Innovative value-based price assessment in data-rich environments: Leveraging online review analytics through data envelopment analysis to empower managers and entrepreneurs

Technological Forecasting & Social Change 182 (2022) 121807

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Innovative value-based price assessment in data-rich environments: Leveraging online review analytics through Data Envelopment Analysis to empower managers and entrepreneurs

Filippo Boccali [a,*], Marcello M. Mariani [b,c,*], Franco Visani [a], Alexandra Mora-Cruz [d]

[a] Department of Management Studies, School of Economics, Management and Statistics, University of Bologna, p.le della Vittoria, 15, 47121 Forlì, FC, Italy
[b] Henley Business School, University of Reading, Greenlands, Henley on Thames, Oxfordshire RG9 3AU, United Kingdom
[c] University of Bologna, Italy
[d] Tecnológico de Costa Rica, Costa Rica

ARTICLE INFO

Keywords:
Price assessment
Online reviews analytics
Big data
Innovation
Electronic word of mouth (eWOM)
Data Envelopment Analysis

ABSTRACT

This work introduces, develops, and empirically applies an innovative approach aimed at assessing selling prices based on the value perceived by the customers, as measured by electronic word-of-mouth (eWOM) in the guise of online reviews. To achieve this aim, it applies a constant return to scale Data Envelopment Analysis (DEA) approach where the price is the input, and the value attributes are the outputs measured through eWOM in the form of online reviews. We empirically apply the model to the hotel sector by considering both the prices and the service attributes (i.e., staff, location, cleanliness, comfort, facilities and free wi-fi) of 364 hotels based in two leading Italian tourism destinations: Milan and Rome. Our findings suggest that online review analytics can be suitably embedded into analytical models to assess prices. The index developed innovatively supports value-based pricing by means of online review analytics and it is easy-to-perform, and parsimonious as it is based on widely available information on the Internet.

1. Introduction

Prices of goods and services have been found to play a key signaling role in multiple markets (Hayek, 1945). More specifically, product prices provide information to different stakeholders, including customers who can take prices as a proxy of the quality of a good or a service (Cao et al., 2000; Dutta et al., 2007; Erdem et al., 2008; Gerstner, 1985) and firms that can use prices for competitive purposes (Griffith and Rust, 1997; Yao and Liu, 2005). Setting the right price is both a science and an art, as witnessed by literature developed in the marketing, revenue management, and operations fields over time (Fishburn and Odlyzko, 1999; Griffith and Rust, 1997; Yao and Liu, 2005).

A significant amount of research has looked at how to set and/or maximize prices. In general, three approaches have been devised to set prices, based on the sources of information and the reference stakeholders considered: (a) cost-based, (b) competition-based and (c) value-based approaches. They respectively look at the cost of production, the practices of competitors, and the value of the product (Cardinaels et al., 2004). In many cases, these approaches have been examined and adopted in isolation and scholars have examined how managers use prices strategically and tactically (e.g., Hsieh et al., 2014; Myers, 1997; Mortensen and Wright, 2002; Zhang et al., 2019), also by means of revenue management techniques, and how customers use prices for their purchase decisions and perceive prices in terms of fairness (Haws and Bearden, 2006; Malc et al., 2016; Xia et al., 2004).

Even though several studies have highlighted the positive impact of value-based pricing practices on company's performance (e.g., Hinterhuber, 2004; Ingenbleek et al., 2013), the approach has been seldom applied, due to the complexity and the cost to collect information about customers' value perceptions (Soriano, 2002, 2003; Mariani and Borghi, 2022; Liozu et al., 2012).

However, over the last few decades, the way price and value information are collected and processed has been significantly modified by the advent and development of digital technologies and platforms (Mariani and Nambisan, 2021; Bresciani et al., 2021). Historically, before the consolidation of online booking platforms and e—commerce

* Corresponding author at: Henley Business School, University of Reading, Greenlands, Henley on Thames, Oxfordshire RG9 3AU, United Kingdom.
E-mail addresses: filippo.boccali2@unibo.it (F. Boccali), m.mariani@henley.ac.uk (M.M. Mariani), franco.visani2@unibo.it (F. Visani), almora@itcr.ac.cr (A. Mora-Cruz).

https://doi.org/10.1016/j.techfore.2022.121807
Received 9 February 2022; Received in revised form 5 June 2022; Accepted 7 June 2022
Available online 22 June 2022

websites, prices were compared by managers by speaking to competitors and/or friends in the same competitive set f-2-f or via phone (Kimes, 2010) and customers typically collected them by phone or leveraging offline chatter. Today everyone – both managers and customers – can collect prices and customers' value perception from the Internet in a very straightforward way (Yakubu and Kwong, 2021).

In this paper we argue that, as online reviews and especially online review ratings are a good proxy of the value/quality of a product/service (Erdem et al., 2008), they can be innovatively used to assess online prices in a value-based perspective. More specifically, we propose that the online reviews (and the related analytics) and price information made available by booking and e-commerce engines can help managers of competing firms to make sense of the pricing strategies/tactics developed by their competitors, thus supporting innovative approaches to value-based pricing. Therefore, by extending recent research on value-based price assessment (Visani and Boccali, 2020), this study aims to develop and apply an innovative index to assess prices based on the value perceived by the customers, as measured by the ratings of online reviews. Accordingly, we address the following research question: how can prices be assessed based on big data analytics pertaining to online reviews in data-rich environments? In this view, the interaction between customers and suppliers is framed as an input-output relationship where the price paid is the input and the ratings of the online reviews about several value attributes (staff, location, cleanliness, comfort, facilities and free wi-fi) are the outputs obtained by the customer. Accordingly, the new value-based price assessment index is developed by applying Data Envelopment Analysis (DEA) (Charnes et al., 1978), a well-known approach to assess the efficiency of input-output relationships. Finally, we test the model developed on 364 hotels of two leading Italian tourism destinations (Milan and Rome).

The innovative price assessment approach is able to support value-based pricing strategies and it is easy-to-perform and parsimonious, as it is based on widely available data and information on the Internet: online reviews and prices. This approach is generally very suitable for data rich environments such as online markets where big data in the form of online content and prices are available (Wedel and Kannan, 2016). Furthermore, it allows the managers to identify the competitors to compare with and to support the decision-management process with clear information about the value attributes to focus on.

The paper is structured as follows. Section 2 reviews the literature by portraying the theoretical background. Section 3 describes the data and methods deployed. The fourth section illustrates the results. In the fifth and last section we draw our conclusions and put forward the theoretical and methodological contributions of our work as well as the managerial implications, by identifying the limitations and avenues for future research.

2. Theoretical background

2.1. Pricing approaches

Setting prices of products and services is an essential managerial practice, as well as a critical organizational capability with a significant impact on firms' image, growth, and profitability (Dutta et al., 2003; Johansson et al., 2012). Despite the well-known idiosyncratic nature of pricing practices (Hinterhuber and Liozu, 2012; Smith, 1995), the literature has classified them into three main categories based on the reference set of information deployed to set prices: (a) cost-based, (b) competition-based and (c) value-based approach (Ingenbleek et al., 2003; Hinterhuber and Liozu, 2012; Nagle and Holden, 2002).

In a cost-based-pricing approach the selling price is obtained by applying the expected or requested mark-up to the allowable cost (i.e., the expected/actual cost of manufacturing the product or providing the service). This approach is aimed to keep the margins under control, but it can lead to pricing policies inconsistent with the value perceived by the customers or the market prices set by the competitors, thus reducing the market share of the company (Hanson, 1992).

On the other hand, competition-based and value-based pricing practices are more focused on the external environment than on the internal organization and costs (Kienzler and Kowalkowski, 2017). Competition-based pricing entails taking the prices set by the competitors for similar products and services as a reference, while value-based pricing involves embedding in the price the value perceived by the customer (Ingenbleek, 2014; Kienzler, 2018). These approaches are aimed to obtain prices that can be accepted, understood, and appreciated by the market, thus leading the company to set target costs (Ahn et al., 2018) able to generate profit at the given market price. The three approaches (i.e., cost-based, competition-based, and value-based pricing) can be obviously combined, in order to exploit the benefits and reduce the disadvantages of each model (Ingenbleek et al., 2003).

Even if several scholars and practitioners have highlighted the potential of value-based pricing practices to increase the profitability of the company (e.g., Hinterhuber, 2004; Monroe, 2003; Nagle and Holden, 2002) and more generally to improve firm's performance (e.g., Ingenbleek et al., 2013; Liozu and Hinterhuber, 2013), most companies still rely primarily or exclusively on cost-based or competition-based pricing (Hinterhuber, 2008; Indounas, 2009; Kurz and Többens, 2012; Liozu, 2017).

The main reasons of this paradox identified and analyzed by previous research in this field (Liozu et al., 2012) deal with organizational problems related to the design of the pricing processes (e.g., Nagle and Holden, 2002), the commitment of top management and the involvement of salespeople (e.g., Forbis and Mehta, 1981; Nagle and Holden, 2002).

In order to move to an effective value-based pricing approach, all the firm's functions and departments - including R&D, Sales, Operations and Marketing - need to address their attention from the product/service, its technical issues and cost, to the customers, their needs, their preferences, their wants, and more generally their value perceptions (Hinterhuber, 2004).

To capture customers' value perceptions, it is critical to access information on the value perceived by the customers (e.g., Guizzardi et al., 2022; Mariani and Borghi, 2022; Töytäri et al., 2015). While information pertaining to costs is part of internal data widely available to the company and information related to competitors' prices can be obtained quite easily (especially in B2C markets), value-based pricing requires a deep knowledge of the actual and potential value perceived by the customer that is very complex to obtain and process (Guizzardi et al., 2022; Töytäri and Rajala, 2015; Ingenbleek, 2014; Nagle and Holden, 2002). Therefore, to develop an effective and widely applicable value-based pricing approach it is essential to collect and access data about the value perceived by the customers. Furthermore, the information provided by the system should be easy-to-read and easy-to use, to simplify the whole process (Hallberg, 2018), thus increasing the “pricing capabilities” of the company (Dutta et al., 2003; Liozu, 2015).

2.2. Electronic word of mouth, big data, and online review analytics for decision making

The growth and expansion of the Internet, social media and digital platforms have sparked a spread of large volumes of data in the form of user generated content (UGC) defined as “media content created or produced by the general public, rather than paid professionals and primarily distributed on the Internet” (Daughtery et al., 2008: p. 16) across a wide number of industries. UGC constitutes an important source of information for both managers and customers in data rich environments such as online markets (Erevelles et al., 2016; Wedel and Kannan, 2016), and can come under the guise of posts on social media and online reviews (ORs) (Duan et al., 2008; Vrontis et al., 2022). The latter ones assist prospective, actual, or prior consumers to express and share their views and opinions related to services, products, experiences, brands and even firms on the Internet (Hennig-Thurau et al., 2004). In the wider marketing (and information/computer science) literature, they have been labelled as electronic word-of-mouth (eWOM) and have become the object of increasing scholarly attention as eWOM is more powerful than traditional word-of-mouth due to its speed, one-to-many and many-to-many reach, lack of face-to-face interaction, convenience, and potential anonymity (Sun et al., 2006).

The eWOM body of literature has dug in depth about the drivers (e.g., Fang, 2014) and outcomes (e.g., Sun et al., 2006) of eWOM. In relation to the outcomes, eWOM has been found to influence consumer decisions (e.g., Forman et al., 2008) on one hand and firm performance such as sales and revenues (e.g., Chintagunta et al., 2010; Hu et al., 2014; Babić Rosario et al., 2016) on the other hand.

