Developing and testing a DEA-based index for the evaluation of value for money in the hospitality industry

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Abstract

Purpose - This paper achieves three purposes: 1) develops a brand-new index of value for money leveraging Data Envelopment Analysis (DEA) methodology: the "DEA VFM"; 2) validates the "DEA VFM" index; 3) compares the "DEA VFM" with the Booking.com value for money index, thus demonstrating the superiority of the proposed index for managerial decision making.

Design/methodology/approach - PIM-DEA software was used to develop an input-oriented DEA model with one input (i.e., the median price) and six outputs (i.e., the standardized scores of cleanliness, staff, location, facilities, free wi-fi, comfort) on 613 Italian hotels. Both input and outputs are based on Booking.com data related to hotels located in four different popular destinations: Rome, Florence, Milan, and Venice.

Findings - We developed and validated a new index of value for money based on DEA methodology: the "DEA VFM". The DEA VFM shows a very low correlation with Booking VFM scores, and it demonstrates a superior performance when assessing hotels' value for money. Booking VFM essentially measures perceived value rather than the relationship between price and value.

Research Implications - From a theoretical perspective, the paper i) builds an innovative bridge between pricing and efficiency research in hospitality; ii) contributes to hedonic pricing literature by offering a real indicator of the price-value relationship; iii) extends DEA use in hospitality by applying it to VFM evaluation; iv) adds to the emerging stream using DEA to analyze pricing policies. From a managerial perspective: i) online hotel reservation platforms could integrate the DEA VFM indicator to offer a more reliable VFM measure; ii) hotel managers can use the DEA VFM indicator to benchmark performance against competitors and identify improvement areas; iii) customers can use the DEA VFM indicator to make more informed decisions.

Originality - This is the only and first study in the hospitality management literature that develops and validates a new index of value for money (VFM) based on the DEA methodology: the "DEA VFM". Moreover, we demonstrate the superiority of the DEA VFM index on the Booking.com VFM.

Keywords: value for money; hospitality; indicator; DEA; prices.

1. Introduction

Today prospective hotel customers searching for hotels' information to make a reservation, increasingly deploy online reviews, as clear from both industry research (Statista, 2022) and academic research (Wen et al., 2021). After looking at overall online scores, prospective customers often also focus on different hotel service attributes such as location, staff, service, cleanliness, comfort, value for money. In particular, Value for Money (VFM) is a circumlocution frequently used in the hospitality industry, but very little industry and academic research has been carried out on the relevance of the VFM attribute provided by leading online reservation platforms such as Booking.com. In detail, the VFM score displayed by Booking.com (from now on Booking VFM) is the outcome of how previous hotel guests have assessed their perception of the value they received in exchange for the price they paid.

However, the Booking VFM score exhibits two significant limitations: i) it is determined by the subjective budget, expectations, experiences and evaluative approach of previous guests; ii) it is based on reviews written in the past, when prices were likely different, and does not take into account price changes which can be very significant over time. To summarize, Booking VFM index is prone to subjectivity but also narrowly focused on past prices. This is a major drawback of the Booking VFM as it is not capable to support in a meaningful way the pricing activity of hotel managers. To bridge this methodological, theoretical and research gap, our paper sets to address the ensuing research question: is there an objective and accurate index of VFM informed by the most updated hotel prices that can support the pricing decisions of hotel managers?

In this study we address this question by noting that such an index does not exist, and we go further: we develop a VFM index that is less subjective than most indexes deployed by major hotel booking platforms and that accurately reflects the median price at the time of the booking and not at the time when the VFM score is actually read by online review consumers. To address the aforesaid research question, we leverage Data Envelopment Analysis (DEA) to develop an objective and theoretically robust VFM index that we call "DEA VFM". We later compare the DEA VFM with the Booking VFM and demonstrate the superiority of our index. We do so by calculating the value of the two indexes for 613 hotels located in four leading Italian tourism destinations (ISTAT, 2023): Florence (141 hotels), Milan (145), Rome (157) and Venice (170). In so doing, we contribute to extant hospitality management literature in two relevant ways by: 1) developing a new index of value for money: the DEA VFM; 2) validating the DEA VFM index; 3) comparing the DEA VFM with the Booking VFM and thus demonstrating the superiority of our index for managerial decision making.

The remaining part of the paper is organized as follows. In the second section, we review different bodies of literature: electronic word of mouth and pricing, DEA modelling. In the third section, we illustrate our data and methodology. The ensuing section elucidates the findings. In section 5 we develop a discussion and conclusion, whereby we discuss the major theoretical and methodological contributions of this work, and we discuss research limitations and an agenda for further research.

