Factors Influencing Hotels’ Online Prices

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ABSTRACT

Digital corporations are creating new paths of business driven by consumers empowered by social media. Understanding the role that each feature drawn from online platforms has on price fluctuation is vital for leveraging decision-making. In this study, 5,603 simulations of online reservations from 23 Portuguese cities were gathered, including characterizing features from social media, web visibility, and hotel amenities, from four renowned online sources: Booking.com, TripAdvisor, Google, and Facebook. After data preparation, including removal of irrelevant features in terms of modeling and outlier cleaning, a tuned dataset of 3,137 simulations and 30 features (including the price charged per day) was used first for evaluating the modeling performance of an ensemble of multilayer perceptrons, and then for extracting valuable knowledge through the data-based sensitivity analysis. Findings show that all features from the encompassed factors (social media, online reservation, hotel characteristics, web visibility, and city) play a significant role in price.

Introduction

Pricing is at the core of any marketing strategy, including in the hospitality industry leveraging new paradigms of revenue management to incorporate technological evolution (McGuire, 2016). In the most recent decades, a plethora of new technologies have emerged to change the landscape of hotel accommodation booking. The advent of the Internet, which has been revolutionizing businesses worldwide since the 1990s, virtually enabled every organization, regardless of its size, to keep a cyber-presence, boosting its brand

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image to a planetary scale (Doherty & Ellis-Chadwick, 2010). Websites have evolved from static to dynamic user-generated contents as a result of the Web 2.0 revolution, by empowering consumers to an unforeseen level: Virtually every user is a content producer and may provide feedback on any product or service, thus influencing others through electronic word-of-mouth (eWOM) (Labrecque, Vor Dem Esche, Mathwick, Novak, & Hofacker, 2013). Corporations worldwide need to keep pace of their websites’ performance, measured by the rank position in queries performed on search engines, especially in Google, which dominates the landscape across the globe (Paraskevas, Katsogridakis, Law, & Buhalis, 2011). Google Ads is a tool commercialized by Google to help companies gain some control on the position its webpage ranks (Lee, 2011). Additionally, secured online payment systems enable hotel website visitors to finish the transaction and book rooms at the distance of a click (Li, Wang, & Yu, 2015). Furthermore, global scale pure digital players have emerged to dominate markets by offering digital services which facilitate customer acquisition of third-party products or services, such as hotel rooms’ booking (Alt & Zimmermann, 2015). Particularly relevant in the hospitality industry are especially designed customer feedback sites such as TripAdvisor, where users may score hotel units and/or analyze other tourists’ opinions (Ayeh, Au, & Law, 2016). Such profusion of information can be effectively used by managers to support their pricing strategies.

Social media and Online Travel Agencies (OTAs) have brought price transparency to an unforeseen level from a consumer perspective (McGuire, 2016). Today a tourist will likely access to an online customer reviews’ platform to assess others’ opinions before making the purchase, probably complementing the information by going to the hotel’s website to obtain additional information on the amenities provided and detailed photos. Then, the user can access an OTA and compare the prices practiced by the different alternatives previously identified, before finally booking a room. This motivational example highlights the need for hoteliers to account for all the information that may influence tourists’ decisions when defining prices (Xu, Xiao, & Gursoy, 2017). Two recent studies were also devoted to analyzing prices on a wide scale (Oses, Gerrikagoitia, & Alzua, 2016a, 2016b). The first study gathered data from digital footprint from the Balearic Islands, while the second used a data scraping bot to collect prices from Booking.com from the Basque Country. Nevertheless, neither considered hotels’ scores on social media nor hotels’ amenities. The present study aims at filling such research gap by unveiling the factors contributing to price definition through an advanced data mining model.

**Literature review**

**Online booking and social media**

The development of new Internet-based information systems has driven the task of booking rooms in hotels toward online booking, whether using hotels’ websites or through global OTAs, with the latter prevailing as the dominant source of online booking (Park, Ha, & Park, 2017; Tse, 2013). Moreover, the hospitality industry was among the first sectors to embrace online customer feedback. Through specifically designed review sites such as TripAdvisor, tourists are able to report their experiences in both quantitative scores and textual comments, influencing prospective users (Jeacle & Carter, 2011).
Generic social networks can also be powerful eWOM tools within the hospitality industry, with literature acknowledging such relevance (Nunkoo, Gursoy, & Ramkissoon, 2013). Specifically, hotel managers are aware of the importance of Facebook, and most hotels currently have an official Facebook page where users can write comments, or “like” publications (Leung, Bai, & Stahura, 2015). Additionally, hotels can also be rated, and tourists who stayed in the hotel can mark their photos as having been there, increasing the count of the number of stays at the hotel. Nevertheless, no study was found using such specific information.

