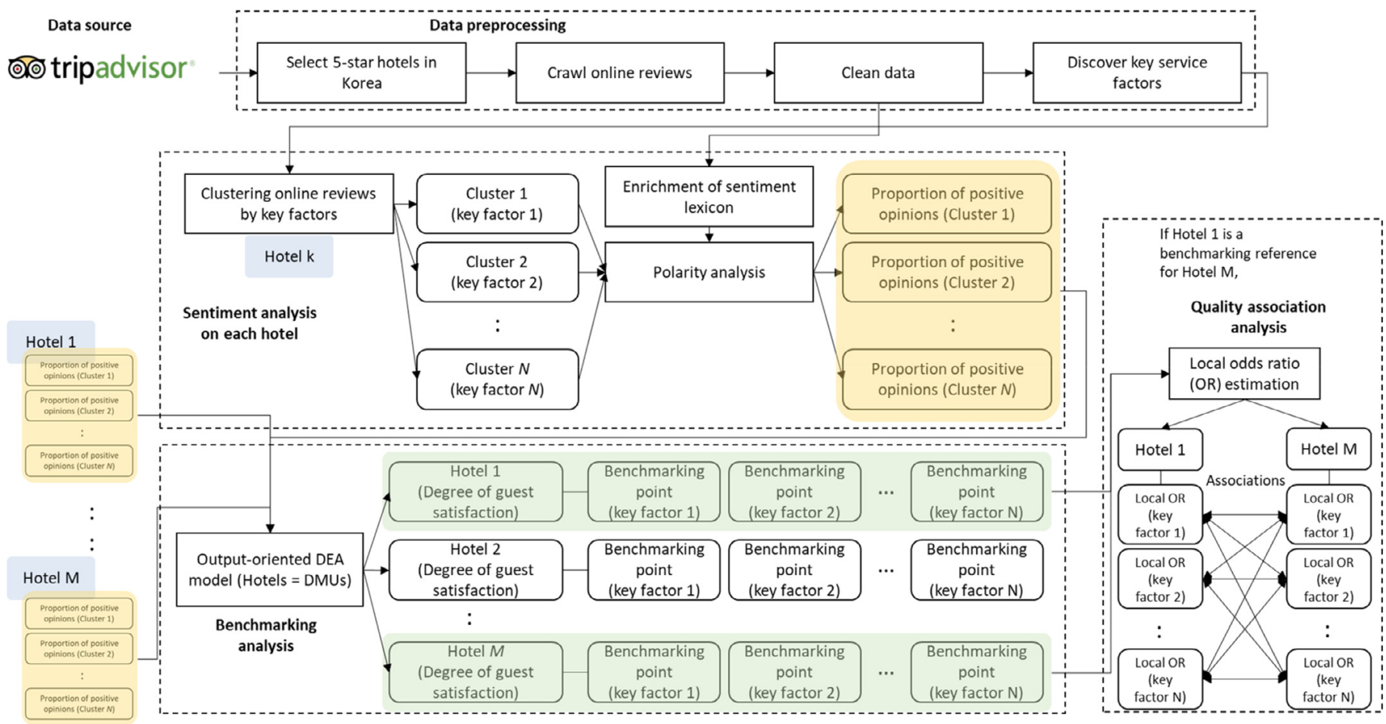

Fig. 1. Decision-support framework for hotel service.

- ***Quality association analysis***: The resulting guest satisfaction identifies underperforming hotels and their benchmarks (best practice hotels). It is noted that an underperforming hotel should refer to its benchmark (i.e., best practice hotel) to improve guest satisfaction in favor of key service attributes. The framework estimates the degrees of association of a key service attribute with another for a pair of underperforming and best-practice hotels.

The objective of the proposed framework is to offer benchmarking strategies based on guest satisfaction so that hotel managers can recognize their relative positions along key service attributes and understand the direction and extent of service quality improvements. The subsequent subsections address the necessary components of the proposed decision-support framework depicted in Fig. 1, comprising data preprocessing, sentiment analysis, benchmarking analysis, and quality association analysis.

3.1. Data preprocessing

Online reviews possess various guest feedbacks based on the experiences of hotel service quality. This step discovers key service attributes commonly applicable to all hotels from online reviews by observing the frequency of occurrence. Although a tourism website introduces a set of rating features for guests, it would be sound to discover them directly from the online reviews without being restricted by the ratings.

The online reviews of five-star hotels in Korea were crawled on TripAdvisor (https://www.tripadvisor.com), one of the most popular travel websites worldwide. The “rvest” package (https://cran.r-project.org/web/packages/rvest/index.html) from the R program language was applied for crawling. All the reviews included in this study were written in Korean. Thus, Korean sentence structures were used as the basis of semantics. The crawled data were cleaned by removing special characters (e.g., %, !, @, *, #, etc.) and unclarified numbers, and by using consistent same-but-different expressions with errata (e.g., “checked-out,” “chekc out,” and “chacking-out” (sic)) into the same expression (e.g., “check-out”). Sentences were identified by recognizing punctuation characters and tabs (e.g., !, ?, ‘…’, ‘.’, ~, etc.). The data science package, RapidMiner (https://rapidminer.com/), was used to clean the crawled texts.

The well-known term-frequency–inverse document frequency (TF-IDF) algorithm was applied to the prepared sentence set (i.e., review) to discover a number of key service attributes provided by the guests. The TF-IDF result provides the statistical information required to evaluate the importance of words based on frequency, both document- and text-wise [33,64,81]. To improve the accuracy of TF-IDF results, a Korean stop-words dictionary[3] was applied to remove numerous types of stop-word morphemes, such as postpositions for subjects and objects, prepositions, and pronouns, though the special characters and unclarified numbers were filtered out when performing the data cleaning process with RapidMiner.

Throughout the TF-IDF analysis, words with high weightage scores were identified for all reviews and sorted in descending order. Meanwhile, if a word was identified as important, but was a type of emotional expression (e.g., “happy,” “wonderful,” or “unpleasant”), it was excluded. The top 20% important words were chosen after filtering to identify the key service attributes.

3.2. Clustering by key service attributes

Owing to the discovered key service attributes representing the dimensions of service quality, this step clustered the sentence dataset of each hotel into a number of clusters according to the discovered key service attributes for further analysis. The num-

[3] It is important to eliminate stop-words and typing errors to analyze text data with the TF-IDF algorithm. As different languages might require their own ways to identify stop-words, it is often suggested to refer to stop-words dictionaries to filter out stop-words [69,74,78]. This study uses a stop-word dictionary integrated with the stop-words list [37] extracted from National Institute of Korean Language with a web-available stop-words dictionary (https://gist.github.com/spikeekips/40eea22ef4a89f629abd87eed535ac6a).

ber of clusters was determined by the number of key service attributes. Since the decision-support framework aims to comprehensively evaluate the degree of guest satisfaction for a hotel in multiple dimensions, where each dimension refers to the number of positive opinions corresponding to a key service attribute, an effective clustering is imperative to estimate the polarity of opinions in each cluster. The pattern-matching function, "match," in the R program language (https://stat.ethz.ch/R-manual/R-devel/library/base/html/match.html) was applied to cluster sentences.

Procedure: Clustering reviews by each hotel
Indices, Set, and Parameters:
i: index of sentences in a review ($i = 1, 2, \ldots, I$)
j: index of hotel ($j = 1, 2, \ldots, J$)
k: index of key service attribute ($k = 1, 2, \ldots, K$)
F_k: k^{th} key service attribute
S_{ij}: i^{th} sentence of reviews in j^{th} hotel
G_{kj}: k^{th} key service attribute group for j^{th} hotel
Method:
While $j \le J$ do {
While $k \le K$ do {
Apply the "match" function to detect if F_k exists in S_{ij}.
Classify S_{ij} into G_{kj} if F_k matches one of the lexicons in S_{ij}.
}
}

By applying the match function, the clustering procedure searches to determine whether the k^{th} key service attribute exists in the i^{th} sentence of reviews for the j^{th} hotel. If the k^{th} key service attribute matches one of the lexicons in the i^{th} sentence of reviews for the j^{th} hotel, the sentence is clustered into a group, G_{kj}. This procedure was repeated for all hotels. Consequentially, the reviews of j^{th} hotels were clustered into K groups. Note that if a sentence included multiple key service attributes, it could be clustered simultaneously into all the corresponding groups.

3.3. Sentiment analysis

A constructed cluster is the collection of review sentences for a key service attribute of a hotel. This subsection describes the sentiment analysis applied to each cluster, with the aim to estimate the polarity of opinions from the review collection in the cluster. A single review can contain multiple sentences for each subject, and a single sentence can include multiple opinions for an entity. For a more fine-grained view based on different opinions and deriving various emotions from reviews, this study set sentences as the units for conducting sentiment analysis to obtain polarity decisions (i.e., positive, negative, or neutral). This subsection describes the detailed procedure for identifying emotional sentences.

The sentiment analysis resulted in numbers (counts) of positive, neutral, and negative opinions for each cluster of a hotel by means of the two phases of sentence processing. The first phase segments the sentence into clauses and identifies predicates and tenses. When a sentence comprises homogeneous opinions or emotions, it is easy to determine polarity. However, when it is made up of heterogeneous emotions (e.g., sentimental inversion), it is more difficult. Therefore, in this study, sentences were broken down into clauses, with each clause containing homogeneous opinions. For example, let us consider the following two sentences: "*Staff and managers are friendly*" and "*Staff and managers are friendly, but facilities are poor*." The first sentence has a single and homogeneous emotion with a positive word, "*friendly,*" and the polarity decision of this sentence is positive. The second sentence presents heterogeneous emotions consisting of two clauses having the conjunction, "*but,*" where the first clause possesses the positive word, "*friendly*," and the second possesses the negative word, "*poor.*"

In the second phase of processing, the sentiment analysis splits a heterogeneous emotional sentence into a number of smaller sentences based on the clauses. Hence, the second example sentence is split into "*Staff and managers are friendly*" and "*facilities are poor*" to further refine polarity. Note that a set of linguistic linkers and connectors (e.g., "*and*," "*or*," "*neither-nor*," "*either-or*," "*but*," "*however*," "*nevertheless*," etc.) is used to split a sentence having heterogeneous emotional clauses into individual sentences.