2.Background literature

2.1 Electronic Word of Mouth and pricing in the hospitality management literature

The growing proliferation of digital platforms has engendered the generation of an increasing volume of digital data in the guise of user-generated content (UGC) that is nothing but content produced by online users rather than advertising companies and that is diffused on the Web (Malthouse et al., 2016). UGC represents a relevant information source for consumers in environments characterized by abundant data (Acikgoz et al., 2024), which might consist of online reviews (ORs) and social media posts. The former helps actual, potential and past consumers share their opinions on services and experiences online. Within the scholarly marketing domain, those are named Electronic Word-Of-Mouth (E-WOM) and have been increasingly examined in the literature. E-WOM is more effective, and dominant compared to offline word-of-mouth thanks to a number of characteristics that have been described by Sun et al. (2006) when they emphasized its velocity, suitability, absence of de visu interaction, one-to-many as well as many-to-many reach, and potential anonymity.

E-WOM scholars have explored deeply both the drivers and outcomes of E-WOM. As far as the outcomes are concerned, scholars found that E-WOM can influence consumer behaviors and decisions as well as firm performance (Babić Rosario et al., 2016). Also in the hospitality management field, significant research has been focusing on E-WOM (Cantallops and Salvi, 2014). More specifically, scholars have investigated how E-WOM influences consumer behavior and intentions (Zhao et al., 2015) and how E-WOM influences hotel performance in the guise of RevPAR and ADR (Yang et al., 2018). Most hospitality management scholars have focused on online reviews as the reference form of E-WOM (Kwok et al., 2017), examining how online review valence, variance and quantity/volume can influence hotel performance (Yang et al., 2018).

In the hospitality management body of research, hotels whose OR embed higher scores have been found to engender higher sales and revenues (Mariani and Borghi, 2020), enlarge market shares (Dursun-Cengizci and Caber, 2025) and ultimately improve profitability (Nieto et al., 2014).

A specific stream of research has focused on understanding the relationships between E-WOM and pricing. These studies specifically fall into the large category of hedonic pricing, where the product/service is seen as a set of attributes capable of driving purchasing behaviors and, specifically, the price the consumer is keen on paying. This approach to pricing, developed already in the 1970s by marketing scholars (Lancaster, 1966), has been extensively applied also in the hospitality management domain (e.g. Juaneda et al., 2011).

Given the relevance of E-WOM in influencing hotel customers' purchasing decisions, it has become the subject of analyses assessing its impact on hotel pricing. For example, Zhang et al. (2011) applied the concept of hedonic pricing to investigate how reviews on TripAdvisor helped explain the pricing of 243 New York hotels, highlighting the significant role played by travelers' reviews on room and location features on hotel pricing. The study by Abrate and Viglia (2016) shows that increasing the level of online reviews represents a more direct tool for increasing pricing than entering a complex and costly process of improving the star rating. However, despite the increasing development of E-WOM in the hotel sector and its demonstrated impact on influencing the sale price, the phenomenon remains under-studied (Hu and Yang, 2020).

Specifically, concerning the goal of this paper, there is a lack of development of an indicator that highlights the value of the sale price about the qualitative characteristics presented by online reviews. Indeed, "customers evaluate alternatives based on ... the trade-off between perceived benefits (partly implied by reviews) and costs (partly represented by price information)" (Zaman et al., 2025; Carvalho and Alves, 2023; Hu and Yang, 2020, p. 1), but no academic study has developed an indicator that can represent this relationship between value and pricing. This concept is what Booking.com labels as "value for money" (Booking VFM): "an assessment of what guests think your property is worth in relation to its price... A property with high prices but service that doesn't meet guests' expectations will likely earn a low VFM, and vice versa.". As explained by Andersson 2010 (p. 237), even if included in the list of attributes by Booking.com, VFM "is not a hotel attribute" as it is not a resource with an implicit price but rather a measure of consumer surplus.

The VFM score in Booking.com is provided by the guests when reviewing the hotel, but it has two significant theoretical limitations: i) it is determined by the subjective budget, expectations, experiences and scoring approach of each guest; ii) it is based on reviews made in the past concerning a different price and therefore does not consider price changes which can be very significant over time. In sum, the index is subjective and focused on past pricing policies, while to support hotel managers in day-to-day price setting, an index should be developed to be as objective as possible and focused on the actual prices, because this matters for potential guests when choosing accommodation services.

This study aims to develop an objective and theoretically robust VFM indicator that we call DEA VFM, and to compare it with Booking VFM.

2.2 A DEA-based index measuring "value for money" in the hospitality industry

In the hospitality field, the relationship between price and E-WOM can be represented as an input-output relationship. When evaluating accommodation options, customers are cognizant of the necessity to pay a price for the hotel stay (input) to obtain multiple value attributes assessed by the E-WOM (the outputs). Input/output analyses have traditionally focused on measuring efficiency in terms of productivity in different industries, ranging from banking (Quaranta et al., 2018), to food and beverage and tourism (Tzeremes and Tzeremes, 2021). Despite that, any process that entails a transformation can be examined from an input-output standpoint, thus in terms of efficiency (Nurmatov et al., 2021).