Each of the numerous available sources of information can play a role in the consumer purchasing decision (Moon & Kamakura, 2017). Murphy and Chen (2016) evaluated online sources used in hotel bookings and concluded that all online communication channels should be accounted for within a consistent marketing communication strategy, including search engines for a first assessment of hotel offers, and OTAs and review sites on a second information level.

Understanding the distinct influencing dimensions on users’ behavior is a key asset for supporting managerial decisions in the current Big Data world. As such, hoteliers need to cope with all available variables, including those they cannot control, in order to incorporate in-depth knowledge in their e-marketing strategies to thrive and excel in a smaller and interconnected world.

**Hotel booking and pricing**

Revenue management emerged in the hospitality industry to leverage decision-making on the most profitable mix of variables influencing revenue, including the number of rooms sold and the price paid for each room. However, new communication media including both OTAs and online reviews’ platforms pose big challenges in a social world (Noone, Enz, & Glassmire, 2017). Managers need to conceive adequate pricing strategies in a difficult context facing price transparency, as users now can simulate bookings at the distance of a click and easily compare the prices offered for similar services (McGuire, 2016).

Recently, Kimes (2017) identified the following major drivers for change in revenue management: information technology, data analytics followed by mobile technology and economic conditions. Moreover, Yacouel and Fleischer (2012) found that hotels which received higher scores on OTAs charge higher prices, showing an effect of price based on customer rating. Ling, Guo, and Yang (2014) studied an optimal online pricing strategy for a hotel being promoted in an OTA. Through sensitivity analysis, these authors unveiled a higher likelihood of larger profits for hotel units with a lower occupancy rate prior to establishing a promotion agreement with an OTA. However, their study considered only both hotel and OTA characteristics, not accounting for other dimensions such as consumer behavior (e.g., the days ahead of reservation or the length of stay) or the social media effect. According to Anderson (2012), social media holds the potential to move markets by driving consumers’ purchasing intentions, thus influencing lodging performance. In fact, online feedback on social media platforms is a driving force that hotel managers cannot afford to neglect (Calheiros, Moro, & Rita, 2017).
Data and text mining on hotel booking website

Several techniques are available for modeling price, such as the traditional linear regression, and decision trees, along with the most sophisticated neural networks and support vector machines (Cortez, 2010). While data mining models can provide predictive knowledge by directly applying the model to new input data for prediction of an outcome, these models can also be used to obtain explanatory knowledge, by understanding how the model was conceived when it acquired knowledge from the data used for training it. A few methods can be used, such as rules extraction and sensitivity analysis. While the former might fail at assessing the representativeness of the model due to disregard of relevant rules and danger of generalization mainly resultant of discretization of the complex nonlinear relations hidden within the model, the latter constitutes an interesting approach by its noninvasive nature as it is based on varying the input features through their range of possible values to assess how sensitive such changes are on the outcome (Cortez & Embrechts, 2013). Moreover, in the present study, the data-based sensitivity analysis (DSA) is adopted as it considers variations of multiple features at the same time, allowing to disentangle inter-related features. Although such method is recent (it was introduced in 2013), it has already been successfully applied to a wide range of problems such as in bank telemarketing (Moro, Cortez, & Rita, 2015) and social media (Moro, Rita, & Vala, 2016), as well as for modeling TripAdvisor’s score of hotels (Moro, Rita, & Coelho, 2017).

Recent research suggests that data mining is an increasingly relevant trend in tourism and hospitality, especially in the current Big Data age with manifold sources (Schuckert, Liu, & Law, 2015). Nevertheless, it should be stressed that a large portion of research on tourism using data mining is still devoted to forecasting tourism demand, one of the most prolific and interesting domains from a managerial perspective (Moro & Rita, 2016). Radojevic, Stanisic, and Stanic (2015) included as inputs to their linear mixed model features on hotel amenities, the hotel number of stars, location, and the price effect, as measured by the average city accommodation price and the specific hotel price. The same authors modeled customer experience (hotel score given by tourists) and found that the most influencing features on the score were the hotel star rating system and the prices. A recent hot topic consists in extracting knowledge from unstructured textual contents gathered from social media, such as the comments contained in online reviews (Calheiros et al., 2017). Text mining enables to find hidden patterns within text, helping to achieve a deeper understanding of customer feedback through the analysis of a large number of reviews. Such knowledge may be presented in coherent topics aggregating meaningful reviews classified by relevant words (Guo, Barnes, & Jia, 2017) or through the identification of determinant factors characterized by high-loading terms (Xu & Li, 2016).