Sentiment analysis uses lexicon-based sentiment analysis [16] to compare the number of positive words with the number of negative words in a sentence and determine the polarity of the sentence. If the two numbers are the same, then it becomes neutral. Let L^p and L^n be a set of positive and negative lexicons in a sentiment lexicon dictionary, respectively, and S_i be the i^{th} sentence in the reviews of a hotel. Each sentence is determined as positive, negative, or neutral by $S_i^* = w_i^p - w_i^n$, where w_i^p is the number of positive words found in S_i referring to L^p, and w_i^n is the number of negative words found in S_i referring to L^n. If $S_i^* > 0$ entails S_i is regarded as positive, the opposite is regarded as negative, and S_i is neutral otherwise. Consider the following review comment, *"My friend recommended me to use this hotel. The facilities are quite good, but breakfast quality is a bit unsatisfactory."* This comment can be split into three sentences. Note that {'good'} and {'unsatisfactory'} are counted as positive and negative lexicons, respectively, in the sentiment lexicon dictionary. The first sentence is regarded as neutral ($S_1^* = 0$), the second sentence is regarded as positive ($S_2^* > 0$), and the third sentence is regarded as negative ($S_3^* < 0$). As a result, this review comment contains one positive, one negative, and one neutral sentence.

An unsupervised learning-based analysis was used to identify the polarity of sentences by referring to an emotional lexicon dictionary enriched by this study based on KNU, the Korean Sentiment Lexicon (https://github.com/park1200656/KnuSentiLex). As emotional expressions in Korean often appear as colloquial predicates and the colloquial form of Korean languages has numerous expression types and tenses, this study compared words in the emotional lexicon dictionary with those in the crawled online reviews and added non-registered words to the lexicon dictionary before conducting the sentiment analysis.

This study proposes that a greater number of positive opinions reflects higher guest satisfaction, as guests are likely to compliment the service quality for their satisfaction instead of complaining about unsatisfactory services. This study adopts the definition of odds [2] to express the magnitude of positive opinions against other types of opinions, Ω_{Pos}, for a key service attribute of a hotel.

$$\Omega_{Pos} = \frac{p_{Pos}}{1 - p_{Pos}}, \tag{1}$$

where p_{Pos} is the probability of having positive opinions among all kinds of opinions in the review sentences for a hotel, and $1 - p_{Pos}$ is the sum of probabilities of having negative and neutral opinions, $p_{Neg} + p_{Neu}$. The higher the Ω_{Pos}, the higher the magnitude of positive opinions. When $\Omega_{Pos} = 1$, the magnitude of positive opinions equals the sum of the rest. An odds value corresponds exactly to the probability value of having positive opinions according to its formula, $p_{Pos} = \Omega_{Pos}/(1 + \Omega_{Pos})$. This one-to-one correspondence helps hotel managers interpret guest satisfaction based on positive opinions or vice versa.

3.4. Benchmarking analysis

Sentiment analysis provides multiple dimensions (i.e., key service attributes) of polarity results for a hotel. This step conducts a benchmarking analysis of hotels with multiple dimensions to evaluate the degree of guest satisfaction of each hotel encompassing multiple dimensions, estimate benchmarking goals over multiple dimensions, and provide benchmarks (hotels) for hotels with low degrees of guest satisfaction. The degree of guest satisfaction addresses guests' perceptions of the experienced service. However, it provides little guidance for the selection of benchmarks. Benchmarking goals should be measurable, attainable, and actionable. Thus, the purpose of benchmarking is to find a reference point for learning and/or following-up on performance-measure improvements.

Hotels with the highest degree of guest satisfaction are likely to be considered to have the best practices, but it does not make sense to urge all hotels to follow these practices because the best outperforming hotel overall might be an underperforming hotel in certain dimensions. Each hotel can have different sets of benchmarks. A more rational approach is to assign different relevant benchmarks to different hotels considering their similarities. A popular approach for this is DEA, which assigns a set of efficient DMUs (i.e., hotels to be benchmarked) having similar input and output structures to the other set of inefficient DMUs (i.e., hotels requiring benchmarks). After benchmarks are identified, goals should be determined for the improvement of input and output values.

DEA models typically evaluate the efficiency scores of DMUs when inputs and outputs of each DMU are provided. The underlying basis of this study is that the magnitudes of positive opinions have a positive effect on service quality and benchmarking strategies, that is, the larger a hotel's score in favor of the magnitudes of positive opinions with respect to different key service attributes, the higher the guest satisfaction and the more likely they are to be benchmarked. Based on the requirement that the proposed DEA model needs to calculate the optimal service quality scores (i.e., degrees of guest satisfaction) of hotels for multi-criteria decision-making over key service attributes, both the underlying basis and the estimation of magnitudes of positive opinions allow the development of a DEA model's output-maximizing multiplier with multiple outputs (i.e., magnitudes of positive opinions) without considering inputs. That is, the proposed DEA model fixes the input as a constant value in evaluating the degree of guest satisfaction. Output-oriented DEA models with multiple outputs and a fixed input have been introduced [13] and successfully applied to application studies of multi-criteria decision-making, such as ABC inventory controls [53,59,67,87]. The general DEA model assumes that all inputs or outputs are discretionary in evaluating efficiencies. An inefficient DMU might reduce inputs or increase outputs to improve its efficiency, implying that all inputs and outputs of the inefficient DMU could be freely reduced or expanded for this purpose. However, certain inputs or outputs require a great deal of time and cost to improve efficiency, and they are recommended to be non-discretionary factors in the evaluation. Non-discretionary factors are useful for measuring efficiency but not for improving efficiency via reduction or expansion. Non-discretionary DEA models [6,12,13,35,38] consider non-discretionary factors in efficiency evaluation but exclude them in determining the amount of improvement for benchmarking. Among the outputs, the magnitudes of positive opinions for location are set to the non-discretionary factors because the location involves heavy capital cost and would not be a benchmark for improving hotel service quality.

In summary, this subsection applies an output-oriented non-discretionary CCR model of DEA with multiple outputs and a constant input that lets the magnitude of positive opinions for location be an uncontrollable output in the model.

Output-oriented non-discretionary CCR model:

$$Max\ G_k = \theta_k + \epsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \tag{2}$$

$$s.t.\ \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = \theta_k y_{rk},\ \ r \in D \tag{3}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{rk},\ \ r \in ND \tag{4}$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{ik},\ \ i = 1, \ldots, m \tag{5}$$

$$\lambda_j,\ s_i^-,\ s_r^+\ \geq 0,\ \ \forall j, i, r, \tag{6}$$

where s_r^+ and s_i^- are the slack variables associated with outputs and inputs, respectively. D is a set of discretionary (or controllable) outputs; ND is a set of non-discretionary (or uncontrollable) outputs; y_{rk} is the r^{th} output of the evaluated hotel, k; x_{ik} is the i^{th} input of the evaluated hotel, k; and λ_j is the dual variable (weight) assigned to the j^{th} hotel. Note that this study considers constant inputs in the model owing to its pure output orientation. Thus, all inputs have fixed values. According to the evaluation results of degrees of guest satisfaction (i.e., benchmarking scores, G_k), all hotels are classified into two groups, namely, benchmarks (i.e., best-practice hotels) if a hotel is given a score of 1 and underperforming hotels requiring a benchmark for service quality improvement. The benchmark of an underperforming hotel is determined by λ_j, when $\lambda_j = 1$. The amount of resources to be improved (Δy_{rk}) to achieve the benchmark can be calculated using Eq. (7):

$$\Delta y_{rk} = y_{rk} - \left(\theta_k^* y_{rk} + s_r^{+*}\right). \tag{7}$$

3.5. Quality association analysis

The benchmarking results via the DEA model provide the guest satisfaction score and improvement requirements needed to reach benchmark frontiers, but the results provide little information on the level of quality association for key service attributes over hotels. The DEA model provides benchmarking information for underperforming hotels. Hence, this step analyzes the quality association between underperforming and best practice hotels by comparatively estimating the degrees of association across key service attributes of the hotels.

This study applies the definition of the local odds ratio [2] to estimate the degree of association of a key service attribute of an underperforming hotel with another attribute of the benchmark. The local odds ratios (ORs), by definition, pick up two particular features across the selected groups and address the relationship between the groups. Hence, the local odds ratio is applicable to estimate the proposed quality association by selectively comparing the magnitude of positive opinions (i.e., odds) of a key service attribute (e.g., lodging charges) for an underperforming hotel (e.g., Hotel 29) with the odds of another key service attribute (e.g., facilities) for a benchmark (i.e., Hotel 35) of the underperforming hotel. From this example, the estimate is expressed as follows:

$$q_{(Hotel\ 29,\ lodging\ charges)}^{(Hotel\ 35,\ facilities)} = \frac{n_{(Hotel\ 35,\ facilities)} n_{(Hotel\ 29,\ lodging\ charges)}}{n_{(Hotel\ 29,\ facilties)} n_{(Hotel\ 29,\ loding\ charges)}}, \tag{8}$$

where $n_{(Hotel\ 30,\ facilities)}$ is the sample size of the positive opinions for a benchmark (i.e., Hotel 30) regarding a key service attribute (i.e., facilities). The quality association, in this case, is explained by the likelihood of having positive opinions about facilities instead of lodging charges for Hotel 30 as estimated to be $q_{(Hotel\ 29,\ lodging\ charges)}^{(Hotel\ 35,\ facilities)}$ times that of Hotel 29.

4. Experiment for the framework

We experimented with five-star hotels to satisfy the homogeneity criterion among DMUs. We found that 52 five-star hotels across

Table 1
Five-star hotels with 100 or more reviews.