As for the specific measuring approach, if the relationship is defined by a single/main output and a single/main input, a ratio between them is sufficient to measure the efficiency of the relationship. It is not the case with hotel prices, where a single input (the price) is exchanged with a bundle of outputs (location, staff courtesy, cleanliness, etc..).

Another way to measure input-output relationships is based on frontier analysis (Nurmatov et al., 2021). Among several approaches to develop efficiency frontiers, Data Envelopment Analysis (DEA) consists of non-parametric models whereby efficiency is measured considering the weighted sum of inputs and outputs (Banker et al., 1984). Its purpose is to single out a frontier of efficient Decision-Making Units (DMUs) that "envelopes" the other units. Thanks to its technical features (Nurmatov et al., 2021), DEA is the most deployed technique to assess efficiency in general (Emrouznejad and Yang, 2018) and in hospitality and tourism management (Assaf and Josiassen, 2016). Despite this extensive use in the hospitality and tourism domains, the main focus was placed on organizational efficiency by comparing different kinds of inputs (mainly employees, rooms available and total assets) to several kinds of outputs (mainly revenues and guests) (Guizzardi et al., 2017). More recently, measures related to customer satisfaction (Chen et al., 2018) and electronic word-of-mouth (Mariani and Visani, 2019) have been introduced in DEA-based efficiency models, to consider not only the financial outputs but also the reputational outcomes of the activity.

That said, there is a call for broadening the scope of the DEA applications to the tourism and hospitality industries (Nurmatov et al., 2021), leveraging on the ability of the DEA to handle assessment problems characterized by multiple-criteria that vary by DMUs (Cook et al., 2014). Furthermore, DEA has already been applied in different contexts to gauge the relationship between price and value. For instance, Wang et al. (2016) developed a DEA-based approach to pricing named Competitive Pricing DEA, remaining at a conceptual level. More recently, Visani and Boccali (2020) developed a DEA-based Purchasing Price Assessment framework (PPA-DEA) to support the buyers in evaluating the purchasing price of leverage items in BtoB relationships.

Based on these considerations, the objective of this paper is threefold. First, it develops a DEA-based index VFM in the hotel industry. Secondly, it evaluates the ability of the proposed index to gauge the underlying variable properly. Thirdly, it compares the effectiveness of the proposed index and the measure “value for money” available on Booking.com.

3. Methodology

3.1 Measuring value for money: a CCR DEA-based model

In this work, the DEA-based model has been developed according to the model proposed by Charnes et al. (1978). The model can be presented as follows. Imagine that there are n DMUs, and that each DMU j (j = 1,...,n) uses m Inputs x_{ij} (i = 1,...,m) to generate s Outputs y_{rj} (r = 1,...,s), with non-negative values of both inputs and outputs. We can now focus on the input and output multipliers, $\bar{v}_i$ and $\bar{u}_r$ respectively.

When these are known, the efficiency score $\bar{e}_j$ of DMU_j can be depicted as the ratio between the weighted outputs and the weighted inputs:

$$\sum_r \bar{u}_r y_{rj} \,/ \sum_i \bar{v}_i \, x_{ij} \tag{1}$$

In situations involving unknown multipliers, Charnes et al. (1978) recommended addressing the issue by solving a specific fractional programming problem:

$$\begin{aligned} e_0 = max \sum_r u_r y_{r0} \,/ \sum_i v_i x_{i0} \\ s.t. \quad \sum_r u_r y_{rj} - \sum_i v_i x_{ij} \leq 0, \quad \forall j \\ u_r, v_i \geq \varepsilon, \quad \forall\, r, i \end{aligned} \tag{2}$$

Through some algebraic transformations and by using duality theory, the model can be reformulated in an equivalent way as the following ordinary linear programming problem:

$$e_0 = max \sum_r \mu_r \, y_{r0}$$

$$s.t. \quad \sum_i v_i x_{i0} = 1$$

$$s.t. \quad \sum_r u_r y_{rj} - \sum_i v_i x_{ij} \leq 0, \quad \forall j$$
$$u_r, v_i \geq \varepsilon, \quad \forall r, i \tag{3}$$

in which μ_r and v_i are the decision variables and the upper bound of DMU efficiency is set to 1.

In this work, a DMU j consists of hotel j to which a customer pays a price to get a set of services with varying values and e_j is the Value for Money perceived by the customer obtained through a DEA-based approach (DEA VFM).