Methods

Data collection and preparation

The geographic location of hotel units is a known key influencing factor of tourism demand and thus of the prices charged for accommodation (Radojevic et al., 2015). It is usually associated with the brand image and awareness of each specific tourist location (Sahin & Baloglu, 2014). Therefore, this study focuses on Portugal, an attractive tourist
country, with tourism accounting as one of the major economic sectors. Although being a small country in Europe, it holds regional asymmetries and a high seasonality degree, with a summer peak as a result of its attractive shore line with renowned beaches (Andraz, Norte, & Gonçalves, 2015). The tourist destinations included the 18 continental district capitals plus five renowned tourist cities.

Data are the key raw ingredient for successful data mining experiments. Considering the present research is an attempt to incorporate as many factors as possible that may have an impact on hotel price, several sources were in demand for collecting the required data. In order to maximize the impact each information source has on users, the chosen online sources were the top ranked brands for each type of information. As a main source for all online booking simulations, Booking.com was used, as it is considered one of the main-streams in OTA (Yacouel & Fleischer, 2012). Although Booking.com also implements a scoring system for tourists to rate hotel units, the recent research note by Mellinas, María-Dolores, and García (2015) uncovered an important limitation: Its rating system ranges from 2.5 to 10, although several previous studies using data from Booking.com seem to account for a more standard 0–10 scale. Subsequent study by the same authors concludes its rating system significantly distorts scores, particularly in hotels with low and medium scores (Mellinas, María-Dolores, & García, 2016). Given such evidence, the present study does not include scores granted on Booking.com; instead, it adopts the most renowned tourism and hospitality scoring platform, TripAdvisor (Jeacle & Carter, 2011), and the social network that spreads across the globe, Facebook, reaching 2.01 billion monthly active users as of June 30, 2017 (Facebook, 2017). Furthermore, recent literature has shown consistency between Booking.com and TripAdvisor (e.g., Băltescu, 2015; Marchiori, Eynard, Inversini, Cantoni, & Cerretti, 2011). Nevertheless, a comparison was made between the scores granted on Booking.com and on TripAdvisor. Table 1 shows consistency between the two platforms for the hotels considered in the dataset. As tourists are becoming increasingly aware of online reviews, it seems to contribute to standardizing hotels’ scores in online platforms. Yet, it is a subject where more research is in demand to fully assess such level of standardization. The fourth source included is Google, the search engines’ conspicuous market leader (Miklošík & Daňo, 2016). Figure 1 shows how each of the four global online data sources was used in the procedure to gather all data (and provides a few examples of the collected features), which is explained shortly.

The procedure for collecting the data consisted in creating a set of online booking scenarios for each of the 23 cities, considering the following guidelines: attempting to book a room through Booking.com on a few hotel units, varying the number of adults (one or two, considering most hotels do not allow more than two adults in the same room), the number of children (to a maximum of two, considering also most hotels do not allow more than two in the same room with adults, and setting the age to the constant of

| TripAdvisor score | Average | Std. dev. |
|-------------------|---------|-----------|
| 3.0               | 7.43    | 0.44      |
| 3.5               | 7.80    | 0.35      |
| 4.0               | 8.33    | 0.31      |
| 4.5               | 8.95    | 0.28      |
| 5.0               | 9.24    | 0.32      |
4 years), the number of days ahead of reservation (considering short-, medium-, and long-
term schedules, during 2016 and 2017), and the duration of the stay. To accomplish such
task, 23 volunteers were assigned a city each and asked to perform bookings considering
real scenarios that would make sense in their case for different real situations (including
business and leisure travels). After reaching the purchase page (but without
finishing it),
all required reservation data were collected, thus ensuring real online information would
be used for the empirical research. At least 200 simulations were collected for each city, to
assure a reasonable number of different cases.

The experiments were conducted in the first quarter of 2016, with all reservations
encompassed within the years of 2016 and 2017 (from February 2016 to August 2017). The
hotel characteristics (e.g., number of stars) were gathered from Booking.com, while also
performing a search on Google and collecting additional data if the hotel had a website.
While a vast number of amenities are available, this study focused specifically on those which
are different among the studied hotels. Therefore, we considered free Wi-Fi, as Radojevic
et al. (2015) also did, but did not include the other two used by the aforementioned authors
(air conditioning and lobby bar), since all the units in the dataset offered them. Additionally,
eight other amenities were included that presented a differentiating factor among the studied units. While many more could be included, it is very difficult to identify all possible features that may affect customer satisfaction, given the vast array available.