Over the last two decades scholars in the computer science, information system, management, and marketing fields have increasingly examined the big data stemming from increasingly large volumes of online data (Chong et al., 2017; Filieri and Mariani, 2021; Mariani and Matarazzo, 2021), in line with studies that have emphasized the relevance of business analytics (Chaudhuri et al., 2021; Davenport, 2006) and big data to generate insights on societal and business issues (Blazquez and Domenech, 2018). Scholars have progressively emphasized that big data per se are not enough, but that big data analytics (BDA) (Dubey et al., 2019; Iqbal et al., 2020; Wamba et al., 2017) and big data analytics capabilities (BDAC) (Gupta and George, 2016) are necessary.

Big data consumer analytics and the related big data capabilities have been emphasized as a key driver of analytics supporting the decision making of marketing managers (Erevelles et al., 2016; Wedel and Kannan, 2016) as well as innovation managers (Chaudhuri et al., 2021; Mariani and Nambisan, 2021; Mariani and Wamba, 2020). Despite some scholars emphasizing the dark side of (big) data analytics (e.g., Rana et al., 2021), OR analytics have been found particularly useful to generate business insights conducive to better business intelligence and market knowledge across multiple sectors including consumer goods (Dekimpe, 2020; Erevelles et al., 2016), and hospitality and tourism services (Mariani et al., 2018; Mariani and Baggio, 2022).

As ORs include both structured and unstructured data, eWOM scholars have progressively examined several features including the ratings of online reviews, their volume, as well as several measures related to the text (Guo et al., 2017). Among the key online review analytics there are: 1) valence, i.e., the rating of the OR; 2) volume, i.e., the number of ORs; and 3) variance, i.e., the dispersion of online review ratings. The most frequently analyzed feature in relation to product or firm performance is valence. As far as OR valence is concerned, products and firms displaying higher ratings in ORs have been found to generate higher sales (e.g., Chevalier and Mayzlin, 2006; Chintagunta et al., 2010; Kim et al., 2015; Sun, 2012), higher prices (e.g., Zhang et al., 2011), higher market shares and profitability. Only a minority of studies have found a non-significant effect of OR valence on sales (e.g., Duan et al., 2008). For instance, the higher the hotel OR scores, the more pronounced their sales (Anderson, 2012; Kim et al., 2015; Öğüt and Onur Taş, 2012; Ye et al., 2009), which entails higher prices, higher average daily rates (ADR) (Anderson, 2012; Kim et al., 2015), higher revenue per available room (RevPAR) (Anderson, 2012; Mariani and Borghi, 2020; Phillips et al., 2015), higher market shares (Duverger, 2013), higher perceived profitability from managers (Nieto et al., 2014).

The underlying reason for this is that online review ratings embody information cues that subsume the "wisdom of the crowd" (Filieri, 2015), as average ratings equate to the average evaluation that reviewers have given to the various attributes of a product/service, and therefore indicate the quality and perceived value of hotel services. This seems consistent with previous literature informed by social influence (M.K. Lee et al., 2011; S. Lee et al., 2011) that has found that positive social influence reinforces a) the effect of beliefs and attitude toward online shopping, b) the effect of attitude on intention to shop.

Several studies have focused on the relationship between ORs and price and have found that ORs influence price sensitivity (e.g., Park and Kim, 2008) as highly valenced ORs increase consumers' willingness to pay a premium price for the products reviewed. Most of the practitioners involved with marketing and pricing decisions today view ORs as a component of the communications mix to be managed and one that goes hand in hand with price (Chen and Xie, 2008). Moreover, ORs have the capability to incorporate and deliver signaling information about products and services almost immediately after consumption (e.g., information about product quality is updated frequently each time an OR is posted) and allow prospective buyers to compare products and services in real time, anonymously and conveniently (Sun et al., 2006).

In this work we suggest that the valence of ORs (and their analytics) can be deployed as a relevant, reliable, and updated data source to assess prices in a value-based perspective. As such, we innovatively show how OR analytics can help managers to effectively evaluate and set prices.

2.3. Value-based price assessment based on Data Envelopment Analysis applied to online review analytics

The present research draws on the consideration that online review analytics could provide real-time, reliable, and cheap information about the value perceived by the customers in order to support the development of an effective and easy-to manage value-based price assessment. Therefore, they would help solving one of the main issues that limit a wide adoption of value-based pricing: the lack of information about the value perceived by the customer (Shipley and Jobber, 2001; Brennan et al., 2007).

In the context of this study, the customer-supplier relationship is framed as an input-output relationship where the customer pays a price (input) and obtains in return a certain level of value (output), represented by the contingent product/service attributes to which he/she gives relevance. For this reason, from a technical point of view, we ground our approach into Data Envelopment Analysis (DEA) (Charnes et al., 1978), which is widely known and used to measure the efficiency of Input/Output relationships.

DEA is a linear programming-based technique aimed to assess the relative efficiency of a set of homogeneous 'units' called decision making units (DMUs), that consume inputs to produce outputs (Cook et al., 2009, 2013). Being a non-parametric approach (Choi et al., 2012), DEA is widely applied in situations where the relationships between the multiple Inputs and Outputs involved are complex and/or unknown. DEA provides an efficiency score for each DMU analyzed, obtained through the maximization of the ratio of the weighted sum of Outputs to the weighted sum of Inputs (Cook et al., 2014). The DMUs with an efficiency score equal to 1 are considered "fully efficient" and determine the frontier that "envelops" all the remaining inefficient DMUs. DEA models have been widely applied to contexts where a certain number of inputs are transformed into certain number of outputs, including: the hospitality and tourism industry (Huang et al., 2014; Mariani and Visani, 2019; Yin et al., 2020), the financial sector (Quaranta et al., 2018), sustainability measurement (Zhou et al., 2018; Pan et al., 2021), the education sector (Liu et al., 2013; Shamohammadi and Oh, 2019).

DEA has also been used in the wide field of pricing. Wang et al. (2016) proposed a theoretical DEA-based pricing approach called Competitive Pricing DEA, with a very specific application on oscilloscopes focusing on suppliers in B2B manufacturing market. More concretely, Visani and Boccali (2020) proposed a Purchasing Price Assessment DEA model (PPA-DEA), where the inputs entailed the price and volume purchased by the customer, and the outputs consisted of several technical attributes of the product. The innovative idea behind the approach is that the relationship between the customer and the supplier can be framed as an input-output relationship where the customer inputs the price (input) to get some value attributes (outputs). Accordingly, DEA can be used to assess the efficiency of the relationship, i.e., how the price is "good" compared to the value provided to the customer. The model was applied to two supply categories of a manufacturing company, to assess the prices of all the purchased items, thus generating several managerial insights for the buyers and actual cost savings. In that case, the target was not to support the pricing decisions of the supplier, but to support the customer in assessing the prices. Furthermore, the outputs of the model were technical attributes (the weight of the component, the surface, the width, etc.), directly measured by the company and thus available only for the items purchased. Moreover, in that case, attributes were not value-related measures included in online review analytics and accessible to any the competitors on the market.

Based on these considerations, the distinctive aim of the present study is to develop and test a price assessment approach able to jointly consider the price set by the companies and the value perceived by the customers, by exploiting and leveraging the information generated by online review analytics. In our DEA approach, the selling prices set by the companies are the inputs of the model, while the valence stemming from the online review analytics, expressed in relation to several service attributes, represent the outputs (see Fig. 1).

Consequently, the score generated by the DEA model proxies the “price efficiency” of each DMU (Visani and Boccali, 2020), i.e., the consistence between the price and the value perceived by the customer. When the index (from now on β) is equal to 1 the price set is efficient, thus it is not possible to find any competitor offering higher value at a lower or equal price, or the same value at a lower price. When β < 1 the price is too high compared to the value perceived by the customer, and it should be lowered by a percentage equal to (1 − β) to reach the frontier set by competitors' prices. Doing that, the proposed approach conjointly blends value-based pricing and competition-based pricing, because scores are generated taking into consideration the price-value relationship of all the competitors. Therefore, the proposed approach is novel and distinctive because: 1) the frontier is the consequence of the pricing practices and the value generated by all the players in the market; 2) it allows to blend two perspectives - competition-based and value-based - into a single indicator.

3. Methodology

3.1. A DEA model for value-based price assessment

Among the different DEA models summarized by Cook and Seiford (2009) the DEA-based model proposed in this study is built upon the one developed by Charnes et al. (1978) twenty years after Farrell's seminal work on the measurement of productive efficiency (Farrell, 1957). Such a model, usually referred to as CCR (Charnes, Cooper and Rhodes), is presented below.

Let us suppose we have a set of n DMUs, and that each DMU j ($j = 1, \dots, n$) uses m Inputs x_{ij} ($i = 1, \dots, m$) in order to obtain s Outputs y_{rj} ($r = 1, \dots, s$), with the values of inputs and outputs that are non-negative.[1] Let us also consider the input and output multipliers, $\overline{u}_r$ and $\overline{v}_i$ respectively. In case such multipliers are known, we can express the efficiency score $\overline{e}_j$ of DMU$_j$ as the ratio between the weighted outputs and the weighted inputs:

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

In case of unknown multipliers, Charnes et al. (1978) proposed to solve the problem by solving a specific non-linear programming problem. In more detail, to measure the technical efficiency for a specific DMU$_o$ under evaluation, a fractional programming problem must be solved:

$$\begin{aligned} & e_o = max \sum_r u_r y_{ro} \Big/ \sum_i v_i x_{io} \\ & s.t.\ \sum_r u_r y_{rj} - \sum_i v_i x_{ij} \le 0, \quad \forall j \\ & \quad u_r, v_i \ge \varepsilon, \quad \forall r, i. \end{aligned} \tag{2}$$

where ε is a non-Archimedean value, which goal is that of enforcing strict positivity on the variables. This model is referred to as the input-oriented model, and it can be converted to a linear programming (LP) model by applying the theory of fractional programming (Charnes and Cooper, 1962). To do so, the change of variables $\mu_r = tu_r$ and $\upsilon_i = tv_i$, where $t = \left(\sum_i v_i x_{io}\right)^{-1}$, has to be made. Therefore, the LP model can be expressed as follows:

$$\begin{aligned} & e_o = max \sum_r \mu_r y_{ro} \\ & s.t. \quad \sum_i \upsilon_i x_{i0} = 1 \\ & \sum_r \mu_r y_{rj} - \sum_i \upsilon_i x_{ij} \le 0, \quad \forall j \\ & \mu_r, \upsilon_i \ge \varepsilon, \quad \forall r, i. \end{aligned} \tag{3}$$

By duality, this problem is equivalent to the following linear programming problem:

$$\begin{aligned} & min \quad \theta_o - \varepsilon \left(\sum_r s_r^+ + \sum_i s_i^- \right) \\ & s.t. \quad \sum_j \lambda_j x_{ij} + s_i^- = \theta_o x_{io}, \quad i = 1, \dots, m \\ & \sum_j \lambda_j y_{rj} - s_r^+ = y_{ro}, \quad r = 1, \dots, s \\ & \lambda_j, s_i^-, s_r^+ \ge 0, \quad \forall i, j, r \end{aligned} \tag{4}$$

A meaningful byproduct of developing the DEA-based model, are the Lambda values. For a given DMU (i.e., a hotel), the Lambdas represent the weights of inputs and outputs of all the remaining DMUs that are needed to solve problem (4). So, for a generic DMU$_o$ there is a vector of parameters λ_o that represents the weights applied to the inputs and outputs of the j DMUs in the model needed to work out the efficiency of the DMU (θ_o). When a DMU is efficient the Lambda is equal to 1 with itself, while all the lambdas linking it with the remaining DMUs are equal to 0. If the DMU is not efficient it can have one or more positive Lambdas, which link it to one or more efficient DMUs. The Lambda values could be interpreted as a sort of “similarity indexes”, linking each inefficient DMU with the closest DMU on the frontier. If the value is equal to 0, it means that the two DMUs (one efficient and the other one inefficient) have different inputs-outputs combinations, so that the efficient DMU can hardly be considered a real benchmark for the inefficient one. On the other hand, if the value is positive, the efficient DMU is one of the closest on the frontier, with at least a partially similar combination of inputs and outputs.