No.	Hotels	Number of reviews	Number of sentences
1	Banyan Tree Club & Spa Seoul	218	1,113
2	Conrad	667	2,844
3	Four Seasons	654	3,039
4	Grand Hilton Seoul	406	1,940
5	Grand Hyatt Incheon	690	2,155
6	Grand Inter-Continental Parnas	501	2,770
7	Grand Walker-hill Seoul	504	2,089
8	Grand Mercure	148	662
9	Grand Pullman	649	3,298
10	Gyeongwonjae Ambassador Incheon Associated with Accor-Incheon	182	890
11	Haevichi Jeju	227	1,030
12	Imperial	659	1,811
13	Inter-Continental COEX	611	3,425
14	Shilla Jeju	444	2,077
15	JW Marriott Dongdaemun Square	671	4,162
16	Lotte Ulsan	173	809
17	Lotte Jeju	513	2,242
18	Lotte World	639	2,138
19	Lotte Seoul	655	2,497
20	Marriott Jeju	373	1,137
21	Mayfield	256	835
22	Millennium Hilton Seoul	670	3,040
23	Novotel Ambassador Dongdaemun	139	2,908
24	Novotel Ambassador Gangnam	635	655
25	Oakwood Premier Coex Center	645	2,674
26	Paradise City Incheon	127	570
27	Park Hyatt Seoul	508	2,703
28	Ramada Plaza Jeju	470	1,739
29	SEAMARQ Hotel Gangneung	64	333
30	Sheraton Grand Incheon	370	1,896
31	Sheraton Seoul D Cube City	549	3,115
32	Sheraton Seoul Palace Gangnam	279	1,605
33	Shinla	589	3,082
34	Signiel	180	703
35	THE PLAZA Seoul	600	3,404
36	Vista Walkerhill Seoul	417	1,651
37	Westin Chosun Seoul	655	2,802
38	Lotte Busan	655	2,184
39	Westin Chosun Busan	110	469
40	Paradise Busan	389	1,933
41	Park Hyatt Busan	690	1,958
42	Hillton Busan	370	1,340

South Korea and their 26,001 reviews could be crawled at TripAdvisor.com. Among the 52 hotels, 10 were excluded from the list owing to small sample sizes (i.e., fewer than 100 reviews). Table 1 displays the five-star hotels with more than 100 reviews on TripAdvisor.com. After data clearance, 85,925 sentences were available for further analysis. The identified sentences helped enrich the KNU sentiment lexicon and comprised the sentence dataset.

4.1. Results of key service attributes and sentiment analysis

Polarity analysis was conducted without clustering to understand overall guest responses toward hotel services, and the outcome is depicted in Fig. 2. According to the polarity results, the average percentage of positive opinions was 46.2%, which was much higher than that of negative opinions (7.6%). However, neutral opinions were 46.2% on average, which is nearly equivalent to the number of positive opinions. The highest and lowest percentages of positive opinions were 52.8% at Hotel 13 (Inter Continental COEX) and 35.4% at Hotel 29 (SEAMARQ Hotel Gangneung).

When applying the TF-IDF algorithm to the sentence dataset, the weighted values were calculated for a total of 176 words. After removing emotional expressions, the final 104 words were derived as key service attribute candidates. The five distinctive key service attributes are chosen by categorizing words with similar meanings into the same group. They are nearly the top 5% of the candidates in terms of TF-IDF scores, and the sum of their TF-IDF scores is 84% of the total score. The key service attributes were facilities (TF-IDF score of 2,879), locations (2,759), lodging charges (3,230), meals (2,480), and guest service (2,289). The key service attribute, “facilities,” included a number of similar variants, such as rooms, bathrooms, swimming pools, and other subsidiary facilities. The variants for “locations” were transportation, accessibility, subway stations, and other geographical names. Several monetized representations were discovered for “lodging charges,” including package, happy hours, and promotion. “Meals” represented food, breakfast, beverages, and other dining items. “Guest service” was set to a wide category of room service, concierge service, porter, and staff kindness, representing the courtesy aspects of hotel staff. The distributions of key service attribute candidates are presented in the Appendix.

The sentences were clustered and arranged via the discovered key service attributes per hotel; the results are presented in Table 2. The polarity results for each cluster are summarized in Table 3. The positive opinions were generally higher than the negative ones with higher standard deviations over the key service attributes.

According to the clustering results shown in Tables 4 and 5, the magnitude of positive opinions was relatively higher for facilities and locations than for lodging charge and meals. Note that this study took the odds of positive opinions against other opinions to

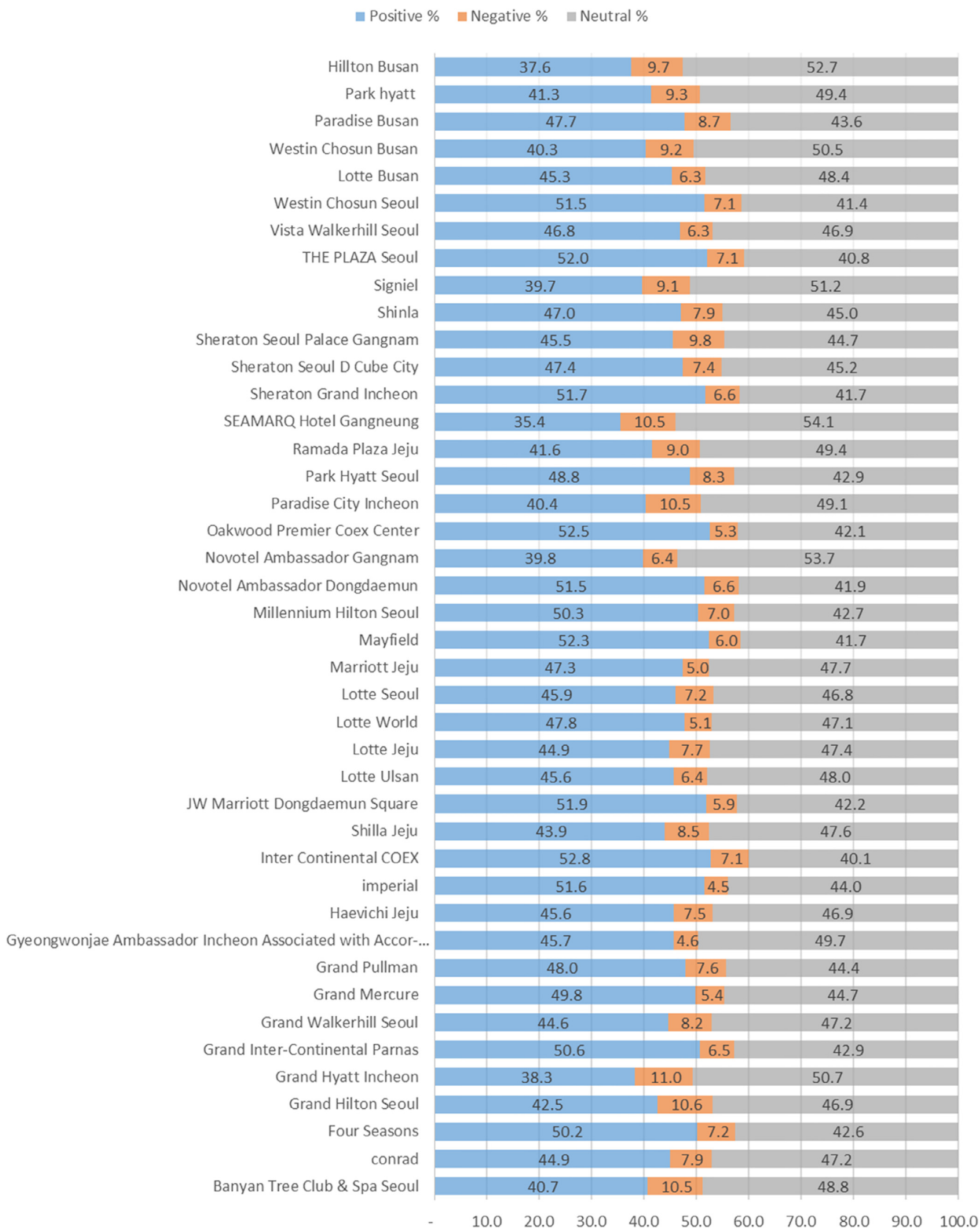

Fig. 2. Polarity results for hotels without clustering.

Table 2
Number of sentences clustered into the key service attributes.

ID	Hotels	Number of sentences				
		Facilities	Locations	Lodging charges	Meals	Guest Service
1	Banyan Tree Club & Spa Seoul	418	159	178	231	392
2	Conrad	595	551	239	752	893
3	Four Seasons	872	1014	308	163	1315
4	Grand Hilton Seoul	420	503	205	379	474
5	Grand Hyatt Incheon	406	173	114	328	424
6	Grand Inter-Continental Parnas	565	1160	224	297	1031
7	Grand Walkerhill Seoul	285	287	130	257	513
8	Grand Mercure	183	52	54	180	412
9	Grand Pullman	641	908	361	656	1013
10	Gyeongwonjae Ambassador Incheon Associated with Accor-Incheon	191	125	31	151	236
11	Haevichi Jeju	301	272	163	199	143
12	Imperial	258	113	129	205	436
13	Inter Continental COEX	696	1386	415	259	1376
14	Shilla Jeju	565	186	297	337	613
15	JW Marriott Dongdaemun Square	842	1700	235	288	1718
16	Lotte Ulsan	176	240	109	93	516
17	Lotte Jeju	422	231	236	269	499
18	Lotte World	381	227	62	346	526
19	Lotte Seoul	407	469	185	390	877
20	Marriott Jeju	461	46	85	295	202
21	Mayfield	141	83	94	101	145
22	Millennium Hilton Seoul	497	1094	275	412	869
23	Novotel Ambassador Dongdaemun	138	136	41	113	143
24	Novotel Ambassador Gangnam	570	1023	468	425	803
25	Oakwood Premier Coex Center	786	852	181	198	698
26	Paradise City Incheon	284	100	122	82	153
27	Park Hyatt Seoul	548	880	198	230	1031
28	Ramada Plaza Jeju	320	263	226	448	276
29	SEAMARQ Hotel Gangneung	216	96	95	118	234
30	Sheraton Grand Incheon	381	463	181	223	524
31	Sheraton Seoul D Cube City	624	1042	238	226	1030
32	Sheraton Seoul Palace Gangnam	316	593	255	166	377
33	Shinla	633	567	512	419	1321
34	Signiel	176	51	92	177	296
35	THE PLAZA Seoul	621	1874	361	225	1110
36	Vista Walkerhill Seoul	299	60	54	165	346
37	Westin Chosun Seoul	579	974	171	451	983
38	Lotte Busan	342	549	163	325	524
39	Westin Chosun Busan	128	172	72	127	78
40	Paradise Busan	391	640	252	230	458
41	Park Hyatt Busan	397	337	274	414	557
42	Hillton Busan	445	122	117	294	292
	Total	17,917	21,773	8,202	11,644	25,857

Table 3
Polarity results across hotels.