Both TripAdvisor and Facebook were accessed to gather customer scores on the hotels. Table 2 shows all the features collected. The selected hotels were the ones shown on the first page results from the query on Booking.com for each city, while the simulations consisted in varying the period of stay and the number of people (features marked with source = “user”). The price considered for this study was the lowest result among the different types of rooms available for the designated number of people and period, considering Booking.com suggests a few possibilities, when available. Google was used for two types of search: first, by querying with the quoted hotel name; then, by querying with “hotels” plus the city name, for assessing

| Table 2. Features collected. | Feature name | Source | Type | Description |
|-------------------------------|--------------|--------|------|-------------|
| city                          | –            | Categorical | City |             |
| hotel.name                   | User         | Categorical | Hotel name |             |
| stars                        | Booking      | Numerical | Stars in the hotel ranking system |             |
| outdoor.pool                 | Booking      | Categorical | If it has outdoor pool (yes/no) |             |
| indoor.pool                  | Booking      | Categorical | If it has indoor pool (yes/no) |             |
| spa                           | Booking      | Categorical | If it has SPA (yes/no) |             |
| free.park                    | Booking      | Categorical | If it has free park (yes/no) |             |
| free.wifi                    | Booking      | Categorical | If it has free Wi-Fi (yes/no) |             |
| late.checkout                | Booking      | Categorical | If it allows late checkout (yes/no) |             |
| near.beach                   | Booking      | Categorical | If it is located near a beach (yes/no) |             |
| near.city.center             | Booking      | Categorical | If it is located near city center (yes/no) |             |
| all.inclusive. option        | Booking      | Categorical | If it has all inclusive option (yes/no) |             |
| day.reserv                   | User         | Date     | Day when the reservation was made |             |
| stay.start.dt                | User         | Date     | Start of the period of stay |             |
| stay.finish.dt               | User         | Date     | End of the period of stay |             |
| stay.length                  | User         | Numerical | Length of stay in number of days |             |
| nr.adults                    | User         | Numerical | Number of adults booked |             |
| nr.children                  | User         | Numerical | Number of children (with 4 years old) |             |
| price                        | Booking      | Numerical | Lowest price available for the stay |             |
| nr.hits                      | Google       | Numerical | Number of hits when searching for the hotel name in Google (within quotation) |             |
| nr.hits.hotel.plus.city      | Google       | Numerical | Number of hits when searching for the string “hotels <city name>” in Google |             |
| website                      | Google       | Categorical | If it has a website |             |
| website.booking              | Hotel        | Categorical | If its website (assuming it has one) allows online reservation |             |
| website.online. pay          | Hotel website | Categorical | If its website (assuming it has one) allows online payment |             |
| google.ads                   | Google       | Categorical | If the hotel appears in Google Ads (yes/no) |             |
| google.ads.link              | Google       | Categorical | The page that the Google Ads links to: Hotel website; Online travel agency; Others. |             |
| has.facebook                 | Facebook     | Categorical | If the hotel has a Facebook page |             |
| fb.official                  | Facebook     | Categorical | If it is an official Facebook page |             |
| fb.likes                     | Facebook     | Numerical | Number of likes in Facebook (0 if no Facebook page) |             |
| fb.stays                     | Facebook     | Numerical | Number of stays identified in Facebook (0 if no page) |             |
| fb.nr.reviews                | Facebook     | Numerical | Number of reviews of the hotel in Facebook (0 if no page) |             |
| fb.score                     | Facebook     | Numerical | Score of the hotel in Facebook |             |
| tripadvisor.nr. reviews      | TripAdvisor  | Numerical | Number of reviews of the hotel in TripAdvisor |             |
| geo.type                     | Booking      | Categorical | (Urban; Resort; Others) |             |
| global.brand                 | Booking      | Categorical | If it is a global or an independent brand (yes/no) |             |
| service.level                | Booking      | Categorical | (Word-class; Mid-range; Limited) |             |
| tripadvisor.score            | TripAdvisor  | Numerical | Score of the hotel in TripAdvisor |             |
the range of hits as a result of the brand image associated with the city name, which may influence hotel prices (Sahin & Baloglu, 2014). For hotels with their own websites, two types of information were gathered: if the website allowed online reservation, and if it provided an online payment system. For the case of Google Ads, besides finding if the hotel appeared in any advertisement, the link to which the ad redirected the browser was also accounted for, as shown in Table 2. From Facebook, a few different metrics were collected. Some hotels have official Facebook pages, while other pages are marked as unofficial. Also, besides the usual number of likes, if a user stays in a hotel and publishes a photo marking it as being taken in the hotel, the number of stays increases. Facebook also provides a scoring system from 1 to 5, similar to TripAdvisor, which was also taken into account, along with the number of reviews (with a higher number strengthening the hotel score, helping to build its reputation, as shown by Yacouel & Fleischer, 2012).