To apply and test the proposed model, we chose the hospitality industry, because it is significantly affected by eWOM. Hotel companies are perhaps the most influenced by eWOM (Cantallops and Salvi, 2014) because of the establishment and growth of Online Travel Agencies (OTAs) like Booking.com and Expedia.com. In such a context, ORs represent a unique source of information for prospective buyers of hotel services whose quality is frequently unknown before consumption and generally challenging to evaluate before purchase and consumption (Gretzel and Yoo, 2008). More in detail, in the context of this study, a DMU is a hotel for which a customer pays a certain amount of money (price) to receive a set of services of different value. Therefore, the proposed DEA model recognizes the price paid as the only input, and the value perceived by customers with reference to 6 different service

[1] In a situation characterized by negative output(s), externalities may arise, and a more recent approach called Directional Distance Function (DDF) could be adopted (Falavigna et al., 2015), thus measuring efficiency while incorporating undesirable outputs.

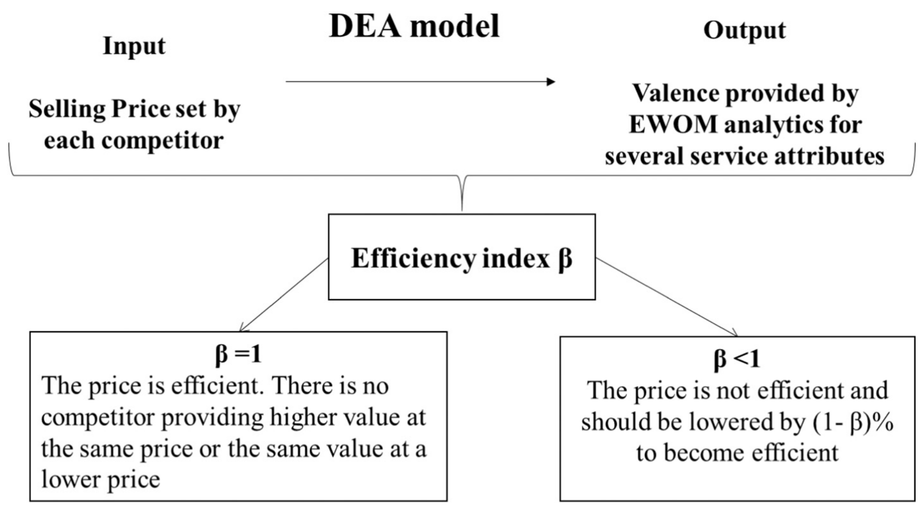

Fig. 1. The model applied.

attributes –as outputs. Indeed, at the end of their hotel stay, as observed in previous research (Mariani and Borghi, 2018), every customer is asked to assess, on a scale from 1 to 10, the following value attributes of the hotel: the service received by the staff of the hotel, the location, the general cleanliness of the room and of the common spaces, the comfort perceived, the facilities (garden, parking, swimming pool, etc.) and the quality of the wi-fi network. The average values for each value attribute are displayed on Booking.com for every hotel. These data are very interesting, because they come from the evaluations of thousands of customers, they are freely available, and they constitute evaluations provided by real customers who actually stayed at the hotel.

The definition of the orientation of a DEA model is a relevant aspect: the aim of an input-oriented model is that of minimizing the input(s) for a given level of output(s), while the aim of an output-oriented model is that of maximizing the level of output(s) for a given level of input(s) (Charnes et al., 1981). As such, the DEA formulation stated by (4) looks for a maximum contraction of all inputs, while keeping constant the outputs level. In this study, the models presented are input-oriented, reflecting the focus on the pricing dimension. The choice of a model based on constant return to scale depends on the relationship between the dynamics of price (input) and the value perceived by the customers (outputs) in the specific industry we chose to apply and test the model (Völckner and Hofmann, 2007). In this context, indeed, the specific range of value perceived affects the pricing dynamics. More specifically, in the tourism industry, when the value perceived is low it often happens that a limited price increase might encourage the customer to switch to a different supplier able to generate value for the customer more than proportionally (increasing return to scales). Contrarily, when the quality level is already high, the price increase needed to obtain higher quality is often very high (decreasing returns to scale). Finally, within a given limited range of quality perceived, it is reasonable to assume the presence of constant returns to scale in line with the tourism and hospitality management literature (Aissa and Goaied, 2016; Brown and Ragsdale, 2002; Hwang and Chang, 2003; Ramanathan et al., 2016). In keeping with extant literature, this is the approach we followed. Therefore, we decided to split the sample in groups of hotels that are homogeneous in terms of perceived quality, and we applied a constant return to scale approach.

3.2. Sample selection and data collection

To apply and test the proposed model in the hospitality industry, the first step was to identify specific locations. We focused on Italy as it is a major leading destination worldwide, ranking consistently among the top 5 destination countries by the United Nations World Tourism Organization (UNWTO) since the 1980s (UNWTO, 2021). The Italian cities of Milan and Rome were chosen as empirical settings for several reasons. Firstly, they are the two top destinations in Italy, and are highly ranked worldwide (16th and 34th respectively) (Euromonitor International, 2019). Secondly, this choice allows to analyze both a business (Milan) and a leisure (Rome) travel destination, accounting for the most common form of tourism differentiation (Gallego and Van Ryzin, 1994). In fact, different hotel attributes and facilities are required by the two groups of customers (Yavas and Babakus, 2005), with location, reputation and price that are extremely important especially for business travelers (Dolnicar, 2002). Thirdly, the high number of hotels of these destinations ensures the effectiveness of a DEA approach, avoiding technical problems due to an insufficient number of DMUs. As regards this aspect, a good rule of thumb is that the number of DMUs should be at least three times the number of inputs and outputs selected (Coelli et al., 2005; Banker et al., 1989). Finally, price competition is more intense in destinations that are in high demand, and this is an additional point that makes them two suitable candidates for an analysis focused on value-based price assessment. As for the choice of the specific location, being spatial competition related to a narrow radius of kilometers (Guizzardi et al., 2017) a specific district for each destination has been identified in Booking.com: the Milan City Center for Milan and the Central Station for Rome. Having clarified the sampling process used, it needs to be emphasized that the methodology proposed and applied in this study can be applied to any online review data related to any geographical area.

To calculate a median price (so a DEA score) that can be representative of the hotel's pricing strategy regardless the specific day of the week, data related to four different booking-dates were collected. Specifically, all the booking-dates were in four different (and consecutive) weeks of June, and mixed workweek and weekend days. The inclusion of different dates is extremely important because the leisure and the business segments are usually more heavily focused on different periods: the former tends to prefer weekend periods and the latter weekdays (M. K. Lee et al., 2011; S. Lee et al., 2011). Furthermore, price discounts differ along the week, and are usually given for weekends (Hanks et al., 2002).

Consistently with Abrate et al. (2019), the price for the same booking-date has been observed several times. The rationale was to consider different pricing strategies while approaching the check-in date, and to calculate a median price that could be embedded into the DEA approach. Consistently, and according to dynamic pricing literature (Abrate et al., 2019), data were collected from the beginning of April 2019 with reference to each target booking-date by simulating the booking process using 60, 45, 30, 20, 10, 5, 3 and 1 days in advance (thus, 8 data collections for each booking-date and 32 for each hotel).

Furthermore, to standardize the data collection and get reliable DEA efficiency indexes, each search concerned the best available price for a one-night reservation for two persons (double room accommodation). According to specific filtering options activated in the online booking platform, each search provides information on the best available price for the hotels in the sample in the selected location and district.

Considering the list of hotels with double room accommodation availability for the target booking-dates at the beginning of the data collection process and excluding those with <100 reviews as suggested by the extant eWOM literature in the hospitality industry (Schuckert et al., 2015), the samples for the two selected districts of Milan and Rome consisted of 184 and 180 hotels respectively. In more detail, the sample of Milan was made up of 80 budget/midscale hotels (i.e., 1-, 2- and 3-star hotels) and 104 higher-end hotels (i.e., 4- and 5-star hotels). Instead, the sample of Rome consisted of 128 budget/midscale hotels and 52 higher-end hotels. For all the hotels in our sample we also collected the online review ratings for the service attributes related to staff, location, cleanliness, comfort, facilities and free wi-fi. All the data were collected from Booking.com. Finally, we computed the median price for each hotel.

The descriptive statistics for the two samples in terms of number of hotels and prices are reported in Tables 1 and 2, while the descriptive statistics pertaining to the scores of the service attributes are reported in Tables 3 and 4.

3.3. Data analysis

According to the general framework presented in Section 3.1, an input-oriented DEA model was developed, with the median price as the only input and the scores obtained by the hotel for staff, location, cleanliness, comfort, facilities and free wi-fi service attributes as outputs. All the analyses have been carried out through the PIM-DEA software, version 3.2.

Before running the DEA model for the two sub-samples (Milan and Rome), 1-star hotels were excluded (14 for Milan and 9 for Rome) to follow the most common distinction adopted in hospitality literature (2- and 3-star hotels versus 4- and 5-star hotels). Then, the scores of the outputs were standardized and stretched in the range from 0 to 1, to avoid problems related to the relatively flat distribution of such scores and thus increasing the sensitivity of the DEA score to changes in the level of the values of such outputs.

With the aim to eliminate DMUs with prices that can be considered as "outliers", we developed a super-efficiency approach (Banker and Gifford, 1988). Differently from conventional DEA, the super efficiency approach excludes from the reference set the specific DMU under evaluation, thus allowing efficiency scores to reach values >100/100. DMUs with very high scores (we set the threshold at 120/100, according to Banker and Chang, 2006) are often characterized by Input/Output data errors or by extraordinary operating conditions. If not excluded from the sample, super-efficient DMUs would affect the shape of the efficient frontier and the efficiency scores of all the DMUs. Accordingly, we excluded from the analysis all the DMUs of the four sub-samples with a DEA index higher than the threshold of 120/100, 5 DMUs in total (two from the sub-sample of the budget/midscale hotels of Milan, one from the sub-sample of the budget/midscale hotels of Rome and two from the higher-end hotels of Rome).

As a result of the exclusion of 1-star hotels and of the super-efficiency analysis, the final samples were as follows: 64 budget/midscale hotels and 104 higher-end hotels located in Milan, and 118 budget/midscale hotels and 50 higher-end hotels located in Rome. The rule of thumb commonly applied in the field of DEA is that the number of DMUs must be higher than three times the sum of inputs and outputs (Coelli et al., 2005; Banker et al., 1989). The model is based on 1 input and 6 outputs, so the number of available hotels for each cluster is more than sufficient.