Clusters Values	Facilities		Locations		Lodging charges		Meals		Guest service	
	$100p_{Pos}$	$100p_{Neg}$	$100p_{Pos}$	$100p_{Neg}$	$100p_{Pos}$	$100p_{Neg}$	$100p_{Pos}$	$100p_{Neg}$	$100p_{Pos}$	$100p_{Neg}$
Maximum	58.0	13.0	56.8	13.7	55.0	16.7	54.5	14.7	55.0	13.3
Minimum	24.1	3.4	32.4	2.2	31.6	2.4	32.3	1.0	30.8	3.6
Mean	47.7	7.6	48.7	6.7	44.2	9.2	43.2	7.8	45.7	7.8
Standard deviation	6.8	2.6	6.5	2.3	6.2	3.3	5.6	2.8	5.8	2.1

represent the magnitude of positive opinions. Since the estimated odds results were generally less than 1, the positive opinions for hotel services were interpreted as being generally lower than those of the other areas, and that hotels were likely to have plenty of room to improve their services in the selected key service areas.

4.2. Benchmarking analysis results

The benchmarking results of the non-discretionary output-oriented CCR-DEA model are displayed in Tables 6 and 7. A hotel with a satisfaction score of 1 (i.e., the highest degree of guest satisfaction) has a high chance of becoming a benchmark for underperforming hotels having scores less than 1.

A total of seven hotels became the benchmarking targets of the remaining hotels with respect to the service attributes shown in Table 6. Hotel 30 (Sheraton Grand Incheon) was referred 21 times to other underperforming hotels for benchmarking, whereas Hotel 12 (Imperial) and Hotel 24 (Novotel Ambassador Gangnam) were not referred to as benchmarks for any other hotels, even though they are best-practice hotels. In benchmarking studies using DEA models, a hotel with a lower degree of guest satisfaction looks for the most ideal benchmarks (i.e., hotels having a score of 1) regarding the combination of the four key service attributes (i.e., facilities, lodging charges, meals, and guest service). This study observed that the underperforming hotels mostly considered Hotel 13 (Inter Continental COEX), Hotel 30 (Sheraton Grand Incheon),

Table 4
Estimated magnitudes of positive opinions.

ID	Hotels	Magnitudes of positive opinions				
		Facilities	Locations	Lodging charges	Meals	Guest Service
1	Banyan Tree Club & Spa Seoul	0.88	0.79	0.60	0.52	0.67
2	Conrad	0.89	1.06	0.56	0.70	0.82
3	Four Seasons	1.07	1.25	0.73	0.83	1.05
4	Grand Hilton Seoul	0.78	0.86	0.72	0.59	0.85
5	Grand Hyatt Incheon	0.72	0.48	0.63	0.48	0.59
6	Grand Inter-Continental Parnas	1.08	1.17	0.85	0.65	1.09
7	Grand Walkerhill Seoul	0.94	1.02	1.06	0.80	0.81
8	Grand Mercure	0.91	1.08	0.59	1.02	0.87
9	Grand Pullman	1.13	1.18	0.94	0.78	0.95
10	Gyeongwonjae Ambassador Incheon Associated with Accor-Incheon	0.80	1.23	0.72	0.86	0.82
11	Haevichi Jeju	0.87	0.99	0.75	0.79	0.86
12	Imperial	0.84	1.17	1.22	0.77	1.09
13	Inter Continental COEX	1.38	1.31	1.10	0.79	1.10
14	Shilla Jeju	0.78	0.65	0.79	0.90	0.61
15	JW Marriott Dongdaemun Square	1.31	1.30	1.01	0.80	1.19
16	Lotte Ulsan	0.96	0.83	0.70	0.50	0.86
17	Lotte Jeju	0.94	1.01	0.79	0.66	0.90
18	Lotte World	1.08	1.05	0.82	0.97	0.91
19	Lotte Seoul	1.00	0.91	0.76	1.02	0.82
20	Marriott Jeju	0.92	0.77	0.98	1.02	0.46
21	Mayfield	0.96	0.63	1.19	1.20	0.77
22	Millennium Hilton Seoul	1.11	1.24	1.10	0.72	1.14
23	Novotel Ambassador Dongdaemun	0.79	0.81	0.86	0.66	0.72
24	Novotel Ambassador Gangnam	1.24	1.31	1.04	0.81	1.10
25	Oakwood Premier Coex Center	1.15	1.20	0.99	0.98	1.07
26	Paradise City Incheon	0.79	0.61	0.53	0.78	0.63
27	Park Hyatt Seoul	1.21	1.18	0.87	0.87	0.98
28	Ramada Plaza Jeju	0.78	0.80	0.71	0.62	0.89
29	SEAMARQ Hotel Gangneung	0.32	0.66	0.61	0.51	0.44
30	Sheraton Grand Incheon	1.20	1.28	0.95	1.12	1.05
31	Sheraton Seoul D Cube City	0.98	1.06	0.89	0.85	0.84
32	Sheraton Seoul Palace Gangnam	0.82	1.01	0.89	0.54	0.89
33	Shinla	1.05	1.05	0.82	0.76	0.92
34	Signiel	0.56	0.59	0.48	0.64	0.73
35	THE PLAZA Seoul	1.21	1.21	1.20	1.08	1.22
36	Vista Walkerhill Seoul	1.20	1.14	0.64	0.79	0.85
37	Westin Chosun Seoul	1.02	1.17	0.97	0.93	1.01
38	Lotte Busan	1.11	0.89	0.68	0.84	0.68
39	Westin Chosun Busan	0.41	0.72	0.57	0.61	0.73
40	Paradise Busan	0.95	1.06	0.58	0.58	0.88
41	Park Hyatt Busan	0.69	0.72	0.77	0.71	0.76
42	Hillton Busan	0.69	0.65	0.46	0.62	0.54

Table 5
Summary of estimated magnitudes of positive opinions.

Values	Magnitudes of positive opinions				
	Facilities	Locations	Lodging charges	Meals	Guest Service
Maximum	1.38	1.31	1.22	1.20	1.22
Minimum	0.32	0.48	0.46	0.48	0.44
Mean	0.94	0.98	0.81	0.78	0.86
Standard deviation	0.23	0.24	0.20	0.18	0.19

Table 6
Best-practice hotels (Benchmarks).

No.	Hotels	Scores	Benchmarking goals				Number of benchmarked
			Facilities	Lodging charges	Meals	Guest service	
12	Imperial	1.00	0.85	1.22	0.75	1.08	0
13	Inter Continental COEX	1.00	1.38	1.08	0.79	1.08	14
15	JW Marriott Dongdaemun Square	1.00	1.33	1.00	0.79	1.17	3
21	Mayfield	1.00	0.96	1.17	1.17	0.75	6
24	Novotel Ambassador Gangnam	1.00	1.22	1.04	0.82	1.08	0
30	Sheraton Grand Incheon	1.00	1.22	0.96	1.13	1.04	21
35	THE PLAZA Seoul	1.00	1.22	1.22	1.08	1.22	16

Table 7
Benchmarking goals and improvement requirement from the CCR-DEA model.

No.	Hotels	Scores	Ranks	Benchmarking goals				Improvement requirement				Benchmarks (Hotel No.)
				Facilities	Lodging charge	Meals	Guest service	Facilities	Lodging charge	Meals	Guest service	
12	Imperial	1.00	1	0.85	1.22	0.75	1.08	0.00	0.00	0.00	0.00	-
13	Inter Continental COEX	1.00	1	1.38	1.08	0.79	1.08	0.00	0.00	0.00	0.00	-
15	JW Marriott Dongdaemun Square	1.00	1	1.33	1.00	0.79	1.17	0.00	0.00	0.00	0.00	-
21	Mayfield	1.00	1	0.96	1.17	1.17	0.75	0.00	0.00	0.00	0.00	-
24	Novotel Ambassador Gangnam	1.00	1	1.22	1.04	0.82	1.08	0.00	0.00	0.00	0.00	-
30	Sheraton Grand Incheon	1.00	1	1.22	0.96	1.13	1.04	0.00	0.00	0.00	0.00	-
35	THE PLAZA Seoul	1.00	1	1.22	1.22	1.08	1.22	0.00	0.00	0.00	0.00	-
27	Park Hyatt Seoul	0.94	8	1.31	1.03	0.95	1.06	0.08	0.17	0.06	0.10	13, 30
22	Millennium Hilton Seoul	0.93	9	1.22	1.22	1.08	1.22	0.09	0.14	0.36	0.09	35
8	Grand Mercure	0.91	10	1.16	1.00	1.14	0.97	0.24	0.42	0.10	0.08	21, 30
25	Oakwood Premier Coex Center	0.91	11	1.24	1.17	1.05	1.19	0.11	0.17	0.09	0.10	13, 30, 35
36	Vista Walkerhill Seoul	0.91	12	1.35	1.05	0.86	1.07	0.12	0.41	0.08	0.22	13, 30
19	Lotte Seoul	0.91	13	1.10	1.06	1.15	0.91	0.10	0.30	0.11	0.09	21, 30
20	Marriott Jeju	0.90	14	1.03	1.12	1.16	0.82	0.11	0.16	0.12	0.35	21, 30
6	Grand Inter-Continental Parnas	0.89	15	1.22	1.22	1.08	1.22	0.14	0.37	0.44	0.14	35
7	Grand Walkerhill Seoul	0.89	15	1.22	1.22	1.08	1.22	0.30	0.14	0.29	0.40	35
18	Lotte World	0.87	17	1.24	0.98	1.10	1.06	0.15	0.16	0.14	0.13	13,30, 35
38	Lotte Busan	0.87	18	1.29	1.01	0.98	1.05	0.16	0.34	0.12	0.39	13, 30
3	Four Seasons	0.87	19	1.27	1.12	0.95	1.20	0.19	0.40	0.13	0.16	15, 35
9	Grand Pullman	0.86	20	1.31	1.11	0.91	1.12	0.18	0.19	0.13	0.16	13, 30, 35
37	Westin Chosun Seoul	0.84	21	1.22	1.17	1.09	1.18	0.22	0.21	0.17	0.18	30, 35
31	Sheraton Seoul D Cube City	0.80	22	1.24	1.10	1.06	1.14	0.24	0.22	0.21	0.29	13, 30, 35
33	Shinla	0.80	23	1.30	1.15	0.94	1.15	0.26	0.33	0.19	0.23	13, 30, 35
14	Shilla Jeju	0.77	24	1.02	1.11	1.16	0.83	0.24	0.32	0.27	0.22	21, 30
10	Gyeongwonjae Ambassador Incheon Associated with Accor-Incheon	0.76	25	1.22	1.02	1.12	1.08	0.40	0.30	0.27	0.26	30, 35
40	Paradise Busan	0.75	26	1.29	1.09	0.91	1.19	0.32	0.50	0.32	0.30	13, 35
17	Lotte Jeju	0.74	27	1.25	1.16	1.00	1.20	0.33	0.37	0.34	0.32	15, 35
28	Ramada Plaza Jeju	0.73	28	1.21	1.23	1.08	1.22	0.43	0.50	0.47	0.33	35
32	Sheraton Seoul Palace Gangnam	0.73	28	1.22	1.22	1.08	1.22	0.40	0.33	0.54	0.33	35
11	Haevichi Jeju	0.73	30	1.22	1.15	1.08	1.17	0.33	0.40	0.29	0.32	13, 30, 35
16	Lotte Ulsan	0.72	31	1.33	1.02	0.81	1.18	0.36	0.32	0.32	0.32	15, 35
2	Conrad	0.70	32	1.27	1.17	0.99	1.17	0.38	0.61	0.30	0.35	13, 30, 35
4	Grand Hilton Seoul	0.70	33	1.21	1.23	1.08	1.22	0.43	0.50	0.49	0.37	35
23	Novotel Ambassador Dongdaemun	0.70	33	1.21	1.22	1.08	1.23	0.43	0.37	0.41	0.50	35
26	Paradise City Incheon	0.69	35	1.14	1.02	1.14	0.95	0.35	0.50	0.35	0.31	21, 30
41	Park Hyatt Busan	0.66	36	1.21	1.15	1.11	1.15	0.52	0.40	0.38	0.40	21, 30, 35
1	Banyan Tree Club & Spa Seoul	0.65	37	1.37	1.08	0.80	1.07	0.48	0.47	0.28	0.41	13, 30
34	Signiel	0.59	38	1.22	1.22	1.08	1.22	0.66	0.73	0.44	0.50	30, 35
39	Westin Chosun Busan	0.59	39	1.22	1.22	1.08	1.23	0.81	0.66	0.47	0.50	35
42	Hillton Busan	0.56	40	1.25	0.97	1.10	1.04	0.55	0.50	0.49	0.50	13, 30
5	Grand Hyatt Incheon	0.56	41	1.30	1.15	0.94	1.15	0.58	0.51	0.47	0.56	13, 35
29	SEAMARQ Hotel Gangneung	0.50	42	1.21	1.23	1.07	1.22	0.90	0.61	0.56	0.77	35