Indeed, when choosing accommodation, customers are aware that they have to pay a price for the hotel stay to obtain multiple value attributes measured by the E-WOM. Accordingly, the DEA model put forward considers the paid price as the sole input (m=1), and customer-perceived value across 6 different service attributes as outputs (s=6). Following their stay, on Booking.com guests are requested to rate on a scale from 1 to 10 the hotel based on specific value attributes, including the service provided by the staff, cleanliness, location, comfort, facilities, wi-fi presence/quality. The average scores for each attribute stem from the valuations of many real customers and are publicly available for every hotel. The same scores have been used by previous research to proxy E-WOM in the hotel industry (Mariani and Visani, 2019).

As regards the choice of the return to scale, there is no evidence of the specific dynamic of a relationship between price and E-WOM. Given the diminishing marginal value of price increases, if all hotels of a city were grouped into a single cluster for the DEA calculation, it would be appropriate to consider variable returns to scale. But the hotels in each city are organised into four distinct clusters, with limited price variation within each one. Consequently, there is no basis for assuming that returns to scale are variable, and consistently with previous research in the field (Abrate and Viglia, 2016) we applied a constant return to scale. As for the orientation of the DEA model, given our focus on the price dimension, the models presented are input-oriented.

3.2 Data collection and analysis

The most suitable destinations for our intended analysis are those in high demand and for which spatial competition is more intense. Additionally, in line with Gallego and Van Ryzin (1994) we analyze both business and leisure travel destinations, as business and leisure customers have somewhat different needs about hotel attributes. Furthermore, as noted by Guizzardi et al. (2017), spatial competition is limited to a spatial radius. Thus, a confined area/district has been selected on Booking.com.

More specifically, four leading Italian destinations were considered due to their capability to attract tourism demand: Florence, Milan, Venice and Rome (ISTAT, 2023). More specifically, we focused on the city center for Florence and Milan and the central station neighborhoods for Venice and Rome; this allowed us to capture spatial competition that happens within a few kilometers (e.g., Guizzardi et al., 2017).

To calculate a DEA score reflecting the VFM of each hotel, it was necessary to gather from Booking.com the online review scores for the service attributes and information about pricing. Subsequently, the output scores were standardized and normalized to a range between 0 and 1. This was done to mitigate issues stemming from the relatively uniform distribution of these scores, consequently enhancing the sensitivity of the DEA scoring to variations of the output levels.

To avoid price distortion and following the literature on dynamic pricing (Abrate et al., 2019), we gathered prices by analyzing rates on both workweek and weekend days over consecutive weeks in May and June 2023. In addition, to standardize the data collection, we selected the best offered price for a double room one-night booking for two individuals, excluding hotels with less than 100 reviews, consistent with prior literature (Schuckert et al., 2015). In further detail, we monitored the pricing strategy multiple times leading up to 6 different booking dates. We gathered data for each by simulating the booking process with lead times of 60, 45, 30, 20, 10, 5, 3 and 1 days in advance, resulting in 48 data gatherings for each hotel (6 booking dates multiplied by 8 lead times). The price was recorded multiple times due to its high variability. In contrast, the scores related to value attributes were collected only once when the data collection process started, as they represent averages derived from hundreds or thousands of reviews and are reset only every three years. After confirming that these values remained entirely stable across different data collection points, we decided to retain only the initially recorded values.

Following this, to compare homogeneous DMUs, we caried out a hierarchical clustering based on the median price of the hotels for each location. This approach allowed us to assign hotels with similar customer expectations to the same cluster, thereby aligning with the concept of internal reference price (Mazumdar et al., 2005). When assessing value for money, indeed, it might not be appropriate to rely on the common star rating system (2-3 star versus 4–5-star hotels). This is because the price variability within each class is significantly high, whereas the variation range in value attributes is more limited.

The clustering method indicated an optimal number of clusters between 4 and 5 for Florence, Milan, and Venice, and between 3 and 4 for Rome. These findings were then fine-tuned based on judgmental screening to expand the numerosity of hotels included in the evaluation while simultaneously narrowing the price range within each cluster.

Four distinctively different clusters were singled out for each of the four areas, and they were labelled: A, B, C and D. The descriptive statistics by location and cluster are illustrated in Table I.

[Insert Table I here]

Table I – Descriptive statistics by location and cluster: price range, number of hotels and reviews (Source: Developed by authors)

As shown in Table I, clusters C and D exhibit a wider price range. This results from the inverse relationship between price sensitivity and absolute price.

Consistent with the framework outlined in section 3.1, we used version 3.2 of the PIM-DEA software to develop an input-oriented DEA model with one input (i.e., the median price) and six outputs (the standardized score of staff, cleanliness, location, facilities, free wi-fi, and comfort attributes). Additionally, to drop DMUs whose prices are "outliers", we crafted a super-efficiency approach (Banker and Gifford, 1988), and according to Banker and Chang (2006) we excluded all the DMUs with a score higher than 120/100 (7 DMUs in total).