On the selected samples we ran an Input-Oriented CCR-DEA model, accordingly to the model presented in Section 3.1. In more detail, we ran two DEA models for each location, one for budget/midscale hotels and one for higher-end hotels. Once run the models, we realized the presence of a serious problem of negative correlation between prices and DEA indexes (the values of the Pearson correlation indexes were respectively −0.62 and −0.81 for the two subsamples of Milan and −0,55 and −0,81 for the two subsamples of Rome). These results point out that the common distinction between 2–3 star and 4–5 star might is not suitable to assess prices following a value-based perspective, because within each class the price (input) variability is very high, while the range of variation of the value attributes (outputs) is much lower. The standardization of the scores is only partially able to manage this difference.

All that considered, to compare homogeneous DMUs and solve the problem, we clustered the data according to the median price of the hotels. Doing so, we include in the same cluster hotels for which the expectations of the customer are similar, according to the logics of the internal reference price (Rajendran and Tellis, 1994; Mazumdar et al., 2005; Winer, 1986).

As a first step, we performed a hierarchical clustering on prices using the Ward method for Milan and Rome separately. The clustering procedure suggested an optimal number of clusters between 4 and 5 for Milan and between 3 and 4 for Rome. This result was than refined through judgmental considerations aimed to maximize the number of hotels to include in the analysis and to keep as narrow as possible the range of prices of each cluster at the same time.

Four different clusters for each location were identified, labelled: "low budget hotels" (LB Hotels), "mid-low budget hotels" (MLB Hotels), "mid-high budget hotels" (MHB Hotels), "high budget hotels" (HB Hotels). The descriptive statistics for each cluster are reported in Tables 5 and 6 for Milan and Rome respectively.

As shown in Tables 5 and 6, the range is larger in MHB and HB Hotels clusters, because when the absolute price increases the price sensitivity decreases.

For each cluster we repeated the same procedure previously described, from data standardization to DEA model development.

As a result of the super-efficiency analysis, the final samples were as follows: 29 LB hotels, 38 MLB hotels, 46 MHB hotels and 30 HB hotels for Milan; 39 LB hotels, 58 MLB hotels, 27 MHB hotels and 28 HB hotels for Rome.

Table 1
Descriptive statistics for Milan: number of hotels by star rating and statistics on price.

Hotel star rating	Number of hotels in the final sample	Average number of reviews	Price			
			Mean	Min	Max	S.D.
One-star	14	928	71.0	56.3	92.4	11.5
Two-star	19	920	72.8	54.5	103.7	12.1
Three-star	47	1848	104.0	55.1	184.4	25.8
Four-star	88	1705	153.8	94.1	305.6	47.0
Five-star	16	962	415.7	216.5	961.8	206.7

Table 2
Descriptive statistics for Rome: number of hotels by star rating and statistics on price.

Hotel star rating	Number of hotels in the final sample	Average number of reviews	Price			
			Mean	Min	Max	S.D.
One-star	9	456	69.0	54.8	83.2	7.8
Two-star	36	917	82.8	59.7	131.0	14.7
Three-star	83	1020	110.2	72.1	238.4	28.2
Four-star	48	1441	181.3	73.4	342.1	57.4
Five-star	4	759	363.7	258.7	513.2	92.8

Table 3
Descriptive statistics for Milan: the scores of the service attributes and the number of reviews by star rating.

Hotel star rating	Staff				Location				Cleanliness				Comfort				Facilities				Free wi-fi			
	Mean	Min	Max	S.D.	Mean	Min	Max	S.D.	Mean	Min	Max	S.D.	Mean	Min	Max	S.D.	Mean	Min	Max	S.D.	Mean	Min	Max	S.D.
One-star	7.9	6.2	8.7	0.8	8.3	6.2	9.5	0.7	7.4	5.1	8.7	1.1	6.8	4.8	8.2	1.1	6.7	4.7	8.1	1.0	7.7	6.6	9.9	0.8
Two-star	7.9	7.1	8.6	0.7	8.0	7.1	9.3	0.5	7.7	6.4	8.6	0.7	6.9	5.6	8.0	0.7	6.9	5.8	7.9	0.7	7.6	6.1	8.8	0.6
Three-star	8.3	6.8	9.6	0.6	8.6	6.8	9.7	0.6	8.3	6.9	9.6	0.7	7.6	6.0	9.2	0.8	7.6	5.9	9.0	0.7	7.9	5.5	8.9	0.6
Four-star	8.7	7.3	9.7	0.4	8.9	7.3	9.9	0.6	8.7	5.1	9.7	0.6	8.4	6.3	9.4	0.6	8.2	6.3	9.2	0.5	8.1	5.5	9.3	0.7
Five-star	9.0	7.9	9.6	0.4	9.0	7.9	9.8	0.5	9.1	8.1	9.6	0.4	8.9	7.8	9.5	0.5	8.7	7.5	9.4	0.6	8.6	7.3	9.5	0.6

Table 4
Descriptive statistics for Rome: the scores of the service attributes and the number of reviews by star rating.

Hotel star rating	Staff				Location				Cleanliness				Comfort				Facilities				Free wi-fi			
	Mean	Min	Max	S.D.	Mean	Min	Max	S.D.	Mean	Min	Max	S.D.	Mean	Min	Max	S.D.	Mean	Min	Max	S.D.	Mean	Min	Max	S.D.
One-star	7.9	7.4	8.4	0.7	8.3	7.4	9.1	0.6	7.3	5.7	8.4	0.9	6.7	5.5	7.7	0.8	6.6	5.4	7.6	0.8	7.4	6.2	8.5	0.9
Two-star	8.1	6.1	9.1	0.7	8.5	6.1	9.2	0.6	7.5	5.1	9.1	0.9	6.8	4.8	8.1	0.8	6.8	4.8	8.0	0.8	6.8	3.2	8.6	1.5
Three-star	8.3	6.6	9.4	0.7	8.6	6.6	9.4	0.6	8.0	5.9	9.4	0.8	7.3	5.5	9.1	0.8	7.2	5.3	8.9	0.8	7.1	3.2	9.4	1.3
Four-star	8.7	7.1	9.7	0.5	8.8	7.1	9.4	0.5	8.6	6.8	9.7	0.7	8.1	6.1	9.6	0.8	8.0	6.1	9.4	0.8	8.0	4.2	9.6	0.9
Five-star	8.7	8.5	9.1	0.4	8.8	8.5	9.1	0.3	8.7	7.7	9.1	0.6	8.4	7.2	9.0	0.7	8.2	7.0	8.7	0.7	8.2	7.4	8.7	0.5

Table 5
Descriptive statistics for the clusters of Milan: price range and number of DMUs (hotels) included.

	Cluster			
	LB	MLB	MHB	HB
Price range	55–80	80.1–105	105.1–135	135.1–170
Range width (€)	25	25	30	35
No hotels	30	39	46	30

Table 6
Descriptive statistics for the clusters of Rome: price range and number of DMUs (hotels) included.

	Cluster			
	LB	MLB	MHB	HB
Price range	60–85	85.5–110	110.1–145	145.1–185
Cluster width (€)	25	25	35	40
No hotels	41	58	29	29

4. Findings

4.1. The DEA-scores obtained

After running the different DEA models, we focused on the analysis of the distribution of the DEA scores in each cluster.[2] Fig. 2 (Milan) and Fig. 3 (Rome) respectively report the price and the DEA index of each hotel of the eight clusters.

The low values of correlation highlighted in Table 7, which reports the descriptive statistics of each cluster, confirm the effectiveness of the clustering procedure. The values range from −0.43 for the LB Hotels of Rome to 0.07 for the LB Hotels of Milan. The mean DEA indexes show values higher than 80 and lower than 90 in all the 8 clusters, while the standard deviation ranges from 10.48 (Milan HB hotels) to 18.05 (Milan LB hotels).

Efficient DMUs account for almost 15–20 % of each cluster, with the exception for the MHB hotels of Rome (29.6 % of fully efficient DMUs).

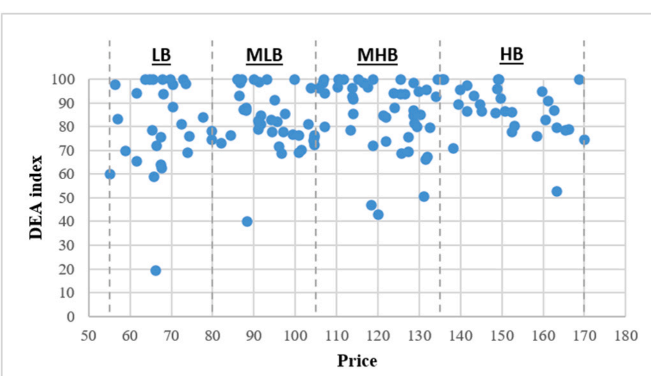

Fig. 2. Price and DEA index for each hotel of Milan by cluster.

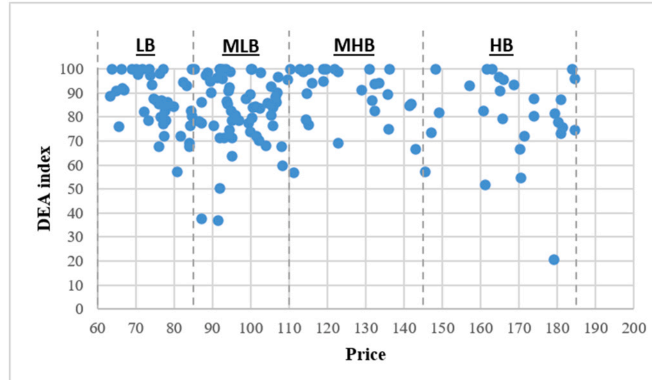

Fig. 3. Price and the DEA index for each hotel of Rome by cluster.

Finally, in line with Section 2.3, the actual price set by each hotel can be by multiplied by (1 − β), that represents the percentage discount required to reach the frontier set by competitors' prices. The average price discount by cluster and location is reported in the last line of Table 7.

4.2. Peers' analysis

According to Section 3.1, by looking at the number of inefficient DMUs for which an efficient DMU shows positive Lambda values, we can understand which companies can represent real "best practices" for the remaining organizations in terms of price-value consistency. If an efficient hotel shows positive lambdas with several inefficient hotels, it can be seen as a reference point for them, because it means they share a similar combination of attributes.

As an example, Table 8 reports the Lambda values for the MHB hotels of Rome.

If we look at the last two lines of the table, "Hotel San Remo", "Hotel Martini" and "Flower Garden Hotel" are efficient, but they don't show a positive Lambda for any of the "inefficient" hotels. It means that they are on the frontier, but far from the input-output combinations of most of the competitors. Instead, "Hotel Marcantonio" shows positive Lambda values for 12 Hotels and "Domus Australia" for 15. This is an additional information to the DEA index, which helps to highlight the real peers for the inefficient DMUs. To better illustrate this point, for each of the six outputs and for each cluster, we worked out the position of the hotels in the valence ranking. As an example, Table 9 reports the values for a) the DMU with the highest number of positive Lambdas among the MHB Hotels of Rome ("Domus Australia", see Table 8); b) two DMUs linked to it by the highest Lambdas ("Hotel Camelia" and "Hotel Des Artistest") and c) two DMUs linked to it by the lowest Lambdas ("Hotel Aberdeen" and "Hotel Lirico").