A total of 5,603 simulations were made and gathered through the procedure described and illustrated in Figure 1. However, 2,466 were discarded (almost 42.6%) due to four main reasons identified in Table 3. Hence, a total of 3,137 remained to be used for building the pricing model. The data preparation procedure resulted in 11 original features being removed (Table 4). Outliers for numerical data were identified using boxplots (e.g., Figure 2), and extremely unbalanced binary features were also discarded, according to Forman's (2003) recommendation. Also, new features were computed, as described in Table 5. For example, a new feature accounting for the non-working days

### Table 3. Simulations discarded.

| No. of simulations | Discarded | Reason                                                                 |
|--------------------|-----------|------------------------------------------------------------------------|
| 5603               | 1345      | A significant portion of the simulations resulted in that there was no room available for the hotel in the chosen period (since there was no price to be modeled, the rows were discarded). |
| 4258               | 551       | Some of the accommodation units were not hotels at all (e.g., hostels), thus were not rated with the star system, which was considered highly influential by Radojevic et al. (2015). |
| 3707               | 489       | Although Facebook is the most widely studied social network concerning brand image, some hotels do not have yet a Facebook page. |
| 3218               | 81        | Most of the simulations encompassed a stay period of seven or less days. Figure 2 enabled to identify outliers, which were removed (Schwertman, Owens, & Adnan, 2004). |
| 3137               | 2466      |                                                                           |

### Table 4. Features discarded.

| Feature               | Reason                                                                 |
|-----------------------|------------------------------------------------------------------------|
| hotel.name            | Data were collected for 216 hotels, a too diverse number for being useful for modeling. Both of these features were used for computing the number of days ahead of schedule. |
| day.reserv            | This feature does not add information, as the dataset also contains the length of stay. The price collected represents all the days of the stay, while the price to be modeled is the price per day, which was computed by dividing the price by the length of stay. |
| stay.start.dt         |                                                                           |
| stay.finish.dt        |                                                                           |
| price                 |                                                                           |
| google.ads            | This feature was removed considering every search resulted in at least one advertisement, hence it was set to “Yes” for every case. |
| has.facebook          | Since all simulations with hotels that did not have a Facebook page were discarded, this feature turned useless. |
| website               | Since most hotels have websites and allow online booking, these features were removed, keeping only “website.online.pay”, which is directly dependent on the remaining two. |
| website.booking       |                                                                           |
| free.wifi             | Only 2.1% did not offer Wi-Fi; offering Wi-Fi is a trend which is expected to increase in the future (Mellán-González & Bulchand-Gidumal, 2016). |
| all.inclusive.option  | Only 2.73% of the hotels considered offered all inclusive option. |

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encompassed in the period of stay was computed to address the different prices practiced by hoteliers depending on the days (Sainaghi, 2010). The resulting dataset included a total of 30 features listed in Table 6, including the price per day (the outcome feature to be modeled) and 3,137 simulations.

**Data mining and knowledge extraction**

The result of the data collection and preparation procedures was a tuned dataset ready to feed a data mining algorithm to build the pricing model based on the remaining 29

**Table 5. New features computed.**

| Feature name          | Type     | Description                                                                                                                                 |
|-----------------------|----------|---------------------------------------------------------------------------------------------------------------------------------------------|
| reserv.days.ahead     | Numerical| stay.start.dt - day.reserv (in days); See Table 1 for details on the two features used for computing this one.                                |
| season                | Categorical| For the Northern Hemisphere, where Portugal is located: Spring (21/March–20/June); Summer (21/June–20/September); Autumn (21/September–20/December); Winter (21/December–20/March) |
| non.working.days      | Numerical| Accounts for the total number of weekend days (Saturdays and Sundays) and holidays during the length of stay.                               |
| price.per.day         | Numerical| price/stay.length                                                                                                                           |

Figure 2. Boxplot for the period of stay.