4. Results

4.1 The scores of the DEA VFM obtained

Once we ran the DEA models, we analyzed DEA scores within each cluster. Table II reports, for each location and cluster: 1) the average price of the hotels, 2) the average value of the six value attributes, 3) the average value of Booking VFM, 4) the average DEA VFM, 5) and 6) the ratio between standard deviation and average value for both Booking VFM and DEA VFM, 7) the correlation between Booking VFM and the average score of the six value attributes, 8) the correlation between DEA VFM and Booking VFM, 9) the number of Fully Efficient Hotels (i.e. the hotels for which the VFM DEA is equal to 100).

Firstly, the relatively low number of fully efficient hotels reported in column 9 is a positive indicator of the model's reliability. As noted in the literature, an excessively high number of efficient DMUs may suggest potential issues in model specification, such as an insufficient number of units relative to the input and output variables (Cooper et al., 2011).

Upon examining columns 1 and 2, it becomes clear that as the price range of hotels increases (progressing from one cluster to the next), the average values of the value attributes also rise. This indicates that higher prices are typically linked to greater customer satisfaction. Furthermore, Booking VFM, as illustrated in column 3, shows a consistently upward trend alongside rising prices. However, this trend does not hold for DEA VFM, as indicated in column 4. The behaviour of DEA

VFM appears more credible than that of Booking VFM. In fact, it is relatively implausible that VFM would consistently increase with higher price ranges across all cities, as shown by Booking VFM. At least in some cases, we would expect price increases to be more than proportional to the perceived value gained, thereby resulting in a lower VFM.

The strong relationship between the dynamics of value attributes and Booking VFM is illustrated by the high correlation observed in column 7. The correlation values are exceptionally high for each cluster, ranging from 0.94 to 0.98. This suggests that Booking VFM communicates similar information to that provided by the value attributes. However, ideally, the two should offer distinct types of insights: value attributes should reflect the perceived quality of the service, irrespective of the paid price, while Booking VFM should link this perceived value to the actual price paid.

On the contrary, the average DEA VFM (column 4) varies across different locations and clusters, contingent upon the specific relationship between price and value attributes, and the correlation between DEA VFM and Booking VFM (column 8) ranges from 0.43 to 0.85, thus highlighting that the two measures represent different concepts.

[Insert Table II here]

Table II – VFM-related statistics by location and cluster (Source: Developed by authors)

Furthermore, the relative standard deviation (Standard Deviation/Average) of the DEA VFM (column 6) is always higher than that of the Booking VFM (column 5). This indicates that the DEA VFM is better at emphasising hotel differences.

4.2 DEA model validation and comparison with Booking.com Value for Money

The next step was to validate the capability of the DEA VFM to proxy the VFM of the hotels and to compare it in detail with the Booking VFM. Accordingly, we applied the classification proposed by Sargent (2013, p. 19) classification of operational validity to identify the most suitable validation approach to apply in the context of this study (see Figure 1).

[Insert Figure 1 here]

Figure 1 – Operational validity classification (Source: Sargent, 2013)

Initially, we considered the observable versus non-observable nature of the problem entity, as it determines the type of applicable approaches (refer to the two columns in Figure 1). Our case fits the "non-observable" category since operational data (i.e., the VFM of the hotels) is not accessible. Consequently, it is not feasible to compare the outcomes from the DEA-based approach with the “real” VFM of the hotels using statistical tests.

Furthermore, due to the availability of the Booking VFM a subjective approach has been developed to assess the consistency of the model's behavior, comparing the results provided by the DEA-based model and by Booking.com. In doing so, we are evaluating the effectiveness of the DEA VFM to proxy the VFM by assessing the consistency of the model's behavior with specific combinations of price and value attributes of the hotels.

In more detail, we tested the capability of the DEA-based measure to correctly represent the four situations summarized in Figure 2.

[Insert Figure 2 here]

Figure 2 – Different combinations of price and value attribute scores (Source: Developed by authors)

Indeed, to be considered a reliable proxy of value for money, an indicator must meet the following conditions:

- Case 1 - when the prices of two DMUs are equal (or very similar), the DEA score has to be higher for the DMU with higher (or very similar) value for all the attribute scores (1.b) and lower for the DMU with lower value for all the attribute scores (1.a).
- Case 2 - when a DMU (2.a) displays both lower price and attribute scores than a competitor (2.b), it's not possible to anticipate which hotel will display a higher Value for Money. It will depend on the relative distance of prices and value attributes and the specific weight assigned by the customers to each value attribute;
- Case 3 - in instances where a DMU is capable of generating superior value attributes at a lower price (3.a) in comparison to a competitor (3.b), the DEA-based indicator for the former should reflect a higher value;
- Case 4 - finally, for the same level of value attribute scores, the indicator for the DMU with a lower price (4.a) must be higher compared to the hotel with a higher price (4.b).