The DMUs linked by high Lambda values with "Domus Australia", exactly as their peer, show high performances in "Cleanliness", "Comfort", "Staff" and "Facilities", while show low values for "Location". On the contrary, "Hotel Aberdeen" and "Hotel Lirico" show the highest position in the ranking for "Location", exactly the value attribute for which "Domus Australia" shows the worst performance. On the contrary they perform poorly on average for the most important value attributes of "Domus Australia". This example helps to understand how the Lambda values can show the similarity between DMUs in terms of price-value attributes combinations, thus explaining to the inefficient DMUs which efficient peer can be considered a "best practice" to compare with.

We repeated the same analysis for all the clusters of hotels to evaluate which efficient DMUs can be considered as real best practices in terms of price efficiency. The results highlighted that in each cluster there are efficient DMUs that can be considered a reference point for a very high number of peers of the clusters and others that are efficient, but with input-output combinations very dissimilar from most, if not all,

[2] In the DEA model developed, the outputs are subjective evaluations of the customers, that can be considered as "fuzzy" data. Accordingly, we tested the results of our CCR model by developing a specific Fuzzy CCR model, comparing the different DEA scores through correlation analysis. A positive and strong correlation was highlighted. Since the target of the present study is to develop an easy model to be applied in the real world, we prefer to focus on the traditional CCR approach. The details of the Fuzzy model and the correlation analysis are presented in the Appendix.

Table 7
Descriptive statistics for the 4 clusters of each location.

		Milan				Rome			
		LB	MLB	MHB	HB	LB	MLB	MHB	HB
DEA index	Mean	80.81	83.10	86.04	87.03	86.44	83.14	89.27	80.24
	Minimum	19.49	40.16	43.11	52.83	57.24	36.93	56.96	20.68
	Maximum	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
	S.D.	18.05	12.29	14.46	10.48	11.06	14.37	11.72	17.76
	Efficient DMUs	6	5	8	5	8	7	8	4
	Efficient DMUs (%)	20.7 %	13.2 %	17.4 %	16.7 %	20.0 %	12.1 %	29.6 %	14.3 %
	Correlation price/DEA	0.07	−0.27	−0.30	−0.42	−0.43	0.01	−0.17	−0.07
	Average price discount	19.2 %	16.9 %	14.0 %	13.0 %	13.6 %	16.9 %	10.7 %	19.8 %

Table 8
Lambda values for the inefficient DMUs of the MHB hotels of Rome.

Inefficient DMUs/efficient DMUs	Hotel San Remo	Hotel Sonya	Hotel Martini	Hotel Marcantonio	Hotel Astoria Garden	Flower Garden Hotel	Hotel Oceania	Domus Australia
Raeli Hotel Archimede	–	–	–	0.53	–	–	–	–
Hotel Lirico	–	0.59	–	0.37	–	–	–	0.01
Hotel Emona Aquaeductus	–	–	–	–	0.11	–	0.59	–
Madison Hotel	–	–	–	0.87	–	–	–	–
Hotel Amadeus	–	–	–	0.70	–	–	–	0.04
Hotel Windrose	–	0.32	–	0.46	–	–	–	0.14
Hotel California	–	1.00	–	–	–	–	–	–
Best Western Hotel Artdeco	–	–	–	–	–	–	–	0.63
Exe Domus Aurea	–	–	–	0.50	–	–	–	0.46
Hotel Select Garden	–	–	–	0.25	0.14	–	–	0.53
Hotel Montecarlo	–	–	–	–	–	–	0.19	0.66
Hotel Milani	–	0.21	–	0.56	–	–	–	0.14
Hotel Impero	–	1.00	–	–	–	–	–	–
Hotel Camelia	–	–	–	–	–	–	0.02	0.90
Hotel Tito	–	0.52	–	0.27	–	–	–	0.23
Hotel Des Artistest	–	–	–	–	–	–	–	0.75
Hotel Aberdeen	–	–	–	0.50	0.34	–	–	0.15
Al Viminiale Hill Inn & Hotel	–	0.52	–	0.27	–	–	–	0.23
Hotel Aphrodite	–	–	–	0.58	–	–	–	0.20
Number of DMUs with positive Lambdas	**0**	**7**	**0**	**12**	**3**	**0**	**3**	**15**
Average Lambda	**0**	**0.59**	**0**	**0.49**	**0.20**	**0**	**0.27**	**0.34**

Table 9
Position in the ranking of MHB Hotels of Rome for one efficient DMU and some peers.

DMU	Lambda	Staff	Location	Cleanliness	Comfort	Facilities	Free wi-fi
Domus Australia (**efficient**)		1	17	1	1	1	2
Hotel Camelia	0.90	3	20	2	2	2	5
Hotel Des Artistest	0.75	13	23	4	4	4	18
Hotel Aberdeen	0.15	5	4	15	17	11	18
Hotel Lirico	0.01	13	4	15	15	17	24

the other DMUs. This analysis enables to isolate the best practices of each cluster and to select the real peer(s) for each inefficient DMU.

5. Discussion and conclusion

5.1. Concluding remarks

The main objective of this work was to understand if and to what extent eWOM, and more specifically online review analytics, could be used to assess prices according to a value-based pricing approach, thus overcoming the typical practical limitation inherent in value-based pricing: limited availability of information and data on customers' perceived value. The novel model developed and proposed is unique and distinctive as it: 1) is one of the first to leverage an easy-to –access data source in digital settings such as online reviews for pricing decisions adopting a managerial perspective; 2) allows to take into account price/value relationships pertaining to competitors, thus allowing decision makers involved in pricing decision to blend both competition-based and value-based pricing considerations.

5.2. Theoretical and methodological implications

This study makes several theoretical and methodological contributions at the intersection of (value-based) pricing literature, efficiency modelling and eWOM. First, from a methodological point of view, we put forward an innovative approach able to support value-based price assessment by means of eWOM, and more specifically online review analytics. Previous studies had just hypothesized the possibility to apply DEA to purchasing prices (Wang et al., 2016) or had developed DEA-based price assessment approaches for industrial activities (Visani and Boccali, 2020), where the attributes were real features of the object (length, weight, etc.) measured by the operators of the company, not online reviews freely available online. This approach is easy-to-perform and parsimonious as it is based on widely available information on the Internet, and on the mathematical model of DEA, which can be easily run through cheap software or even by deploying an Excel spreadsheet.

This way we extend previous big data research calling for data analytical methods relying on potentially very large volumes of data (Blazquez and Domenech, 2018) as well as prior value-based pricing literature (Hinterhuber, 2004, 2008; Kienzler, 2018; Liozu, 2017; Töytäri et al., 2015) and enrich it by developing an innovative approach to support value-based pricing decisions.

Second, we contribute to the revenue management literature (Klein et al., 2020; Shen and Su, 2007) by suggesting that analytics from ORs constitute an effective source of data for revenue management decisions and price assessment. Relatedly, we offer insights on the way analytics from potentially large amounts of data such as big data from online review platforms can be leveraged to generate big data analytics that are potentially conducive to better decision making (Akter et al., 2016, 2019), namely pricing decisions. Future research might detect if better pricing decision would eventually translate also into better firm performance (Wamba et al., 2015) which seems to be one of the ultimate goals of the use of large volumes of data.

Third, we contribute to the eWOM literature (Liang and Corkindale, 2019; Hennig-Thurau et al., 2004), by suggesting that eWOM – and generally vast amounts of online reviews - can be suitably embedded to assess prices in a value-based perspective in data rich environments (Erevelles et al., 2016; Wedel and Kannan, 2016). This extends the nascent research stream that has deployed eWOM (and more specifically OR data) to determine the efficiency of firms (Mariani and Visani, 2019) and firms' performance (Mariani and Borghi, 2020), thus suggesting that eWOM is critical in today's firm efficiency evaluations and that it is conducive to enhanced performance. We therefore strengthen the theoretical argument that eWOM is a key determinant of both firm efficiency and firm performance.

Fourth, we contribute both the established big data consumer analytics research stream in marketing (Erevelles et al., 2016) and the nascent stream of big data analytics research within the hospitality and tourism management field (Mariani et al., 2018), by extending previous research that has suggested that hospitality and tourism firms adopting analytics on large volumes (big data) of UGC can generate business intelligence (Mariani et al., 2018; Mariani and Wamba, 2020) that translates into better firm performance for (Mariani and Borghi, 2020; Yang et al., 2018).

Last, we contribute to the recent and emerging set of efficiency studies that have deployed DEA to support price assessment and setting (Wang et al., 2016; Visani and Boccali, 2020). In their study, Wang et al. (2016) proposed a theoretical DEA-based pricing approach called Competitive Pricing DEA, without providing tangible results and focusing on suppliers in B2B manufacturing market. Visani and Boccali (2020) found instead that DEA could be suitably deployed to assess prices in a B2B manufacturing market, providing also empirical results from real-world applications, but the focus was again on B2B manufacturing market and the value dimension was not considered To the best of our knowledge this is the first study to deploy DEA to assess prices in services industries that today make up more than two thirds of the world GDP (Zeithaml et al., 2018) and focuses on consumer markets that are becoming critical for value chains and systems (Porter, 2001).

5.3. Practical implications

This study bears important managerial implications. First, the innovative approach developed can assist managers in gaining a better understanding of the customers' price/value perceptions which can translate into either a revision of prices or a modification of the value proposition and the value brought about by products and services sold (Bresciani et al., 2015). This might be deployed to justify the actual prices. The strength of this approach is that it is based on online review data that are broadly and freely available and easy to collect. Second and related to the previous point, the results provided by the approach are very easy to understand for managers, as they are based on a single index ranging from 0 to 1. The simplicity of interpretation of the score is critical to overcome two typical issues arising when carrying out value-based management: the involvement of the salespeople (Nagle and Holden, 2002) and the need of top management's commitment (Liozu, 2017). Third, by analyzing the Lambdas, managers involved in pricing decisions might be able to identify the most efficient firms among those operating on the market adopting similar competitive approaches, i.e. the peers displaying a better price/value ratio. They could evaluate whether the "peers" are real competitors for them and if being more efficient in terms of value/price relationship is a real source of profitability and growth. In any case, they could deeply analyze the online reviews of their competitors to understand what processes should be modified to achieve a better quality and/or contain costs. Otherwise, if managers think that a different combination of value attributes could be more interesting in terms of economic value, they could analyze the performance and the reviews of other peers. This would prompt important managerial initiatives.

Fourth, as far as customers are concerned, the index generated by the DEA model provides prospective customers with reliable information on the value/price relationship, thus supporting the information search phase of purchase decision processes and generally paving the way for more informed purchase decisions. This is extremely relevant in today's markets whose features are covered by an extensive and continuous flux of data and information. Fifth and related to the previous point, the index could be suitably embedded by online review platforms such as e-commerce websites (e.g., Amazon), online travel agencies (e.g., Booking.com) and online travel review websites (e.g., Tripadvisor). This way online customers would be allowed to access a meaningful metric before making a purchase. More generally, the index could be built into each digital platform hosting transactions whereby information about price and attributes is available. Accordingly, the index proposed is applicable to goods and services from multiple industries – ranging from consumer electronics to media and entertainment products, to retailing – that are transacted on platforms enabling consumers to post online reviews.