**Table 6. Features used for modeling.**

| Features                                                                 |
|--------------------------------------------------------------------------|
| From Table 2: city, stars, outdoor.pool, indoor.pool, spa, free.park, late.checkout, near.beach, near.city.center, stay.length, nr.adults, nr.children, nr.hits, nr.hits.hotel.plus.city, website.online.pay, google.ads, fb.official, fb.likes, fb.stays, fb.nr.reviews, fb.score, tripadvisor.nr.reviews, geo.type, global.brand, service.level, tripadvisor.score |
| From Table 5: reserv.days.ahead, season, non.working.days, price.per.day  |
| Total:                                                                  | 30                                                                                   |
features (identified in Table 6). For modeling price, the technique adopted was an ensemble of multilayer perceptrons, which has provided the most accurate models in several previous studies when compared to other advanced modeling techniques such as support vector machines (Moro, Cortez, & Rita, 2014). Neural networks are a computerized attempt to mimic the human brain, with neurons interconnected to determine a certain outcome based on patterns previously detected on input features which were used to train the network (Russell & Norvig, 2002). The multilayer perceptron is the most popular neural network architecture, with hidden layers (in most cases, one is enough) composed of several hidden nodes (neurons) and one final output node (Haykin, 2009). Figure 3 exhibits the structure of a simple network with one hidden layer composed of $m$ neurons, and $n$ input features, where each neuron is activated through an activation function $s_i = f_a \left( w_{i,0} + \sum_{j \in I} w_{ij}s_j \right)$. 

As a mean to assure modeling robustness, the followed procedure comprised of two stages: a model evaluation stage, and a knowledge extraction stage (both are illustrated in Figure 4). During model evaluation, the dataset was split into deciles, and a $k$-fold cross-validation computation was executed, with 9/10 of the simulations used for training the model and the remaining 1/10 for testing its performance in unforeseen data, allowing to assess prediction accuracy (Berry, McKeen, Pugsley, & Dalai, 2004). To further validate the procedure, a total of $N = 20$ runs were executed, and the average predictions were computed to address the fact that artificial neural networks are complex nonlinear models, thus each execution may provide different results. In this stage, both mean absolute error (MAE) and mean absolute percentage error (MAPE) were computed and evaluated to assure reasonable performance prediction metrics before stepping into the next stage. Knowledge extraction was accomplished by first building a model upon all the data, thus reflecting the hidden patterns of knowledge from all the gathered simulations. Thereafter, the most relevant features were analyzed in-depth through DSA for acquiring its effects on price, translating it into actionable knowledge to leverage hospitality business.

All the experiments described were programmed into the R statistical platform, a freeware and open source tool with a worldwide community of enthusiasts which provide a

![Figure 3. Scheme of a multilayer perceptron.](image-url)
myriad of packages for numerous purposes. Among those is the `rminer`, which implements a simple set of coherent functions for data mining, including the DSA (Cortez, 2010).

**Results and discussion**

The result of both the modeling evaluation and knowledge extraction model is displayed in Table 7 for both metrics. In the realistic predictive scenario of the modeling evaluation stage, MAE reveals an average discrepancy of €14.32 to the real prices, with MAPE showing a relative deviation of 12.70%. These metrics express good predictions, considering a multilayer perceptron model achieves an approximation of around 87% when modeling price. Hence, this first stage procedure validates the dataset and modeling technique. For knowledge extraction, all data are used to build the model, and the same data are then used to compute the difference of the model outcomes to the real prices, thus testing the fitting of the actual data. For this reason, MAE and MAPE are obviously better, achieving slightly lower error metrics. With an MAPE of around 10.6%, the model is then opened using DSA to extract knowledge on how it makes its decisions.

Table 7. Model performance metrics.

| Stages/metrics     | MAE      | MAPE     |
|--------------------|----------|----------|
| Modeling evaluation| €14.32   | 12.70%   |
| Knowledge extraction | €11.42€ | 10.64%   |

Figure 4. Data mining procedure.
DSA provided a rank of the booking simulation features that were used for modeling price. Table 8 shows the results in descending order of its relevance. The first interesting result to note is the fact that, while some features have a significantly higher relevance, there is not a single feature or group of features that clearly stand out, implying that each individual feature plays a role on price definition. To summarize the findings and provide a visual picture, each feature was categorized under one of five influencing groups: social media, reservation, hotel, city, and web visibility. Figure 5 unveils social media, hotel, and reservation features as the three most influencing groups. The results for Portugal are consistent with the current state of the art, as social media are increasingly relevant in pricing (Noone, McGuire, & Rohlfs, 2011), to add up to known influence of both hotel (Dev, Hamilton, & Rust, 2017) and reservation (Guo, Ling, Yang, Li, & Liang, 2013) features. Thus, the presented results emphasize the intrinsic bidirectional relationship between managers, which are concerned with their hotel’s brand image on social media and possibly adjust prices accordingly, and users’ eWOM. In addition to social media impact, web visibility is also playing a significant role, holding a relevance of around 15% to the price model, confirming previous studies (e.g., Yang, Pan, & Song, 2014). Therefore, it is actually possible to accurately model accommodation prices in hotels by including digital marketing variables on both social media and web visibility on searches, which together accounted for 42% of influence on prices (at least for the sample of gathered bookings). Such finding may be considered as a response to the research marketing agenda proposed by Kannan (2017).