and Hotel 35 (THE PLAZA Seoul) as benchmarks. The benchmarking goal could be interpreted as the goal of having a score of 1 by benchmarking a best-practice hotel in the magnitude of positive opinions. As depicted in Table 6, the best practice hotels had benchmarking goals that had exactly the same magnitudes of positive opinions. Thus, those hotels benchmarked themselves.

Apart from the seven best-practice hotels, the other 35 presented corresponding benchmarks, as depicted in Table 7. For example, Hotel 29 (SEAMARQ Hotel Gangneung) had the lowest benchmarking score of 0.5 and was recommended to benchmark Hotel 35. Hotel 29 obtained the benchmarking goals (i.e., goals to reach best practical guest satisfaction) of 1.21 (facilities), 1.23 (lodging charges), 1.07 (meals), and 1.22 (guest service) to become a best practical hotel (i.e., the benchmarking score of 1) by benchmarking the chosen best practice (e.g., Hotel 35) regarding the combination of the four key service attributes. The improve-

Table 8
Sentence polarity and quality association for Hotels 29 (underperforming) and 35 (benchmark).

Hotels		Number of sentences for facilities		Number of sentences for lodging charges		Number of sentences for meals		Number of sentences for guest service	
		Positive	Non-positive	Positive	Non-positive	Positive	Non-positive	Positive	Non-positive
Hotel 35		340	281	197	164	117	108	611	499
Hotel 29		52	164	36	59	40	78	72	162
local odds ratio (positives)		3.82		1.97		2.11		2.76	
local odds ratio (positive-cross)		Hotel 29 Facilities		Lodging charges		Meals		Guest service	
Hotel 35	Facilities	-		1.19		2.24		0.77	
	Lodging charges	0.84 (= 1/1.19)		-		1.87		0.64	
	Meals	0.45 (= 1/2.24)		0.53 (= 1/1.87)		-		0.34	
	Guest service	1.30 (= 1/0.77)		1.55 (= 1/0.64)		2.90 (= 1/0.34)		-	

ment requirements to reach the benchmarking goals were estimated as 0.90 (facilities), 0.61 (lodging charges), 0.56 (meals), and 0.77 (guest service). This means that Hotel 29 needed to improve by 0.61 of the magnitude of positive opinions for lodging charges to reach best-practical guest satisfaction by benchmarking to the chosen best practice. The improvement requirement of 0.61 corresponded equivalently to the probability of having positive opinions (p_{Pos}) at 38%, according to the one-to-one correspondence of Eq. (1) in the key service attribute of lodging charges. Therefore, Hotel 29 needed to gain more than 38% positive opinion in lodging charges of the current 62.1% of non-positive opinions to reach the best practical guest satisfaction or to reduce the non-positive opinions to less than 24.1%. The same applies to the improvement requirement for the other key service attributes. The hotel needed to increase more than 47.3% (facilities), 35.7% (meals), and 43.5% (guest services) from the current magnitudes of positive opinions (31.7% for facilities, 51.3% for meals, and 44.4% for guest service).

As for the observation of multiple benchmarks, Hotel 41 (Park Hyatt Busan) found three benchmarks: Hotel 21 (Mayfield), Hotel 30 (Sheraton Grand Incheon), and Hotel 35 (THE PLAZA Seoul). The multiple benchmarks were a result of the evaluation that they were equally suitable as best practice hotels for the underperforming hotel (i.e., Hotel 41) based on the evaluated degrees of guest satisfaction. According to the observations of benchmarking goals, Hotel 41 needed to set the benchmarking goals of facilities, lodging charges, meals, and guest service to 1.21, 1.15, 1.11, and 1.15, respectively, to reach the highest degree of guest satisfaction (i.e., best practice) by benchmarking to Hotels 21, 30, and 35. As a result of the improvement requirement (0.52 for facilities, 0.40 for lodging charges, 0.38 for meals, and 0.40 for guest services) of benchmarking, it was recommended that Hotel 41 gain at least 34.2%, 28.4%, 27.6%, and 28.4% positive opinions from the current 59.2%, 56.6%, 58.5%, and 56.9% non-positive opinions of facilities, lodging charges, meals, and guest service, respectively.

Hotel 27 (Park Hyatt Seoul) had a benchmarking score of 0.94, which was nearly best-practical, and was appointed two benchmarks comprising Hotel 13 (Inter Continental COEX) and Hotel 30 (Sheraton Grand Incheon) to reach best-practice guest satisfaction. The benchmarking goals for key service attributes were estimated as 1.31 (facilities), 1.03 (lodging charges), 0.95 (meals), and 1.06 (guest service), where the current magnitudes of positive opinions were 1.21, 0.87, 0.87, and 0.98, respectively. Due to the minor difference between the benchmarking goal and the current status, the improvement requirements were estimated as 0.08, 0.17, 0.06, and 0.10 for facilities, lodging charges, meals, and guest service, respectively, indicating that the recommended gains in the probabilities of positive opinions were expected to be at least 7.8%, 14.8%, 5.8%, and 9.2% for the key service attributes.

4.3. Quality association results

This subsection re-examines the polarity of opinions for an underperforming hotel with the best-practice hotel (i.e., benchmark) to estimate quality association by means of local ORs between key service attributes in a pair of underperforming and benchmark hotels. The estimated local ORs could play a supplementary role in enriching the benchmarking results, as improvement requirements (Table 7) explain the amounts of improvement requirements on key service attributes for an underperforming hotel to become a best-practical hotel, whereas the local ORs (quality association) explain the amount of similarity (or dissimilarity) on key service attributes between the underperforming hotel and the benchmark.

According to the benchmarking results, Hotel 29 is an underperforming hotel and Hotel 35 is the benchmark for Hotel 29. When looking into the sentence polarity of Hotels 29 and 35 (benchmark) in Table 8, the likelihood of having positive opinions instead of non-positive opinions regarding facilities for the benchmark was estimated to be 3.82 ($=\frac{340 \times 164}{52 \times 281}$) times that for the underperforming hotel. According to the estimation of the other local ORs, the likelihoods of having positive opinions for the benchmark were estimated to be 1.97 times (lodging charges), 2.11 times (meals), and 2.76 times (guest service) of those for the underperforming hotel (i.e., Hotel 29).

The cross-evaluation of positive opinions across the key service attributes for the two hotels provided a different view of quality association. The likelihood of having positive opinions about facilities instead of lodging charges for the benchmark (i.e., Hotel 35) was estimated to be 1.19 ($=\frac{340 \times 36}{52 \times 197}$) times that for the underperforming hotel (i.e., Hotel 29). Likewise, the likelihood of having positive guest feedback about lodging charges instead of guest service for the benchmark was estimated to be 0.64 times that for the underperforming hotel. The further the estimate is from 1, the stronger the degree of quality of association between the two attributes across hotels.

It is observed that another underperforming hotel (i.e., Hotel 27) had two benchmarks (Hotels 13 and 30). As presented in Tables 9 and 10, the likelihoods of having positive opinions instead of non-positive opinions for Hotels 13 and 30 (i.e., benchmarks) were estimated to be 1.14 and 0.99 times (facilities), 1.26 and 1.09 times (lodging charges), 0.90 and 1.29 times (meals), and 1.12 and 1.07 times (guest service) those for Hotel 27. Although the two benchmarks were equivalently estimated for the underperforming hotel in favor of magnitudes of positive opinions, the three key service attributes (i.e., facilities, lodging charges, and guest service) of Hotel 13 were estimated to have 15.1%p, 15.8%p, and 4.8%p higher degree of quality association than those of Hotel 30. Additionally, the other service attribute (i.e., meals) of Hotel 13 was estimated

Table 9
Sentence polarity and quality association for Hotel 27 (underperforming) and Hotel 13 (benchmark).