5.4. Limitations and future developments

This research is not without limitations. First, for illustrative purposes this model was applied to the hospitality industry where eWOM in the form of online reviews is widely available, accessible and reliable, especially when it originates from e-commerce platforms like Booking where ORs are certified. This implies that future studies may seek to test the model in other contexts and platforms, as well as distinguishing mobile vs. nonmobile channels (Kim et al., 2021) to generalize our findings. Moreover, the approach adopted might need to be validated also across different industries. That said, we believe that similar results could be achieved by considering other sectors and products as the way e-commerce platform work is rather similar across products and services in B2C markets. Second, we considered two specific destinations: future studies might consider multiple destinations across different countries to improve the generalizability of this study. We do not anticipate contrasting results as the way hospitality services are transacted and evaluated on online platforms is similar regardless of the destination/location considered. In terms of research agenda, future studies might examine – possibly by means of a two-stage DEA, what factors influence price efficiency. Moreover, they might analyze if firms that are efficient in terms of value-based price are also generating higher revenues to better ascertain if prices consistent with the value generated are only useful for customers or also for firms' managers. This represents a relevant way to understand the value of the proposed analysis. In a completely rational world, it is reasonable to expect that a higher price/value ratio should lead to higher revenues and profits. However, in several fields - for instance the fashion industry - this is not always the case. Thus, future studies could deeply analyze the environmental factors that affect the relevance of increasing the price/value efficiency.

CRediT authorship contribution statement

Filippo Boccali: Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Marcello M. Mariani:** Conceptualization, Validation, Data curation, Methodology, Writing – original draft, Writing – review & editing, Supervision. **Franco Visani:** Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Supervision, Project administration. **Alexandra Mora-Cruz:** Writing – review & editing.

Declaration of competing interest

None.

Appendix A. A Fuzzy DEA approach

In the DEA model developed, the outputs are subjective evaluations of the customers. As such, they can be considered as "fuzzy" data. Accordingly, we tested the results of our CCR model by developing a Fuzzy CCR model, in more detail a multiplier input oriented CCR model, according to Allahviranloo and Firozja (2010) and Hosseinzadeh et al. (2016).

Let n decision-making units (DMUs) to be evaluated and each DMU_j (j = 1, …, n) transforms inputs $\widetilde{X}_j$ into outputs $\widetilde{Y}_j$. For each DMU_j $\widetilde{x}_{ij}$ ($i = 1, \ldots, m$) and $\widetilde{y}_{rj}$ ($r = 1, \ldots, s$) are positive LR fuzzy numbers.

The multiplier form of the CCR model in input orientation according to the ranking functions defined by Allahviranloo and Firozja (2010) and Hosseinzadeh et al. (2016), according to our specific set of data where the inputs are crisp data and outputs are fuzzy data, is as follows:

$$max\ \widetilde{Z} = \sum_{r=1}^{s} u_r \widetilde{y}_{r0}$$

$$s.t. \quad \sum_{i=1}^{m} v_i x_{i0} = 1$$

$$\sum_{r=1}^{s} u_r\, \widetilde{y}_{rj} - \sum_{i=1}^{m} v_i\, x_{ij} \lesssim \widetilde{0},$$

$$\text{j} = 1, \ldots, \text{n},$$

$$u \geq \varepsilon, v \geq \varepsilon$$

Then we compared the results generated by the Fuzzy DEA approach with those provided by the CCR approach. Tables A.1 and A.2 respectively report the results of correlation analysis for the hotels located in Rome and Milan. The tables highlight a positive and strong correlation between both the cardinal and ordinal values generated by the two approaches. The confidence Intervals (CIs) are tight and they do not include zero. Accordingly, the null hypothesis H0: rho = 0, is rejected for all the three coefficients. The result is confirmed by the bootstrap p-values.

Table A.1
DEA and Fuzzy DEA of the hotels located in Rome: correlaztion analysis via bootstrap.

	Rho	Bias	SE	CI	*p*-Value
Pearson	0.824	0.004	0.054	(0.707; 0.919)	0.000***
Spearman	0.866	−0.002	0.029	(0.804; 0.914)	0.000***
Kendall	0.730	0.001	0.034	(0.663; 0.793)	0.000***

*p-Value < 0.05; **p-value < 0.01; ***p-value < 0.001; NS = not significant.

Table A.2
DEA and Fuzzy DEA of the hotels located in Milan: correlation analysis via bootstrap.

	Rho	Bias	SE	CI	p-Value
Pearson	0.858	0.0002	0.056	(0.733, 0.949)	0.000***
Spearman	0.866	−0.0002	0.039	(0.782, 0.933)	0.000***
Kendall	0.735	0.000	0.035	(0.666, 0.803)	0.000***

*p-Value < 0.05; **p-value < 0.01; ***p-value < 0.001; NS = not significant.

The target of the present study is to develop an approach able to evaluate the relationship between prices and value that could be easy applied in the real world, by using widely available data and tools. As a consequence, we prefer to focus on the traditional input oriented CCR approach that could be developed much easier by the management accounting departments.

References

Abrate, G., Nicolau, J.L., Viglia, G., 2019. The impact of dynamic price variability on revenue maximization. Tour. Manag. 74, 224–233.
Ahn, H., Clermont, M., Schwetschke, S., 2018. Research on target costing: past, present and future. Manag. Rev. Q. 68 (3), 321–354.
Aissa, S.B., Goaied, M., 2016. Determinants of Tunisian hotel profitability: the role of managerial efficiency. Tour. Manag. 52, 478–487.
Akter, S., Wamba, S.F., Gunasekaran, A., Dubey, R., Childe, S.J., 2016. How to improve firm performance using big data analytics capability and business strategy alignment? Int. J. Prod. Econ. 182, 113–131.
Akter, S., Bandara, R., Hani, U., Wamba, S.F., Foropon, C., Papadopoulos, T., 2019. Analytics-based decision-making for service systems: a qualitative study and agenda for future research. Int. J. Inf. Manag. 48, 85–95.
Allahviranloo, T., Firozja, M.A., 2010. Ranking of fuzzy numbers by a new metric. Soft. Comput. 14, 773–782.
Anderson, C.K., 2012. The impact of social media on lodging performance. In: Cornell Hospitality Report, 12, pp. 4–11.
Babić Rosario, A., Sotgiu, F., De Valck, K., Bijmolt, T.H., 2016. The effect of electronic word of mouth on sales: a meta-analytic review of platform, product, and metric factors. J. Mark. Res. 53 (3), 297–318.