In the analysis we defined a threshold of ±5% to determine whether one price is higher or lower than another, and a threshold of ±3% to assess whether the value attribute score of one hotel is higher or lower than that of another. We used a lower threshold for the value attributes because their variation range is lower. In any case, we tested different thresholds, and the overall results of the analysis were not significantly affected.

To thoroughly analyse the situation, we carried out a pairwise analysis for each of the 16 clusters, comparing each hotel with all the others based on price, value attribute scores, DEA VFM and Booking VFM to verify whether DEA VFM and Booking VFM were able to provide results consistent with expectations in the different cases.

First of all, it is essential to recognize that many comparisons, specifically 5,298, cannot be classified according to Figure 2. This limitation arises from the multifaceted nature of customer value, which encompasses six distinct attributes: cleanliness, staff, location, facilities, free Wi-Fi, and comfort. A hotel may excel in some areas while underperforming in others, complicating the determination of which hotel provides superior overall performance (as illustrated in the columns of Figure 2). Relying solely on average values to draw conclusions is inappropriate, as each attribute carries varying levels of importance in assessing overall customer satisfaction. These significance levels can differ not only between hotels but also among individual customers, rendering both arithmetic and weighted averages unreliable. Therefore, the only cases that can be accurately assessed, according to Figure 2, are those in which one hotel consistently scores higher than or equal to another across all six attributes. Only in these circumstances can a hotel's performance be properly classified as superior, equal, or inferior to that of another.

Furthermore, even when a clear ranking of value attributes is established, the scenario depicted in case 2 (3,228 cases) does not allow for quantitative verification as previously described. Thus, only cases 1, 3, and 4 illustrated in Figure 2 can be verified (4,349 comparisons). In all those cases, for each cluster, we first verified whether the DEA VFM provided indications consistent with the expectations outlined in Figure 2. Subsequently, we conducted the same verification using the Booking DEA.

To understand the analysis performed, see Table 3, which provides an example of analysis for each of the three cases in which verification is possible.

[Insert Table III here]

Table III – Examples of the reliability of DEA VFM and Booking VFM in cases 1,3 and 4 (Source: Developed by authors)

In Case 1, the two hotels have essentially the same price, but hotel MMLB 22 consistently exhibits value attributes that are greater than or equal to those of hotel MMLB 17. This should result in a higher VFM for hotel MMLB 22. This expectation is clearly captured by the VFM DEA (100 vs. 87,9), but it is not reflected when using the Booking VFM (8,2 for both hotels).

In Case 3, the price of hotel RMHB 5 is higher than that of hotel RMHB 9, yet all value attribute scores are lower or equal. This should result in a higher VFM for hotel RMHB 9. In this case, both the VFM DEA (98.8 vs. 75.1) and the Booking VFM (8 vs. 7,2) accurately reflect the situation.

Finally, in Case 4, hotel VMHB 39 has a lower price than hotel VMHB 25 but higher overall service. In this scenario, it should have a higher VFM. Here too, both the VFM DEA (91.9 vs. 75.1) and the Booking VFM (8.1 vs. 7.1) provide reliable results.

We applied the same approach to all meaningful comparisons within each cluster of each city, and out of 4,349 pairwise comparisons the DEA VFM yielded results consistent with expectations in 3,964 cases (91%), while the Booking VFM did so in only 2,950 cases (68%). This highlights, on the one hand, the ability of DEA VFM to effectively capture the phenomenon under investigation, and on the other hand, its evident superiority over Booking VFM. Furthermore, in as many as 1,128 cases (26% of the total), only the DEA VFM provides conceptually consistent results, whereas it occurs only 114 times (3%) that exclusively the Booking VFM yields results consistent with expectations.

The results are also confirmed by an analysis by case type or cluster (see Table A in the supplementary materials for details of the pairwise analysis).

5. Discussions and conclusion

5.1 Conclusions

Based on the literature of hedonic pricing in the hospitality industry, this study introduces a DEA-based model to measure VFM in the hospitality industry and compares it with the VFM indicator provided by Booking.com. The model utilises DEA to compare hotel prices with the various dimensions of value perceived by customers (represented by online reviews). By doing so, the model can deploy the vast amount of available information regarding customer-perceived value and help understand its impact on the selling price (Zhang et al., 2011).