### Table 8. Individual relevance of each feature for modeling price.

| #  | Feature                              | Influencing group | Relevance (%) | Total |
|----|--------------------------------------|-------------------|--------------|-------|
| 1  | hotel.avg.score.tripadvisor          | Social media      | 9.32         |       |
| 2  | nr.children                         | Reservation       | 7.40         |       |
| 3  | City                                 | City              | 6.92         |       |
| 4  | stars                                | Hotel             | 6.36         |       |
| 5  | nr.hits.hotel.plus.city             | Web visibility    | 6.31         |       |
| 6  | reserv.days.ahead                   | Reservation       | 6.00         |       |
| 7  | stay.length                         | Reservation       | 5.42         |       |
| 8  | website.online.pay                  | Web visibility    | 4.17         |       |
| 9  | fb.score                             | Social media      | 4.09         |       |
| 10 | global.brand                        | Hotel             | 3.86         | 59.84%|
| 11 | fb.likes                             | Social media      | 3.75         |       |
| 12 | fb.stays                            | Social media      | 3.29         |       |
| 13 | service.level                       | Hotel             | 3.07         |       |
| 14 | near.beach                          | Hotel             | 2.92         |       |
| 15 | google.ads                          | Web visibility    | 2.60         |       |
| 16 | geo.type                            | Hotel             | 2.55         |       |
| 17 | fb.nr.reviews                       | Social media      | 2.54         |       |
| 18 | nr.hits                             | Web visibility    | 2.28         |       |
| 19 | non.working.days                    | Reservation       | 2.17         |       |
| 20 | season                              | Reservation       | 2.10         |       |
| 21 | nr.reviews.tripadvisor              | Social media      | 1.93         |       |
| 22 | fb.official                         | Social media      | 1.89         |       |
| 23 | nr.adults                           | Reservation       | 1.88         |       |
| 24 | late.checkout                       | Hotel             | 1.86         |       |
| 25 | near.city.center                    | Hotel             | 1.61         |       |
| 26 | indoor.pool                         | Hotel             | 1.23         |       |
| 27 | outdoor.pool                        | Hotel             | 1.18         |       |
| 28 | spa                                  | Hotel             | 0.91         |       |
| 29 | free.park                           | Hotel             | 0.42         | 100.00%|
To further enlighten on the influence of the most relevant features, next paragraphs are devoted to analyze the 10 features that encompass around 60% of relevance, marked in white in Table 8. Figure 6 shows the pronounced effect that TripAdvisor score has on price. A previous study by Jeong and Mindy Jeon (2008) also found a similar effect on hotel’s performance, with experiments based on New York hotels. Therefore, this finding provides further evidence that hotel managers are paying special attention to TripAdvisor performance when deciding upon pricing strategies. The increasing global awareness toward the most known online reviews’ platforms implies that tourists are making judged decisions based on others’ opinions. Hotel managers are particularly concerned with the

Figure 5. Relevance per influencing group of features.

![Relevance per influencing group of features](image)

Figure 6. Influence of TripAdvisor score.

![Influence of TripAdvisor score](image)
undeniable power of TripAdvisor (Ayeh, Au, & Law, 2013) while, simultaneously, they are trying to use it as a competitive advantage to boost the positive visibility of their units (Calheiros et al., 2017). This dichotomy is expected to continue in the upcoming years.

The second most relevant feature discovered is the number of children included when booking the accommodation, with a relevance of 7.40%, almost 2% below the TripAdvisor score, emphasizing the influence of online reviews' platforms, in particular, TripAdvisor. Typically, hotels may provide one or two extra beds in the same room by charging an additional fee. Results illustrated in Figure 7 suggest that price increases from 101 to around 128 euros, almost 27% above the original price, while the second additional bed comes at a cost of around 34% over the price of a room with only one extra bed. According to Emel, Taskin, and Akat (2007), price-conscious travelers devote particular attention to the cost charged for extra beds, thus managers should carefully balance the fees by minimizing the impact on consumer's choice while aiming at a higher profit.

Even in a small country such as Portugal, the location context plays a key role, affecting hotels' prices: This is the third most relevant feature. It is possible to observe from Figure 8 that the capital and largest city, Lisboa, charges the highest prices. Interestingly, two highly promoted destinations with brand images known to online tourism (Oliveira, 2013), namely, Cascais and Sintra, charge similar prices to Lisboa. The next three cities associated with higher prices are Porto and Coimbra, the second and third largest Portuguese cities, and Faro, the Algarve district capital, highly potentiated by summer tourism (Andraz et al., 2015).