Banker, R.D., Chang, H., 2006. The super-efficiency procedure for outlier identification, not for ranking efficient units. Eur. J. Oper. Res. 175 (2), 1311–1320.
Banker, R.D., Gifford, J.L., 1988. A Relative Efficiency Model for the Evaluation of Public Health Nurse Productivity. Carnegie Mellon University, Pittsburgh.
Banker, R.D., Charnes, A., Cooper, W.W., Swarts, J., Thomas, D., 1989. An introduction to data envelopment analysis with some of its models and their uses. Res. Gov. Nonprofit Account. 5 (1), 125–163.
Blazquez, D., Domenech, J., 2018. Big data sources and methods for social and economic analyses. Technol. Forecast. Soc. Chang. 130, 99–113.
Brennan, R., Canning, L., McDowell, R., 2007. Price-setting in business-to-business markets. Mark. Rev. 7 (3), 207–234.
Bresciani, S., Thrassou, A., Vrontis, D., 2015. Determinants of performance in the hotel industry-an empirical analysis of Italy. Glob. Bus. Econ. Rev. 17 (1), 19–34.
Bresciani, S., Ferraris, A., Huarng, K.H., Malhotra, A., 2021. Digital transformation as a springboard for product, process and business model innovation. J. Bus. Res. 128, 204–210.
Brown, J.R., Ragsdale, C.T., 2002. The competitive market efficiency of hotel brands: an application of data envelopment analysis. J. Hosp. Tourism Res. 26 (4), 332–360.
Cantallops, A.S., Salvi, F., 2014. New consumer behavior: a review of research on eWOM and hotels. Int. J. Hosp. Manag. 36, 41–51.
Cao, C., Ghysels, E., Hatheway, F., 2000. Price discovery without trading: evidence from the Nasdaq preopening. J. Financ. 55 (3), 1339–1365.
Cardinaels, E., Roodhooft, F., Warlop, L., 2004. The value of activity-based costing in competitive pricing decisions. J. Manag. Account. Res. 16 (1), 133–148.
Charnes, A., Cooper, W.W., 1962. Programming with linear fractional functionals. Naval Res. Logist. Q. 9 (3–4), 181–186.
Charnes, A., Cooper, W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2 (6), 429–444.
Charnes, A., Cooper, W.W., Rhodes, E., 1981. Evaluating program and managerial efficiency: an application of data envelopment analysis to program follow through. Manag. Sci. 27 (6), 668–697.
Chaudhuri, R., Chatterjee, S., Vrontis, D., Thrassou, A., 2021. Adoption of robust business analytics for product innovation and organizational performance: the mediating role of organizational data-driven culture. Ann. Oper. Res. https://doi.org/10.1007/s10479-021-04407-3.
Chen, Y., Xie, J., 2008. Online consumer review: word-of-mouth as a new element of marketing communication mix. Manag. Sci. 54 (3), 477–491.
Chevalier, J.A., Mayzlin, D., 2006. The effect of word of mouth on sales: online book reviews. J. Mark. Res. 43 (3), 345–354.
Chintagunta, P.K., Gopinath, S., Venkataraman, S., 2010. The effects of online user reviews on movie box office performance: accounting for sequential rollout and aggregation across local markets. Mark. Sci. 29 (5), 944–957.
Choi, Y., Zhang, N., Zhou, P., 2012. Efficiency and abatement costs of energy-related CO2 emissions in China: a slacks-based efficiency measure. Appl. Energy 98, 198–208.
Chong, A.Y.L., Ch`ng, E., Liu, M.J., Li, B., 2017. Predicting consumer product demands via Big Data: the roles of online promotional marketing and online reviews. Int. J. Prod. Res. 55 (17), 5142–5156.
Coelli, T.J., Rao, D.S.P., O'Donnell, C.J., Battese, G.E., 2005. An Introduction to Efficiency and Productivity Analysis. Springer Science & Business Media.
Cook, W.D., Seiford, L.M., 2009. Data envelopment analysis (DEA)–Thirty years on. Eur. J. Oper. Res. 192 (1), 1–17.
Cook, W.D., Liang, L., Zha, Y., Zhu, J., 2009. A modified super-efficiency DEA model for infeasibility. J. Oper. Res. Soc. 60 (2), 276–281.
Cook, W.D., Harrison, J., Imanirad, R., Rouse, P., Zhu, J., 2013. Data envelopment analysis with nonhomogeneous DMUs. Oper. Res. 61 (3), 666–676.
Cook, W.D., Tone, K., Zhu, J., 2014. Data envelopment analysis: prior to choosing a model. Omega 44, 1–4.
Daughtery, T., Eastin, M., Bright, L., 2008. Exploring consumer motivations for creating user-generated content. J. Interact. Advert. 8 (2), 16–25.
Davenport, T.H., 2006. Competing on analytics. Harv. Bus. Rev. 84 (1), 98.
Dekimpe, M.G., 2020. Retailing and retailing research in the age of big data analytics. Int. J. Res. Mark. 37 (1), 3–14.
Dolnicar, S., 2002. Business travellers' hotel expectations and disappointments: a different perspective to hotel attribute importance investigation. Asia Pac. J. Tourism Res. 7 (1), 29–35.
Duan, W., Gu, B., Whinston, A.B., 2008. Do online reviews matter?—an empirical investigation of panel data. Decis. Support. Syst. 45 (4), 1007–1016.
Dubey, R., Gunasekaran, A., Childe, S.J., Roubaud, D., Wamba, S.F., Giannakis, M., Foropon, C., 2019. Big data analytics and organizational culture as complements to swift trust and collaborative performance in the humanitarian supply chain. Int. J. Prod. Econ. 210, 120–136.
Dutta, S., Zbaracki, M.J., Bergen, M., 2003. Pricing process as a capability: a resource-based perspective. Strateg. Manag. J. 24 (7), 615–630.
Dutta, S., Biswas, A., Grewal, D., 2007. Low price signal default: an empirical investigation of its consequences. J. Acad. Mark. Sci. 35 (1), 76–88.
Duverger, P., 2013. Curvilinear effects of user-generated content on hotels' market share: a dynamic panel-data analysis. J. Travel Res. 52 (4), 465–478.
Erdem, T., Keane, M.P., Sun, B., 2008. A dynamic model of brand choice when price and advertising signal product quality. Mark. Sci. 27 (6), 1111–1125.
Erevelles, S., Fukawa, N., Swayne, L., 2016. Big data consumer analytics and the transformation of marketing. J. Bus. Res. 69 (2), 897–904.
Euromonitor International, 2019. Top 100 City Destinations, 2019 Edition. Retrieved from: http://go.euromonitor.com/rs/805-KOK719/images/wpTop100Cities19.pdf. Accessed 18.04.2022.
Falavigna, G., Ippoliti, R., Manello, A., Ramello, G.B., 2015. Judicial productivity, delay and efficiency: a directional distance function (DDF) approach. Eur. J. Oper. Res. 240 (2), 592–601.
Fang, Y.H., 2014. Beyond the credibility of electronic word of mouth: exploring eWOM adoption on social networking sites from affective and curiosity perspectives. Int. J. Electron. Commer. 18 (3), 67–102.
Farrell, M.J., 1957. The measurement of productive efficiency. J. R. Stat. Soc. 120, 253–281.
Filieri, R., 2015. What makes online reviews helpful? A diagnosticity-adoption framework to explain informational and normative influences in e-WOM. J. Bus. Res. 68 (6), 1261–1270.
Filieri, R., Mariani, M., 2021. The role of cultural values in consumers' evaluation of online review helpfulness: a big data approach. Int. Mark. Rev. 38 (6), 1267–1288.
Fishburn, P.C., Odlyzko, A.M., 1999. Competitive pricing of information goods: subscription pricing versus pay-per-use. Economic Theory 13 (2), 447–470.
Forbis, J.L., Mehta, N.T., 1981. Value-based strategies for industrial products. Bus. Horiz. 24 (3), 32–42.
Forman, C., Ghose, A., Wiesenfeld, B., 2008. Examining the relationship between reviews and sales: the role of reviewer identity disclosure in electronic markets. Inf. Syst. Res. 19 (3), 291–313.
Gallego, G., Van Ryzin, G., 1994. Optimal dynamic pricing of inventories with stochastic demand over finite horizons. Manag. Sci. 40 (8), 999–1020.
Gerstner, E., 1985. Do higher prices signal higher quality? J. Mark. Res. 22 (2), 209–215.
Gretzel, U., Yoo, K.H., 2008. Use and impact of online travel reviews. In: Information and Communication Technologies in Tourism, 2008, pp. 35–46.
Griffith, D.E., Rust, R.T., 1997. The price of competitiveness in competitive pricing. J. Acad. Mark. Sci. 25 (2), 109.
Guizzardi, A., Pons, F.M.E., Ranieri, E., 2017. Advance booking and hotel price variability online: any opportunity for business customers? Int. J. Hosp. Manag. 64, 85–93.
Guizzardi, A., Mariani, M.M., Stacchini, A., 2022. A temporal construal theory explanation of the price-quality relationship in online dynamic pricing. J. Bus. Res. 146, 32–44.
Guo, Y., Barnes, S.J., Jia, Q., 2017. Mining meaning from online ratings and reviews: tourist satisfaction analysis using latent dirichlet allocation. Tour. Manag. 59, 467–483.
Gupta, M., George, J.F., 2016. Toward the development of a big data analytics capability. Inf. Manag. 53 (8), 1049–1064.
Hallberg, N.L., 2018. Managing value appropriation in buyer–supplier relationships: the role of commercial decision resources. Eur. Manag. J. 36 (1), 125–134.
Hanks, R.D., Cross, R.G., Noland, R.P., 2002. Discounting in the hotel industry: a new approach. Cornell Hotel Restaur. Admin. Q. 43 (4), 94–103.
Hanson, W., 1992. The dynamics of cost-plus pricing. Manag. Decis. Econ. 13 (2), 149–161.
Haws, K.L., Bearden, W.O., 2006. Dynamic pricing and consumer fairness perceptions. J. Consum. Res. 33 (3), 304–311.
Hayek, F.A., 1945. The use of knowledge in society. Am. Econ. Rev. 35 (4), 519–530.
Hennig-Thurau, T., Gwinner, K.P., Walsh, G., Gremler, D.D., 2004. Electronic word-of-mouth via consumer-opinion platforms: what motivates consumers to articulate themselves on the internet? J. Interact. Mark. 18 (1), 38–52.
Hinterhuber, A., 2004. Towards value-based pricing—An integrative framework for decision making. Ind. Mark. Manag. 33 (8), 765–778.
Hinterhuber, A., 2008. Customer value-based pricing strategies: why companies resist. J. Bus. Strateg. 29 (4), 41–50. https://doi.org/10.1108/02756660810887079.
Hinterhuber, A., Liozu, S.M., 2012. Is it time to rethink your pricing strategy? MIT Sloan Manag. Rev. 53 (4), 69–77.
Hosseinzadeh, A., Hosseinzadeh Lotfi, F., Moghaddas, Z., 2016. Fuzzy efficiency: multiplier and enveloping CCR models. Int. J. Ind. Math. 8 (1), 1–8.
Hsieh, C.C., Chang, Y.L., Wu, C.H., 2014. Competitive pricing and ordering decisions in a multiple-channel supply chain. Int. J. Prod. Econ. 154, 156–165.
Hu, N., Koh, N.S., Reddy, S.K., 2014. Ratings lead you to the product, reviews help you clinch it? The mediating role of online review sentiments on product sales. Decis. Support. Syst. 57, 42–53.
Huang, C.W., Ho, F.N., Chiu, Y.H., 2014. Measurement of tourist hotels′ productive efficiency, occupancy, and catering service effectiveness using a modified two-stage DEA model in Taiwan. Omega 48, 49–59.
Hwang, S.N., Chang, T.Y., 2003. Using data envelopment analysis to measure hotel managerial efficiency change in Taiwan. Tour. Manag. 24 (4), 357–369.
Indounas, K., 2009. Successful industrial service pricing. J. Bus. Ind. Mark. 24 (1–2), 86–96.
Ingenbleek, P., 2014. The theoretical foundations of value-informed pricing in the service-dominant logic of marketing. Manag. Decis. 52 (1), 33–53.
Ingenbleek, P., Debruyne, M., Frambach, R.T., Verhallen, T.M.M., 2003. Successful new product pricing practices: a contingency approach. Mark. Lett. 14 (4), 289–305.
Ingenbleek, P.T.M., Frambach, R.T., Verhallen, T.M.M., 2013. Best practices for new product pricing: impact on market performance and price level under different conditions. J. Prod. Innov. Manag. 30 (3), 560–573.
Iqbal, R., Doctor, F., More, B., Mahmud, S., Yousuf, U., 2020. Big data analytics: computational intelligence techniques and application areas. Technol. Forecast. Soc. Chang. 153, 119253.
Johansson, M., Hallberg, N., Hinterhuber, A., Zbaracki, M., Liozu, S., 2012. Pricing strategies and pricing capabilities. J. Revenue Pricing Manag. 11 (1), 4–11.
Kienzler, M., 2018. Value-based pricing and cognitive biases: an overview for business markets. Ind. Mark. Manag. 68, 86–94.
Kienzler, M., Kowalkowski, C., 2017. Pricing strategy: a review of 22 years of marketing research. J. Bus. Res. 78, 101–110.