Hotels		Number of sentences for facilities		Number of sentences for lodging charges		Number of sentences for meals		Number of sentences for guest service	
		Positive	Non-positive	Positive	Non-positive	Positive	Non-positive	Positive	Non-positive
Hotel 13		404	292	217	198	114	145	720	656
Hotel 27		300	248	92	106	107	123	510	521
local odds ratio (positives)		1.14		1.26		0.90		1.12	
local odds ratio (positive-cross)		Hotel 27 Facilities		Lodging charges		Meals		Guest service	
Hotel 13	Facilities	-		0.57		1.26		0.95	
	Lodging charges	1.75 (= 1/0.57)		-		2.21		1.67	
	Meals	0.79 (= 1/1.26)		0.45 (= 1/2.21)		-		0.75	
	Guest service	1.05 (=1.0.95)		0.60 (= 1/1.67)		1.33 (= 1/0.75)		-	

Table 10
Sentence polarity and quality association for Hotel 27 (underperforming) and Hotel 30 (benchmark).

Hotels		Number of sentences for facilities		Number of sentences for lodging charges		Number of sentences for meals		Number of sentences for guest service	
		Positive	Non-positive	Positive	Non-positive	Positive	Non-positive	Positive	Non-positive
Hotel 13		208	173	88	93	118	105	268	256
Hotel 30		300	248	92	106	107	123	510	521
local odds ratio (positives)		0.99		1.09		1.29		1.07	
local odds ratio (positive-cross)		Hotel 30 Facilities		Lodging charges		Meals		Guest service	
Hotel 13	Facilities			0.72		0.63		1.32	
	Lodging charges	1.38 (= 1/0.72)				0.87		1.82	
	Meals	1.59 (= 1/0.63)		1.15 (= 1/0.87)				2.10	
	Guest service	0.76 (= 1/1.32)		0.55 (= 1/1.82)		0.48 (= 1/2.10)			

to have 30%p lower degree of quality association than that of Hotel 30, with the corresponding service attributes of Hotel 27.

The underperforming hotel (i.e., Hotel 27) has a subtle degree of quality association (i.e., 1.09) regarding lodging charges with that of a benchmark (i.e., Hotel 30), where the required amount of effort for improving service quality on facilities to reach best-practice guest satisfaction was estimated to be 0.17 (i.e., 14.8% of probability of positive opinions). The recommended increase in the probability of positive opinions regarding lodging charges is the same when the hotel managers benchmark to Hotel 13 because Hotel 27 appointed the two benchmarks equivalently in the degree of guest satisfaction (i.e., benchmarking score). However, the degree of quality association regarding lodging charges of Hotel 27 is estimated to be 1.26 with that of Hotel 13, which is 15.8%p higher.

According to the cross-evaluation results, the likelihood of having positive guest feedback regarding lodging charges instead of meals for Hotel 27 was estimated to be negatively associated (i.e., 0.45 times) with that of Hotel 13, but positively associated (i.e., 1.15 times) with that of Hotel 30. Instead, the likelihood of having positive guest feedback for meals instead of guest service for Hotel 27 was estimated to be positively associated (i.e., 1.33 times) with that of Hotel 13, but negatively associated (i.e., 0.48 times) with that of Hotel 30.

5. Cross-validation against tourism websites

The tourism website, TripAdvisor.com, has been used as a rating survey system for guests to choose the satisfaction level for each of the predetermined service attributes. The experiment was conducted to understand the effect of using the key service attributes instead of applying the predetermined service attributes to evaluate the degree of guest satisfaction as described in Subsections 3.4 and 4.2.

The website provided four service attributes consisting of “location”, “cleanliness”, “guest service”, and “lodging charges”, which are similar to the key service attributes estimated from the online reviews in this study. This study applied the TF-IDF algorithm for the service attribute “cleanliness” to the cleaned online reviews and found 818 related sentences comprising words such as “smell”, “clean”, “cleanliness”, “dust”, “stain”, and “dirty”. It was found that the number of sentences for cleanliness was very low compared to the others (e.g., 11,644 sentences for “meals” and 17,917 sentences for “facilities” as displayed in Table 2), despite the website providing this service attribute for rating scores.

It was found that the evaluated degrees of guest satisfaction had considerable similarity over the hotels between the uses of four predetermined and five proposed service attributes, as can be seen in Fig. 3. The correlation coefficient was estimated to be 0.796 for the two types of degrees of guest satisfaction. The minor differences in the number of service attributes and the composite of service attributes had an insignificant influence on the evaluation of guest satisfaction.

As can be seen in Fig. 4, the number of hotels was much more evenly distributed over quantiles in degrees of guest satisfaction for the five proposed service attributes than for the four predetermined service attributes, and a monotonic increase in quantile points was observed when the five proposed service attributes were used instead of the four predetermined service attributes. Moreover, the standard deviation (i.e., 0.14) of the degree of guest satisfaction for the five proposed service attributes was 17.9% lower than that for the four predetermined service attributes. Therefore, it can be concluded that the five proposed service attributes con-

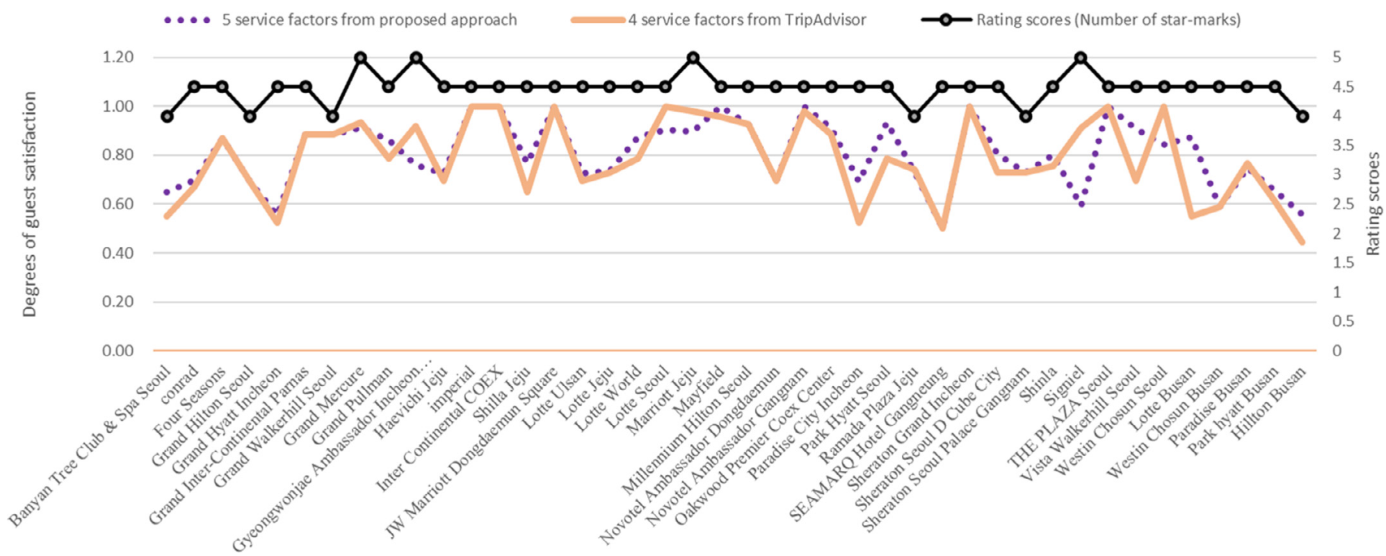

Fig. 3. Comparative degrees of guest satisfaction for predetermined and extracted service attributes, and the rating scores evaluated on the tourism website.

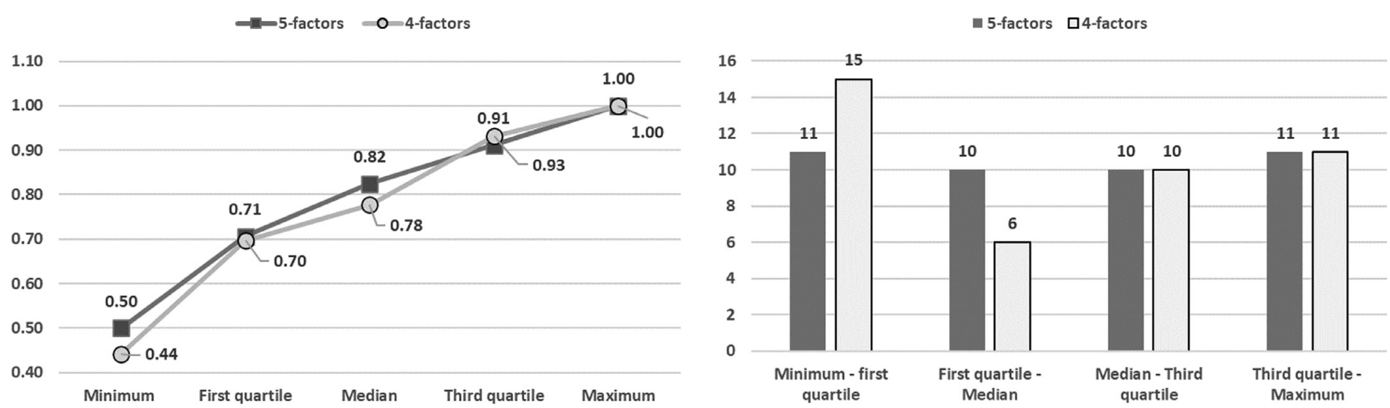

Fig. 4. Quartiles of degrees of guest satisfaction (left) and the occurrences of each quartile (right) for five and four service attributes.

tributed to higher discrimination power over quartiles in evaluating guest satisfaction within a narrower boundary of deviations due to a higher number of dimensions and/or superior composite of service attributes.

The experiment also compared the evaluated degrees of guest satisfaction with the overall star-rating scores provided by the tourism website. The website provided rating scores ranging from 0 to 5 with discretization of 0.5. It was found that the rating scores had little discrimination power over the hotels, as shown in Fig. 3. When observing the rating scores, 32 of the 42 hotels had the rating score of 4.5. For example, Hotels 17, 18, and 19 ("Lotte Jeju", "Lotte World", and "Lotte Seoul") had the same rating score of 4.5 whereas their evaluated degrees of guest satisfaction using the predetermined service attributes were 0.73, 0.79, and 1, respectively. It was also found that the three hotels (i.e., "Lotte Jeju", "Lotte World", and "Lotte Seoul") had the same overall rating score. When breaking the score down to each of the service attributes as shown in Table 11, moderate discrimination was found over the service attributes even though Lotte World had higher ratings regarding location and lodging charges than Lotte Jeju, and Lotte Seoul had higher ratings than Lotte World regarding location. The overall rating scores of the three hotels were same to one another as 4.5. These experimental results are in line with those of previous studies [43,55], 2013b; [54], which questioned the usefulness of star ratings as a good indicator of hotel service quality and disclosed that the star-rating system is not relevant to hotel efficiency.