The low correlation of the results provided by DEA VFM and Booking VFM highlighted how the two approaches measure different concepts. The high correlation of Booking VFM with the average value attributes' scores given by customers indicates that it often measures perceived value rather than serving as an indicator of the relationship between price and value. Moreover, unlike DEA VFM, it exhibits limited variance, thereby reducing its ability to effectively discriminate between different hotels. This analysis thus provided an initial set of insights into the limitations of Booking VFM and the potential superiority of the new DEA-based indicator. These insights were subsequently confirmed and reinforced by the pairwise analysis conducted. According to Sargent's validation model (2013), our analysis demonstrates that the DEA VFM indicator is theoretically robust and can effectively represent the phenomenon under investigation. The pairwise analysis just conducted has demonstrated that, in cases where validation is possible, DEA VFM provides results consistent with expectations in 91% of cases. This result proves to be robust across different types of cases and hotel categories. In the same analysis, Booking VFM provided results consistent with expectations in only 68% of cases and was outperformed by DEA VFM in 26% of the cases, while the opposite situation happened in only 3% of the cases.

Booking VFM is based on historical prices seen and paid for by past customers, without any association with the continuous and fast dynamics of real prices. Furthermore, it is provided directly by the customers, thus being affected by their subjectivity, personal experience and perceived reference prices, without a real knowledge of the prices and services of the other hotels. In contrast, the proposed DEA-based model uses standardised and normalised data of all the hotels of the price range and geographical area to evaluate current price and service attributes, ensuring a more accurate and real-time value assessment. This methodological improvement aligns with previous research highlighting the importance of integrating various customer satisfaction metrics into performance evaluations (Assaf and Magnini, 2012; Mariani and Visani, 2019).

By providing a more consistent and objective measure, our approach helps to mitigate the limitations associated with subjective evaluations, offering a clearer picture of hotel performance in terms of price/value relationships.

5.2 Theoretical contributions

Our work contributes in several ways to extant literature. First, it extends pricing knowledge in the field of hospitality and tourism by building an innovative bridge between pricing research (for a recent literature review see Han and Bai, 2022) and efficiency research (e.g., Kumar et al., 2024). Secondly, it contributes to the body of literature on hedonic pricing, by putting forward a comparative evaluation framework and by providing a real indicator of the relationship between price and value perceived by the customers. In so doing, we innovatively shift the focus from an absolute to a relative measurement that enhances the applicability of hedonic pricing theories in the hospitality sector (Trabandt et al., 2024), thus offering a fresh lens through which pricing strategies can be assessed and optimized. By considering the competitive landscape, our framework proves to be more realistic in view of understanding how different attributes influence hotel pricing.

Third, this work makes an important methodological contribution to the DEA-based hospitality management literature. Indeed, by building on previous studies (Nurmatov et al., 2021), this research extends the use of DEA in hospitality management. More specifically, by applying the DEA methodology to the evaluation of the VFM, we demonstrate the technique's versatility and robustness in handling complex, multi-dimensional data. This application not only broadens the original scope of DEA but also provides a valuable methodological tool for future research in the field. Indeed, the incorporation of DEA allows for a more detailed and rigorous analysis of efficiency, facilitating the identification of best practices and areas for improvement within the competitive set of a focal hotel and potentially the industry.

Fourth, we contribute to the nascent research stream adopting DEA for analysing pricing policies. Indeed, so far only very few papers have been developed (e.g., Visani and Boccali, 2020). Extant studies focused on the manufacturing industries in B2B settings and ignored E-WOM in the underlying input/output relationships of the DEA model. In this study, we innovatively recognize the theoretical relevance of E-WOM as a critical element of DEA methodology techniques meant to improve our understanding of the pricing as well as the price/value for money relationship in the hospitality sector. This certainly represents a radical innovation compared to the mere reliance on E-WOM to assess the relative efficiency of hotels, regardless of prices as several studies (e.g., Mariani and Visani, 2019) pointed out. Accordingly, this study creates a brand new research stream for hospitality management studies.

5.3 Practical Implications

This study brings about several implications that can be leveraged by online hotel reservation platforms, hotel managers and hotel service providers.

Regarding online hotel reservation platforms, their managers could embed the DEA VFM indicator to improve and make the information provided to the users of online hotel reservation platforms more current. By providing a more accurate and reliable measure of VFM, platforms can enhance user experience and trust, potentially increasing customer satisfaction and loyalty. Given the increasing reliance on online reviews and E-WOM, this might be very relevant. More specifically, the information provided to users and hotel managers could include two different DEA VFM measures.

The first would be calculated using the average price values recorded on multiple dates and with different lead times, as done in the present research, allowing users to understand the long-term VFM of hotels. This information would be useful to understand hotels' average VFM, regardless of specific promotions and special prices and would be useful to managers to understand their competitive positions towards competitors.