Kim, W.G., Lim, H., Brymer, R.A., 2015. The effectiveness of managing social media on hotel performance. Int. J. Hosp. Manag. 44, 165–171.
Kim, J.M., Lee, E., Mariani, M.M., 2021. The influence of launching mobile channels on online customer reviews. J. Bus. Res. 137, 366–378.
Kimes, S.E., 2010. Strategic Pricing Through Revenue Management.
Klein, R., Koch, S., Steinhardt, C., Strauss, A.K., 2020. A review of revenue management: recent generalizations and advances in industry applications. Eur. J. Oper. Res. 284 (2), 397–412.
Kurz, W., Többens, T., 2012. Global pricing survey: Managing global pricing excellence. Retrieved from. https://www2.deloitte.com/content/dam/Deloitte/de/Documents/strategy/C-studie-b2b-pricing_122012.pdf.
Lee, M.K., Shi, N., Cheung, C.M., Lim, K.H., Sia, C.L., 2011. Consumer's decision to shop online: the moderating role of positive informational social influence. Inf. Manag. 48 (6), 185–191.
Lee, S., Garrow, L.A., Higbie, J.A., Keskinocak, P., Koushik, D., 2011. Do you really know who your customers are?: a study of US retail hotel demand. Journal of Revenue and Pricing Management 10 (1), 73–86.
Liang, W.K., Corkindale, D., 2019. How eWord of mouth valences affect price perceptions. Int. J. Mark. Res. 61 (1), 50–63.
Liozu, S.M., 2015. Pricing superheroes: how a confident sales team can influence firm performance. Ind. Mark. Manag. 47, 26–38.
Liozu, S.M., 2017. State of value-based-pricing survey: perceptions, challenges, and impact. J. Revenue Pricing Manag. 16 (1), 18–29.
Liozu, S.M., Hinterhuber, A., 2013. Pricing orientation, pricing capabilities, and firm performance. Manag. Decis. 51 (3), 594–614.
Liozu, S.M., Hinterhuber, A., Perelli, S., Boland, R., 2012. Mindful pricing: transforming organizations through value-based pricing. J. Strateg. Mark. 20 (3), 197–209.
Liu, J.S., Lu, L.Y., Lu, W.M., Lin, B.J., 2013. A survey of DEA applications. Omega 41 (5), 893–902.
Malc, D., Mumel, D., Pisnik, A., 2016. Exploring price fairness perceptions and their influence on consumer behavior. J. Bus. Res. 69 (9), 3693–3697.
Mariani, M., Wamba, S.F., 2020. Exploring how consumer goods companies innovate in the digital age: The role of big data analytics companies. J. Bus. Res. 121, 338–352.
Mariani, M., Baggio, R., 2022. Big data and analytics in hospitality and tourism: a systematic literature review. Int. J. Contemp. Hosp. Manag. 34 (1), 231–278.
Mariani, M.M., Borghi, M., 2018. Effects of the Booking. com rating system: Bringing hotel class into the picture. Tour. Manage. 66, 47–52.
Mariani, M.M., Borghi, M., 2020. Online review helpfulness and firms' financial performance: an empirical study in a service industry. Int. J. Electron. Commer. 24 (4), 421–449.
Mariani, M., Borghi, M., 2022. Exploring environmental concerns on digital platforms through big data: the effect of online consumers' environmental discourse on online review ratings. J. Sustain. Tour. https://doi.org/10.1080/09669582.2022.2033982.
Mariani, M.M., Matarazzo, M., 2021. Does cultural distance affect online review ratings? Measuring international customers' satisfaction with services leveraging digital platforms and big data. J. Manag. Gov. 25 (4), 1057–1078.
Mariani, M.M., Nambisan, S., 2021. Innovation analytics and digital innovation experimentation: the rise of research-driven online review platforms. Technol. Forecast. Soc. Chang. 172, 121009.
Mariani, M.M., Visani, F., 2019. Embedding eWOM into efficiency DEA modelling: an application to the hospitality sector. Int. J. Hosp. Manag. 80, 1–12.
Mariani, M., Baggio, R., Fuchs, M., Höepken, W., 2018. Business intelligence and big data in hospitality and tourism: a systematic literature review. Int. J. Contemp. Hosp. Manag. 30 (12), 3514–3554.
Mazumdar, T., Raj, S.P., Sinha, I., 2005. Reference price research: review and propositions. J. Mark. 69 (4), 84–102.
Monroe, K.B., 2003. Pricing: Making Profitable Decisions, 3rd ed. McGraw-Hill, New York, NY.
Mortensen, D.T., Wright, R., 2002. Competitive pricing and efficiency in search equilibrium. Int. Econ. Rev. 43 (1), 1–20.
Myers, M.B., 1997. The pricing of export products: why aren't managers satisfied with the results? J. World Bus. 32 (3), 277–289.
Nagle, T.T., Holden, R.K., 2002. The Strategy and Tactics of Pricing: A Guide to Growing More Profitably. Pearson/Prentice Hall, Upper Saddle River, NJ.
Nieto, J., Hernández-Maestro, R.M., Muñoz-Gallego, P.A., 2014. Marketing decisions, customer reviews, and business performance: the use of the toprural website by spanish rural lodging establishments. Tour. Manag. 45, 115–123.
Öğüt, H., Onur Taş, B.K., 2012. The influence of internet customer reviews on the online sales and prices in hotel industry. Serv. Ind. J. 32 (2), 197–214.
Pan, W.T., Zhuang, M.E., Zhou, Y.Y., Yang, J.J., 2021. Research on sustainable development and efficiency of China's E-agriculture based on a data envelopment analysis-malmquist model. Technol. Forecast. Soc. Chang. 162, 120298.
Park, D.H., Kim, S., 2008. The effects of consumer knowledge on message processing of electronic word-of-mouth via online consumer reviews. Electron. Commer. Res. Appl. 7 (4), 399–410.
Phillips, P., Zigan, K., Silva, M.M.S., Schegg, R., 2015. The interactive effects of online reviews on the determinants of Swiss hotel performance: a neural network analysis. Tour. Manag. 50, 130–141.
Porter, M.E., 2001. The value chain and competitive advantage. In: Understanding Business Processes, pp. 50–66.
Quaranta, A.G., Raffoni, A., Visani, F., 2018. A multidimensional approach to measuring bank branch efficiency. Eur. J. Oper. Res. 266 (2), 746–760.
Rajendran, K.N., Tellis, G.J., 1994. Contextual and temporal components of reference price. J. Mark. 58 (1), 22–34.
Ramanathan, R., Ramanathan, U., Zhang, Y., 2016. Linking operations, marketing and environmental capabilities and diversification to hotel performance: a data envelopment analysis approach. Int. J. Prod. Econ. 176, 111–122.
Rana, N.P., Chatterjee, S., Dwivedi, Y.K., Akter, S., 2021. Understanding dark side of artificial intelligence (AI) integrated business analytics: assessing firm's operational inefficiency and competitiveness. Eur. J. Inf. Syst. https://doi.org/10.1080/0960085X.2021.1955628.
Schuckert, M., Liu, X., Law, R., 2015. A segmentation of online reviews by language groups: how english and non-english speakers rate hotels differently. Int. J. Hosp. Manag. 48, 143–149.
Shamohammadi, M., Oh, D.H., 2019. Measuring the efficiency changes of private universities of Korea: a two-stage network data envelopment analysis. Technol. Forecast. Soc. Chang. 148, 119730.
Shen, Z.J.M., Su, X., 2007. Customer behavior modeling in revenue management and auctions: a review and new research opportunities. Prod. Oper. Manag. 16 (6), 713–728.
Shipley, D., Jobber, D., 2001. Integrative pricing via the pricing wheel. Ind. Mark. Manag. 30 (3), 301–314.
Smith, G.E., 1995. Managerial pricing orientation: the process of making pricing decisions. Pricing Strat. Pract. 3 (3), 28.
Soriano, D.R., 2002. Customers' expectations factors in restaurants: the situation in Spain. Int. J. Qual. Reliabil. Manag. 19 (8/9), 1055–1067.
Soriano, D.R., 2003. The spanish restaurant sector: evaluating the perceptions of quality. Serv. Ind. J. 23 (2), 183–194.
Sun, M., 2012. How does the variance of product ratings matter? Manag. Sci. 58 (4), 696–707.
Sun, T., Youn, S., Wu, G., Kuntaraporn, M., 2006. Online word-of-mouth (or mouse): an exploration of its antecedents and consequences. J. Comput.-Mediat. Commun. 11 (4), 1104–1127.
Töytäri, P., Rajala, R., 2015. Value-based selling: an organizational capability perspective. Ind. Mark. Manag. 45, 101–112.
Töytäri, P., Rajala, R., Alejandro, T.B., 2015. Organizational and institutional barriers to value-based pricing in industrial relationships. Ind. Mark. Manag. 47, 53–64.
UNWTO, 2021. International tourism highlights. Retrieved 21.04.2020 from: https://www.e-unwto.org/doi/pdf/10.18111/9789284422456.
Visani, F., Boccali, F., 2020. Purchasing price assessment of leverage items: a data envelopment analysis approach. Int. J. Prod. Econ. 223, 107521.
Völckner, F., Hofmann, J., 2007. The price-perceived quality relationship: a meta-analytic review and assessment of its determinants. Mark. Lett. 18 (3), 181–196.
Vrontis, D., Siachou, E., Sakka, G., Chatterjee, S., Chaudhuri, R., Ghosh, A., 2022. Societal effects of social media in organizations: reflective points deriving from a systematic literature review and a bibliometric meta-analysis. Eur. Manag. J. 40 (2), 151–162.
Wamba, S.F., Akter, S., Edwards, A., Chopin, G., Gnanzou, D., 2015. How 'big data'can make big impact: findings from a systematic review and a longitudinal case study. Int. J. Prod. Econ. 165, 234–246.
Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J.F., Dubey, R., Childe, S.J., 2017. Big data analytics and firm performance: effects of dynamic capabilities. J. Bus. Res. 70, 356–365.
Wang, B., Anderson, T.R., Zehr, W., 2016. Competitive pricing using data envelopment analysis—pricing for oscilloscopes. Int. J. Innov. Technol. Manag. 13 (01), 1650006.
Wedel, M., Kannan, P.K., 2016. Marketing analytics for data-rich environments. J. Mark. 80 (6), 97–121.
Winer, R.S., 1986. A reference price model of brand choice for frequently purchased products. J. Consum. Res. 13 (2), 250–256.
Xia, L., Monroe, K.B., Cox, J.L., 2004. The price is unfair! A conceptual framework of price fairness perceptions. J. Mark. 68 (4), 1–15.
Yakubu, H., Kwong, C.K., 2021. Forecasting the importance of product attributes using online customer reviews and Google trends. Technol. Forecast. Soc. Chang. 171, 120983.
Yang, Y., Park, S., Hu, X., 2018. Electronic word of mouth and hotel performance: a meta-analysis. Tour. Manag. 67, 248–260.
Yao, D.Q., Liu, J.J., 2005. Competitive pricing of mixed retail and e-tail distribution channels. Omega 33 (3), 235–247.
Yavas, U., Babakus, E., 2005. Dimensions of hotel choice criteria: congruence between business and leisure travelers. Int. J. Hosp. Manag. 24 (3), 359–367.
Ye, Q., Law, R., Gu, B., 2009. The impact of online user reviews on hotel room sales. Int. J. Hosp. Manag. 28 (1), 180–182.
Yin, P., Chu, J., Wu, J., Ding, J., Yang, M., Wang, Y., 2020. A DEA-based two-stage network approach for hotel performance analysis: an internal cooperation perspective. Omega 93, 102035.
Zeithaml, V.A., Bitner, M.J., Gremler, D.D., 2018. Services marketing: integrating customer focus across the firm. McGraw-Hill Education.
Zhang, Z., Ye, Q., Law, R., 2011. Determinants of hotel room price: An exploration of travelers' hierarchy of accommodation needs. Int. J. Contemp. Hosp. Manag. 23 (7), 972–981. https://doi.org/10.1108/09596111111167551.
Zhang, Q., Tang, W., Zaccour, G., Zhang, J., 2019. Should a manufacturer give up pricing power in a vertical information-sharing channel? Eur. J. Oper. Res. 276 (3), 910–928.
Zhou, H., Yang, Y., Chen, Y., Zhu, J., 2018. Data envelopment analysis application in sustainability: the origins, development and future directions. Eur. J. Oper. Res. 264 (1), 1–16.

Filippo Boccali is a Research Fellow at Department of Management at the University of Bologna. He is engaged in a project on the assessment of the financial impact of innovative industrial additive manufacturing production technologies. He teaches in several full time

Masters or Executive programs at Bologna Business School, with a focus on cost accounting, management control, cost management, performance management systems, and the role that business performance analytics can play to support performance management and decision making processes.

Franco Visani, **Ph.D.**, is an Associate Professor of Management Accounting at the University of Bologna. He is the Director of the Hybrid MBA at Bologna Business School, where he also teaches in several postgraduate and executive programs. In the last 20 years he has been part of several international research projects dealing with performance measurement and management. His research is mainly focused on the role that Business Analytics can play to support performance management and decision making.

Marcello Mariani, **PhD**, is a Professor of Management and Entrepreneurship at the Henley Business School, University of Reading (UK) and University of Bologna (Italy). His current research interests include big data and analytics, digital business models, AI, IoT. His researches have been published in *Harvard Business Review*, *Long Range Planning*, *Technological Forecasting and Social Change*, *Psychology & Marketing*, *MIT Sloan Management Review*, *Industrial and Corporate Change*, *Journal of Business Research*, *Industrial Marketing Management*, *Journal of Advertising*, *International Journal of Electronic Commerce*, *Tourism Management*, *Annals of Tourism Research*, *Journal of Travel Research*, *International Journal of Contemporary Hospitality Management*, *International Journal of Hospitality Management*, *European Management Journal*, *European Accounting Review*, *International Studies in Management and Organizations*, *Journal of Destination Management and Marketing*, and more.

Alexandra Mora-Cruz is a Doctor candidate for the Doctorate in Business Administration from the Technological Institute of Costa Rica (TEC), Business Administrator and Master in Business Administration with an emphasis on Finance. Coordinator of the Center for Research and Business Development (CIDE-TEC). University professor in the area of Administration. Specialist in Mediation of Virtual Environments.