Table 11
Observed rating scores for each of the predetermined service attributes.

Service attributes Hotels	Location	Cleanliness	Guest service	Lodging charge
Lotte Jeju	4	4.5	4.5	3.5
Lotte World	4.5	4.5	4.5	4
Lotte Seoul	5	4.5	4.5	4

The other experiment was conducted to evaluate guest satisfaction over different sets of online reviews collected from different tourism websites. In addition to TripAdvisor.com, this experiment crawled online reviews at Hotels.com (https://www.hotels.com) and HotelsCombined (https://www.hotelscombined.com), which had 152,093 and 27,695 reviews, respectively. The experiment applied the five key service attributes described in Section 4 and evaluated the degree of guest satisfaction. The experimental results are plotted in Fig. 5. As can be seen, the two websites yielded similar patterns for guest satisfaction as TripAdvisor, and the correlation coefficients were estimated as 0.934 and 0.965 with Hotels.com and HotelsCombined, respectively. The results show that the guest perceptions of satisfaction in terms of service quality are generally similar across the tourism websites.

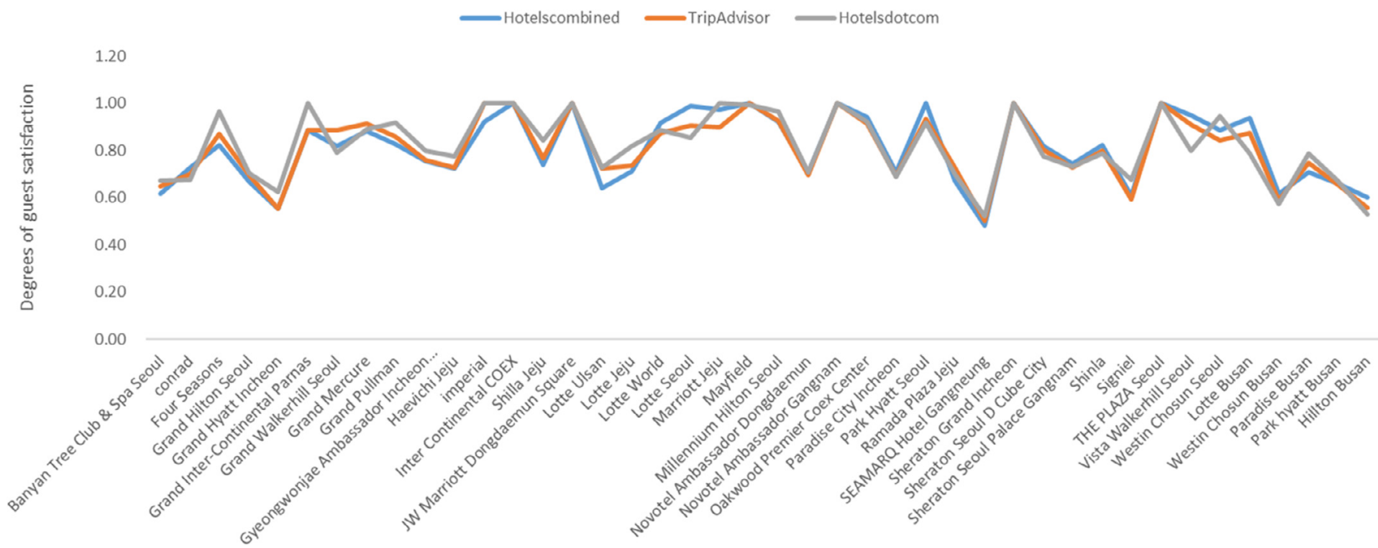

Fig. 5. Degrees of guest satisfaction for different tourism websites.

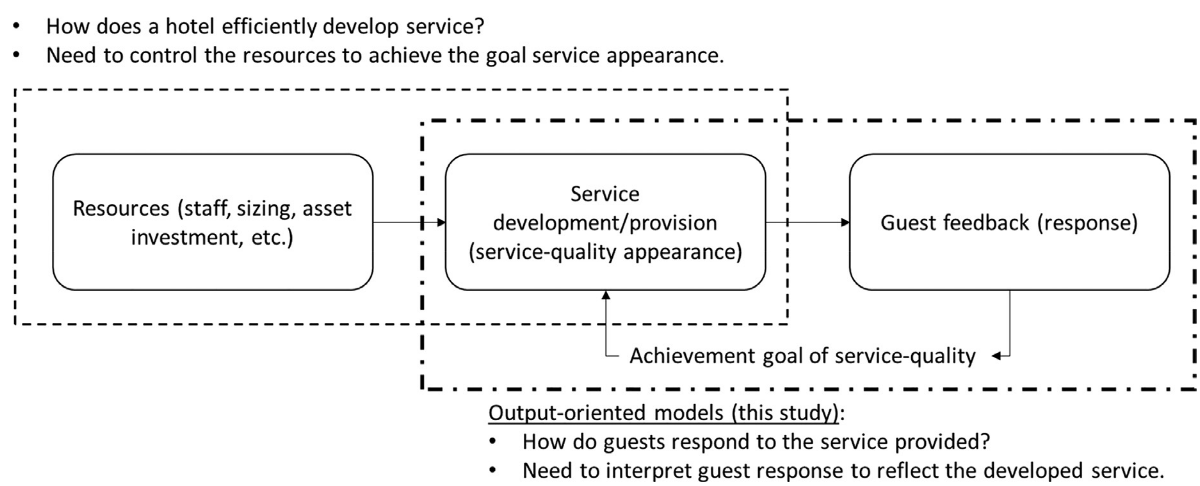

Fig. 6. Setting achievement goals of service-quality from DEA results.

6. Discussions on achievement goals of service quality

This section discusses how a hotel can set the achievement goals of service quality. The achievement goal can be represented as the amount of positive guest feedback to be further achieved (or collected) by transforming non-positive feedback into positive feedback. The achievement goals are comprehensively estimated from the benchmarking analysis results (i.e., improvement requirement) or quality association results (i.e., local OR estimates) demonstrated in Subsections 4.2–4.3.

Guest feedback is critical for hotels to reflect the services provided to their customers (guests). Fig. 6 illustrates the use of the output-oriented modeling approach of this study, where the multiple outputs of a DMU represent the multi-criteria feature of DEA when evaluating degrees of guest satisfaction in favor of benchmarking scores. The modeling approach takes into account a number of service attributes to evaluate the service quality (i.e., degree of guest satisfaction) and provide guidance for revising the goal for service development, as shown in Fig. 6, from the perspective of multi-criteria decision-making. Once the degrees of guest satisfaction for all DMUs are estimated, the discrimination power in the set of degrees of guest satisfaction is important because it helps managers to make decisions efficiently under the settings of multiple dimensions. The well-chosen service attributes had a positive effect on increasing the discrimination power (as discussed in Section 5), as each of the service attributes was responsible for each dimension in the dataset. As a classical DEA model requires well-prepared data for inputs and outputs for each DMU, the data analytical approaches of Subsections 3.1–3.3 were used to investigate and analyze guest feedbacks to prepare outputs for the proposed model. The proposed output-oriented model could have implications for the achievement goals of service quality for intangible service appearance so that hotel managers might control resources to improve their service quality to reach the goal. Note that, through the proposed series of analysis (i.e., Subsections 3.1–3.5), this study contributes to extant efficiency research that has embedded online reviews in DEA modeling, thus extending the study of Mariani and Visani [52].

The achievement goals for service quality were recommended to prioritize the improvement of the magnitudes of positive opinions in accordance with the improvement requirement scores. According to the improvement requirements (Table 7), it was recommended that Hotel 29 should aim to achieve service quality to gain more than 47.3% (facilities), 38% (lodging charges), 35.7%

(meals), and 43.5% (guest service) positive feedback from their current 75.9% (facilities), 62.1% (lodging charges), 66.1% (meals), and 69.2% (guest service) non-positive opinions. Hence, the hotel should give the highest priority among their quality achievement goals to facilities; subsequent priorities should be guest service, lodging charges, and meals, in that order, to achieve the highest benchmarking score (i.e., the greatest degree of guest satisfaction). From the perspective of quality association, the likelihoods of having positive opinions instead of non-positive opinions for Hotel 29 were estimated to be 0.26 (facilities), 0.51 (lodging charges), 0.47 (meals), and 0.36 (guest service) times those of the benchmark, correspondingly. The estimation results show that the key service attributes are strongly and negatively associated, and hence, Hotel 29 needs to prioritize the service improvement in the order of facilities, guest service, meals, and lodging charges to reach the service standards of the benchmark (i.e., Hotel 35), resulting in the same magnitudes of positive guest feedbacks. The two types of priorities on the key service attributes are dependent on setting an achievement goal of service quality, either on benchmarking or on service standard.

When Hotel 29 aims to improve its service standard to match that of its benchmark, the cross-evaluation in local ORs (Table 8) provides a set of trade-offs for achieving the goal of service quality. The likelihoods of having positive opinions of facilities instead of guest service, meals, and lodging charges were estimated to be 1.30, 0.45, and 0.84 times those for the benchmark, correspondingly. The likelihoods of having positive opinions of guest service instead of meals and lodging charges were estimated to be 0.34 and 0.64 times those of the benchmark. The likelihood of having positive opinions of meals instead of lodging charges was estimated to be 1.87 times that of the benchmark. This means that the service quality achievement goal on facilities would be expected to induce 0.77 (1/1.30) times that its goal for the improvement effect of guest service on acquiring positive feedback in a relative manner. However, the achievement goal of improving facilities would induce 2.24 (1/0.45) times for meals and 1.19 (1/0.84) times for lodging charges. When improving the achievement goal of service-quality on guest service subsequently, the improvement effect of guest service would induce 2.90 (1/0.34) times for meals and 1.55 (1/0.64) times for lodging charges. In addition, the goal of improving meals would induce 0.53 (1/1.87) times for lodging charges. The estimated set of trade-offs is considerable when designing the achievement goals of service quality to meet the service standard as much as the benchmark.