The second, instead, would consider only the real-time price as input, providing users with an instant price-quality ratio, more useful to support their real-time booking decisions. In this case, the platform could also point out the price decrease that would allow the short-term VFM of the hotel to reach the best in classes in the same cluster.

A potential challenge may arise for hotels or other accommodation units situated outside urban areas where competitors are few and not easily identifiable. In such cases, a viable solution could involve the formation of clusters comprising hotels that offer similar services and customer experiences, even if geographically dispersed. Even more interestingly, a system could be developed that allows users to select a set of accommodations they consider comparable, regardless of location, with the ability to compute an "on-demand" DEA VFM, enabling more customized and meaningful comparisons.

One of the valuable aspects of the model is, in fact, its ease of implementation once the approach has been defined. DEA models are extremely well-known, and there are numerous free or very low-cost software options available for their development. In carrying out our analysis, most of the effort was related to data collection, while building the DEA models required only a few hours of work and could be fully automated within the platforms.

Regarding hotel managers, the latter can leverage the DEA VFM indicator to benchmark their performance against competitors in the same location and spatial context. This benchmarking capability allows managers to identify strengths and weaknesses, adjust pricing strategies, and improve service quality to enhance their competitive advantage. By utilizing our model, managers can better understand how their hotels compare to others regarding both price and perceived value, enabling more strategic planning and resource allocation. They could also develop semi-automatic systems able to re-align the price of the rooms while also considering the DEA VFM indicator.

Conversely, we do not consider an automatic realignment system to be appropriate, as there may be valid reasons for a hotel to maintain prices that are not justified by the level of value perceived by customers. Automatically setting a price aligned with competitors offering higher VFM could be suboptimal from a profitability standpoint.

Additionally, the DEA VFM indicator can assist hotel managers in identifying specific areas for improvement. For example, if a hotel's DEA score is lower than that of its competitors, managers can analyze the underlying attributes to determine where improvement is needed. This targeted approach to performance improvement can lead to use resources more effectively and efficiently, ultimately resulting in higher customer satisfaction and better financial outcomes. The ability to drill down into specific service attributes provides a granular view of performance, facilitating more precise and impactful management decisions and actions.

As far as customers are concerned, they can use the DEA VFM indicator to make more informed buying and booking decisions. By understanding the VFM of different hotels, customers can choose accommodation services that best meet their expectations and budget, leading to better overall satisfaction with their stay. This enhanced decision-making capability can help customers navigate the often-overwhelming amount of online information, thus simplifying their booking process.

Furthermore, the potential flexibility of the model could lead to additional value elements offered to the customer. When potential customers are not interested in a specific destination but rather in a general travel experience and aim to maximize value for money (VFM), they could simply indicate their vacation goal—for example, "art city," "city suitable for surfing," or "medieval village"—and, once trained, the system could automatically provide a list of hotels with the highest VFM for a given quality level, based on the DEA-VFM approach.

5.4 Limitations and Future Research

This work exhibits a few limitations. One notable constraint is its geographic focus on Italian cities with high levels of competition. Future research should validate the DEA VFM indicator in different destinations, including those with varying competitive dynamics, to assess its generalizability and robustness. Guizzardi et al. (2017) observed that spatial competition can differ significantly across locations; therefore, testing the model in diverse contexts is essential. Future studies could apply the same approach to different types of accommodations and hotels with similar offerings and services, even if they are not geographically proximate.

Additionally, in this study, a simple CCR DEA model was applied, as the primary focus was establishing a new approach for measuring VFM through DEA rather than identifying the specific DEA model best suited for this purpose. Moreover, the study did not aim to explore alternative models that might be more appropriate for different contexts. Future research could explore the application of other models, starting by considering the impact of different assumptions about the dynamics of return to scale.

Other models under the umbrella of Data Envelopment Analysis, such as Fuzzy DEA and Stochastic DEA, could be applied to consider subjectivity and errors in the outputs, thus further refining the measurement of VFM. Furthermore, window DEA or the Malmquist Index could be applied to understand the dynamics of VFM over time.

Moreover, expanding the study to include a wider range of hotel categories (e.g. luxury resorts) could generate valuable insights into how different market segments perceive and respond to value creation by hospitality providers.

Future studies might also be able to capture the strategic and tactical price decisions inherent in revenue management, by operationalizing in a more granular way the dynamic nature of prices over time. Indeed, while our model computes the VFM based on average prices over different advance booking periods, a more sophisticated model might calculate the VFM based on daily prices themselves. Future research should also consider the impact of external factors, such as economic conditions and seasonal variations, on the perceived value and pricing of hotels. By incorporating these variables into the analysis, researchers can develop a more holistic and accurate assessment of the VFM.

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