Figure 9 shows that the number of stars positively affects price, a widely known finding (Yacouel & Fleischer, 2012). While the star rate system is determined by independent entities, it reflects a mixed evaluation of services offered, features, rate, and satisfaction score, thus higher ranked hotels are typically those that charge the highest price.

In terms of web visibility, two features were also found to have an influence on price, namely the number of hits when querying Google with the city name plus the word “hotel”, and the flag that indicates if the hotel’s website implements an online payment system for easing clients’ reservations. For both, the results are consistently expected: Hotels in cities appearing more often in Google tend to charge higher prices (Figure 10), confirming city’s relevance in pricing (Figure 5); also, hotels offering online payment option charge higher

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**Figure 7.** Influence of the number of children.
prices (Figure 11). Both features exemplify the need to appear as an appealing tourist destination in Google while at the same time offering a complete online service to promote direct booking without depending on third-party platforms (e.g., Booking.com). Furthermore, the latter is associated with upscale hotels’ need to meet the expectations of a growing technology generation of tourists (Brochado, Rita, & Margarido, 2016).

With a relevance of 6%, the number of days ahead of reservation is the sixth most relevant feature, anticipating booking results in lower prices (Figure 12), as expected; nevertheless, scheduling more than a hundred days in advance seems to have a small effect on price fluctuation, whereas, as time goes by toward the date of reservation, the effect becomes more pronounced. Also, Sun, Law, and Tse (2016) have found that room prices practiced by Hong Kong hotels increase sharply a week prior to check-in, leading to hypothesize that a more mature market such as Hong Kong with...
high occupation rates acts on the price variable only closer to the predicted check-in date, whereas the Portuguese hospitality industry struggles more to attract tourists. Figure 13 shows the effect of the length of stay (the seventh most relevant feature, contributing with 5.42% of relevance) on price fluctuation. A lengthier stay implies a cost reduction on the price per day, as expected, since hotels invest in attracting tourists for longer periods to keep high occupancy rates. Nevertheless, recent published literature holds conflicting results: While Masiero, Nicolau, and Law (2015) support our finding, Riasi, Schwartz, Liu, and Li (2017) discovered that, on average, hotels charge more per night when the guests stay longer. However, the former study considered bookings in Switzerland, while the latter considered them in the United States. Hence, none of the results are directly comparable to the present study, where Portugal was the considered destination.
The Facebook score holds a relation to room price ranging between around €120 and €150 (Figure 14). It seems that Facebook’s users tend to be more demanding with more expensive hotels; also, experienced Facebook’s users are price sensitive (Best, 2014). Figure 15 shows that global brands offer lower prices, which is an unexpected result, considering branded hotels benefit from brand premium (Ivanov, 2014; Ivanova, Ivanov, & Magnini, 2016). Further studies on Portuguese branded hotels are required to understand this localized phenomenon.

**Conclusions, implications, and limitations**

The present research highlights that pricing encompasses a myriad of characteristics, with all the 29 combined features playing a role in modeling price. Nevertheless, TripAdvisor score was found to have the most significant relevance (almost 10%). Therefore, hotel managers can easily use it as a proxy to analyze the range of prices practiced by the competition without needing to perform a more demanding pricing analysis. There are some features directly

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**Figure 12.** Influence of the days ahead of reservation.

**Figure 13.** Influence of the length of stay.
controlled by hotels that managers believe to be an asset for which tourists are willing to pay more, such as holding an online payment system in their website, as well as some amenities; however, the latter seem to play a lesser relevant role in price definition than other features already widely studied in the literature, such as those related to the geographical location of the hotel (e.g., located in the city, or near a beach). Also, web visibility accounted for 15% of relevance when modeling prices. Clearly this is a confirmation that hotel managers are aware of the groundbreaking digital reality in today’s world and are adjusting prices accordingly. Although dynamic pricing has been practiced in the hospitality industry for a while, as it is possible to observe by the influence of the length of stay and the days ahead of reservation, it is imperative for hoteliers to incorporate social media customer feedback when evaluating revenue management, to reflect its impact on the practiced prices (Noone, 2016).

The present study has a few limitations that must be stated. The most relevant one is that, while the number of simulations is high, the built dataset cannot encompass all possible scenarios. An imposed limitation during the simulations was to set the age of children to 4 years old. Finally, this study is country based. Nevertheless, the procedure is replicable to any other geography; thus, a direction for future research is to build a price fluctuation model in other countries to understand how these behave.
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