Regarding the case of multiple benchmarks (i.e., Hotels 13 and 30) for an underperforming hotel (Hotel 27), Hotel 27 needs to establish the achievement goals of service-quality to gain at least 7.8% (facilities), 14.8% (lodging charges), 5.8% (meals), and 9.2% (guest service) positive opinions from its current 45.3% (facilities), 53.5% (lodging charges), 53.5% (meals), and 50.5% (guest service) non-positive opinions. The service improvement priorities should go to lodging charges, guest service, facilities, and meals, in that order, to achieve best-practice guest satisfaction. When looking into the quality association with a benchmark (i.e., Hotel 13), the likelihoods of having positive opinions instead of non-positive for Hotel 27 were estimated to be 0.87 (facilities), 0.79 (lodging charges), 1.11 (meals), and 0.89 (guest service) times those for the benchmark, correspondingly. Hence, achievement goals should prioritize lodging charges, facilities, guest service, and meals, in that order. However, the quality association with the other benchmark (i.e., Hotel 30) explains that the likelihoods of having positive opinions instead of non-positive were estimated to be 1.01 (facilities), 0.92 (lodging charges), 0.77 (meals), and 0.94 (guest service) times those for Hotel 30. The induced service improvement priorities should follow the order of meals, lodging charges, guest service, and facilities. It was found that the achievement goals of service quality could be different for the two benchmarks equally appointed by Hotel 27 if the hotel managers want to improve the service quality up to the service standards of the benchmarks. Therefore, the improvement priorities for key service attributes are not only determined by the purposes of achievement goals (i.e., benchmarking or service standard) but also by a designated benchmark (i.e., Hotel 13 or 30). The set of trade-offs hints that the achievement goals of service quality can be developed by referring to a designated benchmark when the underperforming hotel aims to improve the service standard as much as the benchmark.

7. Conclusions

This study proposed a decision-support framework to evaluate the degrees of guest satisfaction and provide benchmarking strategies for hotels stemming from online reviews. The framework consists of four data analytical components: (i) data preprocessing (i.e., data cleaning and TF-IDF analysis) discovers the key service attributes from online reviews; (ii) sentiment analysis estimates the polarity of opinions at each key service attribute per hotel after constructing clusters of reviews corresponding to the key service attributes, and represents polarity decisions as magnitudes of positive opinions; (iii) the benchmarking analysis applies an output-oriented non-discretionary DEA model, where the outputs of a DMU (i.e., a hotel) are the estimated magnitudes of positive opinions, to evaluate degrees of guest satisfaction (i.e., benchmarking scores) for hotels, and (iv) the quality association across key service attributes between underperforming hotels and their benchmarks is estimated based on the results (i.e., benchmarking scores, improvement requirement, benchmarks) of benchmarking analysis.

According to the experimental results, the framework determined the relative positioning of hotels in favor of evaluated degrees of guest satisfaction (i.e., benchmarking scores), bounded between 0 and 1, where service quality is represented by positive feedback on discovered key service attributes (i.e., facilities, locations, lodging charges, meals, and guest service) from clustered reviews of 52 five-star hotels in Korea, available from TripAdvisor.com. The framework also found the necessary amount of increasing positive guest feedback (or decreasing non-positive guest feedback) on each key service attribute, referred to as the achievement goals of service quality. The achievement goals and their tradeoffs on the key service attributes were determined by estimating the amount of positive guest feedback to be further achieved toward improvement of guest satisfaction.

This study proposed a clear process of identifying outputs (service attributes) of DMUs for DEA modeling via sentiment analysis of online reviews, statistically represented the outputs to the odds ratios without violating the modeling convexity, identified the positioning of hotels in terms of guest feedbacks, and derived the achievement goal of service quality in the service attributes, where researchers have partially paid attention to each of them in the hotel service sector (Subsections 2.1–2.3).

The experiment also showed the effects of discovering key service attributes on evaluating degrees of guest satisfaction compared with using the predetermined service attributes of the tourism website. The correlation coefficient of the two results of degrees of guest satisfaction was moderately high (i.e., 0.796) owing to the similar composite of service attributes, whereas the extracted key service attributes resulted in evenly distributed discrimination power. The rating scores of the website had little contribution in discriminating guest satisfaction, whereas the results of the framework applying the predetermined service attributes provided great discrimination power. It was also found that the evaluated guest satisfaction had little discrepancy over different tourism websites.

Guest satisfaction could be understood in various ways if the framework adopts novel ways of recognizing reviews, such as device types used for submitting reviews [47], types of languages representing the culture and nationality of guests [46,49–51], and statistical skewness of reviews for hotel classes [48]. It is also noted that the machine-translated languages might lead to a different estimate of guest satisfaction, compared to pure languages. The proposed framework would be improved with a sophisticated multi-stage DEA model allowing inputs (i.e., employees, operating cost, etc.) and outputs (i.e., revenue, profit, etc.) to explain a series of effects of inputs, intermediates, and outputs on guest satisfaction. A dynamic approach is recommended to evaluate the progressive improvement of guest satisfaction over time. Other multi-criteria decision-making techniques would be able to provide different views for benchmarking.

CRediT authorship contribution statement

Jaehun Park: Conceptualization, Methodology, Software, Investigation, Formal analysis. **Byung Kwon Lee:** Conceptualization, Methodology, Investigation, Formal analysis, Writing - original draft, Writing - review & editing.

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Appendix. Distributions of TF-IDF scores

Figs. 7 and 8.

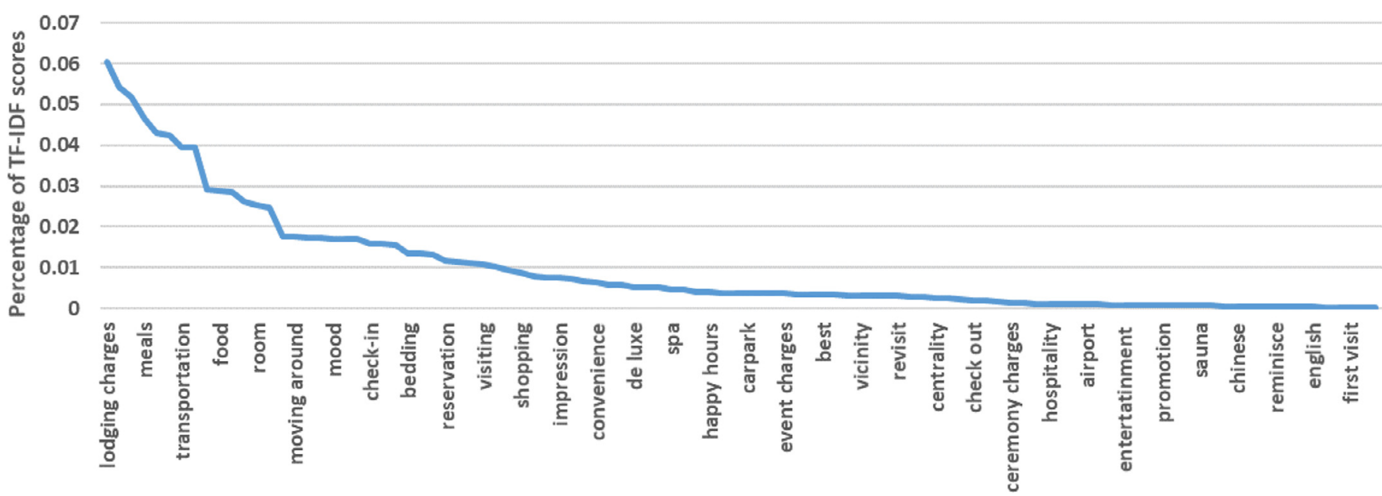

Fig. 7. Percentages of TF-IDF scores for the 104 words discovered for the candidates.

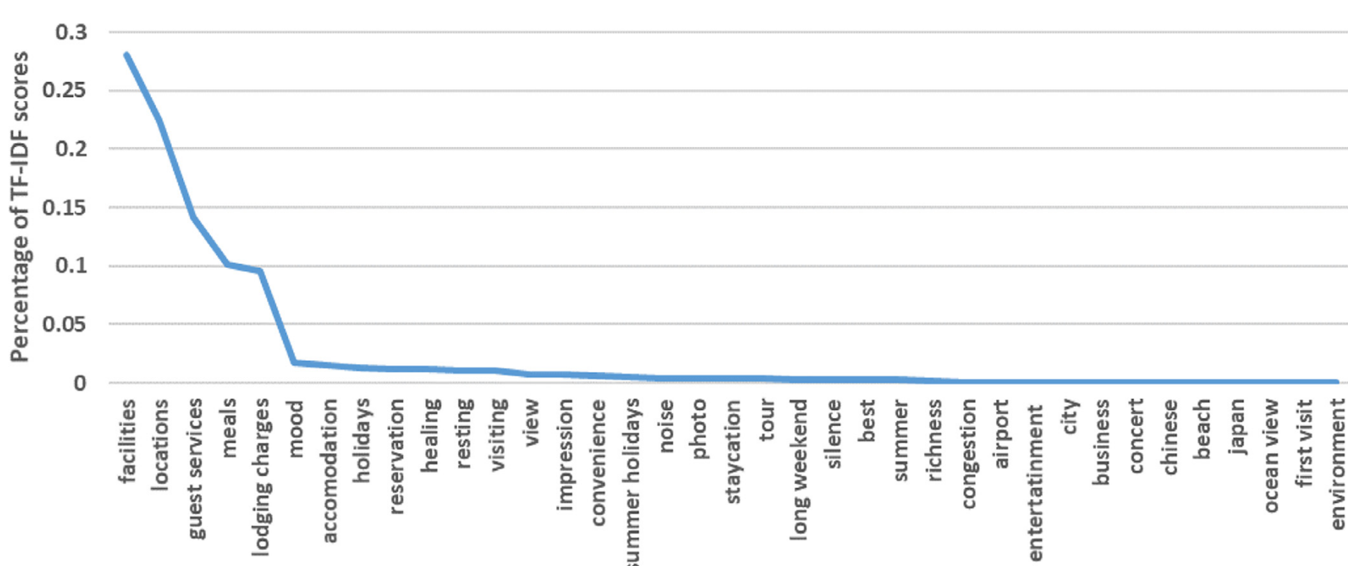

Fig. 8. Percentages of TF-IDF scores after grouping candidates.

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